**European Journal of Sustainable Development Research**
2023, 7(4), em0227
e-ISSN: 2542-4742
https://www.ejosdr.com

MODESTUM

Research Article

OPEN ACCESS

# Analyzing the Brazilian project of energy expansion

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**Citation:** de Macedo, J. L., & de Alencar Nääs, I. (2023). Analyzing the Brazilian project of energy expansion. *European Journal of Sustainable Development Research, 7*(4), em0227. https://doi.org/10.29333/ejosdr/13409

**ARTICLE INFO**

Received: 12 Nov. 2022

Accepted: 09 Jun. 2023

**ABSTRACT**

The Brazilian energy grid encompasses mainly hydroelectric power, despite investments in other energy sources. The country's energy forecast is based on the demand and the contracted projects to supply the consumers' needs. The present study aimed to analyze the Brazilian investment in energy based on the installed capacity and the country's forecast. The research question evaluated whether the future energy investments comply with the country's agreement in reducing emissions and focusing on sustainable development. Primary data were retrieved from governmental open sources and organized. The dependent variables were the data on installed capacity in 2021 (MW), forecast capacity for 2024 (MW), and growth (%). Applying the random forest model, data mining using the Rapidminer Studio was applied to the database. Decision tree algorithms were obtained involving the studied variables. The accuracy was 68% and kappa ($\kappa$)=0.60 (prediction result is suitable when accuracy is ⩾60%, and $\kappa$⩾0.60). Three decision tree models were selected to represent the chosen attributes based on the coherence of the decision flow amongst the studied variables. Using data mining, the prediction models of the energy investment in Brazil show the energy forecast for 2024. The current study points out that future investments in energy sources in the electric grid in Brazil aim for diversity since it plans for solar and wind energy sources; nevertheless, it also includes thermal and hydroelectric energy sources.

**Keywords:** energy distribution, energy capacity, renewable energy, solar energy, wind energy, energy grid

## INTRODUCTION

The late technological development increased energy demand and consumption, which has been noted more in developing countries due to improved socio-economic factors during the current decade. Brazilian energy supply relies mainly on hydroelectric power, and hydropower is considered renewable and sustainable (Bondarik et al., 2018). However, its application is somehow restricted due to the environmental impacts caused by the flooding of large areas, by methane emissions from the anaerobic degradation of organic material submerged by flooding (Santos et al., 2006).

There has been an increase in the construction of small hydropower plants (SHP) in Brazil, using the river resources throughout the country and representing a generation of six MW nowadays (ABRAPCH, 2021). However, despite being widespread, the combined contributions of SHP to electrical grids are frequently low (Couto et al., 2021). Despite their importance, they may threaten migratory fishes and various social values that the fishery supports (Anderson et al., 2018).

Sustainable development aims at the need for self-renewal and predictability for future generations. Hence, the idea of innovation and development of new forms of energy is not subjugated to finite sources but to renewable sources found in inflows that occur naturally on the planet, such as solar, wind, hydroelectric, and tidal energy producing a low environmental impact. Comparing the world energy electric grid in 1973 and 2015, Parizotto (2014) obtained a result in which renewable sources have small participation in the world's energy production process, prioritizing biomass and hydroelectric power and an increase in coal and natural gas while the use of oil decreasing substantially (Basso, 2017).

Following the Paris Climate Change Accord in 2015 and the 23rd Conference of the Parties 2017 (COP23), several countries have taken the initiative to decrease greenhouse gases by adopting renewable energy sources (Kim et al., 2018; Scherhaufer et al., 2017; Ust et al., 2017). Therefore, in recent years, most countries have turned to renewable energy sources, mainly wind and solar (Irfan, 2021). For policy implications, most developing countries focus on sustainable energy technology and lower energy costs, meaning that renewable energy consumption is susceptible to growing in most developing economies. In contrast, sustainable energy consumption becomes much tighter with the gross domestic product per capita in most advanced economies, pointing to

This article is part of the PhD thesis of the first author.

these countries' well-developed infrastructure (Yan & Shi, 2021). Focusing on Brazil, there is a scenario with its composition centralized in the hydroelectric sources (68%), biomass (8%), and wind (5%) against today's global trend using non-renewable sources (Empresa de Pesquisa Energética [Energy Research Company] [EPE], 2018). However, the limitations of expanding its hydroelectric grid and unfavorable hydrological issues with environmental barriers increase the difficulty of approving new projects, having profound environmental impacts as consequences, and emerging wind energy as an option with a higher potential (Parizotto, 2014).

Therefore, countries relying on carbon and hydroelectric energy sources will focus the new energy generation towards sustainable technologies. For instance, let us highlight the world's outstanding installed wind energy potentials of around 140 GW. Germany produces almost twice the energy installed with France, Poland, and the United Kingdom (Magalhães, 2009). The biggest producers in the world are the USA, China, and Spain, with an estimated production of 838 TWh (International Energy Agency [IEA], 2017). According to Parizotto (2014), from 2009 onwards, China stands out with 40% of large parks and small parks supplying small villages and rural areas. China grew exponentially in this segment, reaching the leadership with the USA for around 45% of world production in 2015 and half of the wind power installed on the planet (Gnoatto, 2017)

Countries invest in clean technology to supply the growing energy demand. Expanding the energy grid is costly and requires the governments to balance infrastructure investment allocation. Therefore, projects should be approved and included in governmental budgets before execution. According to national operator of system (NOS) (operador nacional do sistema-ONS, in Portuguese) (EPE, 2018), the expansion of Brazilian energy sources is already made public and encompasses investments in all energy sources. The Brazilian electricity sector faced water rationing starting in 2001, and there was a need to research and apply new sources of electricity. Through laws created in 2004, the government invested in altering and supporting the Brazilian electricity system with greater energy security, higher tariffs, and universalizing its services. Although the Brazilian electrical grid is quite diversified, data obtained from research companies is composed of water resources, thermoelectric, nuclear, wind, and solar; however, it is predominantly hydraulic (EPE, 2018). According to IEA (2014), world energy consumption tends to increase by around 36% between 2015 and 2050, and renewable sources will contribute 29.6% by 2050. It will represent 40% of the electric grid in Brazil.

With the development of computers and automation, the storage and retrieval of large volumes of data have increased. As a result, machine learning techniques, including data mining, have become a valuable tool for identifying and exploring patterns and relationships between many variables (Díez et al., 2006; Pereira et al., 2013). Data mining applications offer benefits in some research areas, including health diagnosis and prognosis (Zhuang et al., 2018) and identifying gaps in education data (Baker et al., 2011). Such predictive models have been used in the energy field (Liu et al., 2019). Jebli et al. (2021) present an approach for predicting solar energy based on machine learning techniques. The Random Forest prediction algorithm is a component of a set of decision trees. This tree-structured classifier utilizes decision rules from a large volume of initial data to obtain knowledge. The trees in a Random Forest are built on a majority vote, indicating an accurate output. The instances or cases in the training dataset are sampled randomly but substituted from the original data (Kara et al., 2020). Within this scenario, the current study aimed to classify the growth of Brazilian investment in energy based on the installed capacity and the forecast for 2024 using the data mining approach.

### Research Question

Brazil signed the Paris Agreement on April 22, 2016, and ratified it on September 12, 2016. The country has committed to reducing greenhouse gas emissions by 37% below 2005 levels by 2025. At COP23, Brazilian delegation participated in negotiations, and the country expressed its commitment to implementing Paris promoting sustainable development. Within described setting, we search for an answer to the research question: Is Brazilian growth of installed energy capacity sustainable, as proposed at previous conferences?

## METHOD

The dataset was built using the primary data extracted from online data (ONS, 2021a, 2021b). A dataset was built using the variables (attributes) as input to the Random Forest algorithm. The output (target) was related to the predicted growth, classified as high, medium, and low. The random forest model (also known as random decision forest) is a collective learning method for classification, prediction, and other tasks run by creating many decision trees during the training (Witten et al., 2016). Random forest output is the class most trees select for prediction tasks. The target in this study was the forecasted growth of energy capacity as a nominal variable (discretized as high, medium, and low). The independent variables selected as attributes were the installed capacity in 2021, the electric grid's energy type, the projected expanded capacity in 2024, and the growth.

The dataset built using the dependent variables was applied to develop trees (drawn with the concept of 'if,' 'then') applying Rapidminer Studio, open-source software based on Java version 9.2 (RapidMiner, Inc., Boston, MA, USA). The database was inserted considering the installed capacity growth range in MW. The operators used were 'retrieved data,' 'split data,' and 'randon forest.' The study used 70% of the data to train the algorithm and 30% to develop the model. The subsequent items in the training set are recognized by attributes ranked against multiple samples in an accurate approach (Lavrac, 1999). The accuracy of the models was calculated using Eq. (1). The kappa ($\kappa$) is a statistical coefficient of inter-rater reliability applied to evaluate the two appraisers' agreement. In this study, it was assumed that the prediction was appropriate when $\kappa \geqslant 0.60$. The schematic of the process is shown in **Figure 1**.

$$Accuracy\ (\%) = \left(\frac{TP+TN}{TP+FP+FN+TN}\right) \times 100, \quad (1)$$

where TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

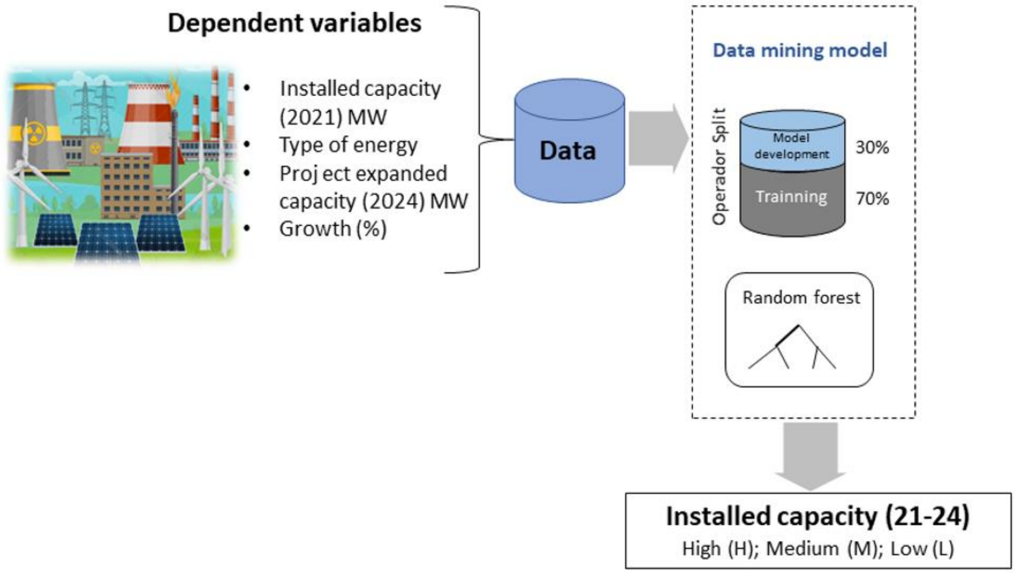


**Figure 1.** Schematic of the Brazilian energy installed capacity (2021-2024) prediction (ONS, 2021b)

**Table 1.** Source of energy, mean installed capacity in 2021, forecast capacity for 2024, and growth

| **Source of** energy | **Installed capacity 2021 (MW)** | **Forecast for installed capacity 2024 (MW)** | **Installed capacity 2024 (%)** | **Growth (%)** |
|---|---|---|---|---|
| Hydroelectricity | 108,147 | 109,164 | 62.2 | 0.9 |
| Wind | 14,975 | 19,320 | 11.0 | 22.5 |
| Biomass | 13,549 | 14,120 | 8.0 | 4.0 |
| Solar | 2,887 | 4,280 | 2.4 | 32.5 |
| Nuclear | 1,990 | 1,990 | 1.1 | 0.0 |
| Thermal (petroleum) | 4,404 | 4,692 | 2.7 | 6.1 |
| Thermal (gas+GNL) | 14,208 | 18,176 | 10.4 | 21.8 |
| Coal | 3,017 | 3,017 | 0.0 | 0.0 |

Note. Source: Adapted from ONS (2021a, 2021b)

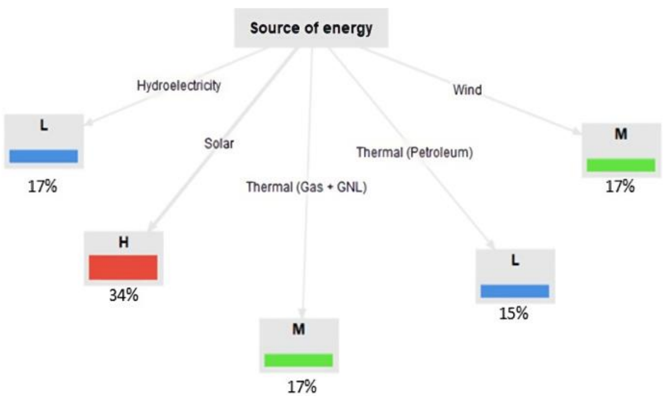


**Figure 2.** Prediction in one instance of future investments in types of energy by label of energy sources (H: High; M: Medium; & L: Low) (Source: Authors' own elaboration)

The dependent variables were

(1) installed capacity 2021 (MW),

(2) type of energy,

(3) project expanded capacity 2024 (MW), and

(4) growth (%).

Since database was not normally distributed, we applied the Poisson distribution. The Poisson distribution that most closely fits an observed frequency distribution is determined by the least squares method, meaning the smallest possible sum of squared distances between the observed frequencies and the Poisson expected frequencies. The complete dataset was organized in a spreadsheet to build trees using the data mining software Rapidminer® Studio, an open-source software tool based on Java version 9.2 (RapidMiner, Inc., Boston, MA, USA). Three different predictions were selected considering the final focus (target) as the installed energy capacity as a nominal variable (label) as high, medium, and low.

# RESULTS

**Table 1** summarizes the mean values of the data used to generate the prediction trees. The data mining results had an accuracy of 68% and $\kappa$=0.60. The thermal source refers to the gas (a mixture of propane and butane, compressed into a liquid state for more accessible storage and transportation) and the liquefied natural gas (GNL). Biomass is a source of electricity in Brazil (nowadays, it represents 8% of the country's total electricity generation). Brazil's primary biomass sources for electricity generation are sugarcane bagasse and wood waste.

Three trees were selected to describe the predictions obtained. **Figure 2** presents the prediction of the forecasted energy sources considering the type of energy as hydroelectricity 'low, ' representing 17% of the total sampling; thermal (petroleum) 'low,' representing 15% of the total sampling, wind 'medium' representing 17% of the sampling, and solar 'high' expressing 34% of the sampling.

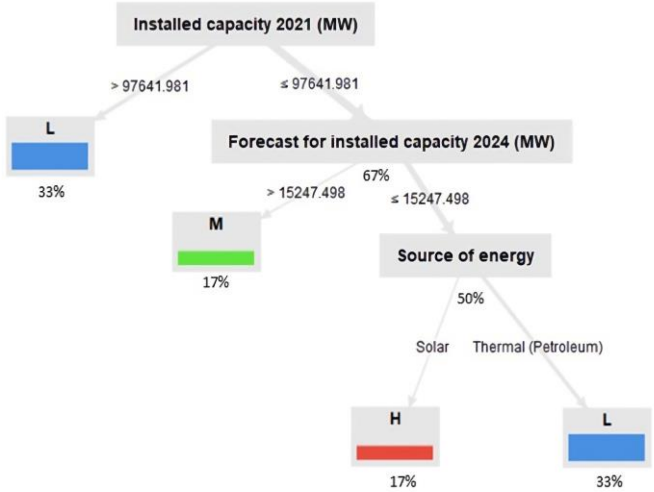


**Figure 3.** Prediction in three instances on installed capacity in 2021, forecast for installed capacity in 2024, and different energy sources (H: High; M: Medium; & L: Low) (Source: Authors' own elaboration)

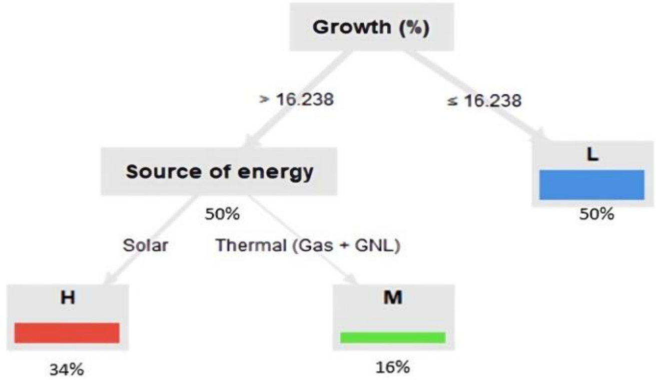


**Figure 4.** Prediction in two instances of growth in energy investment and different energy sources (H: High; M: Medium; & L: Low) (Source: Authors' own elaboration)

**Figure 3** shows the prediction in three instances. 'If' the installed capacity is >97,641.981 MW 'then' the future energy source is 'low.' This way of classifying the installed capacity represents 33% of the sampling. 'If' the installed capacity is ⩽97,641.981 MW 'then' the forecast for installed capacity in 2024 needs to be checked, and this step represents 67% of the sampling. 'If' the forecast for installed capacity in 2024 is >15,247.498 'then' the predicted growth is 'medium' (17%). 'If' the forecast for installed capacity in 2024 is ⩽15,247.498 'then' the energy source needs to be checked (50%). 'If' the source is solar, 'then' the growth is 'high' (17%). 'If' the source is thermal/petroleum 'then' the investment is 'low,' representing 33% of the sampling.

Both found values for the installed capacity in 2021 and 2024 in which the prediction algorithm makes different decisions from the input scenario, are the output of the calculations. They represent the most probable values given the input database. The output only presents the most probable scenario for classifying the forecast growth.

Prediction of **Figure 4** prediction is based on the projected growth shown in two instances. 'If' the predicted growth is >16.238 'then' the energy source needs checking (50%). 'If' the energy source is solar 'then' the predicted growth is 'high' (34%). 'If' the energy source is thermal (gas+GNL) 'then' the growth is 'medium', representing 16% of the sampling.

## DISCUSSION

Using data mining, we aimed to develop prediction models of energy investment in Brazil to verify whether the investment in energy sources complies with international agreements. When using the energy source as the primary attribute, the selected results indicated that investment in solar is high, representing 34% of prediction sampling (**Figure 2**).

The wind source and the thermal (gas+GNL) (17%) were classified as 'medium' followed by the hydroelectricity (17%) and the thermal (petroleum) (15%). Future investment in the other sources was negligible, indicating that Brazil's major investment frontiers in energy sources are solar energy, followed by wind, hydroelectricity, and thermal (gas+GNL). Although it does not appear significant in the results, biomass (from sugarcane bagasse and wood) and small hydroelectric power plants are often used in rural areas away from power distribution companies. This result indicates that the country prioritizes investment in renewable sources of energy. However, it partially complies with the agreement in COP23 since there are still investments in non-renewable energy sources such as thermal (petroleum and gas+GNL). Other countries have adopted such an initiative of expanding the renewable energy grid. For instance, the Korea Electric Power Corporation proposes an interconnected model for determining the acceptable locations and sizing for renewable energy sources (wind and photovoltaic plants) to overcome limitations involved in increasing renewable energy expansion (Kim et al., 2018).

Brazil had a wind energy growth in the years between 2007 and 2016, from 663 GWh to 33.5 TWh, considerably increasing the production of wind energy and standing out as the main responsible for the installed capacity in the country, corresponding to 40% and representing a solid growth in the last three years. Ranked among the ten most prominent producers in 2015, Brazil has an installed capacity of 7.6 GW, highlighting the Northeast region with the representative states of Rio Grande do Norte, Bahia, and Ceará (Dutra, 2008; EPE, 2018). Although wind sources might be a good renewable solution for energy supply, there are still concerns regarding the acceptance from the population. According to Scherhaufer et al. (2017), wind energy is a critical technology in the shift toward a low-carbon society. However, public acceptance is still a limiting factor in achieving large-scale wind deployment targets.

It is estimated that in 2050 the Brazilian hydroelectric source will be reduced by around 46%, and increase in the wind (20%), biomass (17%), and solar (9%). Such a move seeks to reduce environmental impacts and optimize sustainable development by supplying small, decentralized centers that previously lacked electricity access (Basso, 2017). When the primary attribute was the actual installed capacity in 2020 (**Figure 3**), the results indicated that solar energy is a 'high' occurrence; however, the thermal source is present, indicated as 'low.' In general, solar energy appears to be the focus of the expanded energy sources in the country. Despite the late evolution, solar power integration into the grid has challenges and constraints, although advancements in heat engine models may optimize the power output and overall efficiency (Ust et al., 2017, 2020).

For future investments, two energy sources are highlighted thermal (gas+GNL), with low expression (16%), and solar, representing 34% of the sampling (**Figure 4**). Brazil has auspicious natural features of solar irradiation, which enable an essential competitive advantage for using solar energy (Dhere et al., 2005). Studies evaluating Brazilian public policies and the impacts caused by distributed energy systems indicate that increasing the photovoltaic solar source might benefit the environment (Drumond Jr et al., 2021). However, new job creation and potential reduction in electricity bills are the most significant Brazilian potential for using solar energy (dos Santos et al., 2019).

According to Irfan (2021), energy efficiency promotes economic growth for both developed and developing countries. However, energy diversity encourages economic growth just for developing economies. The author suggests that developed economies must focus more on energy-saving behavior and practices. In contrast, developing economies should aim the energy efficiency and diversity to achieve higher economic growth with low carbon emissions.

There are several limits to studies in sustainable energy in Brazil, including lack of funding, infrastructure challenges (such as roads and transmission lines, can also hinder the development and deployment of renewable energy sources), and a shortage of skilled professionals in the field of sustainable energy. The present study's limitation is the lack of data on long-term investments since data availability is just up to 2024.

## CONCLUSIONS

Using the data ming approach, we present three models for classifying the Brazilian growth of installed energy capacity. We verified that most of the future investments in the country are focused on renewable energy, solar, and wind. This scenario might lead to partial compliance with the previous international agreement made at COP23 in 2017. The present study points out that future investments in energy resources in Brazil aim for diversity; however, it also includes thermal energy sources.

**Author contributions: JLM & IAN:** conception, design, data recording, data analysis, & final version; **JLM:** first draft; & **IAN:** supervision. They all agree with the results and conclusions.

**Funding:** No funding source is reported for this study.

**Declaration of interest:** No conflict of interest is declared by the authors.

**Ethical statement:** The authors stated that the study did not require any ethical approval since the data was retrieved from public governmental sources available online.

**Data sharing statement:** Data supporting the findings and conclusions are available upon request from corresponding author.

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