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Optimization of energy forecasts in Boma: study of PSO and Leap-Nemo algorithms (2023-2053)

[Optimisation des prévisions énergétiques à Boma: étude des algorithmes PSO et Leap-Nemo (2023-2053)]

Mampuya Nzita André1[2*], Ndaye Nkanka Bernard[3], Dituba Ngoma Guyh[4], & N'zau Umba-di-Mbudi Clément1[1,2]

[1]*University of Kinshasa (UNIKIN), Kinshsasa, Democratic Republic of the Congo*
[2]*President Joseph Kasa-Vubu University, Faculty of Engineering, Boma, Democratic Republic of the Congo*
[3]*Higher Institute of Applied Techniques, Kinshasa, Democratic Republic of the Congo*
[4]*University of Quebec in Abitibi-Temiscamingue, School of Engineering, Rouyn-Noranda, Canada*

Abstract

Optimizing energy demand is crucial to ensuring sustainable development in developing countries, where imbalances between production and consumption are common. In the context of the commune of Boma, Democratic Republic of Congo, this study examines the challenges associated with energy consumption forecasting in the face of recurring power outages. The main objective is to develop an energy demand forecasting model using the PSO and LEAP-Nemo algorithms to optimize energy production from 2023 to 2053. The methodology includes the collection of qualitative and quantitative data on the infrastructure of the National Electricity Company (SNEL) and consumers, as well as a statistical analysis of the results using correlation and t-tests. The results show that the PSO model tends to overestimate energy demand, with a significant average error, while the BALU scenario offers more realistic and consistent forecasts. In conclusion, this study highlights the importance of adjusting forecasting models to improve their accuracy and recommends the integration of new variables to better capture the dynamics of energy demand in Boma.

Keywords: Optimization, Energy Forecasting, Boma, PSO Algorithms, BALU Scenario

Résumé

L'optimisation de la demande énergétique est essentielle au développement durable des pays en développement, où les déséquilibres entre production et consommation sont fréquents. Dans le contexte de la commune de Boma, en République démocratique du Congo, cette étude examine les défis liés à la prévision de la consommation énergétique face aux coupures de courant récurrentes. L'objectif principal est de développer un modèle de prévision de la demande énergétique utilisant les algorithmes PSO et LEAP-Nemo afin d'optimiser la production énergétique de 2023 à 2053. La méthodologie comprend la collecte de données qualitatives et quantitatives sur les infrastructures de la Société nationale d'électricité (SNEL) et les consommateurs, ainsi qu'une analyse statistique des résultats par corrélation et tests t. Les résultats montrent que le modèle PSO tend à surestimer la demande énergétique, avec une erreur moyenne significative, tandis que le scénario BALU offre des prévisions plus réalistes et cohérentes. En conclusion, cette étude souligne l'importance d'ajuster les modèles de prévision pour en améliorer la précision et recommande l'intégration de nouvelles variables afin de mieux saisir la dynamique de la demande énergétique à Boma.

Mots-clés: Optimisation, Prévisions énergétiques, Boma, Algorithmes PSO, Scénario BALU

*Auteur correspondant: Mampuya Nzita André, (simmlicem57@gmail.com). Tél. : (+243) 999340214
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1. Introduction

Electric power is a fundamental element for a nation's economic and social development. Its continuous production is crucial, as storing surpluses is not always a viable option. This reality creates imbalances between production and demand, leading to significant economic losses and hampering growth. For example, when production exceeds demand, it generates unnecessary costs, while insufficient production harms consumers and can reduce productivity. These dynamics are illustrated in previous studies, highlighting the importance of effective energy management (Gad, 2022). The challenges of forecasting energy demand are complex and involve several uncertainties, including population growth, technological development, economic performance, weather conditions, and consumer behavior. In developing countries, these challenges are exacerbated by a lack of reliable data, political influences, and demand volatility resulting from economic instability (Ayyash & Hejazi, 2022). These elements highlight the importance of these factors in the context of energy demand.

This study focuses on forecasting energy consumption in the commune of Boma, in the Democratic Republic of Congo. This choice stems from the crucial importance of energy for local development and the need to thoroughly understand the population's energy needs. A more accurate forecast could optimize energy production and reduce economic losses, as highlighted in previous work (Nurwahyudin et al., 2022).

The study identifies several major problems. On the one hand, there is an imbalance between production and consumption, with the National Electricity Company (SNEL) sometimes unable to produce enough to meet needs. On the other hand, the lack of reliable data complicates decision-making, which often relies on incomplete information. Fluctuations in demand exacerbate these challenges, making energy planning even more complex (Raza et al., 2022). To address these challenges, the study aims to estimate Boma's energy needs. This will involve collecting qualitative and quantitative data on SNEL infrastructure and tertiary consumers in 2023. An energy consumption forecasting model will be developed, focusing on the districts of Nzadi, Kalamu, and Kabondo. PSO algorithms and the BALU scenario will be used to ensure accurate forecasts through 2053, accompanied by statistical analyses to validate these forecasts using Pearson correlation tests and Student's t-tests for means, using Python Anaconda. To contextualize this research, several previous studies were reviewed. Some studies proposed modeling approaches for energy consumption forecasting, while others explored the impact of emerging technologies on energy demand (Zhao et al., 2022). Other studies have also provided valuable insights into energy consumption behaviors and energy production in developing countries (Koledzi et al., 2011). Studying energy forecasting in Boma is essential for optimizing resource use and supporting local development. By applying advanced methods and statistical analyses, this research aims to offer concrete solutions to current challenges, thus contributing to a more stable and sustainable energy future for the municipality (Akpahou et al., 2024).

2. Materials and Methods

2.1. Introduction to the Study Setting

This study was conducted in Boma, Kongo Central Province, approximately 500 km from Kinshasa. The city covers 4,332 km² and is bordered by Angola and the Atlantic Ocean. Located along the Congo River at coordinates 05°55' S and 12°10' E, Boma faces major energy challenges, including frequent power outages that impact daily life and economic activities (Wanga et al., 2015). The growing population relies on various energy sources, and this study aims to analyze the region's energy demand.

2.2. Data collection

Data collection was a fundamental process for this study. Demographic information was obtained from the Boma town hall, providing a solid basis for analyzing energy consumers. In parallel, electricity consumption data were collected at the SNEL (National Electricity Company) center on October 4, 2024. This data was categorized by tertiary consumers, providing an overview of the different energy user groups in the city.

Table I. Demographic data of the city of Boma

N°	Year	Population of Nzadi	Population of Kabondo	Population of Kalamu	Total
1	2014	72 824	79 729	105 631	258184
2	2015	75 184	80 162	106 263	261609
3	2016	75 601	80 745	107 192	263538
4	2017	110 204	116 312	142 211	368727
5	2018	112 229	116 580	142 589	371977
6	2019	112 808	117 017	143 137	372962
7	2020	117 425	117 195	144 061	378681
8	2021	119 545	117 389	145 168	382102
9	2022	120 017	119 532	146 426	385975
10	2023	122 887	121 062	161 592	405541

The table II show the impacts of these groups on the electricity load, providing an overview of the energy challenges and needs of municipalities in 2023 data.

Table II. Tertiary consumers recorded in the commune of Boma

N°	Tertiary consumers	Nzadi	Kabondo	Kalamu	Total
2	Hospital and health center	15	9	20	44
3	School (primary and secondary)	8	15	29	52
4	University and higher institute	6	2	0	8
5	Hotel-restaurant	19	10	15	44
6	Terrace	45	17	36	98
7	Telecommunications sector (Antenna)	13	6	4	23
8	Orphanage	0	0	1	1
9	Internet cafe	5	1	2	8
10	Public lighting	0	6	7	13
11	Church	14	10	15	39
12	Fuel station	0	1	1	2
13	Party room	6	2	2	10
Total		131	79	132	342

Table II lists 342 tertiary sector consumers in Boma, classified into thirteen categories, with totals for each municipality.

2.3 Data analysis

The study incorporated a methodology combining quantitative and qualitative techniques. A questionnaire was developed to estimate energy consumption among the target groups, including residential consumers. The sample size was determined according to Bernoulli's law, taking into account the total size of consumers, a margin of error of 5%, and the estimated proportion of the population. The equation used to calculate the sample size was carefully formulated to ensure the representativeness of the results (Koledzi et al., 2011). The equation for determining the sample size is defined as follows:

n= (Z_ (sc ore)^2*p*(1-p))/([1+((Z_(sc ore)^2*p*(1-p))/(N*m^2))] m^2) (1)

Where: n is the sample size; N is the total consumer size; m is the margin of error or threshold (5%); p is the estimated proportion of the population that represents the characteristic being studied (generally estimated at 50%), and the 95% confidence interval hence: Z_score=1.96.

Table III illustrates the distribution of semi-industrial, tertiary, and residential consumers surveyed in the city of Boma, by municipality.

Tableau III. Répartition de consommateurs à enquêter dans la Boma par commune (Année 2023)

	Nzadi	Kabondo	Kalamu	Total
Number of inhabitants	122 887	121 062	161 592	405541
Number of tertiary consumers	131	79	132	342
Number of tertiary consumers to be surveyed	65	39	65	169

On the tertiary consumers side, we count 21 hospitals and health centers, 25 primary and secondary schools, 4 universities and higher institutes, 21 hotel-restaurants, 48 terraces, 11 telephone antennas, 1 orphanage, 4 internet cafes, 6 public lighting, 19 churches, 2 fuel stations, and 5 party halls.

After data collection, we conducted a population projection. This step was based on a mathematical formula to estimate the projected population using an exponential rate of change. This made it possible to assess the increase in population over the years, a key indicator for anticipating future energy needs (Ambaravana et al., 2022, Nurwahyudin et al., 2022, Raza et al., 2022, Yulianto et al., 2022). This allows us to carry out a demographic projection based on the extrapolation of trends, translated by:

$$\mathbf{P_t = P_o \times e^{\tau t}} \quad (2)$$

Where: Pt is the projected population; Po is the starting population; e is the base of natural logarithms; t is the number of years and τ is the average rate of change.

The estimation of energy needs was carried out using an energy load modeling model based on a "bottom-up" approach, which focuses on consumption per appliance (Al Hasibi, 2020, Dwiyoka & Sukisno, 2020, Kanugrahan & Hakam, 2023, Kartika et al., 2015, Mustofa & Setiawan,2023, Raza et al.,2022). This method made it possible to collect precise data on the appliances used in semi-industrial sectors during the period from October 06, 2024, to December 20, 2024, and also based on previous studies (Mbuangi Lusuadi et al., 2021; Phanzu Malango et al., 2020).

Table IV continue to provide consumption estimates for other sectors, such as hospitality, illustrating the specific energy needs of each sector.

Table IV. Estimation of the consumption of a hotel-restaurant

Boma City							
Appliance	P(W)	Number	Ku	Tu	P(kWh)	Tp (%)	P(kWh/month)
Lamp	20	24	1	13	6.24	100	275
Fan	60	3	1	18	3.24	30	296
Ceiling Light	60	5	1	18	5.4	85	425
Sleet	2620	6	1	19	298.68	55	1000
Stove	3000	1	0.7	4	8.4	70	825
Water Heater	2200	1	1	1	1	100	201
Freezer	1620	1	1	19	30.78	65	450
Iron	1000	1	1	4	4	100	310
Coal fireplace						30	100kg
Total						-	4584.22

In this modeling, a hotel-restaurant needs 4584.22 kWh per year, and for all the hotel-restaurants (44) in the city of Boma to be supplied during a month, the need is estimated at 470896.8 kWh.

Table V illustrates the overall annual consumption of each branch of the tertiary sector.

Table V. Annual consumption of the tertiary sector in the city of Boma

N°	Tertiary Sector	P(kWh/month) Unitary	Number	P(kWh/month)
1	Terrace	4109.5	98	402731
2	University and higher institute	3269	8	26152
3	Ophanage	3428.44	1	3428.44
4	Internet cafe	1438.4	8	11507.2
5	Primary and secondaire school	360	52	18720
6	Prty room	10831	10	108310
7	Fuel station	4683	2	9366
8	Hotel and restaurant	4584.22	44	201705.68
9	Hospital and health center	4620.63	44	203307.72
10	Church	2677	39	104403
11	Public lighting	998	13	12974
12	Telecommunication Antenna	3836.9	23	88248.7

2.3.1 Tools and Software Used: PSO Algorithm Combined with Machine Learning Techniques

The analyses were performed with the Python Anaconda software, using the PSO algorithm to optimize energy demand in the tertiary sector (Gad, 2022). The script begins by importing the necessary libraries, including Pandas and NumPy for data manipulation, Scikit-learn for preprocessing, and Matplotlib and Seaborn for visualizing the results (He et al., 2022). A function is defined to evaluate the model performance by calculating the mean squared error (MSE) and imposing penalties for underpredictions (Ayyash & Hejazi, 2022). The data are loaded and normalized with StandardScaler to improve training efficiency (Khalil et al., 2022; Zhao et al., 2022). The PSO algorithm is then executed, adjusting the particle positions to optimize the RandomForestRegressor model (Li et al., 2019; Deng et al., 2019). Finally, the model performance is evaluated using a correlation coefficient, and the results are visualized to analyze the predictions (Abdel-Basset et al., 2021; Eseye et al., 2019).

2.3.2 LEAP Software and NEMO Optimization Model

The Low Emission Analysis Platform (LEAP) software and the Next Energy Modeling system for Optimization (NEMO) optimization model are used to analyze policies related to energy system development and evaluate renewable energy implementation scenarios. This study chooses LEAP as the analysis tool due to its efficiency and flexibility, as confirmed by previous research (Al Hasibi & Bawan, 2023). Energy demand analysis in LEAP can be performed using both end-use analysis and scenario analysis approaches. Energy demand (ED_k^D) is the total energy consumption of a sector in kWh and is calculated using (Al Hasibi and Bawan, 2023; Mustofa and Setiawan, 2023; Rivera-Gonzalez et al., 2019):

$$ED_k^D = \sum_i \sum_j I_{i,j,k} \times A_{i,j,k} \quad (3)$$

Where Ai, j,k represents the activity level for each sector i, technology j, and fuel k, and Ii,j,k represents the energy intensity (expressed as energy per unit of activity) for each sector i, technology j, and fuel k.

In the BALU scenario, it is assumed that electricity consumption at the end of the period will continue as it was in the previous year. This means that there are no changes in development policies or forecasts. Basically, the projections remain constant and are not influenced by political decisions (Mustofa & Setiawan, 2023).

3. Results

3.1 Optimization of energy demand in the tertiary sector using the PSO algorithm

As part of energy demand optimization in the tertiary sector, an analysis compared the actual values with those predicted by the PSO algorithm. In the first observation, the actual value was approximately 1.19 million kWh, while the forecast was 1.77 million kWh, resulting in a significant error of 583295 kWh. The algorithm showed a tendency to systematically overestimate energy demand, with a correlation coefficient of 0.9999, indicating an almost perfect relationship between actual and predicted values. The t-statistic of 104.654 and the associated p-value of 0.000 reveal statistically significant differences. The solution quality assessment showed an improvement in fitness, increasing from 1, 189, 200,623.31 to 823, 585,894.84 over the iterations. Despite this progress, adjustments are needed to better align predictions with actual values, highlighting the importance of continuing to refine the model.

Figure 1 illustrates the relationship between predicted and actual energy consumption values.

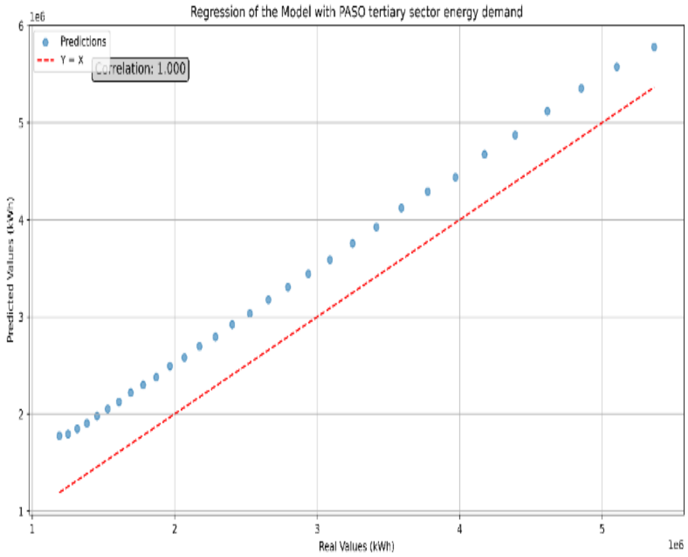

Figure 1. Regression model of the PSO algorithm for tertiary sector energy demand

Figure 1 shows the relationship between actual energy demand and PSO predictions. The blue dots, representing the predictions, are scattered around the ideal correlation red line (y = x). The prediction errors, measured by the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE), are 510,690.15 kWh and 511,389.09 kWh, respectively. In addition, the bias of the predictions ranges from 414,998.75 kWh to 583,294.90 kWh, indicating a general tendency towards overestimation, which requires model optimization.

Figure 2 shows the deviations between the predicted values and the actual values obtained by the PSO algorithm.

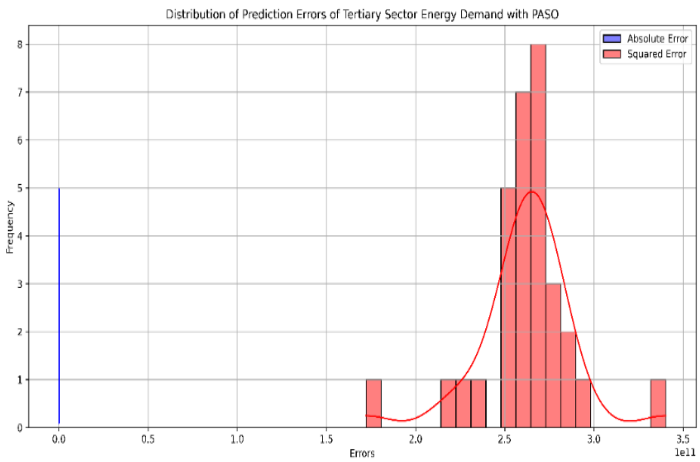

Figure 2. Distribution of prediction errors

Figure 2 shows the distribution of prediction errors, with bars representing absolute errors and a curve for square errors. The majority of errors cluster around zero, but significant errors create peaks in the distribution. The blue bars illustrate absolute errors, while the red bars show that the more dispersed square errors penalize large deviations. The concentration of errors between 1.5×10^{11} and 3.5×10^{11} kWh indicates a tendency toward overestimation of energy demand, requiring adjustments to improve forecast accuracy.

3.2 Optimization of energy demand in the tertiary sector using LEAP-Nemo

Figure 3 illustrates the optimization of energy demand in the tertiary sector using LEAP-Nemo on the BALU scenario.

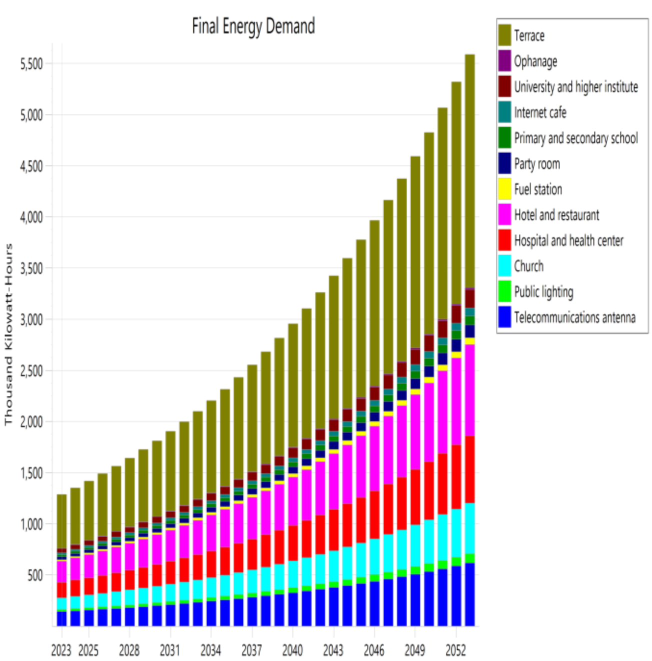

Figure 3 BALU scenario for optimizing energy demand in the tertiary sector

The analysis of energy demand values in the tertiary sector according to the BALU scenario reveals significant trends from 2023 to 2053. In 2023, the total demand is 1,288.5 thousand kWh, increasing to 91,315.5 thousand kWh in 2053. Consumption in the terrace sector increases from 527.1 thousand kWh to 37,270.2 thousand kWh. Hotels and restaurants see their demand increase from 205.2 thousand kWh to 14,565.1 thousand kWh, while educational infrastructure increases from 42.1 thousand kWh to 2,987.6 thousand kWh, highlighting the need for strategic energy planning.

3.3 Statistical analysis of Comparison of actual and predicted values calculated by the PSO algorithm and the BALU scenario

Figure 4 illustrates the comparison of the calculated actual values and predicted values of the PSO algorithm and BALU scenario of energy demand in the tertiary sector from 2023 to 2053.

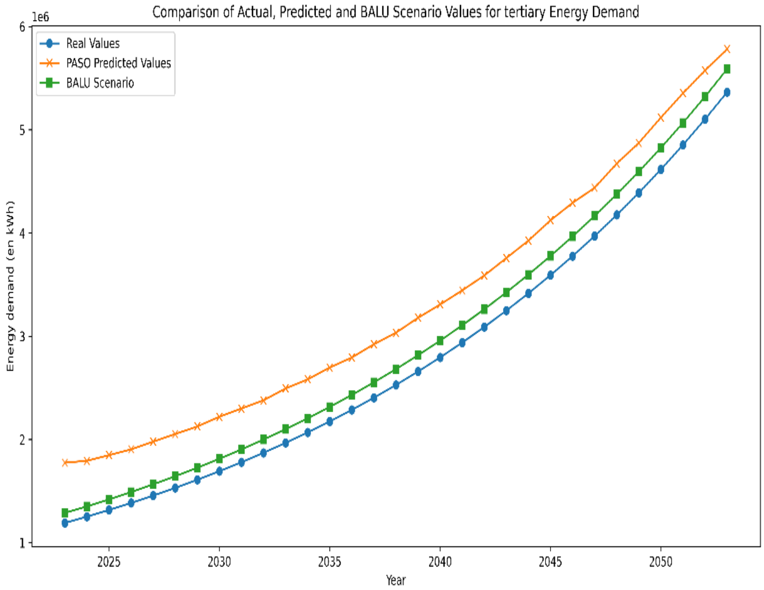

Figure 4. Comparison of actual calculated values, predicted values from the PSO algorithm, and the BALU scenario for energy demand in the tertiary sector

The analysis of the gaps between actual energy d emand and the forecasts of the PSO and BALU model s, illustrated in figure 4, shows significant differences. In 2023, the gap of the PSO model is -583,295.26 kW h, while that of BALU is -97,646.26 kWh. In 2045, the gaps reach -531,627.02 kWh for PSO compared to -18 5,802.02 kWh for BALU. Although the correlation co efficients are 1.000 for both models, the PSO shows a systematic bias, while BALU appears to be a more reli able option for energy forecasting.

Figure 5 shows histograms of the actual and predicted PSO values and the BALU scenario values.

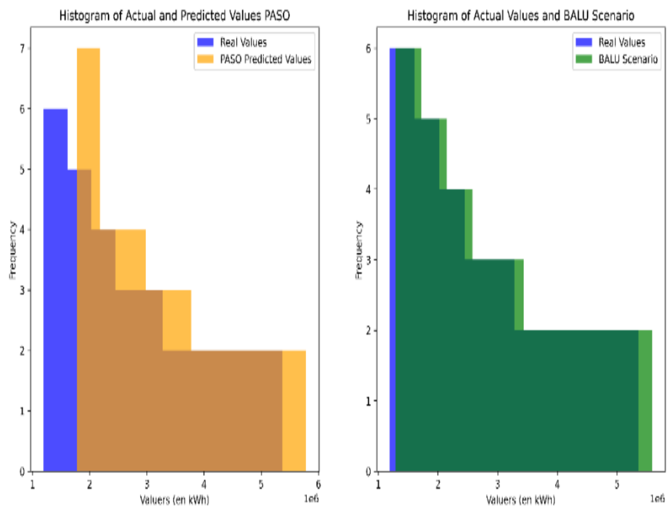

Figure 5. Histograms of actual and predicted values for PSO and the BALU scenario

The analysis of the histograms of actual and predicted values for the PSO and BALU models, presented in figure 5, reveals key information about energy demand forecasting. Actual values, represented by blue bars, are mainly concentrated between 1.5 and 2.5 million kWh. In contrast, the values predicted by PSO in orange go up to 3 million kWh, showing a tendency towards overestimation. The BALU model's forecasts, in green, closely align with actual values, confirming its effectiveness. Thus, BALU is a more reliable model for anticipating energy needs.

Figure 6 illustrates the comparison of actual, predicted PSO, and BALU scenario values using the Student t-test for energy demand in the tertiary sector.

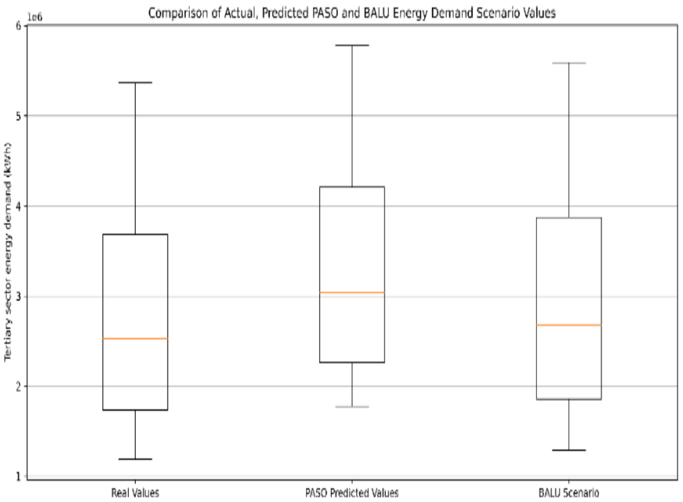

Figure 6. Box plots comparing actual, predicted PSO, and BALU scenario values

A comparative analysis of energy demand in the tertiary sector, illustrated in Figure 6, shows that the p-values of 0.1096 indicate the absence of significant difference between the actual values, the PSO forecasts, and those of the BALU scenario. The average of the actual values is approximately 2, 789,843.33 kWh, while the PSO forecasts reach 3, 300,529.55 kWh and those of BALU, 2, 945,654.84 kWh, highlighting that PSO tends to overestimate demand. The t-statistic of -1.6241 reinforces this tendency, highlighting the need to adjust the models to better reflect reality.

4. Discussion

This study focuses on the comparative analysis of the Particle Swarm Optimization (PSO) and LEAP-Nemo algorithms for predicting energy consumption in the tertiary sector. A crucial aspect of evaluating model accuracy involves comparing actual values with those generated by the PSO algorithm. Khan et al. (2019) highlight the necessity of using real data for model validation, while Gao (2025) emphasizes the importance of direct comparisons for real-time parameter adjustments. The analysis indicates a mean absolute error (MAE) of 510,690.15 kWh and a root mean square error (RMSE) of 511,389.09 kWh, revealing a significant margin of error that necessitates improvements.

Even advanced algorithms like PSO can produce errors, as noted by Gad (2022) and He et al. (2022), who suggest integrating complementary methods to minimize discrepancies and support continuous optimization. Forecast biases vary from 414,998.75 kWh to 583,294.90 kWh, often leading to overpredictions. Ayyash & Hejazi (2022) argue that while a positive bias may ensure adequate supply, Zhao et al. (2022) caution it could reflect an underestimation of future needs. Notably, the correlation coefficient of 0.99983 demonstrates strong alignment between actual and predicted values, boosting confidence in the models. The BALU scenario projects energy demand for 2023 at 1,288.5 thousand kW, with expectations to rise to 91,315.5 thousand kWh by 2053, attributed to the expanding commercial sector (Akpahou et al., 2024).

The PSO model shows larger deviations compared to BALU, indicating a consistent tendency to overpredict. This study underscores the limitations of forecasting models, advocating for hybrid approaches to enhance predictive performance in energy management.

5. Conclusion and Recommendation

The This study highlights the importance of optimizing energy demand forecasts in Boma to address imbalances between production and consumption, exacerbated by frequent power outages. The results show that the PSO model tends to overestimate demand, while the BALU scenario offers more realistic forecasts. Adjustments to forecasting models are recommended to improve their accuracy, particularly by integrating new variables and exploring hybrid approaches. These adjustments will help better capture energy demand dynamics and ensure efficient energy resource management in the future.

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Conflicts of Interest

The authors declare no conflict of interest in the publication process of the research article.

Ethical consideration

This article was prepared in accordance with ethical research principles, ensuring compliance with current standards. It is important to note that no human or animal data were used in this study, ensuring full compliance with ethical requirements.

The authors also declare that they have no conflicts of interest regarding this research, which reinforces the study's credibility. The data used for this analysis were obtained ethically and legally, complying with all relevant regulations. Finally, the study results were presented honestly and transparently, without any data manipulation, to ensure the scientific integrity of the entire work.

Authors Contributions

Each author played a key role in the development and finalization of the research article.

A.M.N. was responsible for drafting and preparing the original version. He also focused on data collection and analysis and validated the final version.

B.N.N. participated in revising the original version to improve its quality and made additional revisions to refine the content.

G.D.N. oversaw the entire process, ensuring that all steps were followed correctly. Finally, C.N.U.-D.-M. performed the final revision, ensuring that the article was ready for publication. All authors have read and approved the final version of the manuscript.

ORCID numbers for authors

Mampuya N.A: https://orcid.org/0009-0007-6092-145X

Ndaye N.B: https://orcid.org/0000-0003-1628-5330

Dituba N.G: https://orcid.org/0000-0002-9671-3819

N'zau N.U.-D.-M.: https://orcid.org/0009-0007-3515-1588

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