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# POWER SYSTEM PLANNING: AN INTEGRATED TECHNO-ECONOMIC AND PORTFOLIO APPROACH

Dissertation submitted to the Applied Economy Graduate Program of the Universidade Federal de Viçosa in partial fulfillment of the requirements for the degree of *Magister Scientiae*

Adviser: Ian Michael Trotter

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Ian Michael Trotter
Adviser

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To my partner.

To my advisor.

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## ABSTRACT

Durigon, Angelo Lucio Freitas, M.Sc., Universidade Federal de Viçosa, April 2024. **Power System Planning: An Integrated Techno-Economic and Portfolio Approach.** Adviser: Ian Michael Trotter.

The electricity sector can be afflicted with different types of risk, in particular fuel price fluctuations can highly impact the price of electricity. The most common tools used in power planning apply a minimum cost approach to it in order to find an appropriate electricity matrix. These tend to ignore risk what could lead to miscalculations on the expected cost of electricity production. In this work we implemented two methods, economic dispatch and CVaR minimization, to address risk and formulate a suitable portfolio for the Brazilian electricity matrix. We found that to minimize the risk in case of extreme fuel price events, our model allocated the Brazilian electricity expansion primarily in wind and biomass energy. This largely coincides with other works that analyze this problem from other perspectives. Our results show that it is possible to minimize risk while at the same time following green energy initiatives that are needed in modern day electricity planning.

Keywords: Portfolio Theory. Optimization. CVaR. Economic Dispatch. Electric Energy. Fossil Fuels. Electricity sector. Risk.

**Resumo**

DURIGON, Angelo Lucio Freitas, M.Sc., Universidade Federal de Viçosa, abril de 2024. **Planejamento de Sistemas Energéticos: Uma Abordagem Integrada Tecno-Econômica e de Teoria do Portfólio**. Orientador: Ian Michael Trotter.

O setor de energia elétrica pode ser afetado por diferentes tipos de risco, em particular flutuações no preço dos combustíveis podem gerar um grande impacto no preço da eletricidade. As ferramentas mais comuns usadas no planejamento energético utilizam métodos de custo mínimo para encontrar uma matriz energética adequada. Estas, tendem a ignorar o risco o que pode levar a erros de cálculo do custo esperado da produção de energia elétrica. Nesse trabalho, nos implementamos dois métodos, despacho econômico e minimização do CVaR, para lidar com o risco e formular um portfolio adequado para a matriz energética brasileira. Nos descobrimos que para minimizar o risco em casos extremos de preços de combustíveis, o nosso modelo escolheu principalmente as energias eólica e de biomassa para a expansão da matriz energética brasileira. Isso coincide com outros trabalhos que analisaram esse problema por outras perspectivas. Nossos resultados mostram que é possível minimizar o risco ao mesmo tempo seguir incitavas de energia verde que são necessárias no planejamento energético moderno.

Palavras-chave: Teoria do portifólio. Otimização. CVaR. Despacho Econômico. Energia Elétrica. Combustíveis Fosseis. Setor de energia elétrica. Risco.

**SUMMARY**

## 1 INTRODUCTION

The electricity sector is key to economic development(OECD, 2012). However, the sector is exposed to many types of risk, from many different sources. These risks must be mitigated so as not to disrupt the functioning of this sector and those that depend on it. The main risks associated with the electricity sector are climate risk which can affect the amount of energy produced, weather volatility which can have a significant impact on energy production and consumption, high volatility in fuel prices leading to cost uncertainties, and geopolitical and policy risk (ARIAS et al., 2020; AWERBUCH, 2006; VAN DER WIEL et al., 2019). Another issue that policy makers must deal with is that an ever growing world population that demand an ever growing amount of energy sources to accommodate its necessities(OECD, 2012). Therefore, energy planning is essential for economic development, and it is important to consider the broad range of risks faced by the sector.

Although risk is an important element to consider in energy planning, many studies in this area use a least cost approach to the energy planning problem. There are several modeling tools used for the electricity sector, among the most popular are ENPEP-BALANCE, TIMES, MESSAGE, LEAP, Balmorel (MIRJAT et al., 2017; WIESE et al., 2018). These modeling tools largely ignore risk in favor of reducing the discounted expected cost of energy production (AWERBUCH, 1993). Focusing exclusively on the expected price of energy can lead to poor results if conditions deviate from expectations.

If not mitigated, risks in the electricity sector may lead to several generation problems that lead to an increase in energy costs and ultimately energy shortages. This can be seen in Europe where since 2022 there has been a rapidly increase in energy costs due to the war in Ukraine and in the beginning of the war there were also risk of disruptions in energy supply (ADOLFSEN et al., 2022). Another example of how electricity sector is essential to maintain business as usual in many sectors was the 2001 scheduled blackouts that happened in Brazil. In this year, due to a delay in infrastructure works related to energy transmission, the government had to schedule blackouts in 16 states for nine months (Oliveira, 2021). In addition, another energy crisis because of low water level that happened in Brazil in 2014. There were blackouts in 14 states and in the federal district, affecting more than 2 million people(TANJI, 2022). These three examples illustrate the importance of taking risk into consideration during energy planning.

Markowitz (1952) introduced a methodology for modeling and reducing financial risk, the mean-variance portfolio. The mean-variance portfolio, also known as Markowitz theory or Modern Portfolio Theory, assumes that the expected return for a set of financial assets is a weighted average of the return of the individual assets, and that the variance of the portfolio returns is a function of the variances and covariances of the individual assets (MARKOWITZ, 1952, 1999). Therefore, selecting portfolio weights in order to minimize the portfolio variance for a given level of expected return can be stated as a quadratic programming problem, and solved efficiently. Modern Portfolio Theory has therefore been applied in recent years to manage risk in energy planning, as an alternative to cost-minimization approaches (AWERBUCH; BERGER, 2003; LOSEKANN et al., 2013; MARRERO; PUCH; RAMOS-REAL, 2015).

Although the portfolio approach to energy planning represents an evolution in the analysis of risk in the sector, it is still not widely applied. Even though the portfolio approaches address the risk, the approaches have so far neglected the cost structure of the electricity sector, by assuming that costs can be represented by a linear combination of installed generation capacity. This is not a realistic representation of the cost structure of the industry, which is far more complex in reality – which depends on climatic, technical, social and economic factors – and is traditionally captured better by the techno-economic cost-minimization models. Therefore, we see an opportunity to address these unrealistic cost assumptions made by existing portfolio approaches by incorporating elements of techno-economic cost-minimization models into the portfolio approach.

The electric power sector in Brazil relies on hydroelectric power for most of its production. The power generation mix is composed of 53.29% large hydroelectric power, 24.6% thermoelectric power, 13.25% wind energy, and the rest is divided among nuclear, small hydroelectric and solar (ANEEL, 2023). Although not the most prominent energy source in the Brazilian portfolio, thermoelectric power is still very significant in the portfolio. This type of energy relies on the combustion of fossil fuels to produce energy. These fossil fuels have high price volatility, which can be a major risk factor in a country's energy portfolio (AWERBUCH; YANG, 2007; FERNÁNDEZ-

YÁÑEZ et al., 2021). This summarizes why including risk in the energy planning analysis is necessary for a better understanding of the electricity market necessities.

As seen before, the Brazilian energy matrix is predominant in hydroelectric power, followed by thermoelectric and wind. There is a low share of nuclear and solar in the generation mix this may suggest a lack of diversification, what could leave Brazil vulnerable to risks in the sector. Therefore, it is particularly interesting to apply the portfolio approach to the Brazilian power sector, as the current power generation mix suggests there may be opportunities to improve the trade-off between cost and risk by increasing the diversification. The years 2040 and 2050 were selected to evaluate the effectiveness of the method because national and international policy planners have used these years as targets to achieve energy planning goals.

According to the EPE (Empresa de Pesquisa Energetica) energy demand in Brazil is expected to increase by 3.9% each year for ther period 2021 until 2026 which would represent an increase of about 20% in five years. It is necessary to consider that an increase in energy demand are also interconnected to increase in GDP (EMPRESA DE PESQUISA ENERGETICA, 2017). Therefore, this research will make two distinct contributions: firstly, this study intends to incorporate a detailed techno-economic power planning model into a portfolio approach to energy planning, in order to generate a more accurate representation of the price and cost formation process in the power sector. Secondly, the portfolio optimization framework will be used in order to identify efficient power generation portfolios for Brazil, the portfolios will consist of the most common power generating technologies, namely hydropower, wind, nuclear and thermoelectrical in order to address the current power generation portfolio that appears to be severely undiversified.

## 1.1 Hypothesis

Incorporating cost formation mechanisms into a portfolio optimization framework will improve portfolio approaches used for energy planning.

## 1.2 General Objectives

Improve portfolio methods for energy planning by incorporating cost formation mechanisms into the models.

### 1.3 Specific Objectives

- Incorporate an economic dispatch model into a conditional value-at-risk (CVaR) minimization framework.
- Implement the economic dispatch/CVaR minimization framework in software.
- Apply the economic dispatch/CVaR minimization framework to identify efficient power generation portfolios for the Brazilian power sector for the years 2040 and 2050.

## 2 THEORICAL REFERENCE

Energy is important to the development of several important areas in a country, as so, it is essential to pursue sustainable and efficient energy sources (OECD, 2012). Moreover, climate change has increased the need for studies in this field, both because it is one of the main sources of greenhouse gas emissions and because it is one of the sectors that will be most affected by climate change (OECD, 2012). For this reason, many studies have been done in the field of energy planning. For each different country there is benefit to independent research on this topic, because for all countries the available energy sources are different, based on geographical, meteorological, climatic, geological, political and social factors.

There are many studies that have used a cost minimization approach to the power system planning. Among them, Eelliston, Macgill, Diesendorf, (2013); Movva, (2015); Timmons et al, (2019); Wright et al, (2019) summarizes some of what has been done in this area. These studies cover a wide range of topics and use different methods to minimize costs. Among them are the energy planning of Mauritus, a small island east of Madagascar, and Australia, both of which aim to minimize the cost of building a sustainable energy matrix for their countries. The other two studies focus on different aspects of electricity sector planning, but still take a cost minimization approach. One of them builds an energy matrix for South Africa considering different scenarios of operation, such as a 100% sustainable matrix and a least-cost matrix. The second study focuses on proposing a different way of minimizing costs by integrating two previous methods. These being the economic dispatch, a model where all the all units in a energy model are defined and the path between these units is optimized and the unit commitment model where these units are turned on or off during the optimization process as needed.

In the works previously analyzed, there were a common problem among the methodologies utilized, they focused on minimizing the cost of energy production. This can lead to problems in extreme situations, for example supply shortages such as the gas shortage in Europe after the beginning of the conflict between Russia and Ukraine or the negative prices for crude oil that happened in the beginning of the Covid-19 pandemic. In these extreme scenarios, a cost minimization approach may lead to higher than anticipated costs of production or even blackouts due to lack of production capacity.

In order to avoid these scenarios, portfolio theory can be used in energy planning, in order to analyze risk as a factor in energy production. Portfolio theory was developed as a financial market tool, used to analyze the risk of financial portfolios and compare it with the expected return. In the electricity sector it was implemented as an alternative to least-cost methods, which don't consider the risk of electricity sector. Also because of the portfolio theory we know that it may be useful to invest in more expensive technologies if they offer less risk, something impossible for the least-cost approaches previously used (AWERBUCH, 2006).

Among the studies we found, we selected a few that show the importance of portfolio analysis in energy planning and how it can be used in different contexts and scenarios. Awerbuch (2006); Awerbuch and Berger (2003); Awerbuch and Yang, (2007); Losekann, et al (2013); Marrero, Puch and Ramos-Real (2015); Araujo (2019) All these studies use the mean-variance portfolio theory to solve different problems related to the electricity sector. In all these studies, the authors aim to find an optimal portfolio located on the efficient frontier: The efficient frontier is where all optimal portfolios lie. If there is a graphical representation, we have a plane formed by risk and return (or risk and cost in some cases), where each point on this plane represents a different portfolio mix. The efficient frontier is the curve where there is no way to have more return without having more risk, or less risk with more return.

Awerbuch (2006); Awerbuch and Berger (2003); Awerbuch and Yang (2007); Marrero, Puch and Ramos-ReaL (2015) discusses the use of portfolio approaches in the European Union, Mexico, the United States, and the OPEP countries. These countries had planned portfolios composed of different energy technologies, and when these portfolios were compared with the optimal portfolios, the studies showed that these countries had inefficient portfolio mixes that were outside the efficient frontier.

The range of inefficiency of the portfolios goes from slightly off the efficient frontier, the case of the European planned mix, to the Mexican case where there was no optimal mix for the same amount of output and for the same risk, there are much better options, this is a case where the application of the mean variance portfolio could lead to improvements in the energy matrix without any drawbacks.

In the case of Marrero, Ruch and Ramos-Real (2015) in addition to the energy matrix, they also applied the mean-variance portfolio to the road fuel sector. In addition, they applied another methodology, the capital asset pricing model, to calculate the systematic and non-systematic risk in these sectors. The results show that with the baseline mix used, there are no optimal results for the same risk, and there is room for improvement for the same cost.

The Studies of Losekann, et al (2013); Araujo (2019) focus on Brazil with two different approaches, both using the mean-variance portfolio. De Araujo (2019) analyzes the differentiation of energy sources in the portfolio, implementing an index to evaluate how many different sources are needed to have a lower risk. On the other hand, Losekann, et al. (2013) try to evaluate how the Brazilian energy matrix in 2020 will be affected by climate changes that have reduced the capacity to produce hydroelectric energy. In both papers, it's possible to access the importance of hydropower in the Brazilian energy matrix and how climate change is reducing its energy potential. In both studies, there has been an increase in other renewable energy sources in the portfolio and a decrease in fossil fuel sources. And in both cases, hydropower remains an important energy source in the Brazilian mix.

These works summarized the way portfolio theory may be used in the electricity sector. On the other hand, there are limitations associated with portfolio theory application for energy planning. These limitations are related to assumptions that are needed to be made to utilize the portfolio theory and that are not necessarily true for the electricity market, such as the efficiency of the electricity market and the normal distribution of the returns (AWERBUCH; BERGER, 2003). The following studies analyze this problem in more depth.

In a literature review, DeLlano-Paz et al. (2017) summarize a number of works on modern portfolio theory (MPT) applied to energy planning. Among the objectives of this study, one of the most relevant for us, to analyze works that apply MPT to energy planning and the limitations of this approach. Among these limitations is the difference between a financial asset, for which MPT was designed, and a real asset, such as those in the electricity sector. This difference requires some adaptation of the original MPT. Another limitation is that the electricity market is not efficient. There are problems related to the transition from an inefficient portfolio to an efficient one, and limitations related to the way the electricity sector operates. The last limitation relevant to this work is that the MPT has difficulty in assessing the relevance of renewable energy sources, because there are many benefits of acquiring this type of technology that go beyond the financial realm.

Considering these limitations, the present study proposes a new approach to the energy planning problem using portfolio theory. Instead of relying on portfolio variance as the risk measure, as in MPT Markowitz (1952) , we choose conditional value-at-risk (CVaR) as our risk measure, a novel approach for the Brazilian electricity market that has been used in many works in the rest of the world. This method allows us to incorporate a techno-economic model of the power sector into the portfolio selection problem. It is important to notice that CVaR can outperform MPT in most situations, although it needs more sophisticated inputs to models based on it and it is show to perform better under markets with low transaction costs (NGUYEN; NGUYEN; ADEGBITE, 2018). By incorporating such a model into the portfolio selection framework and considering that in our model there are no transaction costs, we avoid many of the unrealistic assumptions about the electricity market made by earlier studies based on MPT - specifically the unrealistic assumptions about the cost structure of the industry as a linear combination of fuel costs. An economic dispatch model will more accurately and realistically quantify the production cost of energy, ultimately allowing a more accurate identification of the efficient power generation portfolios.

## 3 METHODOLOGY

The methodology of this work is divided into three parts, in the first part we will explain how the fuel costs were generated to feed the economic dispatch model. This is necessary because the model uses fuel prices as an input to generate power generation costs. The second part will explain what the economic dispatch model is and how it works and give a summary of the code implementation of it. Finally, the last part of the methodology will explain what CVaR is, how it finds a low-risk option, and how it compares to more traditional portfolio solutions. The use of economic dispatch as an input to CVaR minimization is the core idea of this study. It offers the possibility of more realistic representation of power generation costs in a portfolio selection framework, and we will also describe the application of this methodology to the Brazilian electricity sector and investigate efficient power generation portfolios for 2040 and 2050.

### 3.1 Fuel Price Sampling

The first step in implementing the techno-economic model used in this study is to generate a range of possible fuel prices based on previous research on the subject. The Python library scipy was used to generate a multivariate normal distribution and a Monte Carlo simulation was made to obtain fuel price samples of different iterations of the multivariate normal distribution.

$$f(x) = \exp\left(\frac{1}{\sqrt{(2\pi)^k \det \Sigma}} \exp\left(-\frac{1}{2}(x-\mu)^T \Sigma^{-1} (x-\mu)\right)\right) \quad (1)$$

Equation 1 shows us the probability density function of the multivariate normal distribution we simulated. In the equation, μ is the mean of the distribution, $\Sigma$ is the covariance, and $k$ is the rank of the covariance matrix. The fuel price generation only considers the types of energy that use commercialized fuels, namely coal, oil, gas, uranium and biomass. In the case of renewable power – wind, photovoltaic and hydroelectric – these sources do not rely on commercialized fuels. In the case of photovoltaic and wind, energy is generated when there is sunlight and wind respectively. This means they are not affected by fuel price fluctuations, but they are also not dispatchable, and so may not produce energy when it is required. In the case of hydro power, there is a trade-off between current and future power generation: if we use the water reserve to produce energy now, we have less potential energy generation in the future.

The covariance and standard deviation between fuel types were obtained from Awerbuch and Yang (2007), while the mean was zero. Later we collected samples from the modeled distribution and multiplied it by the average price of each fuel for the year 2020. All these observations must be taken into consideration in the model of the power generation costs.

### 3.2 Economic Dispatch

The second step for this study is to use an economic dispatch model to calculate the cost of power production. This model selects the operational decisions that minimize the cost of the generation needed to supply the energy demand at an hourly resolution over a year, given the generation capacities of each type of power plant and a set of fuel prices. To achieve this, the energy output of each generating unit in the system is considered (CONEJO; BARINGO, 2018). The economic dispatch model can be expressed as a linear optimization problem:

$$f(L_g, L_s, L_w, L_h, c_g) = \min_{\{L_{t,h}\}_{t\in T} \cup \{L_{t,g}\}_{(t,g)\in T\times G}} \sum_{t\in T} \sum_{g\in G} c_g L_{t,g} \tag{2}$$

$$\text{s.t. } L_{t,h} + L_{t,w} + L_{t,s} + \sum_{g\in G} L_{t,g} = D_t, \forall t \in T \tag{3}$$

$$H_{t+1} = H_t + I_t - L_{t,h}, \forall t \in T \tag{4}$$

$$H_0 = \overline{H}_0, H_T = \overline{H}_T \tag{5}$$

$$H_t \leq \overline{H}, H_t \geq \underline{H}, L_{t,h} \leq \overline{L}_h, L_{t,h} \geq \underline{L}_h, \forall t \in T \tag{6}$$

$$L_{t,g} \leq \overline{L}_g, L_{t,g} \geq \underline{L}_g, \forall (t,g) \in T \times G \tag{7}$$

Each equation represents the following:

Equation 2 represents the cost-minimization objective function, energy generation times cost, for each dispatchable generation unit and each time period. The variables are $c_g$ that represents the marginal cost for each thermal generator g, in this variable we allocate the fuel price as an energy generation cost. $L_{t,g}$ represents the energy generation for each thermal generator g in every time period t and the variables $L_g, L_s, L_w, L_h$ represent the generation capacities of each technology.

Equation 3 guarantees that the total amount of power generated is equal to the total demand for energy, which is exogenously determined. The variable $L_{t,h}$ represents the level of hydro power generation in each time period, $L_{t,w}$ the level of wind power generation in each time period, and $L_{t,s}$ the level of solar power generation in each time period.

Equation 4 represents the water reservoir levels in t + 1, a transition function for the reservoir level. They are the result of the present amount of water minus the amount used to produce energy plus the inflow. The variables here are $H_{t+1}$, the reservoir level at the start of period t + 1, $H_t$ the reservoir level at the start of the current period t, and $I_t$ is the reservoir inflow during the period t.

Equation 5 binds the initial and final reservoir levels to the levels where $\overline{H}_0$ is the initial reservoir level and $\overline{H}_T$ is the final reservoir level.

Equation 6 ensures that the reservoir level and the hydro generation remains within their maximum and minimum, where $\overline{H}$ and $\underline{H}$ are the maximum and minimum reservoir level respectively. $\overline{L}_h$ and $\underline{L}_h$ are the maximum and minimum generation for the hydroelectric generator.

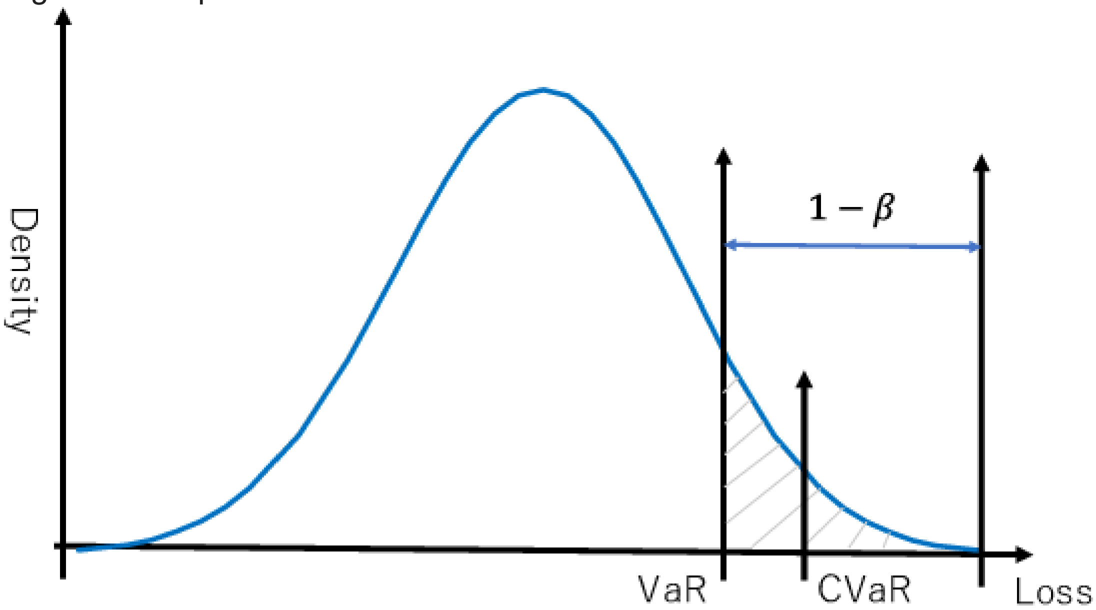
Equation 7 ensures that the thermal generators remain withing their maximum and minimum generation capacities. The variables $\overline{L}_g$ and $\underline{L}_g$ represent the maximum and minimum generation of each thermal generator.

The model was set up as a linear programming problem in Python using the PuLP library, and the CPLEX solver is used to solve the problem.

**3.3 CVaR Minimization**

The final step in this study is to apply the results obtained using the economic dispatch we want to minimize the CVaR for the electricity market. CVaR focuses on reducing the risk of large losses and was chosen because it does not require assumptions about the distribution of random variables used to generate a portfolio, and because it is computationally efficient (ROCKAFELLAR; URYASEV, 2000).

Figure 1 – Representation of VaR and CVaR




Source: NAKAGAWA, NOMA and ABE (2020)

In Figure 1 we have a visual representation of CVaR, this image shows us an important aspect of this method, it measures the expected loss of an extreme risk event. In the electricity market case, this can be translated as the risk of events that generate high production costs, which in the electricity market are high losses to the companies involved.

Another aspect of using CVaR minimization in this work is that we will use the economic dispatch model to simulate operational decisions (power generator dispatch) in order to obtain a realistic representation of the generation costs used in CVaR minimization, whereas the CVaR minimization will be used to select the generation capacities of different power generation technologies. To find the portfolio weights that minimize the CVaR, the following minimization problem can be solved (ROCKAFELLAR; URYASEV, 2000):

$$\min_{\vec{x},\alpha} \ \alpha + \frac{1}{q(1-\beta)}\sum_{i=1}^{q}\left[\mathrm{f}\left(L_g, L_{\mathrm{s}}, L_{\mathrm{w}}, L_{\mathrm{h}}, c_i\right) - \alpha\right]^{+} \ (8)$$

Where β denotes the level of risk, $L_g, L_{\mathrm{s}}, L_{\mathrm{w}}, L_{\mathrm{h}}$ are the generation capacities of each technology and is what will be modified to find the optimal portfolio, and $c_i$ is a vector of random variables with q samples, where i = 1,2,…,q. In our problem, the random variables are the fuel prices generated in the first step of the methodology. $\mathrm{f}\left(L_g, L_{\mathrm{s}}, L_{\mathrm{w}}, L_{\mathrm{h}}, c_i\right)$ represents the cost of energy production calculated by the economic dispatch model. Finally, $\alpha$ is a threshold that separates a normal from an extreme event, it is endogenous to the minimization problem and is a representation of the Value-at-Risk (VaR) as seen in Figure 1. The CVaR that we want to minimize is the expected lost associated with a situation where the energy cost surpasses $\alpha$, therefore we want to minimize it. Intuitively, the objective function represents the mean of those samples whose cost exceeds the threshold $\alpha$ and will be a coincidental output of the optimization.

This version of the CVaR minimization problem is convex, which guarantees the existence of a minimum solution and makes the problem computationally feasible (ROCKAFELLAR; URYASEV, 2000). There are several methods available to solve this type of minimization problem, the most common being gradient descent, where we find a minimum of a function by taking steps towards the target minimum following the slope of the curve (RUDER, 2017). This method is applied to the problem to find the portfolio weights that minimize the CVaR.

To summarize, we first generate fuel prices that are used in the economic dispatch model, and the output of the economic dispatch model will be used to calculate the power generation portfolio that minimizes the CVaR.

### 3.4 Data

Using the proposed methodology, and by selecting the parameters of the models to reflect the Brazilian power sector, we collected data regarding energy capacities, demand for electricity in Brazil and fuel prices for different technologies.

Table 1 – General Data used in the modeling (2018).

| NAME | ENERGY CAPACITIES (MW) | GENERATION COST (USD/MWh) | O&M Cost (USD/MWh) | EXPANSION COST (USD/MW) |
|---|---|---|---|---|
| Hydro | 106,289 | 0 | 3.16 | 1,966,814 |
| Coal | 3,086 | 31.76 | 8.6 | 2,000,000 |
| Oil | 7,180 | 175 | 20 | 0 |
| Gas | 17,056 | 18.83 | 11.21 | 836,735 |
| Nuclear | 1,990 | 9.4 | 15.95 | 5,000,000 |
| Biomass | 16,557 | 5 | 3.16 | 1,020,408 |
| Solar PV | 2,000 | 0 | 6.53 | 816,327 |
| Wind | 16,000 | 0 | 5.98 | 918,367 |

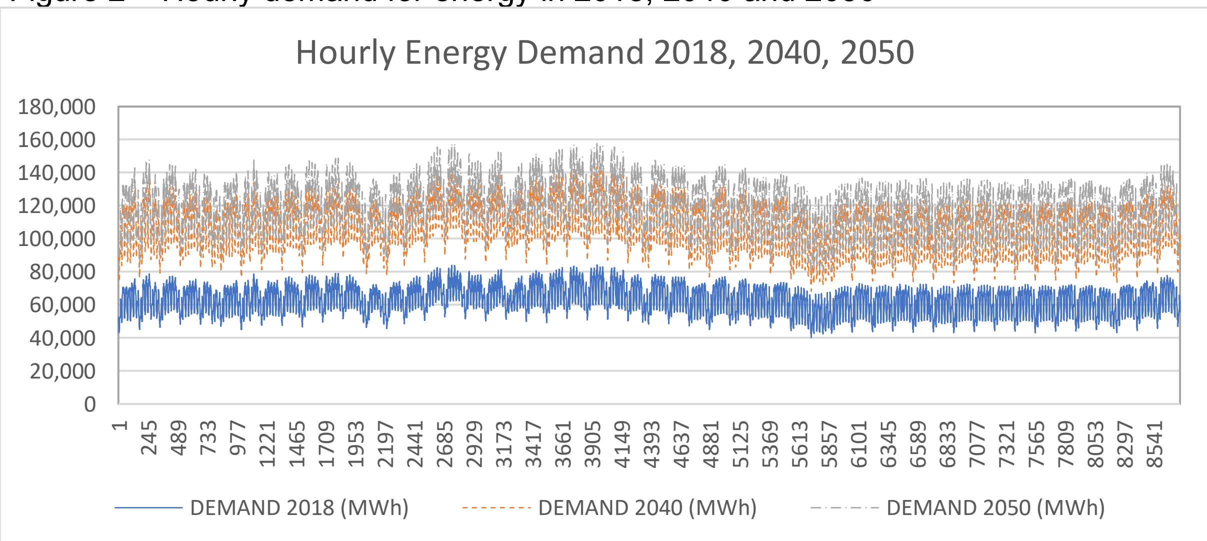
Source: Made by the author, based on data from Awerbuch and Yang 2007

The energy capacities were obtained from a report from the Empresa de Pesquisa Energetica (EPE) (Table 1), except for the generation cost data that was obtained from the IEA. The generation costs were used in the first step of the methodology, where the samples from the normal multivariate distribution were multiplied by the generation cost in order to obtain the final fuel price samples used in the modeling.

There is a great predominance of hydro as the Brazilian energy source, but we found through the same EPE report that the expansion capacity for hydro in Brazil is limited to 111,752 MW mainly due to geographic and physical limitations. We also obtained O&M costs and expansion parameters for the analyzed technologies, except for oil which the report chose not to find an appropriate cost due to oil great capacity for pollution. Because of that we made assumptions regarding the O&M costs for oil. We used the price of 175 USD/MWh using as base the crude oil price in November 2023 of 85,37 USD/bl and a 30% efficiency.

The generation cost, mainly composed from fuel price, was obtained from the International Energy Agency (IEA), and the data was taken from the 2020 data set, except for the oil and biomass data. The biomass data from this dataset gave us a zero-fuel cost because it was produced from the residues of agricultural production. Since this was not feasible in the long run, we implemented a maximum production level of 32 GW for biomass and used a production cost of 5 USD/MWh.

Figure 2 – Hourly demand for energy in 2018, 2040 and 2050

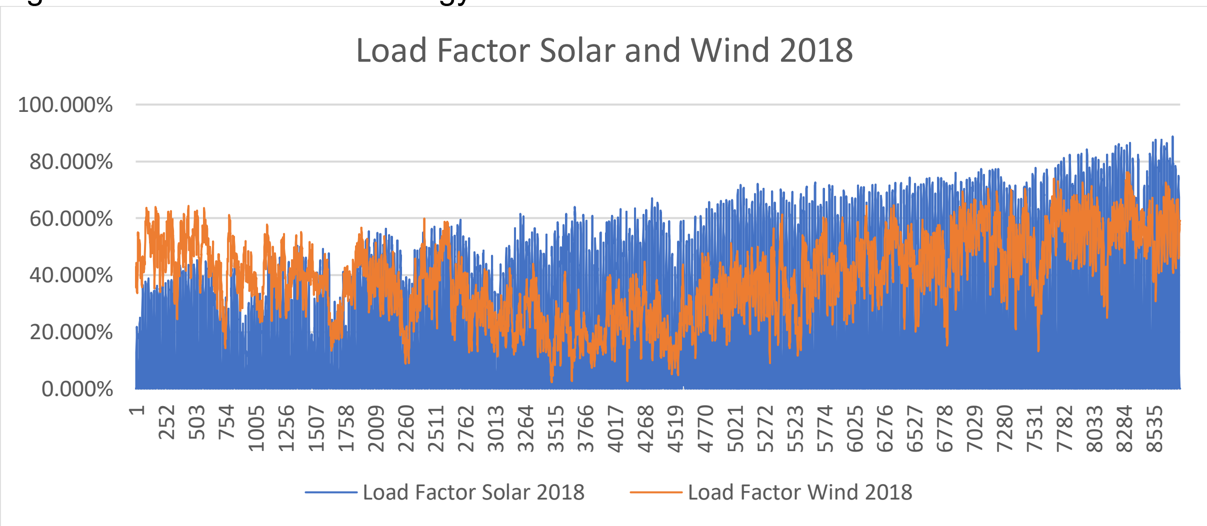



Source: Made by the author, based on data from ONS and Trotter et al (2016)

The demand data used were found on the Operador Nacional de Energia (ONS) website for the base year, and Trotter et al (2016) for demand in future years. The base year chosen was 2018, a recent year that was not affected by the disturbances caused by the Covid-19 pandemic. Demand for 2040 and 2050 was chosen because national and international policy planners have used these years as targets to achieve energy planning goals.

The demand scenarios from Trotter et al (2016) make some assumptions in order to find the demands for future years. In their model, the authors choose to only consider population size as a demographic factor and national income as an economic one. They also choose not to include price in the demand model because the price influence the demand but the demand also influences the price, leading to a modeling problem if this variable were included. These assumptions lead to a demand for energy in 2040 and 2050 that is over twice the ones found in the base year (Figure 1). The difference in demand from 2040 to 2050 is less predominant, although it can still be perceived when compared.

Figure 3 – Wind and solar energy load factors




Source: Made by the author, based on data from ONS

The load factor for solar and wind energy (Figure 2) used in the modeling outlines the daily cycle of production of solar energy and the constant production of wind. This data was used to simulate how much energy these sources could produce if their capacities were increased.

Table 2 – Correlation between fuel prices used in energy production.

| | Coal | Oil | Gas | Uranium | Biomass |
|---|---|---|---|---|---|
| **Coal** | 1.00 | 0.27 | 0.47 | 0.12 | -0.38 |
| **Oil** | 0.27 | 1.00 | 0.49 | 0.08 | -0.17 |
| **Gas** | 0.47 | 0.49 | 1.00 | 0.06 | -0.44 |
| **Uranium** | 0.12 | 0.08 | 0.06 | 1.00 | -0.22 |
| **Biomass** | -0.38 | -0.17 | -0.44 | -0.22 | 1.00 |

Source: Awerbuch and Yang 2007

Table 3 – Standard Deviation data for the electricity sector

| | Fuel |
|---|---|
| **Coal** | 0.14 |
| **Oil** | 0.25 |
| **Gas-CC turbine** | 0.19 |
| **Nuclear** | 0.24 |
| **Hydro-large** | 0.00 |
| **Hydro-small** | 0.00 |
| **Wind** | 0.00 |
| **Wind-offshore** | 0.00 |
| **Biomass** | 0.18 |
| **PV** | 0.00 |
| **Geothermal** | 0.00 |

Source: Adapted from Awerbuch and Yang (2007)

Table 2 shown the correlation between fuel prices obtained in Awerbuch and Yang (2007). From the same source in Table 3 we have the standard deviation of the fuel prices. Using these two data it was possible to calculate the covariance between the fuel prices, simulate and generate samples.

### 3.5 Model Limitations

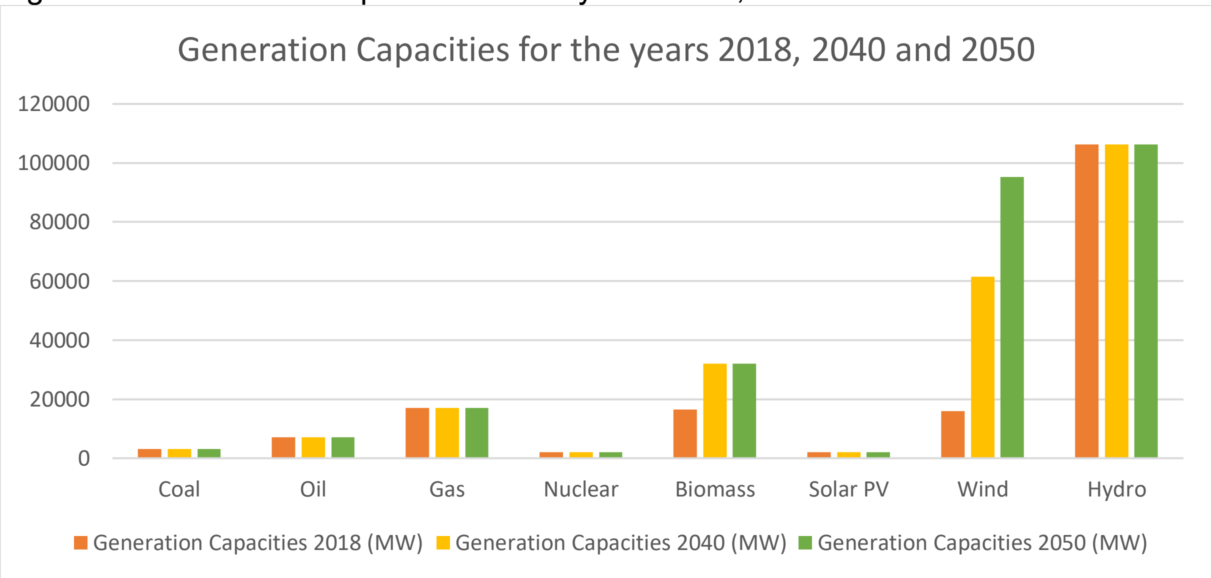
The model, although coherent to evaluate risk impact on the electricity sector, has limitations that need to be addressed. For instance, in our simulation we did not consider storage capacity for non-dispatchable energy sources due to the uncertainties this could generate for our model. Another limitation of our model is that we only evaluate fuel risk what may lead to energy sources that do not use fuel to appear less risky than in reality.

It is important to to address that for the energy planning perspective these limitations can impair the use of our results but they should not be ignored since as a perspective of reality it can shown us very useful information regarding energy, electricity and the fuel price risk associated with it.

## 4 RESULTS

The following chapter describes the results obtained by modeling the Brazilian energy matrix for the years 2040 and 2050. The production results were obtained through portfolios that evolve directly from the 2018 portfolio. The fuel prices were obtained through a Monte Carlo simulation, with the base prices being those of 2020.

Figure 4 – Generation Capacities for the years 2018, 2040 and 2050

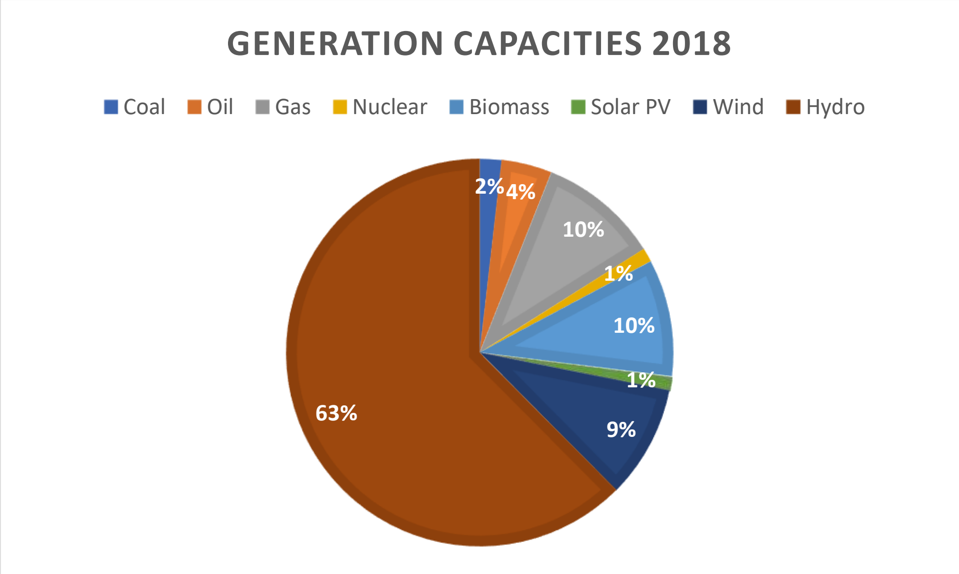



Source: Source: Made by the author, based on data from the research

As can be seen in the first chart, which shows the absolute values of the three different portfolios, the base year 2018 and the year 2040 and 2050, the major change in energy generation capacity is allocated to wind power. Biomass energy capacity also increases, but peaks quickly. This may be because biomass in its current state has a very low cost of energy production, as the main fuel is the waste from agricultural production. Another factor is that biomass fuel has a negative correlation with the fuel prices of other technologies.

The large increase in wind energy production is an important finding of this study because no renewable energy incentive was included in the modeling. The program's selection of wind energy reflects the lower fuel price risk associated with this energy compared to fuel-based technologies. This indicates that it is possible to achieve lower risks in the electricity sector while at the same time maintaining low levels of greenhouse gas emissions related to other energy sources. It is also important to note that wind and hydro can work together to reduce weather risk in an energy matrix. According to Schmidt, Cancella and Pereira (2016), these energies work well together due to the seasonal complementarity of wind and hydro technologies

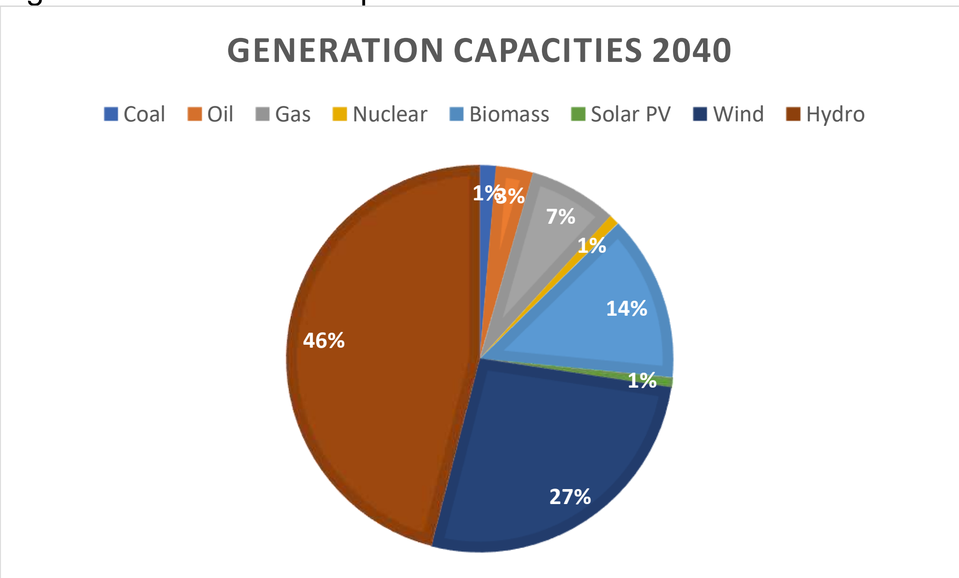
Figure 5 – Generation Capacities 2018 Year Base




Source: Source: Made by the author, based on data from the research

The initial generation capacities as shown in Figure 4 represent the Brazilian generation capacities for 2018 in it is possible to observe the great presence of hydro as the main source of electricity in Brazil. There is a significant share of gas, biomass and wind in the generation capacities. All in all, the Brazilian portfolio is highly dependent on hydro resources, which makes it vulnerable to water-related weather phenomena.

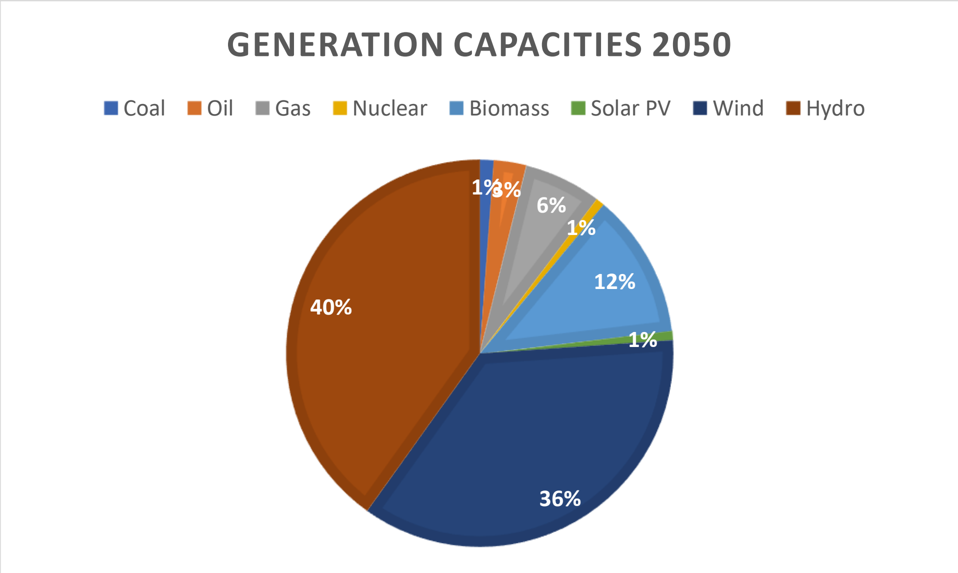
Figure 6 – Generation Capacities 2040




Source: Source: Made by the author, based on data from the research

The 2040 portfolio responds to fuel price fluctuations by increasing the share of wind and biomass in the portfolio and reducing the presence of gas, an energy source with high fuel price volatility, in the mix. This helps to mitigate risks associated with climatic phenomena such as drought. Although improvements have been made, the share of hydro in the mix is still high, mainly due to the initial generation capacity.

Figure 7 - Generation Capacities 2050




Source: Own Making

The 2050 energy matrix continues the trend seen in the 2040 mix of increasing the share of wind energy, bringing it to almost the same level as hydropower, highlighting the ability of these technologies to work well together in a portfolio to reduce risk. The share of biomass remains stable, mainly due to production constraints.

## 5 DISCUSSION

This chapter aims to compare the results found in this research to other works in the same area. The main point of comparison are Brazilian energy plans for the years analyzed, but there are also some works that implemented different methodology to find a portfolio for the Brazilian energy matrix.

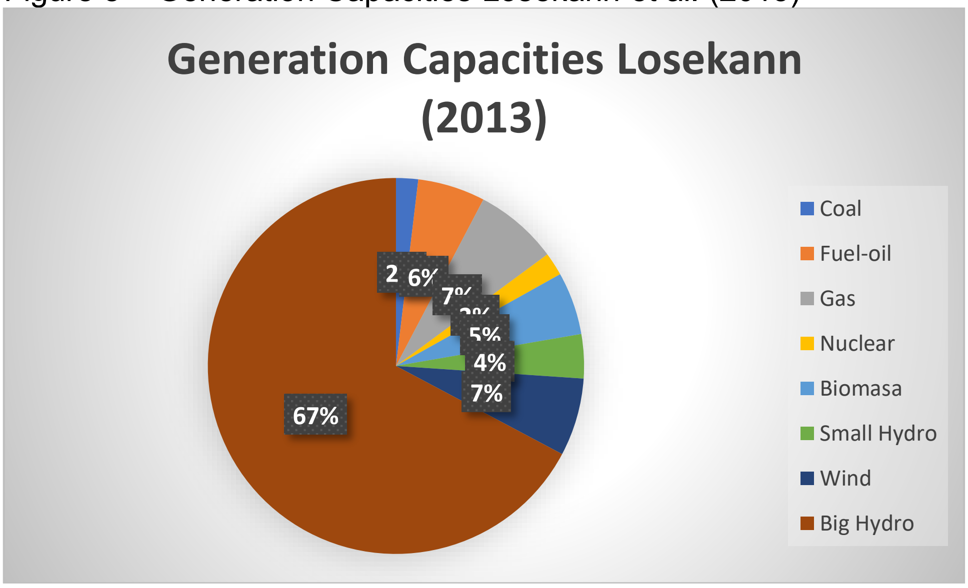
The 2050 PNE (Plano Nacional de Energia) made by EPE (Empresa de Pesquisa Energética) analyzed two scenarios relevant to this study, the first being a stagnation scenario in which energy demand does not change. In this scenario, the installed capacity for hydroelectric generation is 73% of the total Brazilian generation.

In contrast, in our simulation, hydropower represents about 46% and 40% in 2040 and 2050, respectively. This is because their simulation uses data from 2015 and stabilizes demand at that point, their total hydro generation capacity is 52GW, less than half of the total hydro generation in our simulations.

The second PNE scenario proposes 100% clean energy generation. In this scenario, the amount of hydropower goes up to 158 GW with other renewable sources totaling 249 GW, these two sources representing 32% and 51% respectively. This is very close to ours, where the generation for these two sources were 106 GW and 129 GW, representing 40% and 48.8% of the total generation, respectively. Also in this scenario, the expansion of wind energy reaches 42% of the national matrix, this also considers a 100% electrical cars policy. In this scenario, we have very similar results to our own in terms of wind energy participation in the portfolio. To better understand this comparison, we must emphasize that our simulation does not provide a direct incentive to promote clean energy; these results are simply the optimal outcome that minimizes expected cost during extreme situations.

Another work whose results can be compared with ours is Losekann, et al. (2013). Their approach was to generate an efficient portfolio for the Brazilian energy matrix and compare it with the Decennial Plan for Energy Expansion (DPEE) for 2020. Their minimum variance energy matrix is more comparable to ours, as it also aims to minimize risk.

Figure 8 – Generation Capacities Losekann et al. (2013)




Source: Losekann, et al. (2013)

Compared to the 2040 simulation, the two are relatively close, with the largest differences in the share of energy produced by coal and wind. In their mix, coal accounts for 9.2% of total energy production, compared to 1.3% in our model; this may be due to the high volatility of coal prices in our data compared to theirs. In the case of wind energy, their model has wind accounting for only 8.3%, while our model has wind accounting for 26.6% of energy production in 2040. Again, these results may be a difference in price variation. In the case of the 2050 simulation, the comparison is almost the same, except that there is less hydro and even more wind. This results in an even larger gap between the two studies.

Table 3 – Scenarios of Mixes of Technologies and Locations.

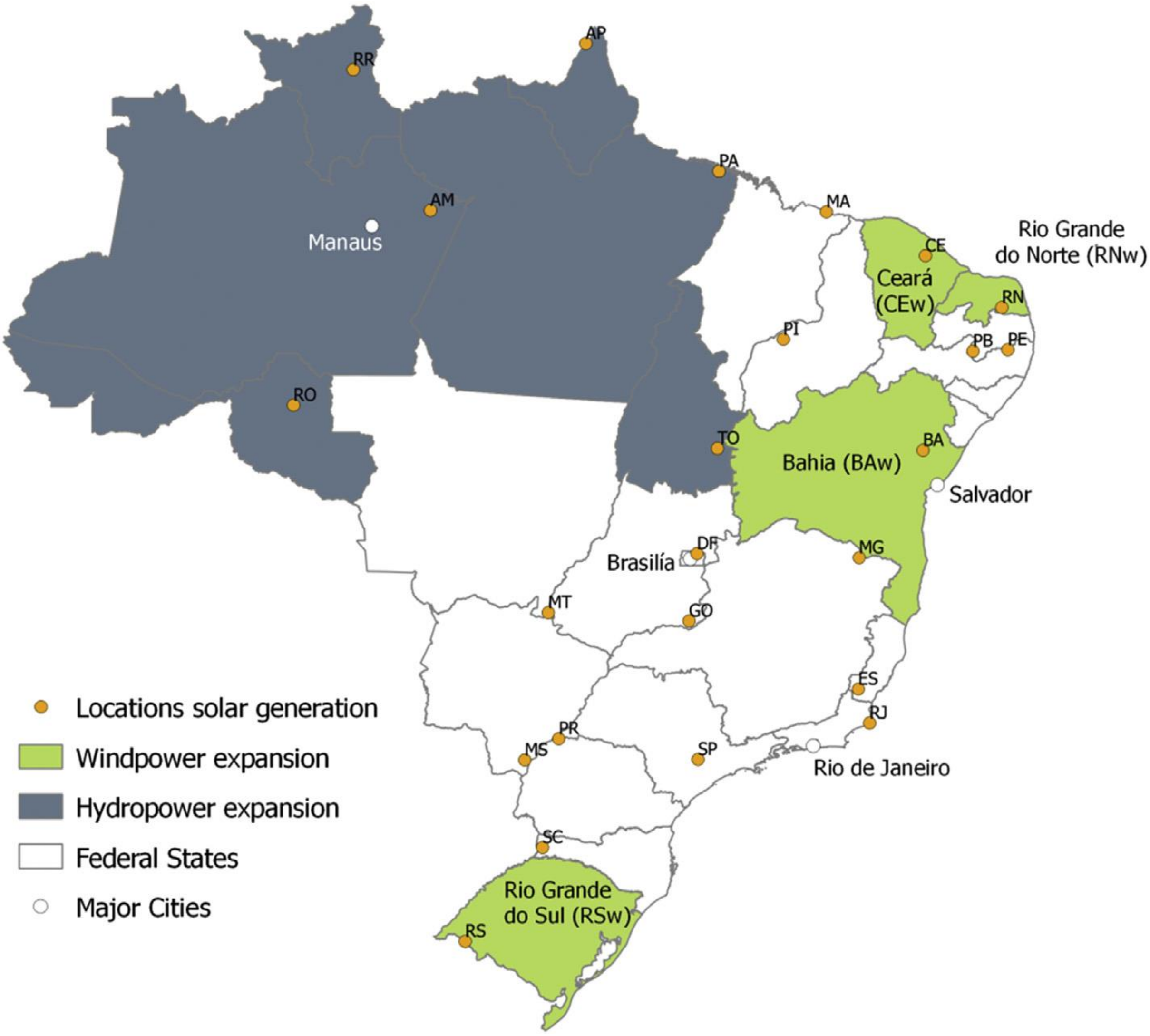
| Technology (% of additional production) | Location (% of participation) | Scenario Name |
|---|---|---|
| **Wind (100%)** | Bahia (100%) | W1 |
| **Wind (100%)** | Ceará (100%) | W2 |
| **Wind (100%)** | Rio Grande do Norte (100%) | W3 |
| **Wind (100%)** | Rio Grande do Sul (100%) | W4 |
| **Solar PV (100%)** | 1 Scenario for each federal state, with the exception of Acre, Alagoas, and Sergipe (100%) | S1-S24 |
| **Hydropower (100%)** | North of Brazil (Amazonas Region) | H1 |
| **Wind (100%)** | All locations equally (25% of total additional production) | M1 |
| **Solar PV (100%)** | All locations equally (1/24) | M2 |
| **Wind (1/2), Solar PV (1/2)** | All locations equally (i.e. 1/8 for wind power and 1/48 for solar PV) | M3 |
| **Wind (1/2), Hydro (1/2)** | All locations equally (i.e. 1/8 for wind power and ½ for hydropower) | M4 |
| **Solar PV (1/2), Hydro (1/2)** | All locations equally (i.e. 1/48 for solar PV and ½ for hydropower) | M5 |
| **Wind (1/3), Solar PV (1/3), Hydropower (1/3)** | All locations equally (i.e. 1/12 for wind power, 1/72 for solar PV, and 1/3 for hydropower) | M6 |

Source: Schmidt, Cancella and Pereira (2016)

The work of Schmidt, Cancella and Pereira (2016) found similar results to our research by different methodology and focusing on weather risk not fuel price risk. They generated 35 scenarios as per the Table 3, in which they used three different energy technologies, wind hydropower and solar PV, in different regions of Brazil.

They calculated the risk of different combinations of the three technologies to need the help of fossil fuel energy sources to maintain the necessary level of production to the Brazilian demand. Their methodology consisted of using an optimization model to minimize risk associated with production fluctuations related to weather conditions, natural to the technologies analyzed.

Figure 9 – Map of the proposed expansion of clean energy in Brazil




Source: Schmidt, Cancella and Pereira (2016)

According to Figure 8, the expansion of hydropower is exclusively in the North region of the country, this happened because there is no room for more expansion in other regions. The figure also shows us that this research has scenarios in different Brazilian states such as Ceará, Bahia, Manaus and Rio Grande do Sul what implicates that Brazil has capacity to accommodate clean energy production in all its territory.

Their results coincide with the ones found in this research, wind and hydro energy together leads to lower risk. Although they found this complementarity between technologies focusing on weather risk, this further corroborates the idea that utilizing wind and hydro together can lead to better results.

In summary, our results coincide with other works that approached the power supply planning from different perspectives. This helps explain that it is possible to address the risk problem while at the same time maintaining a green energy planning.

**6 CONCLUSIONS**

The use of CVaR minimization is a useful way of minimizing the impact of high price risk events that can lead the electricity market to a crisis. Combining this method with economic dispatch improved the accuracy of the risk analysis and the capacity of the model to diminish risk throughout the electricity sector.

The hypothesis of this work was that we could improve portfolio theory analysis of the electricity sector by incorporating price formation mechanisms. We have found that an expansion of wind energy, a clean and renewable source of energy, is the best suited to improve risk management of the electricity sector by minimizing risk in the Brazilian energy matrix.

This result has shown us that there is a possibility to improve energy production by reducing the fuel price risks, while maintaining a low greenhouse gas emission in the energy matrix. At a time when every country is conducting studies on how to reduce its greenhouse gas emissions, this result can lead to an advantage for the Brazilian electricity market in the race for a generation matrix with the lowest possible pollution emissions.

Future work can make significant progress by focusing on the risk mechanisms associated with non-dispatchable energy sources and how the assessment of this risk can improve portfolio theory models. Another possibility is to work on a better modeling focusing on biomass, establishing its real peak. And finally, combining this work with works that analyze other types of risk such as weather can lead to better understanding of a complete scenario of the risks related to the Brazilian energy matrix.

Finally, it is important to address that more work in this area could prove highly beneficial to the electricity market by addressing the Brazilian necessities. This work can be used by decision makers as a starting point to develop a national energy plan that considers fuel risk in its composition. This may lead to better investments made by the government that can minimize problems related to blackouts or sudden rise in fuel prices, bringing more certainty to energy supply.

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