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# Optimizing energy forecasts at Boma for 2023 to 2053 Using machine learning techniques of the PSO algorithm

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**Abstract.** *This research was conducted to optimize energy consumption forecasting in the commune of Boma, in the Democratic Republic of Congo, in the face of persistent imbalances between energy production and demand. The main objective of the study was to assess local energy needs in order to support the economic and social development of the region. To achieve this objective, a methodology integrating quantitative and qualitative techniques was adopted. Data were collected through surveys conducted among residential, semi-industrial, and tertiary consumers, as well as demographic information provided by the town hall. In parallel, machine learning techniques were employed to predict energy consumption, with the Particle Swarm Optimization (PSO) algorithm used to optimize forecasts. The forecasting model was accompanied by statistical analyses, including the Pearson correlation coefficient and the Student t-test, to validate the results. The analysis revealed a very high correlation between actual and predicted values, with a coefficient reaching 0.999, which demonstrates high model accuracy. However, biases were observed, including a tendency to overestimate energy consumption, highlighting the importance of reliable data collection to improve forecast accuracy. In conclusion, the PSO algorithm has proven to be an effective tool for energy demand management, although adjustments are necessary to optimize the results. The lessons learned highlight the need for a thorough understanding of consumption behaviors and regular data updates to adapt forecasts to future developments.*

**Keywords:** Optimization, energy forecasting, PSO algorithm, machine learning techniques, energy management

## Introduction

Electricity is a fundamental element for a nation's economic and social development. Its continuous production is of crucial importance, as storing excess power 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, unnecessary costs are generated. Conversely, insufficient production harms consumers and can reduce productivity. These dynamics are clearly illustrated in previous studies such as [1], [2]. The challenges of energy forecasting are complex and involve several uncertainties, including

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population growth, technological development, economic performance, weather conditions, and consumer behavior. In developing countries, these challenges are exacerbated by the lack of reliable data, political influences, and demand volatility resulting from economic instability. Highlights the importance of these factors in the context of energy demand [3]. In this context, this study addresses a single primary research problem: 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, as well as the need for a thorough understanding of the population's energy needs. A more accurate forecast could lead to optimized energy production and reduced economic losses. The work of Gad [4] highlights the importance of such an approach. The study identifies several major problems related to this issue. First, there is an imbalance between production and consumption, with the National Electricity Company (SNEL) sometimes unable to produce enough to meet needs. Furthermore, the lack of reliable data complicates decision-making, which often relies on incomplete information. Fluctuations in demand further exacerbate these challenges, making energy planning more complex, as indicated by [5], [6].

To address these challenges, the study aims to estimate the energy needs of the Boma municipality. This will involve collecting qualitative and quantitative data on SNEL's infrastructure, as well as low-voltage data for residential, commercial, and semi-industrial consumers in 2023. An energy consumption forecasting model will be developed, focusing on the districts of Nzadi, Kalamu, and Kabondo. The Particle Swarm Optimization (PSO) algorithm will be used to ensure accurate forecasts through 2053, using machine learning techniques implemented in Python via Anaconda to predict demand. This will be accompanied by statistical analyses to validate these forecasts using Pearson correlation tests and Student's t-tests for means, using Python Anaconda [7], [8], [9].

The study will focus specifically on the Boma municipality, taking into account the aforementioned districts. To contextualize this research, several previous studies were analyzed. For example, [10] proposed modeling approaches for energy consumption forecasting, while [11] examined the impact of emerging technologies on energy demand. Other studies, such as those by [12], [13], have also provided valuable insights into energy consumption behaviors and energy production in developing countries. 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, contributing to a more stable and sustainable energy future for the municipality.

Energy optimization is essential for maximizing the efficiency of energy production and consumption. It involves a variety of approaches, such as demand modeling, analyzing consumption patterns, and forecasting future needs. Optimization methods are particularly crucial in energy systems, where accurate planning can reduce costs and improve sustainability [1], [4], [14]. The PSO algorithm, inspired by the social behavior of birds and fish, was developed to solve complex problems by simulating the movement of particles in a search space [15]. Each particle represents a potential solution, and the algorithm uses the interaction between these particles to converge to an optimal solution. PSO is particularly appreciated for its simplicity and efficiency, but it also presents challenges, particularly regarding convergence to local optima and convergence speed in high-dimensional search spaces [4].

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Energy forecasting models, whether based on historical data or advanced techniques such as PSO and machine learning, are essential for anticipating energy needs. These models help optimize energy production and minimize economic losses, which is particularly relevant in the context of decentralized energy systems [1]. Statistical analysis, particularly using methods such as the Pearson correlation coefficient, is crucial for validating the results of predictive models. These tools help assess forecast accuracy and ensure the reliability of the applied algorithms [5], [6]. However, various challenges persist in energy forecasting. Uncertainties related to population growth, economic conditions, and climate variations complicate the task of forecasters. A thorough understanding of these challenges is essential for developing robust models. Optimization algorithms, including PSO, can be applied to many aspects of energy management, such as supply planning and improving energy efficiency in infrastructure. The collection and integration of qualitative and quantitative data are fundamental to the success of these optimizations. This includes not only demographic data and consumption habits but also infrastructure characteristics [10]. In short, this theory lays the necessary foundation for future research, providing a solid conceptual framework for analyzing energy needs in the Boma municipality. Integrating machine learning and optimization algorithms such as PSO into the forecasting process is crucial to address the shortcomings of existing methods and ensure a more reliable approach to energy management in the region.

## Theoretical Background

Energy optimization is essential to maximize the efficiency of energy production and consumption. It involves a variety of approaches, such as demand modeling, analysis of consumption patterns, and forecasting future needs. Optimization methods are particularly crucial in energy systems, where accurate planning can reduce costs and improve sustainability [1], [4], [14]. The PSO algorithm, inspired by the social behavior of birds and fish, was developed to solve complex problems by simulating the movement of particles in a search space [16]. Each particle represents a potential solution, and the algorithm uses an interaction between these particles to converge to an optimal solution. PSO is particularly appreciated for its simplicity and efficiency, but it also presents challenges, particularly regarding convergence to local optima and the speed of convergence in high-dimensional search spaces [4]. Energy forecasting models, whether based on historical data or advanced techniques such as PSO and machine learning, are essential for anticipating energy needs. These models help to optimize energy production and minimize economic losses, which is particularly relevant in the context of decentralized energy systems [1]. Statistical analysis, especially through methods such as the Pearson correlation coefficient, is crucial to validate the results of predictive models. These tools help to assess the accuracy of forecasts and ensure the reliability of the applied algorithms [5], [6]. However, various challenges persist in energy forecasting. Uncertainties related to population growth, economic conditions, and climate variations complicate the task of forecasters. A thorough understanding of these challenges is essential to develop robust models. Optimization algorithms, including PSO, can be applied to many aspects of energy management, such as supply planning and improving energy efficiency in infrastructure. The collection and integration of qualitative and quantitative data is fundamental to the success of these optimizations. This includes not only demographic data and consumption habits but also infrastructure characteristics [10]. In sum, this theoretical section establishes the necessary foundations for future research, providing a solid conceptual framework for the analysis of energy needs in the Boma commune.

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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, contributing to a more stable and sustainable energy future for the municipality.

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In summary, this theoretical section lays the necessary foundation for future research, providing a solid conceptual framework for analyzing energy needs in the Boma municipality. Integrating machine learning and optimization algorithms such as PSO into the forecasting process is crucial to address the shortcomings of existing methods and ensure a more reliable approach to energy management in the region.

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## 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 [17]. 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 1.** Boma City demographics

| N° | Year | Population of Nzadi | Population of Kabondo | Population of Kalamu | Total | Household |
|---|---|---|---|---|---|---|
| **1** | 2014 | 72 824 | 79729 | 105631 | 258184 | 43030.7 |
| **2** | 2015 | 75 184 | 80162 | 106263 | 261609 | 43601.5 |
| **3** | 2016 | 75 601 | 80745 | 107192 | 263538 | 43923.0 |
| **4** | 2017 | 110204 | 116312 | 142211 | 368727 | 61454.5 |
| **5** | 2018 | 112229 | 116580 | 142589 | 371977 | 61996.2 |
| **6** | 2019 | 112808 | 117017 | 143137 | 372962 | 62160.3 |
| **7** | 2020 | 117425 | 117195 | 144061 | 378681 | 63113.5 |
| **8** | 2021 | 119545 | 117389 | 145168 | 382102 | 63683.7 |
| **9** | 2022 | 120017 | 119532 | 146426 | 385975 | 64329.2 |
| **10** | 2023 | 122887 | 121062 | 161592 | 405541 | 67590.2 |

**Tables 2**, **3** and **4** show the impacts of these groups on the electricity load, providing an overview of the energy challenges and needs of municipalities in 2023 data.

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**Table 2.** Semi-industrial consumers recorded in the commune of Boma

| N° | Semi-industrial consumers | Nzadi | Kabondo | Kalamu | Total |
|---|---|---|---|---|---|
| **1** | Welder | 9 | 2 | 4 | 15 |
| **2** | Sawmill | 0 | 15 | 7 | 22 |
| **3** | Bakery | 3 | 2 | 0 | 5 |
| **4** | Cold room | 4 | 10 | 6 | 20 |
| **5** | Mill | 2 | 26 | 30 | 58 |
| **6** | Quado | 3 | 10 | 17 | 30 |
| **7** | Adjuster | 0 | 20 | 38 | 58 |
| **8** | Cold workshop | 2 | 0 | 0 | 2 |
| **9** | Radio channel | 6 | 0 | 0 | 6 |
| | **Total** | 29 | 85 | 102 | 216 |

**Table 2** lists 216 semi-industrial consumers in Boma, divided into nine categories, with totals for each commune.

**Table 3.** Tertiary consumers recorded in the commune of Boma

| N° | Tertiary consumers | Nzadi | Kabondo | Kalamu | Total |
|---|---|---|---|---|---|
| **1** | Butcher's shop | 0 | 21 | 30 | 51 |
| **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 |

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| N° | Tertiary consumers | Nzadi | Kabondo | Kalamu | Total |
|---|---|---|---|---|---|
| **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 | 100 | 162 | 393 |

**Table 3** lists 393 tertiary sector consumers in Boma, classified into thirteen categories, with totals for each municipality.

**Table 4.** Residential consumers recorded in the commune of Boma

| Residential consumers | Nzadi | Kabondo | Kalamu | Total |
|---|---|---|---|---|
| **Household** | 3 672 | 6 191 | 8 064 | 17927 |

**Table 4** lists 17,927 residential consumers in Boma, spread across three municipalities.

*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 [1]. The equation for determining the sample size is defined as follows:

$$\boldsymbol{n} = \frac{\boldsymbol{Z_{sc\,ore}^2 * p * (1-p)}}{\left[\boldsymbol{1} + \left(\frac{\boldsymbol{Z_{sc\,ore}^2 * p * (1-p)}}{\boldsymbol{N * m^2}}\right)\right]\boldsymbol{m^2}} \quad (1)$$

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

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**Table 5.** Distribution of consumers to be surveyed in the Boma by municipality

| | Nzadi | Kabondo | Kalamu | Total |
|---|---|---|---|---|
| **Number of inhabitants** | 122887 | 121062 | 161592 | 405541 |
| **Number of residential consumes to be surveyed** | 77 | 130 | 169 | 376 |
| **Number of semi-industrial consumes to be surveyed** | 19 | 54 | 65 | 138 |
| **Number of tertiary consumes to be surveyed** | 65 | 49 | 80 | 194 |

We need to obtain the details of energy needs through surveys conducted among 376 residential consumers, as well as semi-industrial and tertiary consumers. Among the semi-industrial consumers, there are 10 welders, 14 sawmills, 3 bakeries, 13 cold rooms, 37 mills, 19 quads, 37 adjusters, 1 cold workshop, and 4 radio channels. On the tertiary consumers side, we count 25 bakeries, 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 [3]. This allows us to carry out a demographic projection based on the extrapolation of trends, translated by:

$$\boldsymbol{P_t = P_o \times e^{\tau t}} \tag{2}$$

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 [18].

To illustrate energy consumption, a table was developed, presenting the specifications of the devices used in the residential, tertiary, and semi-industrial sectors. This table detailed the power in watts (P), the number of units, the coefficient of use without unit (Ku), the duration of use in time (Tu), as well as the total energy consumption in kilowatt hours (kWh) for each device. This made it possible to visualize consumption habits and identify the most energy-intensive devices [19], [20], [21]. We collected data on the use of household, semi-industrial and tertiary appliances, representing 23 consumption models and one model is represented in **Table 6**, during the period from October 6, 2024 to December 12, 2024.

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**Table 6.** Estimation of household consumption

| City of Boma | | | | | |
|---|---|---|---|---|---|
| **Device** | P(W) | Number | Ku | Tu | P(kWh) |
| **Lamp** | 40 | 10 | 1 | 13 | 1.3 |
| **Iron** | 1300 | 1 | 1 | 1 | 1.3 |
| **Water heater** | 2200 | 1 | 1 | 1 | 2.2 |
| **Bowl** | 1500 | 1 | 1 | 0.5 | 0.75 |
| **Freezer** | 1620 | 1 | 1 | 22 | 35.64 |
| **hair dryer** | 1600 | 1 | 1 | 0.8 | 0.8 |
| **Fan** | 60 | 2 | 1 | 5 | 0.6 |
| **Ceiling light** | 60 | 4 | 1 | 10 | 2.4 |
| **Laptop** | 45 | 2 | 1 | 3 | 0.27 |
| **Led TV** | 110 | 1 | 1 | 15 | 1.65 |
| **Sleet** | 2620 | 2 | 1 | 8 | 41.92 |
| **Water fountain** | 1000 | 1 | 1 | 0.5 | 0.5 |
| **Charger** | 5 | 5 | 1 | 0.5 | 0.0125 |
| **Fridge** | 250 | 1 | 1 | 4 | 1 |
| **Radio** | 600 | 1 | 1 | 2 | 1.2 |
| **Baffle** | 500 | 1 | 1 | 2 | 1 |
| **Stove** | 2500 | 1 | 0.7 | 4 | 7 |
| | **Total** | | | | 99.655 |

In this modeling, a household needs 99.655 kWh per day, and for all households (17927) in the city of Boma to be supplied during per year, the need is estimated at 53595455.55 kWh.

**Table 7** gives the different estimated consumptions by consumer category and for the entire city.

**Table 7.** Estimated consumption by category and across the city

| Ville de Boma | | | |
|---|---|---|---|
| **Consumer** | Entities | Power per month (kWh/Year) | Total (kWh/Year) |
| **Residential** | Households | 53595455.55 | 53595455.55 |
| **Tertiary** | Butcher's shop | 44235.36 | 921539.42 |
| | Hospital and health center | 87465.84 | |
| | Primary and secondary school | 5329.584 | |
| | University and higher institute | 40125.696 | |
| | Hospital-restaurant | 472216.8 | |
| | Terrace | 181515.6 | |
| | Orphanage | 807.9 | |
| | Internet cafe | 3275.584 | |
| | Public lighting | 10140 | |
| | Church | 3183.252 | |

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| Ville de Boma | | | |
|---|---|---|---|
| **Semi-industrial** | Fuel station | 5522.4 | 517547.33 |
| | Antenna | 65177.4 | |
| | Party room | 2544 | |
| | Welder | 30845.1 | |
| | Bakery | 39997.785 | |
| | Cold room | 361530 | |
| | Mill | 25877.28 | |
| | Quado | 10707.84 | |
| | Adjuster | 6514.56 | |
| | Cold workshop | 496.808 | |
| | Radio channel | 18155.7 | |
| | Sawmill | 23422.256 | |

The rate is calculated over the last ten years in **Table 1** which allows us to determine the rate of increase in the population projection over the last ten years in expression (2):

$$\tau = \frac{ln\left(\frac{P_o}{P_b}\right)}{y} = \frac{ln\left(\frac{405541}{258184}\right)}{9} = 0.05017216 \tag{3}$$

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

In analyzing energy consumption data for the city of Boma, a machine learning approach was implemented, primarily using the Python programming language and dedicated libraries. The process began by defining the initial data, including population, number of households, and consumption rates by sector. This data was carefully organized into a structured format to facilitate subsequent analyses. A linear regression model was then chosen as the analysis method, due to its ability to establish simple relationships between the independent variables (population and demand) and the dependent variable (total energy consumption). To do this, the population growth rate was calculated, allowing future values to be projected over a twenty-year period, from 2023 to 2053. During this phase, computational loops were set up to estimate energy consumption for each year, taking into account projected increases. These calculations were integrated into a dictionary, which was then converted into a DataFrame using the Pandas library. This data format made it easy to manipulate and analyze the information. Once the data was prepared, linear regression was applied. The model was trained with the input data, and the coefficients were extracted to interpret the impact of each variable on total consumption. The predictions generated by the model were added to the DataFrame, providing a comparison between actual and predicted consumption. To present the results visually, graphs were created using the Matplotlib library. These graphs showed energy consumption trends over the years, highlighting the predictions generated by the model. The regression equation, which summarizes the relationships between the variables, was also displayed on the graph for better understanding [1], [3], [4], [5].

The creation of this network was achieved through particle swarm optimization (PSO). The process began with the gathering of the necessary data, followed by the design of the network. After this design phase, the weights and biases were initialized. The network was then trained

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using the PSO algorithm to optimize the model weights. This step reduced the loss function over several iterations, which was essential to improve the accuracy of the network [4]. For the data measurement and analysis methods, an Excel file containing the energy consumption data was first loaded. Once this file was accessible, the input and output data were carefully prepared. The weights and biases were initialized with random values for the particles of the PSO algorithm, ensuring diversity in training. The network training consisted of running the algorithm to refine the weights and reduce the loss function [3]. Once training was completed, the network performance was validated. This included calculating the correlation coefficient as well as other statistical errors, such as the mean absolute error (MAE) and the root mean square error (RMSE). In addition, p-values were calculated to confirm the robustness of the results, as highlighted [5]. This structured approach allows for a clear and consistent follow-up of the process of assessing and analyzing energy needs in the municipalities concerned [1].

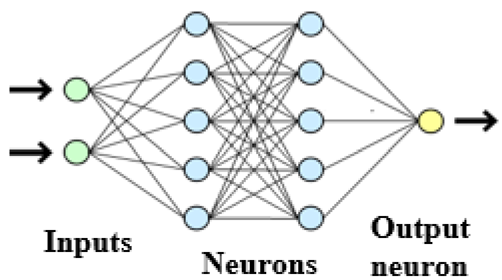


**Figure 1.** Typical architectural model of an artificial neural network

At the end of the process, we used the network to make final predictions on the input data, while taking into account potential biases. Each step of this methodology was crucial to build an efficient regression model based on the data provided, thus ensuring a rigorous and methodological approach in our analysis. Statistical analysis using R software, particularly through methods such as the Pearson correlation coefficient, was instrumental in validating the results of the predictive models, allowing us to assess the accuracy of the predictions and ensure the reliability of the applied algorithms [7], [9], [11]. In addition, we used the Student t-test to compare the means of the values calculated and predicted by the PASO algorithm. This method allowed us to assess whether the differences observed between the predicted and actual values were statistically significant, thus reinforcing the validity of our results.

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 [22].

## Results and Discussion

The analysis of Boma's energy consumption, performed using the sklearn. linear model linear regression model, reveals several important insights into the dynamics of energy demand in this region. By examining the results, including the mean absolute error (MEA) and the root mean squared error (RMSE), we can draw significant conclusions about the model's accuracy and efficiency. The MEA, which is $2.40 \times 10^{-8}$, indicates that, on average, the absolute error between

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actual total energy consumption and that predicted by the model is extremely low. This suggests that the model is highly accurate in its predictions, which is crucial for long-term energy planning. Such a low MEA means that decision-makers can have confidence in the estimates provided, allowing them to better plan for future energy needs. Furthermore, the RMSE of $2.93 \times 10^{-8}$ reinforces this interpretation. The RMSE measures the difference between predicted and actual values, taking into account the error variance. A very low RMSE also indicates that the model's predictions are not only close to the actual values but also consistent throughout the entire period studied. This means that the model is reliable for future projections. Analyzing the energy consumption data for each year, we observe a general upward trend in total consumption. For example, the total consumption forecast for 2023 is approximately $5.50 \times 10^{7}$ kWh, and it gradually increases to approximately $2.48 \times 10^{8}$ kWh by 2053 **Table 8**. This trend is consistent with the population and demand growth rates incorporated into the model. The model also allowed for a comparison of actual consumption values with predicted values for each year. The results show that the model predictions closely align with actual consumption, validating the model structure and the selected variables. This demonstrates the importance of population and demand as key predictors in energy consumption analysis. The use of linear regression to model energy consumption in Boma yielded very promising results. The low MEA and RMSE values indicate good prediction accuracy, and the observed trends provide essential information for future energy planning. These results can help decision-makers design appropriate strategies to meet the growing energy demand in the city.

**Table 8.** Energy Demand Prediction

| Year | Total_Consumption | Predicted_Total_Consumption |
|---|---|---|
| **2023** | 55034540 | 55034540 |
| **2024** | 57866190 | 57866190 |
| **2025** | 60843520 | 60843520 |
| **2026** | 63974050 | 63974050 |
| **2027** | 67265650 | 67265650 |
| **2028** | 70726610 | 70726610 |
| **2029** | 74365640 | 74365640 |
| **2030** | 78191910 | 78191910 |
| **2031** | 82215050 | 82215050 |
| **2032** | 86445180 | 86445180 |
| **2033** | 9.0892970 | 90892970 |
| **2034** | 95569600 | 95569600 |
| **2035** | 10048690 | 100486900 |
| **2036** | 105657100 | 105657100 |
| **2037** | 111093400 | 111093400 |
| **2038** | 116809400 | 116809400 |
| **2039** | 122819500 | 122819500 |
| **2040** | 129138800 | 129138800 |
| **2041** | 135783300 | 135783300 |

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| Year | Total_Consumption | Predicted_Total_Consumption |
|---|---|---|
| **2042** | 142769600 | 142769600 |
| **2043** | 150115400 | 150115400 |
| **2044** | 157839100 | 157839100 |
| **2045** | 165960300 | 165960300 |
| **2046** | 174499300 | 174499300 |
| **2047** | 183477700 | 183477700 |
| **2048** | 192918000 | 192918000 |
| **2049** | 202844000 | 202844000 |
| **2050** | 213280700 | 213280700 |
| **2051** | 224254500 | 224254500 |
| **2052** | 235792900 | 235792900 |
| **2053** | 247924900 | 247924900 |

The equation for predicting total energy consumption for the city of Boma is:

$$Total\ Consumption = -5.96 \times 10^{-8} + 132.04 \times Population + 22.01 \times Demand \tag{4}$$

Where Intercept ($-5.96\times10^{-8}$): This term represents the baseline energy consumption when both population and demand are equal to zero. In a practical context, this intercept may not have any tangible meaning, as it is extremely small. This indicates that when the variables are zero, consumption is close to zero. Population Coefficient (132.04): This coefficient shows the impact of population increase on total energy consumption. For each additional person in the population, total energy consumption increases by 132.04 kWh. This means that a growing population results in a proportional energy demand. Demand Coefficient (22.01): This coefficient represents the effect of demand on total energy consumption. For each additional unit of demand (which could represent a household or another demand indicator), total consumption increases by 22.01 kWh. This shows that even a small increase in demand has an impact on total consumption.

The equation shows how a city's total energy consumption changes based on two key factors: population and demand (three sectors: household, semi-industrial, and tertiary). The impact of population is much more significant than that of demand, as shown by the higher coefficient for population. This suggests that population growth is the main driver of energy consumption.

Figure 2 presents the energy demand forecast for the city of Boma over the period 2023 to 2053.

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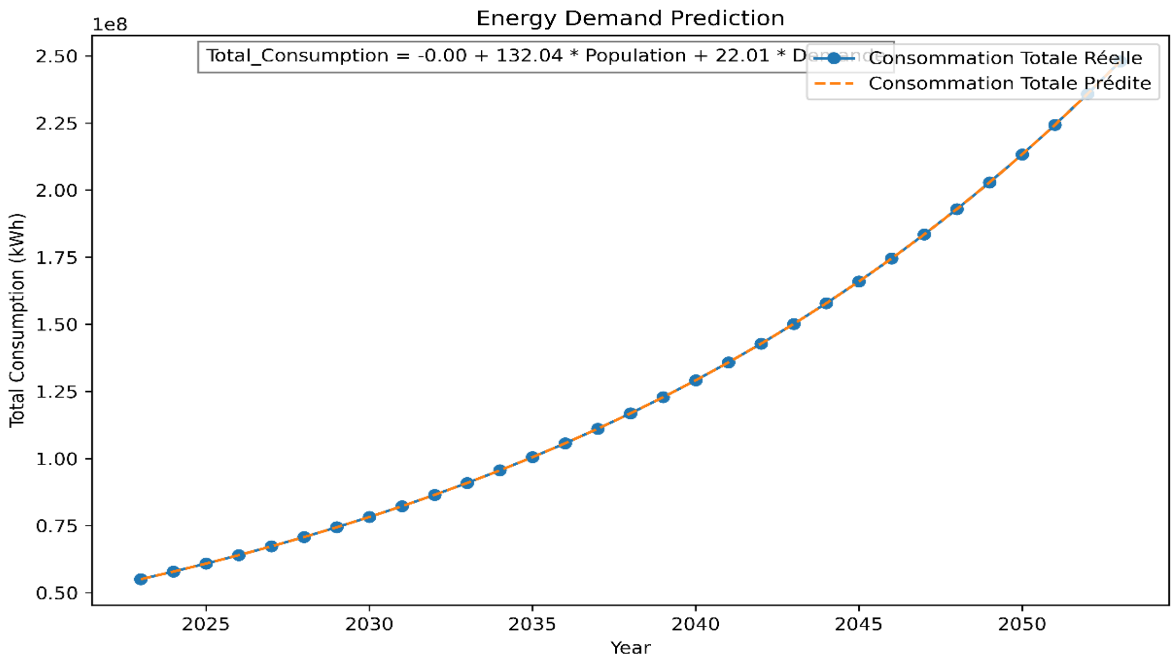


**Figure 2.** Regression model of the Energy Demand Prediction

In this figure 2, the x-axis represents the years, ranging from 2023 to 2053, while the y-axis shows the total energy consumption in kilowatt-hours (kWh). The blue dots represent the actual total energy consumption, while the orange dashed line shows the total consumption predicted by the linear regression model. This visualization allows for a direct comparison of actual values with the model's predictions. Looking at the curve, there is a general upward trend in energy consumption, both in actual and predicted values. This reflects the continued increase in energy demand, likely due to population and household growth in the region. The proximity of the blue dots (actual values) to the orange line (predicted values) demonstrates the model's accuracy. A low divergence between the two indicates that the forecasts are reliable, which is essential for energy planning. The legend embedded in the figure provides additional information about the regression equation that was used to generate the predictions. This equation shows how total energy consumption is influenced by population and demand, illustrating the main factors that determine the city's energy needs. This figure is a powerful visual tool for understanding energy consumption trends and evaluating the effectiveness of the forecasting model. It provides critical information for decision-makers seeking to manage energy demand in a growing environment.

The actual values represent the observed energy consumption, constituting an essential reference for evaluating the accuracy of the model. By comparing them with the predicted values, the effectiveness of the method used can be measured. The predicted values from 81,208,230 at 2023 to 2,646,700 at 2053, on the other hand, are the estimates provided by the model after applying the PSO algorithm, crucial for making informed decisions in energy management. The analysis of the errors, which represent the difference between the predicted and actual values of , allows us to identify weaknesses in the model and make necessary improvements. In addition, the bias values vary, with the results ranging from about 26,173,680 at 2023 to about 1,668,2540 at 2053. The analysis of the biases of the predictions showed that they were often higher than the

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actual values. A key point to emphasize is that forecast bias should be higher to optimize electricity demand, thus ensuring sufficient supply capacity to meet demand.Figure 3 illustrates the relationship between predicted and actual energy consumption values.

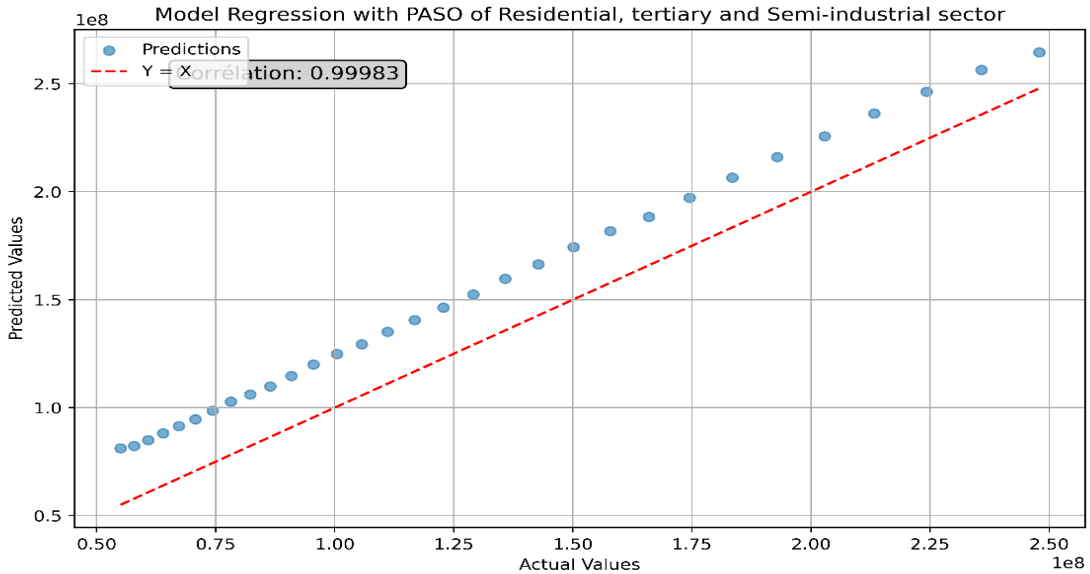


**Figure 3.** Regression model of the PSO algorithm

Meanwhile, the correlation coefficient revealed an impressive value of $9998.3\times10^{-4}$ in Figure 3, indicating a very high agreement between actual and predicted values. This accuracy is essential for making informed decisions regarding energy consumption management, as it increases confidence in the predictions provided by the model.

In the process of optimizing the energy consumption prediction performance, a significant improvement in fitness was observed. Over the iterations of the Particle Swarm Optimization (PSO) algorithm, the fitness values significantly decreased from 2811872071120.951 to 1855323187379.524. This reduction indicates a convergence towards optimal solutions, thus demonstrating the effectiveness of the PSO algorithm in adjusting the model parameters and decreasing the prediction error. Figure 3 shows the deviations between the predicted values and the actual values obtained by the PASO algorithm.

In Figure 4, however, although the predictions are generally close to the actual values, the prediction errors, measured by the mean absolute error (MAE), are 23440773.399 and the root mean square error (RMSE) is 23491676.483, respectively. These results indicate that there is still a certain margin of error, highlighting the importance of taking these values into account when applying the model, as they can have an impact on energy planning. The integration of the PSO algorithm has significantly improved the energy consumption prediction performance. Each result obtained underlines the importance of optimization and rigorous evaluation of models to ensure accurate and reliable predictions, essential for efficient energy management.

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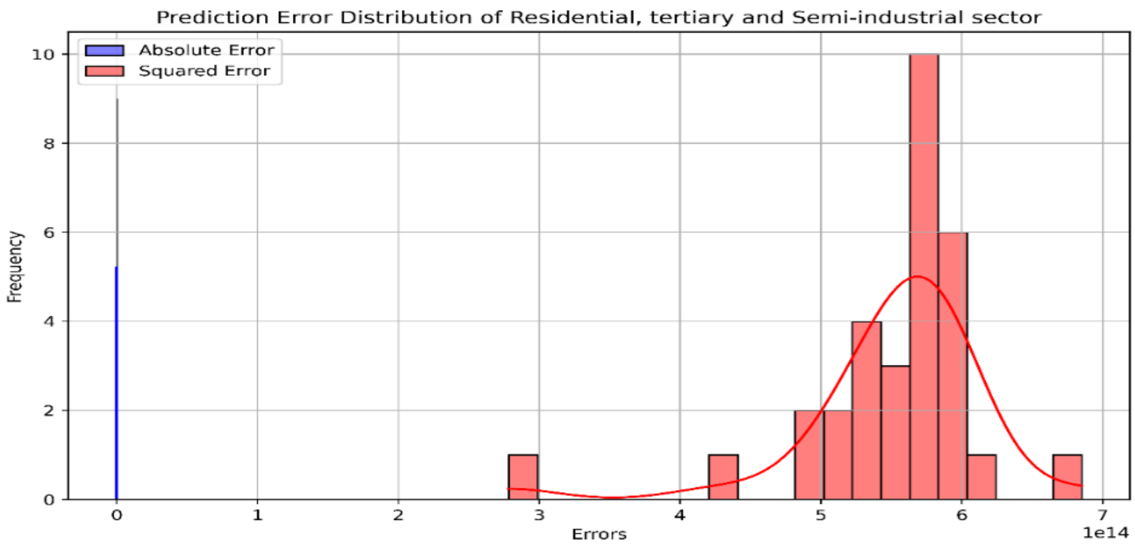


**Figure 4.** Distribution of prediction errors

The Pearson correlation analysis of the results, performed with a threshold of 5%, compares the values calculated and predicted by the PSO algorithm. It shows that the correlation between the actual energy consumption values and those predicted by the PSO algorithm is extremely high, reaching 9998.321 * $10^{-4}$. This value indicates an almost perfect agreement, suggesting that the algorithm's predictions follow the observed values very closely. Such precision testifies to the effectiveness of the algorithm in modeling energy demand. Examining the statistical significance of this correlation, we find that the calculated t is 293.87, with a p-value lower than 2.2* $10^{-16}$. These results allow us to conclude that the observed correlation is statistically significant, thus reinforcing the idea that the PSO algorithm is effective in predicting energy demand. In addition, the 95% confidence interval, which lies between 9996.479* $10^{-4}$ and 9999. 200* $10^{-4}$, provides us with additional assurance about the robustness of the correlation. This means that we are very confident that the true correlation in the population is also very high, which reinforces the reliability of the predictions made by the algorithm. The implications of this high correlation for energy management are significant. It suggests that the PSO algorithm can be considered a reliable tool for energy demand management. This allows decision-makers to make informed decisions based on accurate forecasts, which is essential in a context where resource optimization is paramount. Furthermore, the ability of the PSO algorithm to react quickly and accurately to fluctuations in energy demand is crucial. This responsiveness is essential to optimize resource management and ensure that supply is always matched to demand. Finally, with a very high correlation and clear statistical significance, energy managers can have confidence in the forecasts provided by the PSO algorithm. This facilitates better energy planning and reinforces the ability to anticipate future needs. The PSO algorithm demonstrates exceptional performance in predicting energy demand, supported by significant statistical results and strong correlation with actual values.

Student's t-tests were performed with a threshold of 5% to compare the values calculated and predicted by the PSO algorithm. Analysis of the results reveals that the means of the actual energy consumption values and those predicted by the PSO algorithm are 128,930,829 and 152,371,605, respectively. This comparison highlights that, on average, the algorithm predicts higher energy consumption than observed, suggesting a bias towards higher predictions. To assess the

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significance of this difference, a Student t-test was performed, producing a t of -1.617. This result indicates that there is a slight difference between the two means. The negative value of the t suggests that the algorithm's predictions are above the actual values, which could be of concern to energy managers. However, when we examine the statistical significance of this difference, we note that the p-value is 0.111, which is higher than the conventional threshold of 0.05. This indicates that the observed difference between the means is not statistically significant. In other words, we lack sufficient evidence to conclude that there is a real difference between the values predicted by the algorithm and the observed values. Continuing our analysis, we consider the 95% confidence interval, which extends from -52,448,089 to 5,566,539. This interval shows us that we are uncertain about the direction of the difference. Indeed, since this interval includes both negative and positive values, it is possible that the predictions are either higher or lower than the actual values. The implications of these results for energy management are significant. Since the difference between the predictions and the actual values is not significant, this means that the PASO algorithm, although it can provide higher predictions, does not deviate alarmingly from reality. This situation can be interpreted as an indicator that the algorithm is reasonably reliable for energy demand management, even considering the bias observed in the forecasts.

The assessment of the accuracy of an energy consumption prediction model is mainly based on the comparison between the actual values and those provided by the PSO algorithm. The analysis of energy consumption in Boma, conducted using a linear regression model, produced very promising results. The mean absolute errors (MAE) and root mean square errors (RMSE) were $2.40 \times 10 - 8$ and $2.93 \times 10 - 8$, respectively. These values indicate that the model's predictions are extremely accurate, increasing decision-makers' confidence in the estimates. This is essential for long-term energy planning, as confirmed by [1], who emphasize the importance of reliable models for energy demand management. The data show a general upward trend in total energy consumption, from. This trend is consistent with population and demand growth, as observed in previous studies [3]. These results highlight the need to adapt energy strategies in the face of continued increases in demand. The model predictions show good agreement with actual consumption values, thus validating the model structure and the selected variables. This is supported by [4], who observed similar results in his research on algorithm optimization. This validation is crucial for establishing demand management strategies. The equation for predicting total consumption is given by Total Consumption = $-5.96 \times 10^{(-8)} + 132.04 \times$ Population + 22.01 $\times$ Demand. Although very small, it indicates that consumption is close to zero when both population and demand are zero. Population Coefficient: For each additional person, consumption increases by 132.04 kWh, highlighting the significant impact of population growth. Demand Coefficient: Each additional unit of demand increases consumption by 22.01 kWh, showing that even small increases in demand can have significant effects. The visual comparison between the actual values (blue dots) and the predicted values (orange line) shows a close relationship, which demonstrates the model's accuracy. This visualization is essential for decision-makers, as [10] point out, as it provides an intuitive understanding of consumption trends. The results indicate that population growth is the main driver of energy consumption, which is corroborated by the work of [12]. Decision-makers should therefore focus their planning efforts on the impacts of demographics on energy demand to ensure adequate supplies in the future. The actual values, considered as an essential reference, allow measuring the effectiveness of the prediction method. In this regard, the work of [1] confirms the importance of using real data to validate predictive models. Moreover,[3] supports this approach by stating that the direct comparison of actual values with predicted values is crucial to adjust the model parameters in real time. Analyzing the prediction errors, it is found that the mean absolute error (MAE) is 23,440,773.399 and the root

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mean square error (RMSE) is 23,491,676.483. These figures reveal a significant margin of error that highlights the need for improvements in the model. Points out that even advanced algorithms such as PSO can have errors [4], [5] suggest implementing complementary methods to reduce these errors, reinforcing the idea that optimization should be a continuous process. Analysis of forecast biases shows that they vary between 26,173,680 and 16,682,540, indicating that forecasts are often higher than actual values. In this sense, [10]note that a positive bias could be beneficial to ensure adequate supply capacity, while [11] argue that this bias can also signal an underestimation of future needs. A crucial point in this assessment is the correlation coefficient, which stands at 0.99983, indicating a high agreement between actual and predicted values. Point out that such correlation levels increase confidence in predictive models [1], [23] argue that high correlations are essential for making informed decisions in energy management. Furthermore, a significant improvement in fitness was observed, with fitness values decreasing from 2,811,872,071,120.951 to 1,855,323,187,379.524. Corroborate these results by stating that PSO is effective in optimizing model performance [24], [25] add that this convergence towards optimal solutions is a strong indicator of the algorithm's effectiveness. Statistically, the calculated t is 293.87, with a p-value less than 2.2e-16, demonstrating a statistically significant correlation. Point out that such p-values enhance the robustness of the results [6], [26] encourage the use of such analyses to ensure the reliability of forecasts. By examining the means of the actual and predicted values, respectively 128,930,829 and 152,371,605, it is evident that there is a bias towards higher forecasts. This comparison indicates that, on average, the algorithm predicts higher energy consumption than observed. Point out that while biases in forecasts can be a cause for concern, they do not necessarily indicate model failure [27]. Recommend monitoring these biases in order to adjust forecasts appropriately [28]. Finally, applying a Student T-test reveals a t of -1.6165 with a p-value of 0.1112, indicating that the difference between the means is not statistically significant. Specify that p-values greater than 0.05 do not allow one to conclude that there is a significant difference [29], [30] add that this situation may indicate reasonable reliability of the forecasts.

The PSO algorithm demonstrates exceptional performance in predicting energy demand. Although biases and errors remain, the high correlation and statistical significance of the results strengthen confidence in its use for energy management. Further research results confirm the need for continuous optimization and forecast adjustment, which underlines the importance of a rigorous approach in energy consumption modeling.

To develop more sophisticated forecasting models and improve the accuracy of energy forecasts, it is essential to integrate machine learning techniques. This approach begins with the establishment of a continuous data collection system, allowing monitoring of energy consumption trends over an extended period. This system will provide valuable data to feed the models [4]. In parallel, it is necessary to study in depth the energy consumption behaviors of different groups, including residential, semi-industrial, and tertiary. This analysis will allow for better understanding of the variations in demand according to the specific characteristics of each group. It will also be crucial to analyze the impact of local and national energy policies on energy consumption, in order to assess their influence on the efficiency of forecasts [12]. Another important dimension to explore is the integration of renewable energy sources. Understanding how these sources can affect consumption forecasts and energy demand management is fundamental to adapting models accordingly. In this context, it is also necessary to assess the existing energy infrastructure in Boma in order to identify the improvements needed to support more efficient energy management [10]. The application of advanced algorithms should also be considered. Testing other optimization algorithms, such as genetic algorithms, will allow comparing their efficiency with that of the PASO algorithm, thus providing a broader perspective on best practices in energy forecasting [3]. Furthermore, it is essential to study how external factors, such as climate and economic conditions, influence energy consumption and forecasts in order to refine models by taking these variables into account [11]. Finally, to ensure successful adoption of new energy practices, it is important to promote training programs. These programs will raise awareness among the population about the importance of energy saving and sustainable practices. In addition, fostering collaborations between researchers, policymakers, and industry stakeholders will help develop integrated solutions for energy management, thereby strengthening the effectiveness of forecasts and interventions [28].

## Conclusions

The conclusion of this study highlights the critical importance of optimizing energy forecasts for the municipality of Boma, in the Democratic Republic of Congo, using the Particle Swarm Optimization (PSO) algorithm. The results obtained reveal an impressive correlation of 0.999 between actual and predicted values, highlighting the remarkable accuracy of the developed model. This achievement is comparable to other studies that have also reported high energy forecasting results. However, our research stands out for its integrated approach, combining qualitative and quantitative data specific to Boma. Despite this, biases were identified in our forecasts, including a tendency to overestimate energy consumption. This finding highlights the need for more rigorous data collection and methodological adjustments to challenges similar to those encountered in other contexts, where forecasts are often complicated by incomplete data. Our research expands on the existing literature by demonstrating the effectiveness of the PSO algorithm in a specific context. It also paves the way for more sophisticated forecasting models by integrating machine learning techniques and behavioral analyses. Several recommendations emerge in this regard. It would be beneficial to integrate more historical data and gather information on consumption behaviors to improve forecast accuracy. Furthermore, testing alternative algorithms, such as genetic algorithms, could allow for a comparison of their effectiveness with that of PSO and the identification of best practices. It would also be relevant to assess the impact of integrating renewable energy sources on energy demand and forecasts in order to adapt models accordingly. Examining local and national energy consumption policies could also provide valuable insights to optimize energy management. Finally, developing awareness programs on energy conservation and sustainable practices could encourage behavioral changes among the population, thus enhancing the effectiveness of forecasts.

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