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METHODOLOGY FOR ESTIMATING DAILY SOLAR RADIATION USING NEURAL NETWORKS

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Abstract. *This work aims to establish a methodology to estimate the incident global solar radiation combining an analytical method with artificial neural networks (ANN), using ten cities in the state of São Paulo as reference. The analytical method depends on meteorological parameters, among them the clearness index (Kt), which might not be available. Therefore, to overcome this issue, two different ANN were used to obtain the global solar radiation likewise the Kt, outputs to the networks. For the first network (Network I), day, latitude, longitude and altitude of the location were used as input parameters. For the second one (Network II), in addition to the first network's variables, the average local daily temperature and humidity were also used. The results indicated that the approximation factors of Network I were similar to the performance of the analytical method, while Network II had higher approximation factors. For cities known by the networks, an average approximation factor of 53% was obtained for Network I and 80% for Network II. For nearby cities not present in the training database, the average approximation factor was 57% for Network I and 54% for Network II. Even with limitations, it was possible to estimate global solar radiation using ANN.*

Keywords: *solar energy, solar radiation, neural networks, artificial intelligence.*

1. INTRODUCTION

Climate Change has been causing disasters that directly affect directly an average of 350 million people every year (UN, 2019). One of the effects of these changes is the increase in the average global temperature, which is of 0.7° C in the last 150 years (Molion, 2008), at an unprecedented pace before in human history, due to the action of the greenhouse effect, a phenomenon caused by the emission of greenhouse gases (GHG) (IPCC, 2015). Globally, energy consumption was the sector that most contributed to GHG emissions in 2015, responsible for 72% of the total (UNFCCC, 2017). Furthermore, this is because fossil fuels represented, in the same year, 82% of the World energy matrix (IEA, 2019).

The development and use of renewable energy technologies are increasingly necessary to have a cleaner energy matrix. In this scenario, solar energy has a great potential, due to its great availability as a natural resource over the Earth's surface and infinity, being constantly replaced. However, solar radiation has great variability, regarding availability, since it depends on many factors, such as meteorological (clouds, atmosphere, etc.), astronomical (Earth's Axial Tilt, spatial position) and geographical (latitude, longitude and altitude of the location). Thus, one of the main obstacles to projects of a system that uses this type of energy is the uncertainty regarding the availability of solar radiation throughout the year in a certain location (Pereira et al, 2017).

Therefore, it is crucial to model the phenomenon of solar radiation in order to understand better its behaviour in a location, aiming to install a device to optimize the radiation harvesting on this specific location. Among all the possibilities of tools to model these chaotic natural patterns there are the artificial neural networks (ANN), computational models capable of acquiring knowledge based on data. Since there is a wide range of available data related to radiation in different locations, it is plausible to use this technique to estimate solar radiation. In addition, ANN are an useful method to non-linear applications, also when a function depends on random and transient factors not well defined, as it is the case of solar radiation.

Artificial neural networks (ANN) are a type of application of machine learning and its concepts have been studied for at least fifty years. This computational model was inspired by neurons and neurological interactions present in the mammalian brain. The model of the connections between neurons resembles what happens biologically, that is, based on constant training (Silva et al., 2010). This work uses the multilayer feedfoward architecture. It has an input layer, one or more intermediate layers and an output layer. Each layer can have different amounts of neurons and there is a connection between adjacent layers (Patterson and Gibson, 2017).

One of the main training methods is the backpropagation, which according to Silva et al. (2010) consists of a cycle in which the weights of the intermediate layers starts randomly. Then, there is an insertion of a group of inputs, which have known outputs, in the neural networks, generating a response according to the current weights. The ANN response is compared with the expected response, generating an error, which is used to calibrate the synaptic weights and thus perform a new iteration. This is repeated until the reduction of the error between one iteration and the other is insignificant, or until the error reaches an established level. There are in the literature applications of neural networks for the context of predictions/estimates of meteorological parameters, such as temperature and solar radiation.

Some authors reviewed the use of ANN to estimate meteorological variables. Zhang et al (2017) concluded that usually meteorological and geographical parameters are inputs for the ANN. In this scenario, sunshine duration was the best input data and ambient temperature was the second-best input data to the estimation. The author stablished a methodology for comparing the methods of estimation, the evaluation metrics of the models focused on inputs, outputs and accuracy. In a similar approach, Pazikadin et al. (2020) reviewed five years of studies about the forecasting of solar power generation based on ANN and found that the ANN was able to perform forecasts, but the use of hybrid systems can increase the accuracy of the forecasting.

Other studies developed directly the ANN comparing to other estimation methods. Gürel et al (2020) developed an ANN for four different cities in a daily basis. The feed-forward backpropagation ANN used as inputs the sunshine duration, ambient temperature, pressure, relative humidity and wind speed, being efficient in the estimation. Khosravi et al (2018) studied two types of ANN to predict hourly solar radiation in a given location, the first uses five inputs – pressure, temperature, relative humidity, wind speed and local time – and the second is to use past radiation data to estimate future values.

Kashyap et al. (2015) tested multiple parameters as input data for the ANN, testing the performance of eight different types of ANN based on delay, neurons numbers and transfer function in the estimation of hourly global solar radiation. The authors show the flexibility for the choices of the parameters in different models. The presented ANN performances were satisfactory. Xue (2017) presents two optimization techniques to improve the efficiency and generalization ability of backpropagation ANN models for predicting daily diffuse solar radiation. Were used seven different parameters: month of the year, sunshine duration, mean temperature, rainfall, wind speed, relative humidity and daily global solar radiation. The results shows that the proposed backpropagation ANN have potential in predicting the daily diffuse solar radiation.

There are studies focused on the forecasting, for the future radiation. Di Piazza et al (2020) did a short-term forecast ANN of the hourly solar radiation. According to the authors, ANN were able to forecast solar radiation for short/medium term (30 minutes up to 1 day-ahead). Benali et al. (2019) made a comparison between ANN and other methods of estimation to forecast the three components of hourly solar radiation (global, direct and diffuse) in a horizon of up six hours. The authors show yet that for seasons with more atmospherical variation, the errors increase. Pang et al. (2020) developed a neural network to forecast solar radiation over a period of one day in a city. The model was validated, but the authors highlighted that for days with a lot of cloudiness more input data is needed.

Thus, this work proposes a methodology for the use of ANN to estimate daily solar radiation. As a result, it is possible the facilitation of projects for the use of solar devices and their adaptation to the context of the project locations. In summary, the information about the availability of the solar resource for a location is increased.

2. MATHEMATICAL MODEL

This paper considers two different models to predict the incident solar radiation. The analytical model was developed based on Duffie and Beckman (2013) and the ANN developed for the estimation.

Solar radiation is the energy emitted by the Sun in the form of heat and travels through the space between the Sun and the Earth (Duffie and Beckman, 2013). The difference between irradiation and irradiance lies in the fact that the first is the flow of energy that crosses a certain surface in a certain period of time (W/m²), while the second is the flow of energy that crosses the surface (J/m²) (Plana-Fattori and Ceballos, 2015).

When the solar radiation reaches the Earth's atmosphere, it begins to attenuate, due to diffusion through the air, absorption by particles of water, clouds, dust and ozone in the atmosphere and reflection by clouds, besides other phenomena. The radiation that reaches Earth and has not yet been attenuated is called extraterrestrial radiation (G_o) and the portion that enters the atmosphere and reaches Earth's surface is called global radiation (G). The ratio between global and extraterrestrial radiation is the Clearness Index (Kt) and represents the amount of extraterrestrial radiation that entered the Earth's atmosphere. This amount is related to local atmospheric conditions, with a cleaner sky, there is a greater amount of radiation entering the atmosphere, and as a location gets cloudier or dirtier, less radiation enters the atmosphere. The Equation (1) presents this relation.

$$\mathrm{Kt} = \frac{\mathrm{G}}{\mathrm{G}_o} \tag{1}$$

Other factor that can affect the amount of radiation in a certain point are the day of the year and the zenith angle. The zenith angle is the angle between the sun and the zenith and is influenced by the latitude of the place (ϕ), declination (δ) and the hour angle (ω). The larger the angle, the lower is the radiation in the location, as it has to spread along a larger area. Both, zenith and declination angles, are given in degreess by Equations (2) and (3) respectively.

$$\cos\theta_z = \cos\phi\cos\delta\cos\omega + \sin\phi\sin\delta \tag{2}$$

$$\delta = 23{,}45\sin\left(360\frac{284+n}{365}\right) \tag{3}$$

To calculate the amount of radiation in a location is used the solar constant (G_{sc}), which is the amount of radiation that arrives on earth, and is corrected using the factors previously described, what gives Equation (4). This equation shows the quantity of extraterrestrial radiation in one day at a location, where the sunset angle (ω_s) is given by Equation (5).

$$H_o = \frac{24.3600G_{sc}}{\pi}\left(1 + 0{,}033\cos\left(\frac{360n}{365}\right)\right)\left(\cos\phi\cos\delta\cos\omega_s + \frac{\pi\omega_s}{180}\sin\phi\sin\delta\right) \tag{4}$$

$$\cos\omega_s = \tan\phi\tan\delta \tag{5}$$

Using Equation (1) it is possible to find the global radiation received in one day. Generally, the Kt is obtained using data from weather stations or using the Typical Meteorological Year, to have accurate data of the studied location.

This method allows the calculation of the two components of the solar radiation, being the beam and diffuse ones, their sum gives the global radiation, shown in Equation (6). To find them, first the Collares-Pereira and Rabl (1979) empirical equation, Equation (7), is used to find the diffuse component, and using Equation (6) the beam component is found.

$$H = H_b + H_d \tag{6}$$

$$\frac{H_d}{H} = \begin{cases} 0{,}99 & \text{para } Kt < 0{,}17 \\ 1{,}188 - 2{,}272Kt + 9{,}473Kt^2 - 21{,}865Kt^3 + 14{,}648Kt^4 & \text{para } 0{,}17 < Kt < 0{,}75 \\ -0{,}54Kt + 0{,}632 & \text{para } 0{,}75 < Kt < 0{,}80 \\ 0{,}2 & \text{para } Kt > 0{,}80 \end{cases} \tag{7}$$

3. METHODOLOGY

The first step in the methodology was data collection, which consisted of searching for a meteorological database of Brazilian cities. The selected database was QUALAR, from the Environmental Company of the State of São Paulo (CETESB), as it met the defined criteria. These criteria were that it was required for the database to cover global radiation, average temperature and average humidity. In addition, it was required to contemplate a reasonable time interval for each city through the evaluation if the errors of the ANN tests would be convergent. However, the first analysis using seven years of data presented convergence on the error and, therefore, this time interval was maintained. The database needed to include cities within the same context (same country or state). As the best quality data source found included only stations within the state of São Paulo, the networks operate within the geographic limits of the state and with the same climatic classification according to the Köppen methodology (Rolim et al., 2007). The selected cities are shown in the Figure 1.

Figure 1. Map of cities used for networks validation – State of São Paulo, Brazil

With the data collected, it was necessary to treat it. In addition, the behaviours of the variables were analysed, to identify inconsistent values, as well as the correlation between them. All of this information was used to understand the behaviour of the ANN to be developed. The raw database had missing data in some measurements. To mitigate this problem, the methodology proposed by Carsten Hoyer-Klick and described in Schüler et al (2015) was adapted. The technique used fills gaps of more than four days by copying the values for the same day of adjacent years. For the analysis and treatment of the database, free Python libraries were used. The libraries used were Pandas to open files and create DataFrames, Numpy to manipulate vectors and matrices and Matplotlib to plot some graphics.

Data from the seven imported training cities were available on an hourly basis. However, as this work used the daily basis, it was necessary to integrate the values of the hourly global radiation of the twenty-four hours of each day to obtain the daily global radiation, as well as to calculate the arithmetic mean of the average temperature and humidity. Histograms of the variables used are available in Figure 2. The figure presents an aggregation of all the data in the database, with the objective of understanding the behaviour of the variables and identifying values that extrapolated the common behaviour of the variables, in addition to seeking to understand better the correlation between variables.

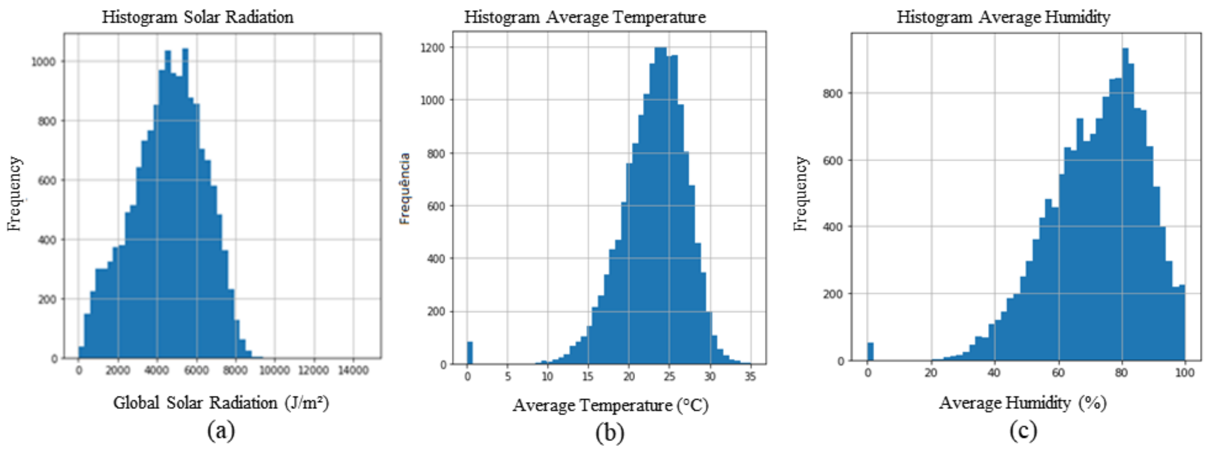

Figure 2. Histograms of the main variables

Another tool used to analyse the data was the correlation of global radiation with each variable, presented in Table 1. It is important to highlight that the correlation must be read through absolute values, this means that with higher values, whether positive or negative, greater the correlation with the compared variable. Positive correlations show that the variables increase together, while the negative values are those proportionally inverse.

Table 1. Correlation of variables with Global Radiation

Correlation	
Radiation	1.000
Temperature	0.467
Latitude	0.379
Altitude	0.173
Day	0.046
Longitude	-0.301
Humidity	-0.540

The correlations, presented in Table 1, showed that the average temperature and the average humidity are the variables that most relate to global radiation, with values of 0.467 and -0.540 respectively. Therefore, it is reasonable to use them as inputs to the ANN. However, although those variables are easy to measure for some cities, it can still be difficult to obtain this data for the most locations. Finally, a normalization process of the input data was carried out, because as the ANN use activation functions that generally work with values between 0 and 1, it is interesting that all the networks inputs are normalized in this interval. For this, each input variable was limited to be between 0 and 1, using the highest and lowest values for each variable, which corresponded to 0 and 1 respectively. A proportion was made with the values between these extremes for normalization. Figure 3 systematizes the steps taken to treat the data

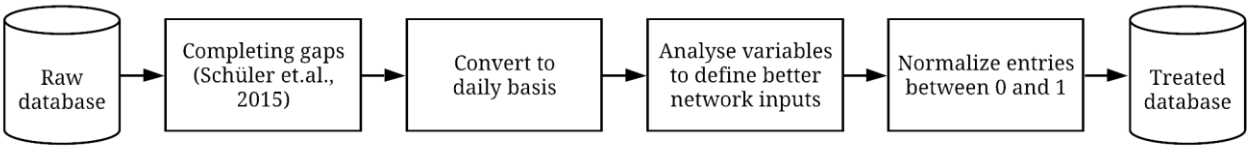

Figure 3. Flow chart of data processing

After data treatment, trainings for each network and the analytical method were developed. The most important factors for the phenomenon of solar radiation are the day of the year and the geographic data of the location, which are latitude, longitude and altitude. These were the input data used for the construction of a first network, called Network I. The second one, Network II, used temperature and humidity data for the localities as inputs, beyond latitude, longitude, altitude and day of the year. Global solar radiation is the common output data. The analytical method uses latitude, day of the year and clearness index (Kt) to predict different kinds of solar radiation. The diagram in Figure 4 represents the inputs and outputs used in each Network, in addition to the structure of the analytical method.

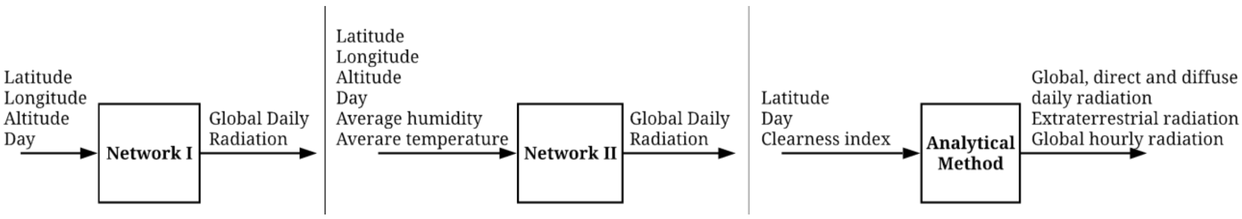

Figure 4. Scheme of the inputs and outputs of the (a) analytical method, (b) Network I, (c) Network II

The analytical method developed estimates solar radiation. It consists in a compilation of equations for the solar radiation phenomenon. The Kt, used as input for this method, was obtained through an average of Kt extracted from the Photovoltaic Geographical Information System-Interactive Maps (JRC European Commission et al., 2014). It was made an average of the Kt values for the same day in different years, in order to increase the accuracy of the calculations. The analytical method calculate the extraterrestrial (H_o), global (H), diffuse (H_d) and direct (H_b) radiation values for the period of one year.

Two ANN were developed using the Python machine learning library, the sklearn. In this stage, data for each network were divided into 80% for training and 20% for testing. The proportion can vary, but it is always necessary to separate more data for the training, since this way the networks will have more data available for a possible reduction of errors during the training (Patterson and Gibson, 2017). The trained networks ran with the test data. This step of the methodology had the objective of understanding the power of approximation of networks for data that it does not know, also called the power of generalization. Both training and testing generate mean square errors fundamental for understanding the performance of each network. Figure 5 represents the general scheme of this stage of the methodology.

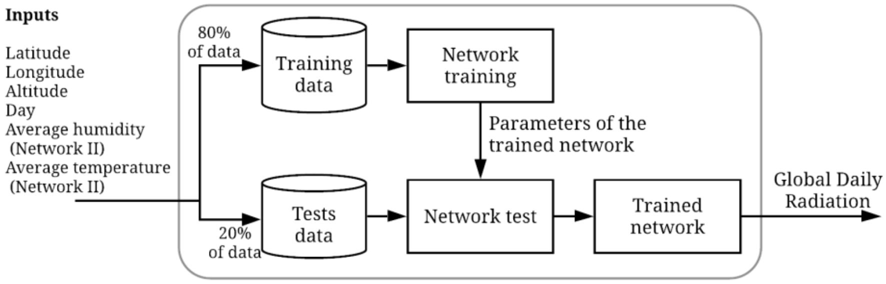

Figure 5. Network training scheme

The collected and treated database was used in feedfoward ANN trained by the backpropagation method, in order to model the behaviour of the desired outputs. The selection of the ANN architecture and training method was due to their capability to model any function, as long as sufficient processing power, internal layers and computational processing power are provided. To define the ideal number of neurons and internal layers for each application, several training sessions were carried out, changing the value of these variables and evaluating the evolution of the mean quadratic error, thus choosing the best networks' topology. When the variation of the mean square error between one training and another was insignificant, the networks' architecture was defined.

After choosing the best architectures and training of each ANN, the estimation was carried out to a random year in each city of the database used in training. The estimated results were compared with real values, from the meteorological station, to verify the ANN accuracies. In a second step, the global daily radiation estimation was performed for cities unknown by the networks. This means that the ANN did not had the data from these cities in its training. This test verified the ANN generalization power beyond the known data.

After the calculation of the global daily radiation through the analytical method and the prediction estimates from the two trained ANN, it was necessary to define a metric to compare the accuracy of the estimates in relation to the real data. Most of the studies in the field of artificial intelligence use the mean quadratic error (Priya and Iqbal, 2015), which in this work was called the approximation factor. This factor consists of calculating the percentage error of each daily forecast for a specific year, performing the arithmetic mean of that error for all days of that year and subtracting this value from 100%, thus obtaining the approximation. Equation (8) is this factor, which was used for each daily data. After calculating each daily approximation factor, an arithmetic average was made of these values by city and by method.

$$\text{aproximation factor} = \left(1 - \left|\frac{\text{value obtained by the method}}{\text{real value extracted from the station}}\right|\right) \cdot 100\% \tag{8}$$

The Figure 6 presents a brief flow chart of the methodology.

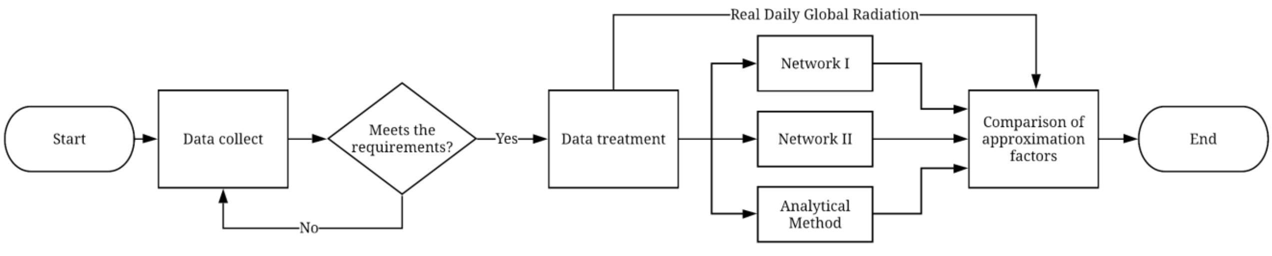

Figure 6. Schematic diagram of the methodology

4. RESULTS

Table 2 presents the approximation factors for Network I, Network II and the analytical method in relation to the real data of these stations.

Table 2. Average approximation factor

Cities known by networks				
City	**Year**	**Analytical**	**Network I**	**Network II**
Araçatuba	2019	73%	68%	89%
Catanduva	2017	68%	68%	89%
Ribeirão Preto	2019	72%	65%	86%
Presidente Prudente	2013	59%	56%	85%
Tatuí	2015	31%	35%	78%
Interlagos	2018	45%	48%	72%
Santos	2017	13%	33%	62%
Cities unknown by networks				
Bauru	2015	73%	67%	77%
Guaratinguetá	2018	63%	61%	51%
São José dos Campos	2017	41%	44%	35%

Network I approximation factor behaves similarly to the analytical method, with values in a similar order of magnitude. As an example, in the cities known by the networks, the three cities with the best average approximation factor, such as Araçatuba, coincide between the analytical method, Networks I and II, presenting the values of 73%, 68% and 89% respectively. In addition, in cities not known by their networks, the three methods follow the same behaviour, where Bauru has the best approach, Guaratinguetá intermediate and S. José dos Campos the worst factor.

Of the results of the cities known by the network, the worst of them was Santos. To understand better the reason for this, a comparison was made of the global radiation data for each year collected from Santos with the average of all of them and we found that this city varies about 52% in relation to the general average. This shows that the global radiation in this city varies widely from one year to the next. This is because it is the only coastal city in the database. To correct this problem, a larger training database with more coastal cities would be needed.

Bauru presented the approximation factors of 73% for the analytical method, 67% for Network I and 77% for Network II, as shown in Table 2. These factors are the best among the cities of generalization. It was decided that it would be more interesting to show the results graphs of Bauru as it is the best result obtained among the cities that were not included in the network's training database. This may be because Bauru is close to four cities known by the networks and has similar climate characteristics. The radiation profiles for Bauru are shown in Figure 7 to Figure 9.

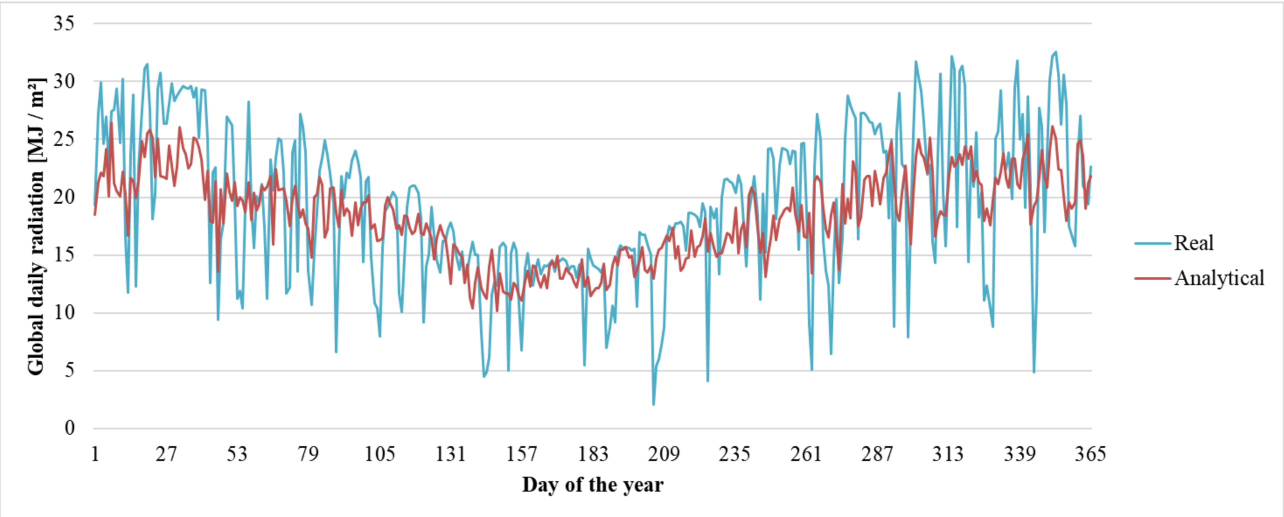

Figure 7. Daily solar global radiation profile obtained by the analytical method in Bauru

The analytical method is able to maintain the same levels of approximation factor, as for the known cities, as shown in the graph in Figure 7, once this method depends only on the daily light indices to make its predictions. This method uses an average of seven years of Kt, so, the daily global radiation has its peaks and valleys softened, which limits the method, generating a single average curve for the local global solar radiation for any year. As these indices are known for that city, it is possible to make the forecast, but if is performed a forecast for a city that does not have Kt in a database, it is not possible to use this method.

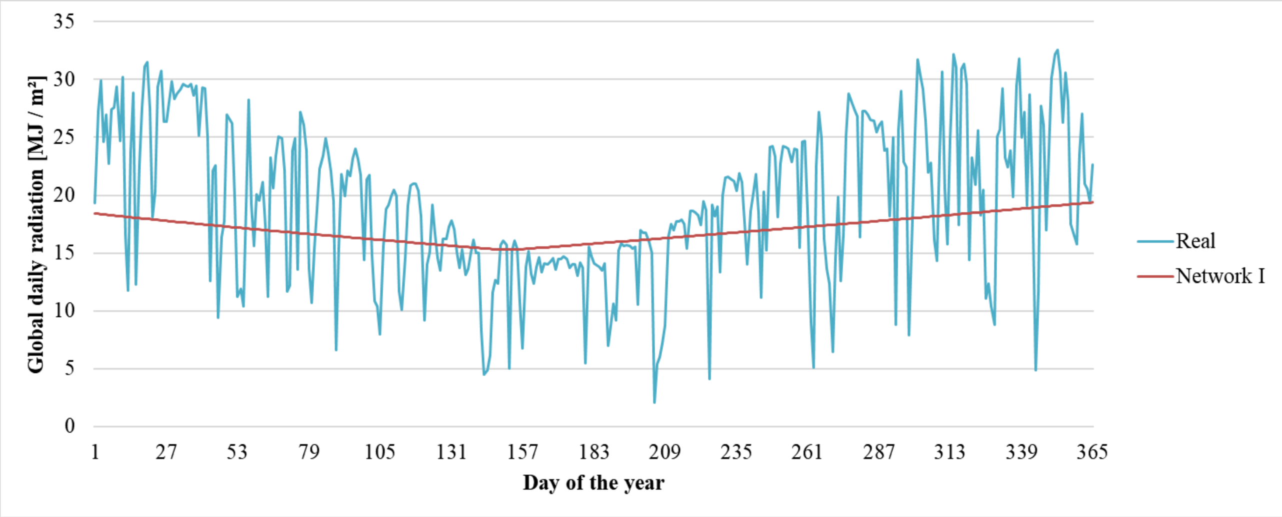

Figure 8. Daily solar global radiation profile obtained by Network I in Bauru

The Network I, which has only latitude, longitude, altitude and day of the year as inputs, captures a general profile of the daily global radiation of the location, since the only entry that varies for a city is the day of the year, as in Figure 8. Even so, the network presented approximation factors close to the analytical method, even to predict the daily global radiation of a city unknown by the ANN. It is possible to estimate solar radiation for cities within the State of São Paulo beyond those already known, once the approximation factors are close to those of the analytical method. In addition, the ANN do not depends on the daily clearness index that is often not available.

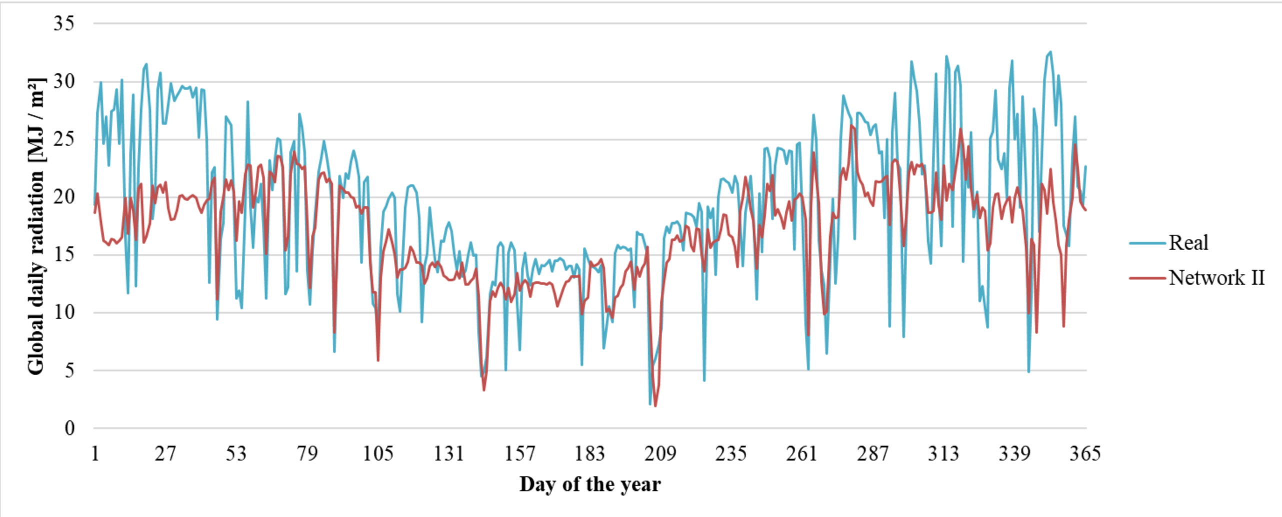

Figure 9. Daily solar global radiation profile obtained by Network II in Bauru

In Network II, is evident a gain of the network's accuracy, as seen in Figure 9, due to the addition of the variables related to global daily radiation as inputs. By using daily average humidity and temperature, in addition to the same inputs as Network I, Network II is able to predict better the daily global solar radiation, reaching an approximation factor of 77%. This shows that there was a generalization beyond the cities known by the network, but there is a drop in this factor in comparison with the known cities. To improve the effectiveness of the estimate, it would be necessary to have a larger database, with more cities and years, then, the sample of cities in the database would better represent the population of cities within the State of São Paulo.

4.1 Estimation of the Clearness Index

Using the daily global radiation obtained by the ANN and the extraterrestrial radiation calculated in the analytical method, it is possible to estimate the monthly clearness index for specific years. This is an advantage, since there is no measurement of this index for many locations. As an example, the monthly clearness index for Bauru in 2014 was estimated, using data from Network II, which had the best approximation factor. Figure 10 presents the comparison between the estimated Kt and the real one.

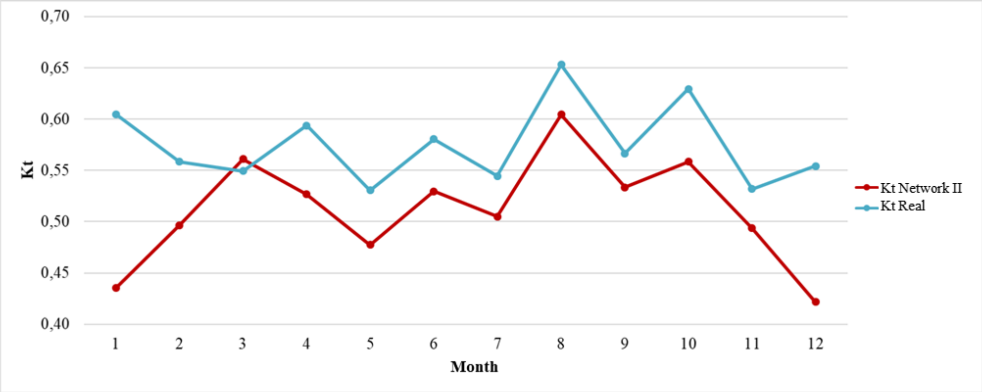

Figure 10. Bauru 2014 Monthly Clearness Index Comparison

There is a drop in the performance for the comparison of a specific year from a city unknown by the network, with the maximum error of 28% in January. Even so, it is possible to predict the general behaviour of the monthly clearness index for the year of 2014 in Bauru, since the average error was 11%.

5. CONCLUSIONS

This paper proposed to establish a methodology based on artificial intelligence to estimate solar radiation, through the use and validation of ANN. These estimates are used for locations that do not have a meteorological station and, therefore, do not have solar radiation data, complicating the understanding of the technical feasibility of projects of application of solar devices.

Meteorological data were obtained from the QUALAR database of CETESB to train, test and validate the ANN. There are different types of ANN training and architectures that can accomplish the task with less computational effort, but the focus of the work was to estimate solar radiation rather than perform a comparative study of topologies of ANN. The architecture and training chosen were adequate to do so, since the results were satisfactory with a large part of the average approximation factors above 60%.

To estimate solar radiation, two ANN trained with daily meteorological data from seven cities in the state of São Paulo were proposed over a period of between four and seven years. After the training, input data from three cities, unknown by the ANN, were submitted to the networks, in order to evaluate the accuracy of the ANN. These cities were selected because they are within the networks' coverage area, which is the region among the cities known by the ANN. Thus, global solar radiation values were generated as output, which were compared to the real data, using the average approximation factor. In addition, to compare methods of prediction of solar radiation, data obtained by the analytical method were also evaluated in relation to the real values.

The average approximation factors for the cities of Araçatuba and Santos were, respectively, the best and the worst, among the cities known by the networks. The cities presented the following approximation factors: Araçatuba - 2019: analytical method - 73%; Network I - 68%; Network II - 89%. Santos - 2017: analytical method - 13%; Network I - 33%; Network II - 62%. Among the cities unknown by the ANN, Bauru presented the best results of an approximation factors: analytical method - 73%; Network I - 67%; Network II - 77%. The worst results among the cities unknown by the ANN came from S. José dos Campos - 2017: analytical method - 41%; Network I - 44%; Network II - 35%.

Through this work, it was possible to estimate the global solar radiation applying the artificial neural network methodology, since the order of magnitude of its approximation factors were similar to the analytical method values for the same locations when compared to the real data of meteorological stations.

6. ACKNOWLEDGEMENTS

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7. REFERENCES

Benali, L., Notton, G., Fouilloy, A., Voyant, C. and Dizene, R., 2019. “Solar radiation forecasting using artificial neural network and random forest methods: Application to normal beam, horizontal diffuse and global components”. *Renewable energy*, 132, 871-884.

Collares-Pereira, M. and Rabl, A., 1979. “The average distribution of solar radiation-correlations between diffuse and hemispherical and between daily and hourly insolation values”. *Solar energy*, 22(2), 155-164.

Di Piazza, A., Di Piazza, M. C., La Tona, G. and Luna, M., 2020. “An artificial neural network-based forecasting model of energy-related time series for electrical grid management”. *Mathematics and Computers in Simulation*.

Duffie, J. A. and Beckman, W. A., 2013. *Solar engineering of thermal processes*. John Wiley & Sons, 4th edition.

Gürel, A. E., Ağbulut, Ü. and Biçen, Y., 2020. “Assessment of machine learning, time series, response surface methodology and empirical models in prediction of global solar radiation”. *Journal of Cleaner Production*, 122353.

IEA, 2019. *World Energy Outlook 2019 - Highlights deep disparities in the global energy system*.

IPCC, 2015. *Climate change 2014, Synthesis Report*. ISBN 978-92-9169-143-2.

JRC European Commission et al, 2014. *Photovoltaic geographical information system-interactive maps*.

Kashyap, Y., Bansal, A. and Sao, A. K., 2015. “Solar radiation forecasting with multiple parameters neural networks”. *Renewable and Sustainable Energy Reviews*, 49, 825-835.

Khosravi, A., Koury, R. N. N., Machado, L. and Pabon, J. J. G. (2018). “Prediction of hourly solar radiation in Abu Musa Island using machine learning algorithms”. *Journal of Cleaner Production*, Vol. 176, 63-75.

Molion, L. C. B., 2008. “Aquecimento global: uma visão crítica”. *Revista brasileira de climatologia*, Vol. 3.

Pang, Z., Niu, F. and O'Neill, Z., 2020. “Solar radiation prediction using recurrent neural network and artificial neural network: A case study with comparisons”. *Renewable Energy*.

Patterson, J. and Gibson, A., 2017. *Deep learning: A practitioner's approach*. O'Reilly Media, Inc.

Pazikadin, A. R., Rifai, D., Ali, K., Malik, M. Z., Abdalla, A. N. and Faraj, M. A., 2020. “Solar irradiance measurement instrumentation and power solar generation forecasting based on Artificial Neural Networks (ANN): A review of five years research trend”. *Science of The Total Environment*, Vol. 715, 136848.

Pereira, E. B., Martins, F. R., Gonçalves, A. R., Costa, R. S., Lima, F. J. L., Rüther, R. and de Souza, J. G., 2017. *Atlas brasileiro de energia solar (2a edição)*. São José dos Campos: Inpe.

Plana-Fattori, A. and Ceballos, J. C., 2015. *Glossário de termos técnicos em radiação atmosférica-versão 2.0*. Available at: http://satelite.cptec.inpe.br/radiacao/. Visited on: 08 junho 2020.

Priya, S. S. and Iqbal, M. H., 2015). “Solar radiation prediction using artificial neural network”. *International Journal of Computer Applications*, Vol. 116(16).

Rolim, G. D. S., Camargo, M. B. P. D., Lania, D. G. and Moraes, J. F. L. D., 2007. *Classificação climática de Köppen e de Thornthwaite e sua aplicabilidade na determinação de zonas agroclimáticas para o estado de são Paulo*. Bragantia [online], vol. 66, n. 4.

Schüler, D., Wilbert, S., Geuder, N., Affolter, R., Wolfertstetter, F., Prahl, C. And Balghouthi, M., 2015. “The enerMENA Meteorological Network–Solar Radiation Measurements in the MENA Region”. *In SolarPACES 2015*.

Silva, I. D., Spatti, D. H. and Flauzino, R. A., 2010. *Redes neurais artificiais para engenharia e ciências aplicadas*. Artliber.

UN, 2019. *Report of the Secretary-General on the work of the Organization*.

UNFCCC, 2017. *Greenhouse Gas Inventory Data - Detailed data by Party*. Available at: http://di.unfccc.int/detailed_data_by_party. Visited on: 12 jun. 2020.

Xue, X., 2017. “Prediction of daily diffuse solar radiation using artificial neural networks”. *International journal of hydrogen energy*, 42(47), 28214-28221.

Zhang, J., Zhao, L., Deng, S., Xu, W. and Zhang, Y., 2017. “A critical review of the models used to estimate solar radiation”. *Renewable and Sustainable Energy Reviews*, 70, 314-329.

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