2026 Volume: 02 Issue: 09 www.ijrpa.com ISSN 2456-9995 Research Article

International Journal Research Publication Analysis

Page: 01-10

PERFORMANCE EVALUATION OF GENETIC ALGORITHM-FINITE ELEMENT BASED MODEL OPTIMIZATION APPLICATION DEVELOPED FOR STREAMFLOW FORECASTING IN HUMID TROPICL WATERSHED OF NIGERIA

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Article Received: 23 July 2026
Article Revised: 11 August 2026
Published on: 01 September 2026

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DOI: https://doi-doi.org/101555/ijrpa.9048

ABSTRACT

Genetic algorithm-finite element streamflow-based optimization model application was developed and applied for the Upper Ebonyi Watershed. To assess the performance capability of the model, hydrograph of the simulated and the optimized for the downstream phase of the watershed were compared with measured hydrograph, and statistically analyzed using three efficiency criteria: coefficient of determination r^2*, Nash Sutcliffe efficiency coefficient* E*, and index of agreement* d*. The comparison of the simulated hydrograph with the measured gave efficiency criteria values of* 92.6 %, 79.8 % *and* 96.0 % *respectively for coefficient of determination* r^2*, Nash-Sutcliffe efficiency* (E) *and Index of agreement* d*, while the optimized hydrograph with measured hydrograph gave efficiency values of* 95.6 %, 86.2 % *and* 97.2 % *respectively, showing an improvement of* 3 %, 6.4 % *and* 1.2 % *respectively with optimization techniques. The simulated and optimized hydrographs were similar, with efficiency values of* 98.6 %, 98.5 % *and* 99.6 % *respectively for* r^2, E *and* d*. From the efficiency criteria results obtained, the incorporation of an optimization capability improved the model prediction, and the model is relatively satisfactory considering the fact that no model can be said to be absolutely perfect as there often uncertainties (errors) still inherent in such a model.*

KEYWORDS: *Genetic Algorithm, Finite Element, Streamflow, Efficiency Criteria, Performance Evaluation, Optimization.*

1.0 INTRODUCTION

The increase in global climate change has impacted negatively on man's environment with the resultant increase in flooding, a significant natural calamity in numerous nations worldwide including Nigeria, with its severe repercussions in terms of lives and property losses. The availability of water resources is essential to economic growth; therefore, simulations and optimization of anticipated future event projection need be achieved by adjustment of values which maximizes/minimizes the objective function of the system.

River related flooding associated with climate change has been identified to bring about indirect dangers from food and water shortages in addition to public health crises, which influence the increase spread of diseases (Aborode et al., 2025). As noted by Aborode et al. (2025), "flooding usually happens when rainfall, overflowing rivers, or dams cover dry ground. As more individuals are being exposed to the negative effects of floods, their effects have become more significant in recent years (Abrak et al., 2024). According to published research, river flooding in Nigeria occurs in the flood plains of the bigger rivers, whereas unexpected, brief flash floods are associated with rivers in inland locations where sudden heavy rainfall can swiftly change them into damaging torrents (Ezezue et al., 2017).

Over the past few decades, it has become more and more crucial to develop accurate flood forecasting techniques with very good efficiency, for practical water resources management in real time. Depetris (2021) emphasized the importance of the predictability of river discharge variability in recent times since discharge monitoring helps detect climatic and environmental change. According to Perazzolo et al. (2025), streamflow forecasting is a crucial component of managing water resources, especially in catchments that react quickly and where short-term forecasts can instantly impact mitigation strategies.

The water cycle is greatly impacted by global climate change, particularly in relation to precipitation and streamflow. Since it reflects the differences in its recharge (increase) and discharge (release), streamflow and its related impact on human survival have drawn a lot of interest worldwide as awareness of the consequences of climate change on both nature and humanity has grown. Obtaining accurate streamflow simulations and forecasts through the development of a dependable forecasting model with an error reduction through optimization procedure became necessary for real-time operational water resources management in order to acknowledge this reality and react appropriately to current development opportunities.

Thus, the significant need for streamflow model development, simulation and optimization procedures remained a great concern and should be applied to humid tropics of Nigerian watershed.

A good number of streamflow models have been developed by different researchers, and these models classified based on the different modelling techniques used for their development. These models include metric models which are based on artificial neural networks (Ahmed, 2023; Metin and Sefa, 2022) and transfer functions (Chabokpour, 2024). Other streamflow models amongst others, are ARIMA which is based on time series according to the works of different researchers (Rana et al., 2017; Fashae et al., 2018; Kaur et al., 2023; Venu and Namitha, 2025; Perazzolo et al., 2025); the k-nearest neighbor (k-NN) approach based on chaotic prediction for runoff forecasting and hydrologic time series (Liu et al., 2016; Yang et al., 2020; Delima, 2020; Ukey et al., 2023); Muskingum flow routing approaches (Lee, 2021), numerical approach in modeling streamflow (Nwaogazie, 2019).

For the humid tropical watershed of Nigeria, a finite element-based streamflow forecasting model with genetic algorithm optimization capability for better improvement in the model predictability was developed for flood forecasting in Upper Ebonyi watershed. It is merely not enough to develop a model; the performance of such model must be such that the error inherent is minimal for good predictability. This paper therefore, focused on the evaluation of the performance of the developed genetic algorithm-based optimization-finite element model application in humid tropics watershed.

2.0 Materials and Methods

2.1 Study Area

The study area used for the model prediction and subsequent performance evaluation is the Upper Ebonyi watershed. The River Ebonyi headwater catchment, as described by Campling et al. (2002), in the study article of Ndulue and Majiorgu (2018), is located on the western side of the Cross River Plains, where the Udi-Nsukka Escarpment predominates. It is situated between the Guinea-Congo wetter-type forest and the Guinea savannah eco-climatological zones. Its elevation ranges from 105 to 565 meters above sea level. The average annual temperature is 23°C, and the average annual rainfall is 1,577 mm. Ndulue and Majiorgu (2018), stated that it is situated between latitudes 6.87°N and 6.93°N and longitudes 7.55°E and 7.62°E.

2.2 Methods

To assess the performance of the streamflow model, it is required that an objective estimate of the closeness of the simulated behaviour of the model to the observed be made. Objective assessment in this case, required the use of efficiency criteria or a mathematical estimate of the error between the simulated and observed values. This efficiency criteria were mathematical measures used to determine how good the simulated fits with the observed. Also undertook, was the objective estimates of the closeness of the optimized behaviour of the model to simulated behaviour.

Coefficient of determination r^2, Nash-Sutcliffe efficiency (E), and index of agreement d, have proved to provide more information on the systematic and dynamic errors inherent in hydrologic models and were thus adopted to ascertain the performance of the model. The choice of the observed discharge records at the upstream and downstream, and simulated and optimized at the downstream were adopted for the performance evaluation.

2.2.1 Coefficient of determination (r^2)

The coefficient of determination r^2 is the squared value of the coefficient of correlation. It is used to measure the degree of correlation between two or more variables (i.e. a measure of the goodness of fit). It estimates the combined dispersion (i.e. the degree to which numerical data tend to spread about an average) against the single dispersion of the observed and simulated series and it is expressed as:

$$r^2 = \left(\frac{\sum_{i=1}^{n} (M_i^n - \bar{M})(S_i^n - \bar{S})}{\sqrt{\sum_{i=1}^{n} (M_i^n - \bar{M})^2} \sqrt{\sum_{i=1}^{n} (S_i^n - \bar{S})^2}} \right)^2 \qquad (1)$$

Where M and S = measured and simulated values respectively, $\bar{M}$ and $\bar{S}$ = mean of the measured and simulated values respectively, n = number of measurements or observations, i = sequence number of measurements or observations and it varies from 1 to n, and $\sum_{i=1}^{n}$ = summation of individual measurements or observations from $i = 1$ to n. The range of values of r^2 lies between 0 and 1 (i.e. $0 \leq r^2 \leq 1$) and it was used to describe the dispersion of the observed from the simulated. A value of zero meant there is no correlation between the observed and simulated, whereas a value of 1 means that the dispersion of the simulated is equal to that of the observed.

2.2.2 Nash-Sutcliffe efficiency (E)

The Nash-Sutcliffe efficiency (E) coefficient is used to assess the predictive power of hydrological models. The efficiency E proposed by Nash and Sutcliffe is defined as one minus the sum of the absolute squared differences between the simulated and measured values normalized by the variance of the measured values during the period under investigation and it is expressed as:

$$E = 1 - \frac{\sum_{i=1}^{n}(M_i^n - S_i^n)^2}{\sum_{i=1}^{n}(M_i^n - \bar{M})^2} \qquad (2)$$

where M and S = observed and simulated values respectively, $\bar{M}$ = mean of the observed or measured values, n = number of measurements or observations, i = sequence number of measurements or observations, and $\sum_{i=1}^{n}$ = summation of individual measurements or observations from $i = 1$ to n. NSE can range from $-\infty$ to 1. An efficiency $E = 1$ corresponds to a perfect match of the simulated data to the measured data. An efficiency $E = 0$ indicates that the model simulations or predictions are as accurate as the mean of the measured data, whereas an efficiency $E < 0$ indicates that the observed mean is a better predictor than the simulated or the residual variance described by the numerator in Equation (2) is larger than the data variance described by the denominator (Perazzolo et a., 2025). The closer the model efficiency E is to 1, the more accurate the model.

2.2.3 Index of agreement (d)

To overcome the insensitivity between the measured and simulated means and variances common with E and r^2, the index of agreement d proposed by Willmott which represents the ratio of the mean square error and the potential error expressed according to Equation (4.3) is applied (Pereira et al., 2018):

$$d = 1 - \frac{\sum_{i=1}^{n}(M_i^n - S_i^n)^2}{\sum_{i=1}^{n}\left(|S_i^n - \bar{M}| + |M_i^n - \bar{M}|\right)^2} \qquad (4.3)$$

Where M and S = measured and simulated values respectively, $\bar{M}$ = mean of the observed values, n = number of measurements or observations, i = sequence number of measurements or observations, and $\sum_{i=1}^{n}$ = summation of individual measurements or observations from $i = 1$ to n. The range of values of d just like r^2, also lies between 0 and 1 (i.e. $0 \le r^2 \le 1$).

A value of zero means there is no correlation between the measured and simulated, whereas a value of 1 means that the fitness of the measured to the simulated is a perfect fit.

3.0 RESULTS AND DISCUSSION

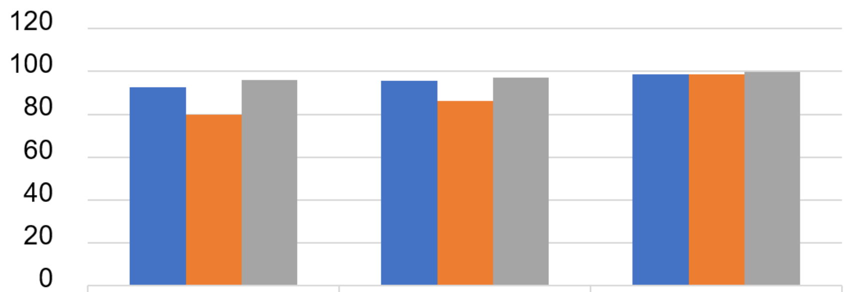
Using the values of the measured, simulated and optimized hydrographs in Table 1, statistical analysis and efficiency criteria values (Table 2 and Figure 1) were estimated using the described methods.

Table 1: Observed, simulated and optimized hydrograph results.

Time period of measurement (days)	Upstream measured (observed) discharge (m^3/s)	Downstream measured discharge (m^3/s)	Downstream simulated discharge (m^3/s)	Downstream optimized discharge (m^3/s)
1	8.32	8.54	8.82	8.85
2	8.35	8.54	8.68	8.42
3	8.50	8.54	8.68	8.71
4	9.45	8.54	8.68	8.31
5	15.50	9.52	8.54	8.92
6	12.30	13.54	14.60	14.51
7	11.10	11.94	12.90	12.86
8	10.10	9.80	11.14	10.95
9	8.75	8.96	9.80	9.32
10	8.56	8.68	8.68	8.91
11	8.56	8.54	8.68	8.65
12	8.45	8.32	8.96	8.85
13	8.43	8.54	8.54	8.52

Table 2: Observed, simulated and optimized hydrograph results.

Efficiency criteria	Downstream measured against downstream simulated	Downstream simulated against downstream optimized	Downstream measured against downstream optimized	Improvement of optimization over measured
Col. 1	Col. 2	Col. 3	Col. 4	Col. 5 = Col. 4 – Col. 2
Coefficient of determination r^2	0.926	0.986	0.956	0.03
Nash-Sutcliffe efficiency (E)	0.798	0.985	0.862	0.064
Index of agreement d	0.960	0.996	0.972	0.012



	Simulated vs. Measured	Optimized vs. Measured	Simulated vs. Optimized
Coefficient of determination, r2	92.6	95.6	98.6
Nash-Sutcliff, E	79.8	86.2	98.5
Index of agreement, d	96	97.2	99.6

Figure 1: Infographic of model efficiency criteria.

The genetic algorithm finite element-based model application was used to simulate streamflow for Upper Ebonyi Watershed and the simulated results compared with the observed results. By comparing simulated and recorded data, differences between model and system were judged in terms of practical significance, such a judgement would be necessarily subjective, depending on model application and utility function of model user. To improve on the model capability, an optimization procedure was incorporated into the model application. Optimization was achieved by adjusting sensitive calibration parameters, thus affecting discharge until reasonable agreement (convergence and numerical stability) was achieved between measured and simulated peaks.

Comparison of the simulated hydrograph with the measured hydrograph gave an efficiency criteria values of $92.6\ \%$, $79.8\ \%$ and $96.0\ \%$ respectively for coefficient of determination r^2, Nash-Sutcliffe efficiency (E) and Index of agreement d, the optimized hydrograph with measured hydrograph gave efficiency criteria values of $95.6\ \%$, $86.2\ \%$ and $97.2\ \%$ respectively, showing an improvement of $3\ \%$, $6.4\ \%$ and $1.2\ \%$ with optimization scheme. The simulated hydrograph and the optimized hydrograph were similar, with efficiency criteria values of $98.6\ \%$, $98.5\ \%$ and $99.6\ \%$ respectively for coefficient of determination r^2, Nash-Sutcliffe efficiency (E) and Index of agreement d efficiency criteria.

Coefficient of determination r^2 and Index of agreement d gave values relatively close to 1, with the exception of the Nash-Sutcliffe efficiency (E) which gave values lower than r^2 and

d for measured against simulated hydrographs and measured against optimized hydrographs. From the results, the model can be said to be relatively satisfactory considering the fact that no model can be said to be absolutely perfect as there are often uncertainties (errors) still inherent in such a model.

4.0 CONCLUSION

In general, only an order of magnitude agreement is to be expected between model simulated and measured hydrographs. This is due to the numerous modelling assumptions and errors inherent in both model structural representation of the real system and model parameters. Hence, the use of efficiency criteria for model performance assessment may be too severe and demanding on simulation results, it however provides some quantitative bases to make comparisons. For this model, based on the results of the efficiency criteria obtained, the model is said to be satisfactory.

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