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STOCHASTIC SIMULATION OF STEAM-FLOW AND ANALYSIS OF RESERVOIR SIZING

(A case study Conducted on Gidabo Dam Reservoir)

By

BY FREW HAILU

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4.	______________________ Chairman	______________ Signature	__________________ Date

ABSTRACT

This thesis is concerned with the problem of stochastic simulation of streamflow and reservoir sizing analysis in the Gidabo reservoir. Measso station with long record period of 29 years was used for the analysis. Four sets of time series models named, ARMA, PARMA (p,q) ,Thomas-Fiering and GAR(1) were tested and inter-compared for the performance in stochastic simulation of monthly stream-flow, accordingly a suitable model were selected.

PARMA models of low order are found to be most appropriate for Measso station than ARMA, Thomas–Fiering and GAR(1) model. The performance PARMA model has MD 0.94 and RRMSD 10.64. Therefore, long year sequence (fifty year) of synthetic flow were generated using PARMA (p,q) model and used for optimization the Gidabo reservoir system.

From the reservoir optimization analysis result it can be deduced that the required maximum capacity of the reservoir system in order to irrigate the potential land under the system without water stress, becomes 37.54MM3 provided that proper release rules are followed.

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ABBREVIATIONS

ARMA - Autoregressive Moving Average

ACF - Autocorrelation Function

PACF- Partial Autocorrelation Function

PARMA- Periodic Autoregressive Moving Average

AICC- Akakia Information Criteria Corrected

SIC- Schwarz Bayesian Criteria

WN- White Nose

SSE- Sum of Squares of Errors

n- Size of Sample

P- Order of Autoregressive

q- Order of Moving Average

k- Sum of P and q

Yν,τ- Stream-Flow Process for Year N and Season T

εν,τ - Uncorrelated Nose Term

δ2τ - Standard Deviation

GAMS - General Algebraic Modeling System

NLP-Non Linear Programing

SOP-Standard Operating Policy

OOP- Optimal Operating Policy.

MD-Mean Deviation

RRMSD-Relative Root Mean Square Deviation

GAR-Gama Auto Regressive Mode

1 INTRODUCTION

1.1 General

A fundamental problem both in design and operation of water resource systems is the appropriate consideration of the variability of the natural inflows. Stochastic models for these inflows are generally utilized for generation of equi-probable future sequences of inflows that preserve basic statistical characteristics of the historic series available that could influence the performance of the systems in the analysis. The generation of synthetic stream flow sequences are required because observed series of stream flows commonly do not include the most extreme cases of floods and cannot provide good estimates of risks involved in the operation of the systems. Generated hydrological sequences can be used in conjunction with simulation models to test and evaluate various proposed strategies for water resource systems or to optimize the sizing and operation of the systems (Oli Gretar B.S, 2014).

The time series is a time oriented or chronological sequence of observation to a variable of interest. The time series models are used to generate stochastic synthetic series variable of interest that may occur in the future. In hydrologic process, in particular, time series has been widely used for planning and management of water resource system, estimating the probability distribution of key decision parameters such as reservoir storage size, forecasting the natural inflow, water supplies and water demands.

Many conventional statistical methods have traditionally dealt with models in which the observations are assumed to be independent. However, a great deal of data in engineering and natural sciences occurs in the form of time series where observations are dependent. The systematic approach available for answering the mathematical and statistical questions posed by these series of dependent observations is called time series analysis.

The objective of time series analysis is generally to understand and identify the stochastic process that produced the observed series and then generate future values of a series from the past and present values alone (Akgun, 2003).

A number of different alternative models are available for modeling of hydrologic time series. The choice of the model should reflect its ability to reproduce important statistics of the process under consideration. The time series is said to be stationary if the statistical properties of the time series do not change with time, that is, the probability distribution of the process is the same at all times. Conversely, if any statistical property depends on time, then the process is non-stationary with regard to that statistical property.

Most parametric time series models assume that the process being modeled is normally distributed and stationary in the mean and variance. (Oli Gretar B.S, 2014)

Currently, due to the importance of hydrologic forecasting, a considerable number of forecasting models and methodologies have been developed and applied in stream flow forecasting.

In this study, Markov, ARIMA, PARMA and GRA (1) model have been selected and used in the modeling of monthly stream flow processes.

1.2 Problem Description

Due to the increasing population growth and resulting demands on limited water resources, an efficient management of existing water resources needs to be put in place for further use rather than building new facilities to meet the challenge. Hence, to combat water shortage issues, maximizing water management efficiency based on stream flow forecasting is crucial. Reliable flow generation is important for long term planning and water management of the reservoir system. However, the inaccurate generation of the stream flow will cause unnecessary bigger or smaller size of the reservoir.

The available steam flow data for Gidabo River at Measso gauging station near Gidabo reservoir is only 29 years flow data, but Gidabo reservoir is envisaged to irrigate for the coming 50 years. This shows a need to extend the inflow data up to the life of the project to see the month to month carry over the storage and size of the reservoir.

In this study, Thomas-Fierring model, ARMA, PARMA and GAR (1) model have been used for long term synthetic data generation and compare the model output with the observed sample flow in order to select best representative model and applied it for the optimized reservoir sizing of Gidabo reservoir.

1.3 Research Questions

- Which stochastic model is applicable to extend the available in flow accurately and reasonably?
- What is the optimal month to month water scheduling of the reservoir?
- What is the optimal size of the reservoir in order to account month to month carry over or water balance?

1.4 The objectives of the Study

The objectives of the study are:

The overall objective of the study is to select the best fit stochastic hydrological model for the generation of long-term inflow data for Gidabo Reservoir and to develop the optimized reservoir sizing.

Specific objective:-

- Identify the best fit stochastic hydrological model using the sample observed flows.
- To generate synthetic long term inflow data based on the best fitted stochastic hydrological model.
- Optimize the reservoir by applying the generated inflow.
- Establish water release guide curve or water scheduling for irrigation schemes.

1.5 Significance of the research

The observed data available at the gauging station are limited, to use this limited stream flow data to a reservoir operation management may cause significant error in the reservoir management and planning. Stochastic data generation aims to provide alternative hydrologic data sequences that are likely to occur in the future and also to assess the reliability of alternative systems in future system performances. In this study, a monthly stream flow for fifty year period are generated using a best representative stochastic hydrologic model and assess the reliability of the design of the Girdabo reservoir during the life span of the project.

1.6 Description of the Study Area

The Gidabo irrigation project is located in Abaya district, at the border Borena zone of Oromia region and Dale district, Sidama zone of SNNPRS near Dilla town to east of Lake Abaya. The project area approximately 756km from Addis Ababa lies between 6°20' and 6° 25' N and 38° 05' and 38°10'E. The Gidabo River has many perennial tributaries originated from the Sidama mountain peaks.

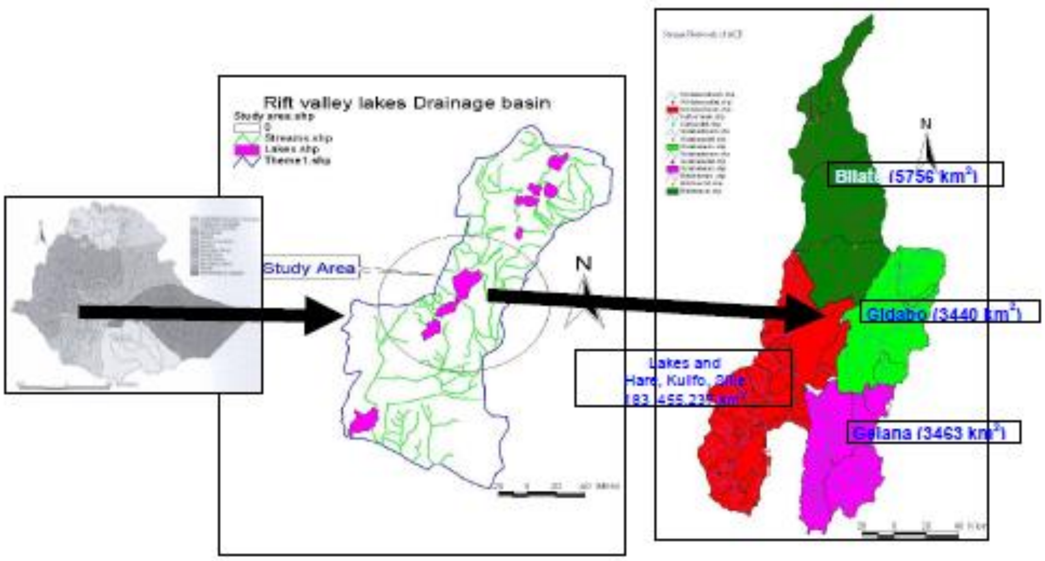


Figure 1-1 Location Map of Study Area

2 LITERATURE REVIEW

2.1 Stochastic Flow Generation

Many dynamic variables in hydrology are observed at more or less regular time intervals. Successive observations from a particular monitoring station observed at regular intervals are called a time series. A time series can either be viewed as real-valued discrete-time random function or a real-valued continuous-time random function that has been observed at discrete times (Marc F.P., Frans C., 2008).

Time series modeling of hydrologic processes has been widely used for planning and management of water resources systems. The time series models are used to generate stochastic synthetic series that may occur in the future, and the series are utilized for estimating the probability distribution of key decision parameters. For proper application of time series models for any hydrologic process, it is important to understand the underlying physical and stochastic mechanisms involved (Oli Gretar B.S, 2014).

The main reasons for analyzing hydrological time series are:

1. Characterization. This includes characteristics such as seasonal behavior and trend.
2. Prediction and forecasting. The aim of prediction and forecasting is to estimate the value of the time series of non-observed points in time.

A number of time series models have been considered in the literature for synthetic generation and forecasting of hydrologic processes. Parametric models are usually capable of preserving the historical statistics, such as the mean, variance, skewness, and covariance. Parametric methods usually assume that the process follows the normal distribution that can introduce biases when transforming generated series back into the original domain. (Oli Gretar B.S, 2014).

Many conventional statistical methods have traditionally dealt with models in which the observations are assumed to be independent. However, a great deal of data in engineering and natural sciences occurs in the form of time series where observations are dependent. The systematic approach available for answering the mathematical and statistical questions posed by these series of dependent observations is called time series analysis.

The objective of time series analysis is generally to understand and identify the stochastic process that produced the observed series and then generate future values of a series from the past and present values alone (Akgun, 2003)

2.1.1 Discrete stationary time series

Most hydrological variables, like river stages, are continuous in time. If we consider the variable Z (t) at regular intervals in time t, the values of the continuous time series at the regular time intervals are:

$$\mathbf{Z}_\mathbf{k} = \mathbf{Z}(k\Delta t) \qquad k = -\infty, \cdots, -1, 0, 1, \cdots, \infty \tag{2.1}$$

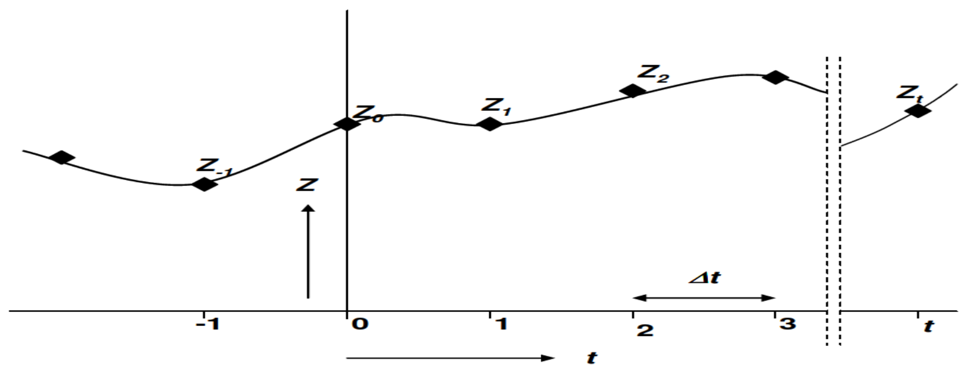


Figure 2-1 schematic of the continues random function observed at discrete times *Z (t)*

The series Zk is called a discrete time series. In the time series literature often the subscript t is used instead of the subscript k.

$$Z_t = \qquad t = -\infty, \cdots, -1, 0, 1, \cdots, \infty \tag{2.2}$$

2.1.2 Moments and Expectation

A single time series is considered to be a stochastic process that can be characterized by its central statistical moments (David Ruppert, 2011). In particular the first and second order moments are relevant: the mean value, the variance and the autocorrelation function. For a statistical stationary process the mean value and the variance are defined by:

$$\mu_z = E(z_t) \tag{2.3}$$

$$\sigma_z^2 = VAR(z_t) = E[(z_t - \mu_z)(z_t - \mu_z)] \quad \textbf{(2.4)}$$

The auto-covariance is a measure of the relationship of the process at two points in time. For two points in time k time steps apart, the auto-covariance is defined by:

$$\text{cov}(z_t, z_{t+k}) = E[(z_t - \mu_z)(z_{t+k} - \mu_z)] \quad \textbf{(2.5)}$$

Often k is called the time lag.

I. Note that for $\text{k} = 0$, $\text{cov}(z_t, z_{t+k}) = \sigma_z^2 = VAR(z_t)$ **(2.6)**

II. Note that $\text{cov}(z_t, z_{t+k}) = \text{cov}(z_{t+k}, z_t) = \text{cov}(z_t, z_{t-k})$ **(2.7)**

2.1.3 Stationary time series

If the statistics of the sample (mean, variance, and covariance) are not functions of the timing or the length of the sample, then the time series is said to be stationary to the second order moment or stationary in the broad sense. Mathematically, one can write as:

$$E(y_t) = \mu, \qquad VAR(y_t) = \sigma^2, and\ COV(y_t, y_{t+k}) = \lambda_k \quad \textbf{(2.8)}$$

In hydrology, moments of the third and higher orders are rarely considered because of unreliability of in their estimates. Second order stationarity, also called covariance stationarity, is usually sufficient in hydrologic time series analysis. A process is strictly stationary when the distribution of X_t does not depend on time and when all simultaneous distributions of the random variables of the process are only dependent on their mutual time-lag. In other words, a process is said to be strictly stationary if its n^{th} (n for any integers) order moments do not depend on time and are dependent only on their time lag. (Chong-Yu Xu, 2002).

2.1.4 Non-stationary time series

If the values of the statistics of the sample (mean, variance, covariance, etc…) are dependent on the timing or the length of the sample, then it is called a non-stationary series. (Chong-yu Xu, 2002). Periodicity in a series means that it is non-stationary. Mathematically, one can write as:

$$E(y_t) = \mu_t, \qquad VAR(y_t) = \sigma_t^2, and\ COV(y_t, y_{t+k}) = \lambda_{k,t} \tag{2.9}$$

2.1.5 Gaussian time series

A Gaussian random process is a process (not necessarily stationary) of which all random variables are normally distributed, and of which all simultaneous distributions of random variables of the process are normal. When a Gaussian random process is strictly stationary, the normal distribution is completely characterized by its first and second order moments. (Chong-Yu Xu, 2002)

2.1.6 Properties of Hydrologic Time Series

Statistical analysis of hydrologic time series involves calculation of basic statistic, estimating the autocorrelation function (ACF), partial ACF (PACF), the seasonal structure, and plotting the time series.. The time series may be tested for normality, trends, and shifts and transformed to normal if necessary. (Oli Gretar B.S, 2014).

2.1.6.1 Mean, Variance, and Skewness

The descriptive basic sample statistics of a time series y_t of length N are the mean, standard deviation, and skewness $\{\bar{y};\ S;\ g\}$ defined by:

$$\bar{y} = \frac{\sum_{t=1}^{N} y_t}{N} \ , S^2 = \frac{\sum_{t=1}^{N}(y_t - \bar{y})^2}{N} \quad , \ g = \frac{(\frac{1}{N})\sum_{i=1}^{N}(y_t - \bar{y})^3}{S^3} \tag{2.10}$$

Where, $\bar{y}$ is a measure of location, S is a measure of spread and g is a measure of the shape. The corresponding population statistics are denoted by$\{\mu;\ \sigma;\ \gamma\}$.

2.1.6.2 ACF and PACF

The lag-k ACF (k) = ρ_k with the corresponding sample estimators r_k is simply the cross-correlation between consecutive values of the process at lag-k:

$$r_k = \frac{c_k}{c_0} = \frac{\frac{1}{N-K}\sum_{t=1}^{N-k}(x_t - \overline{x})(x_{t+k} - \overline{x})}{S^2} \tag{2.11}$$

Where c_k is the lag-k sample autocovariance with c_0 = S^2. The corresponding population auto covariance function, ACVF(k), is $c_k = E(y_{t+k}, y_t) = [(y_{t+k} - \mu)(y_t - \mu)$.

The plot of the ACF versus k is referred to as a correlogram, where a quickly decaying correlogram to zero represents the short memory of the process while a slowly decaying correlogram to zero represents a long memory process often referred to as persistence or storage effect.

The PACF is also a measure of serial dependence like the ACF but with all autocorrelations within the specified lag (i.e. 1 to $k - 1$) partial out. The PACF from a sample time series is estimated by repeatedly fitting AR (p) models of the time series, where the PACF at lag p is equivalent to ϕ_p in the fitted AR (p) model.

Approximate confidence intervals for both the ACF and PACF of a white noise process at the α significance level are $z_{1-\alpha/2}/N^{0.5}$ where z is the quintile of the standard N (0,1) distribution, that is, approximate 95% confidence intervals are estimated by $^{1.96}/_{N^{0.5}}$. (David Ruppert, 2011).

Anderson (1942) determined probability limits for the correlogram of independent series as follows: Anderson (1942) gave the following limits with 95% and 99% probability levels: (Karamouz, S. Nazif, M. Falahi, 2013)

$$r_k(95\%) = \frac{-1 \pm 1.96\sqrt{N-K-1}}{N-K} \tag{2.12}$$

And

$$r_k(99\%) = \frac{-1 \pm 2.326\sqrt{N-K-1}}{N-K} \tag{2.13}$$

for the 95 percent and 99 percent probability level respectively and N is sample size.

2.1.7 Discrete White Noise Process

An important class of time series is the discrete white noise process ε_t. This is a zero mean time series with a Gaussian probability distribution and no correlation in time.

$$E(\varepsilon_t) = 0 \tag{2.14}$$

$$E[\varepsilon_t, \varepsilon_{t+k}] = \begin{cases} \sigma_\varepsilon^2 & if \;\; k = 0 \\ o & if \; k \neq 0 \end{cases} \tag{2.15}$$

Because of the absence of correlation in time, the discrete white noise process at time step t does not contain any information about the process at other time steps.

2.1.8 Components of a Hydrologic Time Series

The main components of a hydrologic time series are as follows:

1. Trend: This is a unidirectional and gradual change (increasing or decreasing) in the time series average value. The trend is smooth and deterministic, and it can be modeled by a continuous and differentiable function of time.
2. Jump: This is a sudden change in the time series in positive or negative direction caused commonly by human activities and natural disruptions.
3. Periodicity: This refers to the cyclic variations in the hydrologic time series. These variations are repeated at fixed intervals.
4. Randomness: These variations are the result of the uncertain nature of the stochastic process. This component of the hydrologic time series can be autoregressive or purely random.

Statistical modeling of time series, it is assumed that the time series is purely random. Therefore, different steps should be taken to remove trends, jumps, and periodicity of the data. (Karamouz, S. Nazif, M. Falahi, 2013).

2.1.9 Time Series Modeling

A number of different alternative models are available for modeling of hydrologic time series. The choice of the model should reflect its ability to reproduce important statistics of the process under consideration. If any statistical property depends on time, then the process is non-stationary with regard to that statistical property. Most parametric time series models assume that the process being modeled is normally distributed and stationary in the mean and variance. (Karamouz, S. Nazif, M. Falahi, 2013).

A systematic approach to hydrologic time series modeling consist of the following main steps (Karamouz, S. Nazif, M. Falahi, 2013)

1. Data preparation: Removing trends, periodicity, outlying observations, and fitting the data to a normal distribution by applying proper transformations.
2. Identification of model composition: In this step, it should be decided whether a univariate or a multivariate model, or a combination of each of these models with disaggregation models should be used. This decision can be taken based on the characteristics of the hydrologic system and availability data.
3. Identification of model type: Different types of models such as autoregressive (AR), autoregressive moving average (ARMA), and autoregressive integrated moving average (ARIMA) as well as GARCH can be selected in this step. Statistical characteristics of the time series and the modeler input and knowledge about different types of models are the key factors in identification of model type.
4. Identification of model form: Form of the selected model should be defined based on the statistical characteristics of the time series. The periodicity of the data and how it can be considered in the structure of the selected model is the main issue in this step
5. Estimation of model parameters: Different methods such as method of moments and method of maximum likelihood can be used for estimating the model parameters.
6. Testing the goodness of fit of the model: In this step, different assumptions, such as independence and normality of residuals should be checked. Different statistics are used for verifying these assumptions,

7. Evaluation of uncertainties: In evaluating the uncertainties, model, parameter, and natural uncertainties in data should be analyzed separately. Model and parameter uncertainties should be evaluated in this step. Model uncertainty may be evaluated by testing whether significant differences in the statistics generated by alternative models exist. Parameter uncertainty may be determined by finding the distribution of parameter estimates, and by using the models with parameters sampled from such distributions.

2.1.10 Model Selection

Often several alternative models may be fitted to the data. The ACF and PACF are often used to get an idea of the appropriate model to fit, and the model with the minimum residual variance is often selected as the best model. This does not penalize for number of parameters and a common practice is to use information criteria for selecting the best model penalizing for the number of parameters used in the model. The corrected Akaike information criterion (AICC) and the Schwarz information criterion (SIC) also referred to as the Bayesian information criterion are defined as

$$\mathrm{AICC} = \mathrm{n} \ln \sigma^2(\varepsilon) + \mathrm{n} + \frac{2(\mathrm{k}+1)\mathrm{n}}{\mathrm{n}-\mathrm{k}-2}\ ;\ \mathrm{SIC} = \mathrm{n} \ln \sigma_\varepsilon^2 + \mathrm{n} + \mathrm{k} \ln \mathrm{n} \qquad \textbf{(2.16)}$$

Where n is the size of the sample used for fitting the model, k is the number of parameters excluding constant terms (k = p + q for the ARMA (p,q) model) and σ_ε^2 is the maximum likelihood estimate of the residual variance.

The AICC statistic is efficient but not consistent and is good for small samples, but tends to over fit for large samples and large k. The SIC is consistent but not efficient and is good for large samples, but tends to under fit for small samples. Efficiency is usually more important than consistency since the true model order is not known for real-world data (Oli Gretar B.S, 2014)

2.1.11 Model Testing

All the sample information on lack of fit is contained in the residuals. In most time series models, the residuals are assumed to be normally distributed with mean zero and varianceσ_ε^2. Thus, a plot of the residuals should look like an independent drawing from the normal distribution. The residuals should be uncorrelated with zero ACF and PACF and also independent of the explanatory variables used in the model. Non-normal residuals may indicate lack of transformation of the data, while correlated residuals with nonzero terms in the ACF and PACF may indicate that a higher-order model is needed. In addition, synthetically simulated series from the model of the same length as the historical series should be capable of approximately reproducing the historical statistical properties of the original time series. (Oli Gretar B.S, 2014)

2.1.12 Univariate Modeling

2.1.12.1 ARMA

A time series is a time-oriented or chronological sequence of observations on a variable of interest (Montgomery et al., 2008). Time series models have become popular in recent years since the publication of the book by Box and Jenkins (1970), and the subsequent development of computer software for applying these models (Mohd 2012). The time can be a discrete value, a time interval or a continuous function, Stationary ARMA models have become widely used for modeling of hydrologic time series and in particular of precipitation and stream-flow. The ARMA models are flexible and can accommodate features of alternative models such as fractional Gaussian noise, broken line, and shifting mean (SM). The ARMA (p, q) of AR order p and moving average order q for a hydrologic process is defined as

$$y_t = \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \Theta q \, \varepsilon_{t-q}$$

$$y_t = \sum_{i}^{p} \phi_i y_{t-i} + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{j-1}$$

Which is rewritten as:

$$(1 - \phi_1 B + \cdots + \phi_p B^P)\, y_t = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \Theta q \, B^q)\varepsilon_t$$

$$\phi(B)\, y_t = \theta(B)\varepsilon_t \quad \textbf{(2.17)}$$

Where

y_t is normally distributed with mean zero and variance $\sigma^2(y)$

ε_t is the independent normally distributed noise term with variance $\sigma^2(\varepsilon)$

$\{\phi_1, \ldots, \phi_p\}$ and $\{\theta_1, \ldots, \theta_p\}$ are the AR and MA parameters, respectively

ε_t is uncorrelated with y_{t-1}, that is, the noise is independent of past observations

2.1.12.2 PAR MA

For seasonal hydrologic time series, such as a 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 by subtracting the seasonal mean and dividing by the seasonal standard deviation (Salas, 2007)

However, this procedure assumes that season-to-season correlations are the same throughout the year for a given lag and thus do not preserve the seasonality in the covariance structure. 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 modeling such periodic dependence structure. A PARMA (p, q) model may be expressed as

$$y_{\nu,\tau} = \sum_{i}^{p} \phi_i y_{\nu,i-1} + \varepsilon_{\nu,\tau} - \sum_{j}^{q} \theta_i y_{\nu,j-1} \quad \textbf{(2.18)}$$

Where

$y_{\nu,\tau}$ Represents the hydrologic process for year ν and season τ

The $\varepsilon_{\nu,\tau}$ is the uncorrelated noise term that for each season is normally distributed with mean zero and variance $\sigma^2(\varepsilon)$

The $\{\phi_{1,\tau}, \dots, \phi_{p,\tau}\}$ and $\{\theta_{1,\tau}, \dots, \theta_{p,\tau}\}$ are the periodic AR and MA parameters

If the number of seasons is ω, then a PARMA (p, q) model consists of ω-number of individual ARMA (p, q) models, where the dependence is across seasons instead of years. In most practical applications, PAR (1), PAR (2), and PARMA (1, 1) have been found to be adequate, although residuals should always be tested to ensure adequate model fit.

There are two options, either to fit a PARMA model with periodic parameters to the data in (a) and (b) or to fit an ARMA model to the seasonally standardized data. The ARMA model would not be able to reproduce seasonality in higher-order moments such as skewness and kurtosis.

Despite this, an ARMA model could prove sufficient if it is not considered important to reproduce those seasonalities, which the PARMA model is capable of doing.

2.1.12.3 Markov (Thomas-Fiering) Model

The monthly flow series are non-stationary and therefore complicated mathematical models are employed in their simulation. The first model that appeared in the hydrology literature for the generation of synthetic monthly flow sequences is that due to Thomas & Fiering (1962). Basically, this model is of a Markovian nature with periodic parameters, namely, the monthly means, standard deviations and the lag-zero cross correlations between successive months. In its simplest form the model consists of twelve regression equations, one for each month. The model implicitly allows for the non-stationarity observed in monthly flow data.

The first order Markov model assumes that the process is stationary in its first three moments. It is possible to generalize the model so that the periodicity in hydrologic data is accounted for to some extent. The main application of this generalization has been in generating monthly streamflow where pronounced seasonality in the monthly flows exists. In its simplest form, the method consists of the use of twelve linear regression equations. If, say, twelve years of record are available, the twelve January flows and the twelve December flows are abstracted and January flow is regressed upon December flow; similarly, February flow is regressed upon January flow, and so on for each month of the year (Chong-Yu Xu, 2002).

$$q_{jan} = \overline{q}_{jan} + b_{jan}(q_{dec} - \overline{q}_{dec}) + t_{jan}S_{jan}(1-\gamma_{dec})^{\frac{1}{2}}$$

$$q_{feb} = \overline{q}_{feb} + b_{feb}\left(q_{jan} - \overline{q}_{jan}\right) + t_{feb}S_{feb}(1-\gamma_{jan})^{\frac{1}{2}}$$

$$\dots\dots\dots\dots\dots.. \tag{2.19}$$

The Thomas Feiring Model considers that the value of an event (i.e. stream flow) at one time correlates with the value of the event of an earlier period (i.e. a serial or autocorrelation exists in the time series). In a first-order Markov process, this correlation exists in two successive values of the events. The first order Markov model, which constitutes the classic approach in synthetic hydrology, states that the value of a variable x in one time period is dependent on the value of x in the preceding time period plus a random component.

If the Markov model's parameters are estimated from data, the standard maximum likelihood estimates consider the first order (single step) transitions only. But for many problems, the first order conditional independence assumptions are not satisfied as a result of the higher order transition probabilities can be poorly approximated by the learned model (Joomizan, 2010).

$$q_{i,j} = \overline{q}_j + b_j \left(q_{i-1,j-1} - \overline{q}_{j-1} \right) + t_{i,j} S_j \left(1 - \gamma_{j-1}\right)^{\frac{1}{2}} \quad \textbf{(2.20)}$$

2.1.12.4 Univariate GAR (1)

The gamma-autoregressive model GAR (1) is similar to the well-known AR (1) model except that the underlying process being modeled is assumed to follow the gamma distribution instead of the normal distribution. Thus, if the intent is to use the GAR (1) model, then the underlying data should not be transformed to normal. The GAR (1) model can be expressed as (Salas, 2007).

$$x_t = \emptyset x_{t-1} + \varepsilon_t \quad \textbf{(2.21)}$$

Where X_t is a gamma variable defined at time t, ϕ is the auto regression coefficient, and ε_t is the independent noise term. X_t is a three-parameter gamma distributed variable with a marginal density function given by:

$$f_x(x) = \frac{\alpha^{\beta} (x-\lambda)^{\beta-1} exp^{[-\alpha(x-\lambda)]}}{\Gamma(\beta)} \quad \textbf{(2.22)}$$

Where λ, α, *and* β are the location, scale, and shape parameters, respectively. Lawrence (1982) found that the independent noise term, ε_t, can be obtained by the following scheme:

$$\varepsilon = \lambda(1-\phi) + \eta \quad where \quad \begin{cases} \eta = 0 \quad , & if\ m = 0 \\ \eta = \sum_{j=1}^{m} y_j \phi^{u_j} , & if\ m > 0 \end{cases} \quad \textbf{(2.23)}$$

Where M is an integer random variable distributed as a Poisson with mean [- β ln (ϕ)], U_j, j =1,2,.... are independent identically distributed (*iid*) random variables with uniform (0,1) distribution, and, Y_j, j =1,2, ...are *iid* random variables distributed as exponential with mean (1/α). The stationary GAR (1) process of Eq. (2.21) has four parameters, namely {ϕ, λ, α, β}. The model parameters are estimated based on a procedure suggested by Fernandez and Salas (Salas, 2007), as illustrated as,

$$\mu = \lambda + \frac{\beta}{\alpha} \qquad \textbf{(2.24)}$$

$$\sigma^2 = \frac{\beta}{\alpha^2} \qquad \textbf{(2.25)}$$

$$\gamma = \frac{2}{\sqrt{\beta}} \qquad \textbf{(2.26)}$$

$$\rho_1 = \phi \qquad \textbf{(2.27)}$$

Where μ, σ_2, γ and ρ_1 are the mean, variance, skewness coefficient, and the lag-one autocorrelation coefficient, respectively.

Estimation of the parameters of the GAR (1) model is based on extensive simulation experiments conducted by Fernandez and Salas (Salas, 2007). These studies suggest the following estimation procedure for the four parameters {ϕ, λ, α, β}. First the sample moments are corrected to ensure unbiased parameter estimates:

$$\hat{\sigma}^2 = s^2 \frac{N-1}{N-k} \qquad \textbf{(2.28)}$$

$$\hat{\rho}_1 = \frac{r_1 N + 1}{N-4} \qquad \textbf{(2.29)}$$

$$\boldsymbol{k} = \frac{\boldsymbol{N\left(1-\hat{\sigma}^2\right) - 2\hat{\rho}_1(1-\hat{\rho}_1{}^N}}{\boldsymbol{N(1-\hat{\rho}_1)^2}} \qquad \textbf{(2.30)}$$

In which r_1 is the lag-1 sample autocorrelation coefficient and s_2 is the sample variance. In addition,

$$\hat{\gamma} = \frac{\hat{\gamma}_0}{1 - 3.1\hat{\rho}_1{}^{3.7}N^{-0.49}} \tag{2.31}$$

Where $\hat{\gamma}_0$ is the skewness coefficient suggested by Bobee and Robitaille (1975) as

$$\hat{\gamma}_0 = \frac{L.g}{\sqrt{N}}\left[A + B\,\frac{L^2 g^2}{N}\right] \tag{2.32}$$

$$A = 1 + \frac{6.51}{N} + \frac{20.2}{N^2} \tag{2.33}$$

$$B = \frac{1.48}{N} + \frac{6.77}{N^2} \tag{2.34}$$

$$\boldsymbol{L} = \frac{\boldsymbol{N-2}}{\sqrt{\boldsymbol{N-1}}} \tag{2.35}$$

respectively. Furthermore, the mean is estimated by the usual sample mean *x*. Therefore, substituting the population statistics μ, σ_2, γ and ρ_1 in the above equation by the corresponding estimates *x*, σˆ2, λˆ, and ρ_1ˆ as above suggested and solving the equations simultaneously give the MOM estimates of the GAR (1) model parameters Fernandez and Salas (Salas, 2007).

2.1.13 Estimation of model parameters

Estimation methods include

1. Method of moments,
2. Least squares, and
3. Maximum likelihood.

2.1.13.1 Method of Moment

The expected value E [x] of a random variable x is called the first population moment of x. In general the expected value E [xr] is the rth population moment of x. Similarly, when dealing with sample x1, x2,…, Xn, the rth sample moment is defined by

$$m^r = \frac{1}{n}\sum x_i^r \qquad \textbf{(2.36)}$$

If the random variable X represents a time series given by a model with parameter α1,…, αp, the population moment is the function of those parameters. Therefore, the moment parameter estimate is obtained by equating population moment and sample moment. If p is the number parameter to estimate, then the first p population and sample moment must be equated and solved simultaneously (Marc F.P., Frans C., 2008).

2.1.13.2 Method of Least Squares

Consider that the model of a sample time series y1, y2,…, yn is yt= f (yt-1, yt-2,…, α1,…, αp) + εt where α1,…, αp are parameters and εt is the residual or error series which has zero mean . The least squares estimating method is based on finding the estimate α1… α1 so that the sum of the squared difference between the observed values y1,…, yn and the estimated expected value yt= f (yt-1, yt-2,…, α1,…, αp) t=1…, N, respectively is minimized. That is α1,…, αp should be chosen to minimize

$$\sum_{t=1}^{N} \varepsilon_t^2 = (y_t - \overline{y_t})^2 = \sum_{t=1}^{N}\left[y_t - f\left(y_{t-1}, \dots, \overline{\alpha_1} \dots \overline{\alpha_p}\right)\right] \qquad \textbf{(2.37)}$$

To find the minimum of the sum, all the partial derivatives of the sum with respect to $\overline{\alpha_1}, \dots, \overline{\alpha_p}$ must be zero. That is

$$\frac{\delta\ \sum_{t=1}^{N}(y_t - \overline{y_t})^2}{\delta\ \overline{\alpha_1}}, \dots, \frac{\delta\ \sum_{t=1}^{N}(y_t - \overline{y_t})^2}{\delta\ \overline{\alpha_p}} = 0 \qquad \textbf{(2.38)}$$

These p equations with p unknown must be solved simultaneously to obtain the parameter estimate $\overline{\alpha_1} \ldots \overline{\alpha_p}$. These parameters are efficient when certain conditions are satisfied (Karamouz, S. Nazif, M. Falahi, 2013)).

2.1.14 Generation and Forecasting

The two major uses and application of modeling hydrologic time series is the generation of synthetic samples (as potential future inputs of water resource systems) and the forecast of hydrologic events.

The modeling of hydrologic time series always reduces it to a noise or independent stochastic component, this approach often called whitening process because it always leads to what is known as white noise. It is ideal for ε to be a white noise, or independent, stationary normal variable.

In such a case, the generation of synthetic time series will start with generation of independent normal variable with mean zero and variance one, then adding the time and special dependence structure as well as periodic components.

The generation of normal independent random number is presented in many standard books which treats the Monte Carlo (sample generation) techniques and similarly, various computer programs are readily available for generating these numbers.

For a single time series, once the independent normal random number is generated, the time series can be readily generated by adding the other component of the model with the corresponding estimated parameters.

2.2 RESERVOIR SIZING

Deciding among alternative course of action is fundamental to water resource engineering as well as too many other aspects of our lives. A broad spectrum of analytical methodologies has been developed to provide a systematic quantitative basis for decision making. Linear and nonlinear programing are used to develop simulation and optimization models to support project selection, reservoir system sizing, water allocation, pollution load allocation, and other water resource planning and management decisions (Ralph A. & Wesley P. ,2014)

A reservoir is a storage structure that stores water in a period of excess flow (over demand) in order to enable a regulation of the storage to best meet the specified demands. Modeling a reservoir system, and assumption one may use to make the model formulation simple enough problem solving known techniques in system analysis. (S Vedula & PP Mujumdar, 2006)

There are two basic approaches for solving and analysis of operating procedures: simulation and optimization.

2.2.1 Simulation

A Simulation model is a representation of a system used to predict its behavior under a given set of condition. Simulation is the process of experimenting the model to analyze the performance of the system under various conditions. Alternative execution of the simulation model is made to analyses alternative plans. (Ralph A. & Wesley P. ,2014)

Simulation relies on trial –and–error to identify near optimal solutions. The search for an optimal alternative is dependent on the engineer's ability to manipulate design variables and operating policies in an efficient manner. There may be no guarantee that a globally optimal alternative is found.

Simulation is not an optimizing procedure. Rather, for any set of design and operating policy parameter values, it merely provides a rapid means for evaluating the anticipated performance of the system. It is necessary for the analyst to specify the trial design (or, equivalently, to allow the computer to do so in accordance with some algorithm), whereupon the simulation model yields estimates of the economic, environmental, and other responses associated with that trial. Simulation methods do not identify the optimal design and operating policy, but they are an excellent means of evaluating the expected performance resulting from any design and operating policy. Hence, they are often used to assist water resource planners in evaluating those designs and operating policies defined by simpler optimization models. (S Vedula & PP Mujumdar, 2006)

2.2.2 Optimization

Optimization is the process of determining the best plan. Optimization includes human judgment use of simulation and or optimization models and use of other decision support tools. A discrete number of plans may be evaluated based on the results of simulating each plan.

The term optimization models is often used, synonymously with mathematical programing, to refer to a mathematical formulation in which a formal algorithm is used to compute a set of decision variable values that minimize or maximize an objective function subject to a given set of constraints. Optimization model automatically search for an optimal decision policy.

Optimization and simulation are two different but overlapping modeling approaches. Many models contain elements of both approaches. Optimization models also simulate the system. Mathematical programming algorithms are often used to perform computation within simulation models (Ralph A. & Wesley P. ,2014)

Mathematical programming has been used to improve the efficiency and reliability of reservoir operations since the 1940s (Masse, 1946; Little, 1955; Yakowitz, 1982; Yeh, 1985; Kirshen and Ginnetti, 1985; Labadie, 2001; McCartney, 2007). Loucks et al. (1981) describe the classic reservoir system optimization problem in which mathematical programming is used to find the optimal set of releases given a description of inflows to a single reservoir.

The three components of a mathematical programming problem are

(1) Decision variables, which are solved to maximize or minimize

(2) Objective functions, and are subject to a set of

(3) Constraints.

- Decision variables: - variable that can be controlled; these are variables for which optimum values are to be determined,
- Decision policy: - each decision variable is assigned a value; a decision policy is a set of values for the decision variables.
- Constraints: - limitation or restriction on possible decision policies
- Feasible policy: - a decision policy that does not violate any constraint.
- Infeasible policy: - a decision policy that violates one or more constraints
- Objective functions: - is a criterion by which optimum is defined and may also be called a criteria function.
- Optimal solution: - a feasible decision policy that optimizes (minimize or maximize) the objective function. (Ralph A. & Wesley P. ,2014)

The most commonly used optimization techniques in water resource problems are Langrage Multipliers, Linear Programming, Non-linear Programming, Dynamic Programming, Quadratic Programming and Geometric Programming. Each of these is highly dependent on the mathematical structure of the model. The choice of techniques usually depends on the characteristics of the reservoir system, on the availability of data, on the objective and constraints specified. Due to its primary relevance for this study only Non-linear programing is briefly explained below.

2.2.3 Nonlinear Programming

Nonlinear programming (NLP) algorithms, such as quadratic programming, geometric programming, and separable programming provide a more general mathematical formulation than LP but the mathematics involved is much more complicated. The NLP techniques have been applied relatively little to problems of optimizing reservoir system sizing. The significant advancements in computer technology in recent years have removed computational constraints which could result in greater use of NLP in the future. Model formulations for two important aspects of reservoir modeling are reservoir sizing.

Nonlinear programming consists of minimizing or maximizing a linear or a nonlinear objective function subject to a set of one or more non-linear constraints.

2.2.3.1 Reservoir Sizing

The annual demand for water at particular sites may be less than the total inflow there, but the time distribution of the demand may not match the time distribution of inflow, resulting in surplus in some period and deficits in some other period of the year. A reservoir serves the purpose of temporarily storing water in periods of excess inflows and releasing it in a period of low flow so that the demand may be met in all periods. The problem of reservoir sizing involves determination of the required storage capacity of the reservoir when the inflow and demand in a sequence of period are given. The total storage can be divided into three components: dead storage (for accumulation of sediments), active storage (for conservation purpose such as irrigation, water supply and hydropower production), and flood storage (for reducing flood peak). (S Vedula & PP Mujumdar, 2006)

3 METHODOLOGY

3.1 Data Processing

3.1.1 Removing Data Trend

The principal assumption in using statistical models for hydrologic time series is that the data is considered as purely random. Therefore, if the series contains unnatural components such as trend, they should be first removed. The time series plot can be used to detect whether there is trend and seasonality in the data. The sample autocorrelation functions show the trend and seasonality. If the sample autocorrelation functions are slowly decaying show the existence of trends in the data. If the sample autocorrelation functions are nearly periodic show the existence of seasonality in the data. Using the above method, time series can be decomposed into trend, seasonality (if it is available), and random components. Widely used method in modeling of time series for removing trend from the data is differencing, especially differencing the time series at lag-1 is a widely used form for trend removal. Lag-1 differencing was mainly related to the family of non-stationary autoregressive integrated moving average (ARIMA) models.

3.1.2 Removal Jump

Jump or slippage in hydrological time series mainly happened due to systematic error or inhomogeneity caused by humans. It also occurs gradually by natural phenomena or rapidly by building dams and water diversions. The values with considerable distance from the mean value should be checked as being a jump. Values with more than 3σ (standard deviation) from the mean can be considered as a jump. If these values are not continued and occurs for a very short time, they must be taken away from time series data being considered as outliers. The removed data can be replaced with the long-term average, the average of two adjacent values or other logical values if the complete time series is needed.

3.1.3 Periodicity (seasonality)

The repetition of a periodic component in time series data is mainly because of the periodicity of day and night, seasons, and years. Periodicity means that statistical specifications vary periodically with time. In monthly data showing a 12 month periodic structure, each month has its own mean and variance. The seasonality in the mean and variance is removed for each season by seasonal standardization which mean subtracting the seasonal mean and dividing by the seasonal standard deviation for each season by

$$Z_{\upsilon,\tau} = \frac{x_{\upsilon,\tau} - \bar{x}_{\tau}}{s_{\tau}} \quad \textbf{(3.1)}$$

Where $z_{\nu,\tau}$ is normally distributed variable with standard deviation one and mean zero for year ν of the seasonal series for season τ. (Oli Gretar B.S, 2014).

3.1.4 Time series memory

The long-term memory of time series is defined based on the frequency of the extreme events during the time of study. During hydrological analysis used for the design of water resources, the time series with a length of 500 to 1000 are produced to involve the expected number of extreme events in the time series. The long-term wet and dry periods that are observed in these long-term series highly affect the design and planning of water resources. Analysis of frequency or long-term memory of time series is considered against the short-term memory. To analyze the adequacy of the considered length of time series, the Hurst coefficient can be employed,

3.1.4.1 Hurst Coefficient

The Hurst coefficient is a measure for checking the adequacy of the length of considered time series. In other words, it determines the long-term memory of a time series. Hurst et al. (1965) used this measure for the first time for evaluating the adequacy of the length of river flow time series in reservoir simulation. This measure determines if the considered length of data involves all of the expected extreme events or not. If the series involves the expected extreme events, it can be used in designs that are based on extreme events; otherwise, the appropriate methods should be used to expand the data length (Karamouz, S. Nazif, M. Falahi, 2013). The Hurst coefficient is estimated as follows:

$$k = \frac{\log(R/\sigma)}{\log(N/2)} \quad \textbf{(3.2)}$$

Where N is the number of data in the considered time series and σ is the standard deviation of the series. R is called range, and it shows the highest surplus and lowest deficit compared to a target release (i.e. average mean flow). R is estimated as follows:

$$R = S^{+} - S^{-} \tag{3.3}$$

Where S+ is the maximum positive cumulative distance from the mean value of the time series and S− is the maximum negative cumulative distance from the mean value of the time series. The values of S are calculated at each time step, Sn, as follows:

$$S_n = \sum_{k=1}^{n} (x_n - \bar{x}) \tag{3.4}$$

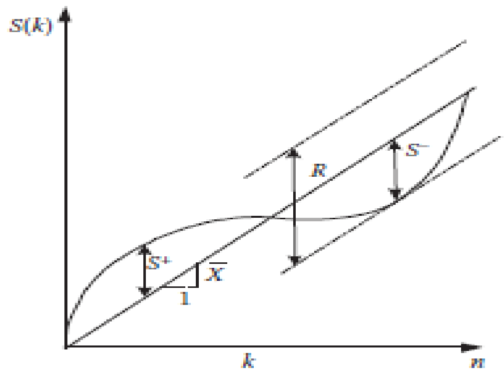


Figure 3-1 Estimation of Hurst Coefficient Parameters

A number of different alternative models are available for modeling of hydrologic time series. The choice of the model should reflect its ability to reproduce important statistics of the process under consideration. The time series is said to be stationary if the statistical properties of the time series do not change with time, that is, the probability distribution of the process is the same at all times. Conversely, if any statistical property depends on time, then the process is non-stationary with regard to that statistical property. Most parametric time series models assume that the process being modeled is normally distributed and stationary in the mean and variance.

3.1.5 Tests of Normality

Plotting the empirical cumulative distribution function (CDF) on a normal probability paper based on selected plotting position formula provides a nonparametric way of visually checking if the data plots as a straight line and conforms to the normal distribution (Q–Q plot). Commonly used plotting position formulas of non-exceedance probabilities for a time series of length N ordered from the smallest to the largest are Cunnane $(i - 0.4)/(N + 0.2)$, Hazen $(i - 0.5)/N$, and

Weibull $i/(N + 1)$ for i = 1,…, N. Probability plot correlation tests of normality are available for different plotting positions with the Filliben probability plot correlation coefficient test of normality being the most popular one. Other tests include the skewness test of normality for testing the hypothesis of zero skewness. The sample skewness g in equation (2.10) is asymptotically distributed as N (0, $\sigma^2 = 6/N$) The null hypothesis H0: g = 0 versus H1: g ≠ 0 is rejected at the α-significance level if ABS (g) > $z_{1-\alpha/2}\sqrt{6/N}$. (Oli Gretar B.S, 2014)

3.1.6 Transformation to Normal

Most time series models assume that the underlying process is normally distributed. Time series failing a normality test can be transformed to normal using variety of parametric transformations. Common transformations include

$$\text{Logarthmic} \qquad Y = \ln(X + a) \tag{3.5}$$

$$\text{Gamma} \qquad Y = \text{Gamma}(X) \tag{3.6}$$

$$\text{Power} \qquad Y = (X + a)^b \tag{3.7}$$

$$\text{Box} - \text{cox} \qquad Y = \frac{(X + a)^b - 1}{b}, b \neq 0 \tag{3.8}$$

Where Y is the transformed normal series and X is the original observed series. The variables Y and X can represent either annual or seasonal data, where for seasonal data, the transformation coefficients a and b can be periodic if a periodic model is to be fitted to the data. Hydrologic data are often positively skewed and a widely used transformation of hydrologic data is the lognormal transformation, assuming that the underlying variable X is approximately log normally distributed with a lower bound a. Transformation is also helpful when a time series shows changing variability with the level of the process. Nonparametric kernel density estimation (KDE) can also be used where the corresponding estimated CDF is mapped onto the normal distribution function to transform the data to normal. This may be useful for modeling bimodality and other behavior that may be difficult to describe by a parametric function.

3.2 Model Type Analysis

3.2.1 Markov Model

3.2.1.1 Identification of Distribution

Generally, the distributions used in the stream flow generation are normal, log- normal and gamma families. The bell-shaped, or normal, distribution is most extensively used in statistical applications because the sum of variables derived from any distribution tends to be distributed normally according to the central limit theorem. To test normality, the historical values of flow are plotted against the percentage of values in the record that are equal to or greater than the plotted value. The flows are arranged in descending order. For each value x_i, the percent is computed by 100 (n – *i* + 1) / n where *i* is the rank of value x_i and n is the number of historic values. If the plot is a straight line, the distribution is normal. The coefficient of skewness also should be close to zero, since the normal distribution has no skewnes.

The second distribution that is widely used in hydrology is log-normal distribution. Log-normal distribution is positively skewed, match with characteristic of many hydrologic variables. This distribution is suitable for low-flow studies because small changes in low values produce large changes in their logarithmic values. A straight-line plot indicates the log-normal distribution, while skewness calculated from the logarithms of value should be close to zero.

3.2.1.2 Generation of Random Numbers

The random number should belong to the same distribution to which the historical record belongs to the generated flow to have similar characteristics. Normal random numbers have a zero mean and one standard deviation.

To get the random normal deviate, *t*, of mean equal to zero and standard deviation equal to one, we use the inverse error function, erf^{-1} (z):

$$\text{erf}^{-1}(z) = \frac{1}{2}\sqrt{\pi}\left(z + \frac{\pi}{12}z^3 + \frac{7\pi^2}{480}z^5 + \frac{127\pi^3}{40320}z^7 + \frac{4369\pi^4}{5806080}z^9 + \frac{34807\pi^5}{182476800}z^{11} + \cdots\right). \qquad \textbf{(3.9)}$$

The Value of z can be obtained from the cumulative distribution function (CDF) of the log-normal distribution:

$$CDF = \frac{1}{2} + \frac{1}{2} erf\left[\frac{\ln x - \mu}{\sqrt{2\sigma^2}}\right] \quad \textbf{(3.10)}$$

As log-normal random numbers has a mean zero and standard deviation equal to one. Therefore, the Equation (3.10) becomes:

$$\text{erf}(z) = erf\left[\frac{\ln x - \mu}{\sqrt{2\sigma^2}}\right] = [RAND(\,) - 0.5]2$$

$$z = [RAND(\,) - 0.5]2$$

$$\frac{\ln x}{\sqrt{2}} = z$$

Therefore,

$$\ln x = z\sqrt{2}$$

3.2.1.3 Formulation of the Markov Model

Formulation of the Markov Model for Non-seasonal flow:

$$x_i = \bar{x} + \gamma_1(x_{i-1} - \bar{x}) + S\sqrt{(1-\gamma_1^2)}t_i \quad \textbf{(3.11)}$$

Where x_i is stream flow at i^{th} time; $\bar{x}$ is mean of recorded flow; γ_1 is lag 1 serial or autocorrelation coefficient; S is the standard deviation of recorded flow; t_i is random variate from an appropriate distribution with a mean of zero and variance of unity; and *i* is i^{th} position in series from 1 to N years.

A model on the same lines for seasonal flows, developed by Thomas and Fiering has the following form:

$$q_{i,j} = \bar{q}_j + b_j\left(q_{i-1,j-1} - \bar{q}_{j-1}\right) + t_{i,j}S_j(1-\gamma_j)^{\frac{1}{2}} \quad \textbf{(3.12)}$$

Where,

i= month in the series, measured from the beginning

j= month in year, j = 1, 2,…, 12 for January to December

$q_{i,j}$ = flow in i^{th} month from the beginning, for j^{th} month of the year

$q_{i,j-1}$ = flow in immediate previous month

$\bar{q}$ = mean flows of i^{th} month (12 values)

b_j = regression coefficient of flows of i^{th} month and flows of $(i-1)^{th}$ month = $r_i S_i/S_{i-1}$ (12 values)

s_j =standard deviation for i^{th} month (12 values)

$t_{i,j}$ =random normal deviate of zero mean and unit standard deviation

3.2.2 Autoregressive Moving Average Modeling

An appropriate ARIMA tentative model are identified and further analyzed with parameter estimation and diagnostic checking to select the best representative model. Examination of the autocorrelation function (ACF) and partial autocorrelation function (PACF) provides a thorough basis for analyzing the system behavior and will suggest the appropriate parameters to include in the model

ARIMA modeling follows three important stages that can be figured in the flow diagram of Box-Jenkins methodology (Figure 3.2).

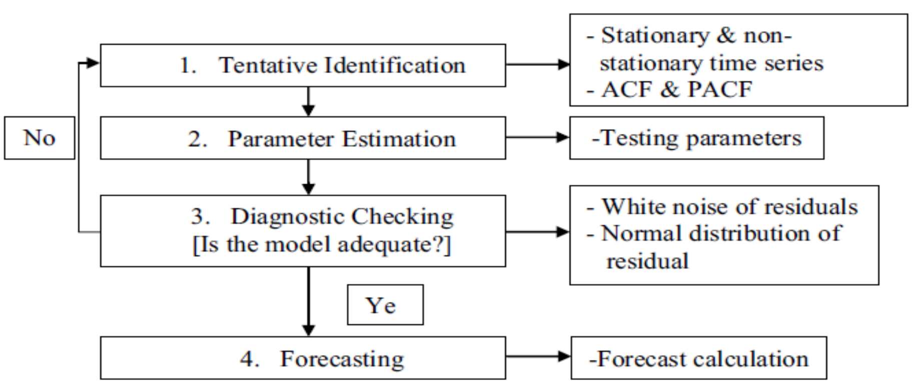


Figure 3-2 Flow Diagram of Box-Jenkins Methodology

An auto regressive model of the order p and moving average model of order q may be combined to obtain the mixed autoregressive moving average (ARMA model of order P, q)

$$z_t = \phi_1 z_{t-1} + \cdots + \phi_p z_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \Theta q \, \varepsilon_{t-q} \quad \textbf{(3.13)}$$

Which can also be represented as

$$z_t = \sum_{j=1}^{p} \phi_j (z_{t-j}) + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \quad \textbf{(3.14)}$$

The parameter of the model is μ, σ_ε^2, φ_1, φ_2,…, φ_q, $\theta_1, \ldots, \theta_q$ a total of p+q+2 parameter must be evaluated from the data.

3.2.2.1 Properties of ARMA Models

The auto covariance of the ARMA (p, q) process is found to be

$$\gamma_k = \sum_{i=1}^{p} \phi_i \gamma_{k-i} - \sum_{i=0}^{q} \theta_i \, \gamma_{z\varepsilon}(k-i) \qquad K < q+1 \quad \textbf{(3.15)}$$

$$\gamma_k = \sum_{i=1}^{p} \phi_i \gamma_{k-i} \quad K \geq q+1 \quad \textbf{(3.16)}$$

For k =0, the variance is

$$\gamma_0 = \sigma_\varepsilon^2 + \sum_{i=1}^{p} \phi_i \gamma_i - \sum_{i=1}^{q} \theta_i \, \gamma_{z\varepsilon}(-i) \quad \textbf{(3.17)}$$

and auto correlation function is

$$\rho_k = \sum_{i=1}^{p} \phi_i \rho_{k-i} \quad K \geq q+1 \quad \textbf{(3.18)}$$

The autocorrelation for the first q lags, $\rho_1, \ldots, \rho_q$ are seen depend on the autoregressive and moving average coefficient, whereas for the higher lags, $\rho_{q+1}, \rho_{q+2},, \ldots \rho_{q+p+2}$, depend only on autoregressive parameter.

The partial autocorrelation $\phi_k(k)$ is obtained by fitting to the given series AR process of order k=1,2….k

$$z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + \cdots + \phi_j z_{t-j} + \cdots + \phi_k(k) z_{t-k} \qquad \textbf{(3.19)}$$

Where $\phi_k(k)$ denotes the k^{th} coefficient of an AR (p) process of order K. The plot of $\phi_k(k)$ vs K is the sample partial autocorrelation function. The partial autocorrelation arises from the Yule Waker equation.

3.2.2.2 Assumption in ARMA Models

For an auto regressive process of order p, the partial autocorrelation $\phi_k(k)$ cutoff at lag p. A moving average process being equivalent to an autoregressive model of infinite order, has a partial autocorrelation, which is infinite in extent and attenuates with the mixture of damped waves and exponential decay. For the mixed process both the ACF and PACF attenuate as damped waves or exponential decay. Before performing the ARMA modeling, some assumptions were made such that (Hasmida, 2009):

3.2.2.3 Stationarity

Classical Box-Jenkins model describe stationary time series. Thus, in order to tentatively identify Box-Jenkins model, we must first determine whether the time series we wish to generate is stationary. The stationarity of monthly stream flow data were examined by graphical representation of the data. The original data were plotted against its time interval. A time series is stationary if the statistical properties (for example, the mean and the variance) of the time series are essentially constant through time (Mohd 2012). In other word, stationary models assume that the process remains in equilibrium about a constant mean level that is when the plotting shows that the data fluctuates around its constant mean (Box et al., 1994). Other graphical method applied in this present study is examined by the ACF and PACF plot of the original data. Stationary data have randomly distributed ACF and PACF plot.

3.2.2.4 Normality Test

Plotting the empirical cumulative distribution function (CDF) on a normal probability paper based on selected plotting position formula provides a nonparametric way of visually checking if the data plots as a straight line and conforms to the normal distribution (Q–Q plot). Commonly used plotting position formulas of non-exceedance probabilities for a time series of length N ordered from the smallest to the largest are Cunnane $(i - 0.4)/(N + 0.2)$, Hazen $(i - 0.5)/N$, and Weibull $i/(N + 1)$ for i = 1,…, N. Probability plot correlation tests of normality are available for different plotting positions with the Filliben probability plot correlation coefficient test of normality being the most popular one. Other tests include the skewness test of normality for testing the hypothesis of zero skewness. The sample skewness g is asymptotically distributed as N (0, $\sigma^2 = 6/N$) The null hypothesis H0: g = 0 versus H1: g ≠ 0 is rejected at the α-significance level if ABS (g) > $z_{1-\alpha/2}\sqrt{6/N}$. (Oli Gretar B.S, 2014)

3.2.2.5 Transformation to Normal

Most time series models assume that the underlying process is normally distributed. Time series failing a normality test can be transformed to normal using variety of parametric transformations. Common transformations include

Logarthmic $$Y = \ln(X + a) \quad \textbf{(3.20)}$$

Gamma $$Y = \text{Gamma}(X) \quad \textbf{(3.21)}$$

Power $$Y = (X + a)^b \quad \textbf{(3.22)}$$

Box − cox $$\mathbf{Y = \frac{(X + a)^b - 1}{b}, b \neq 0} \quad \textbf{(3.23)}$$

Where Y is the transformed normal series and X is the original observed series. The variables Y and X can represent either annual or seasonal data, where for seasonal data, the transformation coefficients a and b can be periodic if a periodic model is to be fitted to the data. Hydrologic data are often positively skewed and a widely used transformation of hydrologic data is the lognormal transformation, assuming that the underlying variable X is approximately log normally distributed with a lower bound a.

3.2.2.6 Testing for the Outlier

An outlier is an observation that lies outside the overall pattern of a distribution (Mohd 2012). The presence of an outlier always indicates some sort of problem. This can be a case which does not fit the model under study or an error in measurement. Outliers are often easy to spot in histograms. This data point should be removed because it is also a sign of nonstationary data (Hasmida, 2009).

(Yafee and McGee (2000) Suggested that data should be replaced by a theoretical defensible algorithm if some data values are missing is observed in the data series. A crude missing data replacement method is to plug in the mean for the overall series. A less crude algorithm is to use the mean of the period within the series in which the observation is missing. Another algorithm is to take the mean of the adjacent observations. Missing value in exponential smoothing often applies one step ahead forecasting from the previous observation. Another form of interpolation employs linear splines, cubic splines, or step function estimation of the missing data.

3.2.2.7 Removal of Seasonality in the Mean and Variance

Hydrologic data are usually affected by the annual cycle, with monthly data showing a 12 month periodic structure and being nonstationary in the mean and the variance. The seasonality in the mean is removed for each season by subtraction of the seasonal sample mean. Similarly, the seasonality in the variance is removed by division of the seasonal standard deviation. Seasonal standardization is done by both subtracting the seasonal mean and dividing by the seasonal standard deviation for each season by

$$Z_{\upsilon,\tau} = \frac{x_{\upsilon,\tau} - \bar{x}_{\tau}}{s_{\tau}} \qquad \textbf{(3.24)}$$

Where $z_{\nu,\tau}$ is normally distributed variable with standard deviation one and mean zero for year ν of the seasonal series for season τ. Alternatively, seasonal differencing can be used for removal of seasonalities, that is, differencing monthly hydrologic time series at lag-12 removes the 12-month periodic hydrologic annual cycle from the time series, it is preferred to use seasonal standardization over seasonal differencing for hydrologic time series that are considered to be physically bounded. (Oli Gretar B.S, 2014)

3.2.2.8 Estimation of Parameter

For fitting the autoregressive moving average ARMA(p,q) model to the time- series, estimation of model parameters is one of procedures. The method of moment (MOM) and least square method (LSM) are used in parameter estimation of ARMA(p,q) models (see also section 2.1.13).

3.2.2.9 Model Selection

Often several alternative models may be fitted to the data. The ACF and PACF are often used to get an idea of the appropriate model to fit. The identification of the appropriate parameter of a time series model depends on the shape of the ACF and PACF. The following Table 3.1 gives general theoretical for identification of the likely model:

Table 3-1 General Theoretical ACF and PACF of ARIMA models

Model	**ACF**	**PACF**
MA (q): moving average of order q	Cut off after lag q	Dies down
AR (p): autoregressive of order p	Dies down	Cuts off after lag p
ARMA (p, q): mixed autoregressive-moving average of order (p, q)	Dies down	Dies down
AR (p) or MA (q)	Cuts off after lag q	Cuts off after lag p
No order AR or MA (White Noise or Random process)	No spike	No spike

Each ARIMA tentative model parameter can be tested using t-values and p-values. Dividing the coefficient by its standard error calculates a t-value. We reject hypothesis null if $|t|> t_{\alpha/2}$,df = n-np (=2.25).The standard error (SE) of the coefficient is the standard deviation of the estimate of a regression coefficient. It measures how precisely your data can estimate the coefficient's unknown value. Its value is always positive, and smaller values indicate a more precise estimate. The standard error of a coefficient helps determine whether the value of the coefficient is significantly different than zero. If the p-value associated with this t-statistic is less than alpha level, we can conclude that the coefficient is significantly different from zero. If the resulting p-value for the coefficient is greater than the common alpha level (0.05), the hypothesis for null cannot be rejected, So we can conclude this coefficient not differs from zero.

The model with the minimum residual variance is often selected as the best model. This does not penalize for number of parameters and a common practice is to use information criteria for selecting the best model penalizing for the number of parameters used in the model. The corrected Akaike information criterion (AICC)

$$\mathrm{AICC} = \mathrm{n}\ln\sigma^2(\varepsilon) + \mathrm{n} + \frac{2(\mathrm{k}+1)\mathrm{n}}{\mathrm{n}-\mathrm{k}-2}\ ; \quad \textbf{(3.25)}$$

Where n is the size of the sample used for fitting the model, k is the number of parameters, excluding constant terms (k = p + q for the ARMA (p, q) model) and σ_ε^2 is the maximum likelihood estimate of the residual variance.

3.2.2.10 Model Testing

All the sample information on lack of fit is contained in the residuals. In most time series models, the residuals are assumed to be normally distributed with mean zero and variance σ_ε^2. Thus, a plot of the residuals should look like an independent drawing from the normal distribution. The residuals should be uncorrelated with zero ACF and PACF and also independent of the explanatory variables used in the model. Non-normal residuals may indicate lack of transformation of the data, while correlated residuals with nonzero terms in the ACF and PACF may indicate that a higher-order model is needed. In addition, synthetically simulated series from the model of the same length as the historical series should be capable of approximately reproducing the historical statistical properties of the original time series. (Oli Gretar B.S, 2014)

During diagnostic check stage also determines whether residual of the ARMA (p, q) model are independent, non-periodic and normally distributed. The test hypothesis that ε_t is independent series is determined by computing the Ljung-Box (modified Box-Pierce) static Q value and compare it with the χ^2 value for L-p degree of freedom in a given confidence level α. If $Q < \chi^2$ (L-p), ε_t is independent and the selected model adequate. If the p-value associated with each Q-statistic is more than alpha level, we can conclude that the residuals are is independent.

3.2.2.11 Minitab Procedures

For modeling ARMA model, a statistical software has been used, which is called Minitab version 17. By using Minitab, ARIMA model fitting steps can be summarized as follows:

1. Identify stationary of data

- If stationary, then go to step No. 2
- If non-stationary, then go to step No. 4

2. Identify the pattern of the data using ACF
   - If ACF is indicating two or three pikes than the confidence level, then go to step No. 5
   - If ACF is indicating more number of higher pikes than the confidence level, then go to step No. 4
3. Identify general theoretical PACF of ARIMA model
4. Apply the standardization or non-seasonal difference
5. Apply the rest of the procedures which are estimation, diagnostic check and generating according to step No. 6 until obtaining the best generating pattern

3.2.2.12 Data Generation using ARMA Model

Once the ARMA model is fitted it may be used ether for generation of synthetic series or forecasting future events. For generating purpose the ARMA (p, q) model equation 3.14 be used recursively to generate synthetic z_t values. During data generation, it is necessary to give p initial z values. By generating a sufficiently long series, and neglecting the first 50 or 100 terms, so that the transient effect of the initial values is generally negligible.

The synthetically generated series is expected to conserve some of the statistical properties of the historical data. These are the mean, variance and the autocorrelation structure. The last value of the observed data series is taken as the initial value. The initial value for ε_t is taken as the last entry in the residual series. A random number generator is used to produce the $\varepsilon_t$values which are normally distributed with zero mean and varianceσ_ε^2.

3.2.3 Periodic Autoregressive Moving Average (PARMA)

An appropriate PARMA tentative model are identified and further analyzed with parameter estimation and diagnostic checking to select the best representative model. Examination of the autocorrelation function (ACF) and partial autocorrelation function (PACF) provides a thorough basis for analyzing the system behavior and will suggest the appropriate parameters to include in the model.

A PARMA (p, q) model may be expressed as

$$y_{\nu,\tau} = \sum_{i}^{p} \phi_i y_{\nu,i-1} + \varepsilon_{\nu,\tau} - \sum_{j}^{q} \theta_i y_{\nu,j-1} \quad \textbf{(3.26)}$$

Where, represents the hydrologic process for year ν and season τ

The $\varepsilon_{\nu,\tau}$ is the uncorrelated noise term that for each season is normally distributed with mean zero and variance $\sigma^2(\varepsilon)$. The $\{\phi_{1,\tau}, \dots, \phi_{p,\tau}\}$ and $\{\theta_{1,\tau}, \dots, \theta_{p,\tau}\}$ are the periodic AR and MA parameters

If the number of seasons is ω, then a PARMA (p, q) model consists of ω-number of individual ARMA (p, q) models, where the dependence is across seasons instead of years. In most practical applications, PAR (1), PAR (2), and PARMA (1, 1) have been found to be adequate, although residuals should always be tested to ensure adequate model fit.

3.2.3.1 Basic Assumption in PARMA Model

Before performing the ARMA modeling, some assumptions were made such that (Hasmida, 2009):

3.2.3.1.1 Stationarity

A hydrologic time series is stationary if it is free of trends, shifts, or periodicity. Slow changes can complicate an analysis considerably, no matter whether they are a naturally occurring trend or actually an error in the data. It is therefore important to know about a trend in a time series to avoid any wrong conclusions or interpretations. The stationarity of the data are tested by looking at the plot of time series data and its fluctuation on the mean value of the series

3.2.3.1.2 Seasonality (Periodicity) Aspect

Hydrologic series defined at time intervals smaller than a year (such as monthly series) generally exhibits distinct seasonal (periodic) patterns. In most analysis and modeling of hydrologic time series, testing for seasonality in statistics is done by using simple procedures, mostly by observing the plot of the statistic under consideration versus the season τ.

3.2.3.1.3 Testing for Normality

PARMA model like other several models and approaches in hydrologic time series modeling assume that the variable under consideration is normally distributed. Therefore, it is usual practice to test the data for normality before further analysis. A widely used method for judging whether a certain data set is normally distributed is to plot the empirical frequency distribution of the data on normal probability paper. There are two commonly used plotting position formulas for plotting of the empirical frequency curve: the Cunnane plotting position, and the Weibull plotting position. The Cunnane plotting position is approximately quantile unbiased while the Weiibull plotting position has unbiased expedience probabilities for all distributions. In general the Cunnane plotting position is preferable (Salas, 2007).

3.2.3.1.4 Transformation to Normal

In cases where the normality tests indicate that the observed series are not normally distributed, the data has to be transformed into normal before applying the PARMA model. To normalize the data, the following transformation functions are commonly used (Salas, 2007)

$$y_{\upsilon,\tau} = \log(x_{\upsilon,\tau}) \tag{3.27}$$

$$y_{\upsilon,\tau} = \frac{\log x_{\upsilon,\tau} - \mu_{x_{\upsilon,\tau}}}{\sigma_{x_{\upsilon,\tau}}} \tag{3.28}$$

$$y_{\upsilon,\tau} = \sqrt{x_{\upsilon,\tau}} \tag{3.29}$$

$$y_{\upsilon,\tau} = a_\tau(x_{\upsilon,\tau} - c_\tau)^{b_\tau} \tag{3.30}$$

3.2.3.1.5 Scaling and Standardization

Scaling of normally distributed data is required when different seasons have values that differ from each other by a couple of orders of magnitude which can cause problems in parameter estimation. This can happen when some of the historical time series are normally distributed and does not need to be transformed to normal while others do. In this case some seasons do not need transformation for normality; where as other seasons for the same station do need to be transformed, thus in such conditions the scaling is needed. Scaling in this context is dividing all the time series equation which have not been transformed by the standard deviation.

3.2.3.2 Estimation of Parameter

Before fitting the periodic autoregressive moving average (PARMA) model of the time- series, estimation of model parameters is the first procedures. In parameter estimation of PARMA (p, q) models, the method of moments (MOM) and the methods least square method (LS) are used.

3.2.3.3 Model Selection

Initial identification methods are applied to a set of data to indicate the kind of representational model that is worthy of further investigation. The specific aim is to gain some idea of the values of p and q needed in the general PARMA model and to obtain initial guesses of the parameters.

Seasonal patterns of time series can be examined via correlograms. Accordingly, ACF and PACF functions have been used for prior identification of the dependence structure in the data series.

A basic tenet of model building is to keep the model as simple as possible, but at the same time provide a good fit to the data being modeled (Hipel & McLeod 1994). Different automatic selection criteria are available for balancing the apparently contradictory goals of a good statistical fit and model simplicity. Among the automatic selection criteria used in model discrimination, Akaike information criterion (AICC) and a Bayes information criterion (BIC) are common (Hipel & McLeod, 1994)

The diagnostic check stage determines whether residual are independent, homoscedastic and normally distributed.

Akaike Information Criterion Corrected (AICC)

In order to find the most appropriate model, the AIC is quite powerful (Burnham & Anderson 2002). The mathematical definition of AIC is given as given by equation 3.25. Because of AICC tends to overestimate the order of auto regression, a Bayesian extension of the minimum Akaike criterion (SIC) is developed. Schwarz Bayesian criterion (SIC), is also used in this study.

Schwarz Bayesian criterion (SIC)

$$SIC = nln\sigma_{\varepsilon}^{2} + n + kln\, n \qquad \textbf{(3.31)}$$

The SIC has a structure quite similar to that of AICC. Where n, k and σ_{ε}^{2} are defined in the same way as AICC. The *model* that gives the minimum AICC and SIC is selected as parsimonious. After identifying the model, Normality test, statistical analysis and White noise test are performed on a plot of ACF of the residuals in order to determine whether the residual of the model are independent, homoscedastic and normally distributed.

3.2.3.4 Model Testing

The diagnostic check stage determines whether residual are independent, homoscedastic and normally distributed.

3.2.3.5 SAMS Software for modeling PARMA Model

SAMS is a computer software package that deals with the stochastic analysis, modeling, and simulation of hydrologic time series. It consists of three primary application modules:

The “Data Analysis” is one of the main applications of SAMS. The functions of this module consist of

- Data plotting,
- Checking the normality of the data,
- Data transformation, and computing and
- Displaying the statistical (stochastic) characteristics of the data

The second main application of SAMS “Fit Model” includes

- Parameter estimation and model

The two parameter estimation methods available in the SAMS are the method of moments (MOM) and the least squares method (LS). The third main application of SAMS is “Generate Series”, i.e. simulating synthetic data.

3.2.4 Univariate GAR (1)

The gamma-autoregressive model GAR (1) is similar to the well-known AR (1) model except that the underlying process being modeled is assumed to follow the gamma distribution instead of the normal distribution. Thus, in using the GAR (1) model, the underlying data should not be transformed to normal by SAMS.

The GAR (1) model can be expressed as (Salas et al., 2007)

$$x_t = \emptyset x_{t-1} + \varepsilon_t \quad \textbf{(3.32)}$$

Where X_t is a gamma variable defined at time t, ϕ is the auto regression coefficient, and ε_t is the independent noise term. X_t is a three-parameter gamma distributed variable with marginal density function given by:

$$f_x(x) = \frac{\alpha^{\beta}(x-\lambda)^{\beta-1} exp^{[-\alpha(x-\lambda)]}}{\Gamma(\beta)} \quad \textbf{(3.33)}$$

Where λ, α, *and* β are the location, scale, and shape parameters, respectively. Lawrence (1982) found that the independent noise term, ε_t, can be obtained by the following scheme:

$$\varepsilon = \lambda(1-\phi) + \eta \quad where \quad \begin{cases} \eta = 0 \quad , & if\ m = 0 \\ \eta = \sum_{j=1}^{m} y_j \phi^{u_j}, & if\ m > 0 \end{cases} \quad \textbf{(3.34)}$$

Where M is an integer random variable distributed as a Poisson with mean [- β ln (ϕ)], U_j, j =1, 2,.... are independent identically distributed random variables with uniform (0,1) distribution, and, Y_j ,j =1,2, ...are random variables distributed as exponential with mean (1/α). The stationary GAR (1) process of Eq. (3.33) has four parameters, namely {ϕ, λ, α, β}. The model parameters are estimated based on a procedure suggested by Fernandez and Salas (1990), as illustrated in equation 2.24 to 2.35. The parameter of the model is obtained from the SAMS software as mentioned in section of periodic autoregressive moving average model.

3.3 Model Performance Test

Data generation studies for comparing statistical properties of the underlying process are generally undertaken based on samples of equal length as the length of the historical record and based on a certain number of samples which can give enough precision for estimating the statistical properties of concern (SAMS 2007). The statistics $MD(\theta)$ and $RRMSD(\theta)$ are useful for comparing between the historical and model statistics derived from data generated.

3.3.1 The mean deviation (MD)

$$MD(\theta) = \bar{\theta} - \theta(H) \qquad \textbf{(3.35)}$$

$\theta\ (H)$ The mean derived from the historical sample (historical statistic).

$\bar{\theta}$ The mean of the generated sample

3.3.2 The relative root mean square deviations, RRMSD ($\boldsymbol{\theta}$)

$$RRMSD(\theta) = \frac{1}{\theta(H)} \sqrt{\sum_{i=1}^{N} (\theta_i - \theta(H))^2} \qquad \textbf{(3.36)}$$

3.4 System Optimization

The deterministic simulation of the model is only a first step in a process to use information technology to improve the integrated water resources management. While the simulation model provides water managers and users with an improved and shared knowledge of the system dynamics, it cannot explicitly describe the uncertainty of future stream-flow and precipitation. Additionally, it functions only in a descriptive capacity and cannot prescribe optimal operational decisions in its present formulation.

The goal of the non-linear optimization model presented in this section is to consider multiple uncertain futures and optimize current operations to meet current and future needs. The formulation allows the program to be run by operators at any point during the life cycle of the project operations within the forecast horizon.

The NLP uses the same basic system described as the simulation tool, within the life cycle of the project at a specified month time step. The present and future reservoir releases comprise the set of decision variables, which are optimized by an objective function that minimizes the storage capacity incurred both in the present and in the future. The constraint set defines the dynamics of the reservoir. While most of the parameters for the constraint set are non-deterministic.

The objective function in the deterministic equivalent of the NLP solves for the set of releases in the present time step that minimizes the storage capacity in all future inflow scenarios. The NLP itself is coded and solved using the GAMS (Brook et al., 2007) which is interfaced with the Notepad-book. Appendix Code documents the GAMS code produced by the Notepad-book.

In this study the uncertain hydrologic input of concern for the reservoir-irrigation system is reservoir inflows. Reservoir inflows dictate the volume of available water in the reservoir. A precipitation is necessary to determine the irrigation demand, defined as the volume of the crop demand which is not met by rainfall.

3.4.1 Non Linear Optimization

The objective of NLP is to provide the user with an optimized decision for the present time step that minimizes the required storage capacity considering the irrigation demand, reservoir inflow and evaporation. The important outputs for the user of the model are therefore the releases which are recommended for the present time step and the expected value of future releases, spill, and storage volume and reservoir level elevations.

Nonlinear programming models have been applied extensively to optimize resource allocation problems. As the name implies, NLP models have a basic characteristics, that is, the objective function and/or constraints are nonlinear functions of decision variables.

In computational result, we use GAMS (General Algebraic Modeling System). GAMS is specifically designed for modeling linear, nonlinear and mixed integer optimization problems. The system is especially useful for large and complex problems. GAMS is available for using on personal computers, workstations, mainframes and supercomputers. GAMS allows the user to concentrate on the modeling problem by making the setup simple. The system takes care of the time- consuming details of the specific machine and system software implementation. GAMS is especially useful for handling large, complex, and one-of-a-kind problems, which may require many revisions to establish an accurate model. The system models problems in a highly compact and natural way. The user can change the formulation quickly and easily from one solver to another, and can even convert from linear to nonlinear with a little effort.

The objective function of the Non- linear program for the reservoir sizing is defined as:

$$Minimize \quad K_a \qquad \textbf{(3.37)}$$

Subject to:

$$S_{t+1} = S_t + Q_t + P_t - R_t - EV_t - SPILL_t \qquad \forall\, t \qquad \textbf{(3.38)}$$

$$EV_t = e_t\left[\alpha\left(\frac{S_t + S_{t+1}}{2}\right)^{\beta}\right] \qquad \forall\, t \qquad \textbf{(3.39)}$$

$$PP_t = p_t\left[\alpha\left(\frac{S_t + S_{t+1}}{2}\right)^{\beta}\right] \qquad \forall\, t \qquad \textbf{(3.40)}$$

$$S_t \le S_{max} \qquad \forall\, t \qquad \textbf{(3.41)}$$

$$S_t \ge S_{min} \qquad \forall\, t \qquad \textbf{(3.42)}$$

$$R_t \le R_{Max} \qquad \forall\, t \qquad \textbf{(3.43)}$$

Where p_t and e_t are depths of precipitation and evaporation per unit area during period t, respectively.

3.4.2 Storage-Area Relationships

As the reservoir storage-area relationship is nonlinear, an alternatively nonlinear function is possible with the fitting of the storage-area relationship as shown in equation 3.44

$$A = \alpha * \left(\frac{S_{t+1} + S_t}{2}\right)^{\beta} \qquad \textbf{(3.44)}$$

Where A is reservoir area and S_t is the storage volume, α and β are parameters of nonlinear equation 3.44. The optimized value α and β is obtained from GAMS using NLP by minimizing square error.

The objective function of the Non- linear program for the Storage-Area relationship is defined as:

$$minimize \quad \sum_{i=1}^{I} (e_i)^2 \qquad \textbf{(3.45)}$$

Where,

$$e_i = \alpha S_o(i)^{\beta} - A_o(i) \tag{3.46}$$

Where, $S_o(i)$ and $A_o(i)$ are observed reservoir storage and area obtained from topographic survey. The GAMS software is used to calculate the minimum square error to find the value of the parameter. The total evaporation and precipitation in the reservoir is obtained by multiplying the area calculated at the given storage using equation 3.46 by the depth of evaporation and precipitation for the given period t respectively.

3.4.3 Elevation–Storage Relationships

As the reservoir elevation-storage relationship is nonlinear, an alternatively nonlinear function is possible with fitting of the storage-area relationship as shown in equation 3.47.

$$S(r) = \alpha\alpha(h(r) - h_o)^{\beta\beta} \tag{3.47}$$

Where S(r) is reservoir Storage at elevation h(r) obtained from the program and h_o is the minimum elevation. $\alpha\alpha$ and $\beta\beta$ are parameters of nonlinear equation 3.47. The optimized value $\alpha\alpha$ and $\beta\beta$ is obtained from GAMS using NLP by minimizing square error.

The objective function of the Non- linear program for the elevation-storage relationship is defined as:

$$\text{minimize} \sum_{i=1}^{I}(e_i)^2 \tag{3.48}$$

Where,

$$e_t = S(r) - S_o(i) \tag{3.49}$$

Where, $S_o(i)$ is observed reservoir storage obtained from topographic survey. The GAMS software is used to calculate the minimum error to find the reservoir level at the instant of the given storage volume is obtained from the equation (3.34) the elevation storage relationships.

3.5 GAMS

The general Algebraic Modeling System (GAMS) is designed to facilitate the work of the modelers, who create a mathematical model of the real process around us. Thus, the major functional objective of GAMS is to design algorithms for the mathematical models. However, it does not mean that this system can be used only for the mathematical models with algebraic equations.

3.5.1 Model Structure

Each model in the Gams language may have its own distinction. Most of the GAMS models have a structure in the form shown in table (3.2) below.

Table 3-2 Structure of GAMS model

1	SET	Structure consisting of complex of indices or names Declaration of fact of existence
2	DATA	Parameter, Tables, scalars Declaration of fact of existence Determination of value of input parameter Preliminary computations
3	Variables	Variable or array of Variables Declaration with assigning a type of Variable Declaration of Limits for possible changes, initial value
4	Equation	Equation or Complex and arrays of equations Declaration with assigning a name
5	Model Solve	Model and Method of solution
6	Output	Output of information into a separate file

3.5.2 Variables

Variables are the major object with which GAMS operates. To define a list of variables we use the function word Variable. There are five types of variable as indicated in Table 3-3.

Table 3-3 Type of Variable in GAMS

Variable	Variable belong to the entire set of real number from “minus” to “plus” infinity
Positive Variable	Positive variables belong to the entire set of positive real numbers from “zero” to “plus “ infinity
Negative Variable	Negative variable belong to the entire set negative real number from “zero” to “minus “ infinity.
Integer Variable	Integer variables belong to the entire se of positive integers
Binary Variable	Binary variable are Integer variables that can take the value of 1 or 0 only

4 RESULT AND DISCUSSION

In this chapter, detail analysis of time series data for Measso station near Gidabo reservoir using Markov, ARMA, PARMA and GRA (1) model was done. (Station number: 082044).

Monthly flow data from January 1977 to December 2005 was obtained from ministry of water, irrigation and Electricity and used in deriving stochastic models. The monthly flow of measso station near Gidabo reservoir was shown in Appendix **A-1.**

4.1 Model Fitting and Data Generation using Markov Model

4.1.1 Statistical Parameters of Historical Data

The observed sample has a mean flow of 47.73 MM^3 with standard deviation 26.99 and skewness 1.49. The statistical parameters of the observed flow are shown in Table 4.1.

Table 4-1 Descriptive Statistics of Measso Station

Descriptive	Statistic
sample size	348
Mean	47.74
St Dev	26.99
Variance	728.49
Coef Var (%)	56.54
Minimum	16.06
Q1	28.33
Median	39.19
Maximum	162.17
Range	146.11
Skewness	1.49
Kurtosis	2.35

Data calibration and parameter estimation of the Markov model using equation 3.12 is made from monthly historical flow from January 1977 to December 2005. The result of the Markov model is shown in Table 4.2.

Table 4-2 Parameters of Monthly Historical Data

$month$	$\bar{q}_j$	S_j	γ_j	S_{j-1}	b_j	$\bar{q}_{j-1}$
Jan	27.900	5.107	0.820	8.854	0.473	31.669
Feb	25.995	5.033	0.628	5.107	0.619	27.900
Mar	29.443	8.068	0.702	5.033	1.125	25.995
Apr	41.809	13.393	0.594	8.068	0.986	29.443
May	59.413	22.890	0.309	13.393	0.528	41.809
Jun	52.489	26.954	0.304	22.890	0.358	59.413
Jul	50.588	20.982	0.643	26.954	0.500	52.489
Aug	64.824	36.022	0.539	20.982	0.926	50.588
Sep	67.825	27.530	0.536	36.022	0.410	64.824
Oct	77.752	33.895	0.773	27.530	0.952	67.825
Nov	43.174	19.058	0.148	33.895	0.083	77.752
Dec	31.669	8.854	0.277	19.058	0.129	43.174

4.1.2 Transformation to Normal

Log normal distribution is used to transform the stream-flow data of Measso station to normal as discussed in section 3.1.6. Since log-normal distribution is positively skewed, it matched with the characteristic of many hydrologic variables. The Logarithmic transformed values of the monthly observed flow from 1977 until 2005 are shown in appendix **A-2.**

4.1.3 Generation of Random Numbers

The random numbers are generated using Microsoft Excel command RAND ( ) as the procedure discussed in section 3.2.1.2. The random numbers generated only for year 1977-1982 is shown in Appendix **A-3**,

4.1.4 Stream Flow Generation of Markov Model

The deterministic part considering the persistence (influence of previous flows) and combining them with the random part to develop monthly stream flow using the equation 3.12 from year 1977 to 1982 is shown in Appendix **A-4**.

To generated stream flow using Markov model as per equation 3.12 the flow in the i^{th} month from the beginning and for the j^{th} month of the year can be modeled by adding together the mean of flow in the j^{th} month of the year (January to December) with deterministic and random component. The generated flow from 1977 to 2005 are shown in Appendix **A-5**

4.1.5 Validation of Markov Model

The generated stream flow from the model is compared with the observed flow in order to inspect their statistical similarities. The mean, standard deviation and lag one correlation of the generated and historical data are plotted as shown Figure 4.1, 4.2 and 4.3 respectively.

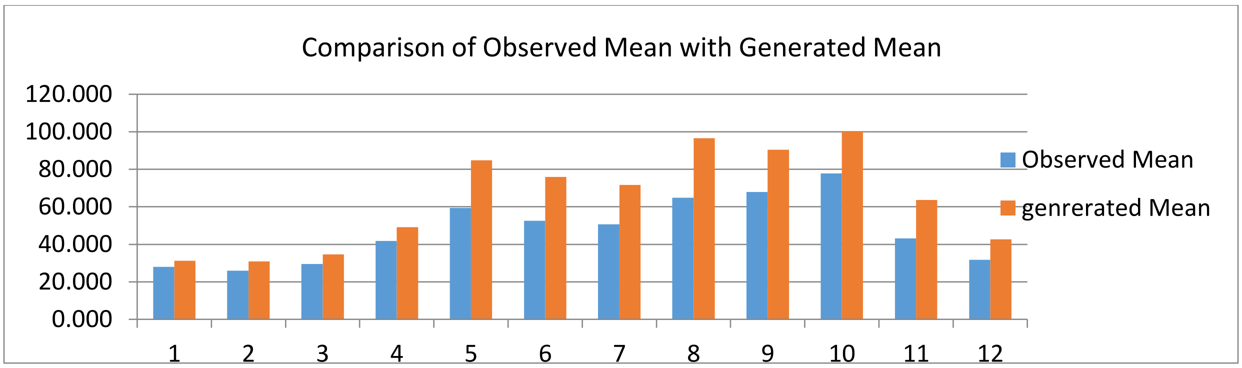


Figure 4-1 Comparison of Observed Mean with Markov Model Mean

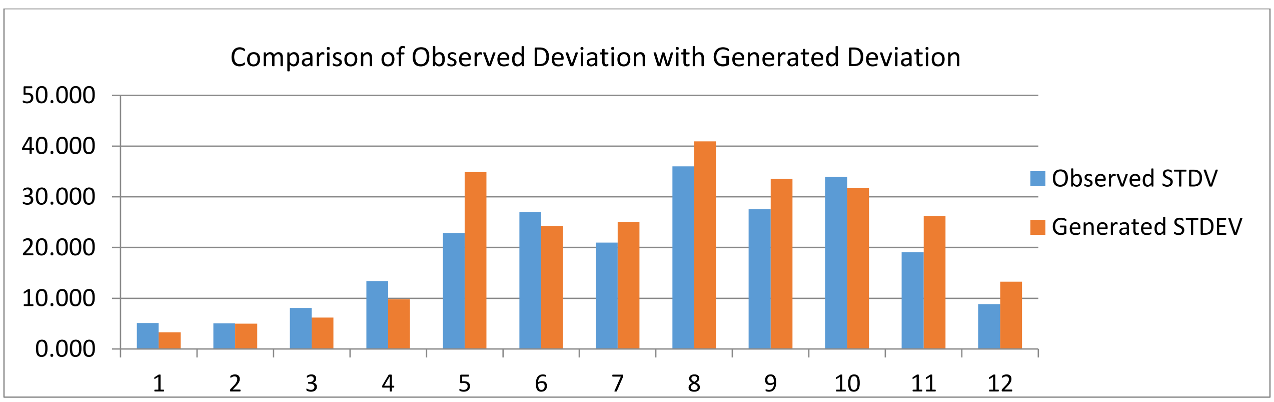


Figure 4-2 Comparison of Observed Deviation with Markov Model Deviation

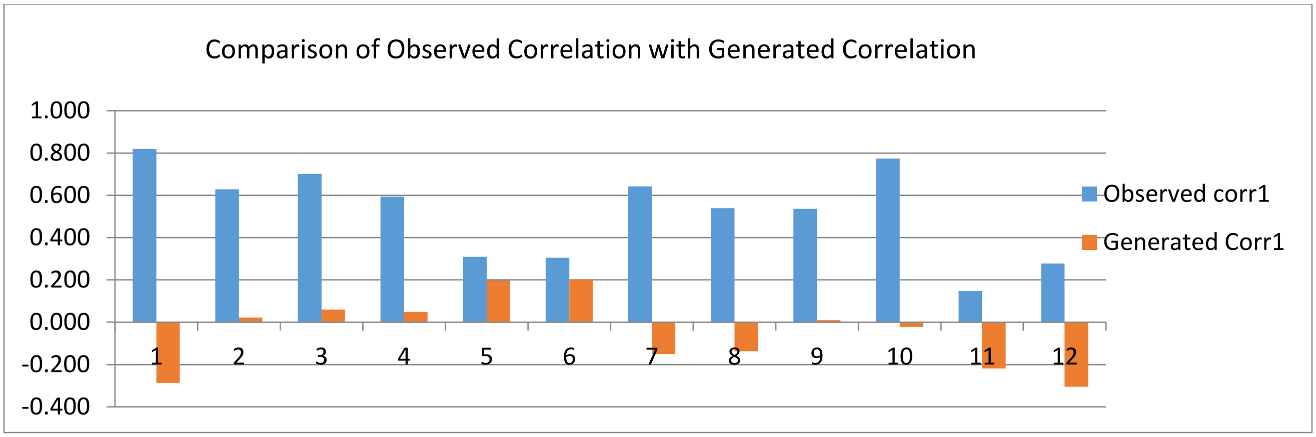


Figure 4-3 Comparison of Observed Correlation with Markov Model Correlation

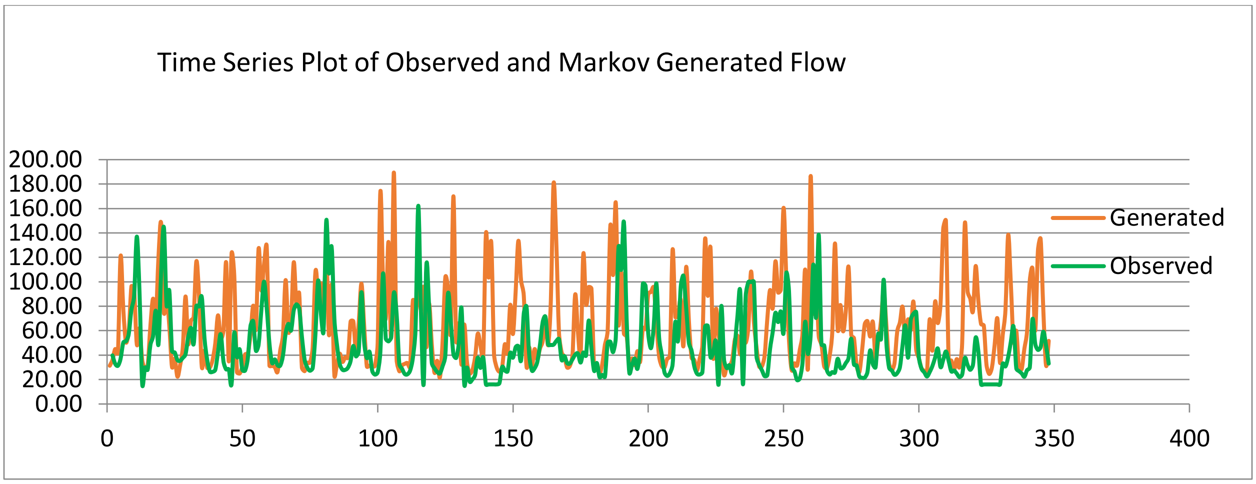


Figure 4-4 Comparison of Observed and Markov Model Flow

Graphically, from Figure 4.4, we can say that Markov model cannot work well for stream-flow generation for Meisso station near Gidabo reservoir because it is not matches well with the actual stream-flow.

The ability of Markov model in stream-flow generation is inspected by using performance evaluation criteria like Mean Deviation (MD) and Relative Root Mean Square Deviation (RRMSD). The result is shown in Table 4.3 and the details of the calculation can be found in Appendix **A-6**.

Table 4-3 Accuracy of the Markov Model

Performance Evaluation Procedure	Markov model
MD	2.49
RRMSD	10.76

4.2 Model Fitting and Simulation ARMA Model

4.2.1 Testing for Normality

The observed stream flow data is plotted on the normal probability paper indicates data are not normal. (Figure 4.5)

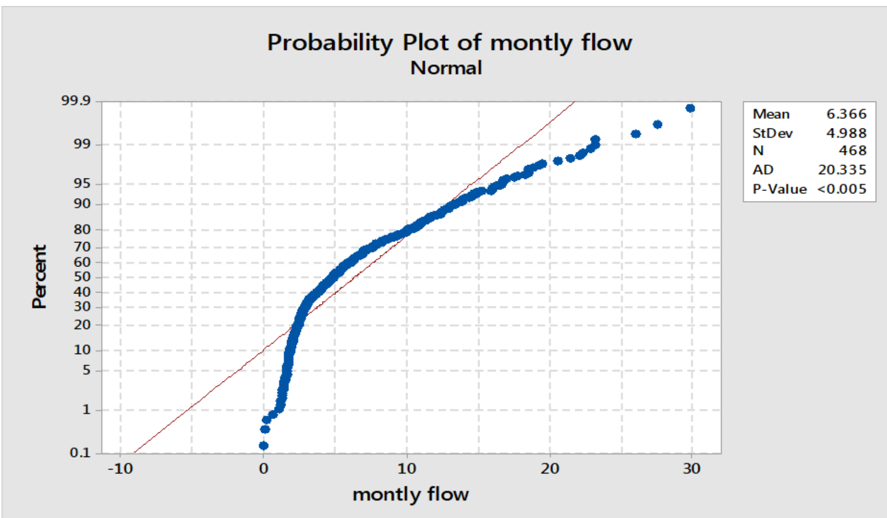


Figure 4-5 Normality the Plot of the Observed Flow

The numerical skewness of the observed data has a value of 1.5 using the equation 2.10. Therefore, a transformation to reduce this skewness to zero is desirable.

4.2.2 Transformation to normal

The following logarithmic transformation equation was applied to transform the observed stream flow to normally distributed data.

$$y_t = \log(x_t - 7) \qquad \textbf{4.1}$$

A log transformed data using the above equation were shown on Appendix **A-7**.

To judge whether the transformed time series is plotted on a normal probability paper as shown in figure 4.6, which indicates that the points follow a straight line and also skeweness value of the transformed data becomes 0.01.

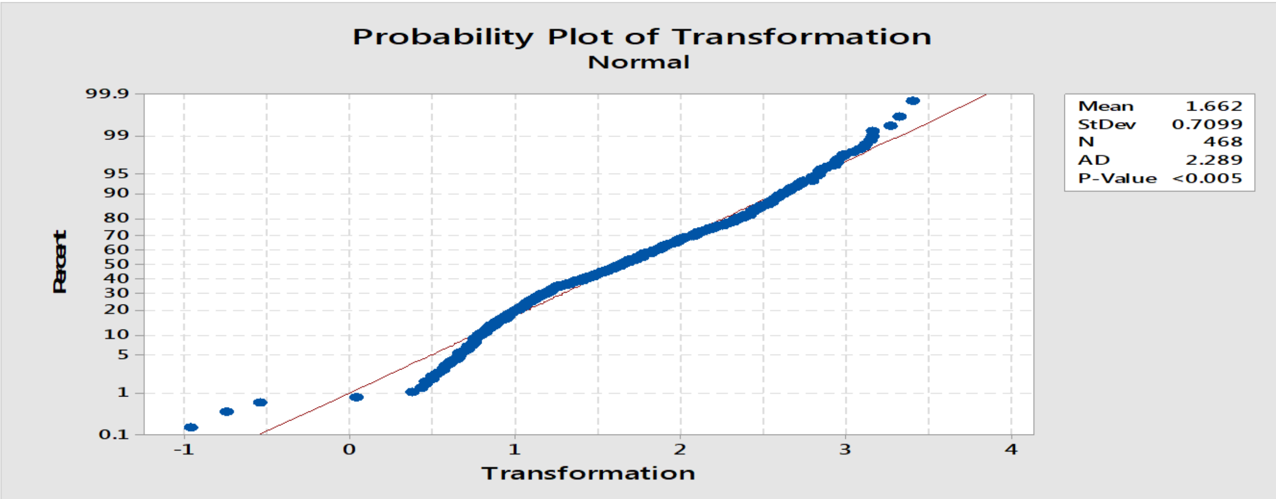


Figure 4-6 Flow Normality the Plot of the Log Transformed Data

4.2.3 Stationarity

The plot of the normally distributed time series was made to identify the basic characteristics of the series and to check the stationarity of the data. Figure 4.7 shows the periodic behavior(non-statinarity) of the monthly flows of the Gidabo Reservoir.

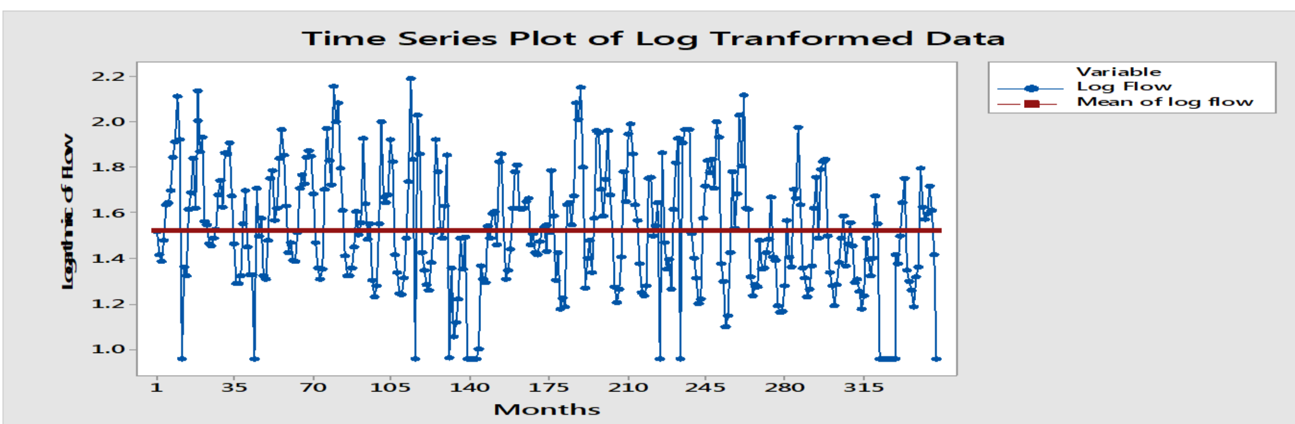


Figure 4-7 Time Series Plot of Log Transformed Data

The fluctuation of the time series data around the mean value of the series as it is on Fig 4.8 indicates periodic behavior or non-stationarity.

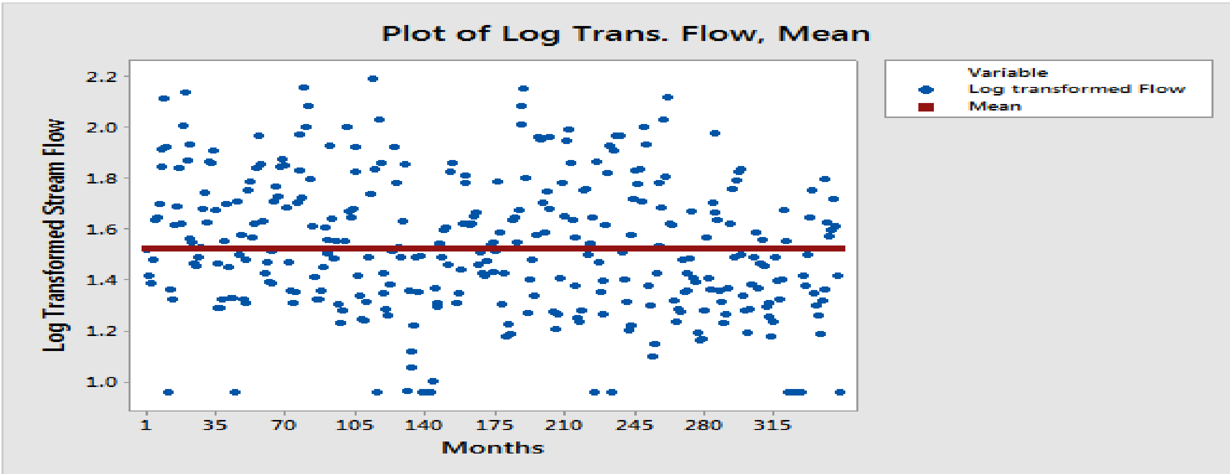


Figure 4-8 Log flow for Measso station near Gidabo reservoir indicating non-stationarity

4.2.3.1 Standardization

Figure 4.7 and 4.8 above shows the non stationarity due to periodic behavior of the transformed flows. As discussed in section 3.2.3.1.5 of chapter 3 Periodicity or Seasonality is removed from the series by standardization using equation 3.24, which transform the data into a zero-mean, unit-variance data series. The standardize series was shown in Appendix **A-8**. Figure 4.9 shows plot of standardize data series indicating significant periodic behavior has removed (the time series becomes random) from the series.

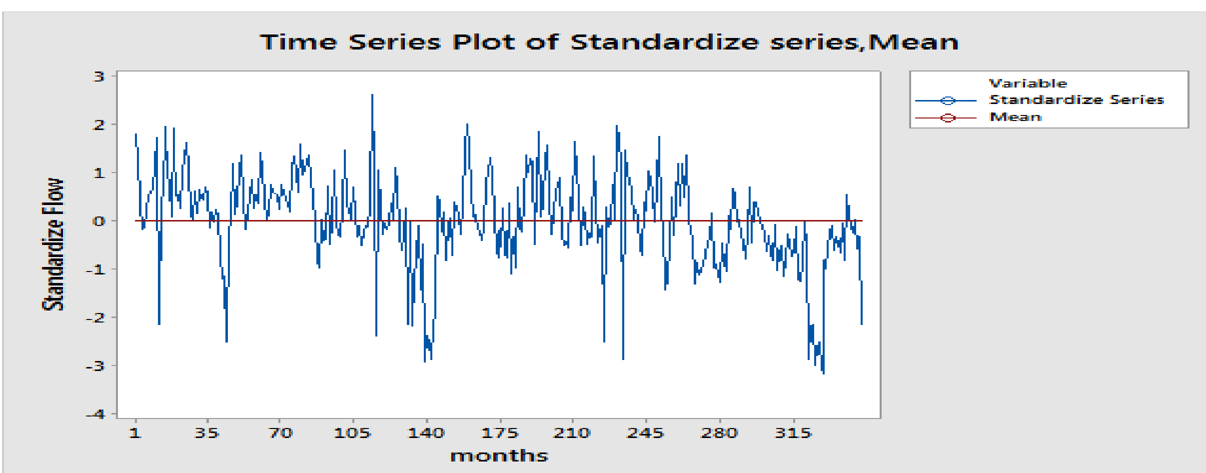


Figure 4-9 Flow Time Series plot after Standardization

4.2.4 ARMA Model Fitting Procedures

The series in this study consists of Standardize series of the average monthly stream-flow (Mm^3) values for Measso stations.

4.2.4.1 Initial Model Identification

ACF and PACF functions have been used for prior identification of the dependence structure in the data series which is used as identification of representative models. The auto covariance, autocorrelation coefficient and partial autocorrelation coefficient are calculated from lag 0 to lag 65 is shown in fig. 4.10 a and b respectively.

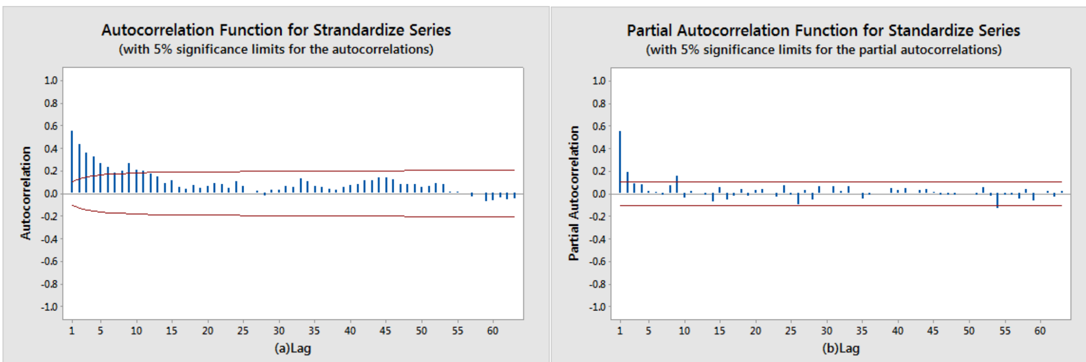


Figure 4-10 The sample ACF(fig. a) and PACF(fig. b) for the Standardize time series of Measso Station near, showing the 95% confidence bounds $\pm 1.96/\sqrt{N}$

The auto correlation coefficient is seen to be positive significance up to lag 5 then it continues to decrease and oscillate within the confidence band between the positive and negative value. The partial autocorrelation coefficient is significant at lag one, and then oscillate within the confidence band which indicates the presence of the 1st order autoregressive component. The autoregressive coefficient seems to decay more slowly indicating the possibility of moving average component.

4.2.5 Estimation of Parameter

the method of moment (MOM) and Least square (LS) is used in parameter estimation of ARMA (p,q) models (see also section 2.1.13).The value of the autoregressive parameter and moving average coefficient were found from the MINITAB 17 are given in Table 4.4.

Table 4-4 Model Parameter coefficient, T and P value of the Tentative Models

Model	Type	coef	SE Coef	T	P
AR(1)	ϕ_1	0.5697	0.0446	12.77	0
AR(2)	ϕ_1	0.4627	0.0533	8.68	0
	ϕ_2	0.1909	0.0532	3.59	0
AR(3)	ϕ_1	0.4459	0.0541	8.24	0
	ϕ_2	0.15	0.0587	2.56	0.011
	ϕ_3	0.0898	0.0541	1.66	0.098
ARMA(1,1)	ϕ_1	0.8285	0.0481	17.21	0
	θ_1	0.4074	0.0781	5.22	0
ARMA(2,1)	ϕ_1	1.1051	0.1532	7.21	0
	ϕ_2	-0.1879	0.1127	-1.67	0.096
	θ_1	0.6664	0.1361	4.9	0
ARMA(2,2)	ϕ_1	1.6021	0.096	16.68	0
	2	-0.6149	0.0694	-8.86	0
	θ_1	1.1738	0.0718	16.35	0
	θ_2	-0.2424	0.0377	-6.43	0
ARMA(3,1)	ϕ_1	1.2716	0.1468	8.66	0
	ϕ_2	-0.2243	0.1	-2.24	0.026
	ϕ_3	-0.0819	0.0732	-1.12	0.264
	θ_1	0.837	0.1334	6.27	0

4.2.6 Diagnostic checking

Each ARIMA tentative model parameter can be tested using t-values and p-values. Dividing the coefficient by its standard error calculates a t-value. If the resulting p-value for the coefficient is greater than common alpha level (0.05), the hypothesis for null cannot be rejected. So we can conclude this coefficient not differs from zero. From Table 4.4 only AR(1),AR(2),ARMA(1,1) and ARMA(2,2) passed the t-test.

The t-test cannot penalize the number of parameter to be involved in the model. Hence, in addition to the automatic maximum likelihood selection criteria mentioned above, Modified Akaike information criterion (AICC) equation 3.25 is also used.

Table 4-5 1Modified Akaike Information Criteria for ARMA model

S.No	K	Model	N	Variance	AICC
1	1	AR(1)	348	0.6593	207.0661
2	2	AR(2)	348	0.6356	196.3611
3	3	AR(3)	348	0.6307	195.7147
4	2	ARMA(1,1)	348	0.6283	192.3411
5	3	ARMA(2,1)	348	0.6263	193.2784
6	4	ARMA(2,2)	348	0.6236	193.8338
7	4	ARMA(3,1)	348	0.6245	194.3357

Use of the minimum AIC value to reinforces and complements the identification, estimation and diagnostic stages of model construction. Table 4.5 and Figure 4.11 shows that ARMA (1,1) has a minimum value which is selected as best representative among the ARMA(p,q) model

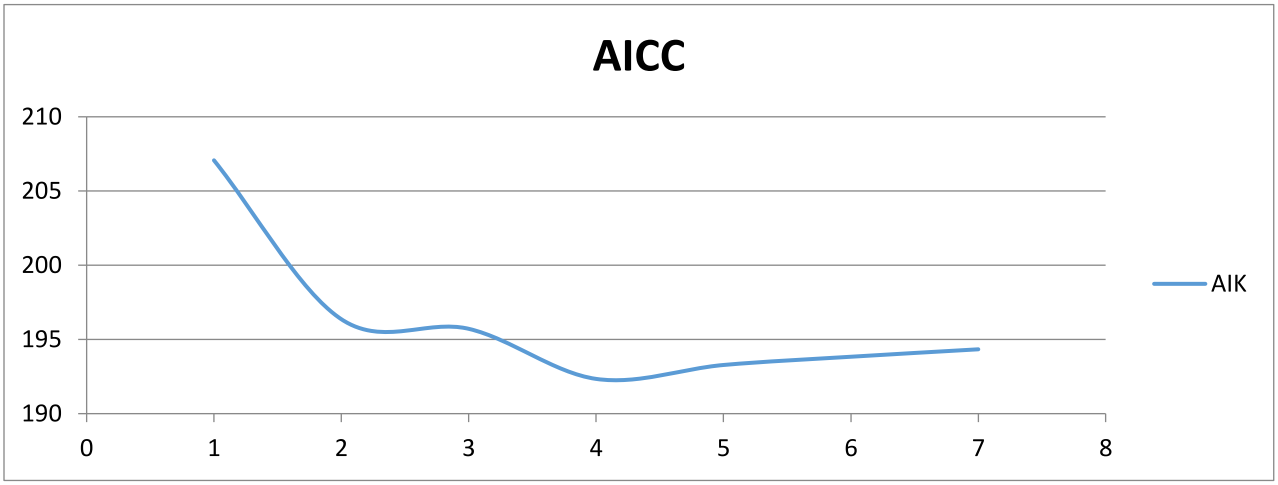


Figure 4-11 Modified AICC for the ARMA model.

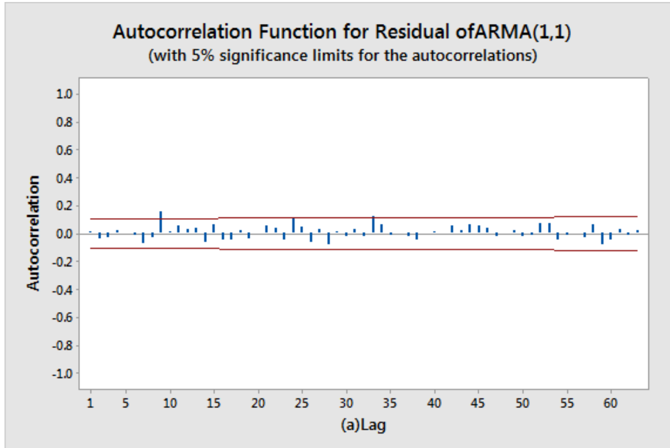
The diagnostic check determines whether residual are independent and normally distributed. To test independence or un-correlation of the residual, the modified Ljung-Box statics have used, which is shown in table 4.6.

Table 4-6 Modified Box-Pierce (Ljung-Box), Chi-Square statistic for the independence test of the residual

ARMA(1,1)	Lag	12	24	36	48
	Chi-Square	13	26.2	39.3	45.1
	DF	9	21	33	45
	P-Value	0.161	0.198	0.208	0.466

ARIMA model residual for independence have been tested by L-jung statistics, if the resulting p-value for first 48 lag autocorrelation is lower than common alpha level (0.05), the hypothesis for null cannot be rejected. So we can conclude this coefficient not differs from zero. From Table 4.6 ARMA (1, 1) indicates the residual of model up to 48 lags becomes independent.

In addition, the autocorrelation and partial autocorrelation of the residual ARMA (1,1) shown Figure 4.12 shows well remain well within 95% confidence interval which indicates that there is no significant correlation within the residuals.



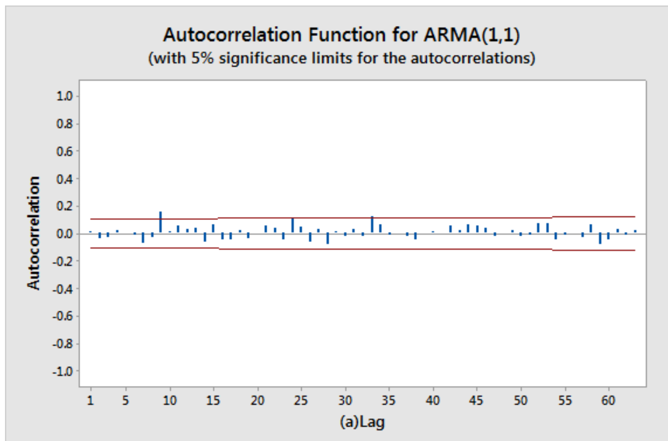


Figure 4-12 Autocorrelation Function (a) and Partial autocorrelation (b) Function for the Residual of ARMA (1,1) Model

The test the hypothesis that the residual ε_t of ARMA(1,1) is normal were determined by plotting the empirical distribution of the residual on a normal probability paper and check if the points follow a straight line. The figure 4.13 shows the residual are normally distributed by following a straight line on probability paper.

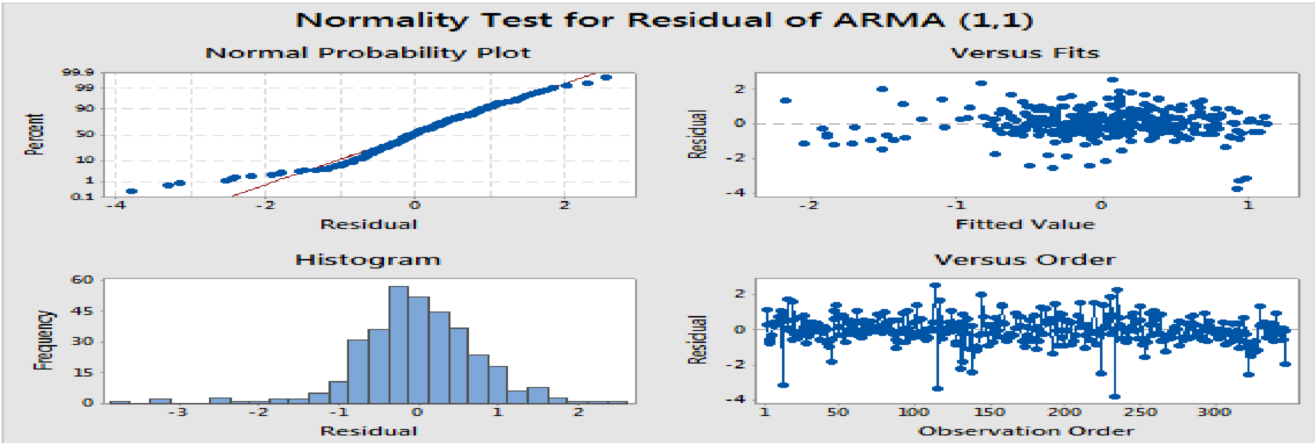


Figure 4-13 Normality Test of the Residual of ARMA (1,1) Model

4.2.7 Synthetic Generation Data

The ARMA (1,1) model is written as the equation below,

$$\boldsymbol{z_t = C + \phi_1 z_{t-1} + \epsilon_t - \theta_1 \epsilon_{t-1}} \qquad \textbf{4. 2}$$

The synthetic series of data are generated using equation 4.2, the last value of the observed series is taken as the initial values. The initial value of the residual ε_{t-1} is taken from last value of the residual series.

The random number generator is used to produce ϵ_t which is normally distributed with zero mean and variance σ_ε^2. Furthermore, the inverse standardization of $\bar{z_\tau}$ will yield a periodic time series models shown in equation 4.3

$$\boldsymbol{y_\tau = \mu_\tau + \sigma_{\tau*} z_\tau} \qquad \textbf{4. 3}$$

Similarly, the inverse logarithmic transformation of $\bar{y_t}$ will yield the generated non normal series $\bar{x_t}$ as shown in equation 4.4

$$\boldsymbol{\bar{x_t} = antilog(\bar{y_t})} \qquad \textbf{4. 4}$$

The synthetically generated stream flow using ARMA(1,1) is given in Appendix Table, **Table A-9**

4.2.8 Validation of ARMA Model

Stream flow generated by ARIMA model is compared with the observed historical flow graphically to examine the statistical similarity between the observed and the generated, as shown in figure 4.14-4.16. The ability of ARIMA model in stream flow generation is inspected using Mean Deviation and Relative Root Mean Square Deviation evaluation measures.

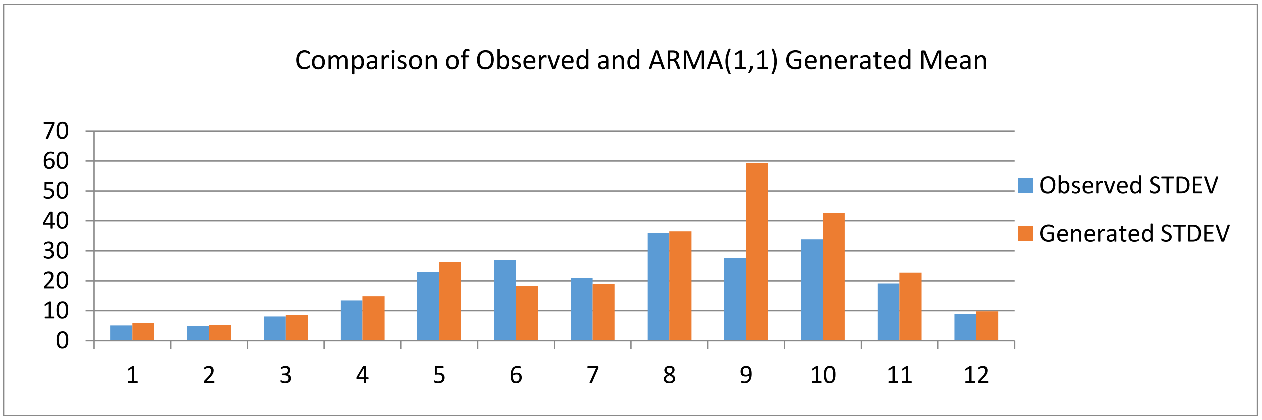


Figure 4-14 Comparison of Observed and ARMA (1,1) Generated Mean

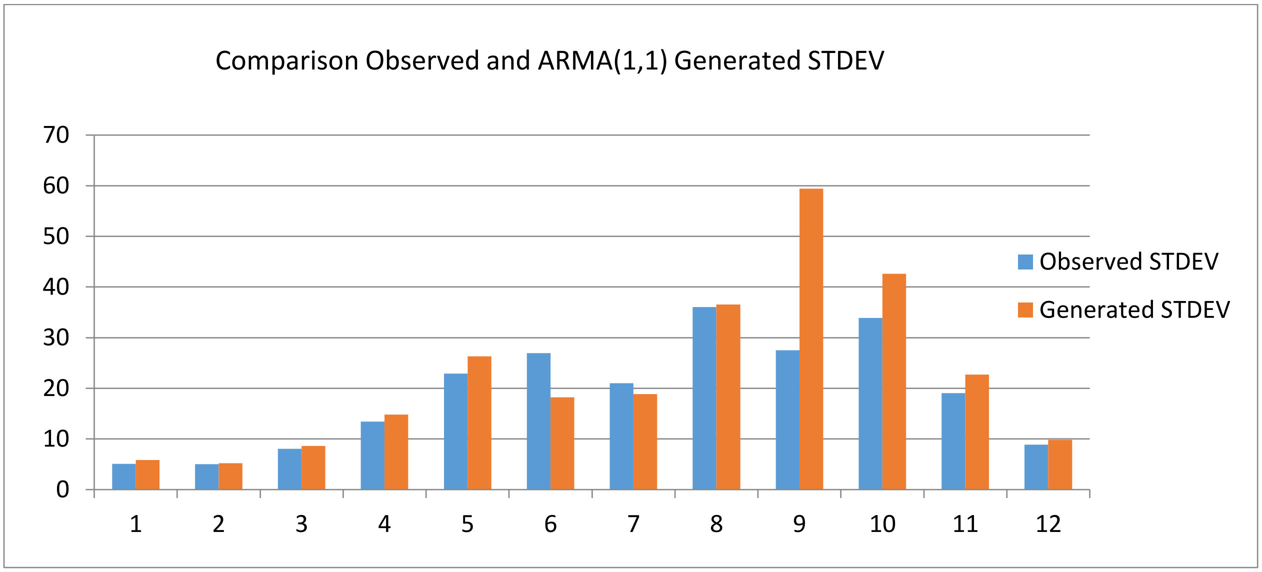


Figure 4-15 Comparison of Observed Deviation with ARMA (1, 1) Model Deviation

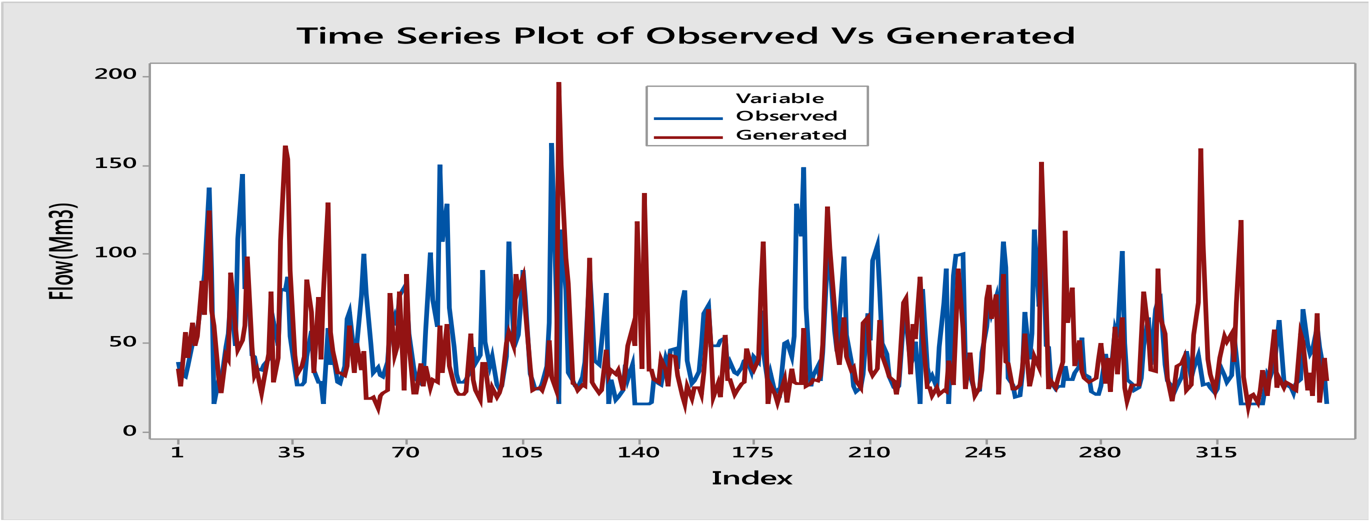


Figure 4-16 Comparison of Observed Flow with ARMA (1, 1) Model Flow

Like in Markov model's validation, the performance evaluation measure like Mean Deviation(MD) and Relative Root Mean Square Deviation (RRMSD) are used to examine the accuracy of ARIMA model. The result of inspection is summarized in Table 4.7 and the details of the calculation can be found in Appendix **A-6**.

Table 4-7 Accuracy of the ARMA (1, 1) Model

Performance Evaluation Procedure	**ARMA model**
MD	-3.43
RRMSD	10.65

4.3 Model Fitting and Simulation PARMA Model

4.3.1 Seasonal Stationarity

The fluctuation of the observed data around the mean value of the series shows a periodic stationarity (Fig 4.17).

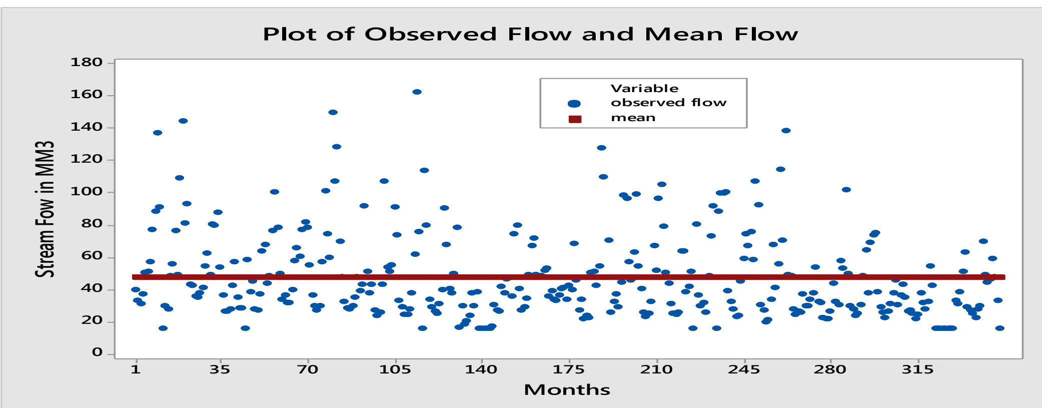


Figure 4-17 Seasonality of the Observed Flow of Measso Station

4.3.2 Seasonality (Periodicity) aspect

Testing for seasonality in statistics is done by using simple procedures, by observing the plot of the statistic under consideration versus the season τ .Fig 4.18 plots of the observed mean $\grave{Y}_\tau$ versus τ =1,….,12 .The plot suggests that the $\grave{Y}_\tau$ during the low flow season are quite different from those of high-flow season. Thus, even though some of the $\grave{Y}$'s in the low-flow season are similar to each other, one would conclude overall that $\grave{Y}_\tau$ is a seasonal (periodic) stationarity.

A similar argument can be made in relation to seasonality in other statistics such as like autocorrelation and spectrum of the series.

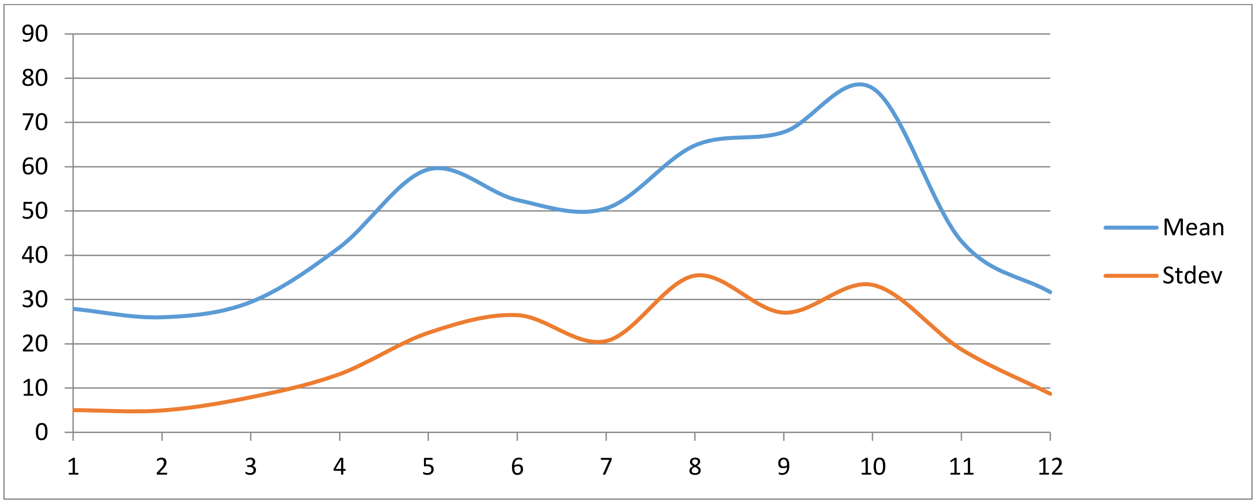


Figure 4-18 Plot of Seasonal mean and standard deviation of the original data for Meisso Station near Gidabo

All stations considered here show distinctive seasonal characteristic with bimodal behavior, the peak being located in around May and October respectively

4.3.3 Testing for Normality

Two normality tests, namely the skewness test of normality and Filliben probability plot correlation test both applied at the 10% significance level. The Cunnane plotting position is used for test.

4.3.4 Transformation to Normal

If the normality tests indicate that the observed series are not normally distributed, the data has to be transformed into normal before applying the PARMA model. To normalize the data equation (3.27-3.30) transformation functions are commonly used.

Fig (4.19) shows the plot of original and transformed data for season 1. Transformation coefficient and the normality test value of all seasons for Measso stations are shown on Table 4.8.

Table 4-8 Transformation Coefficient and Normality Test Value for all Season of Measso Station

Seas	Displayed	Transformation Is		Skewness Test		Filliben Test	
Num	Trans	Coeff a	Coeff b	Comp.V	Result	Comp.V	Results
1	None	0	0	0.0686	accept	0.9841	accept
2	None	0	0	0.5493	accept	0.9727	accept
3	Log	-2.9655	0	0.4015	accept	0.966	REJECT
4	None	0	0	0.6204	accept	0.9716	accept
5	None	0	0	0.3772	accept	0.9863	accept
6	Log	-4.1523	1	0.0927	accept	0.9686	REJECT
7	Log	1	1	-0.1282	accept	0.9843	accept
8	Log	1	1	-0.2119	accept	0.9866	accept
9	None	0	0	-0.2672	accept	0.9883	accept
10	None	0	0	0.279	accept	0.9856	accept
11	Log	1	0	-0.2094	accept	0.9784	accept
12	None	0	0	-0.0221	accept	0.977	accept

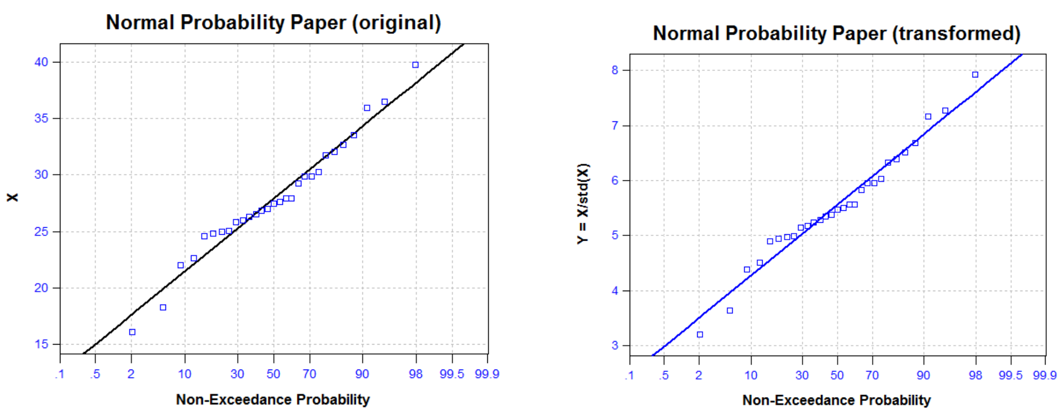


Figure 4-19 Plot of the transformed data on normal probability paper and test of normality for season one at Measso station.

4.3.5 Scaling and Standardization

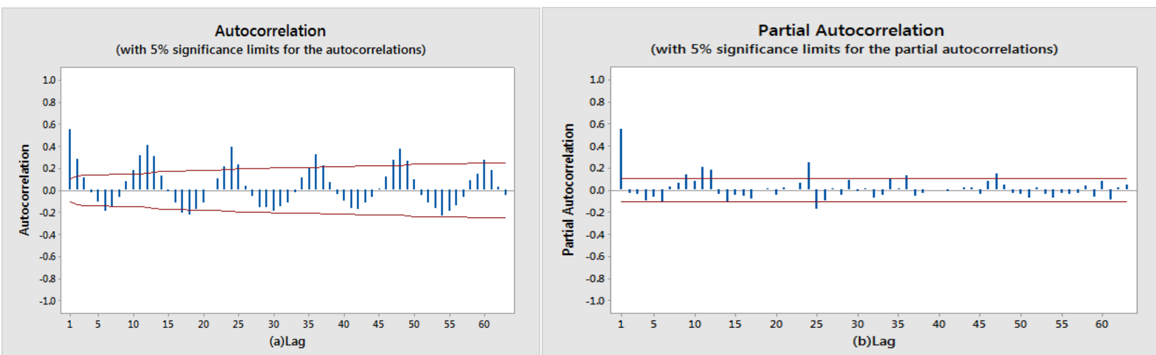
As shown in table 4.8 ,some seasons do not need transformation for normality; for instance, season 1, whereas other seasons for the same station do need to be transformed, thus in such conditions the scaling is needed. Scaling in this context is dividing all the time series which have not been transformed by the standard deviation. In addition, the normalized data are standardized by subtracting the mean and dividing by the standard deviation.

4.3.6 PARMA Model Fitting Procedures

The time series used in this study are average monthly stream-flow (Mm^3) for Meisso stations near Gidabo reservoir which are presented in appendix table, **Table A-1** from January to December, where season 1 corresponds to January and season 12 corresponds to December are used in this study.

4.3.6.1 Initial Model Identification

According to ACF and PACF functions, Figure 4.20, the time series shows of the dependence structure in the seasonal data series which is used as identification of representative model.



Figur**e 4-20** The sample ACF (fig. a) and PACF (fig. b) for the historical time series of Meisso Station near Gidabo, showing the 95% confidence bounds ±1.96/√N**.**

4.3.6.2 Estimation of Parameter

The method of moment (MOM) and least square method (LS) methods are used in parameter estimation of PARMA(p,q) models.The parameters estimated for PARMA(1,0) using the method of moment and least square(LS) by Eq.(2.28-2.29) for Meisso station are shown in Table 4-9 .

Table 4-9 PAR parameters of PARMA (1, 0) model fitted to standardized data of Meisso station**.**

Season	ϕ_1	WN

Jan.	0.261927	0.931394
Feb.	0.821813	0.324623
Mar.	0.694937	0.517062
Apr.	0.692047	0.521070
May.	0.569022	0.676214
Jun.	0.391568	0.846674
July	0.388194	0.849305
Aug.	0.626700	0.607247
Sep.	0.499378	0.750622
Oct.	0.537739	0.710837
Nov.	0.783045	0.386841
Dec.	0.319011	0.898232

The plot of parameters here indicates the seasonality (Periodicity) pattern of both white noises variance (WN) and autoregressive parameters (Φ) (Fig 4.21).

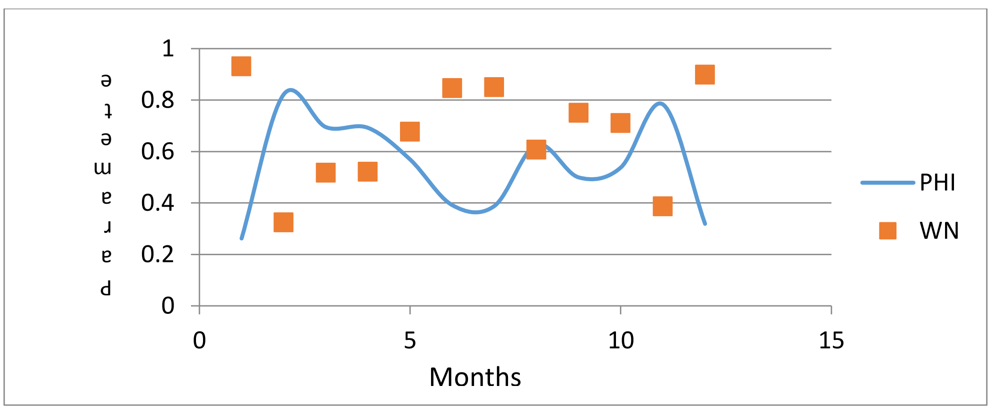


Figure 4-21 Plot of parameters of PARMA (1, 0) at Meisso station.

4.3.6.3 Diagnostic checking

Among the automatic selection criteria used in model discrimination, Akaike information criterion (AICC) and Bayes information criterion (BIC) are used. Table 4-10.

Table 4-10 Goodness of fit of the candidate models to the monthly stream-flow at Measso Station near Gidabo reservoir

Model	Autocorrelation	AICC	SIC	WN
PARMA(1,0)	ALL	30.203	29.109	0.89373
PARMA(1,1)	ALL	32.639	32.413	0.891784
PARMA(2,0)	ALL	32.64	32.414	0.891823
PARMA(2,1)	ALL	35.311	35.747	0.890741

The performance of the candidate models is compared using the white noise variance (WN variance), Akaike information criterion corrected (AICC) and Schwarz Bayesian criterion (SIC) The *model* that gives the minimum AICC and SIC is selected as parsimonious. Normality test and WN test of the residuals are performed through a plot of ACF of the residuals and statistical analysis. (Table 4-10).The WN variance is the ratio of the sum of squares of errors (SSE) divided by the number of observations.

From Table 4-10, it can be seen that as the order of PARMA increases the model fits poorly. Generally, as can be observed from the values of AICC, SIC and sample statistics, the model PARMA (1, 0) is the best among the candidate models, whereas the PARMA (2, 1) model performs poorly.

4.3.7 Synthetic Generation of Stream Flow using PRAMA Model

The PARMA (1,0) model can be written in form:

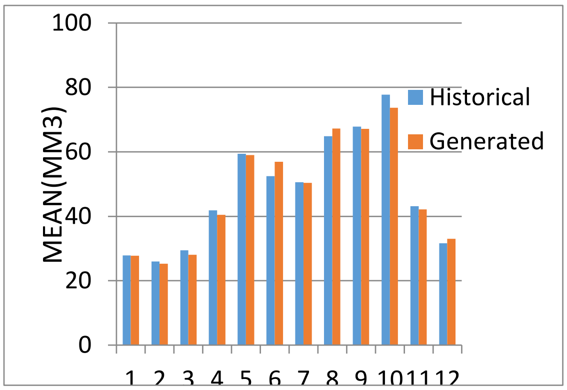
$$\boldsymbol{Y_{\upsilon,\tau} = \phi_{1,\tau} Y_{\upsilon,\tau-1} + \varepsilon_{\upsilon,\tau}} \qquad \textbf{4.5}$$

Where, $Y_{\nu,\tau}$ represents the stream-flow process for year ν and season τ. For each season, τ, this process is normally distributed with mean zero and variance $\delta^2{}_\tau$ (*Y*). The $\varepsilon_{\nu,\tau}$ is the uncorrelated noise term which for each season is normally distributed with mean zero and variance $\delta^2{}_\tau$ (ε).

The synthetically generated stream flow using PARMA(1,0) is given in Appendix **A-10**

4.3.8 Validation of PARMA model

Stream flow generated by PARMA model is compared with the observed historical flow graphically, as shown in figure 4.22. The ability of PARMA model in stream flow generation is inspected using Mean Deviation and Relative Root Mean Square Deviation forecast evaluation measures



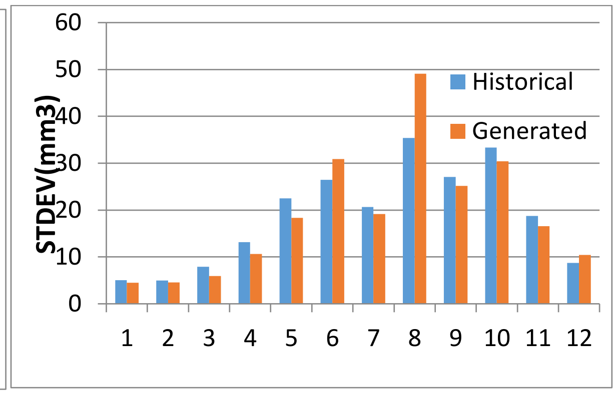


Figure 4-22 Comparison of generated and historic statistics of monthly streamflow at Meisso station near Gidabo reservoir.

Like in Markov and ARMA models validation, the performance evaluation measure like Mean Deviation(MD) and Relative Root Mean Square Deviation (RRMSD) are used to examine the accuracy of PARMA model. The result of inspection is summarized in Table 4-11 and the details of the calculation can be found in Appendix Table, T**able A-6**.

Table 4-11 Accuracy of the PARMA (1,0) Model

Performance Evaluation Procedure	**PARMA model**
MD	0.95
RRMSD	10.54

The PARMA (1, 0) model fits well to the stream flow of Meisso station near Gidabo reservoir as can be seen from the automatic selection criterion (Table 4-11) and the comparison of historic and generated basic statistic values shown in figure 4.22 .

4.4 Model Fitting and Simulation GRA(1) Model

The gamma-autoregressive model GAR(1) is similar to the well-known AR(1) model except that the underlying process being modeled is assumed to follow the gamma distribution instead of the normal distribution. Thus if the intent is to use the GAR(1) model, then the underlying data should not be transformed to normal .

A GAR(1) model was fitted to the monthly data of Measso station. Based on this model, the skewness coefficient of the historical data can be preserved without data transformation. The estimated parameters of the model using equation 2.24 to 2.35 are shown in Table 4-12

Table 4-12 parameter for GAR(1) model

lambda	alpha	beta	phi
12.8816	0.047501	1.655816	0.560359

29 years long were generated using these estimated parameters. The statistical analysis results of the generated data and the historical are shown in table 4-13

Table 4-13 statistical comparison of historical and generated flow using GAR (1) model

statistics	Historical	Generated
mean	47.74	52.46
stDev	26.95	29.98
CV	0.5646	57.16
Min	16.06	14.45
Max	162.2	186.54
Skew	1.48	1.5

Like in Markov, ARMA and PARMA models validation, the performance evaluation measure like Mean Deviation (MD) and Relative Root Mean Square Deviation (RRMSD) are used to examine the accuracy of GAR(1) model. The result of inspection is summarized in Table 4-14 and the details of the calculation can be found in **A-6.**

Table 4-14 Accuracy of the GAR (1) Model

Performance Evaluation Procedure	**PARMA model**

MD	4.72
RRMSD	11.76

4.5 Comparison of Markov, ARMA, PARMA and GAR (1) model

The generated monthly time series stream flow data set compared with the observed monthly data set with performance evaluation test : MD and RRSMD (Table 4-15) and best fitted model was selected.

Table 4-15 Comparisons of Markov, ARMA and PARMA

Performance Evaluation Procedure	Markov model	ARMA Model	PARMA Model	GAR(1)
MD	2.49	-3.43	0.95	4.46
RRMSD	10.76	10.65	10.64	11.76

4.6 Reservoir Sizing

4.6.1 Preparation of Input Data for NLP Reservoir Sizing Model

Reservoir inflow data generation for the consecutive 50 years has prepared from PARMA (1,0)and shown in Appendix Table **A-10.** The evaporation lose coefficients for open water evaporation (e_t) using Penman method and the precipitation coefficients (p_t)over the reservoir are taken from Feasibility Report for Irrigation and Drainage is shown in Appendix Table A-**11.** The values of monthly total irrigation requirement which were computed and the summary of it is given in Appendix Table **A-12**. The elevation Area Capacity relation of the Gidabo reservoir is given in figure 4.25 below. The maximum and minimum topographic limit for the reservoir site is given as 1235 and 1205 m.a.s.l. from the topographic point of view, as much as 240MM3 storage space could be available.

Table 4-16 The Elevation Area Capacity Relation of Gidabo Reservoir.

water Surface Elevation (m.a.s.l)	Surface Area (ha)	Original vol.(Mm3)	water Surface Elevation (m.a.s.l)	Surface Area (ha)	Original vol.(Mm3)
1205	4.1	0.041	1221	882.9	75.321
1206	18.3	0.224	1222	928.2	84.603
1207	43.9	0.663	1223	971	94.312
1208	84.7	1.51	1224	1011.2	104.425
1209	153.3	3.043	1225	1050.9	114.934
1210	236.5	5.407	1226	1092.5	125.859
1211	314.6	8.553	1227	1134.6	137.204
1212	418.7	12.74	1228	1174.6	148.951
1213	500.7	17.747	1229	1212.4	161.075
1214	548.8	23.234	1230	1248.9	173.564
1215	605.6	29.29	1231	1284.4	186.408
1216	655.7	35.847	1232	1321.4	199.622
1217	700.2	42.849	1233	1359.4	213.216
1218	741.9	50.267	1234	1396.7	227.183
1219	787.6	58.144	1235	1434	241.523
1220	834.8	66.492			

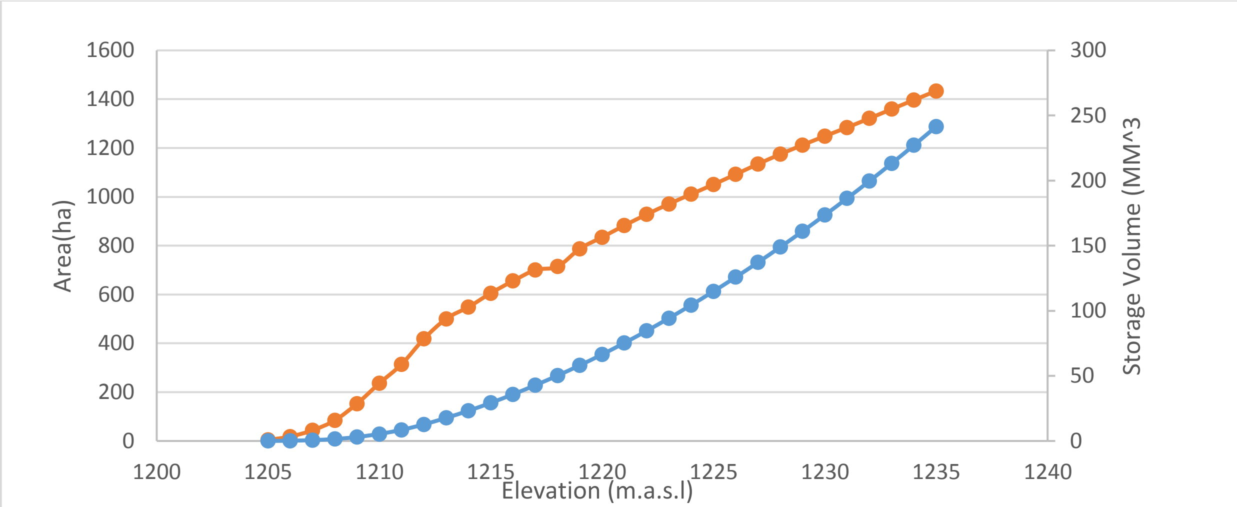


Figure 4-23 The Elevation Area Volume Curve of Gidabo Dam Site

4.6.2 Elevation-Storage Curve

The elevation -area -storage curve of the Gidabo reservoir figure 4-23 whose parameter αα and ββ calculated using the procedure discussed in section 3.4.3 is solved by GAMS software and the comparison of the observed storage and the calculated storage value and the difference between them is shown Appendix A-13 (Figure 4.24) The parameter αα and ββ becomes 0.4046 and 1.8818 respectively.

$$\mathbf{S(r) = 0.4046 * (H(r) - 1205)^{1.88}} \qquad 4.6$$

The storage level at any given period t is obtained from the equation above.

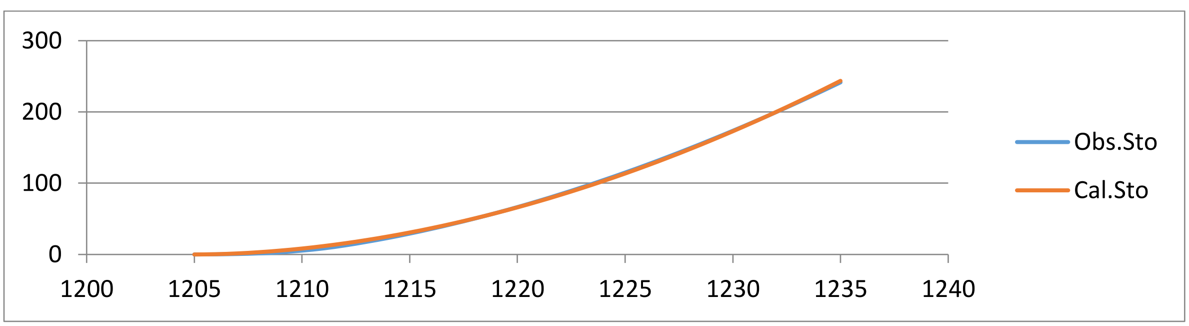


Figure 4-24 Comparison of Observed and Calculated Storage –Elevation curve

4.6.3 Area-Storage Curve

The storage-area curve parameter α and β calculated using the procedure discussed in section 3.4.2 is solved by GAMS software and the comparison of the observed storage-area and the calculated storage-area value and the difference between them is shown Appendix A-14 (Figure4.25). The parameter α and β becomes 1.31 and 0.44 respectively.

$$\mathbf{A(r) = 1.31 * \left(S(r)\right)^{0.44}} \quad 4.7$$

The area at any given period t is obtained from the equation above.

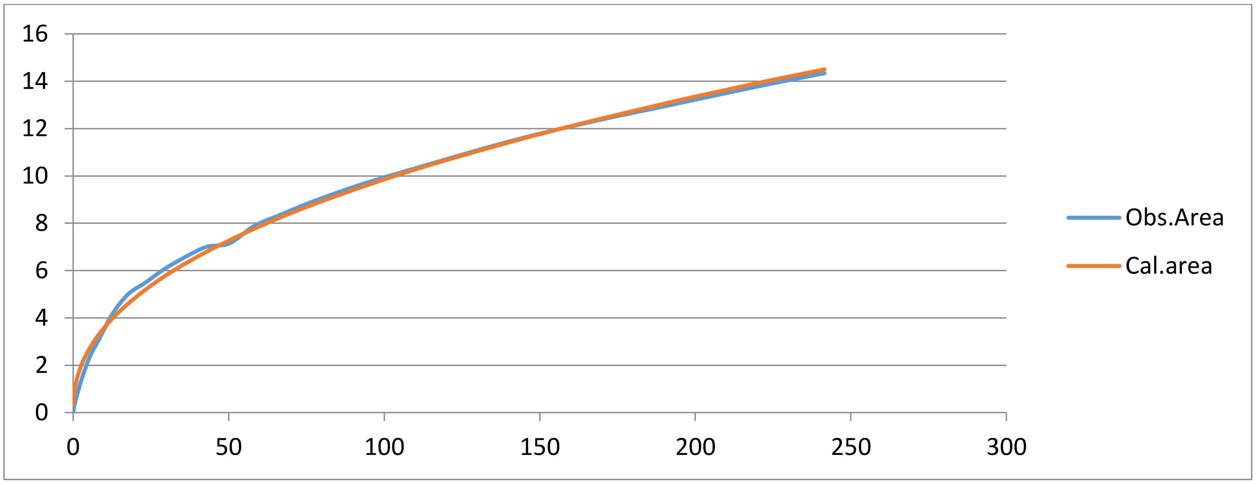


Figure 4-25 Comparison of Observed and Calculated area –Storage curve

4.6.4 Stochastic Non-Linear Optimization

The nonlinear programing model discussed in section 3.5.1 has been solved by GAMS program. The full result of this program is given in Appendix **A-15**. Therefore in this section only the summary of the output of the model of the Gidabo reservoir sizing have been discussed.

4.6.4.1 Optimal size of the reservoir

The required capacity of the reservoir is determined taking in to account the evaporation and precipitation on the reservoir, irrigation demand which vary with time. The maximum required capacity obtained from the model found to be 37.54 Mm^3 .the maximum water level in the reservoir is 1216.10. The dead storage volume is 3.63 and the level of the dead storage is 1208.21. The minimum operating level for the outlet is 1210.47

In this study, the optimization is prepared for the life cycle of the project which is 50 years. The major output of NLP programing model is the storage, spill, level and evaporation and precipitation at monthly time steps and prescribe how water is to be regulated during the subsequent months based on the current stay of the system. The volumes of the decision variables for the first five years are given in Table 4.17.

Table 4-17 Monthly Storage Required, Inflow, Spill and Other Parameter from the Output of NLP (GAMS program).

<u>Reservoir Sizing using GAMS</u>

Maximum Reservoir capacity (Mm3) =	37.54
maximum reservoir level(m) =	1216.10
dead storage volume(Mm3)=	3.64
dead storage level(m)=	1208.21
MDDL volume(Mm3)=	9.89
MDDL level(m) =	1210.49

The coefficient for Area Storage Curve (a & b)

a	b
1.31	0.44

Time Month t	Inflow (Mm3) Q(t)	Begin storage (Mm3) S(t)	End storage (Mm3) S(t+1)	Evapo. (Mm3) E(T)	Pri-rate (Mm3) P(t)	Release (Mm3) spill(t)	Demand (Mm3) Y(t)	Level m L(t)
1	26.33	26.83	21.28	0.70	0.10	5.67	25.62	1214.29
2	26.25	21.28	29.14	0.70	0.13	5.67	12.15	1213.21
3	30.09	29.14	37.54	0.89	0.24	14.55	6.48	1214.71
4	55.73	37.54	37.54	0.85	0.46	49.28	6.07	1216.10
5	77.11	37.54	37.54	0.86	0.41	64.35	12.31	1216.10
6	90.31	37.54	37.54	0.79	0.37	74.98	14.90	1216.10
7	49.52	37.54	24.42	0.66	0.41	49.28	13.12	1216.10
8	44.59	24.42	19.74	0.59	0.28	40.30	8.67	1213.84
9	75.20	19.74	33.32	0.69	0.30	51.44	9.80	1212.89
10	74.23	33.32	37.54	0.80	0.34	52.27	17.28	1215.42
11	34.29	37.54	37.54	0.78	0.15	9.41	24.24	1216.10
12	17.04	37.54	24.11	0.75	0.12	1.00	28.84	1216.10
13	29.27	24.11	27.15	0.72	0.10	0.00	25.62	1213.78
14	24.10	27.15	16.45	0.66	0.12	22.10	12.15	1214.35
15	26.43	16.45	9.98	0.60	0.16	25.99	6.48	1212.16
16	40.65	9.98	37.14	0.69	0.37	7.11	6.07	1210.49
17	50.50	37.14	24.86	0.79	0.38	50.06	12.31	1216.04
18	48.54	24.86	9.98	0.57	0.27	48.21	14.90	1213.92
19	75.75	9.98	16.35	0.45	0.28	56.09	13.12	1210.49
20	126.62	16.35	37.54	0.64	0.31	96.44	8.67	1212.14
21	86.37	37.54	37.54	0.81	0.35	76.12	9.80	1216.10
22	88.79	37.54	37.54	0.82	0.35	71.03	17.28	1216.10
23	38.50	37.54	37.54	0.78	0.15	13.62	24.24	1216.10
24	40.75	37.54	37.54	0.82	0.13	11.22	28.84	1216.10
25	25.45	37.54	34.47	0.83	0.12	2.19	25.62	1216.10
26	24.98	34.47	22.39	0.74	0.14	24.30	12.15	1215.61
27	25.14	22.39	15.98	0.70	0.19	24.56	6.48	1213.44
28	27.87	15.98	9.98	0.53	0.29	27.55	6.07	1212.05
29	33.90	9.98	9.98	0.48	0.23	21.34	12.31	1210.49
30	84.38	9.98	27.23	0.58	0.28	51.91	14.90	1210.49
31	68.44	27.23	30.38	0.64	0.40	51.93	13.12	1214.36
32	90.95	30.38	37.54	0.71	0.34	74.76	8.67	1214.92
33	128.85	37.54	37.38	0.81	0.35	118.75	9.80	1216.10
34	78.78	37.38	37.54	0.82	0.35	60.87	17.28	1216.08
35	55.07	37.54	25.19	0.72	0.14	42.59	24.24	1216.10

36	48.04	25.19	9.98	0.59	0.09	33.91	28.84	1213.98
37	31.15	9.98	9.98	0.47	0.07	5.13	25.62	1210.49
38	31.82	9.98	22.07	0.58	0.11	7.12	12.15	1210.49
39	29.96	22.07	15.59	0.70	0.19	29.45	6.48	1213.37
40	50.11	15.59	16.68	0.58	0.32	42.68	6.07	1211.96
41	48.58	16.68	9.98	0.55	0.26	42.70	12.31	1212.22
42	35.09	9.98	29.84	0.60	0.28	0.00	14.90	1210.49
43	32.04	29.84	16.75	0.58	0.36	31.79	13.12	1214.83
44	35.98	16.75	9.98	0.47	0.23	33.85	8.67	1212.23
45	117.44	9.98	37.54	0.66	0.29	79.71	9.80	1210.49
46	138.13	37.54	37.54	0.82	0.35	120.38	17.28	1216.10
47	88.64	37.54	37.54	0.78	0.15	63.76	24.24	1216.10
48	32.71	37.54	37.54	0.82	0.13	3.17	28.84	1216.10
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
597	82.29	15.76	9.98	0.51	0.22	77.99	9.80	1212.00
598	88.58	9.98	30.93	0.63	0.26	49.98	17.28	1210.49
599	39.21	30.93	36.04	0.74	0.14	9.25	24.24	1215.02
600	25.94	36.04	26.83	0.76	0.12	5.66	28.84	1215.87

The minimal storage of the reservoir is 9.89Mm3, corresponding to the total minimum operating level of the reservoir. As shown in figure 4.26, Demand was fully met except in December, January and February, at this level the amount of water stored decrease to minimum operating level, which signifies an empting reservoir. Large quantity of water was spilled from reservoir from the month September to October. In reservoir sizing the most significant water loss is evaporation from the reservoir surface. The total precipitation amount is considerably lower than the evaporation amount. After comparing the irrigation water requirement in a month December, January and February and the precipitation amount in those months, the need for irrigation becomes clear in those months which are shown in figure 4.26. The reservoir level considering the inflow, demand, evaporation, precipitation and spill is also shown in figure 4.28.

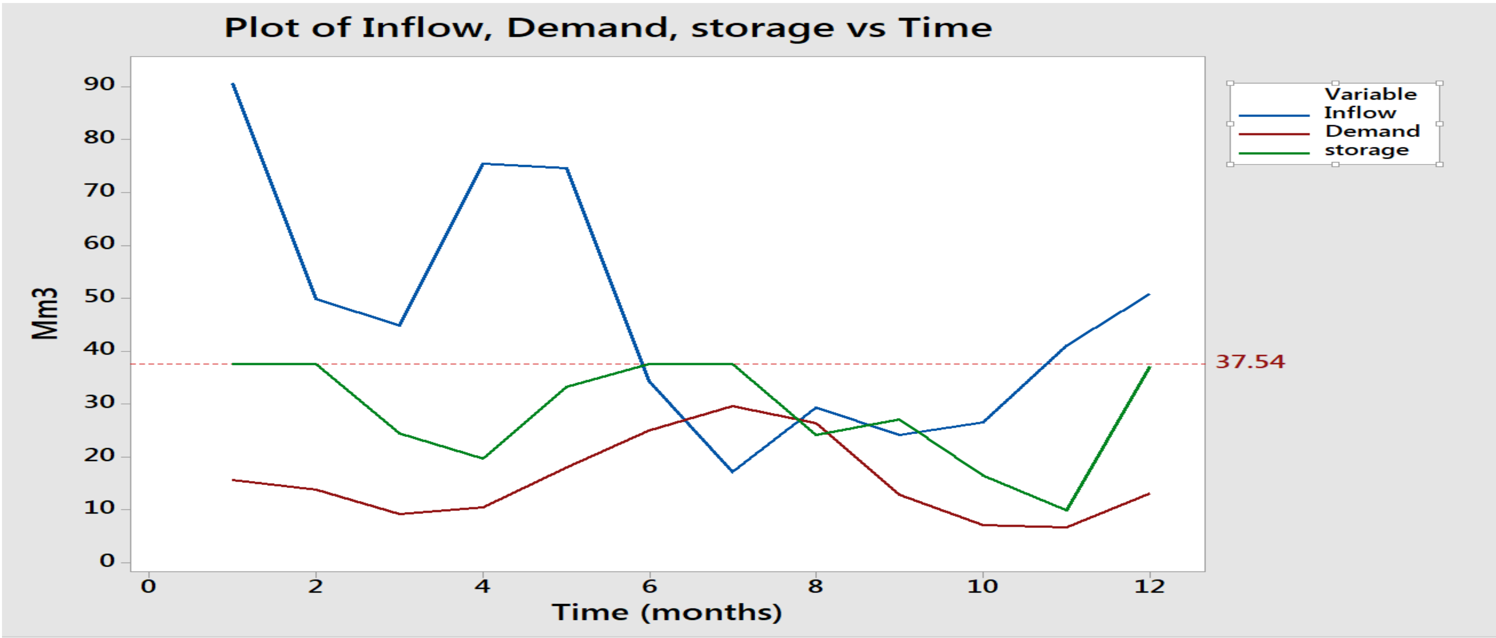


Figure 4-26 Reservoir Sizing for the Gidabo Reservoir

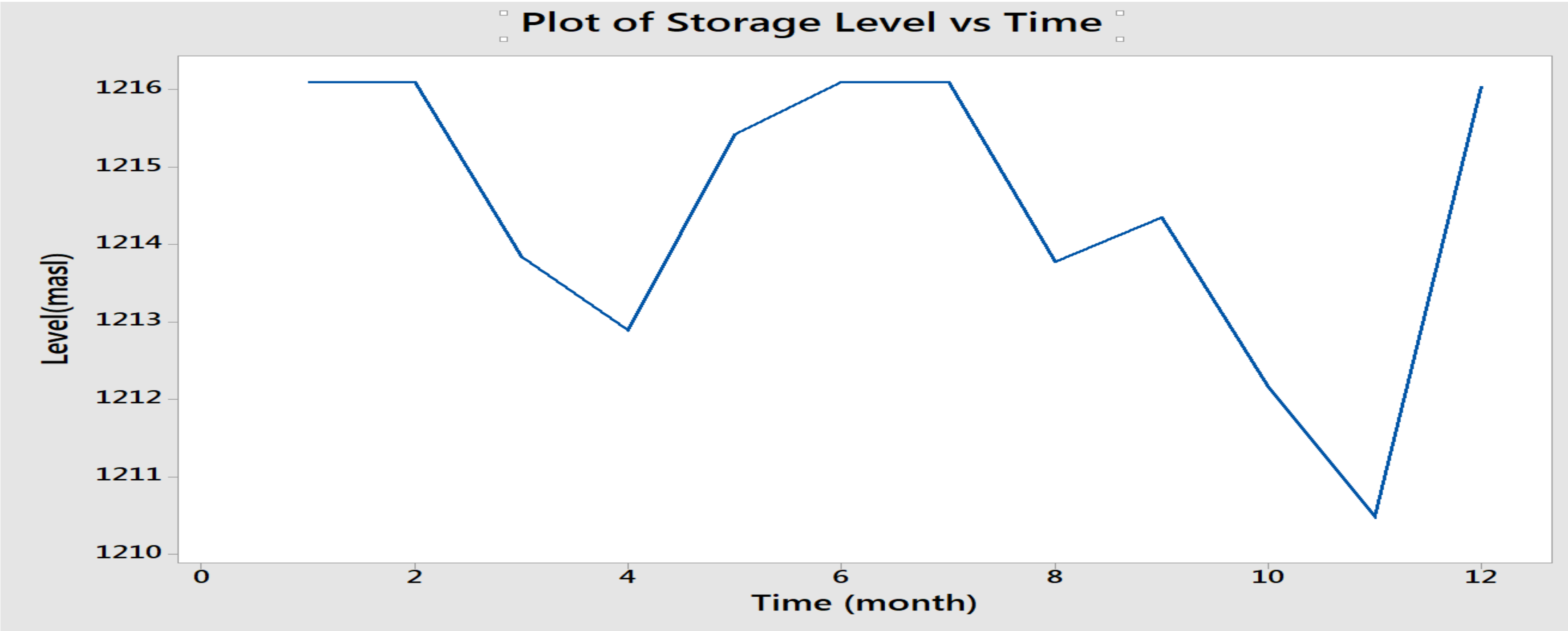


Figure 4-27 Reservoir Level of Gidabo Reservoir

5 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The first part of This study has evaluated the best fit stochastic models Markov, ARMA, PARMA and GAR(1) model and has come with the following conclusions

PARMA (p,q) model is selected as a best fit with sample observed data than MARCOV,ARMA and GAR(1). Low order PARMA (1,0) has a better stream flow generating ability than high order PARMA(p,q) model. From Performance Evaluation procedure, it is found that PARMA model has low value for all ARMA, Marcov and GAR (1). Therefore, PARIMA (1, 0) model has the ability to predict accurately the future monthly stream-flow for Measso Station.

The second part of this study mainly concerned with optimization of Reservoir i.e. sizing of reservoir capacity, preparing the month to month water scheduling curve for the life span of the project (fifty years). Reservoir sizing analysis is carried on the reservoir in monthly basis. Based on the optimization study on reservoir, the following conclusions are arrived at:-

The best fit PARMA (1,0) model selected in the first part of this study was used to generate long (fifty years)series monthly stream flow data. The objective to optimize the maximum reservoir capacity considering the generated inflow, the precipitation on the reservoir, irrigation water demand, evaporation and excess water spill through spillway is 37.54Mm3. The maximum water level obtained from the analysis becomes 1216.16

The reservoir storage-area function has non-linear nonlinear relationship; hence NLP algorithm is employed in the analysis. The value of the coefficient to obtain the optimized area storage relationships becomes 1.31 and 0.44.

The reservoir elevation-storage function has non-linear relationship; hence NLP algorithm is employed in the analysis. The value of the coefficient to obtain the optimized area storage relationships becomes 0.41 & 1.88.

A month to month water scheduling (rule curve) is obtained and graphed for use of the operators .The rule curve has shown the water level in the reservoir maintained the at the end of each month, the required water release to satisfy the irrigation demand, the required spill from the reservoir at the end of each month.

5.2 Recommendation

Do the steam flow generation after removing the outlier. This analysis is made by using PARMA, MARCOV, ARMA and GAR (1) model. Compare the stream flow generation with other generating methods of time series such as exponential smoothing, regression analysis or Fourier series analysis.

Use hybrid model such as contemporaneous multivariate CARMA, univariate shifting-mean SM model and artificial neural network in stream flow generation.

Non-seasonal ARMA model specially used for generating annual series and Seasonal ARMA model for specially used for generating seasonal flow , season may be 12 month,6 month or 4 month.

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APPENDIX A

Appendix A- 1- Monthly stream flow of Measso station near Gidabo Reservoir (taken from Final Feasibility Report for Hydrological Study)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct.	Nov	Dec
1977	39.79	32.89	31.28	37.05	50.32	51.35	57.16	77.13	88.60	137.02	90.69	16.06
1978	29.91	28.03	48.19	55.57	76.33	48.77	108.68	144.59	80.69	92.86	43.33	42.23
1979	35.98	35.38	37.73	40.76	54.67	62.27	48.99	80.24	79.74	87.54	54.02	36.10
1980	26.49	26.32	28.02	42.55	57.14	35.10	28.33	28.33	16.06	58.29	38.37	44.78
1981	27.91	27.33	37.20	63.79	67.80	43.67	48.68	76.36	100.17	78.56	49.59	33.56
1982	36.51	31.71	31.44	39.63	57.85	65.57	60.15	76.78	81.59	78.08	55.25	36.30
1983	29.85	27.21	29.57	57.26	100.93	74.42	59.55	149.93	107.03	128.50	69.79	47.82
1984	32.65	28.06	27.94	29.67	35.26	47.53	38.92	43.16	91.47	50.82	37.61	42.73
1985	27.00	24.05	25.89	42.80	106.93	53.62	51.25	54.81	91.08	73.75	32.99	28.85
1986	24.61	24.31	27.44	37.63	61.61	162.17	75.43	16.06	113.80	79.74	33.75	29.30
1987	26.27	25.11	31.01	39.49	90.42	67.72	40.70	37.70	49.81	78.41	16.15	29.86
1988	18.27	20.10	23.66	37.94	29.50	38.20	16.06	16.06	16.06	16.06	16.06	17.04
1989	30.25	27.37	26.72	41.87	37.88	46.53	47.20	35.78	74.05	79.74	40.35	27.35
1990	29.22	34.52	48.71	67.20	71.40	48.73	48.36	48.57	51.50	53.06	35.94	39.28
1991	33.57	33.12	36.61	40.34	41.32	33.92	42.23	39.62	68.34	45.54	27.15	33.54
1992	22.03	23.81	22.30	50.24	50.99	42.44	54.32	127.92	109.93	148.75	70.11	25.57
1993	32.05	37.14	28.75	44.59	98.38	96.62	57.33	45.68	63.09	98.76	54.57	40.43
1994	25.80	22.99	25.29	32.46	67.20	51.71	96.09	105.00	78.97	50.38	43.79	30.85
1995	24.82	24.15	26.04	63.43	63.93	38.35	41.88	51.14	16.06	80.17	36.38	29.41
1996	31.74	25.46	48.22	72.88	91.81	16.06	88.08	99.78	99.83	100.15	39.10	32.15
1997	27.59	22.79	23.65	44.79	59.06	74.66	67.04	75.72	58.12	107.14	92.48	30.68
1998	26.86	19.55	20.99	33.60	67.36	40.94	55.42	114.07	70.65	138.49	48.81	48.04

1999	27.89	24.13	26.16	25.78	36.99	29.42	29.86	33.52	37.49	53.46	32.41	31.54
2000	22.60	21.48	21.61	26.07	43.92	32.50	30.11	57.61	53.05	101.78	49.92	29.71
2001	27.45	23.91	25.31	30.16	48.55	64.24	37.86	68.80	73.85	75.23	38.41	28.82
2002	25.94	22.51	26.14	31.11	37.92	45.44	30.25	36.14	42.99	35.31	26.67	27.37
2003	24.93	22.03	24.13	37.74	31.96	27.96	32.09	54.45	42.63	16.06	16.06	16.06
2004	16.06	16.06	16.06	16.06	16.06	33.00	30.74	38.38	51.09	63.29	29.22	26.92
2005	25.06	22.34	27.78	30.00	69.49	49.27	44.29	46.58	59.19	47.87	33.07	16.06

Appendix A- 2- logarithmic Monthly stream flow of Measso station near Gidabo Reservoir

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1.600	1.517	1.495	1.569	1.702	1.711	1.757	1.887	1.947	2.137	1.958	1.206
1.476	1.448	1.683	1.745	1.883	1.688	2.036	2.160	1.907	1.968	1.637	1.626
1.556	1.549	1.577	1.610	1.738	1.794	1.690	1.904	1.902	1.942	1.733	1.558
1.423	1.420	1.448	1.629	1.757	1.545	1.452	1.452	1.206	1.766	1.584	1.651
1.446	1.437	1.571	1.805	1.831	1.640	1.687	1.883	2.001	1.895	1.695	1.526
1.562	1.501	1.498	1.598	1.762	1.817	1.779	1.885	1.912	1.893	1.742	1.560
1.475	1.435	1.471	1.758	2.004	1.872	1.775	2.176	2.030	2.109	1.844	1.680
1.514	1.448	1.446	1.472	1.547	1.677	1.590	1.635	1.961	1.706	1.575	1.631
1.431	1.381	1.413	1.631	2.029	1.729	1.710	1.739	1.959	1.868	1.518	1.460
1.391	1.386	1.438	1.576	1.790	2.210	1.878	1.206	2.056	1.902	1.528	1.467
1.420	1.400	1.492	1.597	1.956	1.831	1.610	1.576	1.697	1.894	1.208	1.475
1.262	1.303	1.374	1.579	1.470	1.582	1.206	1.206	1.206	1.206	1.206	1.232
1.481	1.437	1.427	1.622	1.578	1.668	1.674	1.554	1.870	1.902	1.606	1.437
1.466	1.538	1.688	1.827	1.854	1.688	1.685	1.686	1.712	1.725	1.556	1.594
1.526	1.520	1.564	1.606	1.616	1.531	1.626	1.598	1.835	1.658	1.434	1.526
1.343	1.377	1.348	1.701	1.708	1.628	1.735	2.107	2.041	2.173	1.846	1.408
1.506	1.570	1.459	1.649	1.993	1.985	1.758	1.660	1.800	1.995	1.737	1.607
1.412	1.362	1.403	1.511	1.827	1.714	1.983	2.021	1.898	1.702	1.641	1.489
1.395	1.383	1.416	1.802	1.806	1.584	1.622	1.709	1.206	1.904	1.561	1.469
1.502	1.406	1.683	1.863	1.963	1.206	1.945	1.999	1.999	2.001	1.592	1.507
1.441	1.358	1.374	1.651	1.771	1.873	1.826	1.879	1.764	2.030	1.966	1.487
1.429	1.291	1.322	1.526	1.828	1.612	1.744	2.057	1.849	2.141	1.689	1.682
1.445	1.383	1.418	1.411	1.568	1.469	1.475	1.525	1.574	1.728	1.511	1.499
1.354	1.332	1.335	1.416	1.643	1.512	1.479	1.761	1.725	2.008	1.698	1.473
1.439	1.379	1.403	1.479	1.686	1.808	1.578	1.838	1.868	1.876	1.584	1.460
1.414	1.352	1.417	1.493	1.579	1.657	1.481	1.558	1.633	1.548	1.426	1.437
1.397	1.343	1.383	1.577	1.505	1.447	1.506	1.736	1.630	1.206	1.206	1.206
1.206	1.206	1.206	1.206	1.206	1.519	1.488	1.584	1.708	1.801	1.466	1.430
1.399	1.349	1.444	1.477	1.842	1.693	1.646	1.668	1.772	1.680	1.519	1.206

Appendix A- 3- Generation of Random Number for Year 1977-1982

Month	Rand()	Z	erf^{-1}	$t_{i,j}$
1	0.607	0.213	0.191	1.270
2	0.450	-0.100	-0.089	0.875
3	0.400	-0.200	-0.179	0.746
4	0.188	-0.624	-0.626	0.115
5	0.238	-0.524	-0.504	0.287
6	0.299	-0.403	-0.373	0.472
7	0.212	-0.577	-0.566	0.199
8	0.036	-0.928	-1.272	-0.799
9	0.109	-0.782	-0.871	-0.231
10	0.535	0.069	0.062	1.087
11	0.629	0.258	0.233	1.329
12	0.961	0.922	1.248	2.765
13	0.976	0.951	1.394	2.972
14	0.742	0.484	0.459	1.649
15	0.459	-0.081	-0.072	0.898
16	0.427	-0.146	-0.131	0.815
17	0.709	0.418	0.389	1.550
18	0.174	-0.653	-0.665	0.060
19	0.351	-0.297	-0.270	0.618
20	0.322	-0.356	-0.326	0.538
21	0.088	-0.823	-0.956	-0.351
22	0.025	-0.949	-1.381	-0.953
23	0.785	0.569	0.557	1.788
24	0.932	0.863	1.052	2.487
25	0.901	0.802	0.910	2.287
26	0.630	0.261	0.236	1.333
27	0.533	0.066	0.059	1.083
28	0.587	0.174	0.155	1.220
29	0.503	0.006	0.006	1.008
30	0.348	-0.303	-0.276	0.610
31	0.433	-0.134	-0.120	0.831
32	0.754	0.509	0.487	1.688
33	0.370	-0.260	-0.234	0.669
34	0.222	-0.556	-0.541	0.234
35	0.601	0.202	0.181	1.256
36	0.355	-0.290	-0.263	0.628
37	0.182	-0.636	-0.642	0.092
38	0.805	0.610	0.608	1.860
39	0.533	0.067	0.059	1.084

40	0.817	0.634	0.639	1.904
41	0.272	-0.455	-0.428	0.394
42	0.541	0.082	0.073	1.103
43	0.913	0.826	0.961	2.359
44	0.515	0.029	0.026	1.037
45	0.191	-0.619	-0.619	0.124
46	0.396	-0.208	-0.186	0.737
47	0.333	-0.334	-0.306	0.568
48	0.382	-0.235	-0.212	0.700
49	0.325	-0.350	-0.321	0.547
50	0.771	0.542	0.525	1.742
51	0.861	0.722	0.767	2.085
52	0.144	-0.712	-0.751	-0.062
53	0.085	-0.831	-0.972	-0.375
54	0.531	0.061	0.054	1.077
55	0.828	0.655	0.668	1.945
56	0.052	-0.896	-1.148	-0.624
57	0.499	-0.002	-0.002	0.998
58	0.611	0.222	0.200	1.282
59	0.092	-0.815	-0.938	-0.326
60	0.052	-0.896	-1.150	-0.626

Appendix A- 4- Calculation for the Markov model from 1977-1982

q_{j-1}	s_j	r_j	$t_{i,j}$	b_j	$\bar{q}_j + b_j(q_{i-1,j-1} - \bar{q}_{j-1})$	$t_j s_j \sqrt{(1-r^2)}$	$q_{i,j}(log)$	$q_{i,j}$
1.4382	0.0831	0.8406	1.2735	0.5228	1.4382	0.0573	1.4956	31.3009
1.4072	0.0830	0.7224	2.6040	0.7213	1.4072	0.1495	1.5567	36.0321
1.4549	0.1102	0.6979	2.5131	0.9264	1.4549	0.1984	1.6533	45.0046
1.5995	0.1421	0.6645	0.1874	0.8567	1.5995	0.0199	1.6194	41.6331
1.7394	0.1844	0.3440	1.9825	0.4466	1.7394	0.3433	2.0827	120.9702
1.6788	0.1862	0.3173	1.1911	0.3203	1.6788	0.2103	1.8892	77.4768
1.6697	0.1775	0.6260	0.2383	0.5966	1.6697	0.0330	1.7026	50.4237
1.7465	0.2487	0.5248	0.1225	0.7353	1.7465	0.0259	1.7725	59.2188
1.7816	0.2374	0.5237	0.9979	0.5000	1.7816	0.2018	1.9835	96.2612
1.8401	0.2348	0.7894	0.8962	0.7806	1.8401	0.1292	1.9692	93.1590
1.5954	0.1926	0.3166	0.5096	0.2597	1.5954	0.0931	1.6885	48.8035
1.4822	0.1337	0.3144	2.4395	0.2182	1.4822	0.3096	1.7918	61.9181
1.4382	0.0831	0.8406	2.5597	0.5228	1.4382	0.1153	1.5535	35.7667
1.4072	0.0830	0.7224	0.9983	0.7213	1.4072	0.0573	1.4645	29.1416
1.4549	0.1102	0.6979	0.4906	0.9264	1.4549	0.0387	1.4936	31.1618
1.5995	0.1421	0.6645	1.9157	0.8567	1.5995	0.2034	1.8029	63.5229
1.7394	0.1844	0.3440	1.1331	0.4466	1.7394	0.1962	1.9356	86.2147
1.6788	0.1862	0.3173	0.8929	0.3203	1.6788	0.1577	1.8365	68.6321
1.6697	0.1775	0.6260	2.9622	0.5966	1.6697	0.4100	2.0797	120.1321
1.7465	0.2487	0.5248	1.9960	0.7353	1.7465	0.4225	2.1691	147.5946
1.7816	0.2374	0.5237	0.4610	0.5000	1.7816	0.0932	1.8749	74.9674
1.8401	0.2348	0.7894	0.7385	0.7806	1.8401	0.1064	1.9465	88.4096
1.5954	0.1926	0.3166	1.1476	0.2597	1.5954	0.2097	1.8050	63.8300
1.4822	0.1337	0.3144	-0.0024	0.2182	1.4822	-0.0003	1.4819	30.3331
1.4382	0.0831	0.8406	2.9243	0.5228	1.4382	0.1317	1.5699	37.1447
1.4072	0.0830	0.7224	-0.9894	0.7213	1.4072	-0.0568	1.3504	22.4084
1.4549	0.1102	0.6979	0.5985	0.9264	1.4549	0.0472	1.5021	31.7790
1.5995	0.1421	0.6645	0.6555	0.8567	1.5995	0.0696	1.6691	46.6806
1.7394	0.1844	0.3440	1.1855	0.4466	1.7394	0.2053	1.9447	88.0375
1.6788	0.1862	0.3173	0.0727	0.3203	1.6788	0.0128	1.6917	49.1679
1.6697	0.1775	0.6260	1.1911	0.5966	1.6697	0.1649	1.8345	68.3137
1.7465	0.2487	0.5248	0.5002	0.7353	1.7465	0.1059	1.8524	71.1906
1.7816	0.2374	0.5237	1.4127	0.5000	1.7816	0.2857	2.0673	116.7738
1.8401	0.2348	0.7894	0.7181	0.7806	1.8401	0.1035	1.9436	87.8142

1.5954	0.1926	0.3166	-0.6041	0.2597	1.5954	-0.1104	1.4850	30.5485
1.4822	0.1337	0.3144	1.2531	0.2182	1.4822	0.1590	1.6413	43.7780
1.4382	0.0831	0.8406	0.7521	0.5228	1.4382	0.0339	1.4721	29.6535
1.4072	0.0830	0.7224	1.2051	0.7213	1.4072	0.0692	1.4764	29.9490
1.4549	0.1102	0.6979	1.3094	0.9264	1.4549	0.1034	1.5583	36.1621
1.5995	0.1421	0.6645	0.9160	0.8567	1.5995	0.0973	1.6968	49.7500
1.7394	0.1844	0.3440	0.7020	0.4466	1.7394	0.1216	1.8609	72.5989
1.6788	0.1862	0.3173	0.2479	0.3203	1.6788	0.0438	1.7226	52.7987
1.6697	0.1775	0.6260	0.7855	0.5966	1.6697	0.1087	1.7784	60.0300
1.7465	0.2487	0.5248	1.5015	0.7353	1.7465	0.3178	2.0644	115.9790
1.7816	0.2374	0.5237	-1.1862	0.5000	1.7816	-0.2399	1.5417	34.8096
1.8401	0.2348	0.7894	1.7278	0.7806	1.8401	0.2490	2.0891	122.7629
1.5954	0.1926	0.3166	2.3393	0.2597	1.5954	0.4274	2.0227	105.3712
1.4822	0.1337	0.3144	-0.5108	0.2182	1.4822	-0.0648	1.4174	26.1454
1.4382	0.0831	0.8406	-0.9273	0.5228	1.4382	-0.0418	1.3964	24.9143
1.4072	0.0830	0.7224	1.3712	0.7213	1.4072	0.0787	1.4859	30.6141
1.4549	0.1102	0.6979	1.9487	0.9264	1.4549	0.1538	1.6087	40.6170
1.5995	0.1421	0.6645	0.1625	0.8567	1.5995	0.0173	1.6168	41.3805
1.7394	0.1844	0.3440	0.0721	0.4466	1.7394	0.0125	1.7518	56.4734
1.6788	0.1862	0.3173	1.2852	0.3203	1.6788	0.2270	1.9058	80.5015
1.6697	0.1775	0.6260	0.8607	0.5966	1.6697	0.1191	1.7888	61.4868
1.7465	0.2487	0.5248	1.6920	0.7353	1.7465	0.3582	2.1047	127.2638
1.7816	0.2374	0.5237	0.9219	0.5000	1.7816	0.1865	1.9681	92.9162
1.8401	0.2348	0.7894	1.4957	0.7806	1.8401	0.2156	2.0556	113.6636
1.5954	0.1926	0.3166	2.8168	0.2597	1.5954	0.5146	2.1100	128.8164
1.4822	0.1337	0.3144	0.1218	0.2182	1.4822	0.0155	1.4977	31.4540

Appendix A- 5-Markov Model Generated Monthly stream flow of Measso station near Gidabo Reservoir

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1977	31.30	36.03	45.00	41.63	120.97	77.48	50.42	59.22	96.26	93.16	48.80	61.92
1978	35.77	29.14	31.16	63.52	86.21	68.63	120.13	147.59	74.97	88.41	63.83	30.33
1979	37.14	22.41	31.78	46.68	88.04	49.17	68.31	71.19	116.77	87.81	30.55	43.78
1980	29.65	29.95	36.16	49.75	72.60	52.80	60.03	115.98	34.81	122.76	105.37	26.15
1981	24.91	30.61	40.62	41.38	56.47	80.50	61.49	127.26	92.92	113.66	128.82	31.45
1982	31.23	30.05	26.27	44.01	56.45	101.45	58.75	68.66	116.05	80.22	90.48	29.91
1983	26.85	33.77	33.99	46.53	108.26	92.23	98.57	76.36	124.43	56.46	97.53	23.35
1984	33.36	41.21	34.43	38.33	37.82	67.50	67.70	44.38	66.38	98.54	64.31	30.68
1985	31.48	30.65	31.28	49.79	173.86	100.09	69.88	132.57	54.60	189.41	36.75	26.82
1986	31.52	32.84	33.50	30.12	84.23	71.91	100.94	77.20	95.34	46.53	82.22	48.87
1987	25.59	35.36	21.74	51.43	103.55	94.62	58.49	170.04	51.61	66.11	32.09	65.12
1988	34.35	25.04	27.72	38.31	57.57	47.81	37.72	139.06	103.49	131.85	41.07	29.77
1989	26.40	30.10	48.96	41.63	81.09	57.29	92.38	133.57	100.89	88.73	30.78	46.35
1990	30.91	44.93	36.55	45.57	51.42	69.95	48.22	84.71	180.22	133.31	58.84	42.22
1991	38.68	29.93	31.12	39.98	89.66	59.18	40.72	122.87	81.65	95.79	94.41	30.28
1992	31.45	24.67	32.75	48.70	60.37	146.27	105.61	164.71	65.28	107.92	57.68	55.66
1993	32.82	37.38	31.91	43.29	34.62	62.25	61.57	90.22	91.58	95.39	66.54	39.03
1994	30.94	29.96	37.07	39.23	126.40	71.22	72.32	85.22	47.42	112.11	68.67	37.89
1995	36.17	27.38	37.30	48.19	135.11	88.50	127.91	37.92	77.65	57.11	42.00	23.61
1996	30.40	31.39	35.95	52.62	55.80	40.66	62.23	50.11	63.16	108.48	68.40	46.50
1997	30.61	30.86	39.62	69.87	93.23	78.41	116.77	91.17	93.76	160.54	104.08	52.03
1998	27.78	33.32	31.50	44.49	57.63	109.75	29.13	186.24	75.84	100.13	55.60	48.63
1999	30.88	29.03	39.02	58.75	131.46	60.99	81.06	59.48	75.99	112.41	56.61	54.04
2000	31.31	26.08	43.52	65.33	67.83	55.20	67.29	37.62	52.00	67.89	92.49	64.04
2001	33.48	27.59	33.55	59.30	66.73	79.45	50.71	69.27	60.51	83.78	44.68	37.57
2002	29.21	27.23	26.56	69.28	43.71	83.75	66.17	81.34	143.62	149.87	36.78	35.65
2003	27.67	36.77	30.05	49.63	148.11	92.54	86.33	75.91	112.92	83.89	65.34	64.15
2004	31.96	24.56	29.82	48.36	70.17	33.58	56.67	76.95	138.36	97.79	50.59	59.84
2005	29.40	28.51	45.36	59.58	101.19	110.73	59.94	125.44	135.05	76.77	31.61	51.68

Appendix A- 6-Performance evaluation procedure for PARMA, GAR(1), Markov and ARMA Model

S.N	Actual Flow	PARMA		GAR(1)		MARCOV		ARMA	
		Generated flow	RRMSD	Generated flow	RRMSD	Generated flow	RRMSD	Generated flow	RRMSD
1.00	39.43	39.79	73.37	34.08	193.71	35.73	40.22	35.73	40.22
2.00	37.85	32.89	103.00	26.29	471.13	25.90	261.44	25.90	261.44
3.00	41.61	31.28	40.82	43.52	20.07	56.11	197.17	56.11	197.17
4.00	55.73	37.05	59.71	42.14	34.32	41.61	0.21	41.61	0.21
5.00	74.92	50.32	724.65	29.28	350.49	61.25	368.03	61.25	368.03
6.00	64.59	51.35	275.25	22.07	672.35	48.66	43.37	48.66	43.37
7.00	70.74	57.16	517.15	18.03	898.13	54.26	148.52	54.26	148.52
8.00	56.43	77.13	71.10	15.77	1038.92	85.36	1874.22	85.36	1874.22
9.00	73.48	88.60	649.13	21.07	725.17	66.01	573.13	66.01	573.13
10.00	83.93	137.02	1291.12	63.46	238.97	124.63	6815.37	124.63	6815.37
11.00	32.24	90.69	248.44	41.22	45.92	68.16	680.45	68.16	680.45
12.00	18.76	16.06	855.08	52.89	23.90	60.24	330.14	60.24	330.14
13.00	25.26	29.91	517.21	40.93	49.92	30.35	137.45	30.35	137.45
14.00	22.60	28.03	645.07	143.63	9144.38	21.83	409.56	21.83	409.56
15.00	17.35	48.19	939.06	124.45	5844.49	43.55	2.20	43.55	2.20
16.00	26.68	55.57	454.28	112.07	4104.61	40.97	1.20	40.97	1.20
17.00	31.82	76.33	261.69	103.29	3057.23	89.90	2287.41	89.90	2287.41
18.00	35.26	48.77	162.27	63.54	241.63	59.54	305.01	59.54	305.01
19.00	23.07	108.68	621.30	41.27	45.27	46.38	18.54	46.38	18.54
20.00	66.68	144.59	349.15	49.39	1.94	51.64	91.57	51.64	91.57
21.00	70.25	80.69	495.26	40.60	54.71	60.21	329.19	60.21	329.19
22.00	143.80	92.86	9177.88	45.09	8.43	98.86	3224.46	98.86	3224.46
23.00	77.18	43.33	851.56	32.05	254.26	48.16	37.04	48.16	37.04
24.00	22.64	42.23	643.15	143.39	9098.73	31.83	104.86	31.83	104.86
25.00	22.34	35.98	658.29	130.00	6724.20	34.96	50.56	34.96	50.56
26.00	21.47	35.38	703.78	78.51	930.94	21.85	408.73	21.85	408.73
27.00	22.99	37.73	625.38	49.66	2.75	29.60	155.40	29.60	155.40
28.00	32.78	40.76	231.66	49.86	3.47	44.08	4.05	44.08	4.05
29.00	57.63	54.67	92.69	65.11	292.83	78.88	1354.88	78.88	1354.88
30.00	47.61	62.27	0.15	50.49	6.20	28.36	188.07	28.36	188.07
31.00	60.39	48.99	153.64	34.01	195.64	41.53	0.29	41.53	0.29
32.00	66.09	80.24	327.38	24.72	541.81	108.12	4363.11	108.12	4363.11
33.00	56.80	79.74	77.39	19.52	811.25	208.44	27680.02	208.44	27680.02
34.00	99.20	87.54	2621.20	16.60	985.91	153.19	12348.34	153.19	12348.34
35.00	56.12	54.02	65.91	17.54	927.73	91.32	2425.90	91.32	2425.90

36.00	28.34	36.10	386.28	27.96	401.60	43.39	1.75	43.39	1.75
37.00	22.14	26.49	668.61	66.17	330.21	32.84	85.26	32.84	85.26
38.00	25.68	26.32	498.02	42.74	27.63	37.37	22.06	37.37	22.06
39.00	25.58	28.02	502.74	35.86	147.40	42.42	0.12	42.42	0.12
40.00	21.93	42.55	679.37	25.76	494.72	85.83	1915.24	85.83	1915.24
41.00	65.98	57.14	323.29	49.97	3.89	67.55	649.11	67.55	649.11
42.00	44.49	35.10	12.32	112.08	4106.28	33.52	73.15	33.52	73.15
43.00	59.61	28.33	134.89	74.15	683.96	75.78	1136.48	75.78	1136.48
44.00	70.95	28.33	526.66	53.96	35.59	40.79	1.65	40.79	1.65
45.00	91.94	16.06	1930.98	70.53	507.86	78.56	1331.29	78.56	1331.29
46.00	80.58	58.29	1061.45	45.19	7.90	129.15	7582.28	129.15	7582.28
47.00	44.45	38.37	12.56	59.84	140.32	56.53	209.20	56.53	209.20
48.00	23.44	44.78	603.30	39.20	77.46	45.54	12.02	45.54	12.02
49.00	22.46	27.91	652.35	27.93	402.94	33.69	70.19	33.69	70.19
50.00	20.19	27.33	773.52	51.59	12.92	33.82	67.99	33.82	67.99
51.00	15.25	37.20	1072.39	53.80	33.60	31.98	101.73	31.98	101.73
52.00	29.01	63.79	360.44	50.60	6.75	37.23	23.40	37.23	23.40
53.00	40.27	67.80	59.80	96.80	2381.13	59.97	320.53	59.97	320.53
54.00	31.11	43.67	285.22	62.84	220.32	33.67	70.50	33.67	70.50
55.00	33.41	48.68	212.94	112.36	4142.11	50.44	69.99	50.44	69.99
56.00	41.53	76.36	41.83	68.62	425.40	35.27	46.22	35.27	46.22
57.00	44.73	100.17	10.68	44.12	15.07	45.92	14.80	45.92	14.80
58.00	63.51	78.56	240.47	46.57	2.05	19.37	515.16	19.37	515.16
59.00	41.20	49.59	46.25	45.74	5.08	18.76	543.43	18.76	543.43
60.00	23.30	33.56	610.16	40.57	55.14	19.65	502.87	19.65	502.87
…	…	…	…	…	…	…	…	…	…
347	29.67	33.07	335.58	34.11	192.78	41.92	0.022	41.92	0.0223
348	42.07	16.06	35.14	46.13	3.48	29.03	169.81	29.03958	169.81
	48.69	47.99	253024	52.458	318861.1	45.17604	344412.7	45.17604	344412.7
			503.0149		564.6778		586.8669		586.8669
RRMSD			10.64		11.76		10.76		10.65
MD			0.95		4.46		2.49		-3.43

Appendix A- 7- logarithmic Monthly stream flow of Measso station near Gidabo Reservoir for ARMA model

year	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov.	Dec
1977	1.52	1.41	1.39	1.48	1.64	1.65	1.70	1.85	1.91	2.11	1.92	0.96
1978	1.36	1.32	1.61	1.69	1.84	1.62	2.01	2.14	1.87	1.93	1.56	1.55
1979	1.46	1.45	1.49	1.53	1.68	1.74	1.62	1.86	1.86	1.91	1.67	1.46
1980	1.29	1.29	1.32	1.55	1.70	1.45	1.33	1.33	0.96	1.71	1.50	1.58
1981	1.32	1.31	1.48	1.75	1.78	1.56	1.62	1.84	1.97	1.85	1.63	1.42
1982	1.47	1.39	1.39	1.51	1.71	1.77	1.73	1.84	1.87	1.85	1.68	1.47
1983	1.36	1.31	1.35	1.70	1.97	1.83	1.72	2.16	2.00	2.08	1.80	1.61
1984	1.41	1.32	1.32	1.36	1.45	1.61	1.50	1.56	1.93	1.64	1.49	1.55
1985	1.30	1.23	1.28	1.55	2.00	1.67	1.65	1.68	1.92	1.82	1.41	1.34
1986	1.25	1.24	1.31	1.49	1.74	2.19	1.84	0.96	2.03	1.86	1.43	1.35
1987	1.28	1.26	1.38	1.51	1.92	1.78	1.53	1.49	1.63	1.85	0.96	1.36
1988	1.05	1.12	1.22	1.49	1.35	1.49	0.96	0.96	0.96	0.96	0.96	1.00
1989	1.37	1.31	1.29	1.54	1.49	1.60	1.60	1.46	1.83	1.86	1.52	1.31
1990	1.35	1.44	1.62	1.78	1.81	1.62	1.62	1.62	1.65	1.66	1.46	1.51
1991	1.42	1.42	1.47	1.52	1.54	1.43	1.55	1.51	1.79	1.59	1.30	1.42
1992	1.18	1.23	1.18	1.64	1.64	1.55	1.68	2.08	2.01	2.15	1.80	1.27
1993	1.40	1.48	1.34	1.58	1.96	1.95	1.70	1.59	1.75	1.96	1.68	1.52
1994	1.27	1.20	1.26	1.41	1.78	1.65	1.95	1.99	1.86	1.64	1.57	1.38
1995	1.25	1.23	1.28	1.75	1.76	1.50	1.54	1.64	0.96	1.86	1.47	1.35
1996	1.39	1.27	1.62	1.82	1.93	0.96	1.91	1.97	1.97	1.97	1.51	1.40
1997	1.31	1.20	1.22	1.58	1.72	1.83	1.78	1.84	1.71	2.00	1.93	1.37
1998	1.30	1.10	1.15	1.42	1.78	1.53	1.69	2.03	1.80	2.12	1.62	1.61
1999	1.32	1.23	1.28	1.27	1.48	1.35	1.36	1.42	1.48	1.67	1.41	1.39
2000	1.19	1.16	1.16	1.28	1.57	1.41	1.36	1.70	1.66	1.98	1.63	1.36
2001	1.31	1.23	1.26	1.36	1.62	1.76	1.49	1.79	1.83	1.83	1.50	1.34
2002	1.28	1.19	1.28	1.38	1.49	1.58	1.37	1.46	1.56	1.45	1.29	1.31
2003	1.25	1.18	1.23	1.49	1.40	1.32	1.40	1.68	1.55	0.96	0.96	0.96
2004	0.96	0.96	0.96	0.96	0.96	1.41	1.38	1.50	1.64	1.75	1.35	1.30
2005	1.26	1.19	1.32	1.36	1.80	1.63	1.57	1.60	1.72	1.61	1.42	0.96

Appendix A- 8- Standardize Series of logarithmic Monthly stream flow of Measso station near Gidabo Reservoir for ARMA model

year	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov.	Dec
1977	1.80	1.29	0.40	-0.17	-0.16	0.20	0.51	0.57	0.67	1.16	1.72	-2.17
1978	0.46	0.51	1.97	0.99	0.76	0.09	1.92	1.55	0.52	0.53	0.26	1.01
1979	1.34	1.63	1.10	0.11	0.03	0.63	0.15	0.64	0.50	0.44	0.71	0.57
1980	-0.14	0.19	-0.03	0.23	0.13	-0.68	-1.21	-1.15	-2.53	-0.25	0.00	1.18
1981	0.12	0.38	1.05	1.37	0.50	-0.17	0.13	0.56	0.86	0.26	0.53	0.35
1982	1.41	1.11	0.42	0.03	0.15	0.74	0.62	0.57	0.54	0.25	0.75	0.58
1983	0.45	0.36	0.18	1.07	1.35	1.02	0.60	1.61	0.96	1.06	1.22	1.36
1984	0.89	0.51	-0.04	-0.85	-0.99	0.03	-0.40	-0.39	0.72	-0.49	-0.05	1.05
1985	-0.05	-0.28	-0.35	0.25	1.47	0.30	0.25	0.02	0.71	0.15	-0.33	-0.10
1986	-0.52	-0.22	-0.11	-0.13	0.29	2.63	1.13	-2.39	1.06	0.28	-0.28	-0.06
1987	-0.18	-0.05	0.37	0.02	1.12	0.81	-0.29	-0.62	-0.27	0.25	-2.17	0.00
1988	-2.19	-1.27	-0.72	-0.10	-1.43	-0.48	-2.92	-2.39	-2.53	-2.88	-2.18	-1.93
1989	0.52	0.39	-0.22	0.19	-0.81	-0.02	0.06	-0.72	0.38	0.28	0.10	-0.27
1990	0.35	1.52	2.01	1.51	0.61	0.09	0.12	-0.18	-0.22	-0.41	-0.14	0.81
1991	1.02	1.32	0.99	0.08	-0.61	-0.77	-0.20	-0.54	0.25	-0.68	-0.78	0.35
1992	-1.11	-0.33	-0.97	0.71	-0.13	-0.23	0.39	1.36	1.00	1.29	1.23	-0.49
1993	0.80	1.86	0.07	0.37	1.29	1.57	0.51	-0.29	0.12	0.63	0.73	0.89
1994	-0.28	-0.52	-0.44	-0.57	0.48	0.22	1.66	1.06	0.48	-0.50	0.28	0.10
1995	-0.48	-0.26	-0.32	1.35	0.37	-0.47	-0.22	-0.10	-2.53	0.29	-0.12	-0.05
1996	0.75	0.02	1.97	1.73	1.15	-2.88	1.47	0.98	0.85	0.66	0.04	0.22
1997	0.06	-0.57	-0.72	0.38	0.20	1.02	0.87	0.54	-0.01	0.77	1.76	0.08
1998	-0.07	-1.43	-1.24	-0.47	0.49	-0.32	0.44	1.19	0.30	1.18	0.50	1.37
1999	0.12	-0.26	-0.30	-1.31	-0.87	-1.12	-1.07	-0.84	-0.76	-0.40	-0.37	0.17
2000	-0.97	-0.89	-1.11	-1.27	-0.47	-0.87	-1.05	0.10	-0.17	0.68	0.55	-0.01
2001	0.04	-0.31	-0.44	-0.80	-0.24	0.70	-0.47	0.39	0.38	0.18	0.00	-0.11
2002	-0.25	-0.63	-0.31	-0.70	-0.81	-0.07	-1.04	-0.70	-0.52	-1.15	-0.82	-0.27
2003	-0.45	-0.75	-0.64	-0.12	-1.23	-1.25	-0.88	0.01	-0.54	-2.88	-2.18	-2.17
2004	-3.01	-2.65	-2.53	-3.07	-3.20	-0.83	-0.99	-0.59	-0.23	-0.11	-0.61	-0.32
2005	-0.43	-0.67	-0.06	-0.82	0.55	0.11	-0.09	-0.26	0.02	-0.59	-0.33	-2.17

Appendix A- 9-ARMA (1,1) Model Generated Monthly stream flow of Measso station near Gidabo Reservoir

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1977	35.73	25.90	56.11	41.61	61.25	48.66	54.26	85.36	66.01	124.63	68.16	60.24
1978	30.35	21.83	43.55	40.97	89.90	59.54	46.38	51.64	60.21	98.86	48.16	31.83
1979	34.96	21.85	29.60	44.08	78.88	28.36	41.53	108.12	208.44	153.19	91.32	43.39
1980	32.84	37.37	42.42	85.83	67.55	33.52	75.78	40.79	78.56	129.15	56.53	45.54
1981	33.69	33.82	31.98	37.23	59.97	33.67	50.44	35.27	45.92	19.37	18.76	19.65
1982	13.50	20.73	22.27	23.84	78.04	43.40	47.59	78.67	23.65	89.05	49.70	22.07
1983	21.82	38.65	26.06	37.32	25.31	29.89	27.94	59.85	33.32	60.70	37.45	26.33
1984	23.23	21.31	21.31	22.99	55.80	30.02	23.90	18.30	38.48	39.14	16.87	25.06
1985	19.72	21.80	26.90	50.56	56.35	48.71	88.63	79.56	87.34	67.47	36.50	23.43
1986	24.72	25.01	23.50	32.15	51.81	31.30	23.38	196.16	304.52	97.83	83.57	27.23
1987	26.81	23.89	26.43	25.96	98.19	28.41	25.79	21.77	23.35	46.72	32.36	35.25
1988	32.88	35.05	23.77	35.09	48.72	58.70	48.83	118.15	35.95	134.19	34.80	35.19
1989	30.04	28.32	40.94	34.96	25.76	43.62	42.81	32.29	20.98	16.32	25.69	19.29
1990	25.54	25.49	21.28	33.45	69.42	49.46	20.21	27.31	19.49	54.65	29.69	29.51
1991	21.03	23.44	27.26	28.21	47.38	37.28	34.74	40.77	79.76	106.77	16.41	26.70
1992	21.33	16.84	21.09	29.68	17.09	35.61	28.26	27.36	27.46	58.60	25.83	27.71
1993	30.03	28.83	31.82	49.27	126.50	103.17	69.73	46.73	38.31	64.79	42.34	35.08
1994	36.71	28.91	25.45	61.90	64.96	34.81	31.78	35.68	62.81	43.37	36.05	30.99
1995	28.88	21.12	29.63	73.28	75.53	32.83	60.62	52.63	86.96	56.52	25.37	25.01
1996	20.28	25.15	21.27	23.84	23.15	39.98	27.01	59.15	91.62	58.20	24.20	45.20
1997	28.75	20.59	25.24	35.13	75.12	82.42	63.52	77.22	21.33	88.91	39.20	39.08
1998	24.30	24.45	26.64	36.36	55.54	26.09	31.72	42.91	36.87	151.68	73.41	24.25
1999	29.24	25.47	30.77	39.64	113.46	61.71	81.02	36.94	51.68	34.13	30.68	27.93
2000	29.14	30.74	40.90	49.85	27.64	42.19	22.67	59.02	32.84	64.51	25.28	17.25
2001	26.63	26.85	26.73	53.42	79.24	56.12	35.19	34.58	91.92	64.35	55.69	30.84
2002	17.61	26.85	37.45	38.43	42.22	23.42	26.77	54.44	73.30	159.36	105.20	41.02
2003	32.62	23.30	31.50	42.20	53.77	51.20	55.82	39.73	72.60	119.42	31.17	14.57
2004	20.58	21.50	16.48	23.81	34.73	20.37	32.51	57.72	25.31	30.33	25.19	28.36
2005	26.74	24.20	23.77	55.39	50.77	23.57	33.68	20.81	67.19	17.20	41.92	29.04

Appendix A- 10-PARMA (1,0) Fifty Year Model Generated Monthly stream flow of Measso station near Gidabo Reservoir

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
39.43	37.85	41.61	55.73	74.92	64.59	70.74	56.43	73.48	83.93	32.24	18.76
25.26	22.60	17.35	26.68	31.82	35.26	23.07	66.68	70.25	143.80	77.18	22.64
22.34	21.47	22.99	32.78	57.63	47.61	60.39	66.09	56.80	99.20	56.12	28.34
22.14	25.68	25.58	21.93	65.98	44.49	59.61	70.95	91.94	80.58	44.45	23.44
22.46	20.19	15.25	29.01	40.27	31.11	33.41	41.53	44.73	63.51	41.20	23.30
18.87	17.28	16.41	12.06	54.94	39.59	74.62	68.84	67.09	100.54	44.62	37.23
26.58	32.62	45.65	39.39	23.33	42.00	23.60	10.37	34.31	64.32	39.28	39.78
32.63	27.56	34.47	39.93	48.61	31.53	33.63	39.91	61.39	102.28	66.84	25.09
25.42	22.01	29.97	42.57	92.70	104.34	36.43	56.30	103.59	117.82	44.58	25.91
29.44	30.09	38.32	44.15	63.37	30.93	71.73	97.76	105.33	80.82	39.98	32.46
30.64	24.42	26.54	45.59	49.82	31.33	51.37	81.52	76.95	51.04	33.43	36.29
36.09	34.92	46.78	50.39	93.69	91.86	70.95	81.16	66.06	79.99	43.45	32.27
25.63	19.90	22.71	25.82	61.67	35.55	47.31	45.97	30.05	120.35	58.94	32.09
28.15	26.05	23.98	38.94	63.29	86.21	76.36	119.15	81.40	115.74	72.81	37.53
24.25	24.51	35.16	44.40	61.56	49.32	67.57	61.68	83.41	115.91	49.62	30.89
32.52	30.55	44.27	66.47	111.29	92.66	48.39	70.75	82.20	103.53	85.63	36.95
28.32	24.26	22.40	41.76	43.70	31.40	36.86	61.69	63.75	78.84	33.45	28.33
25.35	22.78	27.46	35.08	62.09	34.13	42.86	38.79	40.45	69.03	47.93	30.41
28.51	23.62	27.09	36.11	60.67	31.29	8.80	3.92	11.82	31.70	10.14	19.62
23.04	20.82	24.54	36.07	54.26	58.18	68.55	190.63	106.51	105.78	63.38	34.58
20.70	19.84	24.04	21.02	35.47	43.16	55.31	64.71	55.16	60.82	35.07	20.89
25.93	19.41	21.13	33.02	49.96	46.35	53.73	70.25	96.52	60.22	27.17	30.06
28.63	24.66	22.75	25.36	26.18	35.54	53.14	60.27	84.57	97.22	28.01	33.47
28.46	26.77	24.01	42.33	53.91	64.07	44.72	91.58	90.71	79.40	26.93	35.78
40.62	37.25	31.28	58.64	62.76	153.75	56.29	79.06	49.06	65.35	35.06	30.49
32.58	25.70	37.61	38.99	94.97	82.94	35.69	57.72	66.27	89.37	48.41	28.43
24.37	22.86	28.52	31.74	38.18	32.24	38.31	69.42	73.51	103.34	61.92	40.02
27.12	24.79	35.62	51.18	47.37	34.84	67.91	119.62	74.81	63.23	37.77	37.73
31.16	29.05	23.22	32.52	47.05	53.73	36.84	44.40	103.63	112.39	29.68	42.07

Appendix A- 11-Evaporation Loss (mm) Coefficient and Precipitation (mm)

Month	et(mm/month)	pt.(mm/month)
Jan	192.2	28.2
Feb	193.2	35.4
Mar	201.5	58.2
Apr	162	105.6
May	171	95.2
Jun	144	86.2
Jul	136.4	103.2
Aug	146	82.5
Sep	153	80.9
Oct	164.3	79.6
Nov	177	33.8
Dec	189.1	29.1

Appendix A- 12-Total irrigation demand (taken from Feasibility Report for Irrigation and Drainage

Month	Monthly	Monthly	Monthly	Monthly
	Irr. req	**Irr.req for 7982ha**	**Irr. req at barrage considering 48.6% irrigation efficiency***	**Irrigation requirement at dam 0utlet considering 4.76 Mm3/month compulsory releases**
	(mm)	**(Mm3)**	**(Mm3)**	**(Mm3)**
1	**2**	3	4	5
Jan	127.01	10.138	20.86	25.62
Feb	45	3.592	7.391	12.151
Mar	10.47	0.836	1.719	6.479
Apr	7.98	0.637	1.311	6.071
May	45.95	3.668	7.547	12.307
Jun	61.75	4.929	10.142	14.902
Jul	50.92	4.064	8.363	13.123
Aug	23.79	1.899	3.907	8.667

Appendix A- 13-GAMS Result for the Reservoir Sizing

Reservoir Sizing in GAMS

Maximum Reservoir capacity (Mm3) = 37.54

maximum reservoir level(m) = 1216.10

dead storage volume(Mm3)= 3.64

dead storage level(m)= 1208.21

MDDL volume(Mm3)= 9.89

MDDL level(m) = 1210.49

The coefficient for Area Storage Curve (a & b)

a	b
.31	0.44

Time Month t	Inflow (Mm3) Q(t)	Begin storage (Mm3) S(t)	End storage (Mm3) S(t+1)	Evapo. (Mm3) E(T)	Pri-rate (Mm3) P(t)	Release (Mm3) spill(t)	Demand (Mm3) Y(t)	Level m L(t)
1	26.33	26.83	21.28	0.70	0.10	5.67	25.62	1214.29
2	26.25	21.28	29.14	0.70	0.13	5.67	12.15	1213.21
3	30.09	29.14	37.54	0.89	0.24	14.55	6.48	1214.71
4	55.73	37.54	37.54	0.85	0.46	49.28	6.07	1216.10
5	77.11	37.54	37.54	0.86	0.41	64.35	12.31	1216.10
6	90.31	37.54	37.54	0.79	0.37	74.98	14.90	1216.10
7	49.52	37.54	24.42	0.66	0.41	49.28	13.12	1216.10
8	44.59	24.42	19.74	0.59	0.28	40.30	8.67	1213.84
9	75.20	19.74	33.32	0.69	0.30	51.44	9.80	1212.89
10	74.23	33.32	37.54	0.80	0.34	52.27	17.28	1215.42
11	34.29	37.54	37.54	0.78	0.15	9.41	24.24	1216.10
12	17.04	37.54	24.11	0.75	0.12	1.00	28.84	1216.10
13	29.27	24.11	27.15	0.72	0.10	0.00	25.62	1213.78

14	24.10	27.15	16.45	0.66	0.12	22.10	12.15	1214.35
15	26.43	16.45	9.98	0.60	0.16	25.99	6.48	1212.16
16	40.65	9.98	37.14	0.69	0.37	7.11	6.07	1210.49
17	50.50	37.14	24.86	0.79	0.38	50.06	12.31	1216.04
18	48.54	24.86	9.98	0.57	0.27	48.21	14.90	1213.92
19	75.75	9.98	16.35	0.45	0.28	56.09	13.12	1210.49
20	126.62	16.35	37.54	0.64	0.31	96.44	8.67	1212.14
21	86.37	37.54	37.54	0.81	0.35	76.12	9.80	1216.10
22	88.79	37.54	37.54	0.82	0.35	71.03	17.28	1216.10
23	38.50	37.54	37.54	0.78	0.15	13.62	24.24	1216.10
24	40.75	37.54	37.54	0.82	0.13	11.22	28.84	1216.10
25	25.45	37.54	34.47	0.83	0.12	2.19	25.62	1216.10
26	24.98	34.47	22.39	0.74	0.14	24.30	12.15	1215.61
27	25.14	22.39	15.98	0.70	0.19	24.56	6.48	1213.44
28	27.87	15.98	9.98	0.53	0.29	27.55	6.07	1212.05
29	33.90	9.98	9.98	0.48	0.23	21.34	12.31	1210.49
30	84.38	9.98	27.23	0.58	0.28	51.91	14.90	1210.49
31	68.44	27.23	30.38	0.64	0.40	51.93	13.12	1214.36
32	90.95	30.38	37.54	0.71	0.34	74.76	8.67	1214.92
33	128.85	37.54	37.38	0.81	0.35	118.75	9.80	1216.10
34	78.78	37.38	37.54	0.82	0.35	60.87	17.28	1216.08
35	55.07	37.54	25.19	0.72	0.14	42.59	24.24	1216.10
36	48.04	25.19	9.98	0.59	0.09	33.91	28.84	1213.98
37	31.15	9.98	9.98	0.47	0.07	5.13	25.62	1210.49
38	31.82	9.98	22.07	0.58	0.11	7.12	12.15	1210.49
39	29.96	22.07	15.59	0.70	0.19	29.45	6.48	1213.37
40	50.11	15.59	16.68	0.58	0.32	42.68	6.07	1211.96
41	48.58	16.68	9.98	0.55	0.26	42.70	12.31	1212.22
42	35.09	9.98	29.84	0.60	0.28	0.00	14.90	1210.49
43	32.04	29.84	16.75	0.58	0.36	31.79	13.12	1214.83
44	35.98	16.75	9.98	0.47	0.23	33.85	8.67	1212.23
45	117.44	9.98	37.54	0.66	0.29	79.71	9.80	1210.49
46	138.13	37.54	37.54	0.82	0.35	120.38	17.28	1216.10
47	88.64	37.54	37.54	0.78	0.15	63.76	24.24	1216.10
48	32.71	37.54	37.54	0.82	0.13	3.17	28.84	1216.10
49	36.78	37.54	28.61	0.80	0.12	19.41	25.62	1216.10
50	37.35	28.61	16.46	0.67	0.12	36.80	12.15	1214.61
51	45.87	16.46	9.98	0.60	0.16	45.44	6.48	1212.16
52	59.64	9.98	17.41	0.54	0.29	45.89	6.07	1210.49
53	63.51	17.41	37.54	0.75	0.36	30.68	12.31	1212.38
54	32.66	37.54	23.10	0.72	0.34	31.81	14.90	1216.10
55	44.78	23.10	9.98	0.50	0.31	44.59	13.12	1213.58

56	121.01	9.98	37.54	0.61	0.29	84.47	8.67	1210.49
57	66.43	37.54	37.27	0.81	0.35	56.44	9.80	1216.10
58	78.70	37.27	37.54	0.82	0.35	60.68	17.28	1216.06
59	44.21	37.54	34.33	0.77	0.14	22.55	24.24	1216.10
60	38.38	34.33	37.54	0.81	0.12	5.66	28.84	1215.59
61	26.67	37.54	22.13	0.77	0.11	15.80	25.62	1216.10
62	27.58	22.13	9.98	0.58	0.11	27.11	12.15	1213.39
63	30.92	9.98	11.43	0.54	0.15	22.59	6.48	1210.49
64	41.61	11.43	24.10	0.61	0.33	22.59	6.07	1210.90
65	40.38	24.10	29.19	0.74	0.36	22.60	12.31	1213.77
66	48.45	29.19	37.54	0.75	0.36	24.80	14.90	1214.72
67	44.08	37.54	37.54	0.71	0.45	30.69	13.12	1216.10
68	45.95	37.54	37.54	0.74	0.36	36.90	8.67	1216.10
69	60.80	37.54	37.54	0.81	0.35	50.54	9.80	1216.10
70	50.69	37.54	37.54	0.82	0.35	32.94	17.28	1216.10
71	39.38	37.54	32.73	0.76	0.14	19.33	24.24	1216.10
72	36.85	32.73	20.81	0.71	0.11	19.34	28.84	1215.32
73	28.20	20.81	9.98	0.57	0.08	12.92	25.62	1213.11
74	25.69	9.98	9.98	0.47	0.09	13.15	12.15	1210.49
75	26.56	9.98	10.20	0.53	0.14	19.48	6.48	1210.49
76	24.34	10.20	9.98	0.48	0.26	18.27	6.07	1210.56
77	28.84	9.98	25.42	0.62	0.30	0.77	12.31	1210.49
78	33.24	25.42	37.54	0.74	0.35	5.83	14.90	1214.03
79	31.86	37.54	28.07	0.67	0.42	27.96	13.12	1216.10
80	15.94	28.07	19.62	0.61	0.29	15.41	8.67	1214.51
81	17.81	19.62	10.66	0.54	0.24	16.66	9.80	1212.86
82	30.90	10.66	23.94	0.58	0.25	0.00	17.28	1210.69
83	21.17	23.94	20.37	0.62	0.12	0.00	24.24	1213.74
84	18.92	20.37	9.98	0.55	0.08	0.00	28.84	1213.02
85	27.77	9.98	11.71	0.49	0.07	0.00	25.62	1210.49
86	23.19	11.71	15.68	0.54	0.10	6.62	12.15	1210.98
87	25.63	15.68	9.98	0.59	0.16	24.43	6.48	1211.98
88	19.57	9.98	9.98	0.47	0.26	13.28	6.07	1210.49
89	40.67	9.98	37.28	0.70	0.34	0.70	12.31	1210.49
90	53.33	37.28	37.54	0.79	0.37	37.74	14.90	1216.06
91	43.92	37.54	27.97	0.67	0.42	40.11	13.12	1216.10
92	18.16	27.97	19.31	0.60	0.29	17.85	8.67	1214.50
93	48.81	19.31	9.98	0.53	0.23	48.04	9.80	1212.80
94	106.49	9.98	37.54	0.67	0.28	61.26	17.28	1210.49
95	69.98	37.54	37.54	0.78	0.15	45.11	24.24	1216.10
96	46.16	37.54	37.54	0.82	0.13	16.63	28.84	1216.10
97	27.94	37.54	34.68	0.83	0.12	4.47	25.62	1216.10

98	22.33	34.68	22.53	0.74	0.14	21.72	12.15	1215.65
99	22.32	22.53	16.05	0.70	0.19	21.80	6.48	1213.47
100	25.46	16.05	9.98	0.53	0.29	25.21	6.07	1212.07
101	36.81	9.98	23.01	0.60	0.29	11.16	12.31	1210.49
102	38.68	23.01	22.63	0.64	0.30	23.81	14.90	1213.56
103	45.97	22.63	9.98	0.49	0.31	45.31	13.12	1213.49
104	33.22	9.98	13.65	0.45	0.22	20.65	8.67	1210.49
105	34.77	13.65	9.98	0.49	0.21	28.37	9.80	1211.49
106	47.35	9.98	37.54	0.67	0.28	2.12	17.28	1210.49
107	29.80	37.54	37.54	0.78	0.15	4.92	24.24	1216.10
108	18.87	37.54	26.92	0.77	0.12	0.00	28.84	1216.10
109	20.28	26.92	9.98	0.62	0.09	11.06	25.62	1214.31
110	18.98	9.98	16.38	0.53	0.10	0.00	12.15	1210.49
111	27.08	16.38	9.98	0.60	0.16	26.57	6.48	1212.15
112	38.29	9.98	37.54	0.69	0.38	4.34	6.07	1210.49
113	74.19	37.54	37.54	0.86	0.41	61.43	12.31	1216.10
114	46.03	37.54	30.73	0.76	0.36	37.54	14.90	1216.10
115	44.72	30.73	18.13	0.59	0.37	43.98	13.12	1214.98
116	37.46	18.13	9.98	0.48	0.23	36.69	8.67	1212.54
117	66.52	9.98	24.58	0.57	0.25	41.79	9.80	1210.49
118	77.80	24.58	37.54	0.76	0.32	47.13	17.28	1213.87
119	32.13	37.54	37.54	0.78	0.15	7.25	24.24	1216.10
120	21.39	37.54	11.30	0.68	0.10	18.22	28.84	1216.10
121	24.72	11.30	9.98	0.49	0.07	0.00	25.62	1210.87
122	25.15	9.98	16.12	0.53	0.10	6.43	12.15	1210.49
123	23.99	16.12	9.98	0.59	0.16	23.21	6.48	1212.09
124	39.15	9.98	9.98	0.47	0.26	32.86	6.07	1210.49
125	77.59	9.98	37.54	0.70	0.34	37.36	12.31	1210.49
126	54.94	37.54	23.10	0.72	0.34	54.09	14.90	1216.10
127	32.62	23.10	9.98	0.50	0.31	32.43	13.12	1213.58
128	81.64	9.98	37.54	0.61	0.29	45.10	8.67	1210.49
129	45.23	37.54	37.54	0.81	0.35	34.98	9.80	1216.10
130	35.73	37.54	37.54	0.82	0.35	17.97	17.28	1216.10
131	18.02	37.54	13.46	0.66	0.12	17.32	24.24	1216.10
132	51.50	13.46	35.55	0.68	0.10	0.00	28.84	1211.44
133	24.86	35.55	28.28	0.79	0.11	5.84	25.62	1215.79
134	26.39	28.28	16.29	0.67	0.12	25.68	12.15	1214.55
135	26.49	16.29	9.98	0.59	0.16	25.89	6.48	1212.13
136	53.75	9.98	9.98	0.47	0.26	47.46	6.07	1210.49
137	86.07	9.98	37.54	0.70	0.34	45.84	12.31	1210.49
138	85.16	37.54	37.54	0.79	0.37	69.84	14.90	1216.10
139	35.52	37.54	24.42	0.66	0.41	35.28	13.12	1216.10

140	37.02	24.42	15.75	0.56	0.27	36.73	8.67	1213.84
141	76.81	15.75	37.54	0.70	0.30	44.83	9.80	1212.00
142	111.89	37.54	37.54	0.82	0.35	94.13	17.28	1216.10
143	62.66	37.54	37.54	0.78	0.15	37.78	24.24	1216.10
144	39.51	37.54	37.54	0.82	0.13	9.98	28.84	1216.10
145	34.22	37.54	28.60	0.80	0.12	16.85	25.62	1216.10
146	29.09	28.60	16.45	0.67	0.12	28.54	12.15	1214.61
147	24.00	16.45	9.98	0.60	0.16	23.56	6.48	1212.16
148	36.29	9.98	9.98	0.47	0.26	30.00	6.07	1210.49
149	77.84	9.98	37.54	0.70	0.34	37.61	12.31	1210.49
150	38.81	37.54	31.71	0.77	0.36	29.33	14.90	1216.10
151	29.89	31.71	18.64	0.60	0.38	29.63	13.12	1215.15
152	14.39	18.64	9.98	0.49	0.23	14.13	8.67	1212.65
153	62.65	9.98	9.98	0.45	0.20	52.60	9.80	1210.49
154	84.26	9.98	37.54	0.67	0.28	39.03	17.28	1210.49
155	38.56	37.54	37.54	0.78	0.15	13.68	24.24	1216.10
156	48.46	37.54	37.54	0.82	0.13	18.93	28.84	1216.10
157	30.57	37.54	28.60	0.80	0.12	13.21	25.62	1216.10
158	26.64	28.60	16.45	0.67	0.12	26.09	12.15	1214.61
159	22.96	16.45	9.98	0.60	0.16	22.52	6.48	1212.16
160	38.46	9.98	9.98	0.47	0.26	32.17	6.07	1210.49
161	85.89	9.98	37.54	0.70	0.34	45.66	12.31	1210.49
162	94.11	37.54	31.25	0.76	0.36	85.09	14.90	1216.10
163	117.77	31.25	18.65	0.60	0.37	117.03	13.12	1215.07
164	231.50	18.65	9.98	0.49	0.23	231.25	8.67	1212.66
165	122.03	9.98	37.54	0.66	0.29	84.29	9.80	1210.49
166	88.33	37.54	37.08	0.82	0.34	71.03	17.28	1216.10
167	46.77	37.08	37.54	0.78	0.15	21.43	24.24	1216.03
168	29.11	37.54	37.12	0.82	0.13	0.00	28.84	1216.10
169	22.27	37.12	28.61	0.80	0.12	4.48	25.62	1216.04
170	19.25	28.61	16.46	0.67	0.12	18.70	12.15	1214.61
171	24.86	16.46	9.98	0.60	0.16	24.42	6.48	1212.16
172	50.43	9.98	37.54	0.69	0.38	16.48	6.07	1210.49
173	60.69	37.54	37.54	0.86	0.41	47.94	12.31	1216.10
174	56.37	37.54	22.87	0.72	0.34	55.75	14.90	1216.10
175	46.30	22.87	9.98	0.50	0.31	45.89	13.12	1213.53
176	64.09	9.98	9.98	0.41	0.20	55.21	8.67	1210.49
177	85.99	9.98	37.54	0.66	0.29	48.25	9.80	1210.49
178	99.47	37.54	37.54	0.82	0.35	81.71	17.28	1216.10
179	52.07	37.54	37.54	0.78	0.15	27.19	24.24	1216.10
180	41.98	37.54	37.54	0.82	0.13	12.45	28.84	1216.10
181	29.01	37.54	28.61	0.80	0.12	11.64	25.62	1216.10

182	25.05	28.61	16.46	0.67	0.12	24.50	12.15	1214.61
183	30.26	16.46	9.98	0.60	0.16	29.82	6.48	1212.16
184	43.24	9.98	37.54	0.69	0.38	9.29	6.07	1210.49
185	55.73	37.54	37.54	0.86	0.41	42.97	12.31	1216.10
186	37.02	37.54	23.10	0.72	0.34	36.18	14.90	1216.10
187	27.08	23.10	9.98	0.50	0.31	26.89	13.12	1213.58
188	43.58	9.98	9.98	0.41	0.20	34.70	8.67	1210.49
189	52.01	9.98	9.98	0.45	0.20	41.95	9.80	1210.49
190	96.88	9.98	37.54	0.67	0.28	51.65	17.28	1210.49
191	40.45	37.54	37.54	0.78	0.15	15.57	24.24	1216.10
192	22.30	37.54	12.05	0.68	0.11	18.38	28.84	1216.10
193	23.98	12.05	9.98	0.50	0.07	0.00	25.62	1211.07
194	24.39	9.98	9.98	0.47	0.09	11.85	12.15	1210.49
195	34.36	9.98	9.98	0.53	0.14	27.49	6.48	1210.49
196	53.90	9.98	37.54	0.69	0.38	19.95	6.07	1210.49
197	57.19	37.54	37.54	0.86	0.41	44.43	12.31	1216.10
198	41.21	37.54	23.10	0.72	0.34	40.36	14.90	1216.10
199	49.48	23.10	9.98	0.50	0.31	49.30	13.12	1213.58
200	71.63	9.98	9.98	0.41	0.20	62.75	8.67	1210.49
201	60.43	9.98	37.54	0.66	0.29	22.70	9.80	1210.49
202	89.70	37.54	37.54	0.82	0.35	71.94	17.28	1216.10
203	54.78	37.54	15.16	0.67	0.13	52.38	24.24	1216.10
204	43.74	15.16	29.51	0.65	0.10	0.00	28.84	1211.86
205	34.34	29.51	37.54	0.81	0.12	0.00	25.62	1214.77
206	26.55	37.54	25.40	0.78	0.14	25.91	12.15	1216.10
207	20.66	25.40	28.35	0.81	0.22	10.64	6.48	1214.02
208	20.55	28.35	22.28	0.71	0.39	20.21	6.07	1214.56
209	20.43	22.28	9.98	0.59	0.29	20.12	12.31	1213.42
210	39.36	9.98	34.10	0.63	0.30	0.00	14.90	1210.49
211	37.06	34.10	20.99	0.62	0.39	36.82	13.12	1215.55
212	46.85	20.99	19.77	0.57	0.27	39.12	8.67	1213.15
213	50.04	19.77	9.98	0.54	0.23	49.72	9.80	1212.90
214	87.27	9.98	37.54	0.67	0.28	42.04	17.28	1210.49
215	44.02	37.54	37.54	0.78	0.15	19.14	24.24	1216.10
216	28.18	37.54	9.98	0.67	0.10	26.34	28.84	1216.10
217	34.41	9.98	18.30	0.55	0.08	0.00	25.62	1210.49
218	27.04	18.30	9.98	0.55	0.10	22.76	12.15	1212.58
219	23.48	9.98	9.98	0.53	0.14	16.62	6.48	1210.49
220	29.73	9.98	9.98	0.47	0.26	23.44	6.07	1210.49
221	65.28	9.98	14.63	0.53	0.25	48.05	12.31	1210.49
222	116.42	14.63	37.54	0.68	0.32	78.26	14.90	1211.73
223	68.22	37.54	28.44	0.67	0.42	63.95	13.12	1216.10

224	33.14	28.44	19.77	0.61	0.30	32.83	8.67	1214.58
225	74.66	19.77	9.98	0.54	0.23	74.35	9.80	1212.90
226	84.03	9.98	37.54	0.67	0.28	38.80	17.28	1210.49
227	39.81	37.54	37.54	0.78	0.15	14.94	24.24	1216.10
228	42.89	37.54	37.54	0.82	0.13	13.36	28.84	1216.10
229	25.36	37.54	28.61	0.80	0.12	7.98	25.62	1216.10
230	22.80	28.61	16.46	0.67	0.12	22.25	12.15	1214.61
231	26.97	16.46	9.98	0.60	0.16	26.53	6.48	1212.16
232	37.20	9.98	22.05	0.58	0.32	18.80	6.07	1210.49
233	45.14	22.05	9.98	0.59	0.28	44.59	12.31	1213.37
234	42.33	9.98	9.98	0.44	0.21	27.20	14.90	1210.49
235	56.99	9.98	9.98	0.40	0.25	43.72	13.12	1210.49
236	110.25	9.98	37.54	0.61	0.29	73.71	8.67	1210.49
237	87.05	37.54	37.54	0.81	0.35	76.79	9.80	1216.10
238	57.52	37.54	30.26	0.79	0.33	47.06	17.28	1216.10
239	32.13	30.26	37.54	0.75	0.14	0.00	24.24	1214.90
240	19.94	37.54	11.43	0.68	0.10	16.64	28.84	1216.10
241	24.59	11.43	9.98	0.49	0.07	0.00	25.62	1210.90
242	25.31	9.98	9.98	0.47	0.09	12.77	12.15	1210.49
243	34.64	9.98	9.98	0.53	0.14	27.78	6.48	1210.49
244	57.95	9.98	9.98	0.47	0.26	51.66	6.07	1210.49
245	93.90	9.98	24.50	0.61	0.29	66.75	12.31	1210.49
246	155.73	24.50	9.98	0.56	0.27	155.05	14.90	1213.85
247	70.02	9.98	37.54	0.58	0.37	29.12	13.12	1210.49
248	73.10	37.54	37.54	0.74	0.36	64.05	8.67	1216.10
249	65.18	37.54	37.54	0.81	0.35	54.92	9.80	1216.10
250	122.28	37.54	36.72	0.82	0.34	105.35	17.28	1216.10
251	72.31	36.72	37.54	0.78	0.15	46.62	24.24	1215.97
252	37.16	37.54	37.54	0.82	0.13	7.62	28.84	1216.10
253	37.97	37.54	21.90	0.77	0.11	27.33	25.62	1216.10
254	36.04	21.90	9.98	0.58	0.11	35.34	12.15	1213.34
255	35.87	9.98	9.98	0.53	0.14	29.01	6.48	1210.49
256	37.83	9.98	37.54	0.69	0.38	3.88	6.07	1210.49
257	43.40	37.54	37.54	0.86	0.41	30.64	12.31	1216.10
258	31.65	37.54	22.68	0.72	0.34	31.22	14.90	1216.10
259	54.45	22.68	9.98	0.50	0.31	53.84	13.12	1213.50
260	43.57	9.98	9.98	0.41	0.20	34.69	8.67	1210.49
261	42.68	9.98	37.54	0.66	0.29	4.95	9.80	1210.49
262	29.62	37.54	20.32	0.73	0.31	29.14	17.28	1216.10
263	32.03	20.32	27.58	0.64	0.12	0.00	24.24	1213.01
264	36.70	27.58	34.80	0.76	0.12	0.00	28.84	1214.43
265	28.54	34.80	9.98	0.68	0.10	27.16	25.62	1215.67

266	29.03	9.98	9.98	0.47	0.09	16.49	12.15	1210.49
267	34.52	9.98	12.28	0.55	0.15	25.34	6.48	1210.49
268	42.28	12.28	37.09	0.70	0.38	11.08	6.07	1211.13
269	50.29	37.09	24.83	0.79	0.38	49.83	12.31	1216.03
270	45.61	24.83	9.98	0.57	0.27	45.26	14.90	1213.91
271	56.50	9.98	37.54	0.58	0.37	15.60	13.12	1210.49
272	53.55	37.54	37.54	0.74	0.36	44.50	8.67	1216.10
273	75.82	37.54	37.54	0.81	0.35	65.56	9.80	1216.10
274	14.03	37.54	33.83	0.80	0.34	0.00	17.28	1216.10
275	14.03	33.83	23.06	0.69	0.13	0.00	24.24	1215.51
276	20.45	23.06	14.16	0.60	0.09	0.00	28.84	1213.57
277	21.88	14.16	9.98	0.52	0.07	0.00	25.62	1211.61
278	21.92	9.98	9.98	0.47	0.09	9.39	12.15	1210.49
279	29.93	9.98	9.98	0.53	0.14	23.07	6.48	1210.49
280	35.42	9.98	9.98	0.47	0.26	29.13	6.07	1210.49
281	75.12	9.98	37.54	0.70	0.34	34.89	12.31	1210.49
282	38.44	37.54	23.10	0.72	0.34	37.59	14.90	1216.10
283	56.74	23.10	9.98	0.50	0.31	56.56	13.12	1213.58
284	83.21	9.98	37.54	0.61	0.29	46.67	8.67	1210.49
285	45.53	37.54	27.79	0.76	0.33	45.05	9.80	1216.10
286	40.99	27.79	37.54	0.77	0.33	13.52	17.28	1214.46
287	31.16	37.54	37.54	0.78	0.15	6.28	24.24	1216.10
288	28.33	37.54	36.34	0.82	0.13	0.00	28.84	1216.10
289	21.68	36.34	27.61	0.79	0.11	4.12	25.62	1215.91
290	16.52	27.61	16.46	0.66	0.12	14.98	12.15	1214.43
291	15.90	16.46	9.98	0.60	0.16	15.46	6.48	1212.16
292	46.51	9.98	9.98	0.47	0.26	40.22	6.07	1210.49
293	61.32	9.98	24.87	0.62	0.30	33.81	12.31	1210.49
294	31.81	24.87	9.98	0.57	0.27	31.50	14.90	1213.92
295	66.00	9.98	9.98	0.40	0.25	52.73	13.12	1210.49
296	71.50	9.98	37.54	0.61	0.29	34.96	8.67	1210.49
297	41.89	37.54	27.74	0.76	0.33	41.46	9.80	1216.10
298	82.72	27.74	37.54	0.77	0.33	55.19	17.28	1214.46
299	27.45	37.54	37.54	0.78	0.15	2.57	24.24	1216.10
300	18.19	37.54	9.98	0.67	0.10	16.35	28.84	1216.10
301	28.97	9.98	12.90	0.50	0.07	0.00	25.62	1210.49
302	20.17	12.90	9.98	0.50	0.09	10.53	12.15	1211.29
303	28.51	9.98	9.98	0.53	0.14	21.65	6.48	1210.49
304	49.35	9.98	37.54	0.69	0.38	15.40	6.07	1210.49
305	54.79	37.54	37.54	0.86	0.41	42.04	12.31	1216.10
306	37.65	37.54	31.76	0.77	0.36	28.12	14.90	1216.10
307	14.89	31.76	18.64	0.60	0.38	14.66	13.12	1215.16

308	29.86	18.64	9.98	0.49	0.23	29.60	8.67	1212.65
309	77.25	9.98	37.54	0.66	0.29	39.51	9.80	1210.49
310	76.73	37.54	37.54	0.82	0.35	58.97	17.28	1216.10
311	53.93	37.54	37.54	0.78	0.15	29.05	24.24	1216.10
312	28.98	37.54	14.02	0.70	0.11	23.07	28.84	1216.10
313	22.02	14.02	9.98	0.51	0.07	0.00	25.62	1211.58
314	20.60	9.98	16.32	0.53	0.10	1.68	12.15	1210.49
315	26.12	16.32	9.98	0.59	0.16	25.54	6.48	1212.13
316	39.36	9.98	9.98	0.47	0.26	33.07	6.07	1210.49
317	73.38	9.98	24.88	0.62	0.30	45.85	12.31	1210.49
318	36.22	24.88	9.98	0.57	0.27	35.92	14.90	1213.92
319	64.30	9.98	37.54	0.58	0.37	23.40	13.12	1210.49
320	190.58	37.54	28.87	0.70	0.34	190.22	8.67	1216.10
321	80.67	28.87	37.54	0.77	0.33	61.77	9.80	1214.66
322	40.34	37.54	37.54	0.82	0.35	22.59	17.28	1216.10
323	29.07	37.54	37.54	0.78	0.15	4.19	24.24	1216.10
324	25.29	37.54	9.98	0.67	0.10	23.45	28.84	1216.10
325	29.70	9.98	9.98	0.47	0.07	3.67	25.62	1210.49
326	27.01	9.98	9.98	0.47	0.09	14.47	12.15	1210.49
327	38.26	9.98	37.54	0.77	0.21	3.65	6.48	1210.49
328	41.57	37.54	35.47	0.84	0.45	37.18	6.07	1216.10
329	55.54	35.47	24.88	0.78	0.38	53.42	12.31	1215.78
330	38.57	24.88	9.98	0.57	0.27	38.27	14.90	1213.92
331	49.95	9.98	37.54	0.58	0.37	9.05	13.12	1210.49
332	32.40	37.54	28.87	0.70	0.34	32.04	8.67	1216.10
333	46.99	28.87	19.07	0.66	0.29	46.62	9.80	1214.66
334	89.42	19.07	37.54	0.73	0.31	53.25	17.28	1212.75
335	49.78	37.54	37.54	0.78	0.15	24.90	24.24	1216.10
336	43.68	37.54	37.54	0.82	0.13	14.14	28.84	1216.10
337	26.22	37.54	22.13	0.77	0.11	15.35	25.62	1216.10
338	21.68	22.13	9.98	0.58	0.11	21.21	12.15	1213.39
339	22.13	9.98	9.98	0.53	0.14	15.27	6.48	1210.49
340	37.28	9.98	9.98	0.47	0.26	31.00	6.07	1210.49
341	77.79	9.98	37.54	0.70	0.34	37.56	12.31	1210.49
342	117.35	37.54	36.18	0.79	0.37	103.40	14.90	1216.10
343	46.33	36.18	23.05	0.64	0.40	46.10	13.12	1215.89
344	67.52	23.05	37.54	0.67	0.33	44.02	8.67	1213.57
345	51.86	37.54	37.54	0.81	0.35	41.61	9.80	1216.10
346	51.29	37.54	37.54	0.82	0.35	33.54	17.28	1216.10
347	30.30	37.54	16.08	0.67	0.13	26.96	24.24	1216.10
348	31.54	16.08	18.29	0.58	0.09	0.00	28.84	1212.08
349	29.72	18.29	21.84	0.64	0.09	0.00	25.62	1212.58

350	27.86	21.84	9.98	0.58	0.11	27.10	12.15	1213.33
351	30.12	9.98	9.98	0.53	0.14	23.26	6.48	1210.49
352	41.54	9.98	37.54	0.69	0.38	7.60	6.07	1210.49
353	30.12	37.54	25.35	0.80	0.38	29.60	12.31	1216.10
354	34.14	25.35	22.99	0.66	0.31	21.24	14.90	1214.01
355	29.90	22.99	9.98	0.50	0.31	29.60	13.12	1213.56
356	47.78	9.98	37.54	0.61	0.29	11.24	8.67	1210.49
357	52.13	37.54	27.74	0.76	0.33	51.70	9.80	1216.10
358	58.31	27.74	37.54	0.77	0.33	30.78	17.28	1214.46
359	27.34	37.54	37.54	0.78	0.15	2.46	24.24	1216.10
360	25.26	37.54	10.61	0.68	0.10	22.79	28.84	1216.10
361	25.41	10.61	9.98	0.48	0.07	0.00	25.62	1210.67
362	19.99	9.98	16.41	0.53	0.10	0.98	12.15	1210.49
363	26.62	16.41	9.98	0.60	0.16	26.13	6.48	1212.15
364	35.60	9.98	16.56	0.54	0.29	22.70	6.07	1210.49
365	56.84	16.56	37.54	0.75	0.36	23.17	12.31	1212.19
366	36.79	37.54	22.84	0.72	0.34	36.21	14.90	1216.10
367	50.35	22.84	9.98	0.50	0.31	49.91	13.12	1213.53
368	57.88	9.98	9.98	0.41	0.20	49.00	8.67	1210.49
369	73.59	9.98	37.54	0.66	0.29	35.86	9.80	1210.49
370	88.11	37.54	37.54	0.82	0.35	70.35	17.28	1216.10
371	32.30	37.54	37.54	0.78	0.15	7.42	24.24	1216.10
372	36.03	37.54	37.54	0.82	0.13	6.50	28.84	1216.10
373	29.72	37.54	12.06	0.71	0.10	28.97	25.62	1216.10
374	27.08	12.06	22.24	0.60	0.11	4.27	12.15	1211.07
375	28.19	22.24	15.91	0.70	0.19	27.54	6.48	1213.41
376	31.04	15.91	9.98	0.53	0.29	30.66	6.07	1212.04
377	43.95	9.98	9.98	0.48	0.23	31.39	12.31	1210.49
378	49.99	9.98	9.98	0.44	0.21	34.85	14.90	1210.49
379	68.00	9.98	37.54	0.58	0.37	27.10	13.12	1210.49
380	78.96	37.54	36.92	0.74	0.36	70.53	8.67	1216.10
381	71.50	36.92	27.19	0.75	0.33	71.01	9.80	1216.01
382	72.17	27.19	9.98	0.60	0.25	71.76	17.28	1214.36
383	64.45	9.98	37.54	0.64	0.12	12.13	24.24	1210.49
384	35.14	37.54	37.54	0.82	0.13	5.61	28.84	1216.10
385	30.66	37.54	12.04	0.71	0.10	29.94	25.62	1216.10
386	28.69	12.04	9.98	0.49	0.09	18.20	12.15	1211.07
387	23.36	9.98	9.98	0.53	0.14	16.50	6.48	1210.49
388	43.87	9.98	36.22	0.68	0.37	11.25	6.07	1210.49
389	48.40	36.22	24.40	0.78	0.38	47.50	12.31	1215.89
390	33.66	24.40	9.98	0.56	0.27	32.88	14.90	1213.83
391	33.76	9.98	30.41	0.54	0.34	0.01	13.12	1210.49

392	37.15	30.41	21.75	0.63	0.31	36.82	8.67	1214.93
393	34.77	21.75	11.95	0.57	0.25	34.45	9.80	1213.31
394	82.42	11.95	37.54	0.68	0.29	39.15	17.28	1211.04
395	48.64	37.54	28.49	0.74	0.14	32.85	24.24	1216.10
396	38.55	28.49	37.54	0.78	0.12	0.00	28.84	1214.59
397	9.46	37.54	17.19	0.74	0.11	3.56	25.62	1216.10
398	5.38	17.19	9.98	0.54	0.10	0.00	12.15	1212.33
399	14.98	9.98	14.56	0.58	0.15	3.50	6.48	1210.49
400	8.42	14.56	9.98	0.52	0.28	6.69	6.07	1211.71
401	30.87	9.98	9.98	0.48	0.23	18.31	12.31	1210.49
402	55.14	9.98	30.26	0.60	0.28	19.64	14.90	1210.49
403	32.90	30.26	30.08	0.65	0.41	19.72	13.12	1214.90
404	60.57	30.08	37.54	0.71	0.34	44.08	8.67	1214.87
405	41.71	37.54	37.54	0.81	0.35	31.45	9.80	1216.10
406	39.57	37.54	37.54	0.82	0.35	21.81	17.28	1216.10
407	29.65	37.54	23.69	0.71	0.13	18.68	24.24	1216.10
408	37.89	23.69	13.49	0.60	0.09	18.75	28.84	1213.69
409	32.50	13.49	9.98	0.51	0.07	9.95	25.62	1211.45
410	29.32	9.98	9.98	0.47	0.09	16.79	12.15	1210.49
411	39.35	9.98	22.71	0.65	0.18	19.67	6.48	1210.49
412	58.96	22.71	37.54	0.77	0.42	37.70	6.07	1213.50
413	51.77	37.54	37.54	0.86	0.41	39.01	12.31	1216.10
414	97.87	37.54	37.54	0.79	0.37	82.55	14.90	1216.10
415	57.37	37.54	37.54	0.71	0.45	43.98	13.12	1216.10
416	63.96	37.54	37.54	0.74	0.36	54.92	8.67	1216.10
417	14.00	37.54	30.41	0.77	0.34	10.90	9.80	1216.10
418	15.52	30.41	28.22	0.74	0.31	0.00	17.28	1214.93
419	18.07	28.22	21.52	0.65	0.12	0.00	24.24	1214.54
420	17.77	21.52	9.98	0.56	0.09	0.00	28.84	1213.26
421	26.71	9.98	10.66	0.48	0.07	0.00	25.62	1210.49
422	23.82	10.66	16.23	0.53	0.10	5.65	12.15	1210.69
423	30.53	16.23	9.98	0.59	0.16	29.87	6.48	1212.11
424	46.82	9.98	14.88	0.52	0.28	35.61	6.07	1210.49
425	86.42	14.88	37.54	0.74	0.35	51.07	12.31	1211.79
426	51.38	37.54	37.54	0.79	0.37	36.06	14.90	1216.10
427	55.50	37.54	37.54	0.71	0.45	42.11	13.12	1216.10
428	65.30	37.54	37.54	0.74	0.36	56.25	8.67	1216.10
429	72.60	37.54	37.54	0.81	0.35	62.34	9.80	1216.10
430	72.31	37.54	37.54	0.82	0.35	54.56	17.28	1216.10
431	32.74	37.54	37.54	0.78	0.15	7.86	24.24	1216.10
432	46.73	37.54	23.60	0.75	0.12	31.20	28.84	1216.10
433	32.81	23.60	30.16	0.73	0.11	0.00	25.62	1213.68

434	30.29	30.16	18.02	0.69	0.13	29.72	12.15	1214.89
435	19.21	18.02	11.55	0.63	0.17	18.74	6.48	1212.52
436	33.17	11.55	9.98	0.49	0.27	28.44	6.07	1210.94
437	39.78	9.98	9.98	0.48	0.23	27.22	12.31	1210.49
438	120.63	9.98	37.54	0.65	0.31	77.83	14.90	1210.49
439	53.35	37.54	37.54	0.71	0.45	39.97	13.12	1216.10
440	43.39	37.54	37.54	0.74	0.36	34.34	8.67	1216.10
441	95.57	37.54	37.54	0.81	0.35	85.32	9.80	1216.10
442	134.69	37.54	37.54	0.82	0.35	116.93	17.28	1216.10
443	70.22	37.54	37.54	0.78	0.15	45.34	24.24	1216.10
444	30.25	37.54	37.54	0.82	0.13	0.72	28.84	1216.10
445	27.54	37.54	28.61	0.80	0.12	10.17	25.62	1216.10
446	23.12	28.61	16.46	0.67	0.12	22.57	12.15	1214.61
447	29.47	16.46	9.98	0.60	0.16	29.03	6.48	1212.16
448	51.07	9.98	24.65	0.60	0.33	30.05	6.07	1210.49
449	61.13	24.65	37.54	0.79	0.38	35.52	12.31	1213.88
450	41.26	37.54	33.39	0.78	0.37	30.10	14.90	1216.10
451	66.97	33.39	37.54	0.70	0.44	49.44	13.12	1215.43
452	45.14	37.54	37.54	0.74	0.36	36.09	8.67	1216.10
453	34.64	37.54	31.78	0.78	0.34	30.16	9.80	1216.10
454	74.54	31.78	37.54	0.79	0.33	51.04	17.28	1215.16
455	52.47	37.54	36.71	0.78	0.15	28.43	24.24	1216.10
456	43.40	36.71	37.54	0.82	0.13	13.03	28.84	1215.97
457	26.58	37.54	28.61	0.80	0.12	9.20	25.62	1216.10
458	23.59	28.61	16.46	0.67	0.12	23.04	12.15	1214.61
459	20.27	16.46	9.98	0.60	0.16	19.84	6.48	1212.16
460	39.07	9.98	13.31	0.51	0.27	29.43	6.07	1210.49
461	88.11	13.31	37.54	0.73	0.35	51.19	12.31	1211.40
462	173.99	37.54	31.77	0.77	0.36	164.45	14.90	1216.10
463	115.04	31.77	18.65	0.60	0.38	114.81	13.12	1215.16
464	74.09	18.65	9.98	0.49	0.23	73.84	8.67	1212.66
465	58.38	9.98	9.98	0.45	0.20	48.32	9.80	1210.49
466	67.69	9.98	37.54	0.67	0.28	22.46	17.28	1210.49
467	31.63	37.54	16.01	0.67	0.13	28.37	24.24	1216.10
468	23.77	16.01	10.50	0.52	0.08	0.00	28.84	1212.06
469	32.55	10.50	9.98	0.48	0.07	7.05	25.62	1210.64
470	32.01	9.98	9.98	0.47	0.09	19.48	12.15	1210.49
471	45.26	9.98	18.40	0.62	0.16	29.91	6.48	1210.49
472	65.73	18.40	37.54	0.74	0.40	40.18	6.07	1212.60
473	54.50	37.54	37.54	0.86	0.41	41.75	12.31	1216.10
474	33.75	37.54	27.48	0.75	0.35	28.51	14.90	1216.10
475	29.62	27.48	15.25	0.56	0.35	28.53	13.12	1214.41

476	58.53	15.25	36.24	0.63	0.30	28.54	8.67	1211.88
477	89.43	36.24	26.44	0.75	0.32	89.01	9.80	1215.90
478	76.05	26.44	37.54	0.77	0.32	47.23	17.28	1214.22
479	27.85	37.54	37.54	0.78	0.15	2.97	24.24	1216.10
480	26.15	37.54	23.70	0.75	0.12	10.52	28.84	1216.10
481	24.25	23.70	21.74	0.68	0.10	0.00	25.62	1213.70
482	23.48	21.74	9.98	0.58	0.11	22.63	12.15	1213.31
483	28.76	9.98	9.98	0.53	0.14	21.89	6.48	1210.49
484	41.17	9.98	18.52	0.55	0.30	26.31	6.07	1210.49
485	85.22	18.52	37.54	0.76	0.36	53.49	12.31	1212.63
486	82.26	37.54	22.64	0.72	0.34	81.88	14.90	1216.10
487	67.42	22.64	19.03	0.55	0.35	57.70	13.12	1213.49
488	119.11	19.03	26.20	0.59	0.29	102.97	8.67	1212.74
489	84.95	26.20	37.54	0.75	0.33	63.39	9.80	1214.17
490	89.09	37.54	37.54	0.82	0.35	71.34	17.28	1216.10
491	71.09	37.54	37.54	0.78	0.15	46.21	24.24	1216.10
492	44.09	37.54	37.54	0.82	0.13	14.56	28.84	1216.10
493	23.51	37.54	28.19	0.80	0.12	6.56	25.62	1216.10
494	22.98	28.19	16.25	0.67	0.12	22.22	12.15	1214.54
495	29.01	16.25	9.98	0.59	0.16	28.37	6.48	1212.12
496	27.31	9.98	22.22	0.58	0.32	8.73	6.07	1210.49
497	24.56	22.22	9.98	0.59	0.29	24.19	12.31	1213.40
498	103.08	9.98	9.98	0.44	0.21	87.94	14.90	1210.49
499	128.91	9.98	37.54	0.58	0.37	88.01	13.12	1210.49
500	124.07	37.54	29.57	0.70	0.34	123.01	8.67	1216.10
501	59.83	29.57	19.94	0.67	0.29	59.27	9.80	1214.78
502	81.47	19.94	37.54	0.73	0.31	46.17	17.28	1212.93
503	63.11	37.54	37.54	0.78	0.15	38.23	24.24	1216.10
504	37.74	37.54	20.52	0.73	0.11	25.30	28.84	1216.10
505	34.07	20.52	28.36	0.70	0.10	0.00	25.62	1213.05
506	27.71	28.36	16.33	0.67	0.12	27.04	12.15	1214.57
507	26.29	16.33	9.98	0.60	0.16	25.73	6.48	1212.14
508	54.13	9.98	9.98	0.47	0.26	47.84	6.07	1210.49
509	62.32	9.98	37.54	0.70	0.34	22.09	12.31	1210.49
510	37.36	37.54	30.78	0.76	0.36	28.82	14.90	1216.10
511	59.15	30.78	18.15	0.59	0.37	58.43	13.12	1214.99
512	51.72	18.15	9.98	0.48	0.23	50.97	8.67	1212.55
513	75.68	9.98	9.98	0.45	0.20	65.63	9.80	1210.49
514	86.93	9.98	37.54	0.67	0.28	41.70	17.28	1210.49
515	25.10	37.54	15.83	0.67	0.13	22.02	24.24	1216.10
516	33.18	15.83	19.68	0.59	0.09	0.00	28.84	1212.02
517	28.60	19.68	22.09	0.66	0.09	0.00	25.62	1212.88

518	28.93	22.09	9.98	0.58	0.11	28.42	12.15	1213.38
519	34.50	9.98	9.98	0.53	0.14	27.64	6.48	1210.49
520	54.30	9.98	9.98	0.47	0.26	48.02	6.07	1210.49
521	64.37	9.98	13.72	0.52	0.25	48.06	12.31	1210.49
522	41.50	13.72	9.98	0.48	0.23	30.08	14.90	1211.50
523	65.55	9.98	18.47	0.47	0.29	43.76	13.12	1210.49
524	46.99	18.47	9.98	0.48	0.23	46.57	8.67	1212.62
525	99.47	9.98	37.54	0.66	0.29	61.73	9.80	1210.49
526	74.63	37.54	37.54	0.82	0.35	56.88	17.28	1216.10
527	25.76	37.54	13.30	0.66	0.12	25.22	24.24	1216.10
528	49.06	13.30	32.95	0.66	0.10	0.00	28.84	1211.40
529	32.62	32.95	28.61	0.78	0.11	10.67	25.62	1215.36
530	28.28	28.61	16.46	0.67	0.12	27.73	12.15	1214.61
531	27.19	16.46	9.98	0.60	0.16	26.75	6.48	1212.16
532	43.90	9.98	9.98	0.47	0.26	37.61	6.07	1210.49
533	68.31	9.98	37.54	0.70	0.34	28.08	12.31	1210.49
534	55.87	37.54	23.09	0.72	0.34	55.03	14.90	1216.10
535	41.61	23.09	9.98	0.50	0.31	41.41	13.12	1213.58
536	91.47	9.98	37.54	0.61	0.29	54.93	8.67	1210.49
537	106.48	37.54	37.54	0.81	0.35	96.23	9.80	1216.10
538	79.41	37.54	37.54	0.82	0.35	61.65	17.28	1216.10
539	30.80	37.54	37.54	0.78	0.15	5.92	24.24	1216.10
540	13.44	37.54	13.75	0.69	0.11	7.80	28.84	1216.10
541	22.29	13.75	9.98	0.51	0.07	0.00	25.62	1211.51
542	22.57	9.98	16.17	0.53	0.10	3.80	12.15	1210.49
543	20.89	16.17	9.98	0.59	0.16	20.16	6.48	1212.10
544	34.96	9.98	21.13	0.58	0.31	17.48	6.07	1210.49
545	59.62	21.13	9.98	0.59	0.28	58.15	12.31	1213.18
546	34.11	9.98	28.87	0.60	0.28	0.00	14.90	1210.49
547	63.77	28.87	26.13	0.62	0.39	53.16	13.12	1214.66
548	50.82	26.13	18.62	0.59	0.29	49.36	8.67	1214.16
549	47.35	18.62	9.98	0.53	0.23	45.89	9.80	1212.65
550	103.25	9.98	37.54	0.67	0.28	58.02	17.28	1210.49
551	39.45	37.54	37.54	0.78	0.15	14.58	24.24	1216.10
552	31.39	37.54	37.54	0.82	0.13	1.86	28.84	1216.10
553	18.68	37.54	21.84	0.77	0.11	8.10	25.62	1216.10
554	19.42	21.84	9.98	0.58	0.11	18.66	12.15	1213.33
555	18.84	9.98	16.05	0.59	0.16	5.86	6.48	1210.49
556	14.33	16.05	9.98	0.53	0.29	14.09	6.07	1212.07
557	42.22	9.98	10.47	0.49	0.23	29.16	12.31	1210.49
558	36.76	10.47	22.93	0.56	0.26	9.10	14.90	1210.63
559	56.23	22.93	9.98	0.50	0.31	55.88	13.12	1213.55

560	89.11	9.98	9.98	0.41	0.20	80.23	8.67	1210.49
561	103.51	9.98	9.98	0.45	0.20	93.46	9.80	1210.49
562	127.75	9.98	37.54	0.67	0.28	82.52	17.28	1210.49
563	89.51	37.54	37.54	0.78	0.15	64.63	24.24	1216.10
564	46.43	37.54	37.54	0.82	0.13	16.89	28.84	1216.10
565	21.48	37.54	12.31	0.71	0.10	20.48	25.62	1216.10
566	20.81	12.31	9.98	0.49	0.09	10.59	12.15	1211.14
567	26.33	9.98	15.86	0.59	0.16	13.54	6.48	1210.49
568	17.89	15.86	9.98	0.53	0.29	17.46	6.07	1212.03
569	41.19	9.98	13.37	0.52	0.25	25.23	12.31	1210.49
570	39.43	13.37	37.54	0.67	0.32	0.00	14.90	1211.42
571	24.21	37.54	28.24	0.67	0.42	20.13	13.12	1216.10
572	22.75	28.24	19.77	0.61	0.29	22.25	8.67	1214.55
573	4.72	19.77	9.98	0.54	0.23	4.40	9.80	1212.90
574	74.29	9.98	37.54	0.67	0.28	29.06	17.28	1210.49
575	54.50	37.54	37.54	0.78	0.15	29.63	24.24	1216.10
576	45.38	37.54	34.85	0.81	0.12	18.55	28.84	1216.10
577	28.89	34.85	18.86	0.73	0.11	18.63	25.62	1215.67
578	28.52	18.86	16.02	0.60	0.11	18.71	12.15	1212.70
579	36.69	16.02	26.90	0.74	0.20	18.79	6.48	1212.06
580	73.00	26.90	37.54	0.79	0.43	55.92	6.07	1214.30
581	98.50	37.54	37.54	0.86	0.41	85.75	12.31	1216.10
582	76.06	37.54	37.54	0.79	0.37	60.74	14.90	1216.10
583	70.04	37.54	24.42	0.66	0.41	69.80	13.12	1216.10
584	83.01	24.42	22.13	0.60	0.29	76.32	8.67	1213.84
585	58.82	22.13	37.54	0.73	0.32	33.20	9.80	1213.38
586	40.89	37.54	20.26	0.73	0.31	40.47	17.28	1216.10
587	29.40	20.26	13.18	0.55	0.10	11.79	24.24	1213.00
588	36.94	13.18	9.98	0.49	0.08	10.89	28.84	1211.37
589	27.96	9.98	9.98	0.47	0.07	1.93	25.62	1210.49
590	26.22	9.98	11.81	0.49	0.09	11.84	12.15	1210.49
591	30.01	11.81	22.99	0.67	0.18	11.86	6.48	1211.01
592	56.20	22.99	22.70	0.68	0.37	50.10	6.07	1213.56
593	67.17	22.70	37.54	0.78	0.38	39.62	12.31	1213.50
594	136.18	37.54	37.54	0.79	0.37	120.85	14.90	1216.10
595	54.14	37.54	24.42	0.66	0.41	53.89	13.12	1216.10
596	56.90	24.42	15.76	0.56	0.27	56.61	8.67	1213.84
597	82.29	15.76	9.98	0.51	0.22	77.99	9.80	1212.00
598	88.58	9.98	30.93	0.63	0.26	49.98	17.28	1210.49
599	39.21	30.93	36.04	0.74	0.14	9.25	24.24	1215.02
600	25.94	36.04	26.83	0.76	0.12	5.66	28.84	1215.87

Appendix A- 14 GAMS Code For Reservoir Sizing

```
scalar vmin /3.5/

 scalar hmin /1204/;

  scalar num /600/;

  scalar what/1/;

  Scalar M /100000/

  scalar sec/1/ ;

  sets

  h /r1*r31/

  hek(h)  /r1,r2,r3,r4,r5,r6,r7,r8,r9,r10,r11,r12,r13,r14,r15,r16,r17,r18,r19,r20,r2
      1,r22,r23,r24,r25,r26,r27,r28,r29,r30,r31/ ;

   parameter

    h_s(hek) /r1 1205, r2 1206, r3 1207, r4 1208, r5 1209, r6 1210, r7 1211, r
      8 1212, r9 1213, r10 1214,r11 1215,r12 1216,r13 1217,r14 1218,r15 1219,r16
       1220,r17 1221,r18 1222,r19 1223,r20 1224,r21 1225,r22 1226,r23 1227,r24 1
      228,r25 1229,r26 1230,r27 1231,r28 1232,r29 1233,r30 1234,r31 1235/;


  parameter

  So(hek)  / r1 0.041, r2 0.224, r3 0.663, r4 1.51, r5 3.043, r6 5.407, r7 8
      .553, r8 12.74, r9 17.747, r10 23.234,r11 29.29,r12 35.847,r13 42.849,r14
      50.267,r15 58.144,r16 66.492,r17 75.321,r18 84.603,r19 94.312,r20 104.425,
      r21 114.934,r22 125.859,r23 137.204,r24 148.951,r25 161.075,r26 173.564,r2
```

```
    7 186.408,r28 199.622,r29 213.216,r30 227.183,r31 241.532/;
  parameter
   A0(hek)  / r1 0.041, r2 0.183,r3 0.439,r4 0.847, r5 1.533, r6 2.365, r7 3.
    146, r8 4.187, r9 5.007, r10 5.488,r11 6.056,r12 6.557 ,r13 7.002,r14 7.14
    9,r15 7.876,r16 8.348,r17 8.829,r18 9.282,r19 9.71,r20 10.112,r21 10.509,r
    22 10.925,r23 11.346,r24 11.746,r25 12.124,r26 12.489,r27 12.844,r28 13.21
    4,r29 13.594,r30 13.967,r31 14.34/;
  variable
  aa,bb,oo;
 equation  result;
 result..  oo=E= sum(hek$((h_s(hek)>0)and(So(hek)>0)), ((aa*(h_s(hek)-hmin)
    **bb-So(hek))*(aa*(h_s(hek)-hmin)**bb-So(hek))));
  option iterlim=3000;
 option optcr=0.000000001;
 aa.lo=0.0001;aa.up=200.1; bb.lo=0.0001; bb.up=200.01;
  model gog/result/;
   solve gog using NLP minimizing oo;
  file res /gidaboH_s.txt/
 put res
Put "manner(1 0r 0) 1-in runoff 0-disharge  "/;
Put what:16:0/;
Put " sec in interval     "/;
Put    Sec:16:0/;
```

```
Put “quantity of interval      "/;
Put num:16:0/;
Put " dead level             "/
put  (hmin+(vmin/aa.l)**(1/bb.l)):16:2/;
put "coefficient (a/b) in formula W=a*(H-ho)**b    "/;
put aa.l:16:4/;
put bb.l:16:4/;
put "Morfology        "/;
put " level   volume(real)   volume(calc)   defference"/;
loop(hek, put hek.TL:8, h_s(hek):10:2, So(hek):10:2,((aa.l*(h_s(hek)-hmin)
     **bb.l)$((h_s(hek)>0)and (So(hek)>0))):20:2,((aa.l*(h_s(hek)-hmin)**bb.l-S
     o(hek))$((h_s(hek)>0) and (So(hek)>0))):10:2/;);
positive variables
a,b;
b.up=100;
Variables
e(hek),obj;
equations  residual(hek),objective;
residual(hek).. e(hek)=E= a*(So(hek))**b-A0(hek);
objective..obj=E= SUM(hek,power(e(hek),2));
Model hvs/All/;
  solve hvs using NLP minimizing obj;
File kes / gidabo area.txt/;
```

```
put kes
put " coefficients(a and b) in formula A = a*S**b"/;


put "a=  ",a.L, "  b=  ",  b.L//;
  put "No.        volume    area(real)    area(calc)"/;
  loop(hek,put hek.TL,   So(hek), A0(hek),  ((a.L*So(hek)**b.L))/;);
  scalar beg_s /10/;
  sets
  t /t1*t600/
  tek(t)  /t1*t600/;
scalar MOV /9.89/ ;


parameter


  Q(tek)
  /…./


 D(tek)  /
   /
 ee(tek)
  /
  /
 p(tek)
```

```
 /
 / ;
 D(tek)=D(tek)*sec;
Q(tek)=Q(tek)*sec;
positive variables
s(tek),spill(tek);
 variable error ;
variable vmax capacity1
 binary variable   k(tek);
 equation   balance1(tek),cap(tek),sp(tek);
balance1(tek).. 0=l=S(tek-1)$(ord(tek) gt 1)+ beg_S$(ord(tek)eq 1)-S(tek)+
     Q(tek)-D(tek)-spill(tek)-ee(tek)*(a.l*((((S(tek)+S(tek-1))*0.5)$(ord(tek)
     gt 1)+ ((S(tek) + beg_S)*0.5)$(ord(tek) eq 1))**b.l))+p(tek)*(a.l*((((S(te
     k)+S(tek-1))*0.5)$(ord(tek) gt 1)+ ((S(tek) + beg_S)*0.5)$(ord(tek) eq 1))
     **b.l));
 sp(tek).. spill(tek)=g= S(tek-1)$(ord(tek) gt 1)+ beg_S$(ord(tek)eq 1)-S(t
     ek)+Q(tek)-D(tek)-vmax-ee(tek)*(a.l*((((S(tek)+S(tek-1))*0.5)$(ord(tek) gt
      1)+ ((S(tek) + beg_S)*0.5)$(ord(tek) eq 1))**b.l))+p(tek)*(a.l*((((S(tek)
     +S(tek-1))*0.5)$(ord(tek) gt 1)+ ((S(tek) + beg_S)*0.5)$(ord(tek) eq 1))**
     b.l));
cap(tek)..S(tek) =l= vmax;
     err.. error =e=(0.000000001+ prod(tek,(((1.0001-R(tek)/D(tek))**4))))*sum(
     tek,(((R(tek)-D(tek))*(R(tek)-D(tek))+0.01)**2.1))
```

```
baj..error=e=sum(tek,(((R(tek))-D(tek))*(R(tek)-D(tek))))**0.1

S.lo(tek)=Vmin;

option iterlim=3000;

option optcr=0.000000001

option limrow=12

model gg/all/;

solve gg using NLP minimizing vmax ;

file bajar1/Gidaboper.txt/
```