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Microgeneration of Wind Energy for Micro and Small Businesses: Application of ANN in Sensitivity Analysis for Stochastic Economic Feasibility

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ABSTRACT To reduce the risks of a new energy crisis and increase energy availability, the use of renewable energy sources (RES) is important and recommended. In Brazil, micro and small companies contribute about 25% of gross domestic product (GDP), and electric energy is employed intensively, so the importance of microgeneration is observable. This research aims to analyze the economic viability of the micro-generation wind energy project for micro and small businesses. Thus, three Brazilian states, Rio Grande do Norte, Rio Grande do Sul and Minas Gerais were considered, and different scenarios were proposed. A feasibility analysis is then performed, followed by a stochastic analysis using Monte Carlo simulation (MCS). Finally, models of artificial neural networks (ANN) are used to evaluate the relative importance (RI) of the variables. The results show that none of the states appears economically feasible under the conditions presented. In the stochastic analysis, the probability of viability is between 17% and 24% in all states, which shows the low probability of viability for microgeneration. Through ANN training, it was possible to calculate the RI, in which it is possible to identify the variables that have most impact on the net present value (NPV) in all states; it is considered the most important variable in the project's viability. In addition, the discussion explores the importance of public incentives for promoting investment in renewable energy, which can reduce investment costs and make it attractive to small and medium-sized businesses.

INDEX TERMS Microgeneration, wind power, stochastic feasibility analysis, sensitivity analysis, artificial neural networks.

I. INTRODUCTION

The economic development of nations has been a prerequisite for the availability of energy in quantity and quality, as energy is a strategic asset, while energy security is treated as a matter of global agendas and conferences [1]. In this scenario, Aquila *et al.* [2] comment that the renewable energy market is expanding, and that regulatory changes in Brazil have influenced the energy sector; they discuss the lack of studies on the feasibility of microgeneration and comparisons with different regions.

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The micro and the minigeneration of electric energy increase the availability of energy, as well as electricity savings, which can be very significant for micro and small businesses.

Micro and small businesses, despite having considerable impacts on the economy and society of their regions and countries in which they operate, their activities are responsible for at least 70% of world pollution [3]. However, according to Barbosa *et al.* [3], efforts for sustainable development are greater than expected e sustainability practices could be found in micro and small businesses' agendas. In Brazil, according to Sebrae [4], micro businesses are classified as companies with gross revenues of up to 360 thousand

Brazilian reais (R$), while in small companies this range can vary from 360 thousand to 4.8 million. Together they represent about 98.5% of the total of private companies in Brazil, corresponding to 27% of GDP (gross domestic product), in addition to being responsible for 54% of formal jobs in Brazil.

Through decision criteria the economic feasibility analysis shows the economy generated by renewable sources, in addition to environmental gains and gains as a marketing strategy for the company. Given the shortage of oil and the energy crisis, investments in renewable energy are increasing every day, and the search for clean production is increasing every year.

Killinger *et al.* [5] show in their study that micro and mini-generation as well as cogeneration can be profitable due to network usage rates that show a strong trend for wind turbines. Given this scenario, greater reliability is required in this type of enterprise. Xue *et al.* [6] comment that an economic analysis of a wind farm project is needed so that the cost efficiency of a wind power system can be identified.

In the literature it is already possible to find research involving feasibility analysis of projects from renewable energy sources (RES), and some authors dedicate their studies to wind sources [7]–[12]. Moreover, in some cases, even encompassing Monte Carlo simulation (MCS) for the management of economic risk [2], [13]–[16] are motivated by the high degree of uncertainty inherent in this type of enterprise.

Another computational technique that has been widely used as the basis for RES studies is artificial neural networks (ANN). For example, Sahin [17] concludes that the application of neural networks in wind power projects produces better results in modeling, control, and optimization problems. Some authors analyze the viability of renewable sources using neural networks, but under different optics [18], [19]. However, using the combination of the MCS and ANN methods for simulations and identification of the variables that most impact a financial indicator, such as net present value (NPV), a gap in the literature remains that has scarcely been explored.

It is notable that there are few studies that discuss the need to perform a stochastic and sensitivity analysis, consider several scenarios, and assure the micro and small company investor about the returns that this type of enterprise can generate.

In view of the above, it is necessary to further study Brazilian energy policies with special attention to the microgeneration of electric energy, to show the economic viability of projects with renewable sources. This study aims to address the extent to which the project for the micro and minigeneration of electric energy from a wind turbine is economically feasible using different simulations and scenarios, and identify which are the most relevant variables for the feasibility analysis. Thus, in general terms, this article's main objective is to analyze the economic feasibility of microgeneration of electric energy from the wind power source for micro and small businesses in environments of uncertainty and risk. To do so, this work will use the MCS associated with the application of the concepts of ANN.

II. THEORETICAL BACKGROUND

A. RES INCENTIVE POLICIES

Reducing CO_2 emissions is one of the main objectives proposed by current energy policies, owing to the increase in gases contributing to global warming, and to the fact that humanity is increasingly concerned with these effects. Different policy instruments, such as subsidies for low-carbon technologies, emission standards, or carbon prices can be used to achieve this goal [20]. Aquila *et al.* [2] discuss the strategies that public power can use to leverage the renewable energy market, which may be short- or long-term. The authors comment that the most popular short-term strategies are direct subsidies, reduction of taxes, and collection of tax for a certain amount of CO_2 emissions. For more information on the most widely used long-term strategies, see Aquila *et al.* [2].

In their results, Aquila *et al.* [21] show the importance of regulatory strategies and incentive mechanisms to support the growth of RES, which is not yet economically competitive compared to conventional energy sources. A strategy to support manufacturers and national investments in research and development is crucial to achieving targets in terms of the security of the electricity supply, while a favorable policy environment is essential for the development of renewable technologies [22], [23].

In recent years, few policies have been created in Brazil; the State Program for Energy Development (PRODEEM), encompasses solar and wind energy sources and rewards companies that implement clean energy in their production systems. The program is seen by the market as bureaucratic, superficial, and hostile to the implementation of new technologies [23]. Table 1 shows the main public policies and incentives in Brazil.

Rocha *et al.* [33] argue that incentives for micro-generation of energy are timely in Brazil, as the demand for electricity in recent decades has increased in the industrial and residential sectors. The authors show that with the growth of global energy consumption, there is also an increase in energy costs. Further, in this scenario, microgeneration plays an important role in promoting cleaner energy in homes and businesses.

Finally, Castro [34] comments that microgeneration faces many difficulties in Brazil for expansion, including the lack of appropriate financing options in the market, equipment tax (increase the cost of investments), and the fact that few types of equipment are certified. The author concludes that ANEEL has an opportunity to increase the number of commercial consumers with microgeneration, thereby bringing positive impacts to Brazil.

B. ANALYSIS OF THE ECONOMIC FEASIBILITY OF ENERGY GENERATION FROM RES

Considering the global energy crisis and concern about energy availability, many countries adopt long-term strategies

TABLE 1. Main policies and public incentives in brazil.

Policies	Description	Sources
Normative Resolution No. 687 of November 24, 2015, of Brazilian Electricity Regulatory Agency (ANEEL)	Res. 687/2015. PRODIST [24] (i) remote self-consumption; (ii) reduction in waiting for network connection; (iii) shared generation and (iv) generation in condominium.	Silva et al. [25]; ANEEL [24]; Lacchini and Rüther [26].
Ordinance No. 538, of December 15, 2015	Program for the Development of Distributed Generation of Electric Power - ProGD.	Garcez [27].
Agreement No. 16/15	Exemption in the internal operations related to the circulation of electric energy, subject to billing under the Electric Energy Compensation System, which is dealt with in Normative Resolution No. 482 of 2012, of the National Electric Energy Agency - ANEEL. Brazilian states with membership: RN, CE, TO, BA, MA, MT, DF, A C, AL, MG, RJ, RS, RR, PA, MS, AP, ES, AM, PR and SC.	Ferreira et al. [28]; Pereira et al. [29].
Normative Resolution No. 77 of August 18, 2014, of ANEEL	Establishes the procedures related to the reduction of tariffs for the use of transmission and distribution systems, for hydroelectric projects, and those based on solar energy, wind energy biomass, or qualified cogeneration.	Pinto et al. [23]; Devienne Filho [30]. ANEEL [31]
Normative Resolution No. 481, of April 17, 2012, of ANEEL	Discounts on the tariffs for the use of electric transmission and distribution systems (TUST and TUSD), focusing on the production and consumption of marketed energy.	Pinto et al. [23]; Rodrigues et al. [7]; ANEEL [32].
Normative Resolution No. 482, of April 17, 2012, of ANEEL	Electrical Energy Compensation System for Distributed Microgeneration and Minigeneration.	Rocha et al. [33]; Silva et al. [25]; Castro [34]; Pereira et al. [29]; Lacchini and Rüther [26]; Holdermann et al. [35]; ANEEL [36].
Normative Resolution No. 488, of May 15, 2012, of ANEEL	Luz para todos (Light for all) program.	Santos et al. [37]; Pereira et al. [29]; ANEEL [38].
Normative Resolution Nº 517, of December 11, 2012, of ANEEL	Compensation with the active electric energy consumption of the same consumer unit or other consumer unit with the same ownership of the consumer unit where the credits were generated.	Pinto et al. [23]; Rodrigues et al. [7]; ANEEL [39].
Law Nº 12212, of January 20, 2010	The Social Energy Electricity Tariff is characterized by discounts on the tariff applicable to the residential class of electric power distributors, and is cumulatively calculated according to consumption.	Pinto et al. [23].
Decree No. 5025, of March 30, 2004	PROINFA - Incentive Program for Alternative Energy Sources.	Aquila et al. [21]; Costa et al. [40]; Ruiz et al. [41].
Agreement No. 101/97 - CONFAZ	Exemption of Tax on the Circulation of Goods and Services (ICMS) in operations involving numerous equipment used for electricity generation by solar or wind energy.	Ferreira et al. [28]; Pereira et al. [29].
DNN 2793 - Decree of December 27, 1994	PRODEEM - Program for the Energy Development of States and Municipalities.	Garcez [27]; Costa et al. [40]; Ruiz et al. [41].

to encourage energy production through RES. Several academic studies have emerged with this scientific bias to study the impact of these policies and the technical and economic feasibility of this type of investment.

Holdermann *et al.* [35], in their results concerning economic feasibility, show that photovoltaic systems are currently not economically viable in any of the 63 distribution networks in Brazil. The authors show that the introduction of financing options can make investment feasible, both in the commercial and residential sectors.

Ferreira *et al.* [28] demonstrate the main aspects of the evolution of incentives for using solar energy in Brazil. They comment that for distributed generation, the level of competitiveness is defined from the energy distribution tariffs offered to the final consumer; with this comparison of values, the authors affirm that solar energy is close to economic feasibility. The development of specific credit lines for the generation of solar energy is discussed as being vital to the express entry of this source of power into the Brazilian electricity matrix.

Rocha *et al.* [33] developed a feasibility analysis of a small-scale photovoltaic installation in four cities in Brazil, for which they performed a stochastic analysis using MCS. In the four cities analyzed, microgeneration was economically unfeasible when the ICMS (Tax on Circulation of Goods and Services) was charged, with the probability of viability, which varied between 0% and 8.79%. In the ICMS exemption policy, the feasibility probabilities were 23.27%, 56.66%, 81.49%, and 94.70%, indicating that the project was feasible in most regions. The authors conclude that the ICMS subsidy will provide support for the production of cleaner energy.

Abdelhady *et al.* [42] conducted a technical and economic evaluation for the generation of electricity with eight small wind turbines in 17 distinct regions of Egypt. The authors evaluated the NPV and the payback based on the annual energy production by the wind turbines. The results show that although wind speeds are high at selected sites, small wind turbines are not economically viable. They recommended that turbines with nominal power above 200 kW be adopted.

Hosseinalizadeh *et al.* [43] conducted a feasibility analysis of small wind turbines in various regions of Iran, which showed that in 30% of the regions small wind turbines are viable. The results showed that wind turbines with capacity less than or equal to 3 kW are the most suitable for residential use. Finally, the authors concluded that small wind turbines are profitable in many regions of Iran and suitable for the development of wind power in the residential sector.

Grieser *et al.* [11] show that accurate and reliable tools are essential for assessing economic potential and market prospects. The authors comment that NPV is the most widely used investment analysis method, and discuss its limitations. It was found that current investments in small wind turbines in Germany are economically viable in areas exposed to 4 and 4.5 m/s of minimum average speeds. In its sensitivity analysis, a slight variation in wind speed is seen to substantially affect the NPV and, as a consequence, the investment decision.

Aquila *et al.* [44] present a framework for analysis of investments in wind power generation under uncertainty using Monte Carlo simulation. The authors use MCS for stochastic analysis, analyze the behavior of NPV for the targeted variables, and list those that had an impact on the NPV. In the deterministic analysis, the project presents high economic feasibility in the three scenarios presented. In the stochastic analysis, the project shows a high probability of economic viability, especially if BNDES loans (National Bank for Economic and Social Development) are involved.

Aquila *et al.* [21] analyze the impact of incentive strategies on the financial risk of wind energy project in Brazil. The study presents a statistical analysis with the purpose of facilitating comparison of the risk considered in the different scenarios analyzed. The authors considered two environments: free contracting and regulated contracting. Their results show that in the free contracting environment the wind project will be more likely to be viable in all scenarios at 96.36%, 97.70%, and 98.50%. Comparing the scenarios in the two environments, the authors show that when the risk is higher, it can generate higher returns. They conclude that the sale of carbon credits is not an adequate policy to provide financial security to producers of renewable energy.

Finally, Aquila *et al.* [21] argue that investment analysis has been used to measure the impact of incentive strategies for renewable energy sources, thus proving the importance of economic analysis. They used the NPV decision criterion, and the various risk factors that affect the outcome were treated as random variables.

C. ARTIFICIAL NEURAL NETWORKS APPLIED IN RES

Haykin [45] defines artificial neural networks (ANNs) as a massively distributed processor composed of simple processing units, which has the natural propensity to store experimental knowledge and make it available. The author comments that knowledge is acquired through learning processes and the synaptic weights (similar to the connection between neurons) are used to store the acquired knowledge. The values of the synaptic weights have no value for analysis; individually, they do not present any representativeness and do not allow any readings [19]. Haykin [45] represents a nonlinear model of a neuron in Figure 1.

ANNs have been used in applications on sustainable development in the energy sector in terms of energy production and use. Kennedy *et al.* [46] show ANNs' application of pattern recognition and interpret its influence in predicting customer behavior in relation to technological choice. ANNs provide an ideal solution to many problems in many electrical systems' applications such as control, identification, and classification [47].

Yan *et al.* [48] use ANNs to consider the uncertainty of the forecast in photovoltaic systems. To evaluate this, they use three layers to estimate load and energy prediction errors. Karabacak and Cetin [49] discuss ANNs' applications in

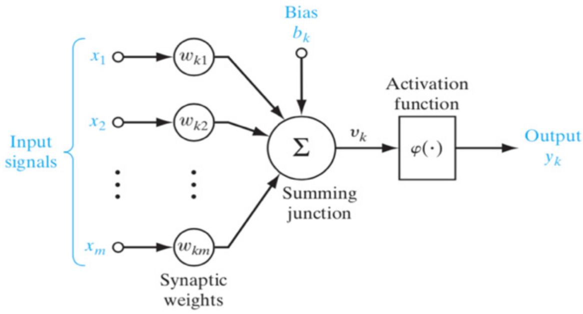

FIGURE 1. Nonlinear model of a neuron. Source: Haykin [45].

renewable energy systems such as photovoltaics, wind power, and hybrid systems. The authors show that for solar energy, studies are based on the prediction of solar irradiation and the design of energy systems. Mokhtar [47] carried out an application for the control and analysis of a photovoltaic generator and the reactive energy in the generation system, proposing a reasonable generation system model.

ANNs have the ability to learn, are data-driven, and have high predictive accuracy compared to other methods. For these reasons they have become alternative methods to conventional techniques in various solar energy applications [50]. Chiteka and Enweremadu [50] developed an ANN model that can be used as an efficient tool to predict solar radiation without direct measurement equipment. In a similar approach, Bou-Rabee *et al.* [51] developed an ANN-based forecast model to predict daily average solar radiation at five different sites and integrated feed-forward architectures. The results show that the model is accurate, applicable, and efficient at 94.75%. The developed model is intended to be an evaluation tool to predict the installation of solar energy to estimate the amount of energy that can be used.

Dervilis *et al.* [52] uses ANN in standard recognition methods in the field of wind power. Manobel *et al.* [53] use an ANN-based method to calculate the power curve of any wind turbine that depends on a minimum set of input variables, such as wind speed and wind direction. The authors conclude that the combination of Gaussian process filtering with ANN modeling provides an automatic and accurate method to calculate the power curve, with subsequent resource savings compared to manual filtering and other parametric and non-parametric methods.

In their study, Singh [54] present a predictive model of wind power in the neural network architecture in feed-forward. They show that ANN is an efficient and valuable tool for estimating energy power for wind generators.

Ozgur [55] use an ANN model based on NPV analysis for the study of economic viability, which shows that wind power systems for different types of turbines are profitable.

Dombayci [56] developed an ANN model to predict the hourly energy consumption of a projected model house; the results show that energy consumption values can be stated with great precision, indicating that ANN is very effective for this type of prediction. In another study, Cabrera *et al.* [57] use ANN as a control system tool for a small-scale prototype of a desalination plant.

In their research, Macedo *et al.* [58] use ANN to choose the most appropriate policies for each type of consumer. The authors show satisfactory performance that allows for the optimization of the system and a dynamic price based on the habits of the consumer. Similarly, Bolanca *et al.* [59] created a model for defining a more efficient and environmentally sustainable policy that should be transferable elsewhere by applying the described ANN training procedure.

Azadeh *et al.* [60] present an approach for optimized estimation and prediction of renewable energy consumption, taking into account environmental and economic factors. In their study, ANN trains and tests the data using the Multi-Layer Perceptron (MLP) approach which, according to Haykin [45], is the most widely used approach in the literature. The authors have shown that the proposed ANN model can be very beneficial in improving and optimizing renewable energy consumption in some remote or rural locations, with no available devices to measure renewable energy consumption.

Aien *et al.* [61] developed a methodology for estimating the real-time state of energy prices by probabilistic optimum power flow studies using the hybrid artificial neural networks concept. Similarly, Barelli *et al.* [62] propose an ANN model to predict the scheduling of programmable loads given the climatic conditions related to the current and the previous day, in addition to the weather forecast for the following day. Furthermore, Aien *et al.* [61] show the use of ANN in different power system applications, such as load forecasting, electricity price forecasting, wind speed prediction, and state estimations in the distribution system.

In a perspective that goes further, Chakrabarty *et al.* [19] propose, in the approach to artificial neural networks, the use of synaptic weights calculated in realizing the sensitivity analysis of the input variables from the calculation of their relative importance.

Considering a well-trained MLP model ($m \times n \times 1$), where m is the number of nodes in the input layer, n the hidden layer nodes, and 1 the output layer node, the relative amounts of input variables can be calculated by (1) [19], [63].

$$RI_i = \frac{r_i}{\sum_{i=1}^{m} |r_i|} \times 100\% \tag{1}$$

For this, the steps stipulated by Chakrabarty *et al.* [19], must be followed as indicated:

a) 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;
b) 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);
c) Calculate the vector $\mathrm{R} = \mathrm{MW}^{\mathrm{T}}$, in which $\mathrm{R} = [\mathrm{r}_1, \mathrm{r}_2, \ldots, \mathrm{r}_m]$;
d) Finally, calculate the relative importance (RI_i), in percentages, of each node i of the input layer, using (1).

TABLE 2. Technical characteristics of the aerogenerator.

Rated power (kW)	Rotor diameter (m)	Rated speed (rpm)	Starting Wind speed (m/s)	Tower height (m)	Average investment value (R$)
2.4	3.72	50 - 325	3.5	18	61,0000

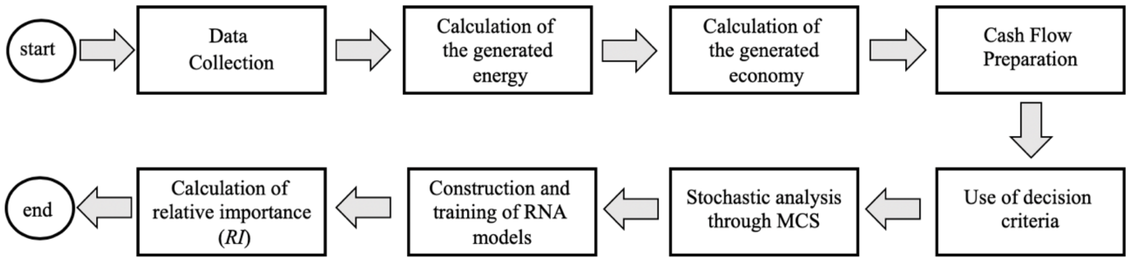

FIGURE 2. Flowchart of the proposed research.

At the end of this analysis, the relative importance *RI* will provide an index referring to the contribution of each of the input variables to the output variable. Such an approach can be used to carry out the sensitivity analysis in economic feasibility analysis projects.

III. MATERIALS AND METHOD

The research was carried out in a sequence of steps, described in Figure 2, the initial step of which was data collection; data were collected on investment, costs related to investment, technical information, wind speed data, financing conditions, and possible interests linked to the operation. We carried out searches in the literature and recommended databases and considered the best practices of similar research.

With the data collected, the calculation is initiated for generating electricity from the wind power source. Considering the information on the amount of energy generated, it is possible to calculate the amount referring to the economy generated by the wind turbine. Then, the construction of the discounted cash flow (DCF) can be constructed, and from there the investment decision criteria applied. Furthermore, a stochastic analysis of economic viability is carried out through MCS. Finally, a deterministic analysis of the economic viability is performed and followed by a stochastic analysis of the viability through MCS.

Similar to Kharseh *et al.* [64], who constructed an ANN model to generate an empirical formula that predicts NPV based on the factors established in photovoltaic projects, an ANN model is constructed to establish the relationship between the NPV and the specific variables.

Then, after the ANN training stage, the approach proposed by Chakrabarty *et al.* [19] and represented by Equation 1 is applied to perform the sensitivity analysis based on the synaptic weights resulting from the network training.

A. INVESTMENT

According to ANEEL regulations [36], microgeneration has installed power up to 75 kW, while minigeneration is defined as one with power above 75 kW and less than or equal to 5 MW (3 MW for water source), connected in the distribution network through facilities of consumer units.

TABLE 3. O&M costs indentified in literature.

Authors	O&M costs
Hosseinalizadeh et al. [43]	2.00%
Li et al. [66]	1.00%
Abdelhady et al. [42]	2.00%
Grieser et al. [1]	1.00%
Fadigas [68]	2.00%

Rocha *et al.* [65] in their study of economic feasibility of wind power, use a wind turbine of 2.4 kW, with the justification being easily found in the market, as well as Grieser *et al.* [11], who also used a 2.4 kW turbine, while Li *et al.* [66] used a 2.3 kW turbine. The investment was calculated to install a wind turbine with a power of 2.4 kW, with the following characteristics presented in Table 2; it was elaborated from data obtained from suppliers.

In this project, the value of the investment is related to the sum of the values of a 2.4 kW wind turbine, the metallic tower, the freight, and the installation of the system. The equipment has an average useful life of 20 years.

B. OPERATION AND MAINTENANCE COSTS

According to Ertürk [67], the operational costs of producing wind power are very low compared to other energy sources, because once installed, there is no cost of fuel and carbon, just operation and maintenance (O&M) costs.

Regarding the maintenance of the turbines, costs may arise with spare parts, preventive maintenance, labor costs, lease of the land, and margins for eventual surprises. These costs may vary according to local conditions and corrosive components in the atmosphere [68]. In the literature, authors who worked economically viable small-scale wind energy, used an annual rate that focused on the value of the investment. The values are described in Table 3.

Therefore, a more conservative approach was adopted for this work and a rate of 2% per year was used on the value of the investment related to the operation and maintenance [42], [43], [68].

C. DEPRECIATION

Depreciation for electrical equipment follows a specific schedule, and wind equipment has a 20-year useful life. As a result, they can be depreciated at an annual rate of 5% according to the COPEL manual [69], and also as adopted by Aquila *et al.* [44].

D. FINANCING

The Brazilian Northeast Bank (Banco do Nordeste) [70] seeks to contribute to the environmental sustainability of the Brazilian energy matrix and offers a line called FNE SOL (financing of micro and distributed electricity minigeneration), used especially for the financing of micro and energy minigeneration systems from renewable sources.

The fees considered are the fees that the bank imposes for the FNE SOL program, with a grace period of six months and up to 96 months for payment. The current rate of inflation was equal to 2.95% [71], so the real interest rate per year considered here was 6.68%.

E. WIND DATA SPEED

The most widely used model to describe wind speed distribution is the Weibull distribution [72]. The Weibull distribution is characterized by two parameters, one of form k and another of scale c [69], [72].

In this research we chose to work with three states: Rio Grande do Norte, Rio Grande do Sul, and Minas Gerais. Two of them were chosen because of their geographic location (they are in the geographic extremes of the country), and will be compared to the state of Minas Gerais, which already has policies to encourage renewable energy. The state has an ICMS exemption on the purchase of equipment.

The average annual wind speed data, as well as the Weibull distribution shape, scale, and gamma factor, from the states of Rio Grande do Norte (RN), Minas Gerais (MG) and Rio do Grande do Sul (RS) were calculated from the sources reported in Table 4. The average wind speed was taken from historical data that NASA provided from 1981 to 2017. The form factor was taken from the Atlas of Brazilian Wind Potential elaborated by Amarante *et al.* [73], and scale and gamma from Custódio [74], which are described in Table 4.

F. ENERGY PRODUCTION

The calculation of the energy production of the wind turbine was considered using the same method as Rocha *et al.* [65], Aquila *et al.* [44], Aquila *et al.* [21], and Li *et al.* [66], which exclusively involve wind energy. We use the probability density function of a Weibull distribution with two parameters according to (2).

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^k} \tag{2}$$

TABLE 4. Wind information by state.

	RN	RS	MG	Sources
Average wind speed	6.46	5.49	5.71	NASA [75]
Form parameter (k)	3.01	1.70	2.50	Amarante et al. [73]
Scale parameter (c)	7.24	6.15	6.44	Custódio [74]
Gamma factor	0.89	0.89	0.89	Custódio [74]

TABLE 5. Collected and calculated data used in the research.

Investment	R$61,000.00
Annual energy production	18,437.90 kWh/year
Equipment life	20 years
Operation and maintenance costs	2.00%
Depreciation	5.00%
R_f	4.04%
R_m	10.10%
Market risk premium (R_m-R_f)	6.06%
R_b	3.87%
Debt cost	6.68%
Beta unlevered	0.69
Beta leveraged	2.30
Cost of equity (CAPM)	21.85%
Deflated cost of equity	19.42%
Discount rate (WACC)	9.02%

where

v represents wind speed;

k is the form parameter; and

c represents the scale parameter.

The variables were obtained from the Atlas of Brazilian Wind Potential elaborated by Amarante *et al.* [73] and they vary from region to region and as a function of the season. The parameter c represents the scale factor; this variable can be calculated by a gamma-like distribution, except for k values ranging from 2 to 3; the scale factor was obtained from Custódio [74] data, which presents relations between the gamma function and the shape parameter.

Moreover, according to Rocha *et al.* [65], Aquila *et al.* [21], and Lima and Bezerra Filho [76], the amount of energy generated in watts can be estimated by (3).

$$P = \frac{1}{2}\rho A_r v^3 Cp\eta \tag{3}$$

where

ρ is the density of air;

A_r is the rotor area;

v is the wind speed;

C_p is the aerodynamic coefficient of the rotor; and

η represents the efficiency of the system.

TABLE 6. Wind speed and economy generated by the state.

	RN	RS	MG	Sources
Average wind speed	6.46	5.49	5.71	Nasa [75]
Generated economy (kWh/year)	7,920.49	4,582.26	5,243.01	Calculated

TABLE 7. NPV results for the states analyzed.

	RN	RS	MG
NPV	R$ -53,254.35	R$ -68,633.71	R$ -63,498.64

The aerodynamic coefficient of the rotor in question, in turn, is calculated by the polynomial equation shown in (4) [21].

$$Cp = -0.08114 + 0.1771v - 0.01539v^2 + 0.00034v^3 \quad (4)$$

The values of the equation's constants were calculated based on the work of Aquila *et al.* [21] and Rocha *et al.* [65], where the authors obtained such constants by means of regression for wind speed values varying from 0 to 25 m/s. Finally, Aquila *et al.* [21], Abdelhady *et al.* [42], and the COPEL manual [69] estimate the annual generation of electricity by (5).

$$AEP = 8,75 \int_{V\min}^{Vm\acute{a}x} P(v)f(v)dv \quad (5)$$

where

AEP represents the annual generated energy, and v is the wind speed.

G. DISCOUNT RATE CALCULATION

The largest companies in the electric energy sector that make up the portfolio of the Stock Exchange, Commodities, and Futures Exchange [77] hold, on average, 65% of their financing composed of third-party capital, and 35% composed of equity. The Bank of the Northeast, which has a specific financing line for microgeneration, provides financing of up to 70% of the renewable energy project. Therefore, in this work, the values provided by Banco do Nordeste were used to calculate the discount rate used in the projection of the cash flow in this wind energy project.

The weighted average cost of capital (WACC) is used as a discount rate within the models used in renewable energy projects; it can be calculated by (6) [21], [67], [78].

$$WACC = k_d D(1-\tau) + k_e E \quad (6)$$

where

k_d represents the cost of debt;

D is defined as the weight of the debt applied to the investment;

τ is the income tax rate;

k_e is the cost of equity; and

E is defined as the weight of equity in investment.

The capital asset pricing model (CAPM), proposed by Sharpe [79] and suggested in some RES studies [21], [65], [78], is used to calculate the cost of equity (k_e) (as presented by (7)). The ANEEL [80] recommends in a note that a Brazilian risk factor (R_b) of 3.87% be added, so that the investor is given a premium for investment in the Brazilian market. In relation to R_f and R_m, ANEEL [80] recommends the use of the values of 4.04% and 10.10%, respectively, for the calculation of the WACC used in the evaluation of electricity generation projects.

$$k_e = CAPM = R_f + \beta_a(R_m - R_f) + R_b \quad (7)$$

where

R_f represents the risk-free rate;

R_m indicates the expected return of market;

R_b represents the Brazilian risk premium; and

β_a represents the risk of the investment.

In addition, to evaluate the beta risk data from Damodaran [81] was used, which indicated the value of the unleveraged beta as 0.69 in the renewable energy sector. Thus, considering the same proportion of equity and third parties, we have 2.3 as the value of the leveraged beta for 2018.

Then, using (7) and the respective suggested values for R_f, R_m, and R_b, it was possible to calculate the cost of equity for this study at 21.85%. Moreover, the deflated value was 19.42%, which corresponds to the adjusted value in relation to U.S. inflation.

To estimate the cost of debt using (8), the real interest rate was calculated at 6.68%.to obtain financing from Banco do Nordeste [70].

$$k_d = R_f + pRisk + R_b \quad (8)$$

where

R_f indicates the risk-free rate;

$pRisk$ represents the debt risk premium; and

R_b indicates the country risk premium.

As described previously by (6), and with the values of cost debt and equity equal to 30% and 70%, respectively, it was possible to calculate the WACC. Here the value of 9.02% was calculated by (7), which was used as the discount rate (minimum attractiveness rate) for the calculations necessary to carry out the feasibility analysis.

IV. RESULTS AND ANALYSIS

A. ECONOMIC FEASIBILITY ANALYSIS

Once the research method was established and the data collection was carried out, the deterministic feasibility analysis was carried out with the elaboration of cash flows. The data collected are summarized in Table 5.

TABLE 8. Parameters and distributions adopted.

Parameter	Distribution	State	Minimum	More probable	Maximum
Energy price (in R$)	Triangular	RN	0.43	0.48	0.53
		RS	0.44	0.49	0.54
		MG	0.53	0.59	0.65
Wind speed	Weibull	RN/RS/MG			
Debt percentage (%)	Uniform	RN/RS/MG	0.00%	70.00%	
Investment (in R$)	Triangular	RN/RS/MG	54,900.00	61,000.00	67,100.00
Equipment life	Triangular	RN/RS/MG	20	20	25
Payment period	Uniform	RN/RS/MG	6	12	

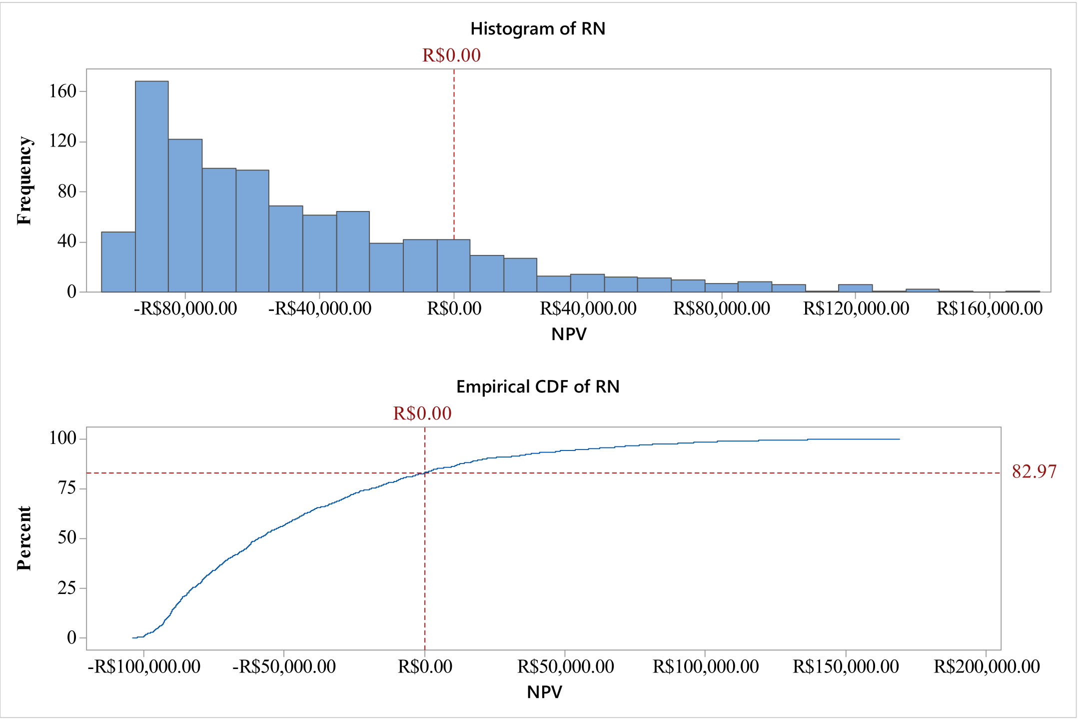

FIGURE 3. Probability of economic feasibility for the RN state.

TABLE 9. Probability of economic feasibility by state.

Probability of feasibility	RN	RS	MG
P (NPV) > 0	17.03%	18.90%	23.60%

TABLE 10. Values of the matrix $M_{(1\times 11)}$.

NPV^T	-1.22	1.07	-0.71	0.55	-0.67	-1.79	-0.17	0.87	-1.73	0.03	-1.28

The average electricity price practiced by the concessionaires, the final consumer of each state, and the average wind speed for each state were considered for calculating the generated economy. Using (2), (3), and (4) it was possible to calculate the generated economy, as Table 6 shows.

By calculating the economy generated for each state, it was possible to prepare the cash flow by scenario and the evaluation by the decision criterion of Net Present Value (NPV), as presented in (9). The deterministic results of NPV for each state are shown in Table 7.

$$NPV = \sum_{t=1}^{n} \frac{FC_t}{(1+i)^t} \tag{9}$$

where

n is the time of the project in years;
i is the minimum rate of attractiveness or discount rate;
t is the period of time to be analyzed; and
FC_t represents the net cash flow in period t.

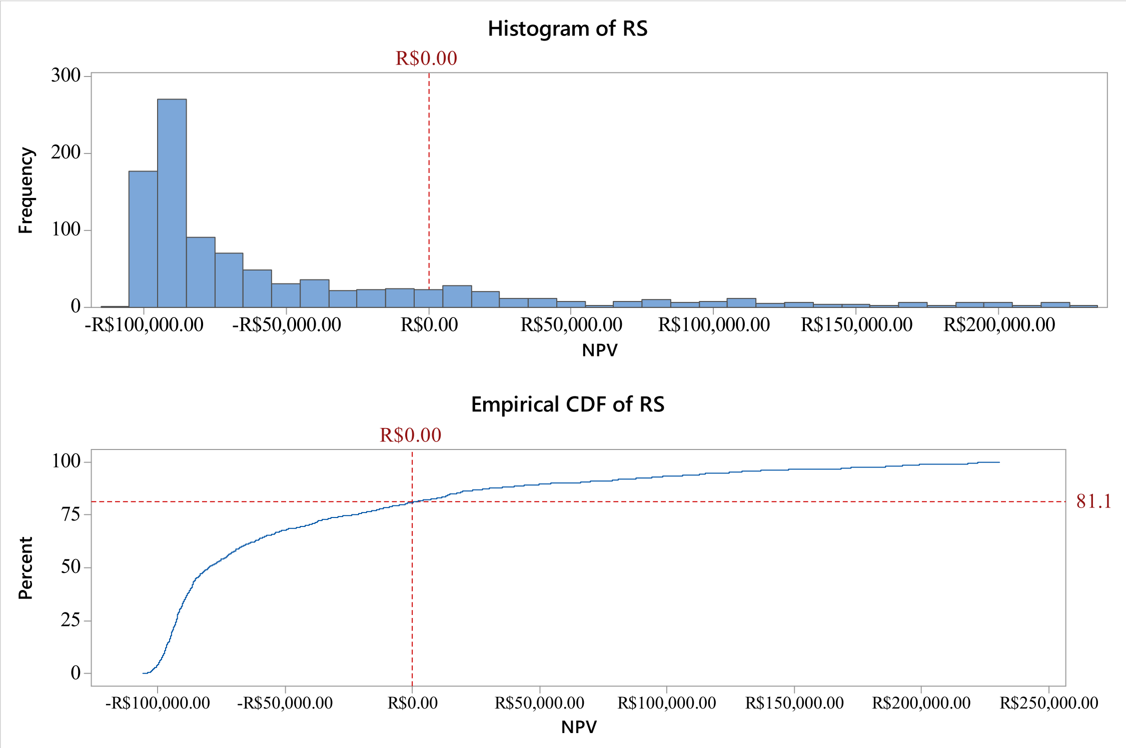

FIGURE 4. Probability of economic feasibility for the RS state.

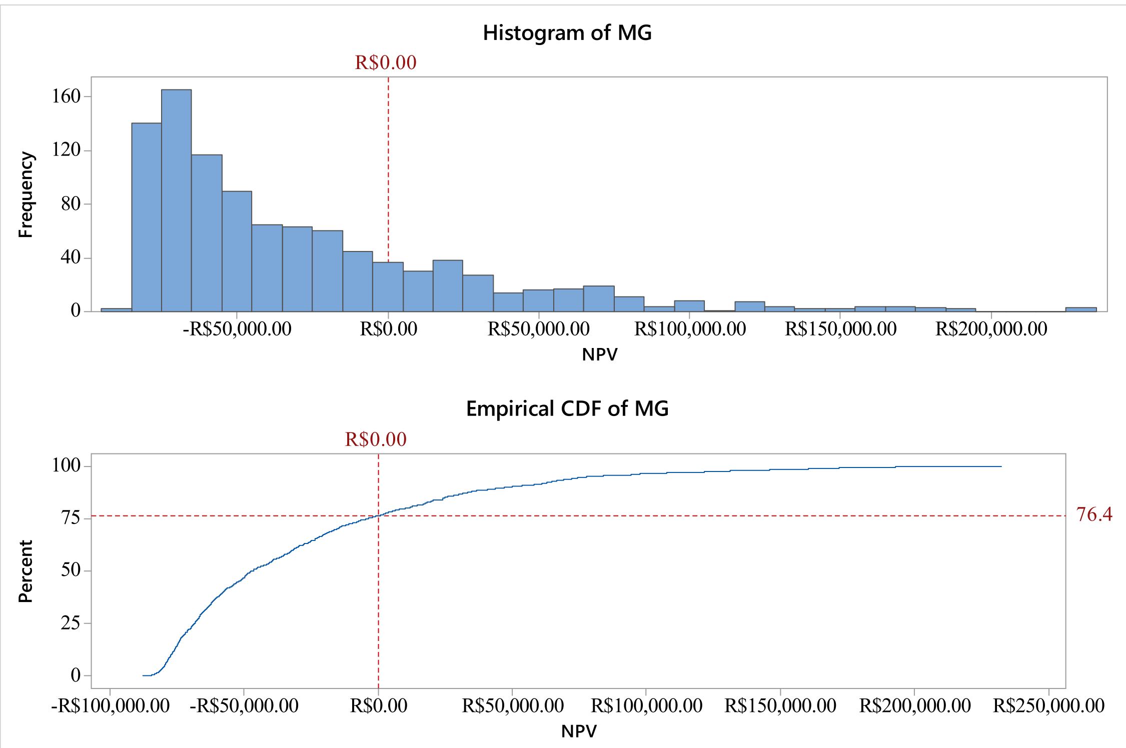

FIGURE 5. Probability of economic feasibility for the MG state.

Initially, it is possible to perceive that there is no viability in any presented scenario, as NPV is negative for all states, given the same investment value in all cases.

After the construction of the cash flows for each scenario and state, stochastic analyses were performed to study the NPV behavior. Table 8 shows the variables studied and their

TABLE 11. Values of the matrix $W_{(11\times 8)}$.

Debt	Depreciation	Investment	O&M	Payment period	Energy Price	Wind speed	Equipment life
0.00	-0.02	-0.05	0.02	-0.02	0.15	-1.33	-0.01
-0.03	0.01	-0.01	0.01	-0.01	0.04	-2.25	-0.01
0.03	0.00	-0.01	-0.01	0.00	0.23	1.52	-0.01
0.14	-0.03	-0.07	0.02	-0.03	-0.07	0.01	-0.03
0.03	-0.05	0.07	-0.06	-0.04	0.08	-1.45	0.00
-0.05	-0.02	-0.01	-0.03	0.01	-0.21	0.68	0.00
-0.06	-0.02	-0.05	-0.01	0.07	0.05	-0.19	-0.08
-0.08	0.01	0.02	-0.04	0.02	0.12	-0.38	-0.01
-0.01	0.05	0.01	0.03	0.02	0.08	-1.46	0.00
-0.06	-0.02	-0.02	-0.08	-0.05	-0.18	-0.25	-0.02
0.03	0.04	0.07	0.02	-0.02	-0.05	-0.30	0.00

TABLE 12. Values of the matrix $R_{(1\times 8)}$.

Debt	Depreciation	Investment	O&M	Payment period	Energy Price	Wind speed	Equipment life
0.00	-0.03	-0.09	-0.01	0.01	-0.01	0.48	0.00
-0.18%	-2.88%	-8.95%	-0.82%	0.60%	-1.39%	47,97%	0.04%

respective probability distributions for operationalization in the stochastic analysis using MCS.

The economically feasible probability results for each state were simulated by considering the wind speed values according to the Weibull distribution parameters for each state described in Table 4. These results are compiled in Table 8.

As reported, the simulations were performed with the Crystal Ball® software, which generated the results of probability of investment feasibility; the graph generated in the simulations of the RN, RS, and MG states can be seen in Figures 3, 4, and 5. Based on the simulations, in Figures 3 to 5, the histogram and cumulative distribution function (CDF) show each state. For example, in the case of the state of RN, the cumulative probability for NPV equal to 0 is 82.97%; then, P (NPV > 0) = 17.03%.

Table 9 shows the stochastic results of NPV for each scenario. In summary, this table shows the probability values of obtaining an NPV > 0.

Table 9 shows that there is a small difference between the probability of viability values in the three states. These results indicate a low probability of economic viability, even in the state of Rio Grande do Norte, which is the only scenario in which a NPV closer to zero was obtained, with a viability probability of 17.03%. Even in the state of Minas Gerais with a reduction in ICMS in the purchase of equipment, a lower investment value is generated, yet it presents a low probability of economic viability at 23.06%.

Rocha *et al.* [65] and Holdermann *et al.* [35] also found low feasibility probabilities in their research, when they analyzed wind and solar energy microenergy generation projects in Brazil. Walters and Walsh [82] found that in 95% of the regions studied, micro-generation of wind energy is not viable, showing that this type of project needs more incentives for tariffs, investments, and financing.

B. SENSITIVITY ANALYSIS USING ANN

As discussed previously, it is possible to perform a sensitivity analysis using ANN concepts through the proposal of Chakrabarty *et al.* [19], represented by the method presented in (1). This was done with the help of Statistica® software. Thus, it was possible to perform the network training, and from this to obtain the equivalent synaptic weights. The synaptic weights provide a basis for measuring the influence of the studied variables on NPV. To calculate RI, the following matrices and vectors of synaptic weights shown in Tables 10 to 12 were used.

The resulting matrix *R* shows the synaptic weights related to the variables studied; the percentage values were then calculated for better observation of the results.

The calculation for the synaptic weights of all states were calculated, and the results converge for the same variables, so we present the results of only one state as a demonstration. The calculation of the synaptic weight was obtained by multiplying matrices (described in the methodology) and the results for the state of Rio Grande do Norte (RN) are described in Table 12.

Table 13 shows the results of the RI calculation in percentage terms of the five best architectures' results obtained through automatic network training. Automatic training seeks

TABLE 13. RI results obtained through network training for the RN state.

Variables	MLP 8-6-1	MLP 8-11-1	MLP 8-10-1	MLP 8-4-1	MLP 8-6-1
Wind speed	31.63%	76.34%	92.35%	91.75%	52.51%
Energy price	30.59%	2.21%	0.31%	1.81%	1.06%
Investment	10.69%	14.25%	4.25%	5.04%	27.66%
Debt percentage	16.31%	0.29%	1.31%	0.20%	3.50%
Depreciation	6.33%	4.58%	1.02%	0.66%	7.89%
Payment period	3.07%	0.95%	0.06%	0.11%	1.80%
Equipament life	0.99%	0.07%	0.07%	0.08%	1.05%
O&M costs	0.39%	1.31%	0.63%	0.35%	4.54%

TABLE 14. Summary table of results by state and architectures.

	RN		RS		MG	
1	MLP 8-11-1	Wind speed	MLP 8-9-1	Wind speed	MLP 8-11-1	Wind speed
		Payment period		Energy price		Investment
		Debt percentage		Payment period		Energy price
2	MLP 8-6-1	Wind speed	MLP 8-4-1	Wind speed	MLP 8-12-1	Wind speed
		Energy price		Investment		Investment
		Debt percentage		Depreciation		Depreciation
3	MLP 8-10-1	Wind speed	MLP 8-11-1	Wind speed	MLP8-7-1	Wind speed
		Investment		Energy price		Investment
		Debt percentage		Debt percentage		Depreciation
4	MLP 8-4-1	Wind speed	MLP 8-7-1	Wind speed	MLP 8-11-1	Wind speed
		Investment		Energy price		Investment
		Energy price		Investment		Depreciation
5	MLP 8-6-1	Wind speed	MLP 8-4-1	Wind speed	MLP 8-6-1	Wind speed
		Investment		Investment		Investment
		Depreciation		Depreciation		Depreciation

to randomly optimize the best parameter settings for network training, and returns the best architectures identified. The values of RI allowed us to analyze which variables have the most impact on the NPV response and what the impact is in percentage terms. In the case of Statistica® software, the returns of the five best MLP architectures and I-H-O numbering are shown, which means the number of neurons in input (I), the hidden (H), and the output (O) layers.

In all of the architectures obtained, it was possible to analyze some variables that stand out in the sensitivity analysis, including the wind speed, investment, debt percentage, energy price, and depreciation of the most sensitive variables in relation to the investment. The results are similar for the RS and MG states, as can be seen in Table 14, which shows the three most impactful variables in the NPV for each state and the five best architectures obtained in the automatic optimization of network training. To obtain the best five architectures, the automated network search (ANS) option was used, available in the Statistica software. This option provides for the creation of neural networks with various settings and configurations with minimal effort. The use of ANS allows for the creation and testing of neural networks for data analysis and prediction problems. It designs a number of networks to solve the problem and then selects those networks that best represent the relationship between the input and target variables (for more, see [83]–[84]).

In the sensitivity analysis, it can be seen that the wind speed is the variable that will most impact the NPV, and can make it unfeasible, as seen in Table 14. From the analysis using the concept of RI, it was perceived that other variables may become relevant and need to be considered and evaluated to enable project viability.

The method of sensitivity analysis using the concept of relative importance brings more accuracy and reliability to the variables' studies, and how they can impact the NPV and its importance within the investment analysis. Micro and small companies that want to invest in energy savings through small wind turbines need to know which variables will most impact viability and help in decision-making, and the concept of RI can be extremely applicable to the realization of sensitivity analysis, acting as a complementary approach to analyzing the variables. In addition, as a complement, this study highlights some variables to which investors of micro and small business should pay attention.

V. CONCLUSIONS

This research had the objective of analyzing the economic viability of micro-generation of wind power for micro and small businesses in environments of uncertainty and risk.

In the sensitivity analysis it was seen that variable wind velocity and energy price are the variables that most impact the NPV, and may even make the project impracticable. Given that wind speed was the most relevant variable for the project, the RN is the state where it is possible to obtain a return with positive NPV, because it has the highest wind speed variation and can reach higher speeds.

In the sensitivity analysis using ANN, the calculation of the synaptic weights made it possible to calculate RI and to better evaluate the variables that most impact this type of investment project, namely, wind speed, investment, third party capital, tariff energy, and depreciation. The result shows that with increased incentives for microgeneration the importance of public policies in the energy field has already seen a significant increase in facilities in the country, but it is still inefficient with regard to the implementation of small wind turbines.

The research supports the perception of feasible wind power micro-generation, with incentives in investment and facilities for financing; for example, microgeneration can become a viable project for micro and small business. This is because the availability of energy, concern for the environment, and the long-term economy can be advantages for small businesses. The results are in line with those of Pereira *et al.* [29], who observes that the installation of microgeneration units can bring tax benefits, and reduction of energy expenditure—-an interesting investment in the long run. Moreover, they are aligned with the research of Ren and Sovacool [85], where they evaluate the persistent development of wind energy, and conclude that investment is a prerequisite for increasing energy security and making it a priority in development planning of renewable energies.

The results are in line with those of Aquila *et al.* [2], who emphasize how important the government's participation is in the growth of renewable energies, through enhancing existing initiatives with short-term policies such as tax exemption and reduction. Small businesses need greater support in relation to investments of this nature, as electric energy is a fundamental input in several production processes.

Micro and small business need greater support in relation to investments of this nature, as electric energy is a fundamental input in several production processes.

Future research can be undertaken using neural networks and renewable energy, such as the creation of a forecast model using ANN to estimate which renewable energy is most appropriate for the small and micro investor, given their historical consumption and diversification of investment; this would make generation of renewable energy in micro and small businesses viable options in the near future. In addition, a forecast model can be created that considers the variables studied for the small wind turbine, and provides the best location and conditions for the investment to become viable. Finally, alternative solution methods based on advanced techniques such as metaheuristic swarm intelligence techniques could be tested, comparing the results.

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