



Predictive Modeling and Optimization of Mozambique's Energy Matrix to 2045 Using GRU Neural Networks

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ABSTRACT: This study develops a predictive model using Gated Recurrent Unit (GRU) neural networks to forecast Mozambique's electricity demand up to 2045 and optimize the national energy mix. Historical peak load data from 2006–2023 reveal a consistent upward trend, with seasonal variations indicating growing demand. The GRU model achieved superior accuracy compared to LSTM and traditional methods, with $R^2 = 0.86$, RMSE = 11.278, and MAE = 9.041 on test data. Comparative analysis of activation functions shows GRU with LeakyReLU delivering the best performance (RMSE = 34.14, MAE = 24.13, $R^2 = 0.69$). Multi-objective optimization results indicate that renewable energy offers the lowest financial costs and minimal emissions, while fossil fuels exhibit escalating costs and $\text{CO}_2/\text{N}_2\text{O}$ emissions after 2039. Nuclear energy maintains low emissions but incurs high financial costs. These findings underscore the need for a diversified energy strategy that balances affordability, reliability, and sustainability to meet Mozambique's projected demand growth.

KEY WORDS: Energy matrix, GRU neural networks, energy planning, Mozambique, multi-objective optimization, renewable energy.

I. INTRODUCTION

Mozambique has one of the largest solar potentials in sub-Saharan Africa, estimated at 23,000 GW, but faces challenges in integrating thermal technologies into the energy mix due to economic and institutional barriers [1,2]. Hydropower, mainly from the Cahora Bassa dam, remains the primary source of electricity, while natural gas has gained importance through projects in the Rovuma Basin. Despite the country's high solar and wind potential, these renewable sources remain largely underutilized as highlighted in recent studies on solar thermal energy in Mozambique [2].

Charcoal production, although essential for the livelihoods of many households, has led to severe environmental impacts, including deforestation and biodiversity loss [3–5]. Recent studies indicate that the charcoal value chain is a major driver of forest degradation in regions such as Combomune and Chicualacuala in southern Mozambique [6].

The energy transition in Mozambique faces structural and socio-economic challenges. Electricity infrastructure is limited and concentrated in urban areas, leaving most rural communities without access to modern energy services [6]. Heavy reliance on fossil fuels and unsustainable biomass exacerbates environmental and climate impacts, hindering progress toward the Sustainable Development Goals (SDGs), particularly SDG 7 (Affordable and Clean Energy) and SDG 15 (Life on Land) [7]. Additional barriers include insufficient public policy implementation, lack of investment in clean technologies, and scarcity of reliable data for energy planning. Furthermore, the country's vulnerability to climate extremes—such as cyclones and droughts—underscores the need for resilient and adaptive energy systems [8].

Artificial Neural Networks (ANNs) have emerged as powerful tools for modeling complex and nonlinear energy systems. Advanced architectures such as Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) networks are widely applied in time series forecasting, including energy demand prediction, due to their ability to



capture long-term dependencies [9]. Recent research highlights the role of artificial intelligence in smart grids, enabling improved demand management, accurate consumption forecasting, and optimization of renewable energy integration [10]. In contexts like Mozambique, where data are scarce and irregular, ANNs offer a robust approach for data reconstruction and scenario simulation.

This study aims to develop a predictive model based on GRU neural networks to project Mozambique's energy demand up to 2045 and propose optimal compositions for the national energy matrix. By analyzing historical data from Electricidade de Moçambique (EDM) and applying artificial intelligence techniques, the research seeks to deliver high-accuracy demand forecasts and simulate alternative scenarios for a sustainable and cost-effective energy transition.

II. LITERATURE SURVEY

Energy Planning in Mozambique

Energy planning is an essential strategic tool to ensure sustainable development and energy security for a country. According to Soares and Cândido [11], planning should reflect the guidelines of energy policy and the complexity of the national energy system. In Mozambique, the government has promoted several initiatives through institutions such as EDM (Electricidade de Moçambique), FUNAE (National Energy Fund), and MIREME (Ministry of Mineral Resources and Energy), with emphasis on the Integrated Master Plan for Electrical Infrastructure and the National Electrification Strategy.

These instruments aim to guarantee universal access to energy, promote diversification of the energy matrix, and integrate renewable sources such as solar and hydro into the national grid. However, planning faces challenges such as the scarcity of reliable data, technical and financial limitations, and the need for greater integration between public policies and technological innovation [12,13].

Applications of Neural Networks in Energy

Artificial Neural Networks (ANNs) have been widely used in energy systems for consumption forecasting, smart grid management, and resource optimization. These techniques are particularly effective in time series modeling, enabling highly accurate predictions of demand patterns [14,15]. In Mozambique, studies such as Nhambiu & Chichango [16] have shown that GRU and LSTM models outperform traditional statistical techniques in forecasting energy demand. ANNs allow the integration of economic, demographic, and climatic variables, offering greater flexibility and adaptability for energy planning. Furthermore, they are promising tools for simulating future scenarios and supporting strategic decisions in contexts of high uncertainty.

Studies in Africa (Nigeria, Kenya, South Africa)

The application of artificial intelligence in the energy sector has grown in African countries. In Nigeria, Fadare et al. [17] used ANNs to predict solar potential, while Muraina et al. [18] explored the use of AI in mini grids for rural electrification in Nigeria, Kenya, and South Africa. These studies demonstrate that even in contexts with data and infrastructure limitations, ANNs can significantly improve the efficiency of energy systems. South Africa has invested in smart grids and hybrid systems, integrating AI for load management and energy storage. These examples reinforce the feasibility of applying neural networks in developing countries, including Mozambique, where energy potential is high but still underutilized.

Limitations of Conventional Statistical Models

Traditional statistical models, such as linear regressions and deterministic series, have limitations in forecasting complex energy systems. These models assume fixed relationships between variables and cannot handle nonlinear behaviors, seasonality, and data disruptions [19]. In Mozambique, demand variability, renewable intermittency, and gaps in historical data require more sophisticated approaches. ANNs, due to their learning and generalization capabilities, offer significant advantages over conventional models, enabling greater accuracy and robustness in long-term projections [20,21].

III. METHODOLOGY

Data Collection and Pre-processing

The dataset was compiled from EDM's Annual Statistical Reports (2006–2023), including annual peak energy demand grouped by production zones: interconnected system, North-Center and Tete, Center (Mavuzi, Chicamba,



Chibata), and South. Missing data for 2016, 2017, 2018, and 2022 were reconstructed using neural network-based interpolation techniques, as recommended in similar studies on energy forecasting [22,23]. Pre-processing steps included integrity checks, noise removal, handling null values, and normalization, following best practices in time-series modeling [24,25]. The final dataset was organized chronologically for predictive modeling.

Modeling with GRU Networks and Activation Functions

Recurrent Neural Network architectures were tested, focusing on GRU (Gated Recurrent Unit) and LSTM (Long Short-Term Memory), widely applied in energy demand forecasting [22,26]. GRU models often outperform LSTM in computational efficiency and accuracy for short- and long-term dependencies [14,15].

Activation functions evaluated:

- ReLU: Efficient for positive data.
- LeakyReLU: Allows small gradients for negative values.
- ELU: Improves convergence and accuracy.
- Tanh: Compresses values between -1 and 1.

Studies confirm that GRU + LeakyReLU combinations yield superior results in energy forecasting tasks [22,23].

Time Series Decomposition

To enhance accuracy, the time series was decomposed into trend, seasonality, and noise, a method widely used in energy forecasting [24,25].

- Trend: Linked to population growth and industrialization.
- Seasonality: Associated with climatic variations and consumption habits.
- Noise: Random fluctuations.

This modular approach aligns with decomposition-based forecasting frameworks for power systems [25,27].

Tools and Frameworks

Implementation was carried out in Python, using TensorFlow, Keras, and Scikit-learn, with Google Colab for GPU acceleration [21]. For multi-objective optimization, the PyMOO framework and NSGA-II algorithm were applied, as recommended in energy optimization literature [28,29]. Objectives included:

- Minimization of economic costs
- Minimization of CO₂ and N₂O emissions
- Compliance with projected demand

Evaluation Metrics

Performance was assessed using MAE, RMSE, and R², standard metrics in energy forecasting studies [22,26].

MAE (Mean Absolute Error): measures the average of the absolute differences between the predicted and actual values.

$$MAE = \frac{\sum_{i=1}^n |y_i - x_i|}{n}, (01)$$

n – Represents the number of samples or forecasts

RMSE (Root Mean Square Error): penalizes larger errors, useful for evaluating overall accuracy.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=0}^n (y_i - x_i)^2}, (02)$$

Where:

x_i - Represents the actual value

y_i - Represents the predicted value

\bar{x} - Represents the average of the values of x

R^2 (Coefficient of Determination): indicates the degree of explanation of the model about the variability of the data.

$$R^2 = 1 - \frac{\sum_{i=0}^n (x_i - y_i)^2}{\sum_{i=0}^n (x_i - \bar{x})^2}, (03)$$

Where:

x-i. - Represents the actual value

y-i. - Represents the predicted value

x. - Represents the average of the values of x

n – Represents the number of samples or forecasts.

Based on the methodology discussed above, it was possible to reach the following results, which are presented below.

IV. RESULTS AND DISCUSSION

Analysis of Historical Data

The analysis of Mozambique’s annual peak loads (2006–2023) in Figure 1, revealed a growing trend in energy demand, with seasonal variations throughout the year.

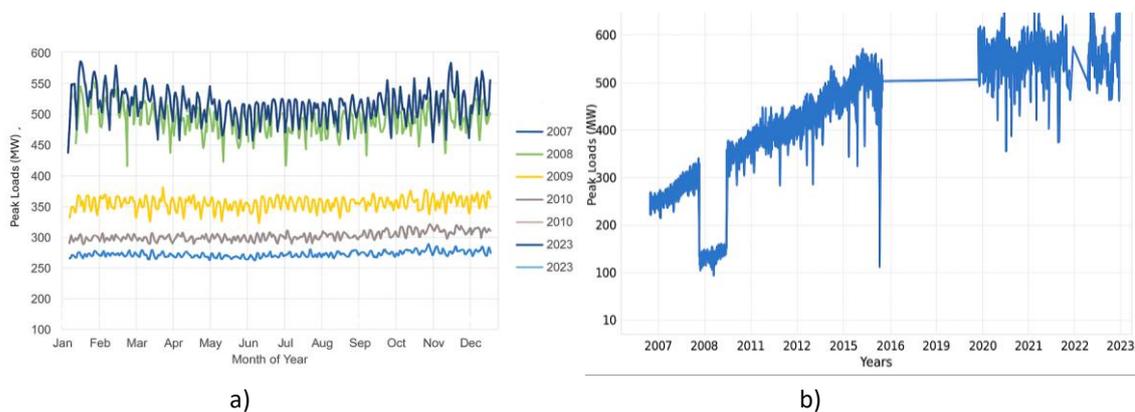


Figure 1: Peak Loads in Mozambique a) annual and b) yearly

Source: Authors

A general increase in demand is observed, despite minor fluctuations in some years, indicating the need for expansion of installed capacity. The overlap of annual series highlights consistent seasonal patterns, useful for predictive modelling. The three-dimensional visualization (Fig. 2) reinforces the growth trend and seasonal repetition.

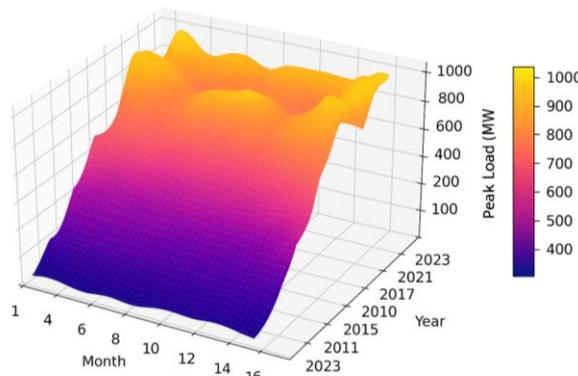


Figure 2: Surface of Peak Loads

Source: Authors

Figure 2 shows a 3D surface of peak loads over time, with months on the X-axis, years on the Y-axis, and peak load in megawatts on the Z-axis. The colour gradient from purple to yellow highlights increasing load values, indicating a clear upward trend in peak demand across years, with seasonal variations visible along the monthly axis.

Performance of Predictive Models

The results of testing LSTM and GRU networks with different activation functions are presented in figure 3 and

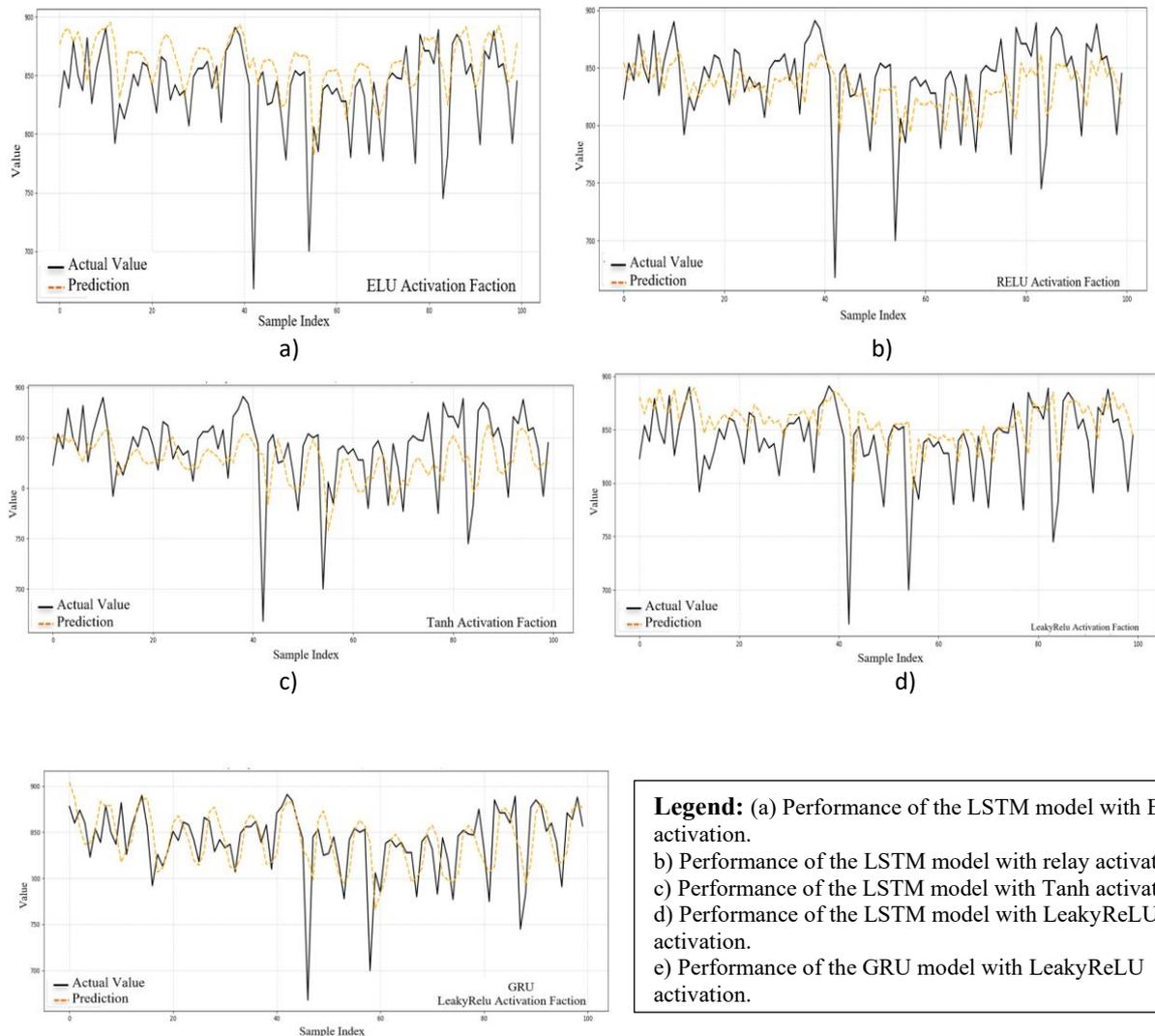


Figure 3: Performance comparison of prediction models

Table 1 summarizes the performance of different activation functions applied to LSTM and GRU networks

**Table 1
Activation Function Results**

| Network Type | Activation | RMSE | MAE | R ² |
|--------------|------------|-------|-------|----------------|
| LSTM | ELU | 40.49 | 29.01 | 0.50 |
| | Tanh | 42.03 | 33.99 | 0.54 |
| | ReLU | 43.73 | 35.58 | 0.50 |
| | LeakyReLU | 40.09 | 31.15 | 0.58 |
| GRU | LeakyReLU | 34.14 | 24.13 | 0.69 |

Source: Authors

Figure 3 and Table 1 compare different activation functions for LSTM and GRU networks. Among all configurations, GRU with LeakyReLU achieved the best performance, presenting the lowest RMSE (34.14), the lowest MAE (24.13), and the highest R² (0.69), which indicates superior predictive accuracy. For LSTM variants, LeakyReLU also outperformed ELU, Tanh, and ReLU, showing better overall results as shown in Figure 4.

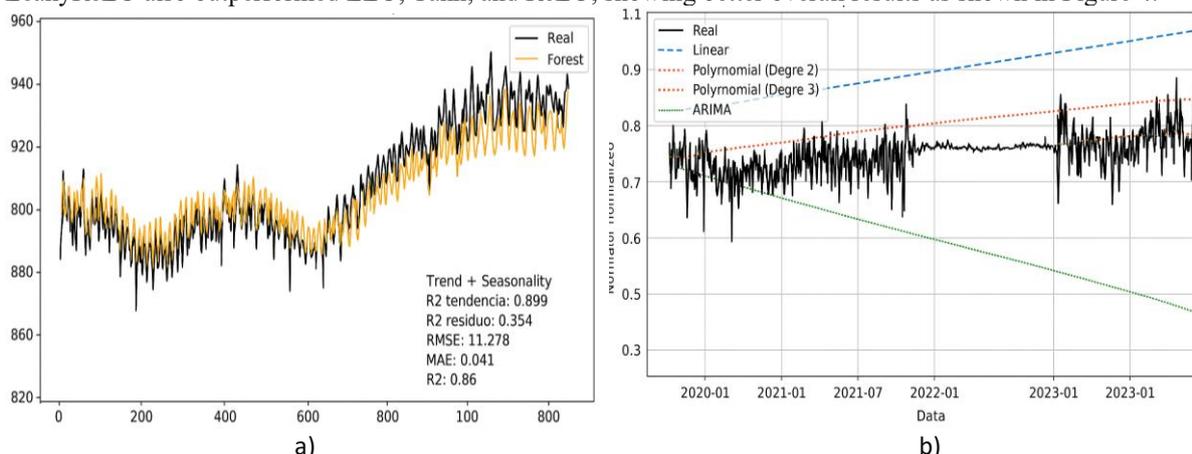


Figure 4: a) Model Performance on Test Data and b) Comparative Evaluation of Time Series Techniques
Source: Authors

Figure 4 illustrates two key analyses:

(a) Model Performance on Test Data: The GRU-based forecast closely follows the actual values, demonstrating strong alignment with observed trends and seasonality. The performance metrics (R² = 0.86, RMSE = 11.278, MAE = 9.041) indicate high predictive accuracy and low error.

(b) Comparative Evaluation of Time Series Techniques: This comparison shows different forecasting approaches—Linear, Polynomial (Degree 2 and 3), and ARIMA—against actual data. Polynomial models exhibit moderate improvement over linear trends, while ARIMA underperforms, highlighting the advantage of advanced neural models for capturing complex patterns.

Future Demand Projections

Figure 5 shows two complementary analyses: (a) Time series decomposition reveals a clear upward trend and stable seasonality in peak loads. The positive trend indicates continuous growth in electricity demand, while seasonal patterns remain consistent over time. (b) In contrast, population growth strongly correlates with the increasing trend of peak loads, suggesting that demographic expansion is a key driver of rising energy requirements. Together, these insights highlight the importance of integrating population dynamics into long-term energy planning.

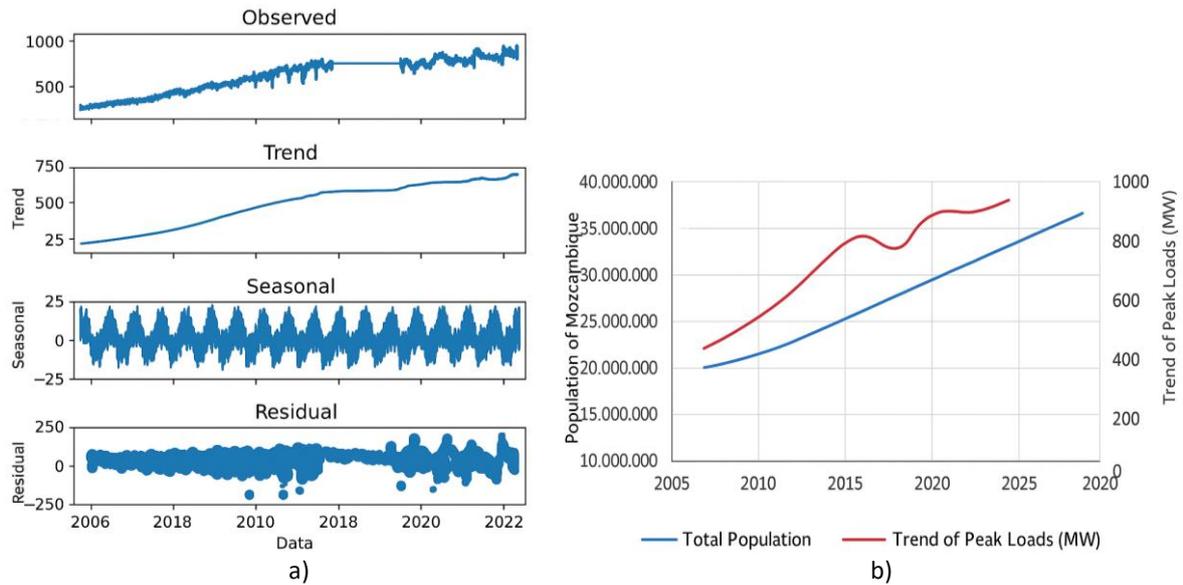
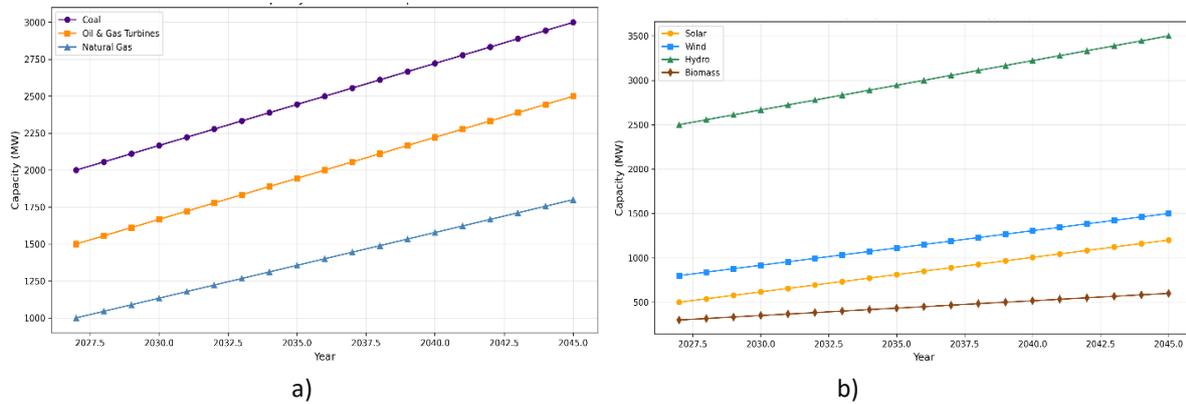


Figure 5: a) Time Series Decomposition – Peak Loads and b) Population vs Trend of Peak Loads
Source: Authors

The figure 5 presents: (a) a time series decomposition of peak loads, showing a clear upward trend and steady seasonal patterns, with residuals reflecting random variation; and (b) a correlation between Mozambique’s population growth and rising peak loads, underscoring demographic impact on energy demand and the importance of planning.

Installed Capacity Scenarios

Three scenarios were considered: fossil-based, nuclear, and renewables (see Figure 6).



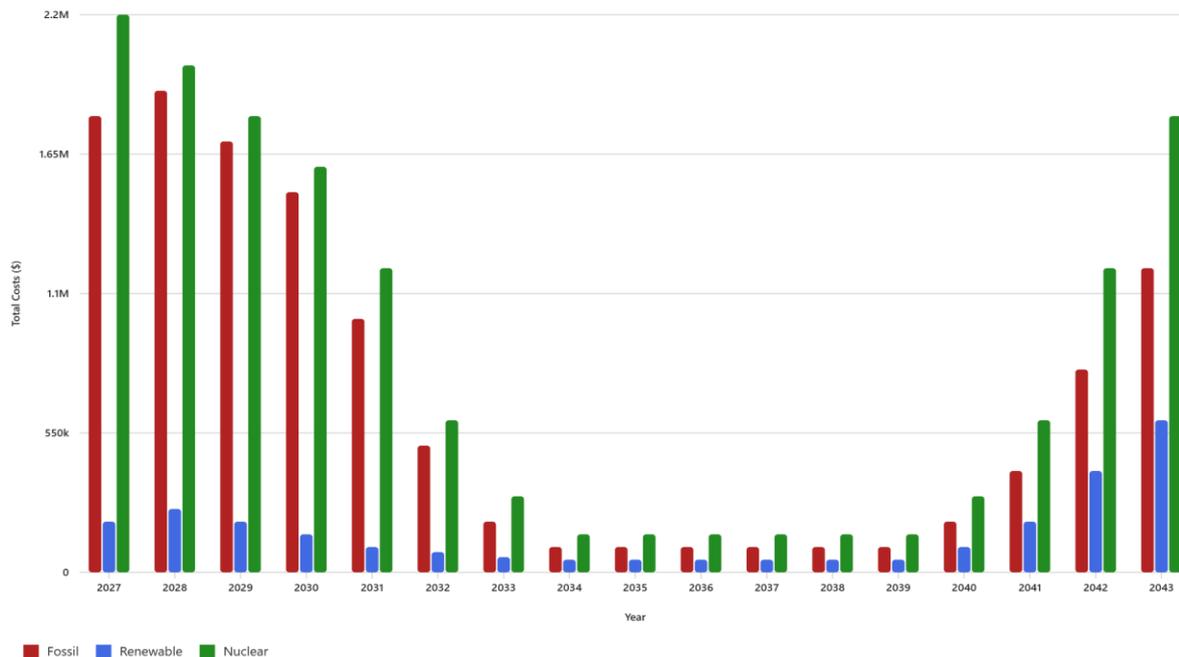


Figure 8: Evolution of Total Financial Costs

Source: Authors

Chart in Figure 8 shows that renewable energy remains the most cost-effective option throughout the period, with minimal growth compared to fossil and nuclear sources. Fossil costs start high, stabilize mid-term, and rise moderately after 2039, while nuclear costs escalate sharply from 2039 onward, reaching the highest values by 2043. This trend suggests that long-term sustainability and economic viability favor renewables over nuclear and fossil energy.

In other hand, the Figure 9 shows the projected CO₂ and N₂O emissions from fossil, renewable, and nuclear energy sources from 2027 to 2043, comparing their environmental impacts over time.

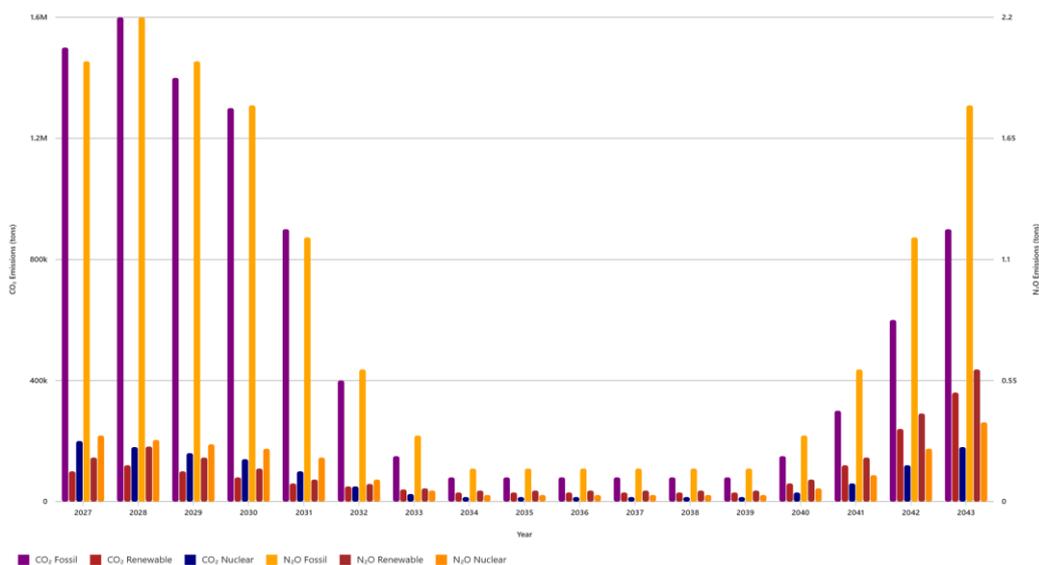


Figure 9: Evolution of Environmental Costs (CO₂ and N₂O Emissions)

Source: Authors

Figure 9 shows that fossil fuels dominate both emissions, with values rising sharply after 2039, while renewables and nuclear remain comparatively low throughout the period, indicating their lower environmental impact.

The findings provide insight into how different energy sources are expected to affect greenhouse gas emissions in the coming years. By analyzing projected CO₂ and N₂O outputs from fossil, renewable, and nuclear technologies between 2027 and 2043, the results highlight their relative environmental impacts and inform future policy and investment choices. Understanding the environmental implications of various energy sources is increasingly important in today's drive for sustainability and reduced greenhouse gas emissions. Examining future projections can help guide decisions about energy policy and technological investments.

V. CONCLUSION AND FUTURE WORK

Mozambique's energy demand is on a steady upward trajectory, driven by population growth and economic development, as evidenced by historical peak load trends and predictive modeling. Advanced neural networks, particularly GRU with LeakyReLU, demonstrated superior forecasting accuracy, reinforcing the importance of modern AI techniques in planning. Installed capacity scenarios highlight the need for diversification, with renewables emerging as the most sustainable and cost-effective option, while fossil fuels pose significant financial and environmental challenges. Nuclear energy offers low emissions but at high financial costs, underscoring the trade-off between economic feasibility and environmental responsibility. Future strategies must balance affordability, reliability, and sustainability, integrating demographic dynamics, technological innovation, and climate commitments to ensure a resilient energy system for Mozambique.

REFERENCES

1. Matavel A, Chaves J. Energia solar em Moçambique: potencial e desafios. *Revista Moçambicana de Energia*. 2015;12(2):45–56.
2. Chichango FA, et al. Solar thermal technologies for sustainable energy in Mozambique. *Journal of Renewable Energy Studies*. 2025;18(3):201–215.
3. Mabote P. Charcoal production and environmental impacts in Mozambique. *Energy Policy Review*. 2011;9(1):33–41.
4. Chavana M. Environmental consequences of charcoal production in rural Mozambique. *African Journal of Ecology*. 2014;22(4):77–89.
5. Chidumayo EN, Gumbo DJ. The environmental impacts of charcoal production in Africa. *Energy for Sustainable Development*. 2013;17(2):86–94.
6. Mabutana J, Molander S, Klintonberg P. Charcoal value chain and forest degradation in Mozambique. *Sustainability*. 2025;17(5):1550. <https://doi.org/10.3390/su17051550>
7. United Nations. *Transforming our world: The 2030 Agenda for Sustainable Development*. New York: UN; 2015.
8. Sedano F, et al. Climate vulnerability and energy systems in Mozambique. *Climatic Change*. 2020;162(1):123–140.
9. Vaccaro A. Advanced GRU and LSTM models for energy forecasting. *Applied Energy*. 2024;310:118–130.
10. Hassanin M, Mansour A, Megahed H. Artificial intelligence applications in smart grids. *Energy Reports*. 2024;12:450–463.
11. Soares L, Cândido A. Energy planning and policy integration. *Energy Policy*. 2020;138:111–120.
12. Silva N, Bermann C. Energy policy challenges in Brazil and Mozambique. *Energy Policy*. 2002;30(5):435–444.
13. Nhambiu A, Chichango FA. Energy planning challenges in Mozambique. *African Energy Journal*. 2024a;15(2):88–102.
14. Shiri H, et al. Neural networks for consumption forecasting. *Energies*. 2024;17(6):2100. <https://doi.org/10.3390/en17062100>
15. Lindemann M, et al. Time series modeling in energy systems. *Renewable Energy*. 2021;170:1200–1215.
16. Nhambiu A, Chichango FA. GRU and LSTM applications in Mozambique. *Energy AI*. 2024b;7:100–115.
17. Fadare DA, Irimese I, Oni AO, Falana A. Modeling of solar energy potential in Africa using an artificial neural network. *Am J Sci Ind Res*. 2010;1(2):144–157. <https://doi.org/10.5251/ajsir.2010.1.2.144.157> scihub.org
18. Muraina SA, Akinbamiwa BP, Abiola DS, Charles SI. Artificial intelligence-driven renewable energy solutions for rural electrification in Africa. *Int J Eng Manag Technol*. 2025;11(3):81–102. <https://doi.org/10.56201/ijemt.vol.11.no3.2025.pg81.102> iardjournals.org
19. Haykin S. *Neural Networks: A Comprehensive Foundation*. 2nd ed. Upper Saddle River: Prentice Hall; 1999. ISBN: 0132733501 Archive
20. Alzubaidi L, Zhang J, Humaidi AJ, Al-Dujaili A, Duan Y, Al-Shamma O, et al. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *J Big Data*. 2021;8:53. <https://doi.org/10.1186/s40537-021-00444-8> Journal of Big Data
21. Google Cloud. The energy sector is innovating with Google Cloud's AI solutions. *Google Cloud Blog*. 2025 Mar 6. <https://doi.org/10.1109/ACCESS.2020.2990567> Google Cloud
22. bumohsen M, Owda AY, Owda M. Electrical load forecasting using LSTM, GRU, and RNN algorithms. *Energies*. 2023;16(5):2283. <https://doi.org/10.3390/en16052283> MDPI
23. Hafedh YA, Ibrahim AA. Forecasting of electrical energy consumption using hybrid models of GRU, CNN, LSTM, and ML regressors. *J Wireless Mobile Netw Ubiquitous Comput Dependable Appl*. 2025;16(1):560–575. <https://doi.org/10.58346/JOWUA.2025.11.033> jowua.com
24. Luan Y, et al. Enhanced data processing and machine learning techniques for energy consumption forecasting. *Electronics*. 2020;13(19):3885. <https://doi.org/10.3390/electronics13193885> MDPI
25. Mbulia N, Mathonsi M, Seitshiro M, Pretorius JHC. Decomposition forecasting methods: a review of applications in power systems. *Energy Reports*. 2020;6:298–306. <https://doi.org/10.1016/j.egy.2020.11.238> ResearchGate



26. Huynh T, Nguyen D. Solving nonlinear energy supply and demand system using physics-informed neural networks. *Algorithms*. 2024;13(1):13. <https://doi.org/10.3390/a13010013> [MDPI](#)
27. Khoshrou A. Singular value decomposition for time series analysis with applications to smart energy systems. PhD Thesis. Delft University of Technology; 2022. <https://doi.org/10.4233/uuid:9bf59202-4b7a-4313-b972-c12b7d272c06> [Delft University of Technology](#)
28. Blank J, Deb K. pymoo: Multi-objective optimization in Python. *IEEE Access*. 2020;8:89497–89509. <https://doi.org/10.1109/ACCESS.2020.2990567> [julianblank.com](#)
29. Deb K, Pratap A, Agarwal S, Meyarivan T. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Trans Evol Comput*. 2002;6(2):182–197. <https://doi.org/10.1109/4235.996017> [Information Services and Technology](#)