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OPTIMAL SIZING OF A HYBRID SOLAR-WIND ENERGY SYSTEM AND BATTERY BANK USING ARTIFICIAL INTELLIGENCE

DIMENSIONAMIENTO ÓPTIMO DE UN SISTEMA HÍBRIDO DE ENERGÍA SOLAR-EÓLICA Y BANCO DE BATERÍAS UTILIZANDO INTELIGENCIA ARTIFICIAL

Oscar E. Gualdron[*], **Raquel I. Laguado R.** [**]. **Elkin G. Florez S.**[*]

[*] **Universidad de Pamplona**, Facultad de Ingenierías y Arquitectura, Programa de Ingeniería Electrónica e Ingeniería Mecánica.
Km 1 vía B/manga, Pamplona, Norte de Santander, Colombia.
E-mail: {oscar.gualdron, eflorez}@unipamplona.edu.co.
[**] **Universidad Francisco de Paula Santander**, Facultad de Ingenierías, Programa de Ingeniería Industrial.
Av. Gran Colombia No. 12E-96 Barrio Colsag, Cúcuta, Norte de Santander, Colombia.
E-mail: requelirenelr@ufps.edu.co.

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Abstract: To carry out the forecast of meteorological data in order to perform an analysis of the solar and wind potential of the Camilo Daza airport of the city of Cúcuta, multilayer Perceptron-type neural networks configured with 9 4-4layer neurons and 10 times or iterations are used to adjust the procedural variables of the regression. For this, the methodology presented by Jorge Aguilera and Leocadio Hontoria and the Weibull probability density distribution are used, with the intention of guaranteeing a lower initial investment with adequate and complete use of the solar system, the wind system and the bank of batteries, so that the cost / investment / benefit ratio is viable.

Keywords: Hybrid System, Neural Networks, Solar Radiation, Wind Speed, Weibull.

Resumen: Para realizar el pronóstico de datos meteorológicos con el fin de realizar un análisis del potencial solar y eólico del aeropuerto Camilo Daza de la ciudad de Cúcuta, redes neuronales multicapa tipo Perceptron configuradas con 9 neuronas de 4-4 capas y 10 tiempos o las iteraciones se utilizan para ajustar las variables de procedimiento de la regresión. Para ello se utiliza la metodología presentada por Jorge Aguilera y Leocadio Hontoria y la distribución de densidad de probabilidad de Weibull, con la intención de garantizar una menor inversión inicial con un uso adecuado y completo del sistema solar, el sistema eólico y el banco de baterías, de modo que que la relación costo/inversión/beneficio sea viable.

Palabras clave: Sistema Híbrido, Redes Neuronales, Radiación Solar, Velocidad del Viento, Weibull

1. INTRODUCCIÓN

Fossil fuels account for more than 79 per cent of the world's primary energy consumption. The production of electricity generates, among other effects, the emission of nitrogen oxides (NOx) and carbon dioxide (CO_2), greenhouse gases and the main responsible for climate change (Figueroa & Mejía, 2014).

It is now established that electricity generation is responsible for producing 35% of the world's carbon emissions, hence the importance of renewable energy, since its implementation involves the use of clean and inexhaustible short-term natural resources for energy generation, In addition to this, the use of hybrid systems optimizes electricity production through a more versatile installation in terms of system power reliability requirements and climatic conditions.

Renewable energies are energies that are automatically renewed by themselves in nature, and are obtained from natural sources which, due to their duration, quantity and self-generation, can be called inexhaustible. (UPME & BID, 2015),(GALLEGO, 2016),(HENRY OSWALDO BENAVIDES BALLESTEROS, OVIDIO SIMBAQUEVA FONSECA, 2017) There are a large number of ways to make use of renewable energies, however, the most relevant and most welcome forms of installed capacity are:

- Solar energy
- Wind energy

Solar energy originates from fusion reactions that occur in the core of the sun, which emit energy in the form of short-wave radiation that travels through space and reaches the atmosphere. The average solar radiation received by the earth is between 1300 and 1400 (W/m^2). These values vary according to climatic conditions, which in turn depend on the geographical location (latitude and longitude) and the period of the year. (UPME & BID, 2015),(GALLEGO, 2016), (HENRY OSWALDO BENAVIDES BALLESTEROS, OVIDIO SIMBAQUEVA FONSECA, 2017), (Gutiérrez, 2015)

On the other hand, wind energy is obtained through the surrounding wind currents over a specific location and bases its operation on the use of kinetic energy generated by the effect of air currents, to be converted into electricity in order to improve the energy consumption of a community. (GALLEGO, 2016; GONZALEZ & YARA, 2009; Pasini & Director, 2019)

2. MATERIALS AND METHODS

2.1 Hybrid System.

Hybrid systems refer to the concept of joining two or more types of renewable energy, this in order to merge operatic characteristics of each system and obtain efficiencies higher than those that could be achieved with the application of a single energy source. (Figueroa & Mejía, 2014; UPME & BID, 2015)

In this sense, there are several factors that affect the dimensioning of a hybrid renewable energy system, such as, among others, the loads borne by the installation and the meteorological variables in situ. Therefore, the criterion by which these installations are dimensioned is carried out with more attention to the reliability of the system. Reliability means to ensure the proper functioning of the system while assuring that the failures are minimal.

2.2 Neural Networks.

One of the challenges facing our generation is the development of agents that emulate the complex behavior of a human brain to solve problems that cannot be solved by a traditional algorithmic approach. (Andrade, 2013), (Basogain, 2015), (Martínez, 2017). Artificial neural networks (Rnas), far from being models parallel to a human brain, achieve the development of certain characteristics that make it function similarly. Well, they have phases of learning, abstraction and generalization of a problem as the data is presented. (Andrade, 2013). There is a great diversity of neural network models, however, this research chooses to implement the Perceptron Multilayer, due to its efficiency in regression and prognostic problems. (Andrade, 2013; Voyant et al., 2017), (Rashid, 2019)

The Multilayer Perceptron is a type of neural network that consists of an input layer, a certain number of intermediate layers or hidden layers, dedicated to data processing and an output layer. Usually, all neurons in one layer are connected to all the neurons of the next layer in a forward propagation scheme (*feedforward*) so that the input data is directed towards the output layer while being transformed by the hidden layers. (Martínez, 2017; Perceptron, 2016)

2.3 Programming Environment.

The code of the neural network and the processing of the data are worked in the programming language python, because it is a freely distributed and developed software, nevertheless, it possesses high level characteristics that makes its codes flexible and with a clear syntax. In addition, being a multi-paradigm programming language, it supports types of programming such as object orientation, imperative programming and to a lesser extent functional programming. (González-Páramo, 2017), (Rashid, 2019), (Tutor:, 2018).

In order to contribute projects that promote the use of renewable resources in a practical, simple and reliable way, the present research aims to analyze the solar and wind potential of the Camilo Daza airport in the city of Cúcuta, to size a hybrid renewable energy system through weather data forecasting. To do this, we use Perceptron multilayer neural networks configured with 9 neurons 4 layers and 10 epochs or iterations that adjust the procedural variables of the regression.

3. RESULTS

From the equations and models described above, certain results are obtained. These are used to determine the viability of the selected methodology, as well as the energy and computational efficiency of the system, when dimensioned with meteorological data, product of a forecast.

3.1 Meteorological characteristics.

The analysis of renewable energy resources available in the area, through multi-year averages of data frequency and statistical methods and Machine Learning to estimate the solar-wind potential, so that the start of the research, is feasible.

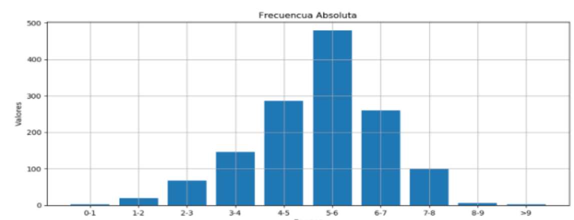
The selection of the Camilo Daza airport as an object of study, lies in the Camilo Daza Airport Station of the Institute of Hydrology, Meteorology and Environmental Studies IDEAM, which, provides the Wind Speed and Solar Radiation data necessary to design the hybrid system, it should be noted, that this data, were measured at a height of 10 meters above the surface.

They have a level of "Definitive" approval (granted by IDEAM), which indicates that this data has gone through the necessary technical validation process, thus guaranteeing the quality of the data for analysis and implementation.

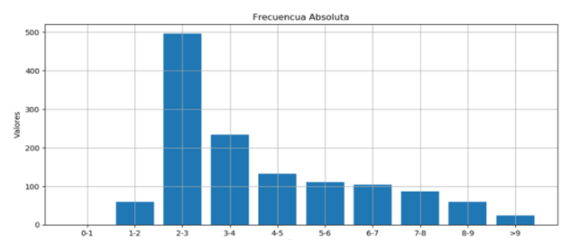
Table 1: General Airport Data Camilo daza

Altitude	405 MSNM
Coordinates	7ponl 55 39 N -72[30 42 O
Operator	Orient and Aerocivil airports

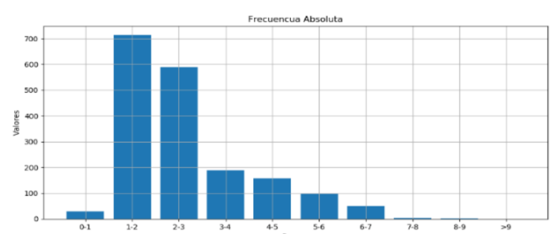
For global solar radiation, a total of 1371 daily data of the average incident radiation at 10 meters above the surface are available, which are distributed in two sets. A first set will contain the data for training the neural network and the second set will contain the data for testing or validation. It should be noted that, of the total data, 70% is used for training and 30% for prognosis. On the other hand, for the wind speed two data intervals are available in order to provide a historical record to the neural network to optimize it´s prognosis.



(a)



(b)



(c)

Fig. 1. Radiation Meteorological Characteristics and Wind Speed Airport Camilo Daza

The data set used to train the network has a total of 1832 measurements of wind speed at 10 meters above the surface and meets the parameter of a normal distribution, with the speeds between 1-2 and 2-3 being the most repeated.

For the neural network design and testing data set, it consists of 1309 daily average wind speed measurements at 10 m above the surface, with a standard deviation of 2.383621 and an overall average of 4.218525 m/s. *b)* The frequency of measurements meets the criterion of normal function, therefore the range 2-3 m/s (c)
is the most likely and most frequent data. Also, the probability of finding wind speeds greater than 4 m/s is 39.648 %. Additionally, it can be seen that the pattern of wind speeds is similar to that of the training set, which indicates the continuous nature of the records.

Training of the neural network.

Since the Multilayer Perceptron will be used as a type of pre-powered neural network, the hyperbolic tangent activation function is chosen, in addition, the mean quadratic equation (MSE) and the mean absolute error (MAE) are used as optimization parameters. of error.

With regard to the selection of the number of layers, neurons and iterations or epochs, it is decided to emphasize computational performance in order to select said parameters.

Table 2: Neural network models

Proposed Model	Number of Layers	Number of Neurons
Configuration #1	3	Range [1,20]
Configuration #2	4	Range [1,20]

Configuration #1 featured a hidden layer, an input layer, and an output layer. Although less than 10% of adjustment errors were obtained, with the increase of neurons in the occult layer, the algorithm lost stability and a cyclic behavior with unexpected peaks incurred throughout the prediction process.

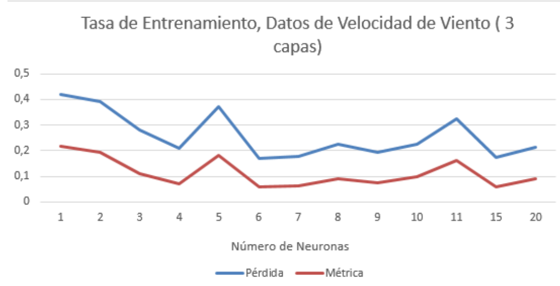


Fig. 2. Configuration Response #1

On the other hand, Configuration #2 (An input layer, two occult layers and an output layer), shows a greater stability in the forecast, with a downward trend in its metric and values close to 5% of error in the adjustment of the synaptic weights, In addition, relatively low changes in error can be observed when the Perceptron Multilayer has more than nine neurons in its structure. In conclusion, the Artificial Neural Network of the Multilayer Perceptron type will consist of four (4) layers and nine (9) neurons in their occult layers.

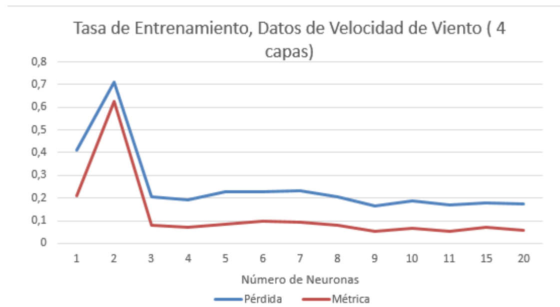


Fig. 3. Configuration Behavior #2

Subsequently, with neurons and layers defined, the number of epochs with which the response of the Multilayer Perceptron was optimized or, failing that, maintained was selected. This process was carried out with the layers and neurons selected in the previous section. In conclusion, a neural network composed of four layers (4), nine neurons in their occult layers (9) and ten epochs (10) shall be used.

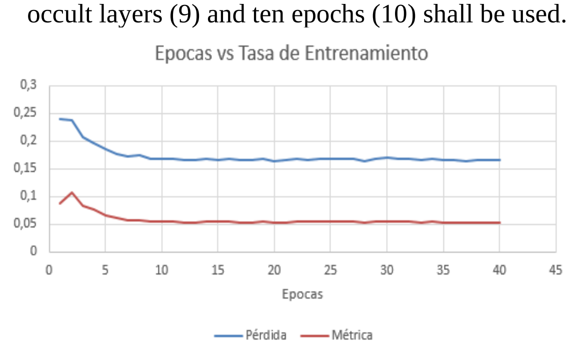


Fig. 4. Convergence of the model with each iteration

The training of the multilayer perceptron released two trained models (Radiation Model and Wind Speed Model). Each of the trained models has different adjustments and tolerances to the prediction of data, however, the differentiating factor is represented mainly by the amount of data with which the training was conducted.

First of all, the training of the Perceptron multi-layer neural network for the wind speed data set, evidences a downward error trend with each iteration, this is due to the number of historical records used to train the neural network and the optimal selection of network convergence parameters. In addition, it can be seen that, during the training phase, the error in the regression of the data was close to 12%, while in the validation phase the error remained close to 16%. This behavior indicates a favorable response of the neural network to data that has not been manipulated. (See *Fig. 5 andFig. 6)*

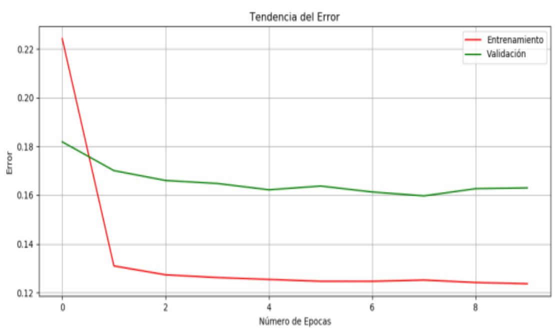


Fig. 5. Error Trend in Wind Speed

Finally, the data forecast for the solar radiation set was made. It should be noted that this set does not have a historical record of measurements, since the equipment that takes these values is in operation since 2015, therefore, the neural network faces the problem of finding a radiation pattern with a reduced amount of data.

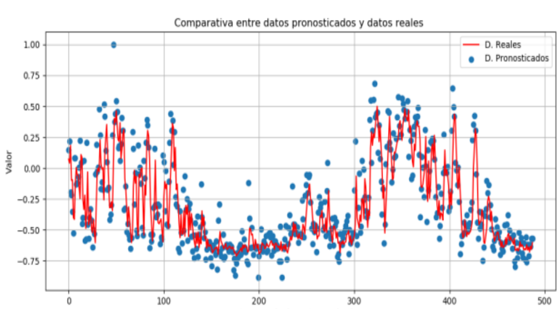


Fig. 6. Wind speed forecast

As can be seen in *Fig. 7*, the behavior of the error in the set of radiation data is variable, however, tends to stabilize at 18.5% in the training phase. In addition, in the validation phase, the error behavior is descending with each iteration and tends towards 19.7 %.

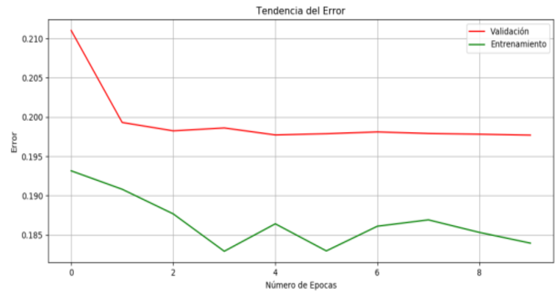


Fig. 7. Global Radiation Set Error

Although the error rate in the training and testing phase is very high, the behavior of the neural network is acceptable, since, as mentioned above, it does not have enough data to establish a value pattern, Therefore, the accuracy of the forecast varies considerably. It is also evident that the function generated by the prognosis of the multilayer Perceptron, presents a graphic typology similar to the real data, however, the model did not satisfactorily estimate the synaptic weights and, therefore, presents disaggregated data. (*See Fig. 8)*

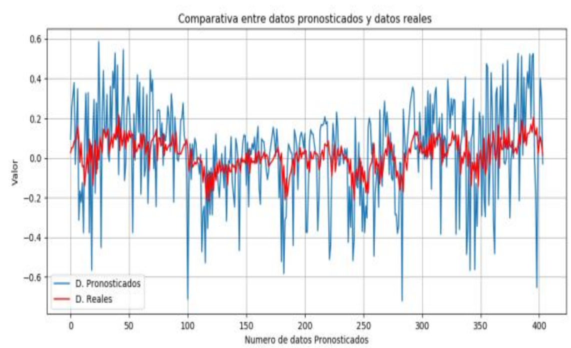


Fig. 8. Global Radiation Forecast

From the data obtained, the selection of the optimal angle of inclination of the photovoltaic panel is made, through the application of the critical month method. This method gives us an optimal angle of 10 ³ and an overall solar radiation on a sloped surface of 3213.62 Wh/m^2.

On the other hand, the calculation of the components of the photovoltaic system was carried out, from the input parameters of the algorithm and the previously selected values of radiation and inclination.

Table 3: Operational characteristics of the solar panels.

Property	Nominal Value
Inclination angle	10 [
Solar radiation on inclined surface	3,213 kWh/m^2
Photovoltaic Module Peak Power	250 Wp
Photovoltaic Module Voltage	24 V
Photovoltaic Module Performance	75 %
Amount of Panels	10 panels
Panel Structure	(10X1) 10 parallel panels, 1 in series

In second place, the operational characteristics for the battery, inverter, and regulator are established based on the system input parameters.

Table 4: Battery, regulator and inverter characteristics

Property	Nominal value
Battery Nominal Capacity in ($\boldsymbol{Wh}$)	53086,42 Wh
Battery Nominal Capacity in ($\boldsymbol{Ah}$)	2211.94 Ah
Battery Voltage	24 V
Battery Autonomy Days	4 days
Discharge Depth	50%
Regulator Maximum Current	66.92 A
Inverter Nominal Power	4837.5 W
Inverter efficiency	90%

Once the calculations to dimension the photovoltaic arrangement are done, the next step is to design a wind system with the wind speed data analyzed in the chapter.

To start, the Weibull probability function shape and scale parameters are estimated, which show very similar values. However, the method of moments shows better adjustment to the wind speed data. Furthermore, according to (Rico, 2007; Serrano Rico, 2013), the maximum probability method leads to errors in some cases.

Afterwards, the monthly power density was calculated at 10 meters above surface, where the maximum generated power observed is 108.01 Wh/m^2 in the month of June.

It is important to highlight that such data were adjusted to a power coefficient of 0.45, which is due to the fact that the three-bladed wind generator was selected as subject of study, and it has a power coefficient that varies between 0.4 and 0.45

Finally, the probability to find wind speed above 3 *m/s* (starting speed for wind generator) is found, which is given in the Weibull probability function by the equation, and it has as a result of 65.34%, that is, 5645.3 hours a year, wind speed above the starting speed can be found. Therefore, the wind generator theoretical nominal power is 609.75 kW.

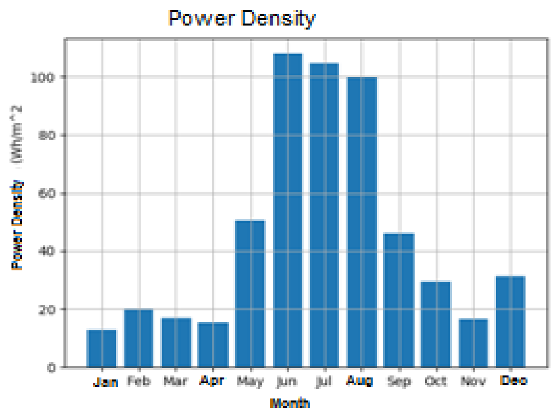


Fig. 9. Power generated withthe wind speed regime analyzed

Afterwards, the operational characteristics of the wind generator are established on *Table 5*

Table 5: Operational Characteristics of the turbine

Property	Nominal value
Nominal Power	609.75 kW
Starting speed	3 m/s
Folding speed	25 m/s
Amount of vanes	3 units
Height	10 meters

In conclusion, the hybrid system is going to be formed by ten panels with a nominal power of 250 Wp (each), an energy storage system with a capacity of 2211.94 Ah, four day-autonomy and a discharge depth of 50%, an inverter with a nominal power of 4837.5 W, a regulator with a maximum current of 66.92 A and a three-bladed wind turbine with a nominal power of 609.75 kW.

It is important to remark that for the preliminary dimensioning of the system, certain efficiency values and other equipment characteristics were assumed, therefore, the reference values for the components have an operational slant.

4. CONCLUSIONS

This type of study generates a great social impact in favor of human well-being and sustainable technological development since energy supply is directly proportional to the development level and life quality of people.

The research environment of this proposal consists of seeking, in a practical and efficient way, to estimate the necessary equipment to perform a hybrid renewable energy installation, through the analysis and weather data forecast supplied by IDEAM. In that context, some assessments were drawn.

The solar resource analysis through the normal distribution showed that the data range that presents a higher repetitiveness is 5-6 kWh/m^2 with a multiannual average for years 2015-2019 of 5.223 kWh/m^2 and 4.7 peak solar hours, besides, the probability to find radiations above the threshold of 4 kWh/m^2 is 82.78%. Because of this, the metropolitan area of the city of Cúcuta, represents a great attractive for photovoltaic applications at a large scale and at domestic level.

Regarding the wind potential at Camilo Daza airport in the city of Cúcuta, the likelihood to find wind speed above 4 m/s is 39.648 % and the data that presents the highest repetitiveness is in the range of 2-3 m/s, therefore, the information in the wind speed map that establishes an average wind speed for the metropolitan area of Cúcuta between 3-4 *m/s* is validated, because the starting speed of the wind generator is m/s, the turbine generates energy 65.34 % of the year. It is necessary to remark that, in spite of the functioning time of the turbine being 5645.3 hours a year, the wind speeds recorded in the zone at 10 meters high, are not appropriate for the development of wind application at a large scale; nevertheless, projects at domestic level or which require a lower energy consumption, can be supplied by this resource.

Python is an appropriate language for the development of software that fosters scientific research, since it is a programming language that allows carrying out analysis, forecast and representation of weather samples contained in databases in a more simple and interactive way, due to the dynamic typing in the code lines and a great number of specialized libraries that can be used. Therefore,

Python's Keras library offers great opportunity to develop artificial intelligence models in a few code lines and with good results, as long as the parameters that have influence on the adjustment of the synaptic weights of the neuronal network are properly selected, an example of this is the multilayer Perceptron that was developed throughout this research, since in the training stage, diagnosis errors lower than 13% were obtained for wind speed and an error of 19.7% in the data set for solar radiation were obtained. While it is true that the obtained slant is relatively large compared to the amount of supplied data, the Perceptron type multilayer neuronal network adjusted the parameters to carry out the forecast appropriately.

The Perceptron type multilayer neuronal network chosen to carry out the forecast (4 layers, 9 neurons y 10 stages) adjusted acceptably to the time series comprehended by the wind resource and the solar resource and settles the research basis for the development of a compact dimensioning method that, by means of the application of artificial intelligence, allows the design of installations of renewable energy.

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