Journal Homepage: -www.journalijar.com

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR)

ISSN NO. 2320-5407

Article DOI:10.21474/IJAR01/13952
DOI URL: http://dx.doi.org/10.21474/IJAR01/13952

RESEARCH ARTICLE

MODELING AND PREDICTING THE MONO RIVER OVERFLOW UPSTREAM OF THE NANGBETO DAM IN WEST AFRICA USING MULTIPLICATIVE DETERMINIST MODEL

Taofic Bacharou[1,2], Vincent Prodjinonto[1] and Côme Agossa Linsoussi[3]

1. Laboratory of Energetics and Applied Mechanics, Polytechnic School of Abomey-Calavi, University of Abomey-Calavi, 01 BP 2009 Cotonou, Benin.
2. Laboratory of Applied Ecology, Faculty of Agronomic Sciences, University of Abomey-Calavi. BP 526 Cotonou, Benin.
3. Laboratory of AppliedHydrology, PolytechnicSchool of Abomey-Calavi, 01 BP: 526 INE/UAC, Cotonou, Benin.

……………………………………………………………………………………………………....

Manuscript Info

……………………..

Manuscript History

Received: 20 October 2021
Final Accepted: 24 November 2021
Published: December 2021

Key words:-

Modeling, Nangbeto Dam, Flooding; Forecast, Deterministic Model, Mono River

Abstract

………………………………………………………………

The variation and non-control of the overflow of the Mono River adversely affects the performance of the Nangbetohydropower plant to the point thatitcan no longermeet the increasinglyincreaseddemand for electricity. This studypresents the development of an operational model for forecastingdaily river flows for the plant's water retention. The overflow of the Mono River at the upstreamhydroelectric dam from 1991 to 2019 wasanalyzed and modeled by the deterministicprocesswith R software in order to makepredictions. First, the flow serieswasanalyzed by the ARIMA model (18, 1, 2) then by a multiplicative model afterremoving the seasonal trends fromtheseseries by the movingaveragemethod. The calculatederror of the results of said model revealsthat the deterministic model integrates the input generationprocesseswith an error of the order of $(er = 28.26\%)$. Finally, an annual flow forecasting program has been developed as a planning tool for the operation of the dam, in order to meet production needs and to plan water releases.

……………………………………………………………………………………………………....

Introduction:-

Today, the evolution of technologyallows the development of manyforecastingtools in severalfieldssuch as hydrology [1], meteorology [2], economics [4], water treatment [5], etc. Hydrologicalforecastingmodels are not onlyvery important for safety, especially in watershedswithhydroelectric installations with high water retentionpotential, but alsoallow an adequateand rapidresponse in crisis [6-7].

The energyfrom the hydroelectric dam, isvery important for the economicdevelopment of modern societies [8]. The countries of Benin and Togo chose this option and in 1987 built the Nangbetohydroelectric dam on the Mono river through the ElectricityCommunity of Benin (ECB) in order to induce a lasting economic impact on the energysupply [9]. However, the construction of large hydroelectricdams on watercourses leads to changes in the hydrological and sedimentologicalregimethatcan lead to changes in the balance of the environment and have negative impacts on the life of the populations and the local economy [10- 11]. The example of the Aswan dam in Egyptisparticularlystriking in this regard [12]. Thus, the typical case of the Nangbeto dam, erected on the Mono

Corresponding Author:- Vincent Prodjinonto
Address**:-** Laboratory of Energetics and Applied Mechanics, Polytechnic School of Abomey-Calavi, University of Abomey-Calavi, 01 BP 2009 Cotonou, Benin.

river since 1987, drastically modifies the natural hydro-sedimentaryregime in the valley and at the mouth [13]. The Mono River drains a well-defined basin of about $30{,}000\ km^2$and emptiesinto the Atlantic Oceanthroughavast system of lagoons [14]. Eachyear, unexpectedfloods, oftencaused by dramatic water releases, are observed in local communitieswithlimited budgets alreadyaffected by cyclicalfloods [15-16]. The degradation and lack of climate control have favored in severalregions of the world deadlyfloodsfollowingdamsthat have collapsed and, in some cases, have caused the reduction of the integrity of their structure.

To date, manyresearchers have alreadyresearched the dam deformation data predictionalgorithm, and manyconventional and efficient predictionalgorithms have been developed. The mostwidelyused model is the AutoregressiveIntegratedMovingAverage (ARIMA) model. The ARIMA algorithmis an algorithmproposed by Box and otherauthors in the last century [1]. The existingliteraturesystematicallydescribes the ARIMA model, the AR model and the MA model, and establishesthat the ARIMA model canwellpredict trends in time series. So itisused in variousfields to predict time series data and getinterestingresults. For example, G. Xu et al used the ARIMA model to predict an original time series of dam deformationwhile Wang Wei and JiancangXieused the ARIMA model to predict monitoring data from the Lijia-xiareservoir [34]. Likewise, GenmiaoYe and Mengqian Huang applied the ARIMA model to a hydropower plant. The model isshown to have clearadvantages for fitting and forecasting dam monitoring data. However, because the model cannotaccuratelyreflectnonlinearcharacteristicsbetween variables, as the predictionperiodincreases, the accuracy of the predictiongraduallydecreases. A preciseestimate of the available water and a good forecast of the dailyintake are therefore essential to efficientlyensure the production of electricalenergy. It willalso help to minimize water loss and damage fromdischarges. It istherefore important to establish a model describing the supplyflows of the dam and a program allowing the forecast.

Description Of The Study Area

The Nangbeto Dam isbuilt in the Mono watershed, located in the Gulf of Guinearegion. The Mono River rises in the northwest of Benin in the Koura Mountains of Bassilaregion. About 560 kilometers long, it serves as a natural border between Togo and Benin over its last 100 kilometers. Itswatershedcovers an area of$27{,}870\ km^2$between latitudes$6°16'$and $9°20'$North and longitudes$0°42'$and $2°45'$East [20], sothatitisinscribed in a rectangle orientedNorth-South, with a length of $340\ km$ and a width of $118\ km$. The slightly uneven relief consists of coastal plains, plateaus, lagoons, and shallows. The vegetationis made up of dense semi-deciduousforests, riparianforests, galleryforests, savannahs, fallows, fields of crops, marshymeadows, and mangroves [9, 15, 21, 22].Severalethnic groups made up mainly of farmers and fishermen live in the watershed[23]. The population density varies between70 and 300 inhabitants $/km^2$.

Materials and Methods:-

Data Collection

The monthly hydrological data cover a period of 25 years (Table 1). In total, three hydrometric stations were taken into account (Figure 1). Note that the Nangbeto flow measurement station was unique before the construction of the dam (1955-1987). Since then, measurements have been made upstream and downstream of the dam (1988-1999).

Table 1:- Summary of data and characteristics of stations.

Types of data	Sources	Area or Station	Period	Characteristics		
				Latitude	**Longitude**	**Altitude (m)**
Water flows	CEB	Upstream Nangbéto	**1991-2019**	7°25'N	1°26'E	150
	CEB	Nangbéto downstream		7°25'N	1°26'E	150

This studywascarried out using the R software (non-commercial version of S-plus). The data used in thisstudy are the dailyrawnaturalflowsmeasured in $m^3.s^{-1}$ over the period from 1991 to 2019, which show that the trend of this series varies very little and appearsmainlyconsisted of seasonal variations. The curvesrepresent the annualdaily contributions. Yearlyflows are from 1 July to 30 June of the followingyear and the contribution to Nangbeto Station has a cyclicevolution of 12 months. Figure 1 shows the evolution of dailynatural flow rates for the periodfrom 1991 to 2019. Each cycle is made up of a succession of 2 phases: a flood phase thatextendsfrom July to October and a low water phase thatrunsfromNovember to June of the followingyear. The months of June and November are transition monthsbetweenthesetwo phases and therefore the yearisconsidered for the periodfrom July to June of the followingyear…

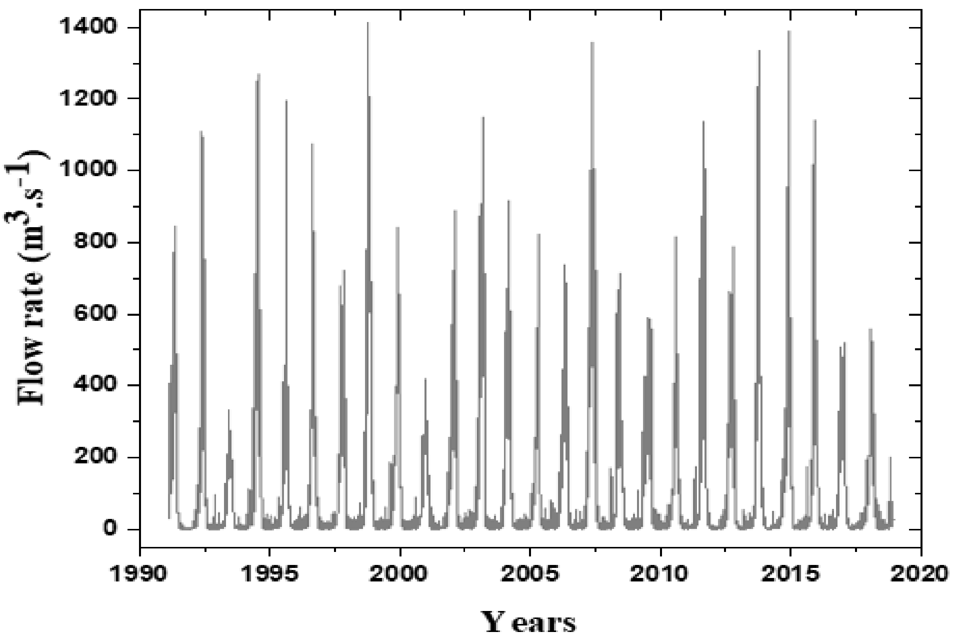

Figure 1:- Evolution of dailynatural flow rates for the periodfrom 1991 to 2019.

Methodology:-

The multiplicative deterministic model [40] wasused for the modeling and forecasting of flows.

Modelling and forecasting of daily flow rates by ARIMA process

The approachproposed by Box and Jenkins (1976)[25]isapplied to the flow rates series, a 28-year time series in which the frequency of observations isdaily, and the periodicitywasannual. This periodwas 365 days.

Elimination of seasonal variations of the series by standardization

This standardizationisgiven by the following formula:

$$Z_{v,t} = (X_{v,t} - \mu_t)/\sigma_t \tag{1}$$

where$v = 1, 2, \cdots, 26$; $t = 1, 2, \cdots, 365$; $v$is the number of a year;t is the number of a day in a year; $X_{v,t}$ is the flow rate of the day t in the year number v ; and $\mu_t$is the empiricalaverage of the flow rates of the daynumber t over the 26 years of observations, thatis:

$$\mu_t = \frac{1}{26}\sum_{v=1}^{26} X_{v,t} \tag{2}$$

$\sigma_t^2$is the variance of the flow rates of the day number$t$ over the 26 years of observations, that is:

$$\sigma_t^2 = \frac{1}{26}\sum_{v=1}^{26} (X_{v,t} - \mu_t)^2 \tag{3}$$

Modeling and forecasting of daily flow rates by the multiplicative model

The multiplicative model [24] implementedconsisted in characterizing the flowsfrom a seasonaladjustment of the series by the method of centeredmovingaverages. This descriptive statistical model involves the calculation of probabilities and supposes that the observation of the seriesat time t is a function of time t and of a variable $\varepsilon_t$centered in error on the model, representing the differencebetween the reality and the proposed model (seetable 2

(3)

of the calculation of adjustmenterrors). The variable $X_t$iswritten in terms of error as the product of the trend by a component of the seasonality

$$X_t = C_t S_t \epsilon_t with t = 1, 2, \dots, n \quad (4)$$

Where$X_t$is the series of flow rates studied, $C_t$is the trend component, $S_t$is the seasonal component and ε_t is the residual or random component.

Table 2:- Adjustmenterrors.

ARIMA model (18,1,2)	Number of days	er (%)	em (m^3/s)	Erm
Adjustment	9490	24.74	56.87	0.27

The trend of the series of flow rates varies verylittlebecauseitisalmostformed of seasonal variations. Thus, in order to expunge the series of itsperiodic intra-annual variations or in otherwords, to seasonallyadjust the series, we use as a mathematical technique the method of centeredmovingaverageswhich has the advantage of making no priorassumptions on the form of the tendency to estimate. The order of the movingaveragethatwe use to seasonallyadjust the seriesis 365. Indeed, the seasonality or period of thisseriesis 365 days. The trend wasestimated by regression of the seasonallyadjustedseries as a function of time.

$$\mathbf{X_t} = (\boldsymbol{\alpha} + \boldsymbol{\beta}\mathbf{t}) \times \left(\sum_{i=1}^{365} \mathbf{S_i} \, \boldsymbol{\gamma}_t^i \right) \times \boldsymbol{\varepsilon}_t \, ; \mathbf{where} \boldsymbol{\gamma}_t^i = \begin{cases} \mathbf{1}, \mathbf{iftcorrespondstoday} \boldsymbol{i} \\ \mathbf{0}, \ \mathbf{otherwise} \end{cases} \quad (5)$$

The process$\varepsilon_t$is then modeled by an ARIMA model $(p, d, and q)$.

Results and Discussions:-

Modeling and forecasting of dailyflows by multiplicative process

The daily flow ismodeledfromaseasonalseparation of the data seriesusing the centeredmovingaveragemethod [27].

Identification of the composition scheme

The regression line of the standard deviations as a function of the mean of the flows for eachyearstudiedisprovided by the followingequation:

$$\boldsymbol{\sigma} = \mathbf{1.833}\boldsymbol{t} - \mathbf{16.8016} \quad (6)$$

Where the coefficient 1.833 isverysignificant and itscriticalprobabilityis$1{,}92 \times 10^{-14}$. This suggests the efficient adaptation of a multiplicative composition scheme for these daily flow rates. The generalform of the equation for this type of model is:

$$\boldsymbol{y_t} = \boldsymbol{C_t S_t \varepsilon_t} \quad (7)$$

Wherey_t is the series of flow rates to be studied, C_t is the trend component, S_t is the seasonal component and ε_t is the residual or random component.

Seasonalseparation of the series

The trend of the series of flow rates varies verylittlebecauseitisalmostformed of seasonal variations. Thus, in order to purge thisseries of itsperiodic intra-annual variations, or in otherwords, to seasonallyadjustthisseries, the method of centeredmovingaveragesisused. This method has the advantage of making no priorassumptions on the form of the tendency to estimate. The order of the movingaverageused to seasonally adjust tthis data seriesis 365. Indeed, the seasonality or period of thisseriesis 365 days.

Calculation of the seasonallyadjustedseries

Figure 2 presents the seasonallyadjustedseries and an estimate of the long-termoverall trend of the series of flow rates.

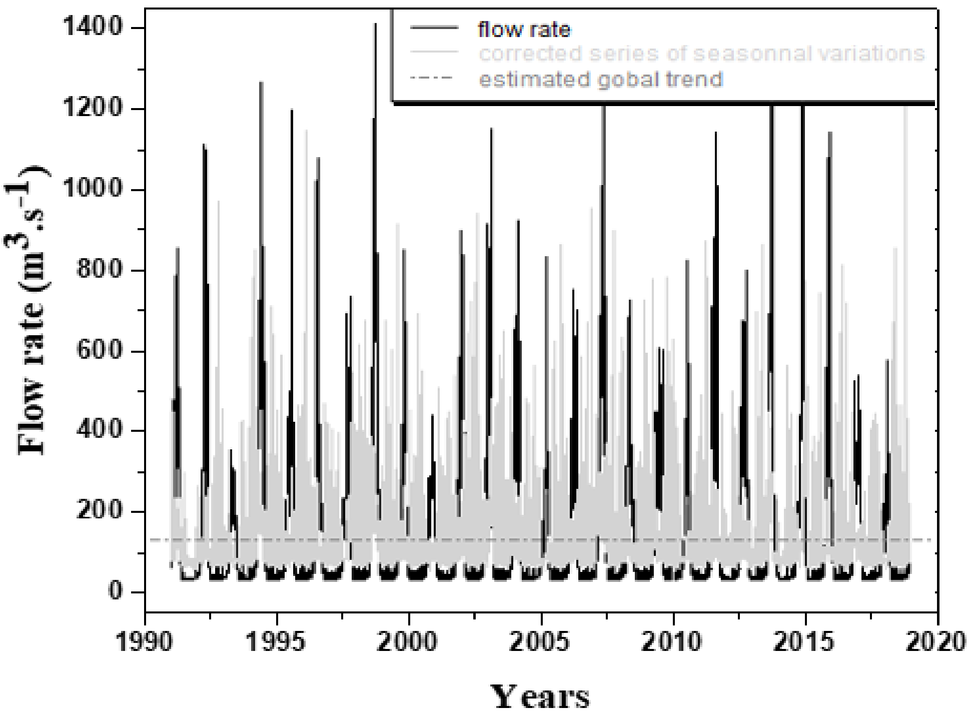

Figure 2:- Seasonallyadjustedseries.

The seasonallyadjustedserieswhichis an estimate of the overall long-term trend of the dischargeseries (Figure 2) shows thatitisalmost constant. This trend wasestimated by regression of the seasonallyadjustedseries as a function of time. The equation for thisestimated trend is:

$$\boldsymbol{C_t = 0.00667t + 106} \tag{8}$$

Where the coefficients 0.00667 and 106 have critical probabilities of 0.095 and 2×10^{-16} respectively. Thus, the slope of this line is not significant and intercept is very highly significant at the threshold of5%. The general equation of this model is:

$$\boldsymbol{y_t = (\alpha + \beta t) \times \left(\sum_{i=1}^{365} S_i \gamma_t^i\right) \times \varepsilon_t \text{ ; where} \gamma_t^i = \begin{cases} 1 \text{ , } if t corresponds to day i \\ 0, \quad otherwise \end{cases}} \tag{9}$$

Estimation and study of residuals

Based on the precedingresults, thisestimated model has the followingform:

$$\boldsymbol{\hat{y}_t = 106 \times (\sum_{i=1}^{365} S_i \gamma_t^i) \times \varepsilon_t} \tag{10}$$

Where$S_i$are the seasonal coefficients.

To check whether the residualsresultingfrom the adjustment of flows by thisestimated model form a white noise the process$\varepsilon_t$is studied throughitsestimated values.

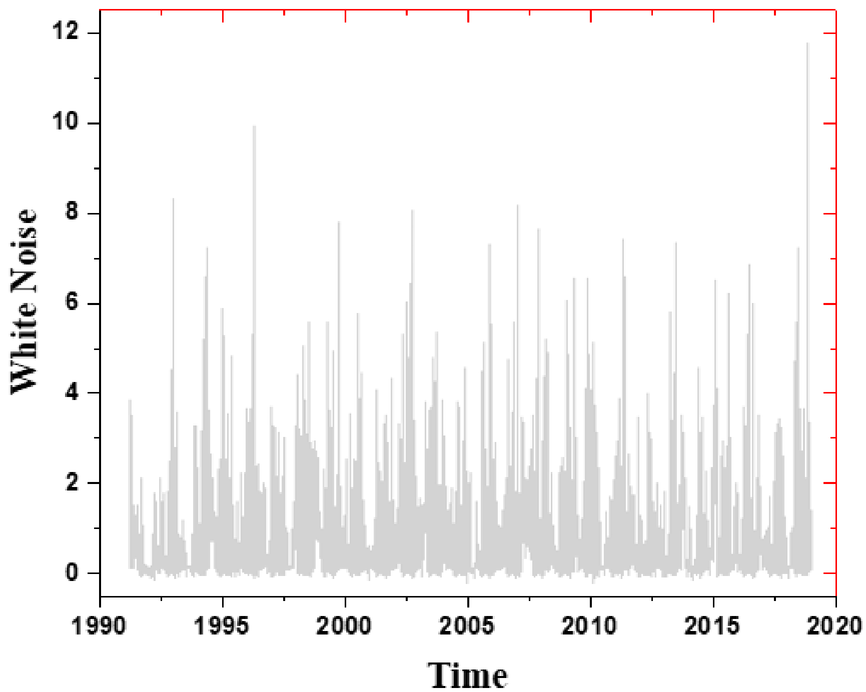

Figure 3:- Graph of standardizedresiduals.

Figure 3 shows the graph of the estimatedresiduals$\hat{\varepsilon}_t = \frac{y_t}{\hat{y}_t}$. The autocorrelation graph (Figures 4a and 4b) shows that the process $\hat{\varepsilon}_t$is not stationary (slow decay of autocorrelations). $\hat{\varepsilon}_t$is not white noise.

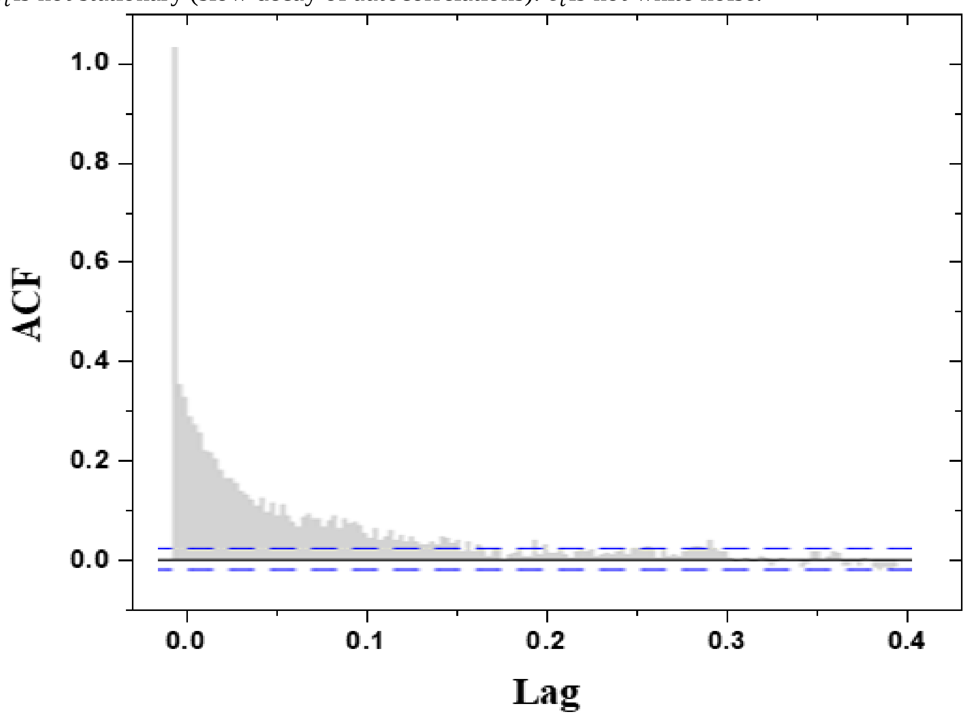

Figure 4a:- ACF of standardizedresiduals.

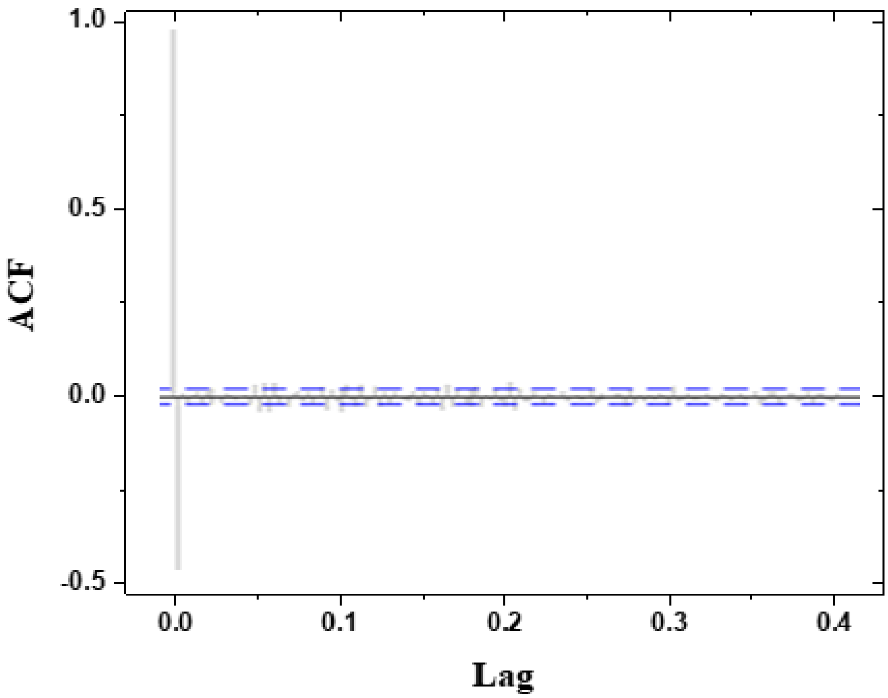

Figure 4b:- ACF of standardized and differentiatedresiduals.

By observing the correlogram and the partial correlogram of the process:

$$\boldsymbol{w_t = (1-B)\varepsilon_t} \tag{11}$$

The process w_t appears stationary (figure 6). Then $\varepsilon_t$is modelled by an ARIMA model $(p,1,q)$. The observation of auto-correlograms (Figure 14) enables to increase the possible pairs (p,q) by the pair $(22,4)$. After multiple modeling with different values of the couple (p,q)satisfying this condition, we maintained the pair $(20,3)$ as the one for which the model's AIC is minimal. The ARIMA model $(20,1,3)$ verified by the ε_t the process has the general equation:

$$\boldsymbol{\sum_{i=1}^{20}(1-ar_i B^i)(1-B)\varepsilon_t = (1+ma_1\,B+\ ma_2B^2\ +\ ma_3B^3)\ \eta_t} \tag{12}$$

Where$\eta_t$is a white noise of variance, the estimatedparameters of this model as well as the corresponding confidence intervalsrecorded in Table 3 show that the coefficients$ar_{20}$and $ma_3$are significant. By verifying the hypothesis of the white noise of the residues$\eta_t$of this model, we observe that these residuals form indeed a white noise (Figure 14).

Table 3:- Coefficients of the multiplicative model.

ARIMA model (18,1,3)	**2,5%**	**coef**	**97,5%**	**ARIMA model (18,1,3)**	**2,5%**	**coef**	**97,5%**	**ARIMA model (18,1,3)**	**2,5%**
ar1	-0.0521	0.1421	0.3364	0.0991	ar12	0.0163	0.0094	0.0352	0.0131
ar2	0.5645	0.7656	0.9667	0.1026	ar13	0.0171	0.0087	0.0345	0.0132
ar3	-0.0544	0.0142	0.0259	0.0205	ar14	0.0423	0.0165	0.0093	0.0132
ar4	-0.0614	0.0263	0.0087	0.0179	ar15	0.0293	0.0035	0.0222	0.0131
ar5	-0.0394	0.0098	0.0198	0.0151	ar16	0.0248	0.0008	0.0263	0.0130
ar6	-0.0440	0.0165	0.0111	0.0141	ar17	0.0276	-0.002	0.0236	0.013
ar7	-0.0251	0.0014	0.0279	0.0135	ar18	0.0017	0.0272	0.0528	0.0130

ar8	-0.0054	0.0206	0.0466	0.0133	ar19	0.0401	0.0149	0.0104	0.0129
ar9	0.0077	0.0339	0.0602	0.0134	ar20	0.0153	0.0092	0.0337	0.0125
ar10	-0.0279	0.0009	0.0261	0.0138	am1	1.1646	0.9706	-0.7766	0.0990
ar11	-0.0505	0.0237	0.0031	0.0137	am2	0.9696	0.6473	0.3250	0.1644

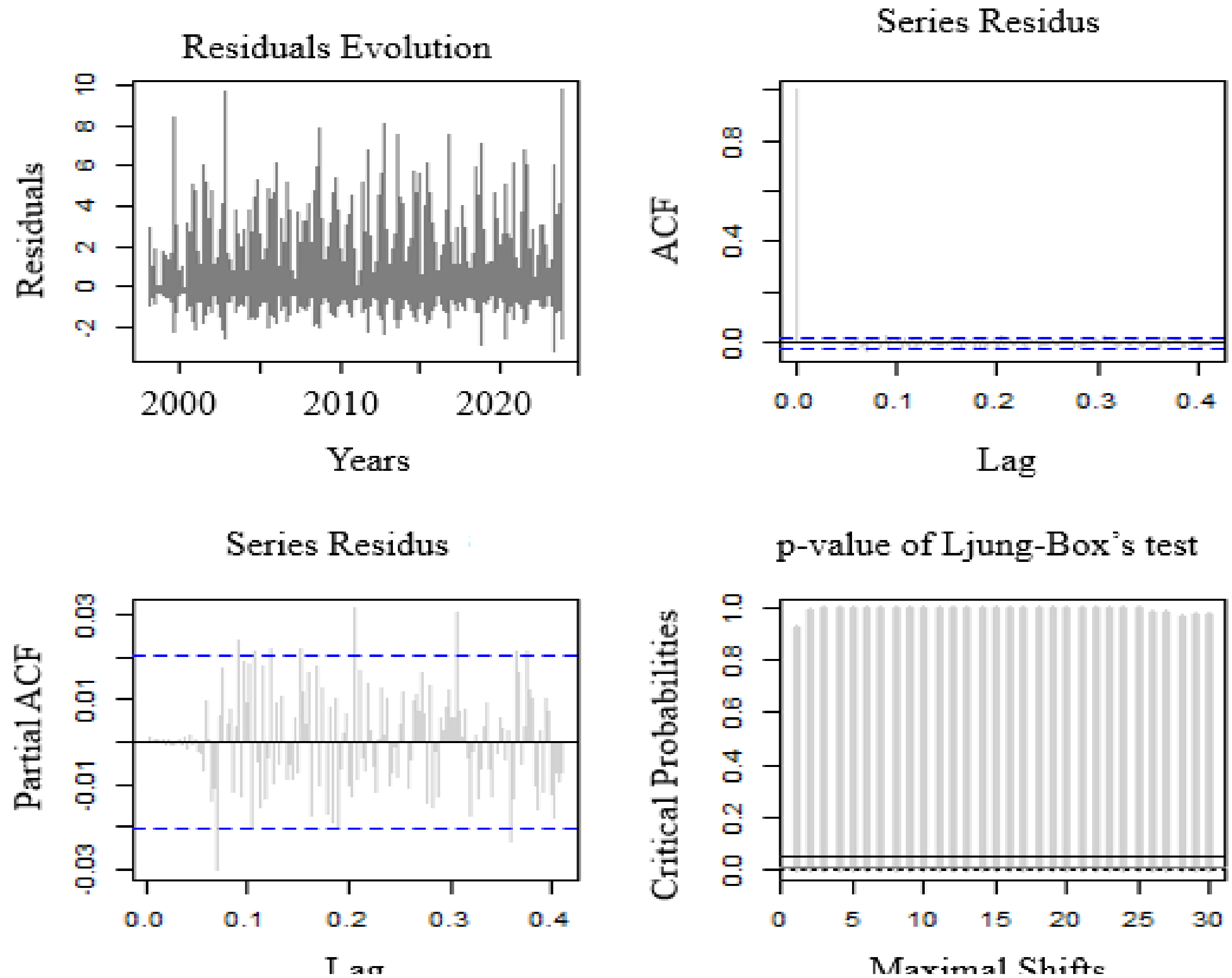

Figure 6:- Analysis of residuals of the ARIMA model$(20, 1, 3)$.

Summary of thismodeling

In sum, the equation of the model verified by the dailynatural flow rates y_t is:

$$\boldsymbol{y_t = (\alpha + \beta t) \times (\sum_{i=1}^{365} \gamma_i S_t^i) \times \varepsilon_t} \tag{13}$$

Where$\varepsilon_t$is a process that follows the ARIMA model $(20, 1, 3)$ whose parameters are recorded in Table 2. This equation is used as the following expression to estimate the values of the series of these flow rates:

$$\boldsymbol{\hat{y}_t = \hat{\alpha} \times (\sum_{i=1}^{365} \hat{S}_i \gamma_t^i) \times \hat{\varepsilon}_t} \tag{14}$$

where the $\hat{\varepsilon}_t$are the process values estimated by the ARIMA model $(20, 1, 3)$. (Figure 7) shows the adjustment of this final model with the series of actual flow rates.

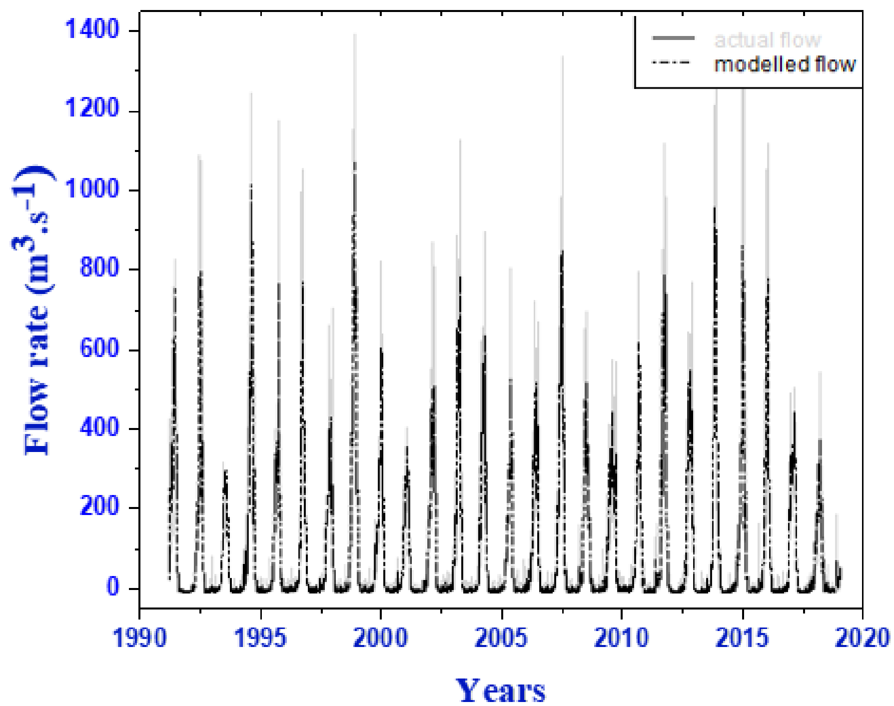

Figure 7:- Evolution of actual flow rates and adjustedflows rates by the multiplicative model.

Table 4presents the quadraticerrorsrelated to thisadjustment.

Table 4:- Quadraticerrorsrelated to thisadjustment.

	Number of days	Er(%)	em(m^3/s)	ermoy
Adjustment	9490	28.26	63.40	0.34

The following formula provides the forecast of dailynatural flow rates for a fixedyear$k$, denoted by $\hat{y}_t$:

$$\hat{\boldsymbol{y}}_t = \hat{\boldsymbol{\alpha}} \times (\sum_{i=1}^{365} \hat{\boldsymbol{S}}_i \, \gamma_t^i) \times \hat{\boldsymbol{\varepsilon}}_t \tag{15}$$

Post-evaluation of the reliability of the model

Table 5depicts the errors of the adjustments and post predictions of the multiplicative model.

Table 5:- Errors of the adjustments and post predictions of the multiplicative model.

Year	Adjustment				Prediction			
	Number of days	er (%)	em (m3/s)	Emoy (m3/s)	Number of days	er (%)	em (m3/s)	emoy (m3/s)
2016 2017	8395	28.09	63.42	0.62	365	39.02	68.31	24.14
2017 2018	8760	28.33	63.40	0.60	365	36.87	96.45	2.9
2018 2019	9125	27.91	63.93	0.57	365	23.16	49.62	-1.27
2019 2020	9490	27.86	62.69	0.553	365	35.98	74.35	-3.40

Each graph in (figure 8) presents the curve of the actual flow rates on whichissuperimposed the one predicted by the multiplicative model.

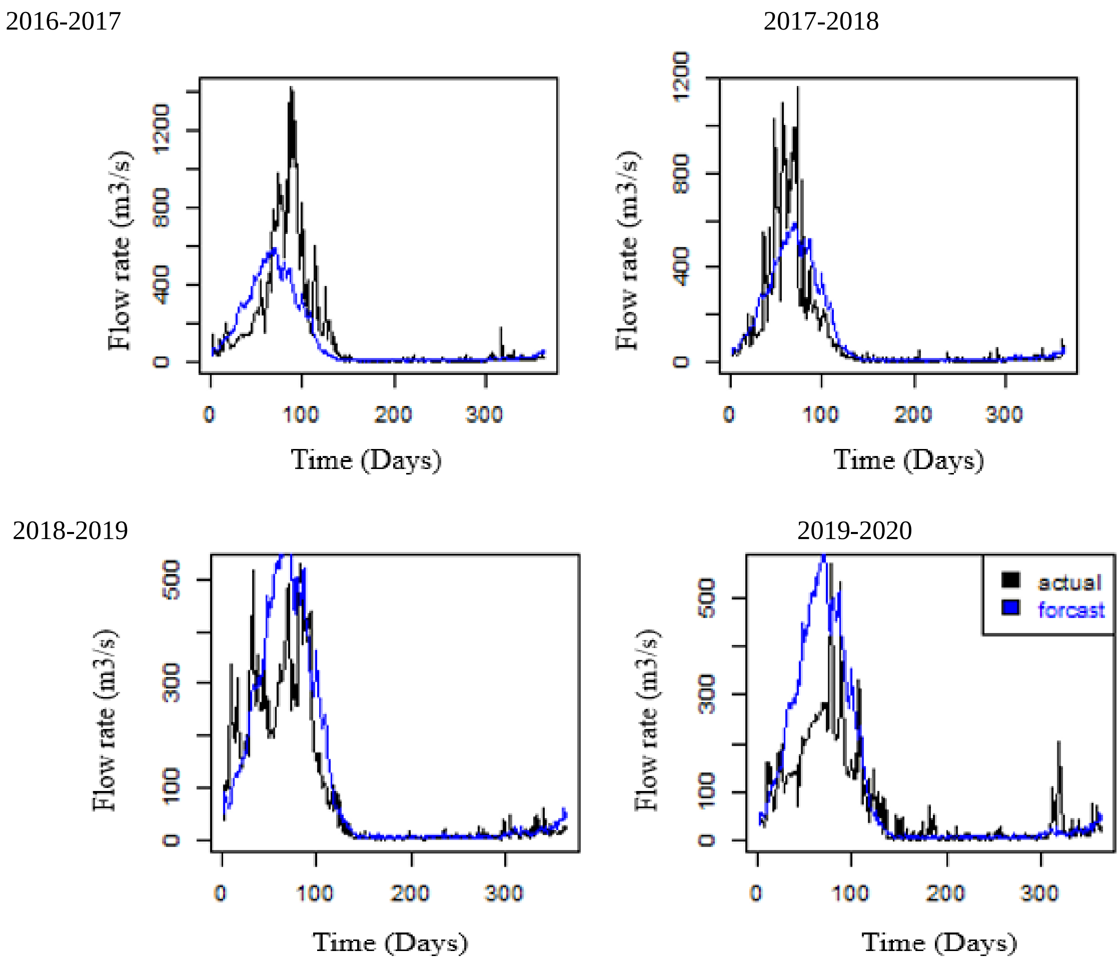

Figure 8:- Curve of actual flow rates predicted flow rates by the multiplicative model.

Conclusion:-

The determination of the flow prediction model at the Nangbeto station iscarried out from the series of flowsrecordedfrom 1991 to 2019 (28 years of monitoring data). The deterministic model of the multiplicative type issuitable for the prediction of time series, afteraseasonalseparation of the data by the method of centeredmean. At the end of thisresearch, the prediction model obtainedisconsideredsatisfactory. However, an analysis of the quadratic and relative errors shows thatthey are somewhat high. A program wasthendrawn up on the basis of the ARIMA model and itwillallow water retention managers to makeannualforecasts. Theseforecastswillbeused for rational management of water retentionthroughbetter planning of discharges.

References:-

1. Unduche, F., et al., (2018): Evaluation of four hydrological models for operational flood forecasting in a Canadian Prairie watershed. 63(8): p. 1133-1149.
2. Dehghani, M., B. Saghafian, and M.J.H.R. Zargar (2019): Probabilistic hydrological drought index forecasting based on meteorological drought index using Archimedean copulas. 50(5): p. 1230-1250.
3. Beyca, O.F., et al., (2019): Using machine learning tools for forecasting natural gas consumption in the province of Istanbul. 80: p. 937-949.
4. Worou, C.N., et al., (2021): Euler's Numerical Method for Ions Rejection Reassessment of a Defect-Free Synthesized Nanofiltration Membrane with Ultrathin Titania Film as the Selective Layer. Coatings, 11(2): p. 184.
5. Wanders, N., et al., (2019): Development and evaluation of a pan-European multimodel seasonal hydrological forecasting system. 20(1): p. 99-115.

6. Bugaets, A., et al., (2018): The integrated system of hydrological forecasting in the Ussuri River basin based on the ECOMAG model. 8(1): p. 5.
7. Ali, M., et al., (2020): Emergy based sustainability evaluation of a hydroelectric dam proposal in South Asia. 264: p. 121-496.
8. Kouadio, K.C.A., et al., (2020): Analysis of hydrological dynamics and hydropower generation in a West African anthropized watershed in a context of climate change. 6(4): p. 2197-2214.
9. Biswas, A.K.J.E.d., (1992): Aswan dam revisited. p. 67-69.
10. Abdelmoneim, H., et al., (2021): Inferring the Joint Operation of High Aswan Dam and Toshka Lakes using Multi-Sensor Satellite Approach. Copernicus Meetings.
11. Mulat, A.G., S.A.J.J.o.W.R. (2014): Moges, and Protection, Assessment of the impact of the Grand Ethiopian Renaissance Dam on the performance of the High Aswan Dam.
12. Adje, K., et al., (2021): Etat de la contamination en éléments traces des sédiments du Lac du barrage hydroélectrique de Nangbéto (Togo).
13. Fagbémi, M.N.A., et al., (2021): Genetic structure of wild and farmed Nile tilapia (Oreochromis niloticus) populations in Benin based on genome wide SNP technology. 535: p. 736432.
14. Laïbi, R., et al., (2012): Apport des séries d'images LANDSAT dans l'étude de la dynamique spatio-temporelle de l'embouchure de l'estuaire des fleuves Mono et Couffo au Bénin, avant et après la construction du barrage de Nangbéto sur le Mono. 10(4): p. 179-198.
15. Ndour, A., et al., (2018): Management strategies for coastal erosion problems in West Africa: analysis, issues, and constraints drawn from the examples of Senegal and Benin. 156: p. 92-106.
16. et après la construction du barrage de Nangbéto sur le Mono. 10(4): p. 179-198.
17. Ndour, A., et al., (2018): Management strategies for coastal erosion problems in West Africa: analysis, issues, and constraints drawn from the examples of Senegal and Benin. 156: p. 92-106.
18. Zwahlen, R., (2003): Identification, assessment, and mitigation of environmental impacts of dam projects, in Modern Trends in Applied Aquatic Ecology. Springer. p. 281-370.
19. Amoussou, E., et al., (2020): Climate and extreme rainfall events in the Mono River basin (West Africa): investigating future changes with regional climate models. 12(3): p. 833.
20. Xu, G., et al., (2020): A dam deformation prediction model based on ARIMA-LSTM. in 2020 IEEE Sixth International Conference on Big Data Computing Service and Applications (BigDataService). IEEE.
21. Lederoun, D., et al., (2016): Length-weight and length-length relationships and condition factors of 30 actinopterygian fish from the Mono basin (Benin and Togo, West Africa). 40(4): p. 267-274.
22. Amoussou, E., et al., (2017): Hydroclimatic variability and flood risk on Naglanou and Akissa forests areas in Mono River Delta (West Africa). 9(6): p. 212-223.
23. Amoussou, E., et al., (2018): Sedimentary evolution and ecosystem change in Ahémé lake, south-west Benin. 377: p. 91-96.
24. HOUNAHO, S.G.-F. (2020): Socio-economic and climate change effects on Fishing Yiekds and Farminig in the Mono River Basin: Case Study of Toho Lake. PAUWES.
25. Gottwald, G.A., I.J.P.o.t.R.S.A.M. Melbourne (2013): Physical, and E. Sciences, Homogenization for deterministic maps and multiplicative noise. 469(2156): p. 20130201.
26. Tseng, F.-M., G.-H.J.F.S. Tzeng, and Systems (2002): A fuzzy seasonal ARIMA model for forecasting. 126(3): p. 367-376.
27. Fard, A.K., M.-R.J.J.o.E. Akbari-Zadeh, and T.A. Intelligence (2014): A hybrid method based on wavelet, ANN and ARIMA model for short-term load forecasting. 26(2): p. 167-182.
28. Grande, J.A., et al., (2010): Quantification of heavy metals from AMD discharged into a public water supply dam in the Iberian Pyrite Belt (SW Spain) using centered moving average.212(1): p. 299-307.