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Modelos de Inteligencia Artificial para Predicción de Producción Hidroeléctrica

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El doctorando ha cumplido con todos los derechos de propiedad intelectual relacionados con la diseminación de los artículos usados en la tesis doctoral.

A continuación, los artículos científicos los cuales fueron usados en la tesis se resumen con su respectivo índice de impacto:

1. **J. Barzola-Monteses**, J. Gómez-Romero, M. Espinoza-Andaluz, and W. Fajardo, "Time series forecasting techniques applied to hydroelectric generation systems," Int. J. Electr. Power Energy Syst., vol. 164, no. December 2024, p. 110424, Mar. 2025, doi: 10.1016/j.ijepes.2024.110424.

   Journal Citation Reports (JCR) – 2023 Impact Factor: 5.0 (Engineering, Electrical & Electronic, Q1, 65/353)

2. **J. Barzola-Monteses**, M. Mite-León, M. Espinoza-Andaluz, J. Gómez-Romero, and W. Fajardo, "Time Series Analysis for Predicting Hydroelectric Power Production: The Ecuador Case," Sustainability, vol. 11, no. 23, p. 6539, Nov. 2019, doi: 10.3390/su11236539

   Journal Citation Reports (JCR) – 2018 Impact Factor: 2.592 (Green & Sustainable Science & Technology, Q2, 3/6; Environmental studies, Q2, 44/116)

3. **J. Barzola-Monteses**, J. Gómez-Romero, M. Espinoza-Andaluz, and W. Fajardo, "Hydropower production prediction using artificial neural networks: an Ecuadorian application case," Neural Comput. Appl., vol. 34, no. 16, pp. 13253–13266, Aug. 2022, doi: 10.1007/s00521-021-06746-5.

   Journal Citation Reports (JCR) – 2020 Impact Factor: 5.606 (Computer Science, Artificial Intelligence, Q1, 31/139). This article is the 98th percentile (ranked 4th) of the 233 tracked articles of a similar age in Neural Computing and Applications.

También se publicaron otros artículos de apoyo en revistas indexadas y actas de congresos que contribuyeron a la formación y el desarrollo del doctorando:

1. M. Mite-León and **J. Barzola-Monteses**, "Statistical Model for the Forecast of Hydropower Production in Ecuador," Int. J. Renew. Energy Res., vol. 10, no. 2, pp. 1130–1137, 2018, doi: 1309-0127. (2023: Q4 JCR; 2017: Q3 SJR, Q2 CiteScore)

2. **J. Barzola-Monteses** and M. Espinoza-Andaluz, "Performance Analysis of Hybrid Solar/H2/Battery Renewable Energy System for Residential Electrification," in 10th International Conference on Applied Energy (ICAE2018), 2019, vol. 158, pp. 9–14, doi: 10.1016/j.egypro.2019.01.024. (Q1 citations in Scopus, FWCI = 2.02)

3. Á. Encalada, **J. Barzola-Monteses**, and M. Espinoza-Andaluz, "A Permeability–Throat Diameter Correlation for a Medium Generated with Delaunay Tessellation and Voronoi Algorithm," Transp. Porous Media, vol. 132, no. 1, pp. 201–217, 2020, doi: 10.1007/s11242-020-01387-z. (2019: Q2 JCR, Q1 SJR, Q1 CiteScore)

4. **J. Barzola-Monteses**, M. Espinoza-Andaluz, M. Mite-Leon, and M. Flores-Moran, "Energy Consumption of a Building by using Long Short-Term Memory Network: A Forecasting Study," in 2020 39th International Conference of the Chilean Computer Science Society (SCCC), Nov. 2020, pp. 1–6, doi: 10.1109/SCCC51225.2020.9281234. (D1 citations in Scopus, FWCI = 6.52)

5. Á. Encalada-Dávila, M. Espinoza-Andaluz, **J. Barzola-Monteses**, S. Li, and M. Andersson, "Transport Parameter Correlations for Digitally Created PEFC Gas Diffusion Layers by Using OpenPNM," Processes, vol. 9, no. 7, p. 1141, Jun. 2021, doi: 10.3390/pr9071141. (2020: Q3 JCR, Q2 SJR, Q3 CiteScore)

6. F. Parrales-Bravo, J. Torres-Urresto, D. Ávila-Maldonado, and **J. Barzola-Monteses**, "Relevant and non-redundant feature subset selection applied to the detection of malware in a network," in 2021 IEEE Fifth Ecuador Technical Chapters Meeting (ETCM), 2021, pp. 1–6. (Q1 citations in Scopus, FWCI = 2.61)

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9. E. Melo, J. Peñafiel, **J. Barzola-Monteses**, and M. Espinoza-Andaluz, "An Initial Approach About Data Preprocessing Techniques Applied to Polymer Electrolyte Fuel Cells: A Case Study," in International Conference on Science, Technology and Innovation for Society - CITIS2021, 2022, vol. 252, pp. 53–64, doi: 10.1007/978-981-16-4126-8. (Q1 citations in Scopus, FWCI = 2.35)

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11. V. Macas-Espinosa, L. Vera-Rodríguez, and **J. Barzola-Monteses**, "Analysis and Evaluation of Energy Efficiency in Buildings Based on Building Information Modeling," vol. 7, no. 1, 2022, pp. 137–149. (Q1 citations in Scopus, FWCI = 1.36)

12. I. Ortiz-Aguirre, M. Espinoza-Andaluz, and **J. Barzola-Monteses**, "Ensemble Learning Models Applied in Energy Time Series of a University Building," in 2022 IEEE Latin American Conference on Computational Intelligence (LA-CCI), Nov. 2022, pp. 1–6, doi: 10.1109/LA-CCI54402.2022.9981839. (Q1 citations in Scopus, FWCI = 1.16)

Dedicatoria

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Acronym	Definition
1D-CNN	One-dimensional convolutional neural networks
ABC	Artificial bee colony
ACO	Ant Colony Optimization
ACS	Artificial Cuckoo Search
AIC	Akaike Information Criterion
AIS	Artificial Immune Systems
ANFIS	Adaptive neural-based fuzzy inference system
ANFIS-GWO	Adaptive neural-based fuzzy inference system and Grey Wolf Optimization
ANN	Artificial neural network
ANN-ABC	Artificial neural network and artificial bee colony
ANN-ANFIS	Artificial neural network - Adaptive neural-based fuzzy inference system
ANN-BA	Artificial Neural Network technique with Bat Algorithm
ANN-BDL	Artificial neural network - based Bayesian dynamic linear model
AR	Autoregressive
AR-FIS	Autoregressive and Fuzzy Inference System
ARIMA	Auto-Regressive Integrated Moing Average
ARIMAX	Auto-Regressive Integrated Moving Average with Exogenous Inputs
ARMA	Autoregressive moving-average
BBO	Biogeography-based optimization
BBO-ANN	Biogeography-based optimization and Artificial Neural Network
BDL	Bayesian dynamic linear
BDT	Boosted Decision Tree
BDTR	Boosted Decision Tree Regression
bestglm	Best generalized linear model
BIAMLP	Bayesian Inference applied to multilayer perceptrons
Bi-LSTM	Bi-directional Long Short Term Memory
Bi-MLP	Bi-directional Multilayer perceptron
BLR	Bayesian Linear Regression
BPTT	Backpropagation Through Time
CC	Correlation coefficient
CI	Confidence index
CL-RNN	Conditioned latent recurrent neural networks model
CNN	Convolutional Neural Network

Conv3D-LSTM	Three 3D convolutional layers - Long Short-Term Memory
d	Index of agreement
DFR	Decision Forest Regression
DGGM	Data grouping approach based grey modelling method
DLNN	Deep-Learning Neural Networks
DNN	Deep neural networks
Dstat	Directional statistic
DT	Decision Trees
E	Mass curve coefficient
EC	Evolutionary Computation
ELM	Extreme Learning Machine
ELM-GA	Extreme Learning Machine and Genetic Algorithm
ELM-GWO	Extreme Learning Machine and Grey Wolf Optimization
ELM-MC	Extreme learning machine based on Monte Carlo algorithm
EM	Expectation Maximization
ESN	Echo state networks
FIS	Fuzzy Inference System
FNN	Feedforward Neural Network
FS	Fuzzy Systems
GA	Genetic algorithm
GA- LSSVR	Genetic algorithm and least squares support vector regression
GA-SVR	Genetic algorithm and Support Vector Regression
GM (1,1)	Grey model (1,1)
GM (1,1)-ANN	Grey model (1,1) based Artificial neural network
GMDH	Group method of data handling
GOA	Grasshopper Optimization Algorithm
GOA-ANN	Grasshopper Optimization Algorithm and Artificial Neural Network
GP	Genetic programming
GRU	Gated Recurrent Units
GWO	Grey Wolf Optimization
HGDNN	Hydropower Generation forecasting with Deep Neural Network
HGS	Hydroelectric generation systems
KGE	Kling Gupta Efficiency
KNN	K-Nearest Neighbors
LR	Linear regression

LSSVR	Least squares support vector regression
LSTM	Long Short-Term Memory
MA	Moving Average
MAD	Median absolute deviation
MAE	Mean Absolute Error
MAPE	Mean absolute percentage error
MASE	Mean absolute scaled error
MI	Mutual information (MI) criterion
ML	Machine Learning
MLI	Maximum likelihood
MLP	Multilayer perceptron
MLP-ANFIS	Multilayer perceptron and Adaptive neural-based fuzzy inference system
MLP-BDL	Multilayer perceptron and Bayesian dynamic linear
MLR	Multiple Linear Regression
MLRM	Multivariable Linear Regressive Model
MPE	Mean Percentage Error
MPSO	PSO based on the Metropolis criterion
MRE	Mean Relative Error
MSE	Mean Square Error
NAE	Natural Affluent Energy
NARNN	Non-Linear Autoregressive Neural Network
NARX	Non-Linear Autoregressive Exogenous Outputs
NECP	National Energy and Climate Plan
nMAE	Normalised mean absolute error
NNR	Neural Network Regression
nRMSE	Normalized Root Mean Squared Error
NSE	Nash–Sutcliffe efficienc
NSRBN	Non-linear sigmoidal regression blocks networks
PAR	Periodic Autoregressive
PARMA	Periodic Auto regressive Moving Average
PCR	Principal component regression
PLSR	Partial least squares regression
PRE	Percentage of relative errors
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
PSO	Particle swarm optimization
PSO-ANN	Particle swarm optimization and Artificial neural network

PSO-LSSVR	Particle swarm optimization and Least squares support vector regression
R2	Coefficient of determination
RBF	Radial basis function networks
RE	Relative error
RF	Random forest
RFBOS	River flow forecast and basin optimization system
RMSE	Root Mean Squared Error
RNN	Recurrent neural network
RSR	Ratio of RMSE to the standard deviation of observations
SAA	Sampled average approximation algorithm
SA-LSSVR	simulated annealing and Least squares support vector regression
SARIMA	Seasonal Autoregressive Integrated Moving Average
SBIC	Schwarz-Bayesian Information Criterion
SD	Seasonal decomposition
SD-LSSVR	Seasonal decomposition based least squares support vector regression
SI	Swarm Intelligence
SMAP	Soil Moisture Accounting Procedure
SSA	Salp Swarm algorithm
SSA-ANN	Salp Swarm algorithm and Artificial neural network
SVC	Support Vector Classification
SVM	Support vector machine
SVM-CGA	Support vector machine and chaotic genetic algorithm
SVM-PSO	Support vector machine and chaotic genetic algorithm
SVR	Support Vector Regression
TG-ELM	Trend-guided extreme learning machine model
TheilU	Theil's U- statistic
VAR	Vector autoregressive
VC	Variation coefficient
VGP	Vanishing Gradient Problem
WA	Wavelet analysis
WA-LSSVR	Wavelet analysis based least squares support vector regression
WAR	Wavelets Auto-Regressive

Resumen

La previsión precisa de la generación de energía hidroeléctrica es crucial para una planificación energética eficaz, la gestión de la red y la integración de las fuentes de energía renovables. Aunque la energía hidroeléctrica es una tecnología renovable consolidada, optimizar su producción mediante previsiones precisas sigue siendo un reto debido a factores complejos. Esta tesis investiga la aplicación de modelos tradicionales y de inteligencia artificial (IA), centrándose en técnicas de predicción de series temporales, para mejorar la estimación de la producción hidroeléctrica. Esta investigación lleva a cabo una revisión exhaustiva de las técnicas de previsión de series temporales aplicadas a los sistemas de generación hidroeléctrica (HGS), identificando los métodos prevalentes y las lagunas de investigación, incluida la exploración limitada de arquitecturas complejas de aprendizaje profundo y el aprendizaje mediante combinación de modelos. Asimismo, la tesis analiza modelos estadísticos tradicionales, como ARIMA y ARIMAX, a través de un estudio de caso de un sistema hidroeléctrico real, examinando sus capacidades para capturar dependencias temporales. Finalmente, la tesis examina patrones y tendencias en series temporales de producción hidroeléctrica utilizando diversas técnicas de IA, centrándose en su relevancia y aplicabilidad para mejorar la previsión de la producción y proponer estrategias de toma de decisiones para la gestión hidroeléctrica. Los resultados de esta investigación ponen de relieve el potencial de los enfoques tradicionales y basados en IA para mejorar la precisión y fiabilidad de las previsiones de producción hidroeléctrica. La revisión sistemática identifica áreas clave para la investigación y el desarrollo futuros, mientras que el estudio de casos proporciona una visión de la aplicación práctica de los modelos estadísticos y de inteligencia artificial. En conjunto, la tesis contribuye al área analizando y aplicando diversas técnicas existentes para una mejor predicción de la producción, sirviendo como base para el diseño de estrategias para optimizar las operaciones hidroeléctricas.

Abstract

Accurate forecasting of hydropower generation is crucial for effective energy planning, grid management, and integration of renewable energy sources. Although hydropower is an established renewable technology, it remains challenging to optimize its production through accurate forecasting due to complex factors. This thesis investigates applying traditional and artificial intelligence (AI) models, focusing on time series forecasting techniques, to improve hydropower production estimation. This research reviews time series forecasting techniques applied to hydropower generation systems (HGS), identifying prevalent methods and research gaps, including limited exploration of complex deep learning architectures and learning by model combination. Also, the thesis analyzes traditional statistical models, such as ARIMA and ARIMAX, through a case study of a real hydropower system, examining their capabilities to capture temporal dependencies. Finally, the thesis uses various AI techniques to examine patterns and trends in hydropower production time series. It focuses on their relevance and applicability for improving production forecasting and proposing decision-making strategies for hydropower management. The results of this research highlight the potential of traditional and AI-based approaches to improve the accuracy and reliability of hydropower production forecasts. The systematic review identifies key areas for future research and development, while the case study provides insight into the practical application of statistical and AI models. Overall, the thesis contributes to the area by analyzing and applying various existing techniques for improved production forecasting, serving as a basis for designing strategies to optimize hydropower operations.

Capítulo 1. Introducción

La energía hidroeléctrica ha sido durante mucho tiempo una piedra angular de la producción mundial de electricidad, aprovechando la energía potencial del agua para generar energía limpia y fiable. A medida que el mundo se orienta cada vez más hacia soluciones energéticas sostenibles, la energía hidroeléctrica sigue siendo un componente fundamental, ya que ofrece una tecnología madura y eficiente para la generación de electricidad. En 2020 la energía hidroeléctrica representó el 61% de todas las fuentes de energía renovables del sector eléctrico [1], lo que pone de relieve su importante contribución a un futuro energético con bajas emisiones de carbono. Sus ventajas incluyen una alta eficiencia de conversión «agua-cable» (en torno al 90%) y una competitividad de costes, a menudo comparable a la de las fuentes de energía térmica tradicionales [2]. Además, los sistemas hidroeléctricos ofrecen valiosos servicios de estabilización de la red mediante la regulación de la carga y la frecuencia, y permiten almacenar energía de forma sencilla a través de instalaciones de almacenamiento por bombeo.

Sin embargo, a pesar de su madurez y de sus ventajas inherentes, la optimización de la producción hidroeléctrica presenta retos constantes. La predicción precisa de la generación hidroeléctrica es crucial para la planificación eficaz de la capacidad, la programación y el funcionamiento general del sistema eléctrico. Como destaca [3], predecir la producción real de los sistemas hidroeléctricos a largo plazo sigue siendo un reto. Mientras que el potencial teórico puede calcularse mediante una ecuación sencilla, la producción real depende de una compleja interacción de factores, entre los que se incluyen las condiciones meteorológicas (caudales de ríos y embalses, precipitaciones), las decisiones operativas (programas de liberación de agua para satisfacer la demanda) e incluso indicadores económicos más amplios (precios de mercado).

La creciente complejidad de las redes eléctricas modernas, impulsada por la integración de fuentes renovables intermitentes como la solar y la eólica, acentúa aún más la necesidad de contar con previsiones precisas y fiables de la producción hidroeléctrica. Estas previsiones permiten a los operadores de la red equilibrar eficazmente la oferta y la demanda, optimizar la gestión de los recursos hídricos y garantizar la estabilidad de la red.

En la literatura se han empleado varios modelos de inteligencia artificial (IA) para predecir la producción hidroeléctrica. Estos modelos aprovechan las técnicas de aprendizaje automático (ML) y aprendizaje profundo (DL) para mejorar la precisión y la fiabilidad mediante el análisis de conjuntos de datos complejos, incluidos datos meteorológicos e hidrológicos, para predecir la producción de energía. Los modelos de predicción, como los modelos ML, los modelos DL, los modelos de series temporales y las técnicas de optimización, han demostrado resultados prometedores y han proporcionado información crucial para los responsables de la toma de decisiones, los proveedores de energía y los investigadores que buscan soluciones energéticas sostenibles. A medida que el campo sigue evolucionando, podemos esperar un mayor refinamiento y nuevas aplicaciones de IA en la predicción de la producción hidroeléctrica, contribuyendo a una gestión energética más eficiente y sostenible [4], [5].

Aunque los modelos de IA han mejorado significativamente la precisión de las predicciones de producción hidroeléctrica, siguen existiendo desafíos. La naturaleza dinámica de las condiciones ambientales y la complejidad de los sistemas hidrológicos requieren una adaptación y validación continuas de los modelos. La integración de estos modelos en los sistemas de gestión energética existentes plantea dificultades técnicas y logísticas. A pesar de estos obstáculos, el desarrollo en curso de modelos de IA es prometedor para una generación hidroeléctrica más eficiente y sostenible.

Esta tesis desarrolla un análisis comparativo de las técnicas tradicionales y de inteligencia artificial para la previsión de series temporales de producción hidroeléctrica, analiza su eficacia y sugiere estrategias para mejorar la previsión y la toma de decisiones en la gestión de sistemas hidroeléctricos. Para ello se estructura como sigue:

El capítulo 2 explora la motivación que subyace al uso de la inteligencia artificial para mejorar los modelos de predicción, abordando las limitaciones de los enfoques tradicionales. También define los objetivos de la investigación, orientando el desarrollo de soluciones basadas en IA para mejorar la previsión de la energía hidroeléctrica.

El capítulo 3 describe la metodología empleada para alcanzar los objetivos de la investigación, incluida una revisión exhaustiva de los modelos de predicción hidroeléctrica tradicionales y basados en IA. También se presenta un estudio de caso real en el que se aplican los modelos ARIMA y ARIMAX y se exploran técnicas de IA para identificar patrones, mejorar las predicciones y apoyar las estrategias de gestión hidroeléctrica.

El capítulo 4 explora la aplicación de la inteligencia artificial a la previsión de la producción hidroeléctrica. Analiza diferentes técnicas de IA, comparando su rendimiento con el de los modelos tradicionales. El estudio destaca las ventajas de la IA para captar patrones complejos, mejorar la precisión de las predicciones y optimizar la gestión de la energía hidroeléctrica para una toma de decisiones más eficiente.

El capítulo 5 examina los modelos estadísticos para la predicción de la producción hidroeléctrica, considera un caso de estudio en Ecuador. Se emplearon modelos estadísticos ARIMA y ARIMAX sobre datos de producción y precipitación (2000–2015), demostrando que el modelo ARIMAX$(1,1,1)(1,0,0)_{12}$ con precipitación en la cuenca del río Napo como variable exógena ofrece la mejor precisión. Este modelo superó al ARIMA en métricas de error como MAE (70.81 GWh), MAPE (10.17%) y MASE (0.57). La metodología evidenció que es posible obtener pronósticos fiables sin necesidad de datos complejos.

El capítulo 6 profundiza en la aplicación de las redes neuronales artificiales a la predicción de la producción hidroeléctrica continuando como caso de estudio en Ecuador. Se analizaron más de 3000 configuraciones de modelos MLP, LSTM y seq2seq, bajo escenarios de predicción a corto (1 mes) y mediano plazo (12 meses), utilizando series temporales de producción y precipitaciones. El mejor desempeño se logró con el modelo MLP univariado con diferenciación, alcanzando un RMSE de 4.09 GWh (corto plazo) y 123.84 GWh (mediano plazo), superando incluso a modelos RNN. Además, el preprocesamiento mediante diferenciación y la inclusión de precipitaciones como variable exógena mejoraron la precisión. Estos resultados destacan la efectividad de las ANN frente a modelos estadísticos tradicionales como ARIMA y ARIMAX.

Los tres capítulos anteriores corresponden a los artículos que componen al compendio de la tesis. Los mismos que han superado los procesos editoriales de cada revista y han sido publicados en la modalidad de acceso. Cabe indicar que, para una mejor lectura y flujo en formato de la tesis, todas las referencias bibliográficas se han unificado y presentado de manera continua.

Finalmente, el capítulo 7 presenta las conclusiones de esta tesis doctoral resumiendo los principales resultados y aportaciones de esta investigación. Si bien modelos estadísticos como ARIMA y ARIMAX ofrecen resultados aceptables, las redes neuronales artificiales, particularmente MLP diferenciadas, presentan un rendimiento superior en escenarios de corto y mediano plazo. La inclusión de variables exógenas, como la precipitación, mejora significativamente la precisión.

Introduction

Hydropower has long been a cornerstone of global electricity production, harnessing the potential energy of water to generate clean, reliable power. As the world increasingly moves towards sustainable energy solutions, hydropower remains a key component, offering a mature and efficient technology for electricity generation. In 2020, hydropower accounted for 61% of all renewable energy sources in the electricity sector [1], highlighting its significant contribution to a low-carbon energy future. Its advantages include high "water-to-wire" conversion efficiency (around 90%) and cost competitiveness, often comparable to that of traditional thermal energy sources [2]. In addition, hydropower systems offer valuable grid stabilization services through load and frequency regulation and allow for simple energy storage through pumped storage facilities.

However, despite its maturity and inherent advantages, optimization of hydropower production presents ongoing challenges. Accurate prediction of hydropower generation is crucial for effective capacity planning, scheduling, and overall power system operation. As highlighted by [3], predicting the actual output of hydropower systems over the long term remains challenging. While theoretical potential can be calculated using a simple equation, actual production depends on a complex interplay of factors, including meteorological conditions (river and reservoir flows, rainfall), operational decisions (water release schedules to meet demand), and even broader economic indicators (market prices).

The increasing complexity of modern power grids, driven by the integration of intermittent renewable sources such as solar and wind, further accentuates the need for accurate and reliable hydroelectric production forecasts. These forecasts enable grid operators to balance supply and demand effectively, optimize water resource management, and ensure grid stability.

Several artificial intelligence (AI) models have been used in the literature to forecast hydropower production. These models leverage machine learning (ML) and deep learning (DL) techniques to improve accuracy and reliability by analyzing complex data sets, including meteorological and hydrological data, to predict power production. Predictive models, such as ML models, DL models, time series models, and optimization techniques, have shown promising results and have provided crucial information for decision-makers, energy providers, and researchers seeking sustainable energy solutions. As the field continues to evolve, we can expect further refinement and new applications of AI in predicting hydropower production, contributing to more efficient and sustainable energy management [4], [5].

Although AI models have significantly improved the accuracy of hydropower production predictions, challenges remain. The dynamic nature of environmental conditions and the complexity of hydrological systems require continuous model adaptation and validation. Integrating these models into existing energy management systems poses technical and logistical difficulties. Despite these obstacles, the ongoing development of AI models holds promise for more efficient and sustainable hydropower generation.

This thesis develops a comparative analysis of traditional and artificial intelligence techniques for hydroelectric production time series forecasting, analyzes their effectiveness, and suggests strategies to improve forecasting and decision-making in hydroelectric system management. It is structured as follows:

Chapter 2 explores the motivation behind using artificial intelligence to improve forecasting models, addressing the limitations of traditional approaches. It also defines the research objectives, guiding the development of AI-based solutions to improve hydropower forecasting.

Chapter 3 describes the methodology to achieve the research objectives, including a comprehensive review of traditional and AI-based hydropower forecasting models. It also presents a real-world case study applying ARIMA and ARIMAX models and exploring AI techniques to identify patterns, improve predictions, and support hydropower management strategies.

Chapter 4 explores the application of artificial intelligence to hydropower production forecasting. It analyzes different AI techniques and compares their performance with that of traditional models. The study highlights the advantages of AI for capturing complex patterns, improving forecast accuracy, and optimizing hydropower management for more efficient decision-making.

Chapter 5 examines statistical models for the prediction of hydropower production and considers a case study in Ecuador. ARIMA and ARIMAX statistical models were employed on production and precipitation data (2000-2015), demonstrating that the ARIMAX$(1,1,1)(1,0,0)_{12}$ model with precipitation in the Napo River basin as an exogenous variable offers the best accuracy. This model outperformed the ARIMA in error metrics such as MAE (70.81 GWh), MAPE (10.17%), and MASE (0.57). The methodology evidenced that obtaining reliable forecasts without complex data is possible.

Chapter 6 delves into the application of artificial neural networks to predict hydroelectric production, continuing with a case study in Ecuador. More than 3000 MLP, LSTM, and seq2seq configurations were analyzed under short (1 month) and medium-term (12 months) prediction scenarios, using production and rainfall time series. The best performance was achieved with the univariate MLP model with differentiation, reaching an RMSE of 4.09 GWh (short term) and 123.84 GWh (medium term), surpassing even RNN models. In addition, preprocessing with differencing and including precipitation as an exogenous variable improved accuracy. These results highlight the effectiveness of ANNs over traditional statistical models such as ARIMA and ARIMAX.

The three previous chapters correspond to the articles that compose the thesis compendium. These articles have passed the editorial processes of each journal and have been published in open-access mode. It should be noted that all the bibliographical references have been unified and presented in a continuous manner for better reading and flow in the thesis format.

Finally, Chapter 7 presents the conclusions of this doctoral thesis, summarizing the main results and contributions of this research. Although statistical models such as ARIMA and ARIMAX offer acceptable results, artificial neural networks, particularly differential MLP, present superior performance in short—and medium-term scenarios. The inclusion of exogenous variables, such as precipitation, significantly improves accuracy.

Capítulo 2. Motivación y Objetivos

La principal motivación para investigar los modelos de IA aplicados a la previsión de la producción hidroeléctrica es mejorar la eficiencia, la fiabilidad y la sostenibilidad de la producción energética. Los modelos de IA ofrecen capacidades avanzadas para manejar conjuntos de datos complejos y predecir resultados con más precisión que los métodos tradicionales. Estos modelos son especialmente valiosos en las energías renovables, donde la variabilidad y la imprevisibilidad plantean importantes retos. La integración de la IA en este campo permite afrontar varios retos, como la variabilidad climática, la gestión de recursos y la eficiencia operativa. Las motivaciones para explorar la IA en este contexto pueden clasificarse en varias áreas clave: i) Mejora de la precisión de las previsiones [6]; ii) Optimización y toma de decisiones [7]; iii) Adaptabilidad a los cambios medioambientales [8] y iv) Sostenibilidad e integración de las energías renovables [9].

Objetivo General:

Desarrollar un análisis comparativo entre modelos estadísticos tradicionales y técnicas de inteligencia artificial para la previsión de series temporales de producción hidroeléctrica, con el fin de evaluar su precisión, aplicabilidad y contribución a la mejora en la gestión y toma de decisiones en sistemas hidroeléctricos.

Objetivos Específicos:

Identificar las diferentes técnicas tradicionales y de inteligencia artificial aplicadas en la previsión de series temporales de producción hidroeléctrica a través de una revisión exhaustiva que perfile y analice los aspectos esenciales de los modelos de previsión de series temporales en sistemas hidroeléctricos.

Analizar los modelos estadísticos tradicionales que se han aplicado en la previsión de series temporales de producción hidroeléctrica a través de un caso de estudio real de un sistema hidroeléctrico utilizando los modelos ARIMA y ARIMAX.

Examinar patrones y tendencias en la previsión de series temporales de producción hidroeléctrica utilizando técnicas de aprendizaje profundo, a través de un caso de estudio real y utilizando modelos de redes neuronales artificiales del tipo FNN y RNN.

Motivation and Objectives

The main motivation for investigating AI models applied to hydropower production forecasting is to improve the efficiency, reliability and sustainability of energy production. AI models offer advanced capabilities to handle complex data sets and predict outcomes more accurately than traditional methods. These models are especially valuable in renewable energy, where variability and unpredictability pose significant challenges. The integration of AI in this field addresses several challenges, such as climate variability, resource management and operational efficiency. The motivations for exploring AI in this context can be classified into several key areas: i) Improving forecast accuracy [6]; ii) Optimization and decision making [7]; iii) Adaptability to environmental changes [8] and iv) Sustainability and integration of renewable energies [9].

General Objective:

To develop a comparative analysis between traditional statistical models and artificial intelligence techniques for hydroelectric production time series forecasting, in order to evaluate their accuracy, applicability and contribution to improve management and decision making in hydroelectric systems.

Specific Objectives:

Identify the different traditional and artificial intelligence techniques applied in hydroelectric production time series forecasting through a comprehensive review that outlines and analyzes the essential aspects of time series forecasting models in hydroelectric systems.

Analyze the traditional statistical models that have been applied in hydroelectric production time series forecasting through a real case study of a hydroelectric system using ARIMA and ARIMAX models.

Examine patterns and trends in hydroelectric production time series forecasting using deep learning techniques, through a real case study and using artificial neural network models of the FNN and RNN type.

Capítulo 3. Metodología

En la sección metodológica de esta tesis se detallará el enfoque sistemático utilizado para investigar y abordar los objetivos trazados en el capítulo 2. La figura 3.1 muestra los pasos seguidos en la metodología de esta investigación:

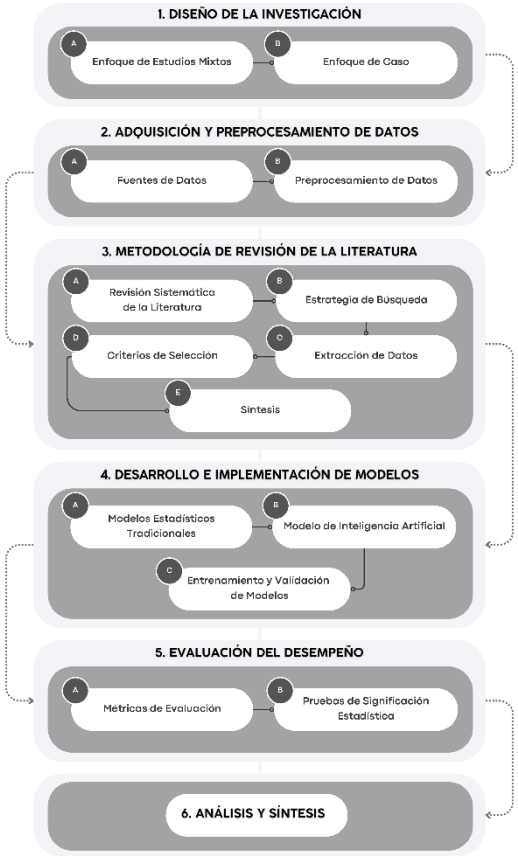

Figure 3.1 Diagrama de flujo de los procesos seguidos en la metodología

1. Diseño de la investigación

    a. *Enfoque de métodos mixtos:* Esta investigación empleará un enfoque de métodos mixtos, combinando un análisis cuantitativo de datos de series de tiempo con un análisis cualitativo de la literatura existente. La revisión de la literatura servirá de base para la selección de técnicas de predicción apropiadas y guiará el diseño del estudio empírico.

    b. *Estudio de caso:* Se seleccionará un sistema hidroeléctrico del mundo real como estudio de caso para la aplicación y evaluación de modelos de predicción.

2. Adquisición y preprocesamiento de datos

    a. *Fuentes de datos:* Los datos para esta investigación se obtendrán de múltiples fuentes, entre ellas:

        i. Datos históricos de generación de energía hidroeléctrica: datos de generación de energía por hora, día o mes del sistema hidroeléctrico seleccionado.

ii. Datos meteorológicos: caudal de los ríos, precipitaciones, temperatura y otras variables meteorológicas relevantes de las agencias meteorológicas locales o nacionales.

b. *Preprocesamiento de datos:* Los datos brutos se preprocesarán para garantizar la calidad y la coherencia. Esto implicará:

i. Limpieza de datos: manejo de valores faltantes, valores atípicos e inconsistencias en los datos.
ii. Transformación de datos: escalado, normalización y eliminación de tendencias de los datos para mejorar el rendimiento del modelo.
iii. Ingeniería de características: creación de nuevas características a partir de datos existentes, como variables retrasadas, medias móviles y componentes estacionales.

3. Metodología de revisión de la literatura

a. *Revisión sistemática de la literatura:* se realizará una revisión sistemática de las técnicas de predicción de series temporales existentes aplicadas a los sistemas de generación hidroeléctrica (HGS), siguiendo las directrices PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses).

b. *Estrategia de búsqueda:* la revisión implicará la búsqueda en bases de datos relevantes (por ejemplo, Web of Science, Scopus, IEEE Xplore) utilizando palabras clave y términos de búsqueda predefinidos.

c. *Criterios de selección:* los trabajos se seleccionarán en base a criterios de inclusión y exclusión predefinidos, centrándose en estudios que apliquen técnicas de predicción de series temporales a la producción hidroeléctrica.
d. *Extracción de datos:* se extraerán datos relevantes, incluidas las técnicas de pronóstico utilizadas, las variables de entrada, las métricas de rendimiento y las brechas de investigación identificadas, de los artículos seleccionados.

e. *Síntesis:* los datos extraídos se sintetizarán para identificar los métodos de pronóstico prevalentes, las brechas clave de investigación y las áreas potenciales de mejora.

4. Desarrollo e implementación de modelos

a. Modelos estadísticos tradicionales:
i. Se implementarán modelos ARIMA (AutoRegressive Integrated Moving Average) para capturar las dependencias lineales en los datos de series temporales.
ii. Los modelos ARIMAX (ARIMA con Variables Exógenas) incorporarán factores externos, como variables meteorológicas y económicas, en el proceso de predicción.

b. Modelos de Inteligencia Artificial:
i. Redes neuronales feed-forward tales como multilayer perceptrón.
ii. Redes neuronales recurrentes tales como LSTM y Seq2Seq.

c. Entrenamiento y validación de modelos:
    i. Los datos disponibles se dividirán en conjuntos de entrenamiento y pruebas.
    ii. Los modelos se entrenarán en el conjunto de entrenamiento y se probarán en el conjunto de pruebas.
    iii. Se utilizarán técnicas de optimización de hiperparámetros (por ejemplo, búsqueda en cuadrícula) para optimizar el rendimiento de los modelos.

5. Evaluación del desempeño

    a. Métricas de evaluación: el rendimiento de los modelos de previsión se evaluará utilizando una serie de métricas, entre las que se incluyen:

        i. Error Absoluto Medio (MAE)
        ii. Error cuadrático medio (RMSE)
        iii. Error porcentual absoluto medio (MAPE)

    b. Pruebas de significación estadística: se utilizarán pruebas de significación estadística para comparar el rendimiento de diferentes modelos y evaluar la significación estadística de los resultados.

6. Análisis y síntesis
    a. Se integran y resumen los procesos anteriores con los resultados logrados para el análisis.
    b. Se realiza un contraste entre los resultados alcanzados para la respectiva discusión de los hallazgos.

El software y herramientas utilizadas en la ejecución del diseño experimental serán el lenguaje de progracion Python con bibliotecas tales como TensorFlow, Keras, scikit-learn, pandas, NumPy, statsmodels. Adicionalmente se considera software estadístico R.

Methodology

The methodological section of this thesis will detail the systematic approach used to investigate and address the objectives outlined in Chapter 2. Figure 3.1 shows the steps followed in the methodology of this research:

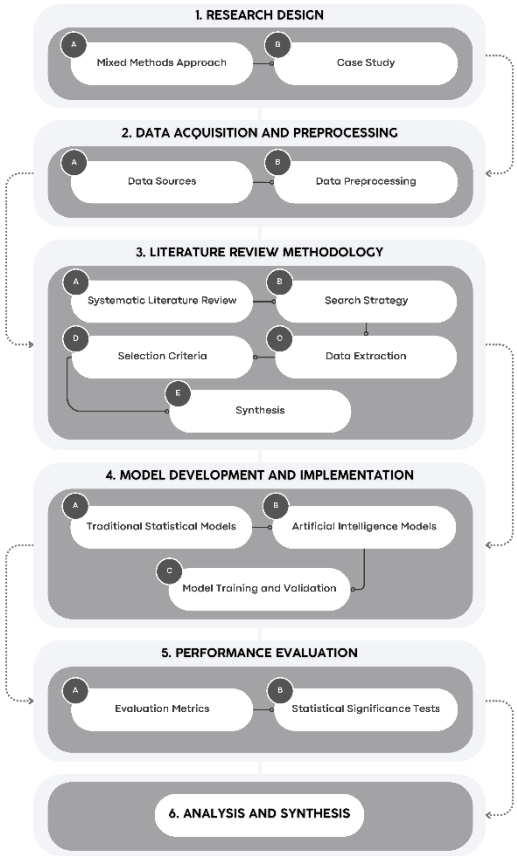

Figure 3.1 Process flow diagram of the processes followed in the methodology

1. Research design
    a. *Mixed-Methods Approach:* This research will employ a mixed-methods approach, combining a quantitative analysis of time series data with a qualitative analysis of the existing literature. The literature review will inform the selection of appropriate forecasting techniques and guide the design of the empirical study.

    b. *Case Study:* A real-world hydropower system will be selected as a case study for the application and evaluation of predictive models.

2. Data acquisition and preprocessing
    a. Data Sources: Data for this research will be obtained from multiple sources, including:

        i. Historical hydropower generation data: Hourly, daily, or monthly power generation data from the selected hydroelectric system.

        ii. Meteorological data: River flow, rainfall, temperature, and other relevant meteorological variables from local or national meteorological agencies.

b. Data Preprocessing: The raw data will be preprocessed to ensure quality and consistency. This will involve:

    i. Data cleaning: handling missing values, outliers, and inconsistencies in the data.

    ii. Data transformation: scaling, normalization, and detrending of the data to improve model performance.

    iii. Feature engineering: creating new features from existing data, such as lagged variables, moving averages, and seasonal components.

3. Literature review methodology

    a. Systematic literature review: A systematic review of existing time series forecasting techniques applied to hydroelectric generation systems (HGS) will be conducted, following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines.

    b. Search strategy: The review will involve searching relevant databases (e.g., Web of Science, Scopus, IEEE Xplore) using predefined keywords and search terms.

    c. Selection criteria: Papers will be selected based on predefined inclusion and exclusion criteria, focusing on studies that apply time series forecasting techniques to hydroelectric production.

    d. Data mining: Relevant data, including the forecasting techniques used, input variables, performance metrics, and research gaps identified, will be extracted from the selected papers.

    e. Synthesis: The extracted data will be synthesized to identify prevalent forecasting methods, key research gaps, and potential areas for improvement.

4. Model Development and Implementation

    a. Traditional Statistical Models:

        i. ARIMA (AutoRegressive Integrated Moving Average) models will be implemented to capture the linear dependencies in the time series data.

        ii. ARIMAX (ARIMA with Exogenous Variables) models will incorporate external factors, such as meteorological and economic variables, into the forecasting process.

    b. Artificial Intelligence Models:

        i. Feed-forward neural networks such as multilayer perceptron.
        ii. Recurrent neural networks such as LSTM and Seq2Seq.

    c. Model training and validation:

        i. The available data will be divided into training and testing sets.
        ii. The models will be trained on the training set and tested on the testing set.

iii. Hyperparameter optimization techniques (e.g., grid search) will be used to optimize the models' performance.

5. Performance evaluation

    a. Evaluation metrics: the performance of the forecasting models will be evaluated using a range of metrics, including:
        i. Mean Absolute Error (MAE)
        ii. Root Mean Squared Error (RMSE)
        iii. Mean Absolute Percentage Error (MAPE)

    b. Statistical significance tests: statistical significance tests will be used to compare the performance of different models and assess the statistical significance of the results.

6. Analysis and synthesis
    a. The above processes are integrated and summarized with the results achieved for analysis.
    b. A contrast is made between the results achieved for discussing the findings.

The software and tools used to execute the experimental design will be the Python programming language with libraries such as TensorFlow, Keras, scikit-learn, pandas, NumPy, and statsmodels. Additionally, R statistical software will be considered.

Capítulo 4. Time Series Forecasting Techniques Applied to Hydroelectric Generation Systems

J. Barzola-Monteses, J. Gómez-Romero, M. Espinoza-Andaluz, and W. Fajardo, "Time series forecasting techniques applied to hydroelectric generation systems," Int. J. Electr. Power Energy Syst., vol. 164, no. December 2024, p. 110424, Mar. 2025, doi: 10.1016/j.ijepes.2024.110424.

Modeling sequential data over time has become an intensive and fast-growing research area. Time series analysis has many applications in the energy field. Time series modeling and forecasting applied to hydropower plants have become essential since reliable and accurate energy production forecasts are needed for capacity planning, scheduling, and power system operation. Although there are numerous recent works in the field of time series forecasting for hydroelectric production, as evidenced in the development of this studio, there are no systematic reviews on this topic. Most of the reviews found in the literature are broader and include optimization and control approaches in hydroelectric systems. In addition, the literature lacks research works revising and analyzing the application of time series forecasting techniques –from statistics, machine and deep learning, and soft computing– to hydropower production –in contrast to the other topics that have been more thoroughly studied, such as energy demand in buildings. This study shows an exhaustive review of the existing time series forecasting techniques applied to hydroelectric generation systems. A thorough literature search was conducted to outline and analyze the essential aspects of the time series forecasting models in hydropower systems. Statistical methods, regression and machine learning, deep learning, and other soft computing and hybrid models were examined. Other aspects, such as the country of origin of the hydropower project, timespan and resolution datasets, regressive and objective variables, and performance evaluation, were also studied and discussed. The results showed research gaps in literature. The findings of this research will help the energy research community improve energy production forecasting in hydropower plants.

4.1 Introduction

Hydropower is a type of renewable energy source in which its transformation into electrical energy is obtained from the potential energy of water flowing from higher to lower elevations. Hydropower is a well-matured technology extensively used worldwide; in 2020, 170 countries/territories reported having installed and in-use hydropower generation capacity. The general use of hydropower relies on two advantages. First, it refers to its high efficiency of electrical energy transformation compared to other renewable sources ---around 90% for "water-to-wire" conversion. Second, hydropower is highly cost-competitive, being today the only renewable technology that produces electricity comparable to the cost of thermal energy sources such as coal, oil, or gas ---typically in the range of USD 2–5c per kWh [1], [10].

In 2020, the global hydropower installed capacity was 1330 GW [10], [11] , i.e., hydropower was the largest renewable energy source in the electricity sector, with an estimated share of 61.0% of all renewables [12]. Furthermore, hydropower production contributed about 16.01% of the worldwide electricity supply in 2019 and was the third-largest source of electricity production behind coal (36.66%) and natural gas (23.47%) [13].

The main advantages of hydropower compared to other sources are the following intrinsic capabilities: (i) load and frequency regulation and (ii) easier energy storage. Regarding (i), hydroelectric systems are load and frequency regulators since they have a faster and more flexible connection and feed to the electrical network. In contrast, thermal plants suffer heat stress and have difficulties starting and connecting to the power network within a short time, while solar and

wind are less predictable. The second (ii) important advantage of hydroelectric systems is straightforward energy storage. For example, suppose the power system is unstable, and the difference between peak and valley load is significant. In that case, a possible solution is to build pumped-storage power plants, using the surplus power at the valley to pump the water from downstream to the upstream reservoir. Therefore, the pumped and stored water will be utilized for hydropower generation during the peak load [14].

Hydroelectric generation systems (HGS) can be located on rivers, streams, and canals, although dams are needed for water supply reliability. Therefore, the storage (reservoir) hydropower plants are the most frequently implemented projects. Formally, energy transformation in the storage hydropower plant is based on impulse-momentum: first, potential energy (water stored in the reservoir) is converted into mechanical energy by rotating the turbine; second, mechanical energy is converted into electrical energy by using a generator. The potential hydropower can be calculated from the following equation:

$$P = Q.\rho.g.h.\eta \quad (1)$$

where P is electric power in KW, Q is the quantity of water flowing through the hydraulic turbine in m3/s, ρ is water density in kg/m3, g is gravitational acceleration in m/s2, h is the head in m, and η is the overall efficiency of the hydropower plant.

While Equation (1) can accurately predict instant electric power, forecasting the real production of hydroelectric systems in the longer term remains a challenge [15], [16] [17]. Q can be affected by meteorological factors –e.g., river and reservoir inflows– but also adjusted by the operators to meet demand satisfaction and other commercial objectives. Therefore, there are many variables impacting the throughput of hydroelectric systems that can be used as proxies for production estimation. For example, the increase of the gross domestic product is an indicator of a higher energy consumption, which in turn usually means approaching the maximum potential production capabilities. At the same time, reliable and accurate hydroelectric generation forecasts are very important for several reasons: capacity planning and grid management, since hydropower can be used strategically to meet peak demand periods; water resource management, to make an optimal and environmental-friendly use of the reservoirs; and flexible adaptation of the energy mix and incorporation of new elements, given the capabilities of hydropower to complement other variable sources.

Data-driven approaches for time series forecasting, powered by deep learning techniques, have been highlighted as a powerful tool given their outstanding performance as the scale and variety of available data increases, particularly for temporal prediction in the energy and fuels area [18]. Driven by the mentioned difficulties and needs, the prediction of hydroelectric energy generation has attracted interest in the intersection of power systems and data science research. However, the literature lacks research works revising and analyzing the application of time series forecasting techniques –from Statistics, Machine and Deep Learning, and Soft Computing– to hydropower production –in contrast to other topics that have been more thoroughly studied, such as energy demand in buildings [19], [20].

This work provides a systematic review of studies published in the last decade focused on time series forecasting techniques applied to HGS. Accordingly, the paper analyzes critical challenges, assesses contributions and advancements in the field, and identifies research gaps to prioritize future research. Specifically, the review addresses the following research questions:

Why has forecasting gained significant attention in the context of HGS?

Which techniques and tools have been prevalent for prediction in HGS?

Which variables have been considered for time series forecasting applied to HGS?

Which are the main research gaps in the related literature?

The HGS is the largest renewable energy source in the electricity sector. The prognostics in these systems are crucial since reliable and accurate energy production forecasts are needed for capacity planning, scheduling, and power system operation. Deep learning and hybrid techniques are the most used to forecast HGS. The regressor variables, such as inflow and precipitation/rainfall, are mainly used as input for models applied to HGS. However, complex deep learning structures have been little explored. Similarly, ensemble learning models have been little studied. As this review is developed, other outcomes will be exposed with more details.

To conduct the review, we have applied the preferred reporting items for systematic review and meta-analyses (PRISMA) methodology, as described in Section 2. First, a list of queries to retrieve candidate papers from specialized databases was designed. Then, the most relevant papers obtained were filtered and classified according to the principal prediction technique used in each case. Finally, we proceeded to the comprehensive analysis and comparison of the approaches and contributions described in the surveyed papers.

The rest of this work is structured as follows. Section 3 shows the time series forecasting techniques used in hydropower systems and recent research on this topic. Section 4 addresses the findings of this study and their discussion. Finally, the concluding remarks and potential future research are provided in Section 5.

4.2 Methodology and classification

Studies related to HGS considering different time series techniques were explored in this review. The literature search was performed using two online databases relevant to the energy field. Therefore, Elsevier (Scopus) and IEEE Xplore were selected. As shown in Fig. 1, the PRISMA methodology [21] was applied, considering the following inclusion-exclusion criteria.

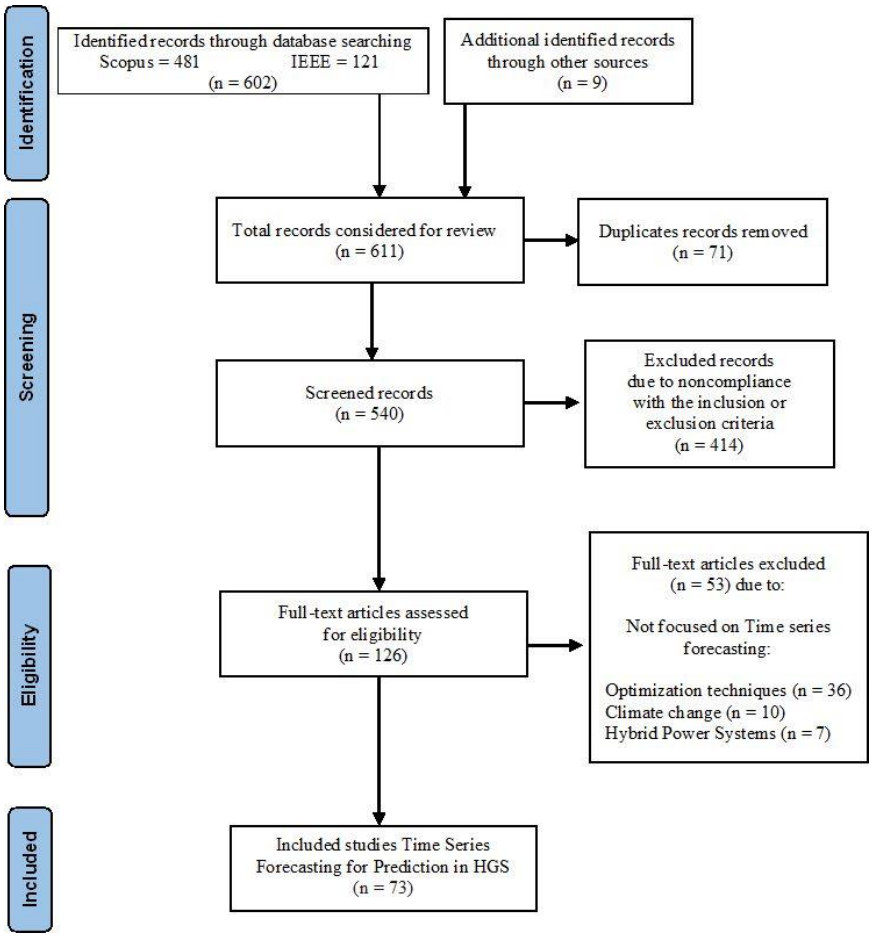

Figure 4.1 PRISMA methodology applied in this review to select works on time series forecasting in HGS

Investigations published between 2011 and 2021 were analyzed. The scoping review included journals, research articles, and conference papers in the selected period. Search strings were associated with prioritized keywords using Boolean operators. The following queries were searched in titles, abstracts, and keywords: ("energy forecast" OR "energy prediction") AND ("hydroelectric system" OR "hydropower systems"), AND ("time series") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "artificial neural networks" OR "evolutionary computation" OR "swarm intelligence" OR "artificial immune systems" OR “fuzzy systems”).

The search in databases returned 602 articles, and another nine from other sources were added, i.e., 611 records were considered for review. After removing 71 duplicate records, the titles and abstracts of 540 were screened, excluding 414 studies that did not meet the specified criteria. Consequently, 126 full-text articles related to energy forecasts in HGS were initially examined. As shown in Fig. 2, we refined this list by narrowing down the topics related to time series forecasting, excluding other techniques. This process finally yielded 73 studies meeting the research objective.

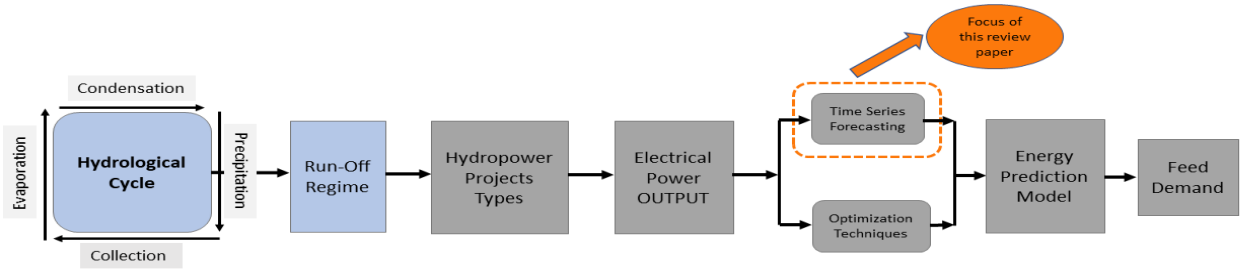

Figure 4.2 Diagram shows the focus of this review paper considering time series forecasting for prediction in HGS

To delimit the scope of the review, we elaborated a broad classification of prediction techniques applied to HGS, including four main research directions: (i) Time series techniques for prediction in HGS, (ii) Optimization techniques for prediction in HGS, (iii) Climate change forecasts considering HGS, and (iv) Hybrid power system (HGS with other sources of energy). We focused on (i) and briefly analyzed the remaining categories.

The articles related to optimization techniques for prediction in HGS were based on improving the scheduling of hydroelectric production. Recent reviews of the algorithms used [22], [23] already exist in the literature. The main techniques and methodologies identified during the screening stage were: statistical methods [24], [25], [26], [27], [28], [29], [30], machine learning [31], deep learning [32], [33], [34], [35], and other soft computing methods such as evolutionary computation [36], [37], [38], [39], swarm intelligence [40], [41], [42], [43], [44], fuzzy systems [45], [46], [47], [48] and hybrid models [49], [50], [51], [52], [53], [54].

Furthermore, a decision support system for operation scheduling and hydropower plant optimization was presented in [55]. Moreover, an approach considering physical models was shown in [56]. Finally, a method based on the energy storage operation chart and time scale effect was described in [57]. In the case of climate change forecasts considering HGS, the principal techniques, and methodologies identified during the screening stage were: statistical methods [58], [59], [60], machine learning [61], deep learning [62], [63], and hydrological models [64], [65], [66], [67]. Similarly, for studies related to hybrid power systems in which hydroelectric production forecasts are complemented with other sources of energy such as solar and wind, the leading techniques and methodologies identified were: statistical methods [68], [69], [70], [71], deep learning [72], and soft computing methods [73]. In addition, a hybrid photovoltaic/small-hydropower study in [74] proposed a microgrid in a smart voltage network to feed a grid-isolated electric vehicle charging system.

4.3 Time Series Forecasting Techniques

In this section, the forecasting techniques applied to HGS identified in the chosen articles will be reviewed. First, the characteristics of the time series are presented, followed by forecasting techniques such as statistical methods for sequence modeling, regression and machine learning (ML) models, deep learning-based modeling, other soft computing methods, and hybrid models.

4.3.1 Time series - Generalities

A time series is a sequence of data or observations that takes a quantitative variable. These values are recorded at time intervals that are usually regular or equitemporal (annual, monthly, daily, hourly, among others). Therefore, a time series is a structured way of representing data. Moreover, time series can be mathematically modeled to extract relevant features o characteristics of the data. These models can forecast future values of the variable of interest [66]. Thirty different methods exist to model and analyze time series [76].

Time series problems can be univariate or multivariate. For the univariate problem, in the model, only one variable is considered in both input (regressor variable) and output (predictor variable). For multivariate cases, two or more regressor variables are considered as input and only one as output (predictor variable).

It is essential to emphasize the need to preprocess the data to model a time series. A treatment that goes from the loss of data by the sensors until some imputation process should be applied. Also, atypical data should be identified through exploratory data analysis, so it is recommended to use robust statistical methods to remove these data. Analyzing the reduction of dimensions or features is another process to be considered. More details of the preprocessing stage can be reviewed in [77].

A first analysis usually applied to time series is to characterize its three components, i.e., trend, seasonality, and residuals [78].

Trend.- It shows the gradual pattern of the variable during the observation period. Seasonality and residuals are not taken into account. This component can present different linear, exponential, or parabolic behaviors.

Seasonality.- It depicts the periodic fluctuation of the analyzed variable over time. This component can be characterized by time, magnitude, and direction.

Residual.- After applying the two previous decompositions, this component of residual values remains. It is mainly an incomprehensible part of the time series. These can sometimes be high enough to mask the other two components mentioned.

Fig. 3 shows how a time series can be decomposed into the abovementioned variables. The time series observed is monthly hydroelectric production from 2000 to 2015 in Ecuador [79], [80].

In general, a time series is a combination of these three components. In real case studies, some forecasting techniques successfully detect trends and seasonality. However, forecasting the residual component is a great challenge. Therefore, there is an interest in analyzing and testing different strategies to assess this time series component.

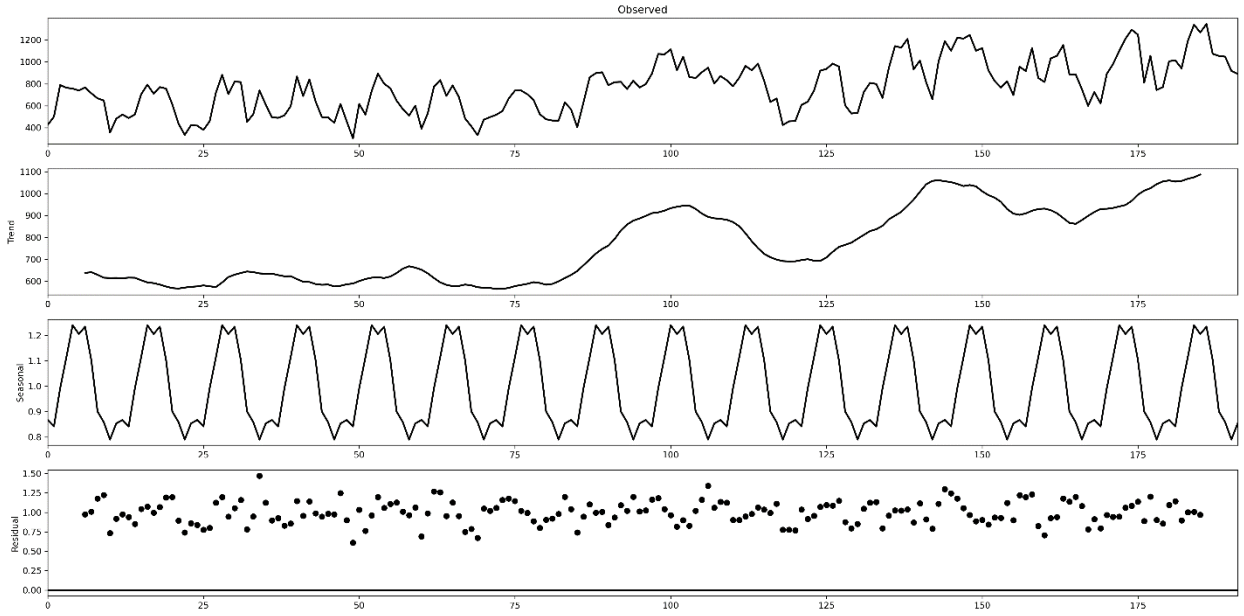

Figure 4.3 Time series principal components decomposition: trend, seasonal, and residuals

4.4 Statistical methods for sequence modeling

This subsection consists of a succinct description of the technique examined and a survey of the most representative research where statistical methods in time series are applied to HGS. Specifically, approaches based on linear methods are described. Classical Box-Jenkins and Box-Tiao-based methods include autoregressive (AR), moving average (MA), autoregressive moving average (ARMA), and autoregressive integrated moving average with and without exogenous input models.

4.4.1 ARIMA models

Statistical approaches deal with learning a forecast model using historical time series data. The forecasting capability of the models occurs when the difference between predictive or fitted values and actual values is reduced. Therefore, the precision of the statistical model hinges on the length and quality of historical input data [81].

Stochastic processes, in which correlated near-time observations can be used to model time series, are also explained. Box-Jenkins is the method most used for fit time series [82], which identifies, estimates and checks prediction models for a specific time series using an autoregressive integrated moving average (ARIMA).

This method uses the maximum likelihood technique and determines the values of the parameters that maximize the probability of obtaining the adjusted values of the observed data. This model is mathematically described as follows:

$$\phi_p(B)(1-B)^d Y_t = \phi_0 + \theta_q(B)\varepsilon_t \tag{2}$$

where $\phi_p(B)$ is the regular AR polynomial of order p, B is the backshift operator, Y_t is the forecasting variable, and d is the d^{th} difference operator. In addition, ϕ_0 is a numerical constant, $\theta_q(B)$ is the regular moving average polynomial of order q, and ε_t is the model's error.

Furthermore, the parameters p, d, and q must be determined in these models. The mentioned parameters have the following attributes: the autoregressive value of the dependent

variable is described by parameter p, the finite difference transformation by d, and the delay of the moving average value or error term of the stochastic models is represented by q. These values are identified to analyze the stationarity of the time series.

The Box-Tiao method is extensively used to analyze multivariate time series, commonly known as the autoregressive integrated moving average with exogenous inputs (ARIMAX), which extends ARIMA with a linear component. ARIMAX includes the observed covariates (explanatory/exogenous variable X) to increase its forecasting performance [83], [84].

The ARIMAX model is formulated as follows:

$$\phi_p(B)(1-B)^d Y_t = \phi_0 + \Theta(B)X_t + \theta_q(B)\varepsilon_t \quad (3)$$

Eq. (3) has a similar structure to Eq. (2). However, in Eq. (3), the term $\Theta(B)X_t$ is the observed value, while $\Theta(B)$ represents the polynomial operator, and X_t is the exogenous variable.

4.4.2 Review of application studies on Statistical based modeling

The ARIMA models, their composition, and extensions have been applied directly and indirectly in studies related to the forecast of hydroelectric production.

The AR models were considered by Gallego-Castillo and Victoria [85] to develop a stochastic model for hydropower production to improve an energy-transition pathway analysis tool developed in previous research. Likewise, AR and periodic autoregressive (PAR) models were used in comparative studies of forecasting monthly stream-flow series from Brazilian hydroelectric plants [86]. In addition, research in [87] showed that the PAR model was applied to stream-flow forecasting of a hydroelectric plant. Finally, a vector autoregressive (VAR) model was used to examine the causal relationship between hydropower consumption, gross domestic product, and carbon dioxide emission in Malaysia [88].

Furthermore, several companies in the Brazilian electrical sector have used the Periodic AutoRegressive Moving Average (PARMA) model developed by Box-Jenkins. Its performance and limitations have been contrasted with other models shown in [89], [90], [91].

ARIMA models have been used to forecast hydropower production in the medium [92] and long-term [93]. Also, studies have analyzed the factors that affect the efficiency [94] and feasibility [95] of generation at mini and micro-hydroelectric systems, respectively. This classic model has also been applied to forecast the hydroelectric generation of a country [96]. It has been contrasted with the ARIMAX model, which considers precipitation an exogenous variable [79]. Another application of these models was the forecast of hydroelectric consumption considering distinct seasonal characteristics of hydropower [97] and supply-demand analysis [98]. This model has been traditionally used as a baseline model to test other techniques [86], [87], [99].

4.5 Regression and machine learning models

This subsection briefly presents the analyzed technique and addresses the most representative studies where regression and machine learning methods are applied to HGS. Machine learning methods can focus on prediction problems such as classification and regression. This work considers the regression approach for temporal sequence analysis applied to HGS.

4.5.1 Linear regression models

4.5.1.1 Simple linear regression

A linear regression (LR) model is a statistical analysis method to predict a quantitative dependent variable Y based on a single predictor variable X (independent variable). It supposes an approximately linear relationship between X and Y. This model describes the behavior of the

unknown quantity y in terms of known quantities x and additional parameters. Mathematically, this linear relationship can be written as [100], [101]:

$$Y \approx \beta_0 + \beta_1 X \tag{4}$$

where β_0 and β_1 are constant parameters representing the intercept (offset) and slope terms, respectively. In the linear model, these parameters are also known as model coefficients. During dataset training, its estimation is achieved, i.e., $\hat{\beta}_0$ and $\hat{\beta}_1$ are computed. Therefore, the following prediction model is produced:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x \tag{5}$$

where $\hat{y}$ displays a prediction of Y based on $X = x$. Furthermore, if the correlation between X and Y is accurate, Eq. (5) can be described as follows:

$$Y = \beta_0 + \beta_1 X + \varepsilon \tag{6}$$

where ε is a mean-zero random error term.

4.5.1.2 Multiple linear regression

An extension of the linear regression model with more than one regressor variable is named multiple linear regression (MLR). Therefore, the MLR model can be formulated as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \varepsilon \tag{7}$$

where X_j is the jth predictor, and β_j quantifies the association between dependent and independent variables. That is, β_j is the mean effect on Y of a one-unit increase in X_j while keeping the rest of the predictors fixed [100].

This model needs fewer samples and shows reasonable interpretation and robust prediction abilities. To estimate the model coefficients, Eq. (5) can be extended as follows:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_p x_p \tag{8}$$

According to [102], it can be rewritten as:

$$\hat{y}_i = \hat{\beta}_0 + \sum_{j=1}^{p} \hat{\beta}_j x_j \tag{9}$$

where $\hat{y}_i$ indicates the predicted y_i and $\hat{\beta}_j$ represents the regression coefficient, which is calculated using the least square method by minimizing Eq. (10):

$$\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{N} \left[y_i - \left(\hat{\beta}_0 + \sum_{j=1}^{p} \hat{\beta}_j x_{ij} \right) \right]^2 \tag{10}$$

4.5.2 Tree-Based Methods

4.5.2.1 Decision trees (DT)

DT is a technique to partition data into groups, i.e., root nodes and a couple of branch nodes. Roughly speaking, DTs are constituted by If/Else rules (splitting criteria) applied to the independent variables (input data) that lead to the model's output, i.e., predictor or response variable. It should be noted that each split produces two new branches further down on the tree, i.e., a recursive binary splitting. To forecast a response, the decisions in the tree from the root

node down to a leaf node must be followed, i.e., the last node contains the predicted value [116]. DTs can be applied to both regression and classification problems depending on the response value ---category or numerical value. In the case of time series, regression DTs are used.

DTs accuracy can be improved by combining or ensembling several base models to produce one potentially optimal predictive model. The two most-widespread types of ensembles are presented: bagging ensemble learning and boosting ensemble learning. Random forest and boosted decision tree models are examples, respectively.

4.5.2.2 Random forests (RF)

Bagging is an approach that searches a different group of ensemble members by varying the training data, i.e., a diverse sample (sampling with replacement) of the same training dataset is considered to train each model. Therefore, the predictions obtained by the ensemble members are combined using statistics, such as averaging for regression problems [104]. This process can be defined as follows:

$$\hat{f}_{bag}(x) = \frac{1}{B}\sum_{b=1}^{B} \hat{f}^{*b}(x) \tag{11}$$

where $\hat{f}_{bag}$ (bagging) is the average of all the predictions, $\hat{f}^{*b}(x)$ are the predictions achieved on the *bth* bootstrapped training system, and *B* is the number of separate training sets.

RF is an improved adaptation of bagged trees. The construction of many decision trees from bootstrap samples from the training dataset remains the same. However, RF randomly chooses a subset of input predictors (features) to build the tree branches at each split point.

4.5.2.3 Boosted Decision Tree (BDT)

Boosting also builds a set of models, but they are not created independently as in bagging. Instead, the models are grown sequentially. In BDT, each new tree is generated considering information from previously grown trees --- usually to minimize the prediction errors. It should be noted that bootstrap sampling is not performed during the boosting process; each tree fits an altered version of the original information. The output of the boosted model can be defined as follows [100]:

$$\hat{f}(x) = \sum_{b=1}^{B} \lambda\, \hat{f}^{b}(x) \tag{12}$$

where $\hat{f}(x)$ is the boosted model, $\hat{f}^{b}(x)$ are *bth* decision trees, *B* is the number of trees, and λ is the shrinkage parameter.

In the algorithm, another parameter, *d,* defines the number of splits in each tree, which controls the complexity of the boosted ensemble.

4.5.2.4 Support Vector Machines (SVM)

SVM aim to obtain a plane in the manifold in which the samples that better separate them into two categories are embedded. This hyperplane, namely the maximal margin hyperplane, divides the two populations so that the separation between them is maximal [118].

It is an optimization problem defined as follows [100]:

$$\underset{\beta_0, \beta_1, \ldots, \beta_{p,\in_1,\cdots,\in_n}, M}{maximize} \quad M \tag{13}$$

$$subject\ to \sum_{j=1}^{P} \beta_j^2 = 1, \tag{14}$$

$$y_i\left(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip}\right) \geq M(1 - \epsilon_i), \tag{15}$$

$$\epsilon_i \geq 0, \qquad \sum_{i=1}^{n} \epsilon_i \leq C, \tag{16}$$

where β_0, $\beta_1 \ldots \beta_p$ are the coefficients of a p-dimensional hyperplane, y_i is the label of observations for all $i = 1, \ldots, n$; M represents the margin; ϵ_i are slack variables, and C is a tuning parameter that indicates the number and severity of the violations to the margin.

SVM has two main approaches: support vector classification (SVC) and support vector regression (SVR). In this review, support vector regression in the time series application is considered.

4.5.3 Review of application studies on regression and machine learning models

Simple linear regression models have been used to forecast the energy recovery potential of micro hydropower plants to feed irrigation networks of great geographical extension [106]. Linear regression has also been implemented to evaluate the accuracy of the prediction models generally used by the electrical system operator to plan and manage the HGS [107]. This regression model has also been taken as a baseline to analyze and validate monitoring hydropower reliability using sensed data from satellite missions, instruments, and field observations [108].

MLR has been used to develop a model for forecasting electricity generation from hydropower plants, considering rainfall and temperature in the dam's catchment area [109]. This model has also been taken as a baseline to analyze the performance of other models [110], [111], [112].

In the application context for hydroelectric production forecasting, DT and RF were used to assess the ability to simulate hydrological variables on a national scale [112]. In another study, RF was used to determine the predictive hydropower considering measurements of an entire river basin, such as temperature, precipitations, soil moisture, and the Standardized Precipitation Evapotranspiration Index [113]. RF was also used to model hydropower generation at the country level based on climate data [114]. Moreover, considering a multi-method ensemble, RF was used with other models to build a probabilistic nonlinear regression to forecast the water supply for the US Department of Agriculture [115].

RF was used to analyze the energy production trends using real-time dam measurements [109]. RF and BDTs regression were also appropriate as a base model to assess the performance of other supervised machine learning algorithms. For instance, forecasting the changes in the water level of a reservoir to model a sustainable hydroelectric production strategy [116]. Another example considered gradient boosting to predict a dam's daily natural flow [117].

Machine learning techniques such as SVR have been widely applied in studies related to time series that depict hydroelectric production, showing outstanding results [110], [118], [119]. SVR has also been beneficial as a base model to compare the performances of other more complex models [43], [117], [120], [121].

4.6 Deep learning-based modeling

An Artificial Neural Network (ANN) is a nonlinear computational model bioinspired by the behavior of neurons in the human brain to process signals. An ANN comprises a group of neurons interconnected by weights in arrangements called a layer. Each ANN has three layers of neurons. The input layer through which data enters the model (regressor variables), then this data passes to the hidden layer and exits through the output layer (predictor variable). The hidden layer can be structured by several layers and is characterized in that both input and output values are unknown.

During the training of an ANN, the input weights of the neurons are adjusted until the output layer's responses are as close as possible to the observed data. This fit calculation typically consists of a weighted average and a nonlinear function. Some optimization methods to train ANN are the classic backpropagation, Levenberg-Marquardt algorithms, and genetic algorithms [122].

Later, we explore the most representative research where ANN methods are applied to HGS. Feedforward neural networks, recurrent neural networks, and unorganized machines are thus reviewed.

4.6.1 Feedforward Neural Network (FNN)

There are some types of ANN, among them the FNN, in which the information flows only in the forward direction, i.e., the data and its processing only travel in one direction from inputs to output layers. The most basic and general FNN is the multilayer perceptron (MLP), depicted in Fig. 4 [123].

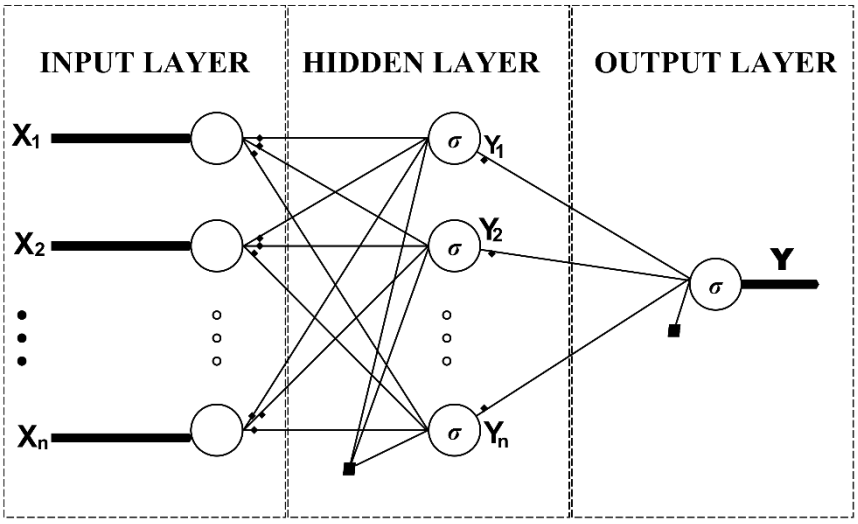

Figure 4.4 A typical FNN topology

Single-layer neural networks are the simplest type of FNN. Rosenblatt introduced an example of these networks, known as the perceptron. The structure of this network was the foundation of other networks with greater complexity [124].

4.6.1.1 Multilayer perceptron

MLP is an improved version of the single-layer perceptron, incorporating hidden layers to fit nonlinear functions. To achieve this goal, MLPs perform two processes as follows:

First is the forward propagation process in which the output response of the network is calculated from the input values. Second is the learning process, in which the errors obtained at the output response of the MLP are propagated backward (backpropagation) through the network to update the weights of the connections and calculate the error gradient function at each neuron. MLPs use these two processes iteratively during training until the error between observed and predicted data is reduced. These processes constitute the stochastic gradient descent method [122].

Thanks to the assumption of independence among the training and test data, MLP, despite its simplicity, has achieved notable performance in various supervised and unsupervised applications [125].

4.6.1.2 Convolutional neural network (CNN)

A CNN is another type of FNN usually aimed at image processing, adding two new operations: convolution and pooling. Convolution is an operation that allows the network to extract patterns on visual features (e.g., lines and shapes) by applying two-dimensional filters with learned weights. Pooling reduces the size of the images resulting from the convolution by sampling, usually taking only one representative value per patch. Interestingly, CNNs can be applied to n-dimensional data, including sequences of one or more dimensions, particularly time series [126].

4.6.2 Group method of data handling (GMDH)

GMDH is a self-organizing machine learning model that attempts to identify the model's most appropriate relationship between inputs and outputs. For this purpose, an inductive procedure to classify polynomial models gradually is used. Moreover, the best solution is selected by external criteria [127].

GMDH over-performs ANN in the following characteristics: GMDH can obtain explicit expressions. GMDH model provides adaptive network representations that can be adapted to the given task. Furthermore, GMDH is robust enough to deal with overfitting when selecting models of optimal complexity [128].

4.6.3 Recurrent Neural Network (RNN)

Time series features ---time-dependency, seasonality, and non-stationarity---do not fit well with FNN, which considers each data point independently. In addition, FNN assumes that inputs and targets are fixed dimensional vectors. For these reasons, RNN, able to add feedback loops in the network and process sequences of unknown length, has been proposed in the literature [129].

4.6.3.1 Simple RNN

The RNN is a type of ANN specialized in processing sequential data or time series. Its architecture allows the network to obtain artificial memory. An essential feature of RNNs is based on recurrent neurons that transmit information forward and backward. At each timestep, the recurrent neuron receives information from the previous neurons and from itself in the last timestep [130]. Fig. 5 shows a simple RNN topology where signals forward and backward are explicit. Here, X_l is an input sequence of vectors, O_l is an output sequence of predictions from the

current activation A_l, and as each element of the series is processed, the same collections of weights *W*, *U*, and *B* are used [100].

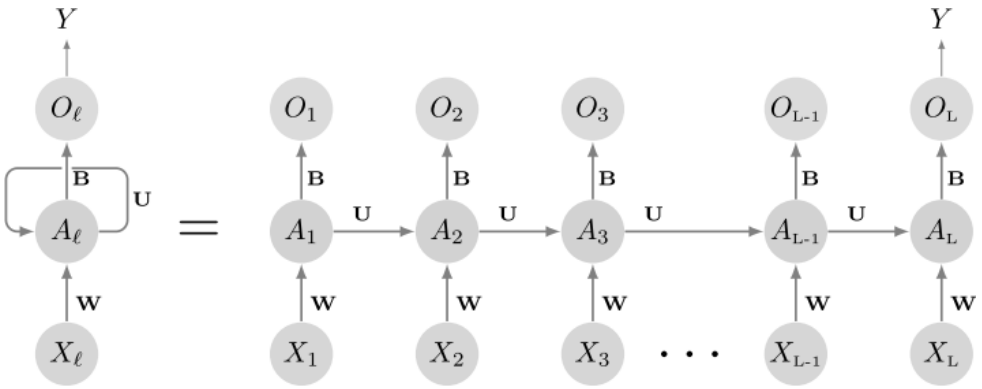

Figure 4.5 A simple RNN topology

4.6.3.2 *Long-Short-Term-Memory (LSTM)*

The backpropagation through time (BPTT) method is applied to train simple RNN models. This method propagates the error signal obtained at the output response layer to earlier layers. However, in real processes, this signal is attenuated as it goes through the complexity of the hidden layers of the neural network, i.e., the error signal tends to zero. This attenuation affects the optimal learning of the neural network during training. This attenuation is known as the vanishing gradient problem (VGP), an effect over very long sequences (long-term dependencies). The VGP can be presented in FNN and RNN architectures [131].

The VGP prompted the development of new architectural proposals to deal with this attenuation. It is how an LSTM-based RNN designed by Hochreiter and Schminhuber emerges. Its structure consists of "memory blocks or gate units" (linear self-loop memory) in each hidden layer. Long-sequence signal gradients can flow through these memory blocks, which can store information. Furthermore, these blocks prevent that old signals can be attenuated during the learning process [131], [132].

A simplified version of LSTM is the gated recurrent units (GRU) proposed by Cho et al. [133]. The GRU reduces the gating signals of the LSTM model to just two values. The reset gate r and the update gate z constitute a GRU cell. The previous hidden state (*t-1*) and the input value at time *t* are considered to determine the hidden state output at time *t* [134].

4.6.4 Unorganized machines

A recent variation of ANN is unorganized machines, which have a particular training process. In unorganized machines, during the learning process, the weights at the hidden layer are selected randomly, and neurons remain untuned. The training process is, therefore, limited to finding the coefficients of a linear combiner, which is the output layer response. An example of unorganized machines based on FNN is extreme learning machines (ELM), while echo state networks (ESN) are an example of unorganized machines based on RNN [135], [136].

4.6.4.1 *Extreme learning machines*

ELM was introduced by Huang et al. [137]. Its architecture is like an FFNN with a single hidden layer. The adjustment of the model is achieved through an output matrix W^{out}, which is determined as follows:

$$W^{out} = \left(X_{hid}^T X_{hid}\right)^{-1} X_{hid}^T d \tag{17}$$

where $X_{hid} \in \mathbb{R}^{|x| \times m}$ is the matrix with hidden layer outputs and m number of neurons for the training set, and d is the predicted output vector.

The Moore-Penrose pseudo-inverse operator is applied to optimize the minimum MSE and fast training. Hence, this process is more efficient than the backpropagation method in FFNN [136]:

4.6.4.2 Echo State Networks

ESN was introduced by Jaeger [138]. Its architecture is like an RNN with a single hidden layer named a dynamic reservoir. Moreover, this layer presents feedback loops. The training process adjusts the output weights using a least-square optimization process, i.e., formulated as a linear regression task. The term *echo* refers to the impression that recent samples and previous states influence the output. This approach tends to have a simpler, more computationally efficient, and faster training process than backpropagation in simple RNN.

For each new input value at time $t+1$, the states of the network are updated, which is calculated as follows: [136]:

$$x_{t+1} = f\left(W^{in} u_{t+1} + W x_t\right) \tag{18}$$

where x_{t+1} is the state of the input value at time t+1, $f(\cdot) = \left(f_1(\cdot), f_2(\cdot), f_3(\cdot), \ldots, f_N(\cdot)\right)$ indicates the activation functions of the neurons in the hidden layer, W^{in} represents the coefficients of the input layer, and u_t is the input vector at time t.

Finally, the output vector $\boldsymbol{y}_{t+1}$ is obtained as follows [136]:

$$y_{t+1} = \mathrm{W}^{out} x_{t+1} \tag{19}$$

where $W^{out} \in \mathbb{R}^{L \times N}$ is the matrix with the weights of the output layer with L number outputs.

4.6.5 Review of application studies on Deep learning-based modeling

Feedforward neural networks have been primarily used for time series forecasting in hydroelectric systems. In 32 studies, about 42% of documents selected for this review, MLP was considered. There are five principal applications of MLP, as described below. Table 1 shows that the main application of MLP is as a base model to contrast other analyzed forecast models (E).

A. MLP is used to predict the potential for hydropower generation.

B. MLP is used for the prediction of hydroelectric generation.

C. MLP is part of a system, tools, or methodological framework for the forecast system to support hydropower production decision-making.

D. MLPs have been used as a base model to contrast the performance of another hydrological forecasting model for effective hydropower production in reservoir management and scheduling.

E. MLPs have been used as a base model to contrast the performance of hydropower consumption series.

Table 4.1 MLP Applications in HGS Time Series Forecasting

Ref.	A	B	C	D	E
Buhan et al. [139]			•		
Medina and Peña [95]				•	
Wang et al. [97]					•
Wang et al. [99]				•	
Crespo Chacón et al. [106]	•				
Essenfelder et al. [110]			•		
Wang et al. [118]				•	
Cheng et al. [120]				•	
Belotti et al. [136]				•	
Ferreira and Leocadio [140]				•	
Barino et al. [141]				•	
Liu et al. [142]					•
Wang et al. [143]				•	
Setiono and Hadiani [144]	•				
Stokelj and Golob [145]	•				
Estoperez and Nagasaka [146]		•			
Patavan et al. [147]		•			
Stokelj et al. [148]		•			
Barzola-Monteses et al [80]		•			
Gomes Lopes et al. [149]				•	
Uzlu et al. [150]				•	
Hussin et al. [151]				•	
Endo and Garcia [152]				•	
Gomes De Paiva et al. [153]				•	
Ballini [154]				•	
Wang et al. [155]				•	
Aquino et al. [156]				•	
Siqueira and Luna [157]				•	
Wang and Qiu [158]				•	
Nabipour et al. [159]				•	
Wang et al. [160]				•	
Apaydin et al. [161]				•	

Other FNN models, such as CNN, have been used in the following cases: Barino et al. [141] proposed using one-dimensional CNN for multi-day ahead river inflow forecasting. In another study, Maciel et al. [162] proposed a methodology in which the SMAP hydrological model was improved using a CNN hybrid structure: Conv3D-LSTM [126]. Results have been used to plan the short-term operation of power systems.

Another FFNN model identified in this review was GMDH. Gomes Lopes et al. [149] employed two different approaches to forecasting energy generation in the Amazon region (Brazil): GMDH and MLP. Forecasts achieved with GMDH were slightly better than MLP.

In this review, we identified studies in which simple RNN, LSTM, GRU, and advanced recurrent neural networks were applied. It is also found applications of bidirectional layers --- layers calculating forward and backward predictions--- to increase accuracy and mitigate forgetting issues, e.g., Bi-LSTM, Bi-GRU, and Bi-GRU-ATT (attention mechanism which can selectively weight relevant fragments of the sequence). Furthermore, we found the use of recurrent dropout to mitigate overfitting in recurrent layers.

Apaydin et al. [161] proposed a comparative analysis of RNN structures for reservoir inflow prediction in arid and semi-arid areas. The models considered were: GRU, LSTM, Bi-LSTM, simple RNN, and baseline MLP models with two hidden layers. The results indicated that LSTM had the best accuracy.

LSTM architectures have been frequently used as part of a system, tool, or methodological framework to forecast systems for supporting decision-making in hydropower production [15], [110], [163].

Hauswirth et al. [112] analyzed data-driven models to forecast hydrological extremes. They concluded that ML and other data-driven models have the potential to predict different hydrological variables. The best results for low and high-flow events were reached by Random Forest and LSTM models.

LSTM has also been used as a base model to contrast the performance of another hydrological forecasting model with effective hydropower production in reservoir management and scheduling [15], [109], [162], [163].

Regarding unorganized neural networks, we found the following applications for time-series forecasting in HGS: ESN was considered to forecast the monthly seasonal inflow series of a particular hydropower plant in Brazil [157]. In addition, Siqueira et al. [87] considered the ELM and ESN to forecast a hydropower plant's monthly seasonal inflow series in Brazil. PAR was used to contrast forecast results. The results indicated that unorganized neural networks outperformed the PAR model. In the same way, Belotti et al. [86] proposed a comparative analysis with different forecast models applied to a series of inflows of a hydropower plant in Brazil. The findings showed that, in most cases, ELM surpasses the linear models. Finally, ELM with a trend-guided [164] was used to forecast the monthly inflow time series of small HGS. This trend was extracted from the power curve and considered a new feature input for the ELM model.

4.7 Other Soft Computing methods

Soft Computing is a term defined by Lotfi Zadeh [165] to denote a sub-branch of AI focused on developing intelligent algorithms with tolerance to uncertainty and imprecision to cope with complex and changing environments. Soft Computing emerges at the intersection of many computational intelligence paradigms, such as ANN, evolutionary computation (EC), swarm intelligence (SI), artificial immune systems (AIS), and fuzzy systems (FS). As we have already reviewed, ANN are inspired by the biological neural system. Similarly, EC resembles natural evolution, SI is based on the social behavior of organisms living in colonies or swarms, AIS simulates the immune system, and FS formalizes human reasoning under imprecision [166].

4.7.1 Evolutionary computation

The EC mimics Darwin's natural evolution processes to solve computational optimization problems [167]. As Darwin's principle states that the fittest individuals are more likely to survive, EC promotes the development of reasonable solutions according to some metrics. More specifically, EC encourages the combination of good answers to generate better solutions (reproduction) and the random modification of solutions to obtain more diverse solutions (mutation). There are many evolutionary algorithms to solve real-world problems, to name a few: Genetic algorithms, Evolutionary programming, Genetic programming, Differential evolution, Evolution strategies, Cultural evolution, and Coevolution.

4.7.2 Swarm intelligence

The SI is a paradigm of computation intelligence that exploits the collective intelligence that emerges from the cooperation of many relatively simple agents. Examples of collective

intelligence are ant colonies, which inspire ant colony optimization algorithms, and bird flocks, which are at the foundation of particle swarm optimization algorithms. SI relies on three principles: loose communication between agents ---brief or indirect messages are exchanged in the swarm---, self-organization ---there is no central management of the swarm---, and division of labor ---no individual aims at solving the entire problem---, which results in higher flexibility and dynamism.

The following SI algorithms have been mainly developed and applied in the solution of real-world problems: particle swarm optimization (PSO), ant colony optimization (ACO), artificial bee colony (ABC) algorithm, and artificial cuckoo search (ACS) [167].

4.7.3 Fuzzy systems

Logical inference and if-then rules are based on binary logic, which cannot deal with uncertainty and imprecision [168]. However, human reasoning is hardly exact, and concepts and perceptions are uncertain (e.g., it is likely to rain) and imprecise (e.g., heavy rain). Fuzzy sets and fuzzy logic provide support for approximate reasoning under imprecision. In fuzzy sets, an element is part of a set to a certain degree, and fuzzy logic defines logical operators to reason, considering this vagueness.

The FS have been successfully applied in several domains and tasks. For instance, fuzzy controllers allow us to define imprecise control roles that are gradually activated depending on environmental conditions [169]. In addition, fuzzy ontologies have been used to model imprecise knowledge and check flexible data constraints [170].

4.7.4 Review of application studies on other Soft Computing methods

Evolutionary computing has been applied in several contexts of HGS and time series forecasting. Medina and Peña [95] proposed forecasting techniques for inflow time series for feasibility analysis of micropower plant production. Among these techniques, evolutionary algorithms were considered, such as genetic algorithms and gene expression programming. The results showed that EC and ANN achieve better forecasting performance than traditional statistical techniques. Genetic programming (GP) was applied by Wang et al. [118] in a comparative study to predict monthly discharge time series in hydropower systems. The results showed that GP was one of the algorithms that obtained the best forecasts. These authors also applied GP to long-term reservoir inflow time series forecasting [155]. The results were contrasted with the ANN model showing that the GP model produced more accurate predictions.

Regarding Swarm intelligence, the following three studies were identified. First, Nabipour et al. [159] proposed SI optimization algorithms, and the results indicated that PSO surpassed other optimization algorithms. Second, Buhan et al. [139] used PSO as part of river flow forecast and basin optimization system architecture. Specifically, PSO was applied in the basin optimization module for long-term energy maximization and short-term flood prevention. Finally, Liu et al. [171] proposed an improved PSO based on the Metropolis criterion, namely MPSO, to predict long-term inflow time series forecasting in reservoirs of hydroelectric systems.

Finally, regarding fuzzy systems, Huamaní et al. [172] proposed a method to forecast daily reservoir flow with a multi-step horizon using fuzzy inference systems (FIS) applied to Brazilian hydroelectric plants. The results indicated an adequate performance of the model. In the same way, Luna et al. [173] used a multi-step horizon considering FIS applied to daily inflow series. The findings showed improvement concerning a hydrological model named Soil Moisture Accounting Procedure (SMAP).

4.8 Hybrid models

Hybrid models originate from combining two or more methods described in the categories above. Usually, this hybridization results in more robust models which complement each other and improve the accuracy of HGS forecasts. Table 2 shows all hybrid models that have been identified in this review. We present the different techniques (OT) incorporated into each method to obtain a hybrid model.

Table 4.2 Hybrid models applied in HGS Time Series Forecasting

Ref.	Statistical + OT	ML + OT	DL+ OT	Other Soft Computing + OT
[97]	SD-LSSVR			
[99]				GA-SVR/GA-LSSVR/ PSO-LSSVR/SA-LSSVR
[117]			ELM-GA	
[118]			ANFIS	
[120]			ELM-GWO	
[140]	BI– MLP			
[142]	GM(1,1)-ANN			
[143]		SVM-CGA		
[150]			ANN-ABC	
[151]			MLP-Bat	
[154]			ANIFS	
[156]			MLP-ANFIS MLP-Fragment	
[158]			ANFIS	
[159]				GOA-ANN/SSA-ANN/ BBO-ANN/PSO-ANN
[160]		SVM-PSO		
[174]	WA-LSSVM			
[175]			ELM-MC	
[176]	AR-FIS			
[177]			MLP-BDL	
[178]			ANFIS	ANFIS-GWO

4.9 Findings and Discussion

This section summarizes and discusses the findings of our review of time series forecasting methods for HGS. The studies presented in the previous sections are summarized in Table 3. First, they are tabulated considering the technique applied. Next, problem formulation criteria are offered, such as the regressor and predictor variables in the experimental design. Then, the dataset of HGS in which the country, timespan, and data resolution are reported. Finally, the performance evaluation metrics of each case are displayed. Consequently, the main findings identified in the seven features shown in Table 3 are discussed.

4.9.1 Techniques

In each study considered in this review, the authors analyzed more than one technique for time series forecasting in HGS. Forty-four studies that used deep learning techniques were identified, accounting for about 60% of the investigations. In addition, statistical methods were used in 28 studies, regression, and machine learning techniques in 18, and other soft computing techniques in 8.

Deep learning models have been frequently used in HGS because they accurately forecast the dynamic, seasonal, and nonlinear aspects of hydroelectric power, inflow, precipitation, and other meteorological variables. MLP models were applied in 32 studies. MLPs are often used as a base model to compare more sophisticated techniques, methodological frameworks, tools, or systems with better-expected performance. In contrast, CNN models for time series were rarely used. Furthermore, RNN and unorganized neural networks were used in the remaining 12 studies that applied deep learning techniques. These models are more complex in structure, with fewer tools to work with, and more challenging to train. Also, they require much more data, which is

unusual for this application problem. Nevertheless, these models should be further explored and analyzed as done with FFNN models.

Classical statistical models for time series have shown significant maturity despite their limitations in capturing nonlinear relations between variables. We identified that ARIMA and its extensions, such as AR, PAR, ARMA, PARMA, and SARIMA, were the most used techniques. The review acknowledges that the incorporation of exogenous variables generally improved their performance. Accordingly, the second most used technique was ARIMAX. The Wavelet analysis ranked third, which exploits frequency-time dependences. Other techniques, such as Holt-Winters, Fourier spectral analysis, and Gray Model, have shown promising results but still need to be explored in this area.

The most used machine learning models not belonging to the neural network family were SVR. This version of SVM for regression performed well in various HGS forecasting tasks. RF and multiple linear regression were the second and third most used techniques. Only a few applications in Bayesian linear regressions and boosting ensemble learning were identified in this review.

Finally, among other soft computing models, the most used paradigms were EC and SI, followed by fuzzy systems. No studies were identified in which the Artificial Immune System paradigm was used. There are few studies in which other soft computing models have been applied individually. However, these models have been used in hybrid architectures, as seen in Table 2, with 20 studies in which hybrid approaches were proposed.

As mentioned at the beginning of this section, the authors applied more than one forecasting technique in most investigations and highlighted which one(s) achieved the best performance. A subsequent analysis, summarized in Table 3, allowed us to establish a ranking of the best techniques. Deep learning showed the best performance in 25 investigations, representing about 34% of the studies analyzed, i.e., these models outperformed other forecasting methods in 1 out of 3 studies. Hybrid models ranked second, performing better than other methods in 21 studies. Finally, the list is completed with regression, machine learning models found in 14 articles, statistical models in 13, and other soft computing models in 5.

4.9.2 Problem formulation

4.9.2.1 Number of input variables

According to Eq. (1), to determine the hydropower potential (P), the variables density, gravitational acceleration, hydraulic head, and efficiency can be approximated as constants. Therefore, the variable Q has a directly proportional role with P and generally is used in Eq. (1) to estimate hydroelectric production. Q is expressed in m^3/s and is referred to as inflow, stream-flow, and discharge. Changes can influence Q values in others, such as meteorological variables (rainfall, temperature, and humidity).

This review identified 42 studies in which only one regressor variable was used as input for the univariate case, i.e., about 58% of the total documents considered the time series problem as univariate and 42% as multivariate. As noted, primarily univariate time series problems applied in HGS forecasts are regarded due to the model´s lower complexity, configuration, and computational cost.

The regressor variables that were mainly used as input in both univariate and multivariate time series problems were inflow (44 studies), precipitation/rainfall (24 studies), hydropower generation/production (14 studies), and hydropower consumption (6 studies).

4.9.2.2 Prediction objective

In this review, 37 studies considered inflow as the target variable to predict. Besides, 18 studies directly addressed hydropower production as an objective, four were identified in the case of hydroelectric potential, and four focused on hydroelectric consumption. Therefore, more than 50% of the studies analyzed have considered inflow as the prediction objective due to the availability of inflow data continuously measured and collected in the hydrographic basins close to the hydroelectric plants.

4.9.3 Dataset

4.9.3.1 Country

In this work, forty-four countries where hydroelectric plants or hydrographic basins were considered to evaluate HGS production and potential. The countries with the largest number of studies were Brazil, China, and Malaysia, with 19, 18, and 4, respectively. These countries account for about 56% of the investigations reviewed.

This result is unsurprising since Brazil and China are leaders in their respective regions regarding installed hydropower capacity. Brazil leads in the South American area with an installed capacity of 109,271 MW, and in 2020 it was the most active country in the region after adding 213 MW of hydropower capacity. Furthermore, China leads in East Asia and the Pacific region with an installed hydropower capacity of 370,160 MW and a record installation of 13,760 MW in 2020 [11].

4.9.3.2 Timespan of dataset

In this review, some studies have considered the timespan of datasets from 1 up to 85 years. About 56% of the studies fall into the following year ranges. Twenty-one studies were identified using dataset lengths ranging from 1 to 10 years, eleven studies from 11 to 20 years, and nine from 21 to 30 years.

Furthermore, dataset length is significant for training forecast models. There is evidence of a dependency between the total number of samples and forecast errors. If the size of the dataset is reduced, the performance metrics of the model that was fitted during training will be lower [179]. This is confirmed in this review. The best forecast metrics were achieved with larger datasets, in which models with complex structures such as RNN and hybrids were analyzed.

4.9.3.3 Resolution of the data

The predictions can be analyzed on different time scales: short, medium, or long-term. Therefore, the data resolution of the dataset is essential to the needs of the electric operator.

In this review, the data resolution principally found was monthly in 37 articles, followed by the daily time step in 15 studies and yearly resolution cases in 10.

4.9.4 Performance evaluation

The RMSE was the most used evaluation metric in the investigations of this review. About 44% of the studies in Table 3 used RMSE as the performance evaluation metric. The MAPE was the second most used metric. The MAE ranked third, the NSE fourth, and R^2 fifth.

Table 4.3 Summary of research works applied to time series forecasting in HGS, along with the applied techniques and other relevant features.

Ref.	Technique	Problem formulation		Dataset			Evaluation metric
		Regressive variable	Prediction objective	Country	Timespan	Data resolution	
[15]	CL-RNN	Inflow/Temperature/Sale price	Hydropower Generation	China	2 years	Hourly	RMSE/MAE/MAPE
[139]	RFBOS	Water level/volume/ precipitation/evaporation	Inflow	Turkey	10 years	Daily	NSE
[85]	NECP	Hydropower generation	Density of the hydropower generation	Spain	5 years	Hourly	RMSE
[86]	PAR/AR/ELM	Inflow	Inflow	Brazil	85 years	Monthly	MSE/MAE/CC/NSE
[87]	ELM/ESN/PAR	Inflow	Inflow	Brazil	80 years	Monthly	MSE/MAE
[88]	VAR	Hydroelectricity consumption	---	Malaysia	46 years	Yearly	---
[89]	NSRBN/PARMA	Inflow	Inflow	Brazil	67 years	Weekly	MAPE
[90]	PARMA/NSRBN	Inflow	Inflow	Brazil	67 years	Monthly	MAPE/RMSE/TheilU
[91]	NSRBN/PARMA	Inflow	Inflow	Brazil	68 years	Monthly	MAPE/RMSE
[92]	Holt-Winters/ARIMA	hydropower generation	Hydropower generation	China	10 years	Monthly	MAPE
[93]	ARIMA	Hydropower production	Hydropower production	Vietnam	4 years	Monthly	MAPE/R^2/BIC
[94]	ARIMA	Temperature/Humidity/ Rainfall	Energy production	Malaysia	6 years	Monthly	CC
[95]	ARIMA/ANN/EC	Inflow	Inflow	Mexico	35 years	Monthly	---
[96]	ARIMA/SARIMA	Hydroelectric generation/ Precipitation	Hydroelectric generation	Ecuador	16 years	Monthly	MAPE/R^2/AIC/BIC
[79]	ARIMA/ ARIMAX	Hydroelectric generation/ Precipitation	Hydroelectric generation	Ecuador	16 years	Monthly	MAE/MAPE/MASE
[97]	SD/SVR/LSSVR/ SD-LSSVR ensemble learning model	Hydropower consumption	Hydropower consumption	China	25 years	Monthly	MAPE/RMSE/Dstat
[98]	ARIMA	Hydroelectric consumption	Hydroelectric consumption	Pakistan	53 years	Yearly	R^2/SBIC/AIC
[99]	GA-LSSVR	Hydropower energy consumption	Hydropower energy consumption	China	13 years and 7 months	Monthly	RMSE/MAPE/Dstat
[106]	Regression models/ANN	Rainfall/evapotranspiration /mean topographical slope/irrigated surface area/theoretical irrigation requirements	energy recovery potential	Spain	177 locations	Yearly	CC/MAE
[107]	LR	Inflow	Inflow	Brazil	84 years	Monthly	R^2
[108]	RF/regression model via MLI	Precipitations/Temperature / Soil moisture/SPEI index	Total installed capacity operating/ Predicting the water/Discharge	Malawi		Daily	R^2

[109]	MLR/KNN/SVR/RF/ LSTM	Temperature/rainfall/ electricity generation/ level of water/Irrigation indent/inflow /Discharge	Energy production	Pakistan	7 years	Monthly	MAE/RMSE
[110]	SVR/ Gaussian processes/ LSTM/NARNN/NARX/DLNN	Precipitation/Snowfall/Temperature/Streamflow of rivers/Data on water volumes	Inflow	Colombia	28 years	Monthly	RMSE/NSE
[111]	bestglm/PCR/PLSR	Inflow	Inflow	India	27 years	Monthly	AIC/BIC
[112]	Multilinear regression/ Lasso Regression/ DT/RF/LSTM	meteorological and hydrological variables	Discharge/ surface water level/surface water temperature/ groundwater levels	The Netherlands	40 years	Daily/ weekly	CC/nRMSE/ KGE
[114]	RF	Inflow/temperature/ precipitation/snow depth	Hydropower generation	Twelve European countries	---	Daily	nMAE
[115]	Multi-method ensemble	Water supplies/Inflow	Seasonal Water Availability	EEUU	30 years	Monthly	RMSE/AIC
[116]	BDTR/DFR/BLR/ NNR	Rainfall/water level/sent out	Water level of a reservoir	Malaysia	34 years	Daily	RMSE/MAE/RSE/R^2
[117]	ELM-GA	Inflow/Humidity/Rainfall/ Evaporation	Inflow	Mozambique	15 years	Daily	R^2/RMSE/MAPE/NSE /KGE
[118]	ARMA/ANN/ANFIS/GP/ SVM	Inflow	Inflow	China	52 years	Monthly	CC/R2/NSE/RMSE/ MAPE/AIC
[119]	SVM/ WA	Inflow/Temperature/ Precipitation	Inflow	Italy	6 years	Daily	NSE/MAE/MAPE/ RMSE/RSR
[120]	ELM/GWO/ELM-GWO	Inflow	Inflow	China	126 years	Monthly	CC/NSE/RMSE/MAP E
[121]	Thomas–Fiering model	Inflow	Inflow	Irak	2 years and 6 months	Monthly	CC
[136]	AR/ARMA/MLP/RBF/ELM/ESN/ Elman/Jordan/ Ensemble	Inflow	Inflow	Brazil	85 years	Monthly	MSE
[140]	BI-MLP	Inflow	Inflow	Brazil	75 years	Monthly	MAPE/BIC
[141]	1D-CNN	Inflow/water turbidity	Inflow	Brazil	8 years	daily	MSE/MAPE/NMRSE/ R^2/NSE
[142]	GM(1,1)/ANN/GM(1,1)-ANN	Population/GDP/Energy demand	Energy consumption	China	20 years	Yearly	PRE
[143]	ANN/SVM-CGA	Inflow	Inflow	China	32 years	Yearly	RMSE/PRE
[144]	ANN	Precipitation	Inflow	Indonesia	12 years	Monthly	CC
[145]	MLP	Inflow/Precipitation	Inflow	Slovenia	1 year	15 min	---
[146]	MLP	Inflow	Inflow	Philippines	3 years	Monthly	RMSE/MAE/MAPE
[147]	MI/ANN	Inflow/Precipitation	Inflow	Slovenia	< 2years	Hourly	---
[148]	ANN	Inflow/Precipitation	Inflow	Slovenia	---	Hourly/ 15 min	PRE
[80]	MLP/LSTM/sequence-to-sequence LSTM	Hydroelectric generation/ Precipitation	Hydroelectric generation	Ecuador	16 years	Monthly	MAE/MAPE/MASE
[149]	GMDH/MLP	Precipitation	Hydropower Potential	Brazil	40 years	Daily	CC/MAE/MAPE

[150]	ANN/ABC/ANN-ABC	Gross electricity energy demand/Energy consumption/Population/ Temperature	Hydroelectric generation	Turkey	32 years	Yearly	RE
[151]	ANN/ANN-BA	Hydropower generation	Hydropower generation	Malaysia	3 years	Monthly	RMSE/MAE/MAPE
[152]	ANN	electric energy generation	electric energy generation	Brazil	2 years and 11 months	Monthly	PRE
[153]	MLP with Levemberg-Marquardt algorithm/SMAP	Inflow	Precipitation	Brazil	29 years	Monthly	NSE/MAPE/RMSE/ MAE
[154]	ANFIS/MLP	Inflow	Inflow	Brazil	60 years	Monthly	MSE/MAD/MRE
[155]	ANN/GP	Inflow	Inflow	China	50 years	Monthly	RMSE/CC
[156]	ANN/ANN-ANFIS/ANN-FRAGMENT	Inflow	Inflow	Brazil	78 years	Monthly	MAPE
[157]	ESN/MLP	Inflow	Inflow	Brazil	60 years	Monthly	MSE/MAE/MAPE
[158]	ANN/ANFIS	Inflow	Inflow	China	23 years	Yearly	PRE
[159]	GOA/SSA/BBO/PSO/ Hybridized models with ANN	Precipitation/discharge	hydrological drought	Iran	54 years	Monthly	R2/RAE/MAE/RMSE/ d/CI/NSE
[160]	ANN/SVM-PSO	Inflow	Inflow	China	23 years	Yearly	RMSE/PRE
[161]	FNN/Simple RNN/LSTM/GRU/Bi-LSTM	Inflow	Inflow	Turkey	7 years	Daily	CC/MAE/RMSE/NSE
[162]	SMAP/DNN(Conv3D-LSTM)/ SMAP-DNN	Precipitation/Evapotranspiration/ inflow	Inflow	Brazil	5 years	Daily	MAE/MAPE/NSE/ RMSE/CC
[163]	HGDNN	Hydropower generation	Hydropower generation	China	1 year	Hourly	RMSE/MAE/MAPE
[164]	TG-ELM	Power generation	Power generation	China	---	Hourly	MAE/RMSE
[171]	MLRM/ MPSO	Inflow	Inflow	China	23 years	Yearly	PRE
[172]	FIS/EM algorithm	Rainfall/Inflow	Inflow	Brazil	3 years	Daily	RMSE/MAPE/MAE/E
[173]	Evolving fuzzy models and a bottom-up approach	Inflow/Precipitation	Inflow	Brazil	2 years	Daily	RMSE/MAPE/MAE/E
[174]	WA/LSSVR/WA-LSSVR	Peak-peak value (PPV) - hydroturbine generating unit	Peak-peak value (ppv) - hydroturbine generating unit	China	---	---	RMSE/MAPE
[176]	AR-FIS	Precipitation	Precipitation	Indonesia	11 years	Monthly	MAPE
[177]	ANN-BDL	Water supply volume	Water supply volume	China	22 years	Yearly	MRE
[178]	ANFIS/GWO/ANFIS-GWO	Hydropower generation/Inflow/ Precipitation	Hydropower generation	Iran	54 years	Monthly	CI/RMSE/NSE/R^2/d/RE/MAE
[180]	GM(1,1)/ SARIMA,/DGGM (1,1)	hydropower production	hydropower production	China	16 years	Quarterly	RMSE/MAE/MAPE/ TheilU
[181]	SAA/GRU	Electricity price/Inflow	Electricity price/Inflow	Sweden	20 years	Daily	Seasonal variation-confidence intervals
[182]	Hydroelectric hierarchy network	Inflow	Inflow	Iceland	51 years	Weekly	---

[183]	WAR	Inflow	NAE	Brazil	84 years	Monthly	MLE
[184]	ELM/MC-ELM	Water storage/Inflow/ Inventory water/Reservoir level/Average water/Consumption for electricity generation	Power generation	China	3 years and 5 months	Monthly	MRE/RMSE
[185]	Water-energy nexus indicators/ temporal analysis	hydro-energy generation/ water pumping	Hydroelectric generation/ Water pumping	Sudan	33 years	Daily	R^2/NSE/MPE

4.10 Conclusion and future directions

This work comprehensively reviews techniques applied to time series forecasting in hydropower generation systems. This is a relevant problem in the context of renewable energies since it is vital to anticipate the energy production of these systems for the energy operator's decision-making. The review is structured in four main areas focused on the last decade's statistical approaches, machine learning (not including neural networks), deep learning, and other soft computing techniques. Also, hybrid approaches have been identified in literature.

The studies reviewed identified artificial neural networks and hybrid models as the most used and best-performing techniques. However, we also discovered that most investigations applied relatively simple feedforward architectures, leaving room for convolutional and recurrent neural network research. Given the size and length of the existing datasets, this absence is justified since the latter techniques perform better with more extensive data.

Statistical techniques are traditionally applied to solve linear problems and perform well. However, due to their non-linearity limitation, they are widely used as a base model to validate the performance metrics of other data mining approaches, such as artificial neural networks and hybrid models, whose accuracy exceeds classical linear modeling. Moreover, it is suggested that future studies consider the advantages of ensemble learning (EL) models since the few studies found in this review showed good performance metrics compared to other approaches. Also, EL models can be suitable for cases with a dataset with few samples.

The hybrid models mainly applied in time series forecasts have deep learning models and another soft computing modeling as their main composition. MLP and ELM (both FFNN types) are often implemented with evolutionary computation paradigms, swarm intelligence, and fuzzy systems. Few hybridizations have been applied between machine learning and other approach models. Therefore, Table 2 can be considered to explore further hybridizations between the four data-driven techniques to forecast HGS.

Brazil and China are the countries where most case studies were found. However, given the increment of the installed hydroelectric capacity expected worldwide in the coming years, we encourage authors and authorities to promote additional research in other scenarios to improve decision-making.

Over half of the reviewed case studies considered a timespan dataset ranging from 1 to 30 years. Moreover, within this interval, more than half fell in the gap between 1 and 10 years. However, for those cases in which there are fewer samples in the dataset, the impact of applying super-resolution techniques to increase the granularity of the datasets in the performance of deep learning and hybrid models could be studied.

The review revealed that univariate formulations of the prediction problem are prevalent because of their simplicity and relatively good results. However, incorporating additional regressor variables generally improved the performance of the models. Therefore, it is recommended that more future studies address multivariate time series problems with larger samples in the datasets. Massive data collection using Big Data and Internet of Things (IoT) technologies can be considered.

Regarding evaluation metrics, the most used ones to validate the accuracy of the models were RMSE and MAPE. Human operators more easily interpret these two metrics than others, like *logloss*, which explains their popularity. Testing other metrics for model training (e.g., as loss function in neural networks) and model selection remains open for future research.

Finally, a monthly resolution is the time-step-ahead prediction most frequently considered in the literature. While this depends on the forecasting problem to resolve, we expect research to consider more variable prediction horizons with the advent of smart grids operated in real-time.

Capítulo 5

5 Time Series Analysis for Predicting Hydroelectric Power Production: the Ecuador case

J. Barzola-Monteses, M. Mite-León, M. Espinoza-Andaluz, J. Gómez-Romero, and W. Fajardo, "Time Series Analysis for Predicting Hydroelectric Power Production: The Ecuador Case," Sustainability, vol. 11, no. 23, p. 6539, Nov. 2019, doi: 10.3390/su11236539.

Electrical generation in Ecuador mainly comes from hydroelectric and thermo-fossil sources, with the former amounting to almost half of the national production. Even though hydroelectric power sources are highly stable, there is a threat of droughts and floods affecting Ecuadorian water reservoirs and producing electrical faults, as it happened in 2009. Therefore, predicting the behavior of the hydroelectric system is crucial to develop appropriate planning strategies and a good starting point for energy policy decisions. In this paper, we develop a time series predictive model of hydroelectric power production in Ecuador. To this aim, we use production and precipitation data from 2000 to 2015 and compare the Box-Jenkins (ARIMA) and the Box-Tiao (ARIMAX) regression methods. The results show that the best model is the ARIMAX (1,1,1)(1,0,0)12, which considers an exogenous variable precipitation in the Napo River basin and can accurately predict monthly production values up to a year in advance. This model can provide valuable insights to Ecuadorian energy managers and policy-makers.

5.1 Introduction

Between 1973 and 2016, the world gross electricity production increased from 6,298 TWh to 25,082 TWh, an average annual growth rate of 3.3% [186], [187]. In 1973, fossil sources generated 75.2% of electric power, while in 2016 they accounted for 65.3% of the production. While the proportion of fossil fuels has decreased during this period, the absolute figures are very high due to the rising world population and per capita energy consumption. As a matter of fact, the amount of CO_2 emissions almost doubled, from 15,460 to 32,316 Mt. Hence, several proposals have recently emerged to incorporate CO_2 reduction criteria to coal/biomass combustion systems [188], [189], [190]. Complementarily, the role of green sources in the energy mix has gained relevance in the last decades.

Ecuador is located in a privileged zone with a huge potential in renewable energies: sunbeams fall almost perpendicular, rainfalls are abundant, and the Andes mountains provide large hydroelectric, geothermal and wind resources [191], [192]. However, several impactful events occurred at the end of the last century prevented proper exploitation of such resources. Economic events, such as the beginning of oil extraction in 1972, the debt crisis in 1982, and natural disasters such as El Niño (1983, 1987 and 1998) and earthquakes (1987, 1995 and 1998) have caused a discontinuous and insufficient development and deployment of renewable energy systems in Ecuador [193].

This situation has been partially reverted in the last decades since large hydroelectric projects have been introduced as a key element of the national development plan. Hydropower offers multiple advantages against other energy sources in Ecuador, since it is cheaper and cleaner, despite the initial investment that it requires [194]. Carvajal et al. [195] showed that Ecuador's energy policy in the period 2007-2017 incentivized a doubling of its hydropower capacity.

However, as shown in Figure 1 shows, the share of production originated by hydroelectric systems has declined from 1990 to 2015: in 1990, 79% of the total energy production came from hydroelectric sources, while for 2015 it was only 49%. This was caused by a misalignment between infrastructure development and exploitation policies, resulting in an increase of the use of fossil fuels despite their social, economic and environmental costs. Given the considerable potential of Ecuadorian basins and the large hydropower capacity installed, there is a common consensus that the decreasing contribution of hydroelectric production should be reversed [196].

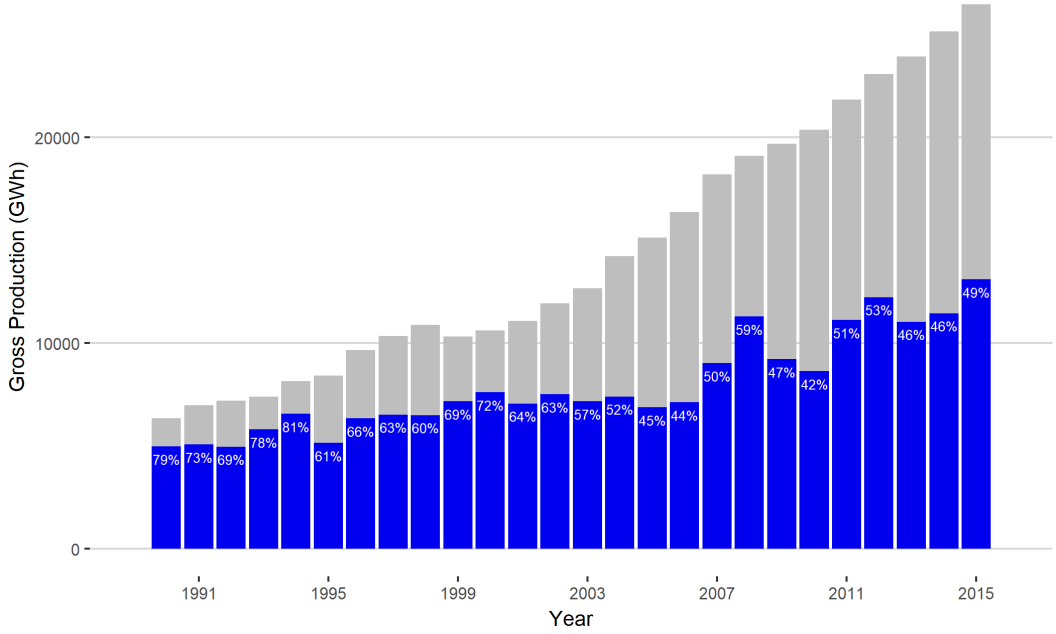

Figure 5.1 Annual development of Ecuador's electricity total generation. Blue bars represent the annual hydroelectric production with respect to the total generation.

Hence, Ecuador is currently implementing the National Master Plan for Electrification 2016-2025, which aims at covering more than 90% of the national electrical demand with hydroelectric sources [197]. The plan is already having an impact in Ecuador's energy production capability [198]. Ecuador ranked third in the global list of countries that added more energy capacity in 2016, only after China and Brazil [199]. By the end of that year, the installed hydroelectric capacity in Ecuador (4400 MW) represented 58% of the total capacity (7587 MW). Generation from hydroelectric systems in 2016 amounted to 57.9% (15814.72 GWh) of the total production (27313.86 GWh). In 2017, the installed capacity of the Ecuadorian electrical system increased to 8036 MW [200]. This year Ecuador achieved energy sovereignty for the first time; i.e., the electricity production satisfied the national electricity demand and even 210 GWh were exported. Despite this fact, the maximum demand used only 47% of the produced electricity, i.e., 53% of the energy that can be generated is not used [201], [202]. In consequence, the management and planning of energy in Ecuador has room for improvement.

Energy production forecasts are of great importance to the operators of the electrical system (to optimize the processes) and the decision-makers (to define better policies and manage risks) . Besides, energy prices can be established considering the estimated future load demand. Therefore, it is crucial for an optimized energy system to accurately model the energy production and the energy demand to offer solutions at different society levels [203].

The objective of this research work is to develop and apply forecasting models for predicting hydroelectric production in Ecuador from historical data. We focus on statistical time series

analysis techniques, which have been successfully applied in the literature [178], [204]. Since hydropower strongly depends on the meteorological conditions, rainfall data will play a key role in our study. This data is easier to obtain than inflow, which was not available for the study. To the best of our knowledge, there is no similar study in the literature focused on the Ecuador case.

The contribution of this paper is twofold. First, we describe a methodology to model the production of hydroelectric plants through time series with the ARIMA univariate and ARIMAX bivariate approaches. Then, we apply this methodology to build and compare models for predicting production in Ecuador. Through this model, the correlation between hydroelectric generation and precipitation is demonstrated and quantified. Furthermore, we show that an ARIMAX model considering an exogenous variable (precipitation in one of the larger basins) can accurately predict monthly production values up to a year in advance. That implies that we do not need very elaborated data to obtain a reliable prediction model. At the same time, we improve the results obtained in a previous work only considering ARIMA [96]. Accordingly, the methodology can be used to develop planning strategies in the energy sector in Ecuador. The applicability of the approach to other countries remains as future work.

The rest of the paper is organized as follow. Section 2 explains the methodology used in this work and Section 3 describes the data. Section 4 shows the experiments and a discussion of the results. Finally, Section 5 includes some concluding remarks and directions for future work.

5.2 Methods

5.2.1 Box - Jenkins and Box - Tiao methods

Time series analysis comprises a wide collection of techniques for analyzing historical temporal data in order to extract meaningful features or characteristics of the data. A forecast model encodes a function that estimates the value of a prediction variable in the future from historical and other relevant data [75]. This prediction variable is usually also used in the input. In our case, the input and the prediction variable is energy production; the additional variable is precipitation.

The accuracy of the model is measured as the difference between the predicted and the actual values. Learning a forecast model means fitting the model parameters to minimize this difference for a given dataset for which the input and the target values are known. It is expected that a forecast model will perform well with values outside the learning dataset. For more details about time series analysis methods, we refer the reader to [205].

In the literature we can find several methods to build forecast models from data. Among them, autoregressive models based on moving averages have proved effective in several problems [76]. We can find applications of autoregressive models to predict renewable energy (wind, solar, hydro) production and demand [206], [207], [208], [209], [210], [211], [212], [213], [214].

Autoregressive models assume that observations are correlated through lagged linear relations and capture this correlation into the model. These models assume that the time series are stationary –i.e. the statistical properties, such as the mean, variance, and autocorrelation, are constant over time.

An autoregressive model of order p AR(p) is of the form:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t \quad (1)$$

where: Y_t is the value of the prediction variable at time t (energy production, in this case), ε_t is a random variable with mean 0 and variance σ^2_w (white noise), and ϕ_l are the parameters of the

models (constants). If we define the backshift operator B as $B_{Yt} = Y_{t-1}$ (and recursively, $B^k{}_{Yt} = Y_{t-k}$), the equation can be rewritten as:

$$\varepsilon_t = (1 - \phi_1 B - \phi_2 B^{2} - \cdots - \phi_p B^p)\, Y_t = \phi_p(B)\, Y_t \quad (2)$$

The Box-Jenkins method identifies, adjusts and checks a prediction model by using an autoregressive integrated moving average (ARIMA) [82]. Box-Jenkins estimates the parameters of the model by applying the maximum likelihood. The model is formulated as follows:

$$\phi_p(B)(1-B)^d Y_t = \phi_0 + \theta_q(B)\varepsilon_t \quad (3)$$

where: $\phi_p(B)$ is the autoregressive polynomial of order p, B is the backshift operator, Y_t is the forecast variable which represents a white noise process with normal distribution $N(0,\sigma^2)$, d is the d^{th} difference operator, ϕ_0 is a numerical constant, $\theta_q(B)$ is the regular moving average (MA) polynomial of order q and ε_t is the error of the model. These parameters (p, d, q) characterize the ARIMA model, and must be identified a priori by analyzing the stationarity of the time series.

If the stationarity (S) is strong, ARIMA is extended to have two components: (1) one with regular structure ARIMA (p,d,q) that models the non-independence associated with the data, and (2) one with ARIMA structure (P,D,Q) that models the seasonality component. In this latter model, P is the autoregressive seasonal term, D is the seasonal term of difference, and Q corresponds to the seasonal term of moving average. A SARIMA model is formalized as follows:

$$\phi_p(B)\Phi_P(B^s)(1 - B^s)^D(1- B)^d\, Y_t = \phi_0 + \theta_q(B)\, \Theta_Q(B^s)\varepsilon_t \quad (4)$$

where: $\Phi_P(B^s)$ is the autoregressive polynomial of order p with seasonality, $\Theta_Q(B^s)$ is the regular moving average (MA) polynomial of order q with seasonality, D is the d^{th} differential operator with seasonality, and B is the backshift operator with seasonality.

The Box-Tiao method extends Box-Jenkins by incorporating the observations of the covariates, also called explanatory or exogenous variables X (ARIMAX). The ARIMAX model is described mathematically as follows:

$$\phi_p(B)(1- B)^d Y_t = \phi_0 + \Theta(B)X_t + \theta_q(B)\varepsilon_t \quad (5)$$

The difference with respect to Eq. (3) is the term $\Theta(B)X_t$ is the observed one while $\Theta(B)$ is the polynomial operator of the exogenous variable X_t.

5.3 Time series analysis process

In order to obtain the ARIMA and the ARIMAX models, we have followed the methodology depicted in Figure 2. First, the time series are transformed to comply with the requirement that they must be stationary. Once the series are stationary, the parameters of the series are estimated through correlogram functions, which are associated with statistical tests. Afterwards, different models are estimated to select the one that best fits the training data. The model is validated through residue analysis and hypothesis testing. Then, the model is tested with additional unseen data to calculate prediction accuracy. These steps are described in the following sub-sections.

5.3.1 Series transformation

The assumption of stationarity must be verified before the identification of a suitable model. A time series can be considered stationary if the mean and variance are constant, and if there are no significant trends and seasonal variations. Usually, logarithm and derivative operations are applied to eliminate the variability and decrease the trend, respectively [81], [205].

5.3.2 Stationary evaluation

The single autocorrelation function (ACF) and partial autocorrelation function (PACF) are correlogram functions to determine the degree of correlation between two consecutive values of the series. ACF and PACF provide an estimation of the p and q values of the ARIMA models [215], [216].

First, the single ACF and PACF functions of the transformed series are calculated and plotted. These functions are useful for diagnosing the p, d, q components of the ARIMA models.

The ACF of order k (k > 0) of a stationary process (Y_t) measures the information that an observation of a period transmits directly to the observation k periods ahead, i.e., $(Y_1, Y_{1+k}), (Y_2, Y_{2+k}), \dots (Y_{n-k}, Y_n)$. It is presented with the following equation:

$$\rho_k \equiv \frac{cov[Y_t, Y_{t+k}]}{Var[Y_t]^{1/2}\ Var[Y_{t+k}]^{1/2}} \equiv \frac{\gamma_k}{\gamma_o} \qquad (k = 1,2, \dots) \tag{6}$$

where: γ_k is the self-covariance of order k. γ_o is the zero order self-covariance of a strictly stationary process, and, $\gamma_o \equiv cov[Y_t, Y_t] \equiv var[Y_t]$.

The PACF measures the information that an observation of a period transmits directly to the observation k periods ahead, eliminating the information $Y_{t-1}, \dots Y_{t-k+1}$ that both contain.

The PACF is denoted by ϕ_{kk}, for k = 1,2, ...; and, represented with the following equations:

$$\phi_{11} = corr([Y_{t+1}, Y_t] \equiv \rho_1 \tag{7}$$

$$\emptyset_{kk} \equiv corr\left(Y_{t+k} - \hat{Y}_{t+k}, Y_t - \hat{Y}_t\right), \quad k \geq 2 \tag{8}$$

The first-order autocorrelation is formally tested with the Durbin-Watson statistic test [217], which measures the linear association between adjacent residuals. The null hypothesis for this case is that the series presents autocorrelation.

Second, the Augmented Dickey Fuller (ADF) test or called unit root test is used to test the stationarity properties of the series [218], [219].

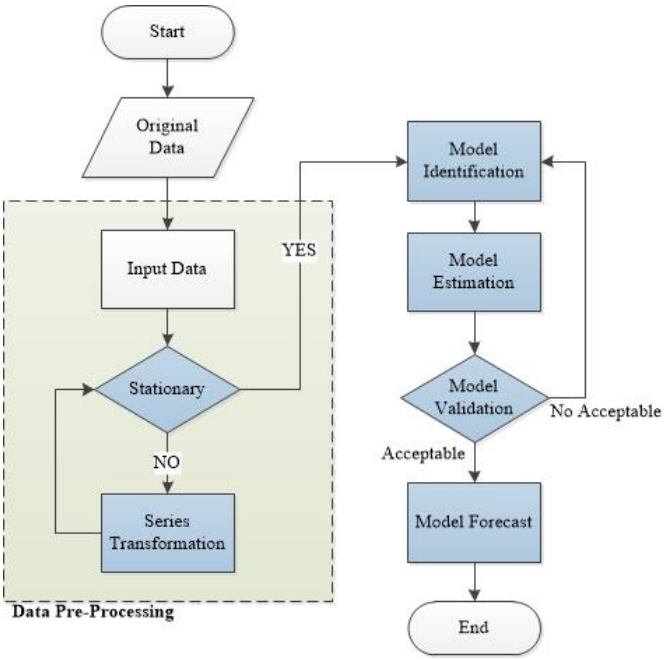

Figure 5.2 Flow chart of the time series analysis methodology.

5.3.3 Model identification

Once the parameters (p, d, q) and (P, D, Q) are identified in previous stages, Auto- Regressive (AR), Moving Average (MA), Seasonal Auto-Regressive (SAR) and eXogenous Regressive (XREG) models are determined. The equations (3), (4) and (5) are used to identify the model that best fits each series.

5.3.4 Model estimation

After models are designed and implemented, the best model is selected considering penalized likelihood criteria, such as Akaike information criterion (AIC) and Bayesian information criterion (BIC) [220]. The AIC and BIC are used here to compare of models' performance [205]. The AIC and BIC are described mathematically as follows:

$$AIC = log\ \hat{\sigma}_k^2 + \frac{n + 2k}{n} \tag{9}$$

$$BIC = log\ \hat{\sigma}_k^2 + \frac{k\ log\ n}{n} \tag{10}$$

where: $\hat{\sigma}_k^2$ is the maximum likelihood estimate of variance, n is the number of dates, and, k is the number of parameters of the model.

The BIC strongly penalizes the number of involved parameters. High values of AIC mean that the observed data does not fit the models, while lower values indicate strong evidence that the observed data fit the models. Similarly, lower values of BIC indicate better fitting of the models.

5.3.5 Model validation

In order to evaluate the prediction accuracy of the models of the Box-Jenkins and Box-Tiao, a residual analysis is performed. Before that, a first plot is done to analyze if there are atypical errors, which indicates the need of an intervention.

In order to ARIMA and ARIMAX models be viable for the adjustments of the observed data, the error term ε_t in equations (1), (2) and (3) should behave as white noise –i.e. zero mean, a constant variance and no correlation. In addition, the term ε_t must follow a normal distribution. To check these assumptions, statistical tests should be applied to the residuals, as in [205], [207].

The most widely-used model is the Box-Ljung test [215], with the null hypothesis being that the series is uncorrelated. Accordingly, a Box-Ljung test is applied to the (squared) residuals to verify that the variance is constant. Afterwards, the Jarque-Bera test [221] is applied to verify that the residuals are normal. In our experiments, these tests were applied to the significance level of α=0.05.

5.3.6 Model forecast

Once the ARIMA and ARIMAX models have been validated, future time series values can be forecasted. In our case, energy production was forecasted for a 12 months horizon, corresponding to the year 2015, with a typical 95% confidence interval (CI) [75].

5.3.7 Measures of accuracy

In order to evaluate the quality of forecasted data of the proposed models, statistical analysis of errors is used. Three typical standards were selected in this research work: MAE, MAPE and MASE.

The mean absolute error (MAE) represents the average error value between the observed and the adjusted series. The MAE is described mathematically as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|v_{adj} - v_{obs}\right| \tag{11}$$

where v_{adj} represents the individual value of the forecasted time series, and v_{obs} corresponds to the individual value of the observed time series, and n is the order of the series. In this study, the MAE is measured in gigawatt hours (GWh) since the predicted variable is hydroelectric production.

The mean absolute percentage error (MAPE) is another statistical parameter considered in this study. The advantage of using this parameter is that it uses percentages (%) to show the data, which allows an easy and quick evaluation of the predicted model [211]. The MAPE is described mathematically as follows:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{v_{adj} - v_{obs}}{v_{obs}}\right| \times 100 \tag{12}$$

Finally, the mean absolute scaled error (MASE) is considered in the analysis. This type of error is independent of the data. Lower values of scaled error (q_t) result in better forecasts [222], [223]. The MASE is described mathematically as follows:

$$q_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n}|Y_i - Y_{i-1}|} \tag{13}$$

$$\mathrm{MASE} = \mathrm{mean}(|q_t|). \tag{14}$$

where e_t represents the error between adjusted and observed values.

5.4 Data

Data for the current study, corresponding to the 2000-2015 period, have been obtained from official and governmental institutions of Ecuador; namely, the Electricity Regulation and Control Agency (ARCONEL) [196] and the National Institute of Meteorology and Hydrology (INAMHI) [224]. The modeling analysis considers the period from 2000 to 2014, and 2015 data have been used to validate the predictivity of the model.

In this section, we present information about the Ecuadorian hydroelectric system, the country's hydrographic basins, the regions and the dataset used in this work, and the time series used to build the models.

5.4.1 Ecuadorian hydroelectric system

The hydroelectric system in Ecuador is concentrated in a relatively small group of stations. In 2016, the 13 largest power stations provided 89.57% of the total hydroelectric generation. Table 1 shows in detail the contributions of hydroelectric generation grouped by management company and geographical region of watersheds.

Coca Codo Sinclair is the largest hydroelectric power plant in the country. In the next years, this plant is expected to have 1500 MW of power and satisfy 35% of the country demand. The socio-economic and environmental impacts of this project have been largely studied [225], [226], [227], but its management and planning has received less attention.

5.4.2 Rainfall and watersheds in Ecuador

The estimated water potential, at the level of river basins and sub-basins, is about 15000 m^3/s distributed on the Ecuadorian continental surface. Its potential is geographically distributed in two regions: Amazon (east) and Pacific (west), with a flow capacity of 71% and 29%, respectively, according to the National Water Resources Council (CNRH) [228]. Twenty-four watersheds are inside the Pacific area, and seven watersheds are inside the Amazon area. The area of the latter is 131,726 km^2, which corresponds to 51% of the country's hydrographic system.

In Ecuador, the following values of the hydroelectric potential have been identified: i) Medium theoretical hydroelectric potential, with an estimated average monthly flow of 91000 MW, ii) Technically feasible potential: 31000 MW (in 11 watersheds), and iii) Economically feasible potential: 22000 MW (in 11 watersheds). Currently, Ecuador has used 24.55% of the economically feasible potential, i.e., 5401 MW [197].

Table 5.1 Electric production of the country's 13 largest hydropower stations during 2016

Electric company	Hydropower station	Watershed	Production [GWh]	Percentage of Total production [%]
CELEC [229] – Hidropaute [230]	Mazar Molino Sopladora	Santiago	6851.61	43.32
CELEC – Coca Codo Sinclair [231]	Quijos Manduriacu Coca Codo Sinclair	Napo	3264.01	20.64
CELEC – Hidroagoyán [232]	Agoyán Pucará San Francisco	Pastaza	2413.73	15.26
CELEC – Hidronación [233]	Baba	Guayas	1209.89	7.65
Elecaustro [234]	Ocaña 1 Machángara Saucay	Santiago	427.99	2.71

TOTAL	**89.58**

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5.4.3 Regions of study and dataset

Evidently, water is the main resource to produce power hydroelectric. Therefore, water inflow is a good predictor of hydroelectric performance [96], [178]. In this study, we use precipitation data as a proxy for hydropower stations water inflow. Precipitation data are relevant because the regions of the study have a considerable rainfall variability, since they are located within a region with warm-humid climate [235]. Besides, precipitation data are typically used in weather derivatives [236] –financial instruments that are linked to cover the effects of adverse or unexpected weather conditions–, and consequently they are a usual input to decision-makers.

Note that the precipitation value is not an estimation of the inflow, but a potential predictor. In the literature, we can find other works using streamflow data collected from sensors installed in the reservoirs [237], [238]. Such approaches provide more accurate water inflow estimations but are also more costly to implement at a larger scale. At the time of this study, these data were not available in Ecuador. An alternative to consider in the future is to use stochastic models to generate this data[239], [240].

We consider precipitation data from the three main Amazon watersheds, namely:

- Napo, with an area of 59505 km^2 fed by 15 rivers.
- Pastaza, with an area of 23190 km^2 fed by 11 rivers.
- Santiago with an area 24920 km^2 fed by 4 rivers.

The three basins add up an area of 107,615 km^2, which represent about 82% of the Amazon hydrological system and 42% of the country's total. They contain the 12 largest hydroelectric stations, generating about 82% of the hydropower production, as shown in Table 1.

Following the aim of the paper, we want to improve production forecasts by considering a minimum but significant amount of additional data; i.e. precipitation data. Precipitation data corresponding to the period 2000-2015 were obtained from pluviometric stations (PS) located inside the basins and managed by the INAMHI: Napo (13 PS), Pastaza (27 PS) and Santiago (28 PS). Figure 3 shows the geographical location of each PS inside their corresponding watersheds.

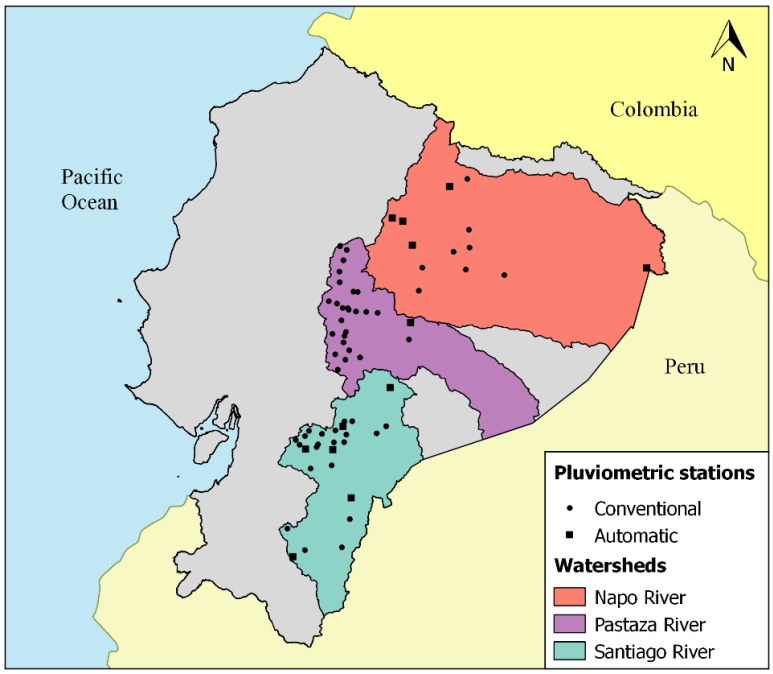


Figure 5.3 Geographical location of conventional and automatic pluviometric stations.

The source data included a single data point per station and month, representing the total rainfall measured by the station in the month. To obtain a single value per basin and month, we averaged these values for each basin. In this way, we have a single value for each basin representing a rough approximation of the expected monthly rainfall at any randomly selected point inside the basin. Furthermore, we assumed that basins are independent, and we thus aggregated the three-monthly values to obtain the overall rainfall that can be potentially used to produce energy. Certainly, this entails a considerable simplification of the problem, and other aggregation methods could be considered.

Figure 4 shows the water shortage that normally occurs on the Amazon region from October to March [241]. The aggregated expected rainfall in the Napo, Pastaza and Santiago basins is represented by the blue bar chart. The average of the total precipitation during these two years was 466.5 mm (black line). Precipitation in the months of October to March, in general, is below the average of the total precipitation since these months correspond to the Ecuadorian dry season. This drought influences the hydroelectric systems, which is evident in the curve of hydroelectric production.

5.4.4 Time series

The following five series have been considered during the period 2000-2014:

Monthly Gross Production (MGP) of hydroelectric systems [GWh]

Average monthly precipitation (AMP) in Napo watershed [mm]

AMP in Pastaza watershed [mm]

AMP in Santiago watershed [mm]

Total average monthly precipitation (TAMP) in the three considered watersheds [mm]

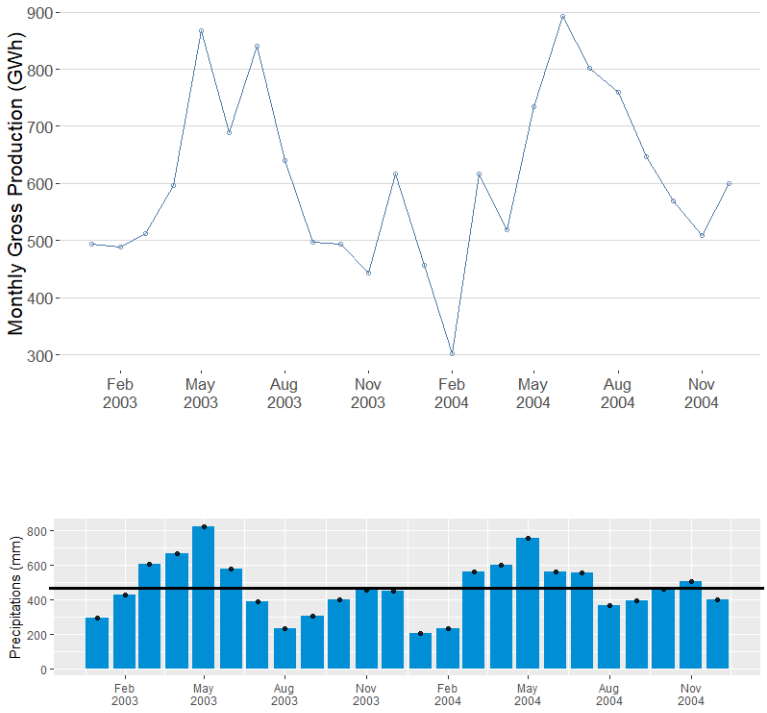


Figure 5.4 Monthly hydroelectric production and total precipitation of the three considered watersheds during 2003-2004.

To know the behavior and better fit in the analysis of the modeling, an analysis of each one of the five series is performed. Correlations between pairs of series have been also studied; in particular: MGP-AMP_{Napo}, MGP-$AMP_{Pastaza}$, MGP-$AMP_{Santiago}$ and MGP-TAMP.

5.5 Experiments and discussion

5.5.1 Exploratory data analysis and series transformation

Figure 5 shows the AMP of the Napo, Pastaza and Santiago watersheds and MGP series during the period 2000-2014. All series show a direct correlation, i.e., as precipitation increases or decreases in watersheds, the production of hydropower increases or decreases. Also, the AMP of the watersheds is correlated with the MGP series. Moreover, the MGP series presents variability and trend over time, in contrast to AMP series that show variability but no trend through the time.

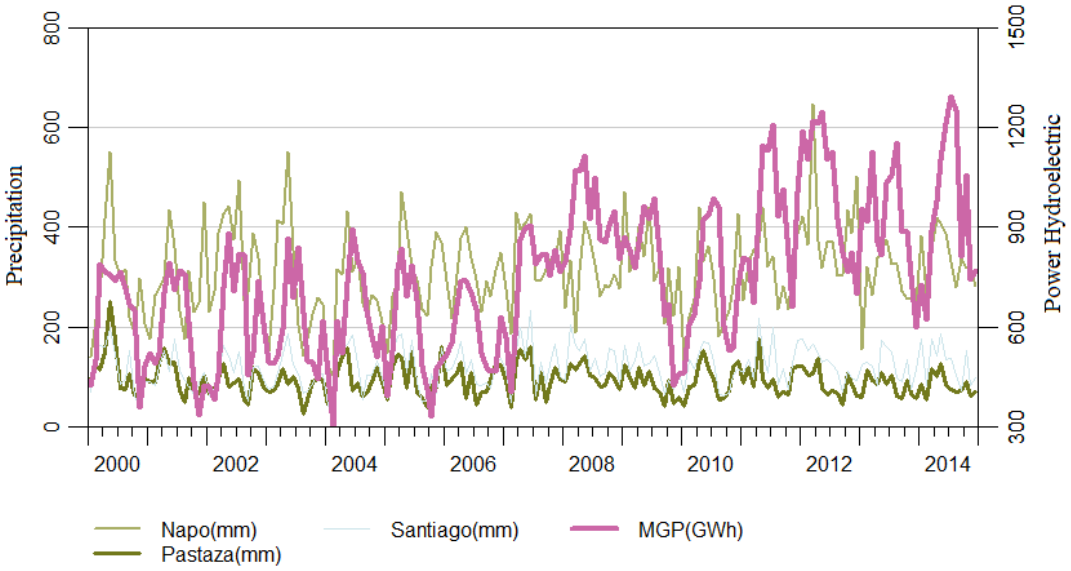


Figure 5.5 Time Series of precipitation [mm] at river basins and hydroelectric production [GWh] in Ecuador 2000-2014.

More specifically, the three series of precipitation data show stationarity and seasonality. The hydroelectric production series that does not show stationarity but seasonality. As part of the study, the hydroelectric production series was transformed to make it stationary.

Figure 6 depicts the cross-correlation function (CCF) between two series at lag k, estimated as follows: if the simple cross-correlation is larger than the standard deviation error, CCF is considered significantly different from zero. When the joint series show correlation, it is necessary to separate the linear association to make them stationary. In the separation step, the residuals of the model are transformed into white noise in a process known as (pre-)whitening. In ARIMA models, through the correlogram functions (ACF-PACF) the possible order values (p, d, q) are diagnosed, to eliminate the trend and variability. In contrast, the dynamic relationship between two series is analyzed through the cross-correlation function (CCF) adjusted to pre-whitened residuals [82], to estimate the best ARIMAX model.

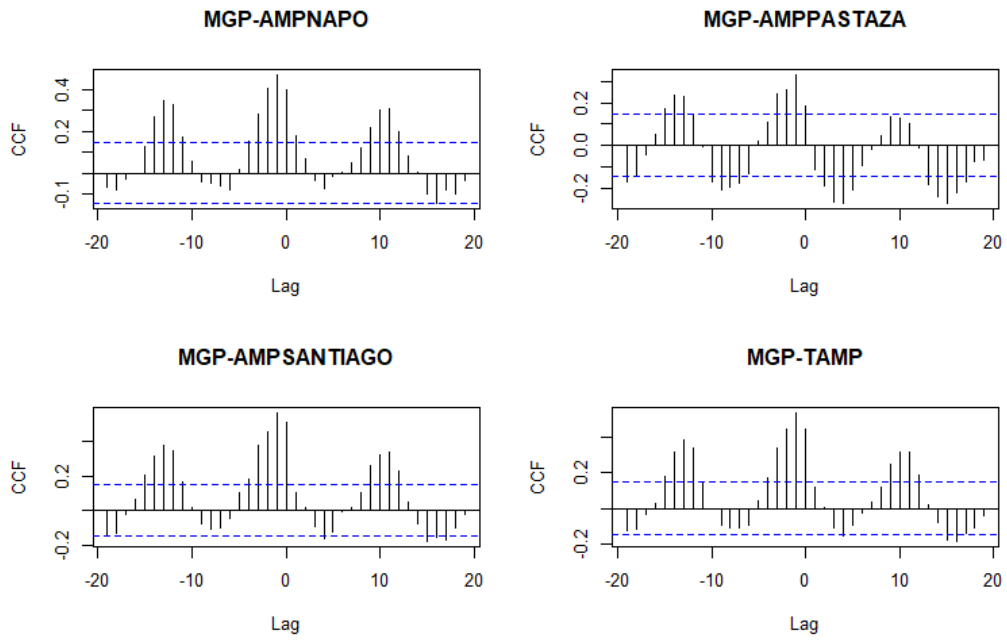


Figure 5.6 Cross-correlation function between precipitation and power hydroelectric.

5.5.2 Hydroelectric energy generation modeled with ARIMA

Now we can proceed to the model identification step described in Figure 2. First, we focused on the ARIMA model.

Figure 7(a) presents the autocorrelation functions ACF and PACF used to evaluate stationary after pre-whitening. Both functions decay exponentially in a delay or lag of 5, which is significant with seasonal frequencies suggested by the SARIMA model. Figure 7(b) shows the same functions applied to the series of differences. The value of the Durbin-Watson statistic parameter obtained is 1.98, so the series presents evidence of weak positive autocorrelation.

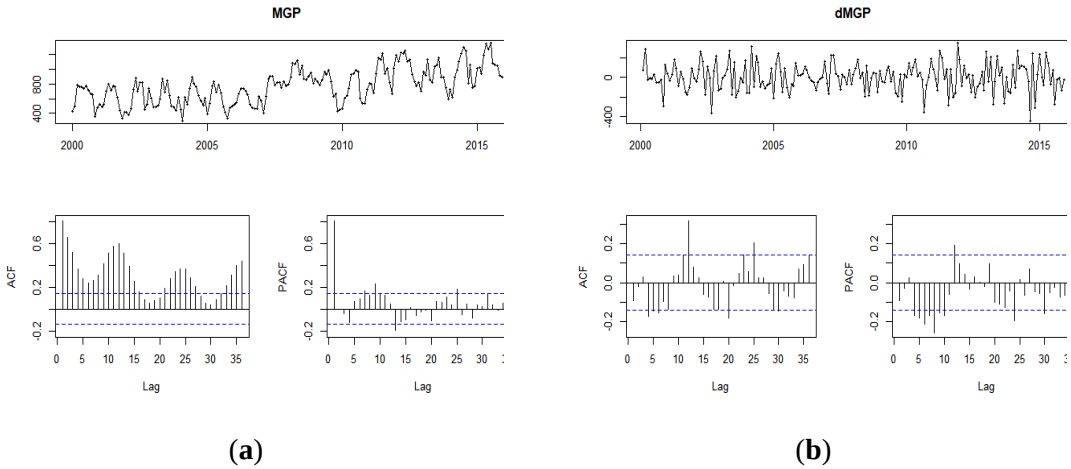


Figure 5.7 ACF and PACF autocorrelation functions. (a) Correlogram functions of the MGP series; (b) Correlogram functions of the Differenced MGP series.

For the analysis of the stationarity of the MGP series, we obtained the ADF statistics, whose value was t-ADF = -8.77 with a p-value of 0.01. There is significant evidence that the series is stationary and has no unit roots, with a maximum delay of 13 months. To determine the variants, the regression test was used to derive the ADF test which resulted to be significant with a value t = -15.06 at $\alpha = 0.05$ of significance level. This means that the series shows a random walk with mean zero.

Once we know that the series is stationary, we can step into the model identification stage. Table 2 shows a summary of the results obtained by applying the Box-Jenkins method to the MGP series. The model minimizing AIC and BIC was ARIMA $(1,1,1)x(0,0,1)_{12}$ with random walk. The model was confirmed to satisfy the assumptions of the SARIMA model. The validation results with the 2015 data are within the designated confidence interval.

Table 5.2 Box-Jenkins method applied in MGP series

Model identification			
	AR(1)	**MA(1)**	**SAR(1)**
Coefficients	0.65	-0.98	0.38
Standard deviation	0.06	0.02	0.07

Model estimation		
Penalized likelihood criteria	**AIC**	**BIC**
Values	2392.85	2405.86

Model Validation		
The model presents atypical values?		NO
Significance level		α=0.05
Box – Ljung test		
H_0	**p-values**	**Validation**
MGP series is uncorrelated	0.735	There is significant evidence that MGP series is uncorrelated
Box – Ljung test with squared residuals		
H_0	**p-values**	**Validation**
MGP series residuals have constant variance	0.957	There is significant evidence that MGP series residuals have constant variance
Jarque – Bera test		
H_0	**p-values**	**Validation**
MGP series residuals are normal	0.215	There is significant evidence that MGP series residuals are normal

Equation of the model
$X_t = 0.65X_{t-1} + \in_t - 0.98\in_{t-1} + 0.38\ X_{t-12}$

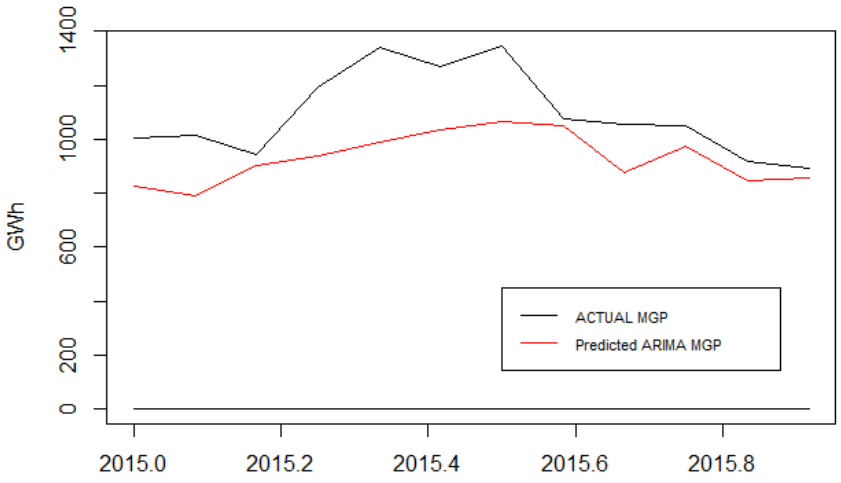
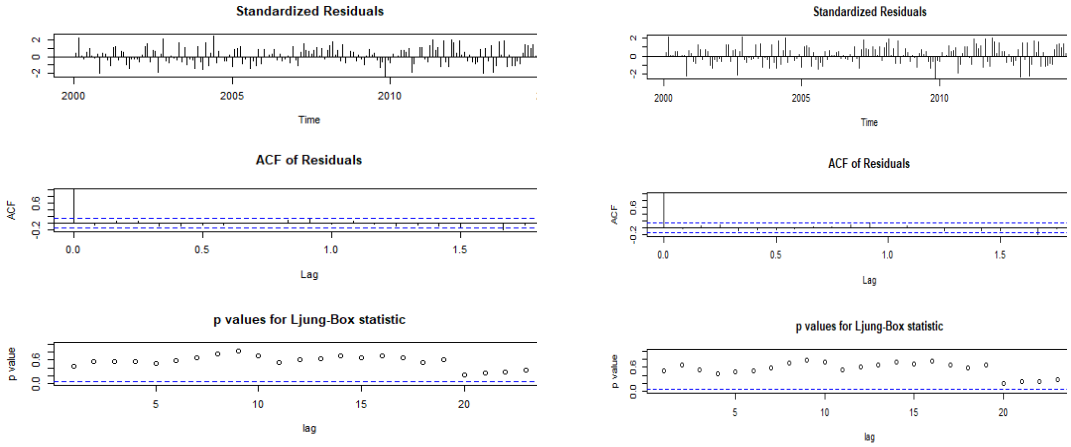


Figure 5.8 Comparison between actual and predicted values with ARIMA Model

5.5.3 Hydroelectric energy generation modelled with ARIMAX

Regarding the ARIMAX model, the amount of precipitation at each watershed was considered as the exogenous variable. The steps described in Section 2 produced the results presented below.

Figure 9 shows the residual diagnosis of each pair of series. The following characteristics are found: i) each series does not present outliers; ii) each pair of series are uncorrelated; iii) ACF lags are not significant; and iv) the p-value of the Ljung-Box test is greater than 0.05, which indicates that the squared residuals are uncorrelated over time, i.e., the standardized residuals are independent.



(a) **(b)**

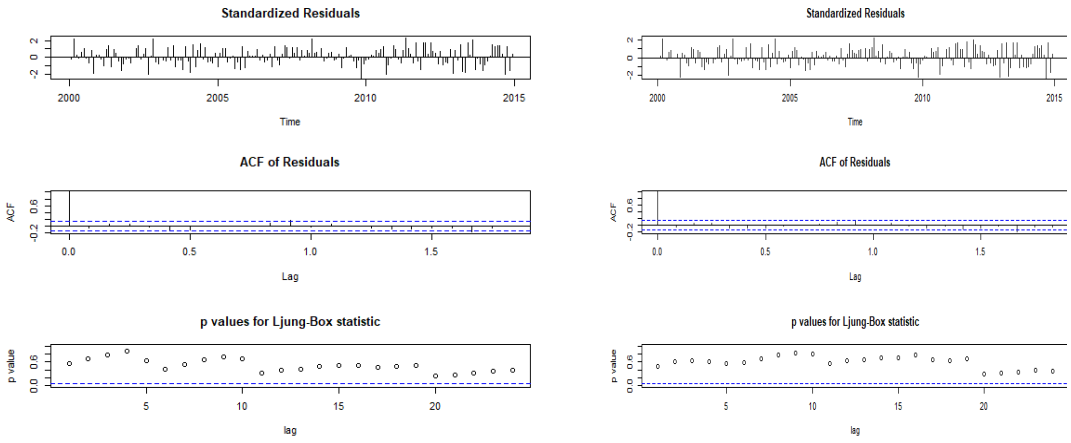


Figure 5.9 Residual diagnosis of each pair of series. (a) Correlogram MGP- AMPPASTAZA; (b) series MGP-AMPNAPO; (c) Correlogram MGP- AMPSANTIAGO; (d) series MGP- TAMP.

Table 3 shows the coefficients of the best ARIMAX models for hydroelectric production with the exogenous variable. The model with the lowest AIC and BIC is the pair of MGP-$AMP_{SANTIAGO}$ series. Figure 10 shows the forecasts of each ARIMAX model for the year 2015.

Table 3. Box-Tiao method applied in MGP series with exogenous variable

Model identification				
Models	**AR (1)**	**MA(1)**	**SAR(1)**	**X_{REG}**
MGP–$AMP_{PASTAZA}$ $ARIMAX(1,1,1)(1,0,0)_{12}$				
Coefficients	0.66	-0.96	0.40	0.80
Standard deviation	0.06	0.02	0.07	0.28
MGP–AMP_{NAPO} $ARIMAX(1,1,1)(1,0,0)_{12}$				
Coefficients	0.66	-0.97	0.38	0.22
Standard deviation	0.06	0.02	0.08	0.10
MGP–$AMP_{SANTIAGO}$ $ARIMAX(1,1,1)(1,0,0)_{12}$				
Coefficients	0.66	-0.97	0.38	1.21
Standard deviation	0.07	0.02	0.08	0.21
MGP-TAMP $ARIMAX(1,1,1)(1,0,0)_{12}$				
Coefficients	0.65	-0.96	0.37	0.25
Standard deviation	0.07	0.02	0.08	0.06

Model estimation				
Penalized likelihood criteria	**MGP–$AMP_{PASTAZA}$**	**MGP–AMP_{NAPO}**	**MGP–$AMP_{SANTIAGO}$**	**MGP-TAMP**
AIC	2237.40	2237.85	2213.66	2230.85
BIC	2253.34	2256.36	2229.60	2246.78

Model Validation			
Models	**Outliers**	**Assumption tests**	**p-values**

MGP–AMP$_{PASTAZA}$	AO and IO were not detected	Box – Ljung	0.44
		Box – Ljung test with squared residuals	0.74
		Jarque – Bera	0.43
MGP–AMP$_{NAPO}$	AO and IO were not detected	Box – Ljung	0.50
		Box – Ljung test with squared residuals	0.70
		Jarque – Bera	0.38
MGP–AMP$_{SANTIAGO}$	AO and IO were not detected	Box – Ljung	0,55
		Box – Ljung test with squared residuals	0.83
		Jarque – Bera	0.35
MGP-TAMP	AO and IO were not detected	Box – Ljung	0.56
		Box – Ljung test with squared residuals	0.69
		Jarque – Bera	0.06

Equation of the models	
MGP–AMP$_{PASTAZA}$	$X_t = 0.66X_{t-1} + \epsilon_t - 0.96\epsilon_{t-1} + 0.40X_{t-12} + 0.80X_{REG}$
MGP–AMP$_{NAPO}$	$X_t = 0.66X_{t-1} + \epsilon_t - 0.97\epsilon_{t-1} + 0.38X_{t-12} + 0.22X_{REG}$
MGP–AMP$_{SANTIAGO}$	$X_t = 0.66X_{t-1} + \epsilon_t - 0.97\epsilon_{t-1} + 0.38X_{t-12} + 1.21X_{REG}$
MGP-TAMP	$X_t = 0.65X_{t-1} + \epsilon_t - 0.96\epsilon_{t-1} + 0.37X_{t-12} + 0.25X_{REG}$

Figure 10 shows the prediction of each ARIMAX model.

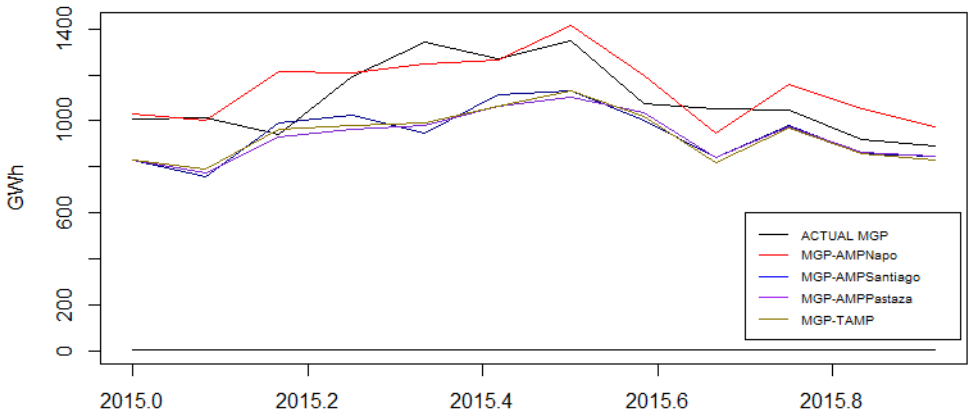


Figure 5.10 Comparison between actual and predicted values 2015 with ARIMAX Models

5.5.4 Comparison and discussion

Table 4 shows the MAE, MAPE and MASE of the forecasts of each model for the year 2015. It can be seen that the best results (lower error) are obtained by the ARIMAX model of MGP-AMP$_{NAPO}$. In figure 10 this is corroborated, which indicated that MGP-AMP$_{NAPO}$ was better.

Table 5.3 Forecast Errors of each Model

Models	MAE (GWh)	MAPE (%)	MASE
MGP – ARIMA	101.08	14.32	0.68
MGP–AMP$_{PASTAZA}$ ARIMAX	71.13	10.21	0.55
MGP–AMP$_{NAPO}$ ARIMAX	70.81	10.17	0.57
MGP–AMP$_{SANTIAGO}$ ARIMAX	91.63	13.31	0.62
MGP-TAMP ARIMAX	97.00	13.88	0.65

Figure 11 visually shows the forecast of hydroelectric production in Ecuador for 2015, considering ARIMA and ARIMAX models. A better forecast is obtained with the ARIMAX models of MGP-AMP$_{NAPO}$

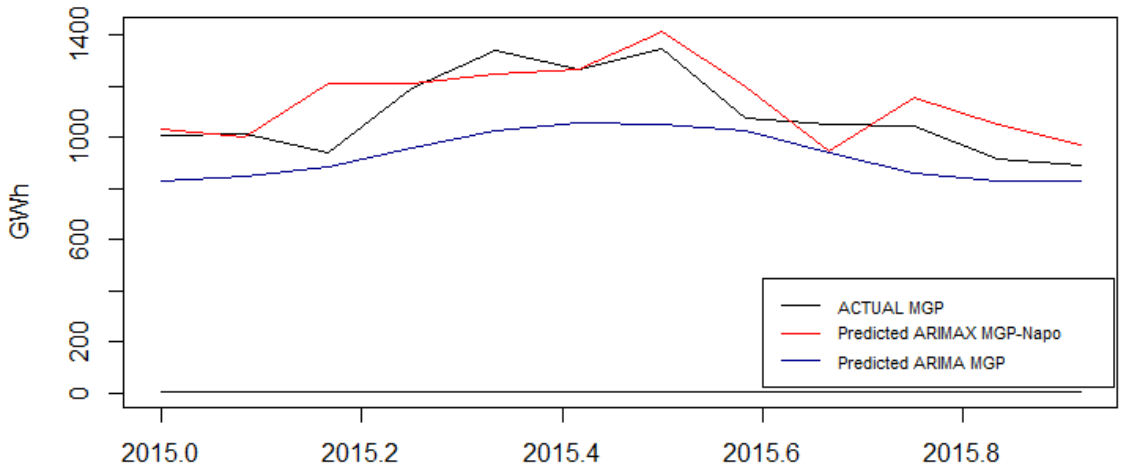


Figure 5.11Predicted Values Comparison of ARIMA, and ARIMAX models

Although ARIMAX model of MGP-AMP$_{SATIAGO}$ has the best estimation model considering the AIC and BIC values, ARIMAX model MGP-AMP$_{NAPO}$ has the lower forecast error values. Hence, ARIMAX model MGP-AMP$_{NAPO}$ was selected.

Figure 11 depicts that ARIMAX MGP-AMPNAPO (1,1,1)(1,0,0)12 model presents a better predictivity of gross monthly hydroelectric energy production in Ecuador. This model has estimated that the occurrence of the production is for the parameter p = 1 and a suitable moving average of q = 1 for the regular component. At the same time, for seasonal component, P = 1 and the strong seasonality established as S = 12. The exogenous variable are precipitation values at Napo watershed. The value of MAE is 70.81 GWh, MAPE is 10.17 % and MASE is 0.57.

5.6 Conclusions

This work shows that the ARIMAX models with an exogenous variable have better performance than the univariate ARIMA models for predicting hydroelectric energy production in Ecuador. Our analysis of the production and the precipitation of the Napo, Pastaza and Santiago basins (alone and aggregated) yielded that the ARIMAX MGP-AMP$_{NAPO}$ $(1,1,1)(1,0,0)_{12}$ model adequately adjusts the data of the hydroelectric energy production in Ecuador series.

This research helps to describe and predict hydropower generation, particularly in Ecuador. Results obtained with the proposed model can be useful for organizing and planning of the electric sector, which are important for the energy policy-maker sector. The methodology can be also extended to other use cases.

Further studies to improve the accuracy of the predictions can be performed including bioinspired techniques and optimization algorithms. Besides, we plan to study the impact of incorporating additional data sources to the model – e.g. synthetic streamflow data, as mentioned in Section 3.3, or other weather parameters, like wind, rain, etc. The applicability of the approach to other countries remains as future work.

Capítulo 6

6 Hydropower production prediction using Artificial Neural Networks: an Ecuadorian application case

J. Barzola-Monteses, J. Gómez-Romero, M. Espinoza-Andaluz, and W. Fajardo, "Hydropower production prediction using artificial neural networks: an Ecuadorian application case," Neural Comput. Appl., vol. 34, no. 16, pp. 13253–13266, Aug. 2022, doi: 10.1007/s00521-021-06746-5.

Hydropower is among the most efficient technologies to produce renewable electrical energy. Hydropower systems present multiple advantages since they provide sustainable and controllable energy. However, hydropower plants' effectiveness is affected by multiple factors such as river/reservoir inflows, temperature, electricity price, among others. The mentioned factors make the prediction and recommendation of a station's operational output a difficult challenge. Therefore, reliable and accurate energy production forecasts are vital and of great importance for capacity planning, scheduling, and power systems operation. This research aims to develop and apply artificial neural network (ANN) models to predict hydroelectric production in Ecuador's short and medium-term, considering historical data such as hydropower production and precipitations. For this purpose, two scenarios based on the prediction horizon have been considered, i.e., one-step and multi-step forecasted problems. Sixteen ANN structures based on multilayer perceptron (MLP), long short-term memory (LSTM), and sequence to sequence (seq2seq) LSTM were designed. More than 3000 models were configured, trained, and validated using a grid search algorithm based on hyperparameters. The results show that the MLP univariate and differentiated model of one-step scenario outperforms the other architectures analyzed in both scenarios. The obtained model can be an important tool for energy planning and decision-making for sustainable hydropower production.

6.1 Introduction

Hydropower is a renewable energy source where electrical energy is derived from water's potential energy moving from higher to lower elevations. Hydropower is a mature technology and widely used; in 2019, a total of 170 countries/territories in the world reported to have installed capacity and generated hydropower. Hydropower is among the most efficient technologies for producing renewable electrical energy, with a typical efficiency of 90%. Hydropower systems are cost-competitive: today, it is the only renewable technology that produces electricity at an equal or lower cost, compared to thermal energy sources like coal, oil, or gas, typically in the range of USD 2–5c per kWh [10], [242].

Ecuador is an emerging hydropower actor in Latin America. The country is currently implementing the National Master Plan for Electrification 2016–2025 to cover more than 90% of the national electrical demand with hydroelectric sources [197]. According to the last official report of Ecuador's electric sector statistics in 2018, Ecuador's hydroelectric capacity (5036.43 MW) represented 62.58 % of the total capacity (8048.11 MW). Generation from hydroelectric systems in 2018 amounted to 70.71% of the total production [243].

Sustainability, controllable energy, and the capability of quickly responding to surges of demand in the grid are among the main advantages of hydroelectric plants. Reliability offered for hydroelectric plants is a pivotal characteristic that cannot be obtained by solar or wind sources due to intermittence. Notwithstanding the multiple advantages, hydropower plants' effectiveness

is affected by factors such as river/reservoir inflows, temperature, seasonal demand, abrupt demands, gross domestic product, electricity price, and particularly their complicated correlations with meteorological and human phenomena. All these aspects make the prediction/recommendation of station operational output a difficult challenge [15]. At the same time, reliable and accurate energy production forecasts are vital to electric energy operators to improve the capacity planning, scheduling, and operation of power systems. Finally, depending on the needs of the electric operator, these forecasts can be accumulated on different time scales: short (hours or days ahead), medium (from a week to months ahead), or long term (years ahead) [17].

This research aims to explore and evaluate the capabilities of ANN models for predicting hydroelectric production in the short and medium terms. We focus our experiments on historical data from Ecuador, but the approach can be extended to any other country. Since hydropower strongly depends on meteorological conditions, rainfall data play a crucial role in our study. Previous works identified some limitations of statistical time analysis techniques [79], [96]: the difficulties in incorporating multiple exogenous variables and the lack of accuracy for long-term predictions. Following the success of neural networks in many areas [244], [245], the departing hypothesis of this paper is that ANN models can better capture the dynamics of hydroelectric production, and therefore, provide better results in our use case --- even though the number of observations is not very large. In the literature, there are a few contributions studying hydroelectric production in countries such as China, Serbia, and Brazil [149], [246], [247]. Still, there are no similar studies in the literature applying recurrent neural networks and focused on a medium-size region during a large period in which the installed capacity has evolved, as is the case in Ecuador. The model obtained represents an interesting tool for energy planning and decision-making for sustainable hydropower production in Ecuador. Furthermore, the paper provides a methodology and tools for model training and configuration that can be extended to other contexts.

The rest of the paper is organized as follows: Section 2 summarizes the ANN techniques used and presents related works on the topic. The experimental design applied in the current study is detailed in Section 3. Experimental evaluations and discussion of the results based on the models are shown in Section 4. Finally, Section 5 includes concluding remarks and directions for future work.

6.2 Background

6.2.1 Neural networks for time series prediction

A time series is a set of data samples collected at regular time intervals. Time series analysis comprises a vast collection of techniques for analyzing historical temporal data to extract meaningful features or information. Time series forecasting using deep learning (a family of machine learning techniques based on artificial neural networks) has shown higher accuracy than other traditional techniques [18].

ANN is a non-linear computational model loosely inspired by the human brain. In general, an ANN is made up of several layers of neurons connected through weighted links. The term “deep learning” means that there are many of these layers and neurons. The output of the network is calculated as the composition of the calculations performed by each neuron. Training an ANN means adjusting the weights to approximate the (unknown) function that relates the (known) inputs and outputs. There are commonly three aspects that characterize an ANN: i) the interconnection pattern between the neurons of the different layers; ii) the optimization algorithm to learn the weights of the interconnections, and iii) the activation function that converts a neuron's weighted input to its output activation [248].

We consider a feed-forward neural network (FFNN) and two recurrent neural networks (RNN) in this work. Specifically, we use multilayer perceptron (MLP), Long-Short-Term-Memory (LSTM) and sequence to sequence LSTM (seq2seq LSTM) models, which are briefly presented below.

6.2.1.1 Multilayer Perceptron model (MLP)

Feed-forward neural networks (FFNNs) are a type of ANN in which the computations proceed only in the forward direction. The most common FFNN is the multilayer perceptron (MLP), in which each neuron in a layer is connected to every neuron in the next layer. MLP networks are typically trained with the stochastic gradient descent method, which iteratively updates the network's weights according to the error between the obtained and the expected outputs. This error flows backward through the network to calculate the gradient at each neuron, a process called backpropagation [122]. Despite its simplicity, MLP has achieved updated performance in various supervised and unsupervised machine learning applications. Its success highly depends on the independence assumption among the training and test data [125]. In this work, we use MLPs to process subsequences of fixed length, i.e., the size of the input layer of the MLP determines the length of the sample of the sequence.

6.2.1.2 Long-Short-Term-Memory model (LSTM)

Recurrent Neural Networks (RNNs) are ANN types that allow cycles in the network, i.e., computations can proceed from one layer to a previous one. In this way, RNNs use the current inputs and previous calculations to compute the network output, thus keeping track of an internal state. RNNs are trained with the backpropagation through time (BPTT) method [122], which applies backpropagation to an “unrolled” version of the network ---unrolling means obtaining an equivalent acyclic version of the network by replicating the components involved in the recurrence and sharing their weights.

Long-short-term models (LSTMs) are a particular type of RNNs purposely designed to learn both short- and long-term temporal dependencies in time series data. Hochreiter and Schmidhuber designed this new architecture based on the concept of "memory blocks or gate units" in each hidden layer. They had as the primary motivation to solve the vanishing and exploding gradients problem [123], [132], [249]. Figure 1a) shows a schematic diagram of an LSTM unit.

Given an input time series $x = \{x_1, x_2, \cdots, x_T\}$, the LSTM maps the input time series to two output time sequences $h = \{h_1, h_2, \cdots, h_T\}$ and $y = \{y_1, y_2, \cdots, y_T\}$ iteratively by updating the states of memory cells with the following procedure [125], [250]:

Each gate is a sigmoid unit that changes every element in [0, 1], i.e., they use a logistic function defined in eq. (1):

$$\sigma(x) = \frac{1}{1 + e^{-x}} \qquad (1)$$

Input gate i_t controls the input of new information that is going to be stored in the new cell state, which derives the following:

$$i_t = \sigma(w_{xi}x_t + w_{hi}h_{t-1} + b_i) \qquad (2)$$

Forgetting gate f_t decides what information must be discarded from cell state, where:

$$f_t = \sigma\left(w_{xf}x_t + w_{hf}h_{t-1} + b_f\right) \qquad (3)$$

Output gate o_t controls and filters the output information flowing out of the cell, where:

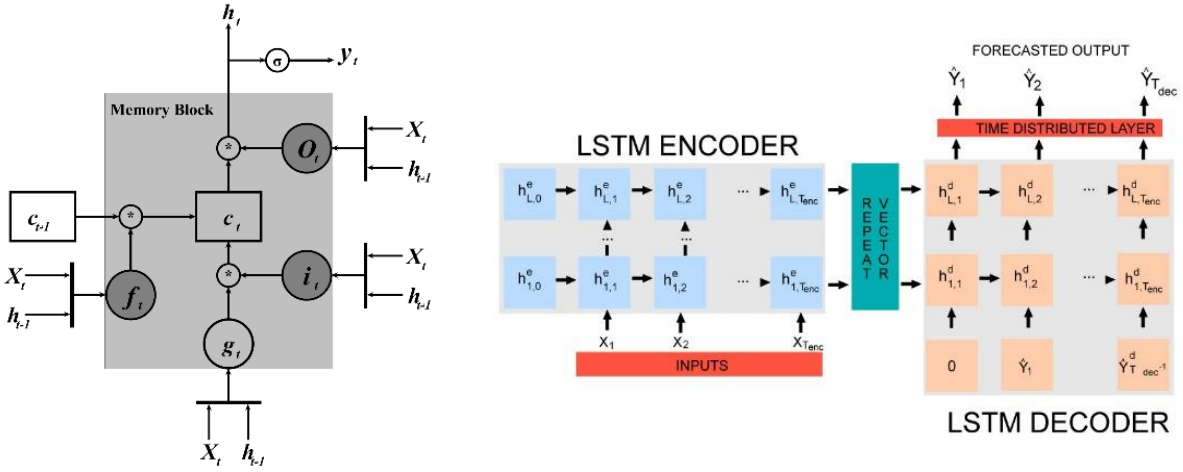
$$o_t = \sigma(w_{xo}x_t + w_{ho}h_{t-1} + b_o) \quad (4)$$

At each time t, the input features are computed by input x_t and the previous hidden state h_{t-1} by using the *tanh* function, as follows:

$$g_t = tanh(w_{xc}x_t + w_{hc}h_{t-1} + b_c) \quad (5)$$

The memory cell is updated by moderated input features and the partial forgetting of the previous memory cell, which yields:

$$c_t = f_t * c_{t-1} + i_t * g_t \quad (6)$$



a) b)

Fig. 1. Schematic diagrams: a) LSTM unit and b) Encoder and decoder in the seq2seq model with L stacked layers

Then, the hidden output state h_t is calculated by the output gate o_t and the memory cell c_t, as follows:

$$h_t = o_t * \tanh(c_t) \quad (7)$$

Finally, the output of LSTM y_t is computed by using the following expression:

$$y_t = \sigma(w_{hy}h_t + b_y) \quad (8)$$

In Eqs. (2)-(8), the matrices w_{xi}, w_{xf}, w_{xo}, and w_{xc} are the appropriate input weighting matrices, while w_{hi}, w_{hf}, w_{ho}, and w_{hc} are the recurrent weighting matrices; and w_{hy} represents the hidden output weight matrix. The vectors b_i, b_f, b_o, b_c, and b_y are the corresponding bias vectors.

LSTMs are trained with BPTT, considering that w_{hi}, w_{hf}, w_{ho}, and w_{hc} are the recurrent weighting matrices. They support the backpropagation of the gradient many time steps into the past, thus preventing the vanishing and exploding gradient problems. For a comprehensive description of the gradient computation of each component of the LSTM gate, we refer the reader to [251].

6.2.1.3 Sequence to Sequence model (seq2seq)

The sequence to sequence model (seq2seq) is a neural architecture that translates one data sequence into another. It has a structure made up of two sub-modules: the encoder to read and encode the input sequence, and the decoder in charge of reading the encoded input sequence and generating the output sequence prediction. Seq2seq models are related to autoencoders, an unsupervised learning architecture aimed at regenerating the input from the output. While autoencoders use the same sequence as input and output, seq2seq allows supervised learning by accepting different sequences at both ends.

Seq2seq model was first introduced by Sutskever et al. in 2014 [129]. Each sub-model can be composed of recurrent neural networks such as gated recurrent unit (GRU) or LSTM [252] and trained accordingly. These models can address challenging sequence-to-sequence prediction problems. In this work, seq2seq LSTM to perform medium-term hydropower production forecasting is considered.

Figure 1b) shows a schematic diagram of seq2seq LSTM. The encoded input sequence representation is repeated multiple times, once each step in the output sequence. This sequence of vectors is presented to the LSTM decoder. Simultaneously, the decoder output sequence is wrapped through the time distributed layer, which allows the wrapped layers to be used for each time step from the decoder [253].

Given an input time series $\chi_{1:T\,\mathrm{enc}} = \chi_1, \chi_2, \cdots, \chi_{T\,\mathrm{enc}}$, the encoder maps the input sequence time series to the fixed-length representation $h^e_{1:L,T\,\mathrm{enc}}$ [254]:

$$h^e_{1:L,T\mathrm{enc}} = f_{enc}(\chi_{1:T\,\mathrm{enc}}) \qquad (9)$$

where $h^e_{1:L,T\mathrm{enc}}$ is the encoder's hidden and/or cell states for all stacked layers at time T_{enc}. Then, the decoder output $\hat{y}_{1:T\ dec}$ is defined as follows:

$$\hat{y}_{1:T\ dec} = f_{dec}\left(h^e_{1:L,T\mathrm{enc}}\right) \qquad (10)$$

Which is a sequence of T_{dec} predictions. A simplified way to denote the composition of the encoder and decoder is using the following expression:

$$\hat{y}_{1:T\ dec} = f_{\mathrm{enc}\rightarrow\mathrm{dec}}(\chi_{1:T\,\mathrm{enc}}) \qquad (11)$$

6.2.2 Related works

Before mentioning some related works, it is necessary to know the classification of hydroelectric power systems. Hydroelectric projects are mainly classified as run of river (RoR) hydropower plant, storage (reservoir) hydropower plant (SHP), pumped-storage hydropower (PSH), and in-stream technologies (Hydrokinetic). An RoR hydropower is a plant where little or no water storage is provided; it generates electricity from the river's available flow. An SHP includes a dam and a reservoir to impound water, store and release later when needed. In a PSH plant, water is pumped from a lower reservoir into an upper reservoir when electricity generation exceeds demand and is released back from the upper reservoir through turbines to generate electricity when demand exceeds the supply. Finally, a hydrokinetic plant can be derived from water's movement (kinetic energy) in rivers, streams, canals, tidal flow, and ocean currents [10].

Table 1 shows the main works related to hydroelectric production's prediction in the last five years. There is more than one approach to develop forecasts, such as: i) statistical techniques to derive mathematical relationships between dependent variables and independent variables, ii) hydrological modeling for the characterization of real hydrological systems using physical models

and computational simulation, iii) satellite mapping techniques in which high-resolution satellite images are considered in studies such as orography and hydrographic basins, iv) optimization algorithms which are procedures that are executed iteratively comparing several solutions until an optimal solution is found, and v) machine learning techniques which use computational methods to learn information directly from data without relying on a predetermined equation as a model.

The most related works to ours are [15], [255], and [149], which also use ANNs for hydrologic (power) time series prediction. In [15], the authors present DeepHydro, a deep learning framework for multivariate time series prediction based on latent recurrent neural networks. The experimentation focused on a 2-year dataset of the stations located across the Dadu River (China) and hourly forecasts. The main influencing variables considered were temperature and water flow, while we use precipitations ---easier to obtain--- as a proxy for the latter. In contrast, we consider larger periods and several watersheds, and more importantly, a dynamic context--Ecuador's installed capacity varies during the study period. A more comprehensive comparison of DeepHydro and fine-tuned LSTMs remains as future work.

In [255], the hydrological flow in Southwest Serbia was estimated instead of the production. Precipitations were identified as a critical predictor of flow, which is a fundamental assumption of our work ---afterward validated in the experimentation. Our methodology for hyperparameter optimization is inspired by their approach, although we apply a more comprehensive set of techniques (i.e., MLPs with different numbers of input nodes, LSTM, seq2seq) beyond the MLPs used in their paper.

Similarly, the research work in [149] focused on MLPs and the group method of data handling (GMDH) ---a variation of MLP that allows zeroing selected nodes of the network--- to predict hydrological production in the Amazon (Brazil). They also used data from several years and rainfall data (aggregated from several basins) as the exogenous variable. Another study developed in South Korea performs a similar analysis considering climate change scenarios and using MLPs [256]. Again, our paper considers more recent techniques aimed explicitly at time series processing, and the comparison with GMDH can be a prospective direction for future work.

Table 6.1 Selected related works of Hydropower Production forecasting

Reference	Geographic location	Hydropower projects	Regressive variable	Prediction variable	Approach to developing forecasts
Zhou et al. [247]	Hydropower stations on the Dadu River (China)	Storage (reservoir) based	-Water flow -External factors (meteorology, time, and sale price)	Power Production	DeepHydro - recurrent neural networks
Kostić et al. [246]	southwestern Serbia	Storage (reservoir) based	-Air temperature -Precipitation	-Hydrological flow rate - Power Production	Multilayer feed-forward perceptron (MLP)
Lopes et al. [149]	Amazon region (Brazil)	run-of-river	-Precipitation	- Monthly potential hydropower generation	Group method of data handling MLP
Jung et al. [256]	Han River basin (South Korea)	Storage (reservoir) based	-Precipitation, -Humidity, -temperature -wind speed	Runoff prediction	Multilayer feed-forward perceptron (MLP)
Razi et al. [257]	Peninsular Malaysia	run-of-river	-Net head -Water flow rate	Power Production	Statistical analysis is applied
Oyerinde et al. [258]	Niger Basin (West Africa)	Storage (reservoir) based	-Precipitation Evapotranspiration	Power Production	A hydrological model is applied
Dehghani et al. [178]	Dez dam (Iran)	Storage (reservoir) based	-Precipitation - Water flow rate - Power Production	Power Production	Grey wolf optimization Adaptive neuro-fuzzy inference system (ANFIS)
Tamm et al. [259]	North Estonia	run-of-river	- Digital elevation map -Land use map - Soil map -Weather data.	Hydropower potential	Soil and Water Assessment Tool (SWAT) model
Chen & Zhong [260]	Tankeng hydropower station (China)	Storage (reservoir) based	-reservoir inflow -electricity price -hydropower consumption rate	Power Production	Multi-time-scale coupling operation Model Dynamic Bayesian network Model Probability-based prediction model
Contreras et al. [261]	Poqueira River basin (South of Spain)	run-of-river	-climate service -historical local data - Seasonal forecast of water inflow	Power Production	Quantile mapping method
Hidalgo et al. [262]	São Francisco river basin (Brazil)	Storage (reservoir) based	-Air temperature -Precipitation	Power Production	Hydrological-hydropower model
Farfán et al. [263]	Machángara sub-basin of the Paute river basin (Ecuador)	Storage (reservoir) based	meteorological data	Water flow	WEAP and GR2M physical models ANN Models ANN hybrid model

6.3 Experimental setup

6.3.1 Data

Data for the current study, corresponding to the 2000–2015 year period, have been obtained from official and governmental institutions of Ecuador, namely the Electricity Regulation and Control Agency (ARCONEL) [196] and the National Institute of Meteorology and Hydrology (INAMHI) [224]. The dataset is built considering the data collected from the annual statistical reports of both institutions. The resolution of the collected dataset is one month.

Figure 2 depicts the monthly gross production (MGP) of hydroelectric systems [GWh] and the total average monthly precipitation [mm] of the three main hydrographic basins of

Ecuador [79]. The entire dataset is divided into a train and test set with zero overlaps. The first 75% of all data were assigned as the training set and the last 25% as the test set.

A time series can be considered stationary if the mean and variance are constant and there are no significant trends and seasonal variations. The MGP series does not present stationary characteristics due to a significant trend. Then, the first difference is applied to decrease the trend, i.e., the series is detrended [81]. Both series were used in the proposed models: original MGP series, i.e., without differentiation, and MGP series with differentiation (D).

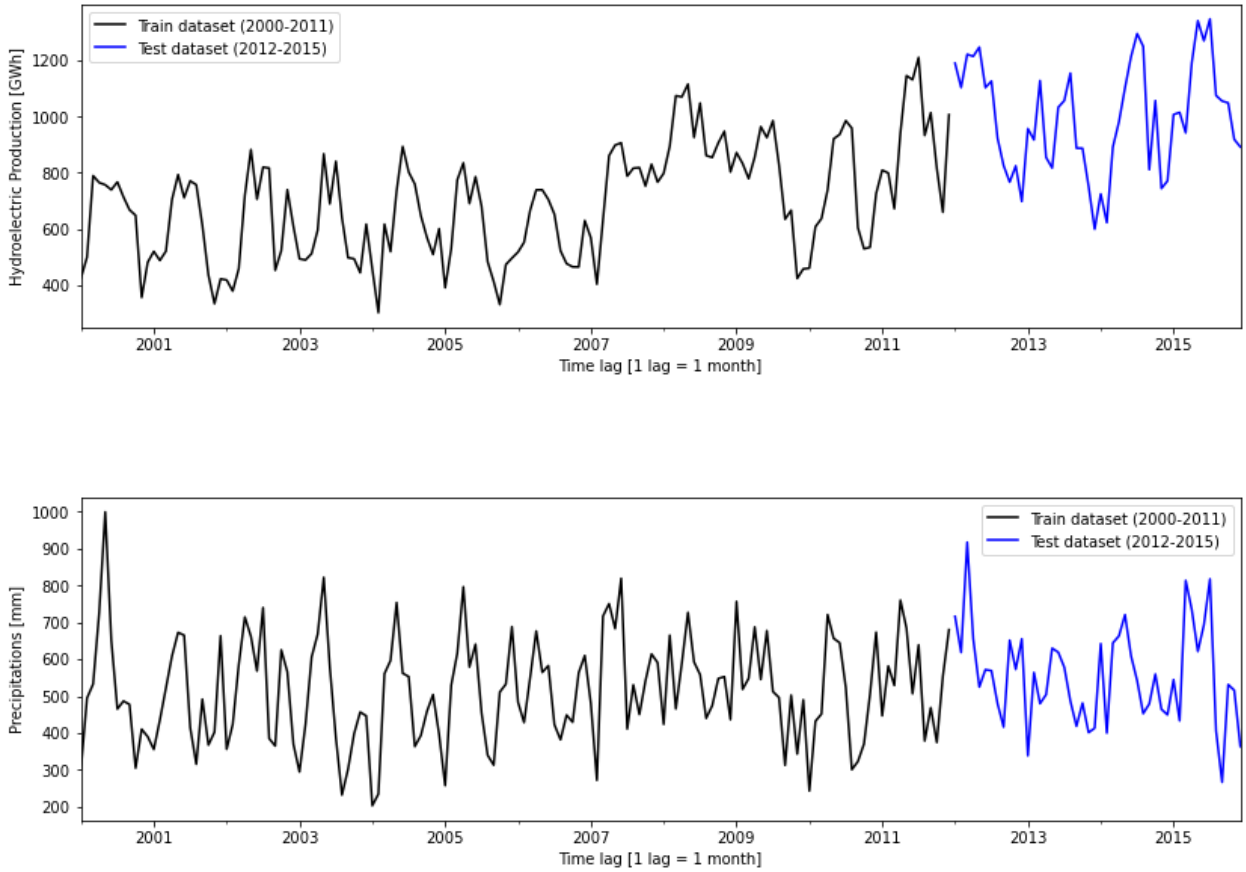


Figure 6.1 Monthly hydroelectric production (up) and total precipitation (down) of the three considered watersheds during 2000–2015

6.3.2 Model features and targets

The experimental design considers a univariate and bivariate time series problem. For the univariate case, only one variable or feature is considered as input (regressor variable) and output (predictor variable) of the model (black box). In this univariate case, the hydroelectric production variable is considered. On the other hand, for the bivariate case, two variables are considered, i.e., two regressor variables at the black box's input and one at the output as a prediction variable. In this bivariate case, hydroelectric production and precipitation are regressive variables, and hydroelectric production is kept as a predictor variable.

The training addressed in the models is of the supervised type. The generated samples to be passed to the model at the input and output have the following structure:

Let one input sample be represented as a matrix, $X \in \mathbb{R}^{T \times f}$, where T is the number of time steps and f is the number of features. As mentioned, the number of features was f =1 (univariate case) and f=2 (bivariate case), where each row of the matrix X is defined as:

$$\text{Univariate case: } x_{[t]} = \left[MGP_{[t]}\right] \quad (12)$$

$$\text{Bivariate case: } x_{[t]} = \left[MGP_{[t]} \quad Prec_{[t]}\right] \quad (13)$$

where $t \in 1, \ldots, T$. For each input sample, one target sample is generated, represented by a vector $y \in \mathbb{R}^{N \times 1}$, where N represents the number of predicted time steps from T. The target vector represents the actual MGP vector, which is given by:

$$y = \left[MGP_{[1]}, \ \ldots \ , \ MGP_{[n]}, \ \ldots \ , \ MGP_{[N]}\right] \quad (14)$$

where $y_{[n]}$ is the actual MGP value at time step n, and $n \in 1, \ldots, N$. This targeting vector is used to compare with the predicted MGP vector, $\hat{y} \in \mathbb{R}^{N \times 1}$.

Problem Framing: A forecast problem that requires a prediction of the next time step is named one-step forecast model. On the other hand, a forecast problem involving a prediction of more than a one-time step is the multi-step forecast model. The current work considers both forecast problems as scenarios. The one-step forecast model implies a month of prediction, while the multi-step forecast model implies twelve months, i.e., one year. The two mentioned scenarios are presented as follows:

One-step scenario:

- Univariate case: Given a recent hydroelectric production, what is the expected hydroelectric production for one step ahead?
- Bivariate case: Given recent hydroelectric production and precipitations, what is the expected hydroelectric production for one step ahead?

Multi-step scenario:

- Univariate case: Given a recent hydroelectric production, what is the expected hydroelectric production for twelve steps ahead?
- Bivariate case: Given a recent hydroelectric production and precipitations, what is the expected hydroelectric production for twelve steps ahead?

Data Transformation: Normalization is applied to each variable's data set and transformed into values between -1 and +1. Input and output are rescaled from one range of values (original values) to a new range of values. The rescaling is often accomplished by using a linear interpretation formula such as:

$$x' = \frac{(x_i - x_{min})}{(x_{max} - x_{min})}\left(x_{new\_max} - x_{new\_min}\right) + x_{new\_min} \quad (15)$$

where x' is the normalized value, x_i is the real value, x_{max} and x_{min} are the maximum and minimum values of the variable, respectively. In this work, x_{new_max} and x_{new_min} are +1 and -1, respectively. Eq (15) is named Min-Max normalization, which can preserve all data relationships [264].

6.3.3 Hyperparameters

Hyperparameters are configuration parameters external to the model itself, whose values generally cannot be estimated from the training data set and are specified by the designer to adjust the learning algorithms. There are mainly three types of hyperparameters: i) structure and topologies, such as number of layers, number of neurons, their activation functions, and others; ii) optimization, such as epochs, batch size, learning rate, momentum, and similar; and iii) Regularization, such as dropout probability, L2 regularization coefficient, and others [254], [265].

In the current work, more than 3000 models were trained. Considering a grid search algorithm, a tuning process was applied to the implemented models by varying hyperparameters to find the configurations that yield the best generalization on the validation data set. The grid search procedure exhaustively considered all the hyperparameter combinations and selected the best subset among them. This has a high computational cost that can be too expensive for models and datasets larger than ours. Hyperparameter optimization algorithms such as HyperBand [266] and Bayesian Optimization [267] can be applied in these cases.

Accordingly, MLP, LSTM, and seq2seq LSTM architectures for the two scenarios specified above have been configured. For the case of the MLP and LSTM models, configurations with one hidden layer are considered. Table 2 shows the variation of hyperparameters used in each of the implemented models.

In Table 2, n_input is the number of prior inputs to use as input for the model, n_nodes is the number of nodes/units to use in the hidden layer, n_epochs is the number of training epochs, n_batch is the number of samples to include in each mini-batch, act_hid is the activation function to use in the hidden layer, and act_out is the activation function to use in the output layer. For the case of seq2seq LSTM, nodes_enc and nodes_dec are the number of LSTM units to use in the encoder and decoder, respectively; nodes_dense is the number of nodes to use in the fully-connected layer; act_enc and act_dec are the activation functions used in the encoder and decoder, respectively.

Table 6.2 Hyperparameters considered for Experiment models MLP, LSTM and seq2seq LSTM

MLP and LSTM models		**seq2seq LSTM model**	
Hyperparameter	**Values**	**Hyperparameter**	**Values**
n_input	Range: 1 to 24, incrementing by powers of 2	n_input	Range: 1 to 24, incrementing by powers of 2
n_nodes	Range: 2 to 64, incrementing by powers of 2	nodes_enc	Range: 2 to 64, incrementing by powers of 2
n_epochs	Range: 25 to 150, incrementing by powers of 25	nodes_dec	Range: 2 to 64, incrementing by powers of 2
n_batch	Range: 2 to 16, incrementing by powers of 2	nodes_dense	Range: 2 to 64, incrementing by powers of 2
act_hid	'sigmoid', 'tanh', 'relu', 'linear'	n_epochs	Range: 25 to 150, incrementing by powers of 25
act_out	'sigmoid', 'tanh', 'relu', 'linear'	n_batch	Range: 2 to 16, incrementing by powers of 2
		act_enc	'sigmoid', 'tanh', 'relu', 'linear'
		act_dec	'sigmoid', 'tanh', 'relu', 'linear'

Table 3 shows all structures used in different configurations with hyperparameters during the execution of the experiments. For simplification reasons, each model is represented through its corresponding acronyms.

On the other hand, due to neural networks' stochastic nature, each structure configuration is trained and validated ten times during the hyperparameter tuning process. The mean of the RMSE errors is determined and registered.

6.3.4 Performance evaluation

Model Evaluation: As known, k-fold cross-validation does not work for time series data because they ignore its temporal relation. Therefore, a rolling-forecast method will be used, also called walk-forward model (WFM) validation. WFM partitions data before and after a selected time point and uses each partition for training and validation, respectively. Since we are interested in predicting for the following years, this method better reflects the expected accuracy of the model in real use. Following [268], each time step of the test dataset is executed one at a time.

Table 6.3 Acronyms of the ANN models considered during the execution of the experiments.

Scenario	Time Series Problem	Model	Acronyms
One-step	Univariate	Multilayer Perceptron without differentiation - univariate	MLP-uni
	Univariate	Multilayer Perceptron with differentiation - univariate	MLP-D-uni
	Univariate	Long Short-Term Memory without differentiation - univariate	LSTM-uni
	Univariate	Long Short-Term Memory with differentiation - univariate	LSTM-D-uni
	Bivariate	Long Short-Term Memory without differentiation - bivariate	LSTM-bi
	Bivariate	Long Short-Term Memory with differentiation - bivariate	LSTM-D-bi
Multi-step	Univariate	Multilayer Perceptron without differentiation - univariate	MLP-uni
	Univariate	Multilayer Perceptron with differentiation - univariate	MLP-D-uni
	Univariate	Long Short-Term Memory without differentiation - univariate	LSTM-uni
	Univariate	Long Short-Term Memory with differentiation - univariate	LSTM-D-uni
	Univariate	Sequence to Sequence LSTM without differentiation - univariate	S2S-uni
	Univariate	Sequence to Sequence LSTM with differentiation - univariate	S2S-D-uni
	Bivariate	Long Short-Term Memory without differentiation - bivariate	LSTM-bi
	Bivariate	Long Short-Term Memory with differentiation - bivariate	LSTM-D-bi
	Bivariate	Sequence to Sequence LSTM without differentiation - bivariate	S2S-bi
	Bivariate	Sequence to Sequence LSTM with differentiation - bivariate	S2S-D-bi

Performance evaluation: In literature reviews, in which model adjustments with energy observations are handled, the RMSE metric is the most used evaluation parameter [268]. Therefore, the RMSE is considered the main metric to select the best configuration model with the lowest forecast error. Others supporting metrics are the MAE and MAPE [130], [250], [269], [270].

6.4 Experimental results and discussion

In this section, the experimental results achieved with MLP, LSTM, and seq2seq LSTM models are presented and discussed. All experiments executed in this research were run on a machine with Intel Core i7-6500U CPU @2.50GHz x 4, equipped with 16 GB physical memory with running operating system Ubuntu 20.04 v. All configuration models were implemented in Python 3.8, using the TensorFlow library.

6.4.1 One-step scenario

After carried out the experiments and fine-tuning hyperparameters using the train dataset and WFM validation on the test dataset, the best topology neural network achieved is as follows: n_input = 1, n_nodes = 64 neuron, n_epochs = 25, n_batch = 1, act_hid = sigmoid and act_out = sigmoid. Table 4. shows the top 10 models based on the RMSE metric.

For this scenario, six structures shown in Table 3 were tested; however, only one appears in the top 10. In this case, MLP structures outperform both LSTM univariate and bivariate models. The best results were obtained using MLP with differentiation–univariate, i.e., applying differentiation to the data of the hydroelectric production variable resulted in better accurate predictions.

From Table 4, it can be noted that in the scenario of predicting a month from past months, the best-obtained models require a look back of one month. In addition, the following characteristics are observed: the number of nodes varies between 16 and 64. The epochs' values

are 25 and 100. The act_hid can be sigmoid and linear functions, whereas for act_out the model has better accuracy with sigmoid and tanh functions. Finally, the common hyperparameters are n_input = 1 and n_batch = 1.

Table 6.4 The top ten results from our hyperparameter search and WFM validation

Model	n_input	n_nodes	n_epochs	n_batch	act_hid	act_out	RMSE [GWh]
MLP-D-uni	1	64	25	1	sigmoid	sigmoid	4.09
MLP-D-uni	1	32	25	1	sigmoid	sigmoid	4.23
MLP-D-uni	1	64	25	1	linear	tanh	4.60
MLP-D-uni	1	64	50	1	linear	tanh	4.69
MLP-D-uni	1	16	50	1	sigmoid	sigmoid	4.78
MLP-D-uni	1	32	25	1	linear	tanh	4.95
MLP-D-uni	1	64	75	1	linear	tanh	5.04
MLP-D-uni	1	32	50	1	linear	tanh	5.23
MLP-D-uni	1	64	100	1	linear	tanh	5.28
MLP-D-uni	1	16	25	1	sigmoid	sigmoid	5.29

Table 5 shows the accuracy results RMSE of the best models of each structure. For the MLP case, a better fit of the prediction data is achieved by transforming the series, i.e., differentiation is applied. Also, LSTM univariate and bivariate structures, the best metrics were obtained by differentiation.

Table 6.5 Accuracy of RMSE results for all models and all cases of one-step scenarios. The number is the average on runs

MLP		**LSTM**			
MLP-uni	MLP-D-uni	LSTM-UNI	LSTM-D-UNI	LSTM-bi	LSTM-D-BI
195.1	**4.09**	177.68	15.49	170.41	**11.23**

From Table 5, it can be noted that MLP outperforms LSTM. For the case of LSTM structures, accuracy can improve if there is more than one regressor variable. For our case study, LSTM-D-bi forecasts improved about 38% compared to the best LSTM univariate. In this work and case study, MLP achieved better error metrics than RNN techniques for one-step scenarios.

LSTM models require more computational time to run. Figure 3 shows that the better average time is around 0.5 minutes per model and it is achieved with the univariate and differentiated MLP. Moreover, its RMSE metric is the lowest among all the one-step architectures. The univariate LSTM model has the worst time, 2.48 min/model. On the other hand, it is noted that when applying differentiation for the bivariate LSTM case, time improves substantially compared to LSTM-D-uni (about 15%). Based on the results, MLP-D-uni is the model with the best RMSE metric and time to run in this scenario.

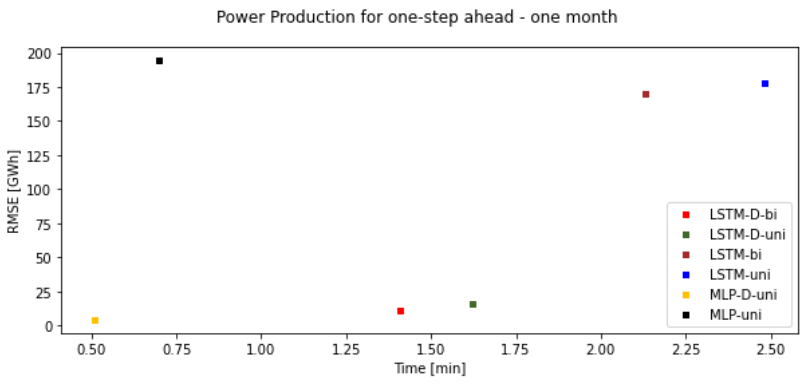


Figure 6.2 Execution times of models contrasted with the RMSE of the best configurations. Results are obtained from the six architectures analyzed in this scenario.

6.4.2 Multi-step scenario

After carried out the experiments and fine-tuning hyperparameters using the train dataset and WFM validation in test dataset, the best topology neural network achieved is as follows: n_input = 5, n_nodes = 84 neurons, n_epochs = 100, n_batch = 16, act_hid = tanh and act_out = linear.

Table 6. shows the top 10 models based on the RMSE metric. For this scenario, ten structures shown in Table 3 were tested; however, only one type appears in the top 10. In this case, MLP outperforms both LSTM and Seq2seq LSTM models. The best model was MLP with differentiation – univariate. Moreover, to all the top ten models showed in Table 6, differentiation to the MGP series was applied, and better accurate predictions were achieved.

Table 6.6 The top ten results from the hyperparameter search (average of 12 steps ahead)

Model	**n_input**	**n_nodes**	**n_epochs**	**n_batch**	**act_hid**	**act_out**	**RMSE [GWh]**
MLP-D-uni	5	84	100	16	tanh	linear	123.84
MLP-D-uni	5	84	75	16	tanh	linear	123.84
MLP-D-uni	5	128	150	16	tanh	linear	123.93
MLP-D-uni	5	94	75	16	tanh	linear	124.00
MLP-D-uni	5	128	50	16	tanh	linear	124.09
MLP-D-uni	5	94	125	16	tanh	linear	124.12
MLP-D-uni	5	84	75	16	tanh	linear	124.16
MLP-D-uni	5	94	50	16	tanh	linear	124.18
MLP-D-uni	5	88	75	16	tanh	linear	124.18
MLP-D-uni	5	104	125	16	tanh	linear	124.19

It is also noted that in this scenario of predicting twelve months from past months, the best-obtained models require a look back of 5 months, i.e., in this multi-step scenario, a lower amount of historical data is required. The following characteristics are also observed: the number of nodes varies between 84 and 128 for MLP-D. The epochs' values vary between 50 and 150. Finally, the common hyperparameters are n_input = 5, n_batch = 16, act_hid = tanh and act_out = linear.

The results achieved with LSTM are not so distant from those achieved by MLP. The RMSE difference between the best MLP-D and LSTM-D-uni is 12.2 GWh, i.e., about 9.9 %. The LSTM-D-uni configuration ranks 2nd with the best accuracy among the ten multi-step architectures considered in Table 3. Despite the limited number of observations, LSTM univariate architecture outperforms LSTM and seq2seq bivariate models. This result should be considered for future studies applied to the energy area.

Table 6.7 Accuracy of RMSE results for all models and all cases of multi-step scenarios. The number is the average of 12 steps ahead and multiple runs

MLP		**LSTM**				**Seq2Seq**			
MLP-uni	MLP-D-uni	LSTM-UNI	LSTM-D-UNI	LSTM-bi	LSTM-D-BI	S2S-uni	S2S-D-uni	S2S-bi	S2S-D-bi
154.35	**123.84**	173.56	**136.04**	190.68	162.01	193.12	**140.42**	179	143.53

Table 7 shows the accuracy results RMSE of the best model of each architecture. In general, the best RMSE values in each architecture considered in this multi-step scenario have been achieved by applying differentiation to the MGP series. Therefore, during data preprocessing, the MGP series differentiation improves the 12-month sequence of hydroelectric production prediction error.

Interestingly enough, there are no significant differences in the errors for each one of the 12-step predictions, particularly for the MLP. Figure 4 shows the validation errors of each month for the best MLP, LSTM, and seq2seq model highlighted in Table 7. These are average errors since the validation data contains four years (2012-2015). As expected, we can find a slight trend in all of them to have larger errors in the farthest predictions, as indicated by the polynomial regression lines (dashed, polynomial degree = 3). MLP and LSTM are better in the shorter (1-4 months) and the longer terms (11-12 months), while seq2seq behaves well in the medium term (6-8 months). This opens the possibility to build an ensemble method, although, given the size of our dataset, it could lead to overfitting.

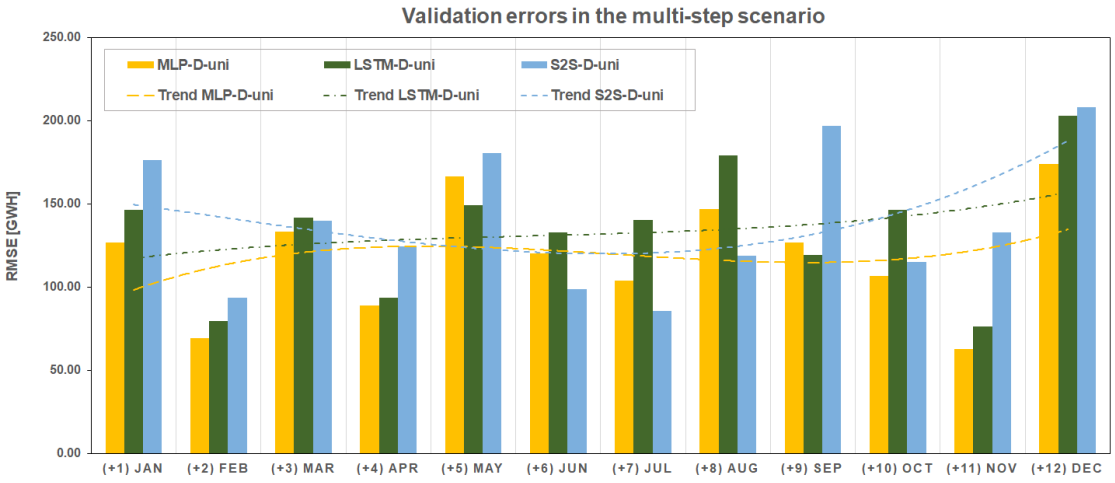


Figure 6.3 Validation errors in the multi-step scenario (validation set).

Figure 5 shows that the best average times per model are achieved with MLP architectures. Nevertheless, the best error between both structures is the MLP-D, with an execution time of around 0.18 minutes. It is noted that the S2S-uni model has the worst time, 2.95 minutes; it is also among the worst RMSE errors in this scenario. On the other hand, LSTM structures require a longer execution time than the MLP structure. Although LSTM-D-uni occupies the 2nd place with the best metric among the ten structures analyzed, its runtime is higher than MPL-D by a factor of 4.

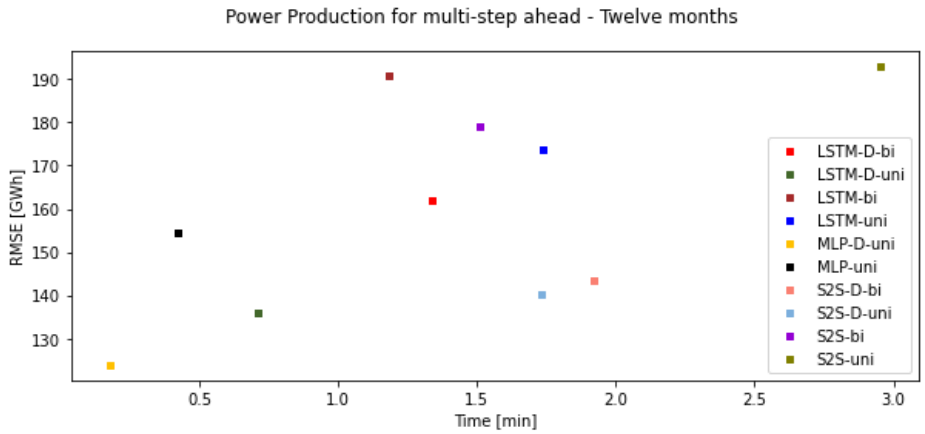


Figure 6.4 Execution times of models contrasted with the RMSE of the best configurations. Results were obtained from 10 architectures analyzed in this scenario.

6.4.3 Scenario evaluation

As mentioned in the experiment setup section, the results' randomness is manifested by the neural networks' stochastic nature. Figures 6 and 7 show the box diagrams of hydropower production predictions' RMSE, MAE, and MAPE errors. The mentioned errors are obtained from 30 repetitions of each best architecture of MLP, LSTM, and sequence to sequence in each scenario analyzed.

Figure 6 depicts the error distribution of one-step scenarios; in this visual comparison of box plots, MLP-D-uni outperforming the other two structures LSTM is ratified. On the other hand, Figure 7 shows the error distribution found when the multi-step scenario is analyzed. In this case, it is again confirmed that MLP-D-uni outperforms the other structures LSTM and seq2seq LSTM.

In this work, a one-step forecast outperforms the multi-step forecast scenario. Although MLP is the best ANN model for predicting power production, RNN bivariate one-step ranks second among all analyzed structures. In contrast, MLP-uni one-step ranks last among the sixteen structures analyzed. This result may be a consequence of training the model without differentiation MGP series. Finally, Figure 7 shows that the detrended S2S-D-uni outperforms LSTM and seq2seq LSTM, both bivariate. Despite the limited number of dataset observations, this sequence-to-sequence model ranks sixth among all the structures analyzed.

ANN presents better forecast error results compared to ARIMA and ARIMAX statistical techniques. Table 8 and Figure 8 show the comparative forecast errors for 2015 obtained with ARIMA and ARIMAX in previous studies [79], [96] that have considered the same dataset and variables.

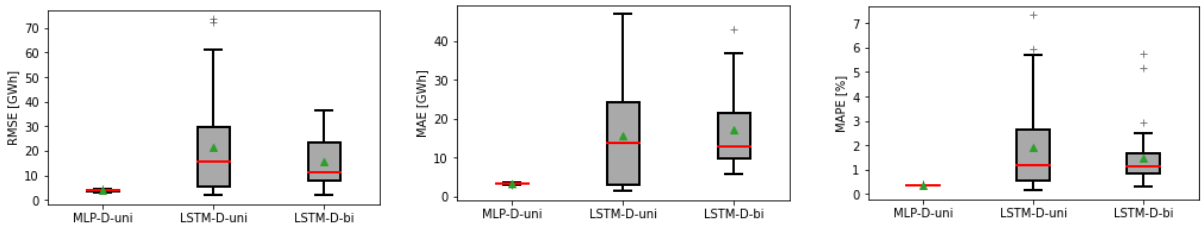


Figure 6.5 Box plot errors of the experiments carried out with the best MLP and LSTM models in the one-step scenario. a) RMSE, b) MAE, and c) MAPE. The red line represents the median, while the green triangle corresponds to the mean.

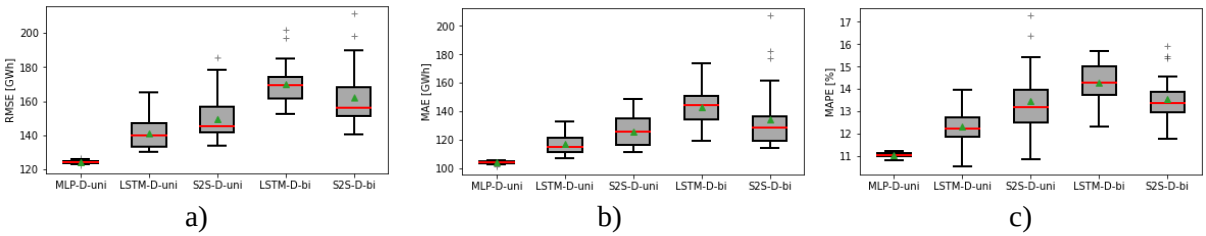


Figure 6.6 Box plot errors of the experiments carried out with the best MLP, LSTM, and seq2seq LSTM models in the multi-step scenario. a) RMSE, b) MAE, and c) MAPE. The red line represents the median, while the green triangle corresponds to the mean.

Table 6.8 Forecast errors of each technique - 2015

Technique	RMSE	MAE	MAPE
ARIMA [96]	193.04	161.65	14.32
ARIMAX [79]	111.54	86.52	8.44
ANN one-step scenario (MLP-D-uni)	4.11	3.39	0.32
ANN multi-step scenario (MLP-D-uni)	110.08	99.96	8.95

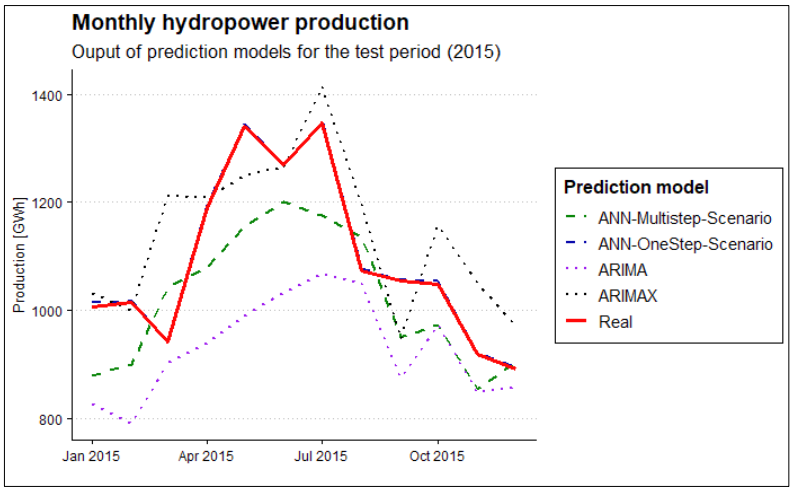


Figure 6.7 Comparison between actual and predicted values 2015 with ANN (MLP-D-uni) and statistical techniques.

6.5 Conclusion and future work

In this study, multiple ANNs were applied to forecast the hydroelectric production of Ecuador. Experiments using a dataset of MGP of hydroelectric systems [GWh] and total average monthly precipitation [mm] of the three main hydrographic basins of Ecuador were carried out.

According to the forecast horizon, two scenarios were considered: one-step (1 month) and multi-step (12 months). More than 3000 MLP, LSTM, and seq2seq LSTM models were configured, trained, and validated. RMSE, MAE, and MAPE were used to select the best model for each type of architecture. With limited observations, MLP with differentiation, univariate and bivariate series obtained the best results. These results evidence that ANN models surpass the traditional statistical models applied in time series. Also, they suggest that RNN models, such as LSTM and seq2seq, are not essentially superior in this problem setup to MLPs when hyperparameters are appropriately selected.

On the other hand, the average execution times of the models in one-step and multi-step scenarios are 1.48 and 1.37 minutes per model, respectively. It is noted, structuring data through sequences for the learning process of these models are slightly less than one-step forecast problems in computational cost.

In all ANN structures considered in one-step and multi-step scenarios, pre-processing the MGP series through differentiation resulted in better prediction errors. Similarly, using another regressive variable such as precipitations for the bivariate analysis in both scenarios positively impacted the learning and generalization of the models.

This research helps to describe and predict hydropower generation, particularly in Ecuador. Results obtained with the proposed ANN model can help organize and plan the electric sector, which is important for the energy policymaker sector. The methodology can also be extended to use in other fields.

Promising results were seen with the seq2seq LSTM architecture but slightly below MLPs. In further studies, we plan to use datasets with a greater number of observations and other recent time series techniques (e.g., latent recurrent neural networks and transformers). In this regard, we will also study the impact of applying super-resolution techniques to increase the granularity of the data set in the performance of recent very deep ANN architectures.

7 Conclusiones y líneas futuras de Investigación

7.1 Conclusiones

Esta tesis ha investigado técnicas de predicción de series temporales para la predicción de la producción hidroeléctrica mediante técnicas estadísticas tradicionales y de inteligencia artificial, centrándose en los modelos de redes neuronales para series temporales. El objetivo general fue profundizar en el conocimiento de estas técnicas, con el propósito de analizar su eficacia y servir como base para el diseño de estrategias que mejoren la toma de decisiones en la gestión de sistemas hidroeléctricos. En este sentido, la investigación logró demostrar que los modelos de inteligencia artificial, en particular las redes neuronales artificiales (MLP, LSTM y seq2seq LSTM), superan en precisión a los modelos estadísticos tradicionales como ARIMA y ARIMAX, evidenciando el potencial de la inteligencia artificial para mejorar la gestión de la energía hidroeléctrica.

Para facilitar la comprensión del alcance del trabajo realizado a continuación se presentan de forma más detallada las conclusiones obtenidas en función de los objetivos específicos inicialmente fijados.

El primer objetivo específico fue identificar las diferentes técnicas de predicción aplicadas en la producción hidroeléctrica a través de una revisión exhaustiva de la literatura. Este objetivo se cumplió mediante un análisis de los métodos estadísticos, de aprendizaje automático y de aprendizaje profundo utilizados en la predicción de series temporales, lo que permitió identificar lagunas en la investigación, como la escasa exploración de arquitecturas avanzadas de IA y la falta de integración de modelos híbridos.

El segundo objetivo planteado fue analizar los modelos estadísticos tradicionales aplicados a la predicción hidroeléctrica mediante un estudio de caso basado en datos reales. En este aspecto, la investigación permitió evaluar el desempeño de los modelos ARIMA y ARIMAX en la predicción de la producción hidroeléctrica en Ecuador, evidenciando sus ventajas y limitaciones. Aunque estos modelos mostraron un desempeño aceptable en la captura de patrones temporales, su precisión fue inferior a la de los modelos de inteligencia artificial, especialmente cuando se incorporaron múltiples variables regresoras.

Asimismo, el tercer objetivo específico buscó examinar patrones y tendencias en la producción hidroeléctrica utilizando técnicas de inteligencia artificial, fundamentalmente redes neuronales. En este sentido, los experimentos realizados demostraron que los modelos MLP lograron los mejores resultados en términos de error de predicción, superando a los modelos recurrentes como LSTM y seq2seq LSTM, se infiere que esto se debe a los datasets considerados que no son de gran longitud y volumen de datos, lo cual limita explotar adecuadamente las capacidades de estas técnicas recurrentes. Además, se comprobó que la inclusión de variables como la precipitación y el preprocesamiento de datos mediante diferenciación de series mejoraron significativamente la capacidad de generalización de los modelos.

Adicionales hallazgos a los encontrados en los objetivos específicos son: i) se encontró que la diferenciación de series y la inclusión de variables regresoras como la precipitación mejoraron significativamente la capacidad de generalización de los modelos de inteligencia artificial; ii) la metodología propuesta tiene aplicaciones directas en la planificación y organización del sector eléctrico, proporcionando herramientas más precisas para la predicción de la generación hidroeléctrica y facilitando la toma de decisiones informadas; y, iii) a pesar de los avances logrados, persisten desafíos relacionados con la integración de estos modelos en sistemas de

gestión energética reales, la necesidad de conjuntos de datos más amplios y la adaptación a la variabilidad climática y operativa.

7.2 Trabajo futuro

Por otra parte, a partir de los resultados obtenidos en esta tesis se identificaron varias direcciones para futuras líneas de investigación las cuales podrán mejorar aún más la precisión y aplicabilidad de estos modelos en entornos reales.

1. *Exploración de arquitecturas avanzadas de IA:* Se sugiere el uso de modelos más sofisticados, como redes neuronales recurrentes avanzadas (e.g., redes neuronales recurrentes latentes) y modelos basados en transformadores, que se han demostrado prometedores en otras aplicaciones de series temporales.

2. *Aplicación de técnicas de superresolución:* Se recomienda investigar el impacto de técnicas de superresolución para aumentar la granularidad de los datos y mejorar el desempeño de modelos de redes neuronales profundas.

3. *Incorporación de más variables predictoras:* Futuras investigaciones podrían incluir datos adicionales como índices de sequía, datos operativos de embalses y pronósticos meteorológicos de mayor resolución para mejorar la robustez de los modelos.

4. *Optimización de modelos híbridos:* Explorar la combinación de modelos estadísticos, modelos físicos e inteligencia artificial para mejorar la interpretabilidad y precisión de las predicciones.

5. *Implementación en sistemas de gestión energética:* Se plantea la necesidad de desarrollar estrategias para la integración práctica de estos modelos en plataformas de gestión y planificación energética en tiempo real.

6. *Generalización a otras fuentes de energía renovable:* Extender la metodología a la predicción de otras fuentes renovables, como energía solar y eólica, lo que contribuiría a una planificación más eficiente del sistema eléctrico.

Conclusions and future lines of research

7.1 Conclusions

This thesis has investigated time series prediction techniques for the prediction of hydroelectric production using traditional statistical techniques and artificial intelligence, focusing on neural network models for time series. The general objective was to deepen the knowledge of these techniques, with the purpose of analyzing their effectiveness and serve as a basis for the design of strategies to improve decision making in the management of hydroelectric systems. In this sense, the research was able to demonstrate that artificial intelligence models, particularly artificial neural networks (MLP, LSTM and seq2seq LSTM), outperform traditional statistical models such as ARIMA and ARIMAX in accuracy, demonstrating the potential of artificial intelligence to improve hydropower management.

In order to facilitate the understanding of the scope of the work carried out, the conclusions obtained according to the specific objectives initially set are presented in more detail below.

The first specific objective was to identify the different prediction techniques applied in hydroelectric production through an exhaustive review of the literature. This objective was met through an analysis of the statistical, machine learning and deep learning methods used in time series prediction, which allowed us to identify gaps in the research, such as the scarce exploration of advanced AI architectures and the lack of integration of hybrid models.

The second objective was to analyze traditional statistical models applied to hydroelectric forecasting through a case study based on real data. In this aspect, the research allowed evaluating the performance of ARIMA and ARIMAX models in the prediction of hydroelectric production in Ecuador, showing their advantages and limitations. Although these models showed an acceptable performance in capturing temporal patterns, their accuracy was lower than that of artificial intelligence models, especially when multiple regressor variables were incorporated.

Likewise, the third specific objective sought to examine patterns and trends in hydroelectric production using artificial intelligence techniques, mainly neural networks. In this sense, the experiments performed showed that MLP models achieved the best results in terms of prediction error, outperforming recurrent models such as LSTM and seq2seq LSTM, it is inferred that this is due to the datasets considered, which are not of great length and volume of data, which limits adequately exploiting the capabilities of these recurrent techniques. In addition, it was found that the inclusion of variables such as precipitation and data preprocessing by series differentiation significantly improved the generalization capability of the models.

Additional findings to those found in the specific objectives are: (i) it was found that the differentiation of series and the inclusion of regressor variables such as precipitation significantly improved the generalization capacity of the artificial intelligence models; (ii) the proposed methodology has direct applications in the planning and organization of the electricity sector, providing more accurate tools for the prediction of hydroelectric generation and facilitating informed decision making; and, iii) despite the progress achieved, challenges remain related to the integration of these models into real energy management systems, the need for larger data sets, and adaptation to climate and operational variability.

7.2 Future research

On the other hand, from the results obtained in this thesis, several directions for future lines of research were identified which could further improve the accuracy and applicability of these models in real environments.

1. Exploration of advanced AI architectures: the use of more sophisticated models, such as advanced recurrent neural networks (e.g., latent recurrent neural networks) and transformer-based models, which have shown promise in other time-series applications, is suggested.

2. Application of superresolution techniques: It is recommended to investigate the impact of superresolution techniques to increase data granularity and improve the performance of deep neural network models.

3. Incorporation of more predictor variables: Future research could include additional data such as drought indices, reservoir operational data, and higher resolution weather forecasts to improve model robustness.

4. Hybrid model optimization: Explore the combination of statistical models, physical models and artificial intelligence to improve the interpretability and accuracy of predictions.

5. Implementation in energy management systems: The need to develop strategies for the practical integration of these models in real-time energy management and planning platforms.

6. Generalization to other renewable energy sources: Extend the methodology to the prediction of other renewable sources, such as solar and wind energy, which would contribute to a more efficient planning of the electrical system.

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