CHAPTER FIVE

LONG MEMORY – ANNUAL FLOW MODELS

The recent advances in the fields of operations reseach and computer technology have had an enormous impact on synthetic hydrology. More and more hydrologists and engineers are using synthetic sequences in the design, operation and management of water resources systems. Even though the determination of an optimum solution by linear or dynamic programming for a given streamflow sequence is deterministic, the stochastic nature of the streamflow enters the system through synthetic streamflow sequences. The various streamflow data generation models existing at present can be classified into two categories-the short-memory type and the long-memory type. Models which exhibit long-term persistance(Hurst effect) are usually more expensive to operate in terms of computer time than the simple autoregressive (Markov) and ARMA models. As a consequence, it has not been widely used in resource evaluation. There are cases, however, where the stochastic component exhibits a long-term dependence. Higher order autoregressive models have been tried but great difficulties have been encountered in computing the coefficients or in deciding on the order of the model to be used (Fiering, 1968; Garcia, 1971). The aim of this chapter is to apply the ffGn and BL models to a set of Northern Thailand streams and to compare the various parameters obtained from the generated sequences to that of the historical sequences. Before going on to the details of ffGn and BL models, a brief description of the Hurst phenomenon is given below.

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HURST PHENOMENON

Let X_1, X_2, ..., X_n be a stochastic sequence. The cumulative sum of the deviations from the mean is given by:

$$D_k = \sum_{i=1}^{k} X_i - (k/n)\sum_{i=1}^{n} X_i \qquad \text{............... (5.1)}$$

The adjusted range is defined as:

$$R = \max_k D_k - \min_k D_k \qquad \text{................ (5.2)}$$

and the rescaled range as the ratio of the adjusted range to the estimate of the standard deviation of the sequence. For short-memory models, which include the Markovian family, the rescaled range varies for long generated sequences the square root of the length. That is:

$$R/S \simeq n^{0.5} \qquad \text{.................. (5.3)}$$

For approximately 900 geophysical time series including streamflow records, Hurst (1951, 1956) found R/S to vary as:

$$R/S \simeq n^{h} \qquad \text{................... (5.4)}$$

where h is a constant. The value of h ranged from 0.46 to 0.96 with a mean of 0.729 and standard deviation 0.092 for all the series. This behavior is called the Hurst phenomenon and the exponent, h, is referred to as the Hurst coefficient, which is estimated from:

$$H = \log(R/S)/\log(n/2) \qquad \text{............... (5.5)}$$

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5.1 FAST FRACTIONAL GAUSSIAN NOISE (ffGn) MODEL

Mandelbrot(1971) suggested the fast fractional Gaussian noise generator (ffGn). The concept is simple and the most efficient of the approximations, which is defined below.

The ffGn variates ($X_f(t;H)$) are obtained by summing both a short memory Markov process and a long memory one. Without loss of generality, assume that $X_f(t;H)$ has zero mean and unit variance:

$$X_f(t;H) = X_L(t;H) + X_h(t) \qquad \text{................. (5.1.1)}$$

where $X_L(t;H)$ and $X_h(t)$ represent the long and short memory Markov terms, respectively.

Mandelbrot (1971) neglected the high frequencies and the very low frequencies and defined the low frequency term as follows:

$$X_L(t;H) = \sum_{m=1}^{L} W_m X(t;r_m) \qquad \text{........... (5.1.2)}$$

where $X(t;r_m)$ is a Markov-Gauss process of zero mean, unit variance, and autocorrelation function $r_m^{\,k}$,

$$r_m = \exp(-B^{-m}) \qquad \text{............. (5.1.3)}$$

$$W_m = [H(2H-1)(B^{1-H}-B^{H-1})B^{-2(1-H)m}/\Gamma(3-2H)]^{1/2} \qquad \text{.... (5.1.4)}$$

$$L = \text{smallest integer above } \log(QT)/\log B \qquad \text{.... (5.1.5)}$$

Where T is the number of time periods of simulation desired, B is the base, and Q is the quality factor, usually taking values around 4, 5 and 6. The base B and the quality factor Q together determine the quality of approximation. Mandelbrot,(1971) has suggested the use of in rang $2 < B < 4$, while Chi et al. (1973) have suggested the use of B in the range $2 < B < 3$ and $L = 20$.

The covariance of the low-frequancy term for lag k is

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$$C_L(k;H) = \sum_{m=1}^{L} W_m^2 \exp(-kB^{-m}) \qquad \text{.......... (5.1.6)}$$

The variance of the process is

$$C_L(0;H) = \sum_{m=1}^{L} W_m^2 \qquad \text{.......... (5.1.7)}$$

$$C_L(0;H) = H(2H-1)B^{-(1-H)} / [(3-2H)\ \{1-B^{-2(1-H)L}\} \qquad \text{.... (5.1.8)}$$

It should be noted that the second term in the braces in Eq. (5.1.8) was left out of Mandelbrot's (1971) paper. Its exclusion does not cause any difference in the value of $C_L(0;H)$ for low to moderate values of H, but for high values of H (say, greater than 0.8) the error is quite significant.

As a result of neglecting the high frequency and some of the low frequency effects in deriving the expression for the low frequency term, the variance of the latter will be less than 1. To make up this deficiency in the high frequency, one could add a simple Markov process to the low frequency variance as follows :

$$\sigma_h^2 = 1-C_L(0;H) \qquad \text{.................... (5.1.9)}$$

$$\sigma_h^2 = 1-\sum_{m=1}^{L} W_m^2 \qquad \text{.................... (5.1.10)}$$

The high frequency lag one autocorrelation coefficient is therefore

$$\rho_h = \{\rho(1)-C_L(1;H)\}/\{1-C_L(0;H)\} \qquad \text{............... (5.1.11)}$$

where $\rho(1)$ is the lag one autocorrelation of the ffGn variates

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$$C_L(1;H) = \sum_{m=1}^{L} W_m^2 \exp(-B^{-m}) \qquad \text{.................. (5.1.12)}$$

from Eq.(5.1.6), and $C_L(0;H)$ is defined in Eq.(5.1.7)

5.1.1 Application of ffGn Model

The steps involved in generating normally distributed flows by using ffGn are briefly describtioned below

Step 1

Obtain the values of the mean ($\bar{X}$), standard deviation(s) lag one autocorrelation coefficient ($\rho(1)$) and Hurst coefficient (H) from the historical sequence. Specify the values of B, Q and T. These values are necessary to calculate L (see Eq. 5.1.5). However, it is found that B = 3 and L = 8 are adequate.

Step 2

Compute the weighting coefficients W_m, m = 1,2, ..., L from Eq.(5.1.4), the autocorrelation of the low frequency Markov processes r_m, m = 1, 2, ..., L from Eq. (5.1.3), and the sums

$$\sum_{m=1}^{L} W_m^2 \quad \text{and} \quad \sum_{m=1}^{L} W_m^2 r_m.$$

Step 3

Compute the variance and the lag one autocorrelation coefficient of the high frequency term from Eq. (5.1.10) and (5.1.11), respectively.

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Step 4

L independent random numbers are assumed to be equal to the L Markov processes to initiate the data generation procedure. (This could easily be done in step 2 after calculating each weighting factor.) Also, set the high frequency Markov process equal to another random number

$$X(0,r_m) = G_m(0) \quad m = 1,2,\ldots,L \qquad \ldots\ldots\ldots\ldots \quad (5.1.13)$$

$$X_h(0) = G(0) \qquad \ldots\ldots\ldots\ldots \quad (5.1.14)$$

Step 5

Compute all the Markov terms in the low frequency expression, and obtain the weighted sum Eq. (5.1.2). This gives the low frequency term

$$X_L(t;r_m) = r_m X_L(t-1;r_m) + (1-r_m^{\,2})^{1/2} G_m(t) \quad \ldots\ldots \quad (5.1.15)$$

$$m = 1, 2, \ldots, L$$

$$X_L(t;H) = \sum_{m=1}^{L} W_m X_L(t;r_m) \qquad \ldots\ldots\ldots\ldots \quad (5.1.16)$$

Step 6

The high frequency Markov term is obtained from

$$X_h(t) = \rho_h X_h(t-1) + (1-\rho_h^{\,2})^{1/2} G(t) \qquad \ldots\ldots\ldots \quad (5.1.17)$$

Step 7

Finally, the ffGn variate is obtained from

$$X_f(t;H) = X_L(t;H) + X_h(t) \qquad \ldots\ldots\ldots\ldots\ldots \quad (5.1.18)$$

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By using the following inverse tranformation, the actual flow value is obtained ;

$$X_t = \overline{X} + sX_f(t;H) \qquad \text{.................. (5.1.19)}$$

Repeat steps 4-7 until the required length of the sequence is generated.

5.1.2 Modifications to Account for the Skewness

Since the ffGn process has been derived for the Gaussian case, an obvious way to generate skewed variates is to use a log normal transformation. Even though low-order moments can be preserved in the generated sequences by using Matalas (1967b) moment transformation equations, the Hurst coefficient will not be the same in the log and the actual flow domains. A simpler and more straightforward approach is to generate the skewed fast fraction noise (ffn) variates by modifying the random numbers used in the generation process rather than using highly nonlinear normalizing transformations. The necessary skewness in the ffn variates may be obtained in different ways, which are described below.

1. Modify the high frequency term only.

The required skewness for the random numbers used in the generation of the high frequency Markov term is given by

$$\gamma(\epsilon) = [1-\rho_h^{\,3}]/\{\sigma_h^{\,3}[(1-\rho_h^{\,2})^{1.5}]\} \qquad \text{............... (5.1.20)}$$

2. Modify the low frequency term only.

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In this approch, there are two possibilities. One is to have all the L Markov process with the same skewness. This means all the random numbers will have different skewnesses given by

$$\gamma(\epsilon_m) = (1-r_m^{\,3})\gamma(x_f)/[(1-r_m^{\,2})^{3/2}\sum_{m=1}^{L} W_m^{\,3}] \quad m = 1,2,\ldots.,\ L \qquad (5.1.21)$$

One is to use the same skewness for all the random numbers used in the low frequency Markov processes. The required commond skewness for the random numbers is given by

$$\gamma(\epsilon_L) = \gamma(X_f)/\{\sum_{m=1}^{L} W_m^{\,3}(1-r_m^{\,2})^{3/2}/(1-r_m^{\,3})\} \quad \ldots\ldots\ldots. \quad (5.1.22)$$

3. Modify both the high and the low frequency term.

Again, two alternatives are available:

a.) If the same skewness is assumed for all the random numbers in the high and low frequency Markov terms, then the required skewness is given by

$$\gamma(\epsilon_t) = \gamma(X_f)/\{\sum_{m=1}^{L} W_m^{\,3}(1-r_m^{\,2})^{3/2}/(1-r_m^{\,3})$$

$$+ \sigma_h^{\,3}(1-\rho_h^{\,2})^{3/2}/(1-\rho_h^{\,3})\} \quad \ldots\ldots\ldots\ldots \quad (5.1.23)$$

b.) The second alternative is to use different skewnesses for the high and low frequency terms. If one divides the total skewness $\gamma(X_f)$ into $\gamma_h(X_f)$ and $\gamma_L(X_f)$ for high and low frequency terms, respectively, such that

$$\gamma(X_f) = \gamma_h(X_f) + \gamma_L(X_f) \quad \ldots\ldots\ldots\ldots\ldots \quad (5.1.24)$$

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then the corresponding skewness for the random numbers in the high and low frequency terms can be obtained from

$$\gamma(\epsilon_h) = (1-\rho_h^{3})\gamma_h(X_f)/\{\sigma_h^{3}(1-\rho_h^{2})^{3/2}\} \quad \ldots\ldots\ldots \quad (5.1.25)$$

$$\gamma(\epsilon_L) = \gamma_L(X_f)/\{\sum_{m=1}^{L} W_m^{3}(1-r_m^{3})^{3/2}/(1-r_m^{3})\} \quad \ldots\ldots\ldots \quad (5.1.26)$$

The sum of the skewness of two variates, in general, will not be equal to the skewness of the resulting variate obtained by summing the variates. Eq. (5.1.24) serves only the purpose of dividing the skewness in two, and the two components are further modified in Eq.(5.1.25) and (5.1.26) in such a way that the resulting ffn will have the desired skewness.

A problem associated with this latter method is how to divide the skewness of the ffn into high and low frequancy components. Theoretically, there is no restriction for dividing the skewness, but because of the limitations of the available transformations such as W-H transformation (McMahon and Miller, 1971), the division can be made in such a way that the skewnesses of the random numbers for both the high and the low frequency term are within the limits of applicability of the skew transformations.

Of these three basic modifications the first one is simple and easy to apply, as one has to modify only one Markov process. Since the W-H transformation is approximate (theoretically, the expected value of the mean is not zero), the quality of simulation depends on how many skewed numbers are used to generate one ffn variate. Sivapalan (1977) and Lettenmaier and Burges (1977b) modified both the high and the low frequency term (modification 3a) to generate skewed flows. The skewed flow can be generated by following the step by step procedure described earlier but replacing G(0) in step 4 and G(t) in step 6 by $\epsilon(0)$ and $\epsilon(t)$,

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respectively, where

$$\epsilon(t) = 2/\gamma(\epsilon)\{1+G(t)\gamma(\epsilon)/6-\gamma(\epsilon)^2/36\}^3-2/\gamma(\epsilon) \quad ..... \quad (5.1.27)$$

It was found that the Wilson-Hilferty transformation Eq. (5.1.27) can be used for values of $\gamma(\epsilon)$ up to 3. For $\gamma(\epsilon) > 3$, Kirby's (1972) modified Wilson-Hilferty transformation could be used.

5.2 BROKEN LINE (BL) MODEL

Mejia et al. (1972, 1974) presented an alternative long-memory model the broken line (BL) process - to the fGn model. The simple BL process which is the basis for the BL processes results from a linear interpolation between equally spaced independent Gaussian random variables in conjunction with random displacement of the starting point of the series in order to make the series stationary (Fig. 5.1).

A simple BL process is given by :

$$\xi(t-ka) = \sum_{m=0}^{\infty} [\eta_m+(\eta_{m+1}-\eta_m)/a(t-ma)]I_{[ma,(m+1)a]}(t) \quad ... \quad (5.2.1)$$

where η_m are independent and identically distributed random numbers with zero mean and variance σ^2 ;k is a random number uniformly distributed over the interval (0,1); a is the time distance among η_m ; and :

$$I_{[ma,(m+1)a]}(t) = \begin{cases} 1, & ma < t < (m+1)a \\ 0, & \text{otherwise} \end{cases} \quad .... \quad (5.2.2)$$

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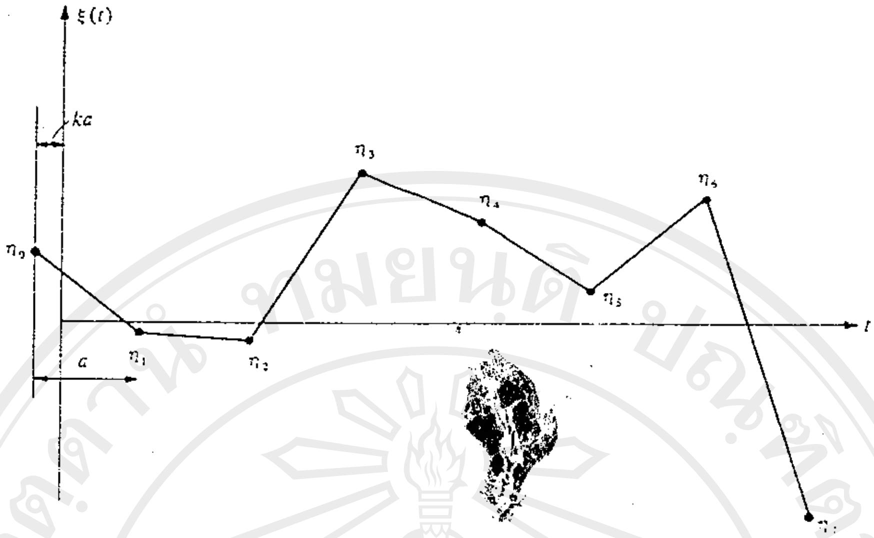

Figure 5.1 Schematic representation of simple broken line (from Mejia et al., 1972)

The variance of the process is $2/3\sigma^2$. Hence the generated η values should be scaled by $(3/(2\sigma)^2)^{1/2}$ so that will have unit variance. The autocorrelation function is given by :

$$\rho(k) = \begin{cases} 1-3/4(k/a)^2(2-k/a), & 0 \leq k \leq a \\ 1/4(2-k/a)^3 \;, & a < k < 2a \\ 0 \;, & 2a \leq k \end{cases} \quad \ldots (5.2.3)$$

5.2.1 Application of BL Model

By adding a number of simple BL process one can generate a further process that will reproduce the phenomenon to be simulated. For instance, various parameters of the BL process can be chosen in such a way to model the ffGn and the necessary derivations are given in Mejia et al. (1972, 1974).

The process Z(t), exhibitting the Hurst phenomena and a given

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lag one autocorrelation coefficient may be constructed from the summation of L+1 simple broken lines,

$$Z(t) = \sum_{m=0}^{L} V_m \xi_m(t) \qquad \ldots\ldots\ldots\ldots\ldots \quad (5.2.4)$$

where

$$V_m = \{a_1^{2(H-1)} b/[2(H-1)](B^{H-1}-B^{1-H})B^{2(H-1)(m-1)}\}^{1/2}$$

$$m = 1,2,3, \ldots , L \qquad \ldots\ldots\ldots \quad (5.2.5)$$

$$V_o = \{1-\sum_{m=1}^{L} V_m^2\}^{1/2} \qquad \ldots\ldots\ldots \quad (5.2.6)$$

$\xi_m(t)$ is a BL process with parameters a_m, k_m, zero mean and unit variance, for m=0 is the high frequency term.

$$b = [H(2H-1)(2H-2)(2H-3)(2H-4)(2H-5)]/[6(2^{3-2H}-1)] \quad (5.2.7)$$

$$a_m = a_1 B^{(m-1)} \qquad \ldots\ldots\ldots\ldots\ldots \quad (5.2.8)$$

and L, B, Q as defined under ffGn

Following Bras and Rodriquez-Iturbe (1985), the value of a_1 depend on a_o, which can be obtained from :

$$\rho(1) = a_1^{2h-2} b/[2(h-1)]\sum_{n=0}^{L-1} \{([1-3/(4(a_1B^n)^2)(2-1/(a_1B^n)]I_1(a_1B^n)$$

$$+ 1/4(2-1/(a_1B^n))I_2(a_1B^n))(B^{h-1}-B^{1-h})B^{2(h-1)n}\},$$

$$\text{for } a_o < 0.50 \quad (5.2.9)$$

or

$$\rho(1) = a_1^{2h-2} b/[2(h-1)]\sum_{n=0}^{L-1} \{([1-3/(4(a_1B^n)^2)(2-1/(a_1B^n)]I_1(a_1B^n)$$

$$+ 1/4(2-1/(a_1B^n))I_2(a_1B^n))(B^{h-1}-B^{1-h})B^{2(h-1)n}\}$$

$$+ (1-b/(2-2h)a_1^{2h-2}B^{1-h})[(1-3/(4a_1^2)(2-1/a_1))I_1(a_1)$$

$$+ 1/4(2-1/a_1)^3 I_2(a_1)],$$

$$\text{for } a_o = a_1 \quad \ldots\ldots \quad (5.2.10)$$

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where

$$I_1(x) = \begin{cases} 1 & \text{if } x > 1 \\ 0 & \text{otherwise} \end{cases} \quad , \quad I_2(x) = \begin{cases} 1 & 0.5 < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

For this process

$$E[(Z(t)] = 0.0 \qquad \ldots\ldots\ldots\ldots\ldots \quad (5.2.11)$$

$$Var[Z(t)] = 2/3\sigma^2 \qquad \ldots\ldots\ldots\ldots\ldots \quad (5.2.12)$$

$$\gamma(Z) = (3/2)^{3/2}\gamma(\eta)/2\sum_{m=0}^{L} V_m^{\ 3} \qquad \ldots\ldots\ldots\ldots\ldots \quad (5.2.13)$$

The process Z(t) can be given a particular skewness by specifying $\gamma(\eta)$. Therefor, it can be used to simulate a phenomenon of a given mean, standard deviation, skewness and that exhibits the Hurst phenomena. The process, X(t), constructed from Z(t) of Eq.(5.2.4)

$$X(t) = \mu_x + \sigma_x(3/2)^{1/2}Z(t) \qquad \ldots\ldots\ldots\ldots\ldots \quad (5.2.14)$$

has a mean of μ_x, varviance $\sigma_x^{\ 2}$, Hurst coefficient H, and $\rho(1)$ defined by the choice of a_1. If the sequence of η used for each simple broken line has skewness coefficient.

$$\gamma(\eta) = 2(2/3)^{3/2}\gamma(X)/\{\sum_{m=0}^{L} V_m^{\ 3}\} \qquad \ldots\ldots\ldots\ldots\ldots \quad (5.2.15)$$

then the skeness of X(t) is $\gamma(X)$.

Alternatively, one can assume a value for a_1 (> 1). In this case let the value of lag one autocorrelation coefficient is given by:

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$$\rho_L = a_1^{2H-2} b(B^{H-1}-B^{1-H})/[2(H-1)] \sum_{m=0}^{L-1} [1-3/(4a_1^2 B^{2m}) (2-1/(a_1 B^m))] B^{2(h-1)m} \quad , \quad a_1 > 1 \qquad \ldots\ldots (5.2.16)$$

Then the high frequency term will be a simple Markov process with variance given by

$$\sigma_h^2 = 1- \sum_{m=1}^{L} V_m^2 \qquad \ldots\ldots\ldots\ldots (5.2.17)$$

and the lag one autocorrelation coefficient :

$$\rho_h = [\rho(1)-\rho_L]/\sigma_h^2 \qquad \ldots\ldots\ldots\ldots (5.2.18)$$

The second alternative is preferred to the first because of the following reasons:

1. By choosing a value for a_1 beforehand avoids the problem of solving Eq.(5.2.9) or (5.2.10) for a_1. Instead, one has to evalute the right-hand side of Eq.(5.2.16) for the chosen a_1.

2. Since $a_1 > 1$, one has to always generate less number of random numbers compared to cases where $a_1 < 1$.

In addition, from the preliminary computer runs using the BL model, Srikanthan and McMahon(1978) observed that the variation of ρ_L with a_1 is not monotonic and the use of larger values of a_1 (>4) resulted in considerable error in the mean of the generated sequences. As a result, a value of 2 was chosen for a_1, and it performed satisfactorily for all the cases studied.

5.2.2 Modifications to Account for the Skewness

To generate skewed flows, The generating equations have to be modified in the manner similar to ffGn. The following procedure applies to the second method of using BL process. Modifying only

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the high frequency term requires it's random numbers to have the skewness given by

$$\gamma(\epsilon_H) = \gamma(1-\rho_H^{3})/[\sigma_H^{3}(1-\rho_H^{2})^{3/2}] \qquad \text{.........} \; (5.2.19)$$

The skewness of the random numbers, when both the high and low frequency terms are modified, is given by

$$\gamma(\epsilon) = \gamma\{1/2(3/2)^{3/2}\sum_{m=1}^{L} V_m^{3} + \sigma_H^{3}(1-\rho_H^{2})^{3/2}/(1-\rho_H^{3})\}^{-1} \; (5.2.20)$$

5.3 APPLICATION FOR ACTUAL DATA

The ffGn and BL models were used to generated the streamflows for all the rivers in Table 3.1. Two procedures were adapted, namely

1. Modifying the high frequency term only
2. Modifying both the high and low frequency terms

The values of B and L were respectively 3 and 8 and the procedures applied to various are as follow:

Hist	- Historical values
FFGN-H	- FFGN with only high frequency term modified
FFGN-HL	- FFGN with both the high and low frequency terms modified
BL-H	- BL with only high frequency term modified
BL-HL	- BL with both the high and low frequency term modified

5.4 DISCUSSION OF RESULTS

The various parameters estimated from the historical sequences and the generated sequences are given in Table 5.1 - 5.2.

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The results in terms of principal statistics are discussed below.

5.4.1 Mean, Standard Deviation and lag one Autocorrelation Coefficient

All the models preserved the mean and standard deviation for all rivers except a few cases. Model FFGN-HL did not preserve the mean and standard deviation for Wang River, Nam Mae Taeng, Nam Mae Rim and Nam Pat. The lag one autocorrelation is found to be larger than the corresponding historical values in all the cases with the exception that the results from model FFGN-HL are lower than the corresponding historical values for Nam Mae Taeng, Nam Mae Rim and Nam Pat.

5.4.2 Skewness and Hurst Coefficient

Most of the models can preserve the skewness except model FFGN-HL, which overestimates it for Wang River, Nam Mae Taeng, Nam Mae Rim and Nam Pat. The Hurst Coefficient are found to be preserved for most of the rivers except Nam Pat, which is slightly underestimated.

5.4.3 Maximum, Minimum and Percentage of zero flows

The maximum values from all the models are larger than the historical values and the minimum values are lower than the historical values for most of the rivers except model FFGN-H on Ping River and Nam Mae Khan. Model FFGN-HL and BL-HL on Ping River give the minimum values larger than the historical values. The amount of zero flows generated by all the models is either zero or very small.

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5.5 SUMMARY

From the above observations, it can be concluded that BL model with both frequency terms modified by W-H transformation is to be preferred than FFGN for all rivers. BL process could be used successfully and efficiently to preserve the long term persistance effects in the generated sequences as evidenced by the Hurst coefficient estimated from the historical sequence.

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TABLE 5.1 COMPARISON OF MEAN ,STANDARD DEVIATION, SKEWNESS AND LAG ONE AUTOCORRELATION FOR HISTORIC DATA AND GENERATED SEQUENCES FROM MODEL

PARAMETER	MODEL	PING	WANG	YOM	NAN	MAE TAENG	MAE CHAEM	MAE RIM	MAE KHAN	NGAO	NAM PAT
Mean	Hist.	2018.061	255.085	2631.718	2655.370	625.856	1145.244	160.193	384.669	96.617	395.580
x 10^6 cu.m	FFGN-H	2061.539	267.415	2707.826	2759.921	642.697	1225.181	177.792	437.452	103.629	404.769
	FFGN-HL	2015.901	175.970	2691.608	2752.112	522.391	1189.170	100.885	380.177	103.627	283.002
	BL-H	1947.212	246.237	2561.959	2544.148	606.520	1065.767	142.457	332.817	90.061	385.369
	BL-HL	2010.792	255.670	2635.466	2766.564	618.237	1140.979	162.929	396.513	91.028	391.021
Standard	Hist.	684.676	113.692	1118.134	1028.907	342.952	362.210	68.406	171.605	40.637	239.624
Deviation	FFGN-H	680.117	105.370	1094.395	1023.190	305.000	364.181	64.196	164.798	40.699	213.414
	FFGN-HL	673.786	85.616	1095.976	1024.436	283.133	360.895	51.614	166.769	40.716	184.154
x10^6 cu.m	BL-H	668.520	103.370	1072.959	1008.244	294.382	340.247	64.250	158.709	40.050	201.758
	BL-HL	696.348	96.573	1107.300	1032.696	277.066	384.527	66.791	189.732	40.526	192.155
Skewness	Hist.	1.218	1.466	0.735	0.498	2.195	0.894	1.588	0.979	0.15	1.815
	FFGN-H	1.409	1.409	0.892	0.672	2.046	1.05	1.136	0.885	0.322	1.827
	FFGN-HL	1.724	2.594	0.69	0.431	5.658	1.045	3.106	1.339	0.197	3.959
	BL-H	1.569	1.855	1.077	0.719	2.426	1.108	1.791	1.221	0.314	2.11
	BL-HL	1.433	1.715	0.962	0.667	2.413	1.16	1.786	1.401	0.297	2.11
Lag one	Hist.	0.297	-0.061	-0.068	0.21	-0.108	0.377	0.403	0.378	0.293	-0.22
auto-	FFGN-H	0.382	0.128	0.037	0.301	0.068	0.47	0.576	0.515	0.38	-0.062
correlation	FFGN-HL	0.363	-0.061	0.029	0.296	-0.155	0.446	0.39	0.435	0.378	-0.241
coefficient	BL-H	0.367	0.084	0.01	0.277	0.07	0.491	0.52	0.516	0.355	-0.045
	BL-HL	0.406	0.171	0.039	0.305	0.08	0.518	0.603	0.571	0.367	-0.052

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TABLE 5.2 COMPARISON OF HURST COEFFICIENT, MAXIMUM, MINIMUM AND % OF ZERO FOR HISTORIC DATA AND GENERATED SEQUENCES FROM MODEL

PARAMETER	MODEL	PING	WANG	YOM	NAN	MAE TAENG	MAE CHAEM	MAE RIM	MAE KHAN	NGAO	NAM PAT
Hurst coefficient	Hist.	0.714	0.729	0.694	0.734	0.682	0.815	0.842	0.863	0.781	0.662
	FFGN-H	0.727	0.74	0.709	0.731	0.715	0.775	0.8	0.754	0.699	0.56
	FFGN-HL	0.741	0.763	0.698	0.724	0.671	0.797	0.833	0.753	0.692	0.565
	BL-H	0.782	0.798	0.765	0.79	0.778	0.841	0.866	0.814	0.766	0.567
	BL-HL	0.809	0.828	0.792	0.805	0.803	0.855	0.873	0.82	0.788	0.567
Maximum	Hist.	4255.187	547.347	5318.144	4738.287	1925.64	2239.832	393.304	867.603	196.355	1163.758
	FFGN-H	5969.186	1017.304	8086.19	7261.489	3121.421	3177.192	611.014	1419.763	266.843	2075.792
	FFGN-HL	6369.82	955.981	7576.146	6967.48	4081.272	3168.237	596.048	1455.008	259.191	2292.038
	BL-H	6854.021	1236.77	9803.424	8130.207	3535.639	3492.348	740.524	1636.707	270.814	2316.643
	BL-HL	7067.195	1117.591	9976.218	8254.039	3405.712	3749.074	706.607	1769.776	271.544	2261.733
Minimum	Hist.	689.726	547.347	914.18	1292.405	325.894	593.739	70.529	43.288	39.784	122.47
	FFGN-H	740.077	0	0	450.797	0	473.6	43.886	54.295	1.059	0
	FFGN-HL	891.323	0	0	246.373	0	467.179	16.804	15.414	0	0
	BL-H	537.899	0	0	63.453	0	269.803	0	0	0	0
	BL-HL	701.754	0	0	216.711	0	393.459	22.171	0	0	0
Percentage of zero flows	Hist.	0	0	0	0	0	0	0	0	0	0
	FFGN-H	0	0.1	0.1	0	0.3	0	0	0	0	0.7
	FFGN-HL	0	0.6	0.1	0	0.6	0	0	0	0.2	1.4
	BL-H	0	0.7	0.1	0	0.6	0	0.1	0.7	0.8	1.4
	BL-HL	0	0.2	0.1	0	0.3	0	0	0.2	1.2	0.9

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