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Prediction of thermal infrared radiation using an artificial neural network applied to the projection and design of processes in renewable energies

Predicción de radiación infrarroja térmica, utilizando una red neuronal artificial, aplicada a proyección y diseño de procesos en energías renovables

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Abstract

This work aims to predict thermal infrared radiation in geographical areas where the necessary measurement devices are not available, through the design of an artificial neural network (RNA). The RNA uses the following variables as input data: specific humidity, relative humidity, ambient temperature, wind speed, and atmospheric pressure, it is important to mention that the sample of space of time is from, (1990 - 2019), they are data from Mexico City, as it is a metropolis with an extensive air quality database, which are obtained from two online tools developed by the National Aeronautics and Space Administration (NASA). In addition, thermal infrared radiation data from NASA are included, to validate the prediction made by the algorithm. Matlab was used to implement RNA, a multiplatform software that offers an integrated development environment with its own programming language. It is recognized for its computational ability and is considered a suitable tool for this purpose.

Irradiance thermal infrared, Artificial Neural Network, Prediction

Resumen

El propósito de este trabajo es llevar a cabo una predicción de la radiación infrarroja térmica en zonas geográficas en donde no se cuenta con los dispositivos de medición necesarios, esto a través del diseño de una red neuronal artificial (RNA). La RNA utiliza como datos de entrada las siguientes variables: humedad específica, la humedad relativa, temperatura ambiente, velocidad del viento y presión atmosférica, es importante mencionar que la muestra de espacio de tiempo es de, (1990 – 2019), son datos de la Ciudad de México, ya que es una metrópolis con una extensa base de datos de calidad del aire, los cuales se obtienen de dos herramientas en línea desarrolladas por la Administración Nacional de Aeronáutica y el Espacio (NASA; por sus siglas en inglés). Además, se incluyen datos de radiación infrarroja térmica de NASA, con la finalidad de validar la predicción realizada por el algoritmo. Para la implementación de la RNA se empleó Matlab, un software multiplataforma que ofrece un entorno de desarrollo integrado junto con un lenguaje de programación propio. Es reconocido por su capacidad en el cómputo y se considera una herramienta adecuada para este propósito.

Radiación infrarroja térmica, Redes Neuronales Artificiales, Predicción

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Introduction

Machine learning models known as neural networks have been inspired by the structure and function of the human brain. These networks consist of a series of interconnected neurons that process and transform input information to generate output. Synaptic weights determine the direction and strength of the neural connections, and adjust as the network receives more inputs.

In the context of the development of ANN for solar irradiance prediction, this approach is now essential. Various applications, such as meteorology, require accurate data, and longwave downward irradiance is closely related to various weather parameters, such as temperature, humidity and wind speed.

By applying neural networks in this field, we seek to take advantage of their ability to capture complex, non-linear relationships between input variables and solar irradiance. By analysing the collected data and implementing learning algorithms, ANN can learn and generalise patterns from the available records. This allows for more accurate and reliable predictions of solar irradiance based on weather conditions and other relevant factors.

The present research focuses on the use of neural networks, analysing the development of ANN for longwave downward irradiance prediction, which is inspired by the functioning of the human brain. This approach is essential for more accurate and relevant results in applications such as meteorology, where data accuracy is crucial.

The ability of neural networks to capture complex relationships and their adaptability as more records are incorporated make them a powerful tool for improving the prediction of solar irradiance and its relationship with weather parameters.

Several algorithms were developed: to calculate the thermal infrared radiation produced in the atmosphere in order to see the behaviour in different environments (INEGYCEI, n.d.).

1. Background

1.1. Artificial Neural Network

Artificial neural network (ANN) is a machine learning approach inspired by biological processes in the human brain (Aitkenhead-Peterson et al., 2007) (Hameed et al., 2019) The basic architecture of an ANN consists of processing units called neurons, which are interconnected by appropriate links. Each individual neuron includes weight activation functions, summation points and outputs, as illustrated in Figure 1.

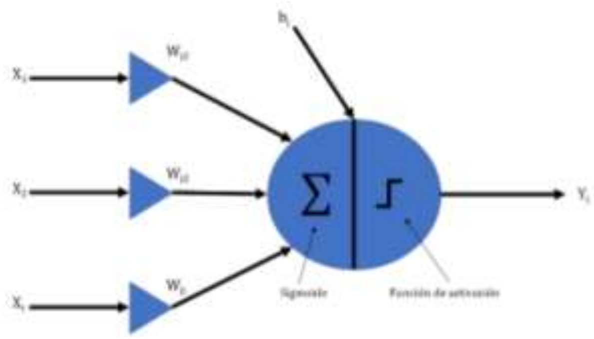

Figure 1 Simplified model of an artificial neuron
Source: Own Elaboration

In the operation of an ANN, the input data, represented by x1, ..., xi, is weighted by input weights wj1, ..., wji, and a bias bj is added before the neuron generates an output yj.

A key aspect of ANNs is their supervised learning capability, using input and output data sets. During the learning process, the network is adjusted to reach the same reference or set point that is set by a supervisor. Training is repeated until the difference between the ANN output and the supervisor's benchmark is within acceptable ranges (Aitkenhead-Peterson et al., 2007).

The most commonly used structure is the feedforward network, which consists of individual neurons organised in layers and connected by weighted connections. An example of a three-layer ANN is shown in Figure 2. (David J. Lvingstone, 2009)

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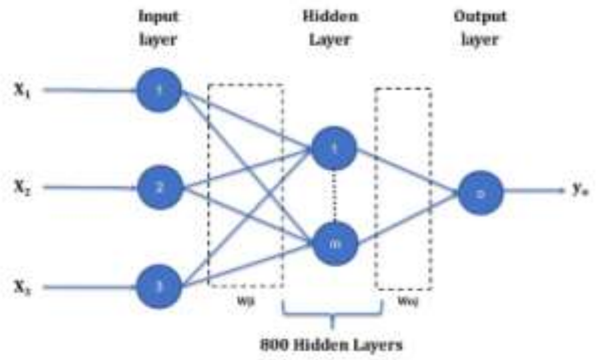

Figure 2 3-layer Artificial Neural Network
Source: Own Elaboration

The backpropagation algorithm is the most popular training method for feedforward networks and is based on supervised learning. The desired input and output data patterns are obtained through simulation studies of the mathematical model of the neuron.

1.2. Thermal infrared radiation in general

The irradiance of the sky surface, also known as thermal infrared radiation, can be calculated using the Stefan-Boltzmann law and considering various atmospheric factors. Here is a general formula for calculating this irradiance (Velasco Ramón Javier, 2019).

$$I = \varepsilon \sigma A T^4 \tag{1}$$

Where:

I is the irradiance of the sky surface (*W/m²*).
ε is the effective emissivity of the sky.
A is the surface area of the emitter
σ is the Stefan-Boltzmann constant $(5.67 \, x \, 10^{-8} W/m^2 \cdot K^4)$
T is the effective sky temperature in Kelvin (K).

1.3. Thermal infrared radiation in the atmosphere

The calculation of atmospheric thermal infrared radiation can be complex and requires consideration of multiple atmospheric factors and radiative properties. Two common methods for calculating atmospheric thermal infrared radiation are listed below:

Use of radiative measurements and atmospheric profiles: This approach uses thermal infrared radiation measurements and atmospheric profiles, such as air temperature, humidity and gas concentration, to calculate atmospheric thermal infrared radiation.

Techniques such as atmospheric spectroscopy and spectral radiation analysis are used to obtain information on the radiative properties of the atmosphere in the thermal infrared range.

2. Radiative transfer model-based method

This method uses transfer models to estimate atmospheric thermal infrared radiation. These models take into account factors such as air temperature, greenhouse gas concentration and atmospheric humidity. The best known model is the broadband or grey body model.

Both methods require detailed knowledge of atmospheric parameters and may involve the use of computer models or specialised measurements. In addition, the accuracy of the calculations will depend on the availability and quality of the atmospheric data used. For this purpose, the radiative transfer model is used to calculate the atmospheric thermal infrared radiation considering greenhouse gases such as: Carbon dioxide (CO_2), Methane (CH4), Nitrous oxide (N_2O), other variables immersed in the calculation are: temperature and humidity:

To relate the thermal infrared radiation equation to atmospheric pressure, temperature, specific humidity, relative humidity and wind speed, it is necessary to understand that each of these factors affects the parameters of this.

3. Emissivity

It is a constant physical property that has the ability to emit energy in the form of thermal radiation from a surface, during different climatic conditions. Emissivity is present on most of the Earth's natural surfaces ranging from 0.6 to 1.0, but surfaces with emissivities below 0.85 are usually restricted to deserts and semi-arid areas. Vegetation, water and ice have high emissivities above 0.95 in the thermal infrared wavelength range. However, it is necessary to consider that specific atmospheric measurements and advanced radiative models are needed to obtain accurate values.

In the case of Mexico City (CDMX), the emissivity of its urban surface, its level differs significantly. A study published in the International Journal of Remote Sensing used satellite imagery to calculate the emissivity of the city's urban surface.

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Where it was estimated to have an emissivity that fluctuates according to texture and material type, ranging from 0.88 to 0.95.(Saleh et al., 2018).

Certain NASA sensors, such as the Advanced Spaceborne Thermal Emission and Reflectance Radiometer (ASTER), Moderate Resolution Imaging Spectroradiometer (MODIS) and Atmospheric Infrared Sounding System (AIRS) (U.S./Japan ASTER Science Team, 2014) are able to detect changes in emissivity.

4. Stefan-Boltzmann constant

The Stefan-Boltzmann constant is a fundamental constant in physics used to relate the temperature of an object to the total amount of thermal radiation it emits. Its value is denoted by the Greek letter sigma (σ) and its approximate value is 5.67 x 10^-8 watts per square metre per kelvin to the fourth power (W/m^2-K^4).

In the context of infrared thermal radiation, the Stefan-Boltzmann constant is used to calculate the power radiated by an object as a function of its temperature and emissivity. Emissivity is a property describing the ability of an object to emit thermal radiation.

The basic formula using the Stefan-Boltzmann constant is:

$$Radiated\ power = \sigma * emissivity * Area * Temperature^{4} \quad (2)$$

Where:

σ is the Stefan-Boltzmann constant.
Emissivity is the emissivity of the object (a value between 0 and 1 indicating how efficiently it emits radiation).
Area is the surface area of the object.
Temperature is the temperature of the object in Kelvin (K).

This formula allows us to calculate the power radiated by an object as a function of its temperature and emissivity. The higher the temperature of the object, the higher the radiated power. Also, a higher emissivity means that the object will emit more thermal radiation.

The Stefan-Boltzmann constant is essential in the estimation of thermal energy fluxes and in the characterisation of celestial bodies, as it allows us to understand and quantify the amount of thermal radiation emitted as a function of the temperature and emissivity properties of objects.

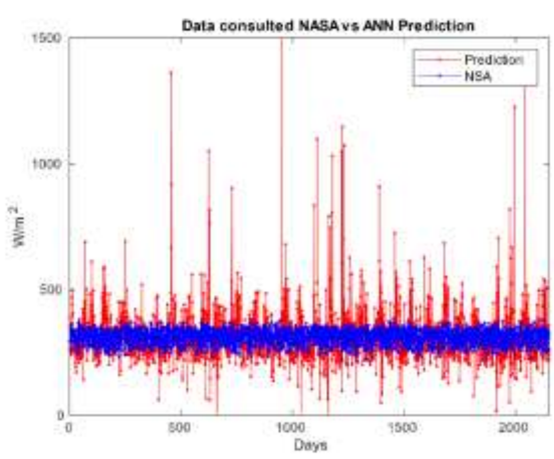
5. Description of the method

During the development of the present project, different methodologies were implemented using the multiplatform Matlab software. In the first instance, a detailed search was carried out on greenhouse gases, obtained from the National Inventory of Emissions of Greenhouse Gases and Compounds (INEGYCEI), period from 1990 to 2019.

Therefore, a script was created to convert the units from gigagrams (Gg) to parts per million (ppm), in order to calculate the concentrations of each gas, through atmospheric parameters such as pressure, temperature and humidity, using the atmospheric thermal infrared radiation formula, which associates emissions with the total volume of the atmosphere. The result obtained is the atmospheric thermal irradiation in W/m^2.

However, a calculation was also developed using the Stefan Boltzman's Law formula to determine the thermal infrared radiation given by the variables of emissivity, temperature, area and distance, in the case of Mexico City, there is an emissivity of 0.95.

6. Results



Graph 1 NASA vs ANN Prediction
Source: Own Elaboration

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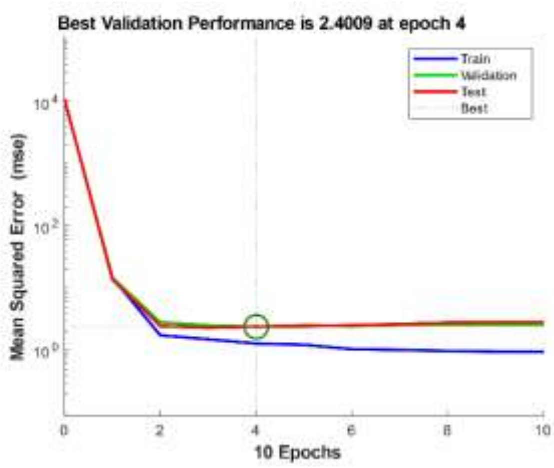
The data were obtained from two online tools provided by NASA, resulting in the ANN prediction where the days queried are set by thermal infrared radiation expressed in W/m^2

```
Algorithm 1 Data processing
Upload: nasa.dat and validation.dat
Divides nasa.dat data into training, validation and test sets
Defines the architecture of the ANN
Train the RNA
Validates the ANN
Calculates error and performance
Perform thermal infrared radiation prediction.
Select random data with validation data
Graph the prediction and the selected data
```

Table 1 Pseudocode used
Source: Own Elaboration

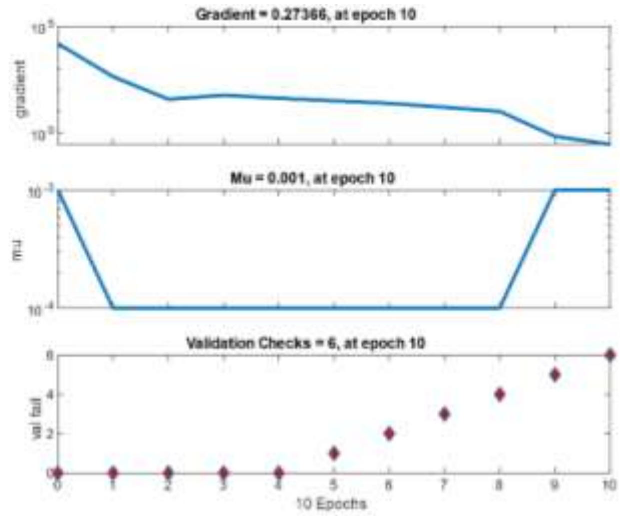
```
Algorithm 2 Data processing
Upload:  Gg.dat
Assigns emissions to individual variables
Determines molar masses of gases in g/mol
Defines the volume of the atmosphere in m^3
Calculates concentrations in ppm of CO2, CH4 y N2O
Sets atmospheric parameters
Assign greenhouse gas concentrations
Defines absorption coefficients of the gases in m^2/kg
Calculates atmospheric thermal infrared radiation
```

Table 2 Pseudocode used
Source: Own Elaboration



Graph 2 Evaluation and selection of the best ANN model
Source: Own Elaboration

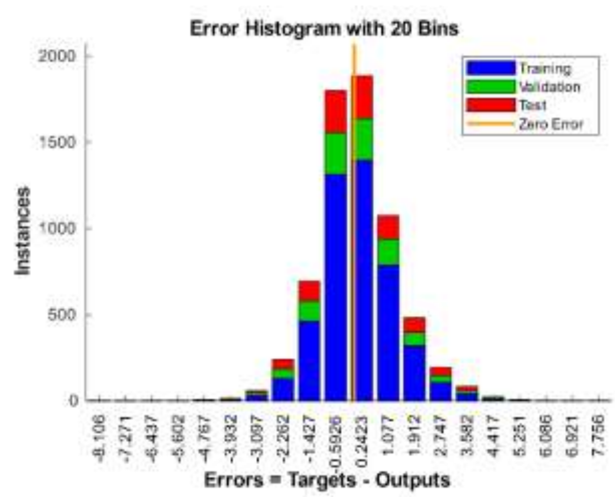
The mean square error is used to evaluate the accuracy of the ANN, it is the root mean square of the differences between the predicted values with the real values of the dataset. However, during the training of the network it was 2.4009 indicating that the model had its best performance after four training epochs.



Graph 3 Evaluation and selection of the best ANN model
Source: Own Elaboration

The gradient is the function that performs changes in weights and biases, in this situation it resulted in a value of 0.27366 during epoch 10. The parameter Mu controls the adjustments that exist within the training network. Mathematically speaking, it is multiplied by the gradient obtained from the backpropagation of the error determining the value of the adjustment of the weights. In this case, the learning rate has a value of 0.001 at epoch 10.

Validation checks are used to evaluate and compare the performance of the model, which in turn is closely related to other parameters such as precision, accuracy or mean square error. This check had 6 checks of which occurred at epoch 10. Also, one validation failure was found during training because it probably requires additional adjustments, modifying or augmenting the training data.



Graph 4 Distribution of errors
Source: Own Elaboration

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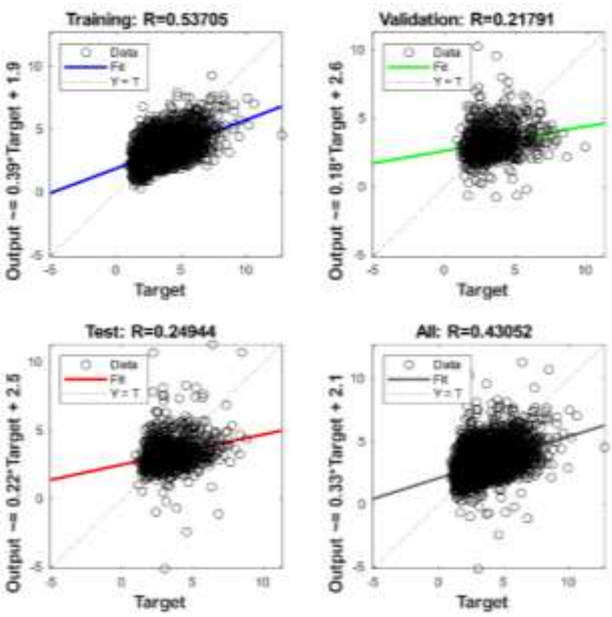
The error histogram refers to the error distribution that exists in the network. For example, when training the ANN there is usually a set of data in training and test, therefore, test data can be used to make predictions, errors and actual values. In other words, errors can be the main difference between the actual and predicted output.

The graph shows 20 bins where the highest value of errors is in the range between -0.5926 and 1.077. Furthermore, it means comparing the actual values and the estimated values for a set of instances.



Graph 5 Training and evaluation of the neural network
Source: Own Elaboration

Training refers to adjusting the parameters of the ANN so that it can learn and make the appropriate prediction, using a set of inputs corresponding to targets known as expected output values. In particular, training was 0.53705, with an output of 0.39 and a test output of 1.9.

Validation is the evaluation of the performance of a data set that was separated that was not occupied during training and is used to verify what its performance might be on previously unseen data. The result of 0.21791 is the coefficient of determination, which ranges from -1 to 1. This means that the model has a weak positive correlation with the validation data.

The test indicates what the precision of the data is, of which gives a value of 0.24944 indicating that there is a slight positive correlation with an output of 0.22 representing the output of a given data set, while the target value of the validation checks is 2.5.

Finally, the last graph points to an average ANN across all the datasets mentioned above. Where the data was most concentrated was at point 5, which is the desired output.

7. Acknowledgements

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8. Conclusions

In conclusion, the application of artificial neural networks to atmospheric thermal infrared radiation makes it possible to model the relationship between this radiation and climate parameters. This process involved collecting accurate data on thermal infrared radiation and climatic variables such as temperature, humidity, atmospheric pressure, altitude and wind speed. They were also subjected to pre-processing including normalisation and splitting into different training, validation and test sets.

Subsequently, the feedback neural network was designed and trained with input layers for the weather variables, also hidden layers where it uses an activation function such as the ReLU function, and an output layer for thermal infrared radiation. The training of the network was performed using the training dataset by adjusting the hyperparameters where good performance was obtained in the validation set.

Finally, the performance of the network was evaluated on the test set to analyse whether it performed well in predicting thermal infrared radiation. It can then be concluded that it was successful in relating weather variables and radiation.

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In summary, the application of artificial neural networks provides a useful tool to study, understand and predict atmospheric thermal infrared radiation, which can have applications in different areas such as meteorology, climatology and renewable energy.

9. References

Aitkenhead-Peterson, J. A., Smart, R. P., Aitkenhead, M. J., Cresser, M. S., & McDowell, W. H. (2007). Spatial and temporal variation of dissolved organic carbon export from gauged and ungauged watersheds of Dee Valley, Scotland: Effect of land cover and C:N. *Water Resources Research*, *43*(5). https://doi.org/10.1029/2006WR004999

David J. Lvingstone. (2009). *Artificial Neural Networks* (David J. Livingstone, Vol. 468). Humana Totowa, NJ. https://doi.org/10:1007/978-1-60327-101-1

Hameed, W. I., Sawadi, B. A., Al-Kamil, S. J., Al-Radhi, M. S., Al-Yasir, Y. I. A., Saleh, A. L., & Abd-Alhameed, R. A. (2019). Prediction of solar irradiance based on artificial neural networks. *Inventions*, *4*(3). https://doi.org/10.3390/inventions4030045

INEGYCEI. (s/f). *Inventario Nacional de Emisiones de Gases y Compuestos de Efecto Invernadero (INEGyCEI)*. Energía Y Medio Ambiente. Recuperado el 11 de agosto de 2023, de https://datos.gob.mx/busca/dataset/inventario-nacional-de-emisiones-de-gases-y-compuestos-de-efecto-invernadero-inegycei

Saleh, A. L., Obaid, B. A., & Obed, A. A. (2018). Motion control of linear induction motor based on optimal recurrent wavelet neural network-PID controller. *International Journal of Engineering and Technology(UAE)*, *7*(4), 2028–2034. https://doi.org/10.14419/ijet.v7i4.13041
U.S./Japan ASTER Science Team. (2014). *NASA Spacecraft Maps Earth's Global Emissivity*. https://www.jpl.nasa.gov/images/pia18833-nasa-spacecraft-maps-earths-global-emissivity

Velasco Ramón Javier. (2019). *Análisis de la temperatura de cielo como sumidero de calor medioambiental y evaluación experimental del comportamiento energético de un sistema de disipación nocturna* [Universidad de Sevilla]. https://idus.us.es/handle/11441/100201