engineering proceedings

Proceeding Paper

Model Development for Discharge Data Extension for Ungauged Rivers Channels: A Case Study of the Proposed River Orle Hydropower Plant †

Luqman Muhammed Audu *, Nicholas Akhaze Musa, Abdulkarim Nasir and Muhammadu Masin Muhammadu

Mechanical Engineering Department, Federal University of Tech, Minna 920211, Nigeria
* Correspondence: luqslama@gmail.com
† Presented at the 2nd International Conference on Advances in Mechanical Engineering (ICAME-22), Islamabad, Pakistan, 25 August 2022.

Abstract: The paper presents a model to carry out a short-term flow data extension for a minimum of 30 years using the Gauss–Newton Empirical Regression Algorithm (GNRA) for the determination of the hydropower generation capacity of rivers in ungauged channels. An averaged 2 years of precipitation, observed experimental discharged data, and 30 years of historical and predictive precipitation data were used to generate a regression model equation after authentication analysis. A minimum, average, and maximum of 30 years of historical, and predictive discharge data and power characteristics of the river were generated. A discharge predictive accuracy of 96.71% and a Pearson Correlation Coefficient of 0.954 were established between the experimental and model results. The river has minimum, average, and peak power potentials of 5 MW, 10 MW, and 20 MW, respectively, and is capable of yielding power throughout the year.

Keywords: data extension; discharge; rivers; hydro; power; regression; analysis

Citation: Audu, L.M.; Musa, N.A.; Nasir, A.; Muhammadu, M.M. Model Development for Discharge Data Extension for Ungauged Rivers Channels: A Case Study of the Proposed River Orle Hydropower Plant. *Eng. Proc.* **2022**, *23*, 27. https://doi.org/10.3390/engproc2022023027

Academic Editors: Mahabat Khan, M. Javed Hyder, Muhammad Irfan and Manzar Masud

Published: 22 September 2022

1. Introduction

The need to improve Nigeria's power generation has emphasized the importance of improving the country's hydropower generation output [1]. However, the development of hydropower resources is currently being hampered by a hydrological data shortage due to large ungauged river channels. Data extension techniques using empirical rainfall-runoff models are used to overcome this challenge [2].

A recent study [3] developed a new hybrid biogeography-based optimization (BBO) technique to achieve a better capability to predict daily stream flow. The study referenced in [4] applied regression analysis and clustering in catchments to give excellent results in the data analysis and forecasting of hydrological runoff; the study referenced in [5] also used the regression tree ensemble approach to develop a model with good accuracy for runoff prediction. Ramana validated the adequacy of regression analysis for runoff prediction with the formulation of a model with three hydrological modules [6]. The present methods of modeling surface runoff involve complex evaluation processes with many interconnecting variables [7] that are not available for most river basins in Nigeria.

The paper presents a faster, cheaper, and more convenient model to carry out short-term flow data extension to a minimum of 30 years using the Gauss–Newton Regression Algorithm (GNRA) for data extension in ungauged river channels. GNRA is one of the most popular, efficient, and simple methods for solving non-linear problems [8].

2. Materials and Methods

The observed 2 years of experimental discharge data were extended to 30 years of discharge data using GNRA. The regression model equation was generated and validated using rainfall data for 2018 and 2019 for the study period. The validated model equation was used to carry out 30 years of the data extension process. Correlation analysis was implemented between the model and experimental results.

Modeling Equations

The general relationship for the empirical modeling process is shown in Equation (1).

$$Q = f[X, Y] \quad (1)$$

where

Q is the runoff output;
X is the input dataset of rainfall;
Y is the input dataset of historical runoff.

The regression model equation generated by the study process is given in Equation (2).

$$\mathrm{D} = 6.5870 + 0.2614\mathrm{F} - 0.0042\mathrm{F}^2 + 0.000019\mathrm{F}^3 \quad (2)$$

D is the discharge (m^3/s);
F is the rainfall (mm).

The hydroelectric power output was evaluated using Equation (3).

$$\mathrm{P} = \rho g h \mathrm{D} \eta \quad (3)$$

where

P is the generated power (MW);
ρ is the density of water (1000 kg/m^3);
g is the acceleration due to gravity (9.81 m^2/s);
h is the head of water (50 m);
η is the plant efficiency (0.90).

3. Results and Discussions

3.1. River Orle Rainfall–Discharge Regression Output Analysis

The River Orle rainfall–discharge output is shown in Figure 1. It indicates a good fit, with the data point close to the regression line plot. This indicates low values of residuals, which equally indicates the agreement between the model and experimental results. Figure 2 represents the plot of the observed experimental results and the regression model output.

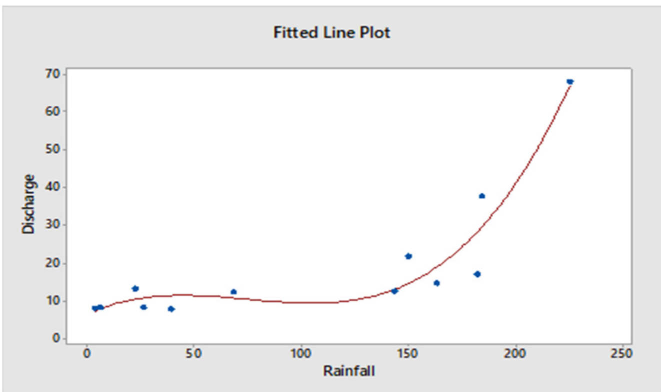

Figure 1. Fitted rainfall–discharge line plot.

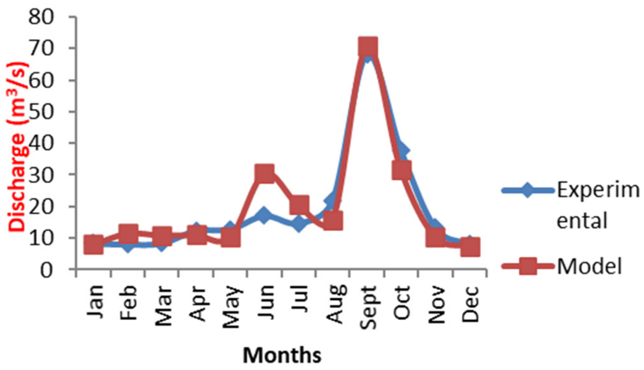

Figure 2. Profile of experimental and model discharge plot.

The mean annual discharge for the experimental and model results are 19.282 m^3/s and 19.937 m^3/s, respectively, whereas the total average discharges are 231.393 m^3/s and 239.252 m^3/s, respectively. This indicates a model discharge predictive accuracy of 96.71%. The large difference in the experiment and model discharge for June and July is because the model data were derived from 60 years of monthly rainfall data, whereas the experimental data were derived from 2 years of average monthly data. This is because there used to be occasional high-volume rainfall between June and July for a number of years.

The proximity in the discharge indicates that the monthly discharge of the river falls within the same range and demonstrates the accuracy and precision of the model.

3.2. Power Generation Analysis

Figure 3 indicates the discharge and power generation profile of the river. The medium flow range of the river, Q_{10} to $Q_{70,}$ is between 10 m^3/s and 42 m^3/s which corresponds to the 5 MW–20 MW power output range. The river has a peak power output of 20 MW, base power of 10 MW, and low power of 5 MW, respectively, within this hydropower power generation range.

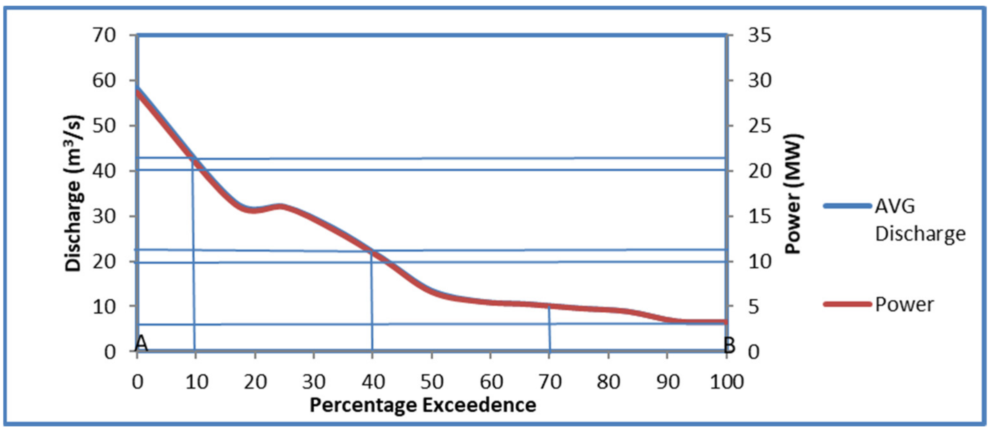

Figure 3. Integrated discharge and power duration curve.

4. Conclusions

A 30-year historical and predictive discharge data extension was carried out using the Gauss–Newton Regression Algorithm from the observed 2 years of experimental discharge data, in order to meet the requirements for the design of hydropower facilities. The profile of the river's average monthly discharge and power generation output was determined with the generated and validated model. Model discharge predictive accuracy of 96.71% and a Pearson Correlation Coefficient of 0.954 were established between the experimental and model results. The river has minimum, average, and peak power potentials of 5 MW, 10 MW, and 20 MW, respectively, within the medium flow range, and is capable of yielding power throughout the year.

Author Contributions: Conceptualization, N.A.M. and A.N.; methodology, L.M.A. and M.M.M.; software, L.M.A. and A.N.; validation, L.M.A. and A.N.; formal analysis, L.M.A.; investigation, L.M.A.; data curation, N.A.M.; writing—original draft preparation, L.M.A.; writing—review and editing, L.M.A. and M.M.M.; supervision, N.A.M. and A.N.; project administration, L.M.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Historical, predictive, and study period meteorological data were obtained from the National Centre for Meteorological Research (CNRM) [9].

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Abdulkadir, T.; Salami, A.; Anwar, A.; Kareem, A. Modelling of Hydropower Reservoir Variables for Energy Generation: Neural Network Approach. *Ethiop. J. Environ. Stud. Manag.* **2013**, *6*, 310–316. [CrossRef]
2. Pechlivanidis, I.G.; Jackson, B.M.; Mcintyre, N.R.; Wheater, H.S. Catchment Scale Hydrological Modelling: A Review of Model Types, Calibration Approaches and Uncertainty Analysis Methods in the Context of Recent Developments in Technology and Applications. *Glob. NEST J.* **2011**, *13*, 193–214.
3. Roy, B.; Singh, M.P. An Empirical-Based Rainfall-Runoff Modelling Using Optimization Technique. *Int. J. River Basin Manag.* **2020**, *18*, 49–67. [CrossRef]
4. Mishra, S.; Saravanan, C.; Dwivedi, V.K.; Shukla, J.P. Rainfall-Runoff Modeling Using Clustering and Regression Analysis for the River Brahmaputra Basin. *J. Geol. Soc. India* **2018**, *92*, 305–312. [CrossRef]
5. Zhang, Y.; Chiew, F.H.S.; Li, M.; Post, D. Predicting Runoff Signatures Using Regression and Hydrological Modeling Approaches. *Water Resour. Res.* **2018**, *54*, 7859–7878. [CrossRef]
6. Ramana, G.V. Regression Analysis of Rainfall and Runoff Process of a Typical Watershed. *Int. J. Sci. Appl. Inf. Technol.* **2014**, *3*, 16–26.
7. Sitterson, J.; Knightes, C.D.; Parmar, R.; Wolfe, K.; Avant, B.; Muche, M.E. An Overview of Rainfall-Runoff Model Types. In Proceedings of the 9th International Congress on Environmental Modelling and Software, Fort Collins, CO, USA, 24–28 June 2018.
8. Siregar, R.W.; Tulus; Ramli, M. Analysis Local Convergence of Gauss-Newton Method. In Proceedings of the IOP Conference Series: Materials Science and Engineering, Medan, Indonesia, 21–23 August 2017; Institute of Physics Publishing: Bristol, UK, 2018; Volume 300. [CrossRef]
9. Centre National de Recherches Météorologiques Softwares and Open Data—National Centre for Meteorological Research. Available online: https://www.umr-cnrm.fr/spip.php?rubrique76&lang=en (accessed on 30 August 2022).