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Wind Power Economic Feasibility under Uncertainty and the Application of ANN in Sensitivity Analysis

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Abstract: Wind power has grown popular in past recent years due to environmental issues and the search for alternative energy sources. Thus, the viability for wind power generation projects must be studied in order to attend to the environmental concerns and still be attractive and profitable. Therefore, this article aims to perform a sensitive analysis in order to identify the variables that influence most in the viability of a wind power investment for small size companies in the Brazilian northeast. For this, a stochastic analysis of viability through Monte Carlo Simulation (MCS) will be made and afterwards, Artificial Neural Networks (ANN) models will be applied for the most relevant variables identification. Through the sensitivity, it appears that the most relevant factors in the analysis are the speed of wind, energy tariff and the investment amount. Thus, the viability of the investment is straightly tied to the region where the wind turbine is installed, and the government incentives may allow decreasing in the investment amount for wind power. Based on this, incentives programs for the production of clean energy include cheaper purchase of wind turbines, lower taxing and financing rates, can make wind power more profitable and attractive.

Keywords: economic feasibility; net present value; artificial neural networks; wind power; sensitivity analysis

1. Introduction

Since the 1960s and affected by the oil crisis episode, the situation of fossil resource level, which is the main source of energy, has become alarming. Consequently, at the same period, the renewable energy sector attracted more investment and greater efforts for technological progress in order to develop an alternative to fossil fuels [1,2].

Rocha et al. [3] stated that renewable energy refers to the form of energy that occurs naturally in a continuous and infinite way. It is known that many types of energy fall into this definition, such as those that comes directly from the sun (for instance, photovoltaic energy), wind, tides and waves.

The popularity of wind power has increased due to environmental problems, fossil fuels price volatility, as well as the risks and geopolitical uncertainties related to the dependence on imports of these fossil resources [1,4,5]. In addition, Mohammadi and Mehrpooya [6] state that the global fossil resources consumption growth, results in several challenges because fossil fuels are exhaustible in the near future, and their combustion leads to environmental problems such as the ozone layer

depletion, acid rain, climate change, etc. Thus, new energy sources are needed in order to overcome these problems.

According to Aquila et al. [7], the renewable energy market is expanding and regulatory changes have influenced the energy sector in Brazil. In 2012, the Electric Power Regulatory Agency (ANEEL), through resolution number 482/2012, introduced a net metering system aiming to promote microgeneration from RES. The authors also discuss the need for studies on microgeneration feasibility and as well as comparisons between different regions. Wong et al. [8] adds that policies related to renewable energy should encourage investors to provide clean energy to consumers and thus create a model of sustainable development.

According to the Energy Research Company [9], Brazil has 41.2% of renewable energy in its energy matrix, 64% of which is hydroelectric. For that reason, Brazil shows a strong dependence on hydropower. However, since 2011, wind energy has been presenting a favorable growth scenario in Brazil. Nowadays, wind energy has a prominence at the Brazilian electricity market. Wind power adoption has increased in Brazil due to the crisis of electricity supply, environmental attractiveness, adoption of incentive programs by the Brazilian government, and the actions to structure a regulatory framework for the production of electricity from RES (renewable energy sources) [10].

In 2014, a drought threatened the supply of electricity in Brazil. Thus, in order to mitigate the hydrological risk in the country, the use of other renewable energy sources had been stimulated [1]. In addition, according to Rocha et al. [3], Brazil has high wind potential, especially in the northeast region, which can be proven by the numerous farms that have been installed in the region.

For Silva et al. [10], the electricity supply crisis and the incentives of the Brazilian government are characteristics that can attract investors to the wind energy generation, thus making it possible to take advantage of Brazil's high wind potential. It is evident that there is a growing trend in the use of Brazilian wind potential. In this perspective, it is necessary to carry out feasibility studies of wind power generation projects, so that these become profitable and attractive investments, as well as addressing environmental concerns.

Therefore, Montes et al. [11] and Arnold and Yildiz [12], determine the detailed planning and analysis of the projects. According to the authors, these actions would maximize the profitability of the investment, as well as it would avoid the installation of unproductive wind farms, which would become obstacles to the short term development. In addition, Haufe and Ehrhart [13] emphasize that in order to eliminate excessive costs, many countries have implemented competition mechanisms, such as auctions. However, the auctions are sensitive to market structure, that is, they depend on the political and economic objectives of each region.

In this context, similar to studies such as Li et al. [14], Rocha et al. [3] and Ertürk [4], which perform the feasibility study of renewable energy generation projects, this present work applies the Monte Carlo Simulation method (MCS) in the project's investment analysis. However, differently from the mentioned articles, this paper uses the Artificial Neural Networks (ANN) in order to analyze the sensitivity of the feasibility in function of the project variables.

In general terms, this article aims to perform a sensitivity analysis in order to identify the variables that most influence the viability of wind power investment in small companies in Brazilian Northeast. For this, a stochastic economic viability analysis will be carried out and later ANN models will be applied to identify the most relevant variables.

2. Theoretical Background

2.1. Economic Feasibility Analysis

There are several methods that evaluate the financial feasibility of investments. However for analyzes of energy generation projects, the Net Present Value method (NPV) is widely used in literature as the main feasibility indicator [4,12,14,15]. In this sense, Hawawini and Viallet [16] affirm that NPV is a desirable decision criterion. In addition to other properties, it considers the expected cash flow of the

project, taking in account its risks and being a measure of value creation. Therefore, when the result of the net present value is greater than zero the project creates value, that is, the investment is feasible.

For Ross et al. [17], NPV is a measure of value created or aggregated for an investment to be realized. In addition, the authors complement that the decisions made using the NPV criterion are defined, solely, based on the result, so that, when positive, the investment should be accepted. However, when the NPV is negative, it should be rejected.

The Net Present Value (NPV) is described by the following Equation (1):

$$NPV = -I + \sum_{j=1}^n \frac{CF_j}{(1+k)^j}, \quad (1)$$

where CF_j represents the cash flow in period j and k indicates the minimum attractiveness rate, which represents the minimum return that the investor seeks to obtain in the investment; and I is the investment.

According to Tao and Finenko [18], cash flow modeling considers money value throughout the project, where a discount rate is used to find the present value. Thus, the flow itself is formatted from the perspective of the developer, who in turn includes both client and investor.

In this case, the risk factors for the revenues from investing in renewable energy projects must be treated as random variables [14], so Monte Carlo Simulation can be used to calculate NPV, as suggested by Arnold and Yildiz [12]. It returns, through random simulations, a probabilistic model that presents the probability of feasibility of the project.

2.2. Weighted Average Cost of Capital

The weighted average cost of capital (WACC) is the method that calculates the rate of return of capital expected by investors applied in the cash flow of the project. Thus, the lower the weighted average cost of capital the higher the project value, since the discount rate reflects the opportunity cost in relation to the investment risk [16,18–20].

According to Ertürk [4] the WACC is calculated by Equation (2):

$$WACC = k_e E + k_d D(1 - t), \quad (2)$$

where k_e represents the cost of equity (calculated preferably by Capital Asset Pricing Model-CAPM); k_d is the cost of debt; E represents the weight of equity in the investment (%); D denotes the weight of debt applied to the investment (%); t is the aliquot of the income tax.

It was noted that the majority of the publicly traded companies in the electricity sector have the proportion of 35% of equity and 65% of capital of debt. In this sense, it is fair to assign these values to variables and, respectively, in Equation (2) [21].

Furthermore, Aquila et al. [1] proposes the use of the interest rate of the National Development Bank (BNDES) in energy generation projects, which has a value of 11.33%, so this value is attributed to the cost of debt (k_d). In addition, it assumed t as 34%, in line with the current value of income taxes in Brazil.

Regarding the calculation of CAPM, the National Electric Energy Agency [22] suggests that a Brazilian risk factor is added so that the Brazilian market investor receives a risk premium. As it can be seen in Equation (3):

$$k_e = R_f + \beta(R_m - R_f) + R_b, \quad (3)$$

where R_f represents the risk-free rate (5.64%); R_m indicates the expected return of market (13.20%); R_b represents the risk premium Brazil (2.62%) [22]; and β denotes the levered beta (equity beta) and measures the project risk in regards to the market.

In addition, to calculate the levered beta (β) it was used the data of Damodaran [23], in which the renewable energy sector has the unlevered beta value of 0.69. Using such data and considering the proportion of equity and debt, the levered beta of 1.54 is found through Equation (4):

$$\beta_a = \beta_d \left[1 + \frac{D}{E} (1 - t) \right], \quad (4)$$

where β_a is the levered beta; β_d is the unlevered beta; D denotes the weight of debt applied to the investment (65%); E represents the weight of equity in the investment (35%), and t is the aliquot of the income tax.

2.3. Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational structures that have as principle the representation of biological processes. These are composed of simple processing units and have the capacity to store experiments and make them available to the user [24,25].

Bigdeli et al. [26] state that Multi-Layer Perceptron (MLP) ANNs make up the model of artificial neural networks most commonly used in the literature. In this model, each unit calculates the scalar product of its input vector with the relative weight vector with each entry. When triggered, the value of the scalar product is used as a variable independent of an activation function, in which the dependent variable is the output of the neuron. However, it is known that the MLP supports more than one output in its mapping, since it does not have theoretical limitations on the data [27].

Figure 1 shows the architecture of an MLP network:

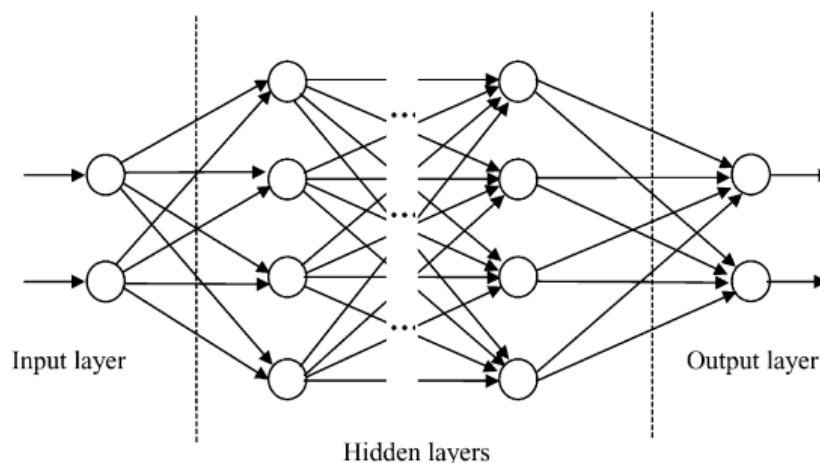


Figure 1. Representation of an MLP network. Adapted from ATA [28].

In this context, the backpropagation algorithm is widely used in the literature to carry out MLP network training, which seeks to learn and correct connection weights, as well as minimizing errors through activation threshold adjustments [27–29].

By designing a well-trained MLP network model ($m \times n \times 1$), where m is the number of nodes in the input layer, n are the nodes of the hidden layer, and 1 is the output layer node, the relative importance of input variables can be calculated by Equation (5) [27,30]:

$$RI_i = \frac{r_i}{\sum_{i=1}^m |r_i|} \times 100\%. \quad (5)$$

For this calculation, Chakrabarty et al. [27] stipulate some steps that must be followed. These are:

- The vector, M ($1 \times n$), must be organized with the interconnection weights between the nodes of the hidden layers (n) and the nodes of the output layers;

- The matrix, W ($m \times n$), must be organized with the interconnection weights between the nodes of the input layers (m) and the nodes of the hidden layers (n);
- Calculate the vector $R = MW^T$, where $R = [r_1, r_2, \dots, r_m]$;
- Finally, we calculate the relative importance (RI_i), in percentage, of each node i of the input layer, as given by Equation (5).

After completing these steps, the relative importance (RI) of each input parameter over the output variable is obtained, of which a sensitivity analysis of these variables will be performed.

3. Materials and Methods

This research is classified as applied in nature. Regarding the objectives, it is characterized as exploratory research, as to the way of approach is quantitative, as numerical data and calculations for the solution of the proposed problem was used. As for the research method, it is classified as a modeling and simulation research, since it tried to reproduce a real system through a computational model [31].

This work proposes to analyze the economic feasibility of an investment directed to the installation and production of electricity from wind power in a small business (SB). To exemplify this proposal, as Rocha et al. [3], a region with high wind speed of the Brazilian northeast was chosen and the wind speed behavior data collected [32]. The Weibull distribution is widely used in literature as the one that best suits the wind speed behavior as a function of time [33]. Thus, the Weibull distribution was employed with values for scale parameter (C) and shape parameter (k) equal to 7.0 and 3.0, respectively [32].

In this context, the investment is based on the purchase of a 30 kW wind turbine, power compatible with the need for a SB. Thus, after research among several companies that provide this type of product, giving priority to suppliers in the Northeast, it was stipulated R\$ 408,950.00 as the average value of the investment. The specifications of the wind turbine are: diameter of 13.2 meters and efficiency of 92%. Furthermore, it was found that the useful life of this type of product is 20 years without maintenance, which is easily found on the market. Then, 5% was determined as depreciation rate, so it is considered that the wind turbine will be totally depreciated after the 20 years.

Rocha et al. [3] present a routine for energy production calculation for wind power generators, as follow. The probability density function of a Weibull distribution with two parameters is given by Equation (6):

$$f(v) = \frac{k}{C} \left(\frac{v}{C} \right)^{k-1} e^{-\left(\frac{v}{C} \right)^k}, \quad (6)$$

where v represents the wind speed (m/s); k denotes the shape parameter; and C represents the scale parameter (m/s).

Electric power in watts is a cubic function of wind speed (v) given by Equation (7):

$$P = \frac{1}{2} \rho A_r v^3 C_p \eta, \quad (7)$$

where ρ represents the air density; A_r stands for the area encompassed by the rotor ($\pi D^2/4$, where D is the rotor diameter); C_p represents the aerodynamic coefficient of rotor power; and η denotes the efficiency of the generator-mechanical set and electric transmissions. The following values were considered for the current study: $\rho = 1.225 \text{ kg/m}^3$; $D = 13.2 \text{ m}$; and $\eta = 0.92$. The C_p for a wind power turbine varies with the wind speed, as follows [3]:

$$C_p = -0.08114 + 0.1771v - 0.01539v^2 + 0.00034v^3. \quad (8)$$

Finally, Equation (6) was used to calculate the annual energy production (AEP):

$$AEP = 8.76 \times \int_{v_{\min}}^{v_{\max}} P(v)f(v)dv(kWh), \quad (9)$$

where v is the wind speed; $P(v)$ is the power curve of the wind turbine; and $f(v)$ is the probability density function in relation to the wind speed.

According to ANEEL [22], taxes were disregarded, as renewable energy producers are exempt from taxes proportional to revenue. However, the financing rate was 11.33%, in accordance with the financing conditions offered by BNDES [1].

According to Rocha et al. [34], in Brazil's net metering, customers who produce surplus energy through microgeneration systems are rewarded with one credit for each energy unit provided to the grid. The ratio between the credit and the price of the energy tariff used by the utilities, which is different in each state, is one-to-one. Considering the savings on electricity expenses that arise from the generated credits as income for the individual who invests in electric microgeneration, it is possible to apply the NPV for the economic feasibility analysis of this type of project.

Thus, in order to assign uncertainty to the project evaluation, a stochastic analysis was carried out through the execution of 10,000 simulations, through the Monte Carlo Simulation (MCS). Then, the sensitivity analysis was then performed in order to define which variables most affect the NPV. For this, the tools Microsoft Excel® and Crystal Ball® were used.

Finally, considering the results obtained by the simulations, these variables were used to train the MLP network and to calculate the relative importance of each input variable in relation to the output (NPV). For this, were used the software Statistica® and Microsoft Excel®. To execute the network training, we opted for the Automated Network Search (ANS) strategy, which seeks to identify the ideal parameters for model construction.

It is worth mentioning that the results obtained with the simulations were used for the network training, simply with the objective of identifying the relative importance of the variables. However, no predictions were made based on simulated data.

4. Results and Discussion

The project cash flow was elaborated based on the values and distributions according to Table 1. Thus, the uncertainty was applied only in the variables of wind speed, investment and energy tariff, since the remaining ones were not shown to be relevant in the NPV or are calculated, as is the case of energy production.

Table 1. Representation of cash flow, its values and distributions.

Parameters	Distribution	Minimum	Probable	Maximum
Wind speed	Weibull		-	
Investment	Triangular	R\$ 368,055.00	R\$ 408,950.00	R\$ 449,845.00
Energy tariff	Triangular	R\$ 0.41	R\$ 0.45	R\$ 0.50
Period (years)	Fixed		20	
Annual tariff readjustment	Fixed		2.30%	
WACC	Fixed	-	10.29%	-
Financing rate	Fixed		11.33%	
Depreciation	Fixed		5%	
Energy production	Calculated		-	

For the electricity tariff, the data collected from the utility was used to compose the parameters of a triangular distribution, in which 0.50 and 0.41 are the largest and smallest values found, respectively, and 0.45 is the average of the values collected. In addition, in agreement with Holdermann et al. [15], it was attributed an annual tariff readjustment of 2.30% per year.

Moreover, for the investment, as these are imported materials and that suffer variations of the exchange rate, a possible oscillation in the value of the investment of R\$ 40,895.00 was considered, i.e., 10% of the total investment. Given this, a triangular distribution was chosen, and the average of the quotations with suppliers was considered as the most probable value.

Furthermore, according to Figure 2, there is a probability of 28.65% of the NPV being greater than zero, i.e., a low probability of feasibility, which can be observed through the average NPV, in the amount of R\$ −90,439.00. Therefore, it can be concluded that investments in wind power generation may be viable in the Brazilian northeast, but this may not be attractive for investors, since in the scenario studied, there is still a lot of uncertainty and a low probability of viability, as well as in studies by Aquila et al. [7], Rocha et al. [3] and Holdermann et al. [15].

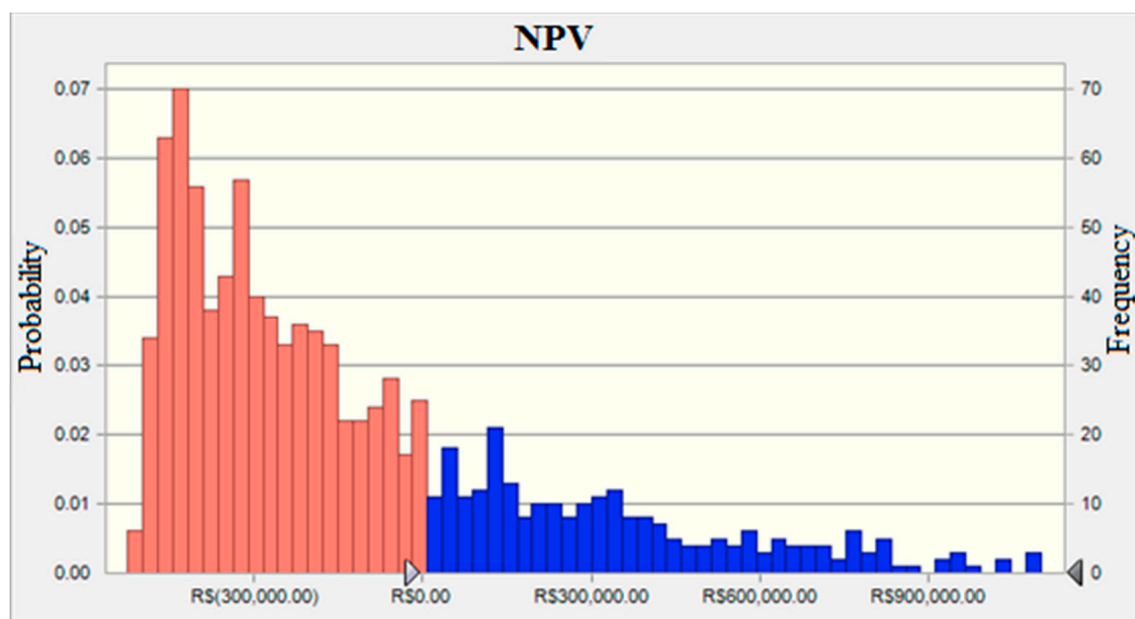


Figure 2. Probability of feasibility resulting from MCS.

In this sense, one should seek to know under which variables the NPV is more sensitive, for which two alternatives have been chosen.

The tornado chart (Figure 3), shows that wind speed is the variable that impacts the net present value (NPV) the most and, consequently, the viability of the project. Moreover, the value of the investment and the energy tariff, even if on a much smaller scale, show a significant value in the NPV, which are variables that are easier to adapt, since they are related to production costs, taxes, financing rates, among others. In this segment, the Brazilian government is fundamentally important, as it can promote types of monetary incentives for this type of project in order to make it more attractive and profitable.

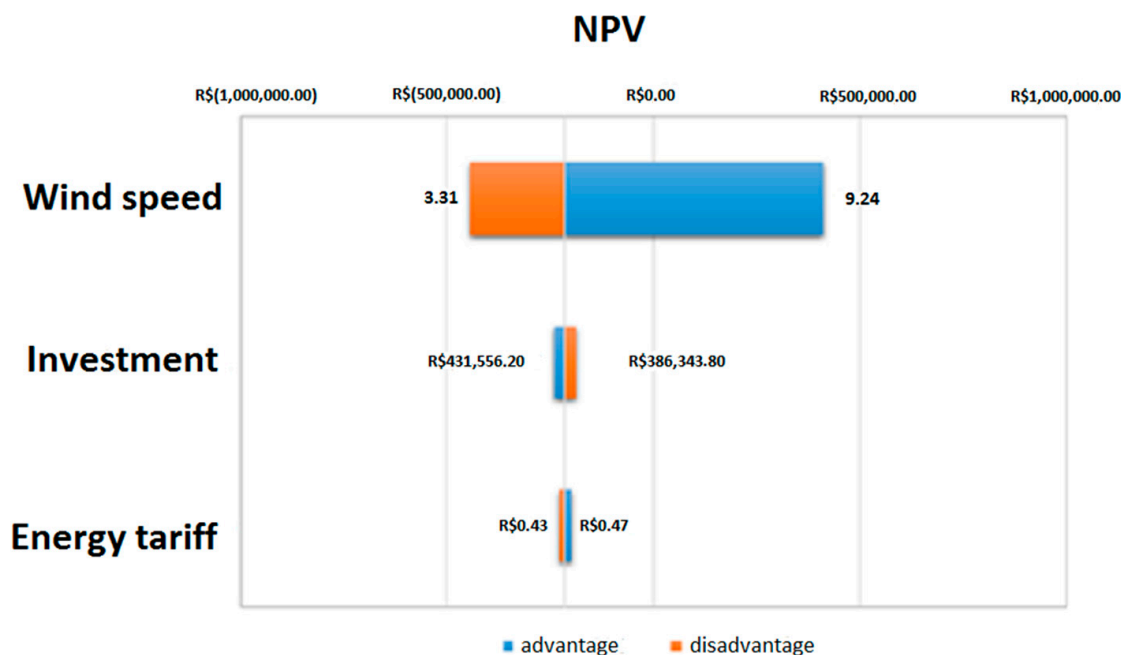


Figure 3. Tornado chart: sensitivity analysis.

In a second analysis, as previously reported, we opted for the Automated Network Search (ANS) strategy, which seeks to identify the ideal parameters for the ANN construction. Under these conditions, the structure identified with the lowest prediction error was the configuration MLP 3-5-1, that is, three is the number of nodes in the input layer, five are the nodes of the hidden layer, and one is the output layer node. In addition, the relative importance (*RI*) of these variables through ANN was estimated (see Table 2 and Figure 4), and therefore, there is consonance about the importance of wind speed in the viability of the project. However, according to *RI* results, the energy tariff was more important than the value of investment in impacting the NPV. Then, it can be concluded that the wind speed has great power of influence in the project. Finally, it should be noted that by calculating *RI* it was possible to obtain a better discrimination of the variables.

Table 2. Representation of the Relative Importance (*RI*) of the parameters in the NPV value.

Parameters	Relative Importance (<i>RI</i>)
Wind speed	56.12%
Energy tariff	27.51%
Investment	16.37%

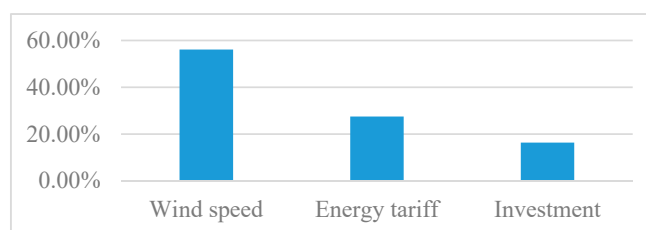


Figure 4. Relative importance (*RI*) through ANN: variables that most impact the NPV.

5. Conclusions

In this work, an economic feasibility analysis of a project of electric power generation from wind power in an SB located in the northeast region was carried out. To better analyze the investment, it was decided to carry out the stochastic analysis of economic viability and to verify which variables have

greater relative importance in the project. Therefore, conclusions showed that the wind speed has the main influence on the problem, followed by similar amounts between the cost of the investment and the energy tariff. Moreover, the relative importance analysis through ANN proved to be feasible, with good discrimination of the variables, being possible to rank them by the impact on NPV.

It can be inferred that because it is directly related to geographic issues, the wind speed is of difficulty adequacy, since it is totally inherent to the location of the project. As a result, it is concluded that this parameter is impossible to be controlled, but it is possible to elaborate forecast studies in order to anticipate the inherent uncertainties of the project. In addition, this result shows the importance of the site selection when projecting the installation of wind turbines.

It has been inferred that the energy tariff and the investment can make projects in wind energy more attractive, since these are directly related to government actions. Thus, programs of incentives for the production of clean energy that make cheaper the purchase of wind turbines and lower taxes and financing rates can make wind power more profitable and attractive.

Finally, this study presented a new systematics for conducting studies on the sensitivity of the variables to the NPV, using ANN. As recommendation for future studies, the application of the presented methodology in other operations is proposed. Furthermore, additional new questions should be investigated, such as identification of suitable locations, size of wind turbine, electrical grid stability and government policy measures.

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