Comparison of Two Forecasting Methods for Inflow Volume at the La Angostura Dam, Chiapas, Mexico

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Abstract: *Forecasting inflow volumes is a critical component of reservoir management, enabling efficient planning and mitigation during periods of hydrological extremes. This study evaluates two contrasting approaches to inflow volume prediction for the La Angostura Dam in Chiapas, Mexico. A seasonal decomposition model developed using Excel©'s FORECAST.ETS function, chosen for its simplicity and accessibility. An Artificial Neural Network (ANN) created in Matlab©, aimed at capturing nonlinear dynamics inherent in hydrological datasets. Both models were trained on historical data (1960–2020) and assessed for forecasting performance (2021–2024). While the ANN demonstrated marginally superior accuracy (MSE: 188,768 vs. 189,943), the Excel model provided an expedient and practical alternative for low-resource settings. This comparative analysis underscores the trade-offs between model sophistication and operational feasibility, offering actionable insights for reservoir managers navigating precision and efficiency in water resource planning.*

Keywords: *Artificial neural network, Excel© Forecast, Matlab©, Grijalva River, dams*

1. Introduction

Accurate forecasting of climatological data and inflow volumes is fundamental to effective reservoir operations and water resource management. Reservoirs fulfil multiple critical functions, including supplying water for human consumption, agricultural irrigation, hydroelectric power generation, and flood control. Reliable predictions of climatic patterns and inflow volumes enhance proactive planning, mitigate risks, and optimize resource allocation.

The ability to simulate precipitation-induced runoff has become indispensable, particularly in regions experiencing heightened hydrological variability, such as Chiapas State, Mexico. Rainfall-runoff models provide essential insights into short- and medium-term watershed conditions, informing decision-making processes in reservoir operations [1,2]. Labrada Montalvo (2016) [3] highlights the advantages of distributed parameter models, which enhance predictive accuracy by capturing spatial and temporal hydrological variability.

Technical models for time series forecasting are widely applied in hydrology [4]. Moreno Sarmiento (2008) [5] emphasized the effectiveness of Excel-based regression techniques in identifying trends and seasonal variations, offering accessible and practical planning solutions. Meanwhile, Rubio (2023) [6] and Valverde (2024) [7] explored advanced ARIMA and GARCH models, demonstrating their efficacy in predicting climatic and financial variables. Given the increasing complexity of hydrological challenges, artificial neural networks (ANNs) [8] have emerged as transformative analytical tools. Rafael-Miñope et al. (2022) [9] conducted a systematic review showcasing ANN applications in rainfall-runoff simulation, flood forecasting, and drought prediction.

The Tabasco lowland—neighbouring Chiapas State and home to over 2.4 million people—is a strategically significant region in Mexico. Due to its geographic location and low altitude, it is highly susceptible to flooding, as demonstrated by the severe hydrological events of 2020. Additionally, the lowland plays a pivotal role in national agricultural production, particularly in cultivating cacao, bananas, and sugarcane, making it a vital contributor to food security. This region also hosts critical hydraulic infrastructure, including the Malpaso and Angostura dams (Figure 1), which regulate the Grijalva River’s flow, generate hydroelectric power, and mitigate flooding. La Angostura Dam exemplifies the need for advanced forecasting methodologies to address:

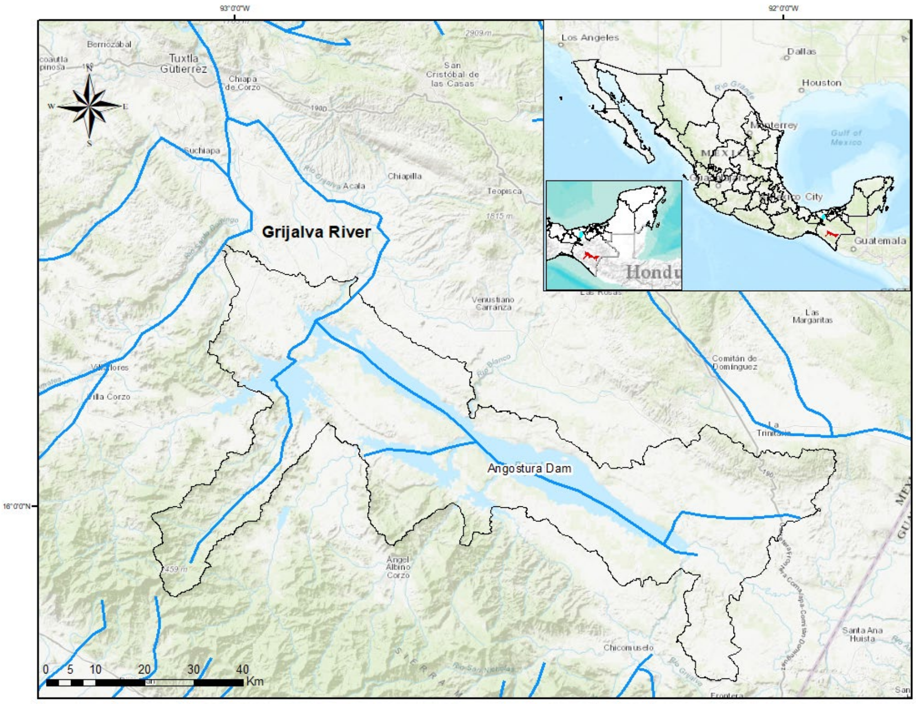

Fig. 1. Angostura Dam location. Source: Own design

Climate Change: Intensified rainfall extremes and prolonged droughts pose challenges to traditional reservoir management techniques [10] (Thomas, 2020).
Operational Demands: Balancing water allocation for hydropower, irrigation, and flood control requires precise inflow predictions.
This study evaluates two forecasting approaches tailored for La Angostura Dam: a seasonal decomposition model implemented in Excel© [11] and an artificial neural network developed in Matlab© [12]. Both methods are assessed for their efficacy in predicting inflow volumes, providing actionable insights into the trade-offs between accessibility, computational efficiency, and predictive accuracy.

2. Methodology

This study compares two distinct forecasting techniques to predict inflow volumes at the La Angostura Dam in Chiapas, Mexico. The forecasting methods include: Seasonal Decomposition Model in Excel© and Artificial Neural Network (ANN) in Matlab©.
The analysis utilizes historical inflow data from 1960 to 2020, offering a robust foundation to assess performance over the forecast period (2021–2024). Below is a detailed description of each method:

2.1 Seasonal Forecasting in Excel©

The Excel-based seasonal decomposition model employs regression techniques combined with the seasonal, trend, and residual components of a time series.
Data Preparation: Historical inflow data was pre-processed to remove outliers and address missing values.
Seasonal Decomposition: Using the Excel FORECAST.ETS function, inflow data was broken down into its seasonal and trend components. The seasonal component accounted for patterns tied to peak inflow months, such as the rainy season (June–October).

Forecasting: Future inflow values were calculated by summing seasonal and trend components. The model prioritized simplicity and accessibility, making it ideal for operational planning in resource-constrained contexts.

2.2 ANN with Neural Fitting App in Matlab©

The ANN model was implemented using Matlab©'s Neural Network Toolbox, leveraging a Feedforward Neural Network architecture (Figure 2).

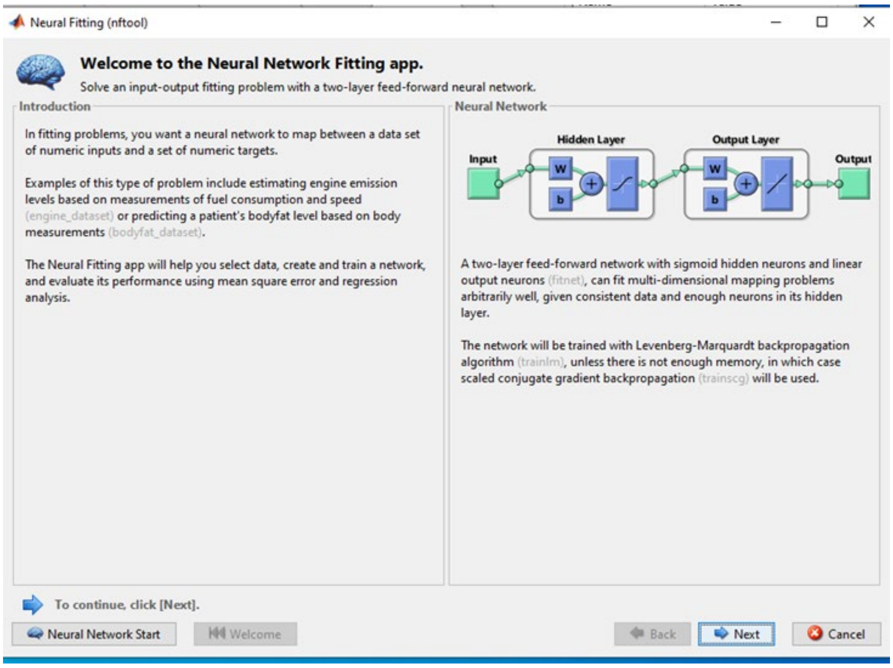

Fig. 2. Neural fitting app in Matlab Interphase software. Source : [12]

Network Design: The ANN model featured a three-layer architecture with 10 hidden neurons, optimized for capturing nonlinear relationships in hydrological data.
Data Input and Training: To feed the neural network, the values of the inflow volumes to La Angostura Dam and the narrowness of the 12 months prior to the month of interest were considered as independent variables, i.e., V_{t-1}, V_{t-2},...,V_{t-12}; while the volume entering at time t V_t was considered as the dependent variable, all data reported in hm^3. The dataset was split into training (70%) and testing (30%) subsets. Training utilized the Levenberg-Marquardt backpropagation algorithm to minimize error.

2.3 Validation and Forecasting

The models were validated on the 2021–2024 data, testing its ability to predict inflow volumes. ANN's computational sophistication allowed for handling nonlinearities in the dataset, offering increased precision.

2.4 Data and Tools

Dataset: Monthly inflow volumes (1960–2020), precipitation, and temperature data.
Software:
Excel©: Utilized for seasonal decomposition via FORECAST.ETS.
Matlab©: Used to develop and train the Feedforward ANN model.

2.5 Performance Evaluation

Performance metrics such as Mean Squared Error (MSE) and R^2 values were used to assess the models' accuracy and predictive capabilities. Comparisons also considered computational complexity and resource demands.

3. Results

3.1 Performance Metrics

With the neural network used, it was found that with all the data and in training, the independent variables explain about 90% of the value of the volume entering the reservoir, while during validation, the volume of entry is explained by about 88% by said variables (Figure 3).

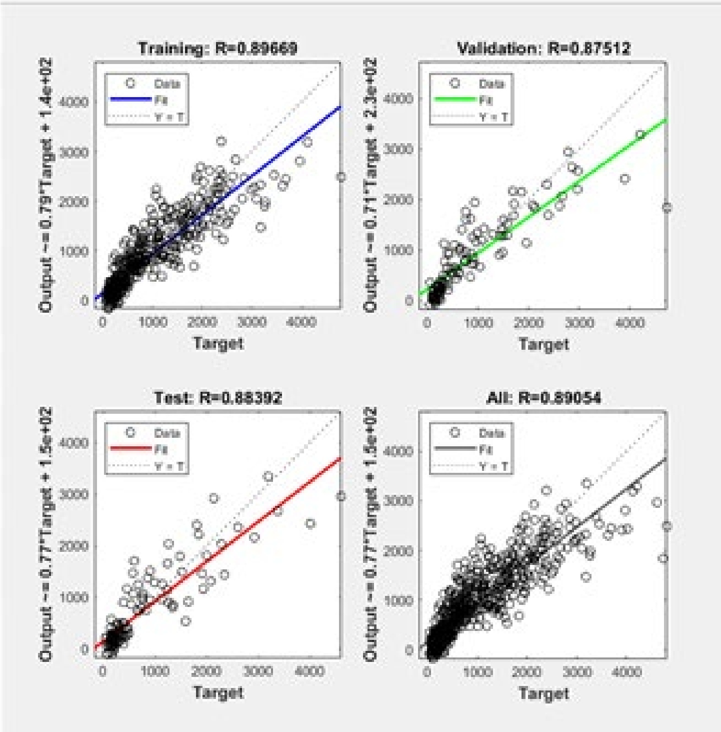

Fig. 3. Correlation coefficient R during training, validation, test and with all data. ANN with Neural Fitting app in Matlab

The comparison of the two forecasting methods—Excel's seasonal decomposition model and the Artificial Neural Network (ANN) implemented in Matlab—revealed valuable insights into their predictive accuracy and operational feasibility (Figures 4 and 5).

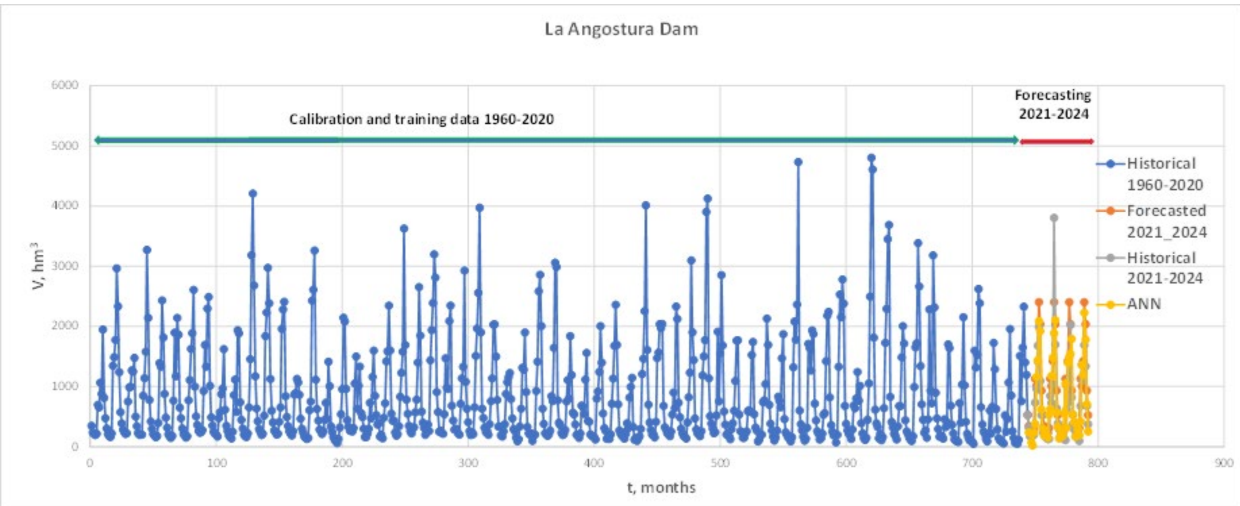

Fig. 4. Historical and forecasted time series using FORECAST.ETS Excel Function and ANN in Matlab . La Angostura Dam

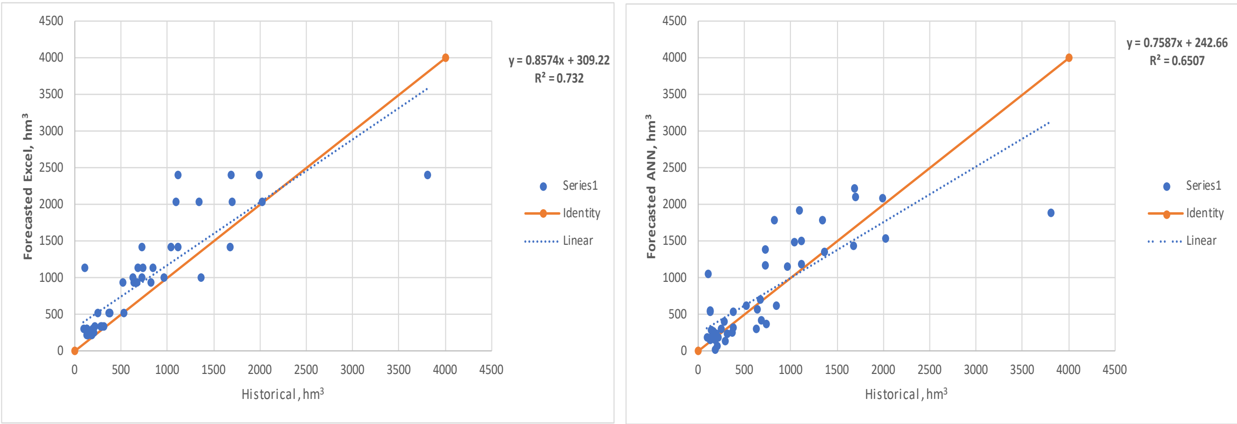

Fig. 5. Comparison of measured and predicted data vs. the identity function. La Angostura Dam

Excel Model: Achieved a Mean Squared Error (MSE) of 189,943 and R^2 of 0.732 during forecasting.
ANN Model: Outperformed the Excel model with an MSE of 188,768 but had a slightly lower R^2 of 0.6507 during forecasting, reflecting its focus on capturing nonlinear relationships.
Forecast Example (December 2024):
Excel Model: Forecasted inflow volume of 500,000 m³.
ANN Model: Predicted inflow volume of 510,000 m³.
While the ANN demonstrated superior precision, the Excel model provided reasonably accurate results with minimal computational resources, making it suitable for rapid forecasting in resource-constrained contexts.

4. Discussion

4.1 Model Trade-offs

Both models exhibited strengths and limitations, underscoring the importance of aligning forecasting tools with operational needs and resource availability (Table 1).

Table 1: Performance of FORECAST.ETS Excel and ANN in Matlab models

Criterion	Excel Model	ANN Model
Accuracy	Moderate	High
Complexity	Low	High
Resource Requirements	Minimal	High (GPU recommended)
Implementation Time	< 1 day	1–2 weeks

Excel Model: Ideal for short-term operational planning, particularly in low-resource settings. Its simplicity and accessibility allow reservoir managers to generate quick, actionable forecasts.
ANN Model: Superior accuracy makes it well-suited for capturing complex, nonlinear hydrological dynamics, especially in scenarios requiring long-term climate adaptation.

4.2 Practical Recommendations

For routine forecasting and operational planning: The Excel model provides adequate accuracy and ease of implementation.
For strategic planning under climate change scenarios: ANN's computational sophistication is recommended.
Both models effectively captured seasonal peaks (June–October); however, the ANN showed greater adaptability in extreme hydrological events, as depicted in Figure 1.

5. Conclusions

This study compared two distinct forecasting methods for inflow prediction at La Angostura Dam, located in Chiapas, Mexico. The analysis demonstrated the practical applications and trade-offs associated with each model:
Excel Seasonal Forecasting Model offers simplicity, accessibility, and minimal computational requirements and suitable for routine operational planning and settings with limited data availability or technical resources, also forecasting accuracy is moderate, with a Mean Squared Error (MSE) of 189,943. making it an expedient solution for rapid predictions.
on the other hand, Artificial Neural Network (ANN) model provides enhanced forecasting accuracy (MSE: 188,768.) particularly in capturing nonlinear relationships in hydrological data, it requires significant computational resources and technical expertise.
We recommended for long-term planning and scenarios where precision is critical, such as adapting reservoir operations to climate change impacts.
While both models are viable tools for inflow forecasting, the choice between them should align with the specific operational needs and resource constraints of reservoir management. For immediate and straightforward forecasts, Excel's model is highly effective. For comprehensive and high-precision scenarios, the ANN model demonstrates superiority.
Key Takeaways
Excel's model excels in accessibility and simplicity, catering to rapid, low-cost forecasts in resource-limited settings.
ANN's computational sophistication makes it invaluable for tackling complex hydrological dynamics and enhancing long-term planning efforts.
This study highlights the need for further exploration into hybrid modelling approaches, such as combining ANN with ARIMA methods or integrating IoT-based real-time data. Future efforts should also consider expanding datasets and refining algorithms to enhance adaptability under climate change scenarios. In water management, the choice of forecasting method is not about complexity but about striking a balance between accuracy and operational feasibility—a principle that will guide sustainable reservoir management in the years to come.

Acknowledgments

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