EISSN: 2707-0425

East African Journal of Science, Technology and Innovation, Vol. 3 (4): September 2022

An inverse artificial neural network algorithm for retrieval of sunshine hours from ground-based global solar irradiation measurements

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Abstract

Availability of meteorological parameter values is important in applications that require solar irradiation. Meteorological parameters such as sunshine hours are best provided by measuring equipment mainly stationed at weather stations. The cost of purchasing the measuring equipment, and setting up and maintaining weather stations is enormous and cannot be easily afforded by many developing countries like Uganda. Furthermore, in Uganda, we have some weather stations which have been measuring global horizontal solar irradiation for quite some time but lacked sunshine duration sensors, and at some others, the sunshine measuring equipment malfunctioned. In this work we present an inverse artificial neural network algorithm that predicts sunshine hours based on horizontal global solar irradiation, the algorithm caters to cases where global horizontal solar irradiation is present but sunshine hour measuring equipment is missing or malfunctioned. A radial basis function neural network (RBF-NN) was trained for forward computation of global horizontal solar irradiation from sunshine hour values. The inverse modelling algorithm employs multidimensional unconstrained non-linear optimization to retrieve sunshine hours. The correlation coefficient (r) between the measured sunshine hour values and those predicted by the inverse artificial neural network algorithm was found to be 0.924. The average value of the ratios of the inverse artificial neural network algorithm computed values to the sunshine duration sensor measurements was 1.043. The algorithm predicted sunshine hour values with a mean bias and relative root mean square error of 0.043 and 0.394, respectively. The algorithm developed provides an affordable, fast and reliable method for determining sunshine hour values based on global horizontal solar irradiation. However, sunshine hour values prediction for low values of global horizontal solar irradiation was less precise, and this could be attributed to high levels of cloudiness. It is recommended that an inverse algorithm that retrieves sunshine hours under cloudy conditions be constructed for the fast, cheap acquisition of weather/climate related data.

Keywords: *Algorithms; Neural Networks; Artificial intelligence; direct sunshine duration; renewable energy; prediction*

Received: 21/10/21
Accepted: 13/07/22
Published: 29/09/22

Cite as: *Nzala et al., (2022)*. An inverse artificial neural network algorithm for retrieval of sunshine hours from ground-based global solar irradiation measurements. *East African Journal of Science, Technology and Innovation 3(4).*

Introduction

The utilisation of solar energy globally has increased because it is clean and abundant renewable energy, whereas nearly all potential sources of hydro-electric energy in Uganda have been developed (Kandirmaz *et al.*, 2014; Wald & Wald, 2018). Studies to measure or predict solar irradiation have been carried out in Uganda and other parts of the world (Angela *et al.,* 2011; Kent *et al.,* 2016; Laidi *et al.,* 2018). Consequently, solar irradiation data availability for more locations in Uganda is destined to increase. Sunshine hours are defined as the period of the day during which direct solar irradiance exceeds a threshold value of 120 Wm^{-2} (Ahmad *et al.,* 2017). Sunshine hours is a dominant indication of the amount of solar energy received in a region. Furthermore, it is an important parameter for the study of atmospheric energy balance, climate change, ecosystem evolution, and social sustainability. The availability of long-term sunshine hour values enables the quantification of climate change (Hannak *et al.,* 2019). Song *et al.,* (2018) reported that sunshine hour values are key in developing the technology of heliostats for deep interior daylighting systems of large buildings. Research has shown that exposure of contaminated water to direct sunshine for at least 6 sunshine hours is known to disinfect the water (Caslake *et al.,* 2004). Pyranometers used to measure solar irradiation, cannot be used to measure sunshine hour values hence you need two instruments to run concurrently to have both parameters.

Inverse artificial neural network algorithms are tools with the capacity to optimise processes based on experimental data. They are used to improve system performance or estimate predictor variables (Hamzaoui *et al.,* 2015). According to Solís-Pérez *et al.,* (2019), optimisation is the estimation of a value(s) to obtain the minimum or maximum potential in the performance of a process. Although increasingly applied in commerce, engineering, industry, and technology, the application of artificial neural network inverse (ANNi) algorithms for the retrieval of meteorological parameters is lacking. An inverse artificial neural network algorithm that retrieves, simultaneously five parameters was developed by Stamnes et al. (2013). The algorithm employs a radial basis transfer function neural network (RBF-NN) forward radiative transfer model to compute the required radiances and Jacobians. In the parameter retrieval part, the model employs the Levenberg-Marquardt optimal estimation scheme to estimate the parameters that best fit the radiance measurements. To ascertain the effect of local factors (e.g., topography) on local climate, Ghosh (1967) measured sunshine hour values using Campbell-Stokes recorders at 8 meteorological stations in and around Kampala, Uganda from 1960 to 1965. He deduced that local factors considerably affect sunshine hour values. Although a general pattern could be obtained for a spot from measurements of a nearby station, an accurate estimation of sunshine hour values is required for the spot for in-depth climate quantification.

There are many meteorological parameters that influence the amount of solar radiation received at a location. These include; air temperature, relative humidity, wind speed, rainfall and sunshine hours. However, the greatest influence is exerted by sunshine hour values (Udo, 2002). In Uganda meteorological parameter measuring equipment is located in a few places and the respective data is scarce. This is due to the high costs involved in buying and maintaining the measuring equipment. In places where solar irradiation data is not available, prediction techniques have been used for its estimation (Mubiru & Banda 2008; Angela *et al.,* 2011; Mubiru, 2011). For cases where sunshine hours' values are lacking but solar irradiation is available nothing much had been done. To address the above challenge a methodology that retrieves sunshine hour values based on global solar irradiation has been developed. The method involves training an RBF-NN to establish the relationship between sunshine hours and global horizontal solar irradiation. The inverse modeling algorithm employs an unconstrained non-linear minimization function (fminsearch) based on the Nelder-Mead method to retrieve sunshine hours.

Materials and methods

The study involved developing an inverse algorithm for an artificial neural network that established a relationship between independent and dependent variables so that ultimately, the independent variable is predicted given the dependent variable. Computer software Matlab version 8.1 was used in developing the forward artificial neural networks (ANN) relation for solar irradiation estimation, and also in the optimisation process to retrieve sunshine hour values. Although sunshine hour values are one of the meteorological parameters used to estimate solar irradiation, the algorithm established acts in reverse so that sunshine hour values can be retrieved from measured global horizontal solar irradiation.

Training the radial basis function neural network and the fminsearch algorithm

Artificial neural networks were used in the forward and inverse modelling parts. The ANN consists of three types of layers: the input, hidden and output layers. In the input layer, raw data is entered and sent to the hidden layer. In the hidden layer, each input x_j is transmitted through a connection that multiplies its strength by a weight w_{ij} to give a product $x_j w_{ij}$. To the sum of the weighted products is added the neural network bias. The ANN bias is a constant specified by the training algorithm to enable a neuron to simulate conditional relationships so that only signal strengths within a desired range are processed. The overall sum gives the strength of the signal where P_s is the sunshine hours and N is the total number of neurons.

Sunshine hour measurements were presented to the input layer which then transmitted to the hidden layer. In the hidden layer, each entry was multiplied by a weight and a neural network bias was added to the weighted sum of input signals for each neuron, then a radial basis function given by Equation (1) was applied to produce a hidden layer output that was transmitted to the output layer. The RBF-NN was trained starting with 2 up to 200 neurons in the RBF layer. The input vector was the sunshine hour values and the output vector was the global horizontal solar irradiation. The number of data points used to train the forward ANN was 1879. For each architecture of a particular neuron number in the RBF layer, the spread (radius) was varied from 5 to 15. Each time, the mean square error (MSE) was calculated. The architecture with 100 neurons in the RBF layer and a spread of 10 presented the least MSE, and thus was selected as the optimum performing architecture. In this research, a radial basis neural network (RBF-NN) was trained based on the relation between solar irradiation H_i and meteorological parameters, given in Equation (1),

$$H_i = \sum_{j=1}^{N} a_{ij} exp\left\{-b^2\left(P_s - c_{jk}\right)^2\right\} + d_i, \tag{1}$$

The purpose of training of the RBF-NN is to determine the optimised coefficients, a_{ij} , b, c_{jk} and d_i. Those coefficients are then used in the sunshine hours' retrieval part. A more detailed description of this methodology can be found in Ssenyonga *et al.*, (2022)

The output layer un-normalised, then presented the tool computed values. In the back propagation stage, weights were adjusted basing on the cost function Equation (2). There is an interconnection between neurons as shown in Figure 1. Sunshine hour values and global horizontal solar irradiation measured over a period of six years at the Physics Department, Makerere University was divided into two; training and testing sets. Matlab software version 8.1 used the first set to train the RBF-NN.

$$C(w,b) = \frac{1}{2n}\sum_x \|y(x) - a\|^2, \tag{2}$$

where w denotes the collection of all weights in the network, b all the biases, n is the total number of training inputs, $y(x)$ is the desired output while a is the vector of outputs from the network when x is input, and the sum is over all training inputs, x.

After training the radial basis neural network (RBF-NN), the empirical relationship between sunshine hours and global horizontal solar irradiation was saved as metPRA. Then the unconstrained non-linear minimisation function, fminsearch, was applied to another cost function to derive sunshine hour values basing on the inverted empirical relation between global horizontal solar irradiation and sunshine hours as shown in Figure 1. Global horizontal solar irradiation was the input while sunshine hour values were the output.

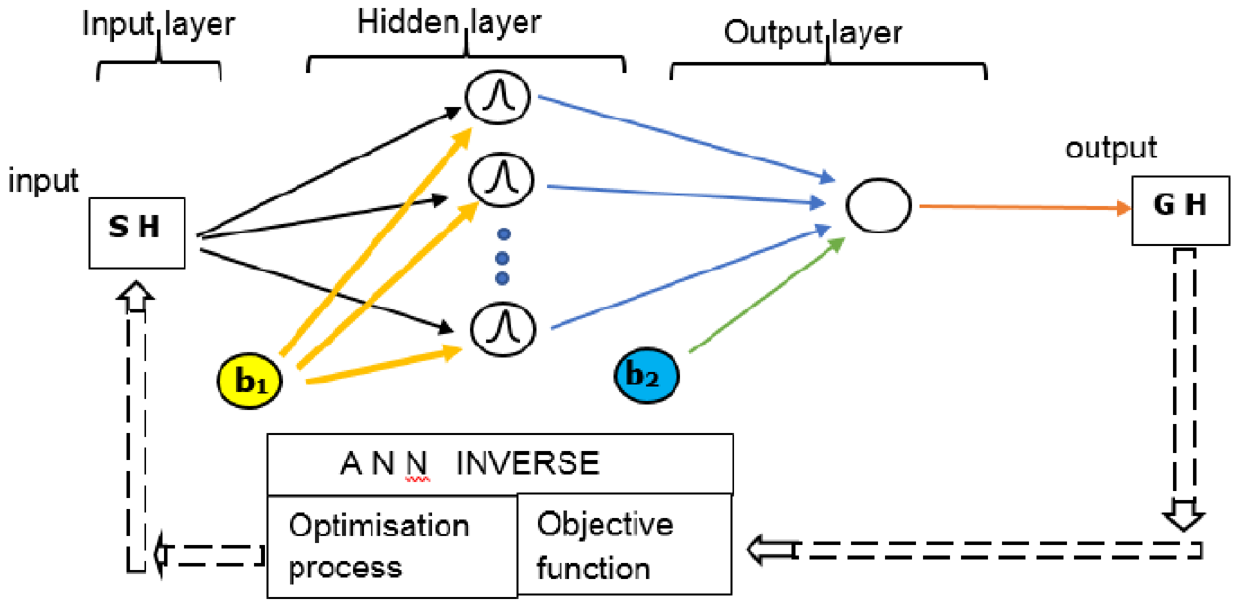

Figure 1. RBF-NN for inverse ANN sunshine hours' retrieval

Evaluating the inverse retrieval algorithm

We conducted linear regressions to determine correlation coefficients r between the ANNi predicted values and the sunshine duration sensor measured data. The relative difference (RD), mean bias (MnB), mean square error (MSE) and relative root mean square error ($RRMSE$) were also computed using the equations:

$$r_i = \frac{\sum_i (y_{ip} - \bar{y}_{ip})(y_{im} - \bar{y}_{im})}{\left\{\sum_i (y_{ip} - \bar{y}_{ip})^2\right\}^{\frac{1}{2}} \{\sum_i (y_{im} - \bar{y}_{im})^2\}^{\frac{1}{2}}}\,, \tag{3}$$

where y_{ip} and y_{im} are the predicted and measured parameter i, while $\bar{y}_{ip}$ and $\bar{y}_{im}$ are their corresponding average values, respectively.

$$RD = \frac{(y_{ip} - y_{im})}{y_{im}}\,, \tag{4}$$

whereas,

$$MnB = \frac{1}{N}\sum_{i=1}^{N} \frac{(y_{ip} - y_{im})}{y_{im}}\,, \tag{5}$$

where N is the number of observations, the other terms have the same meaning as in equation (3).

$$MSE = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{y_{ip} - y_{im}}{y_{im}}\right)^2 \tag{6}$$

and

$$RRMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \left(\frac{y_{ip} - y_{im}}{y_{im}}\right)^2} \tag{7}$$

where the terms carry the same meaning as in Equation (5).

Data collection

Data collected between 2011 and 2016 at Makerere University, Kampala was used to train the forward and inverse ANN algorithms. Instruments used to measure solar irradiation are of two basic types; pyrheliometers and pyranometers. The two types of instruments widely used to measure time, in hours, of bright sunshine are Campbell-Stokes sunshine recorders and photoelectric sunshine sensors. Global horizontal solar irradiation was measured using a pyranometer (model: CMP6, serial number: 070213) which has a wide spectral range of 285 nm to 2800 nm, a wide operating temperature range from -40°C to 80°C, and a wide field of view of solid angle 2π sr. Its sensitivity is 16.56 $\mu VW^{-1}m^{-2}$ and the instrument can measure irradiance up to a maximum value of 2000 Wm^{-2}.

The sunshine duration sensor (model: CSD 3, serial number: 070252) that was used to measure sunshine hour values has a wide operating temperature range of -30°C to 70°C. The instantaneous values for each hour are integrated to give the hour's sunshine duration. Those hours' sunshine duration recordings are summed for the 24 hours to give the sunshine hours of the day and recorded by the data logger that was externally connected.

Results

The performance of Artificial Neural network model using RBF as the training function

For each architecture of a particular neuron number in the RBF layer, the spread (radius) was varied from 5 to 15. Each time, the mean square error (MSE) was calculated. The architecture with 100 neurons in the RBF layer and spread of 10 presented the least MSE, and thus was selected as the optimum performing architecture.

Figure 2(a) is a scatter plot of global horizontal solar irradiation predicted by the RBF-NN against that measured by the pyranometer. The correlation coefficient, mean bias (MnB) and the relative root mean square error were 0.93, 0.0019, and 0.11, respectively. There was a good positive correlation between solar irradiation values modelled by the RBF-NN and those measured by the pyranometer. Further analysis of the performance of the RBF-NN was carried out using graphs of ratios of the predicted to measured values, given in Figure 4(a). Figure 4(a) gives ratios of the global horizontal solar irradiation values predicted by the forward RBF-NN to those measured by the pyranometer and 95% of the data varied in the range 0.5 -2.

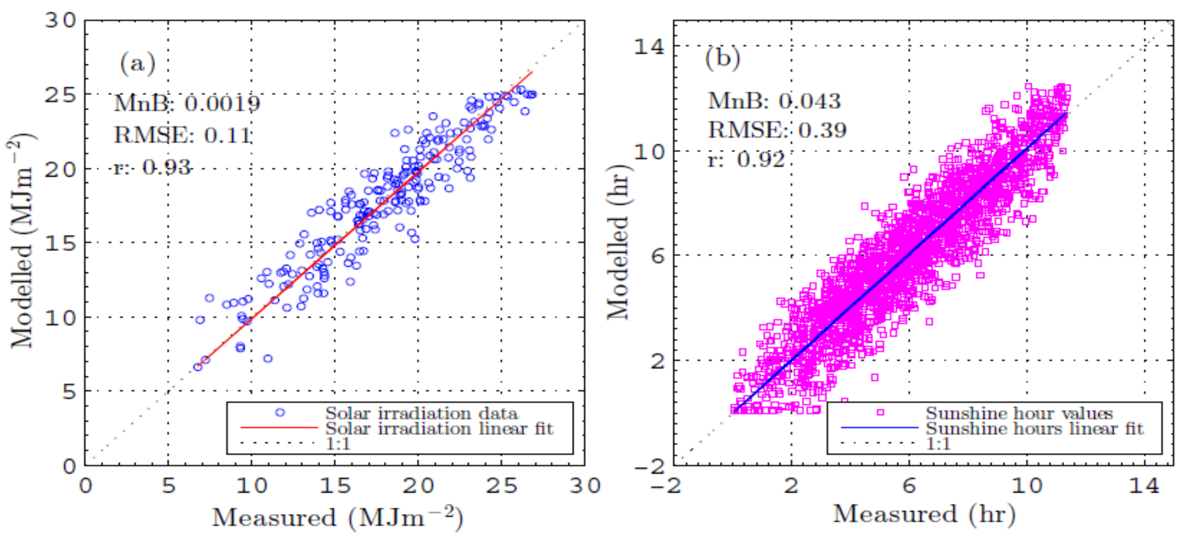

Figure 2. Scatter plots of: (a) solar irradiation computed by the RBF-NN against that measured by the pyranometer. (b) sunshine hour values predicted by the ANNi against those measured by the CSD 3 sensor

The relative difference between the predicted and the measured global horizontal solar irradiation for RBF-NN is shown in Figure 3. It was observed that for 95% of the data points for the days between the years 2011-2016, the relative difference ranged between -20% and 20%. The negative and positive values of the relative difference indicate model underestimation and overestimation of measured values, respectively. The highest value for overestimation of the data by the model had a relative difference of 0.42 and the highest value for underestimation of the global solar irradiation by the model had a relative difference of 0.14.

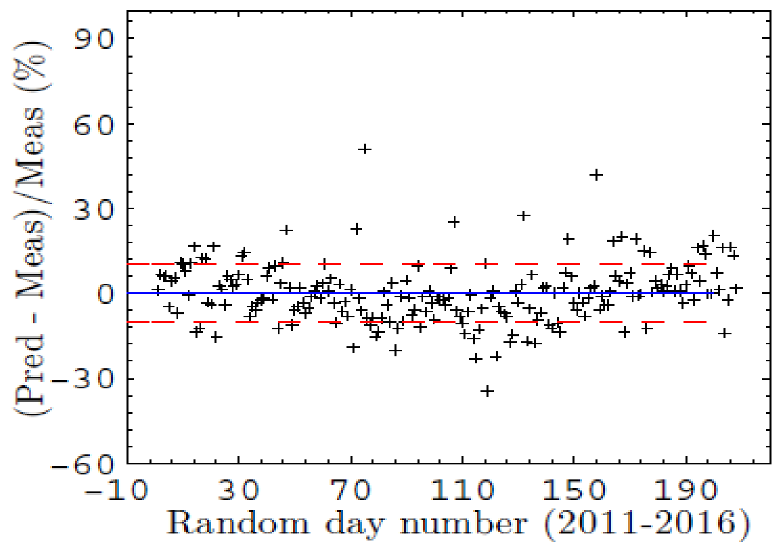

Figure 3. Percentage relative difference between solar irradiation computed by the RBF- NN and that measured by the pyranometer

The performance of the Inverse Artificial Neural network model

In the inverse retrieval algorithm, global horizontal solar irradiation values were used as the input parameter to compute the sunshine hour values. Figure 2(b) is a scatter plot of sunshine hour values predicted by the ANNi against those measured by the CSD 3 sunshine duration sensor. The correlation coefficient, mean bias (MnB) and the relative root mean square error were 0.92, 0.043, and 0.39, respectively. The graph showed a very good positive correlation between the ANNi predicted and sunshine duration sensor measured values.

Further analysis of the general performance of the ANNi retrieval algorithm was carried out using ratios of the predicted sunshine hours to measured sunshine hours, as shown in Figure 4(b). The fminsearch minimisation function was used in the ANNi algorithm to predict the sunshine hours using the horizontal global solar irradiation as the input. Furthermore, from Figure 4(b) it was observed that 95% of ratios of the predicted to measured values of sunshine hours were in the range of 0 - 1.9. The average value of the ratios of the modelled to measured values of sunshine hours was 1.04. Table 1 gives global horizontal solar irradiation and sunshine hour values for days where very high values of model underestimation and overestimation were obtained. From Table 1 the highest relative difference of 7.6 was obtained and this shows that the model overestimation of the sunshine hours was very large. This overestimation occurred on a cloudy day with the lowest measured sunshine hours of 0.167 hours.

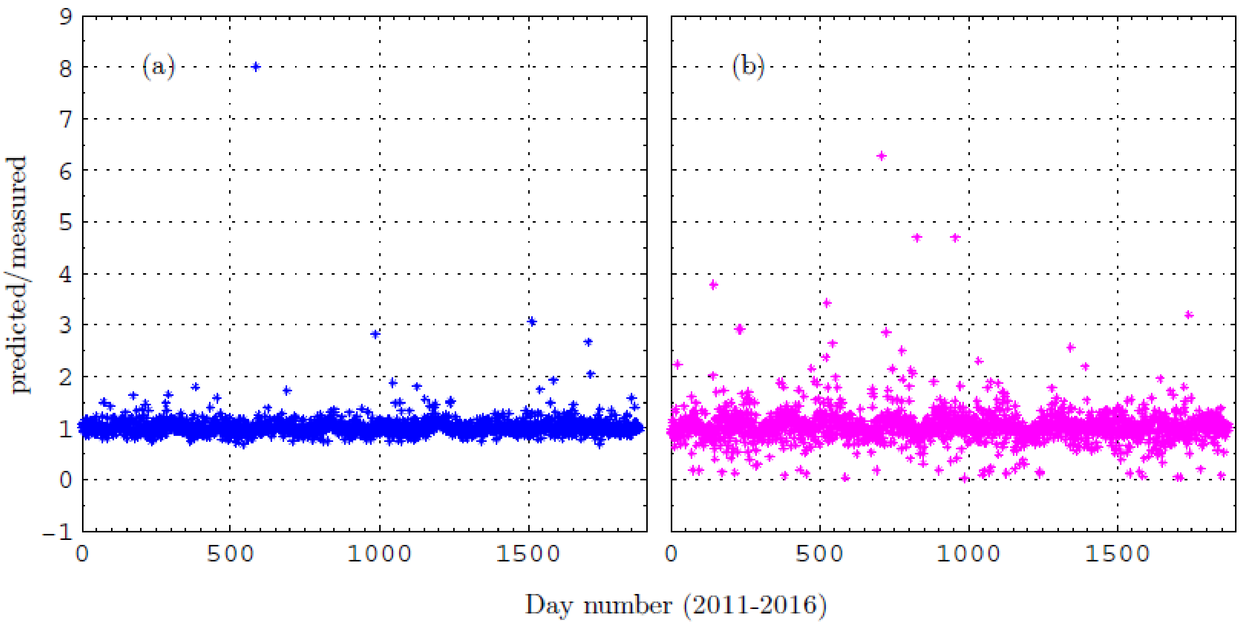

Figure 4. Ratio plots for days in period 2011-2016 of: (a) solar irradiation predicted by the RBF-NN to that measured by the pyranometer. (b) sunshine hour values predicted by the fminsearch minimisation function to those measured by the CSD 3 sensor

Table 1. Measured sunshine hour values and their corresponding ratios for days poorly predicted by the forward and inverse algorithms

Day number	Solar irradiation (MJm^{-2})	Sunshine hours (hr)	Ratio (pred/meas)	Relative difference (Pred-meas)/meas
22	9.3198	0.633	2.2	1.2
211	6.759	0.067	2.9	1.9
301	9.221	0.466	2.9	1.9
609	8.430	0.267	3.4	2.4
673	1.467	2.816	0.1	-1.0
854	9.365	0.167	8.6	7.6
977	8.482	0.150	6.3	5.3
1095	9.577	0.333	4.7	3.7
1225	8.620	0.217	4.7	3.7
1256	5.176	4.454	0.1	-1.0
1783	2.228	0.265	1.0	0.1
1889	6.570	3.315	0.1	-1.0
2008	4.059	2.282	0.1	-1.0
2047	12.606	1.033	3.2	2.2

ANNi performance for six categories of sunshine hour values

The relative difference of 6 categories of measured sunshine hour values was evaluated as shown in Table 2. Sunshine hours (SH) categories include; All SH, SH>3, SH>5, SH>7, SH<7, and 3<SH<7, and the relative differences between ANNi model sunshine values and measured sunshine values are given in Figures 5, 6, and 7.

Figure 5(a) is a graph of relative difference (RD) against day number for all sunshine hour values measured by the CSD 3 sunshine duration sensor. It includes values between 0 and 12 hr. In Table 2 a relative difference range of -10% to 10% was considered. For 2087 data points, 43.2% had percentage RD between -10% and 10%.

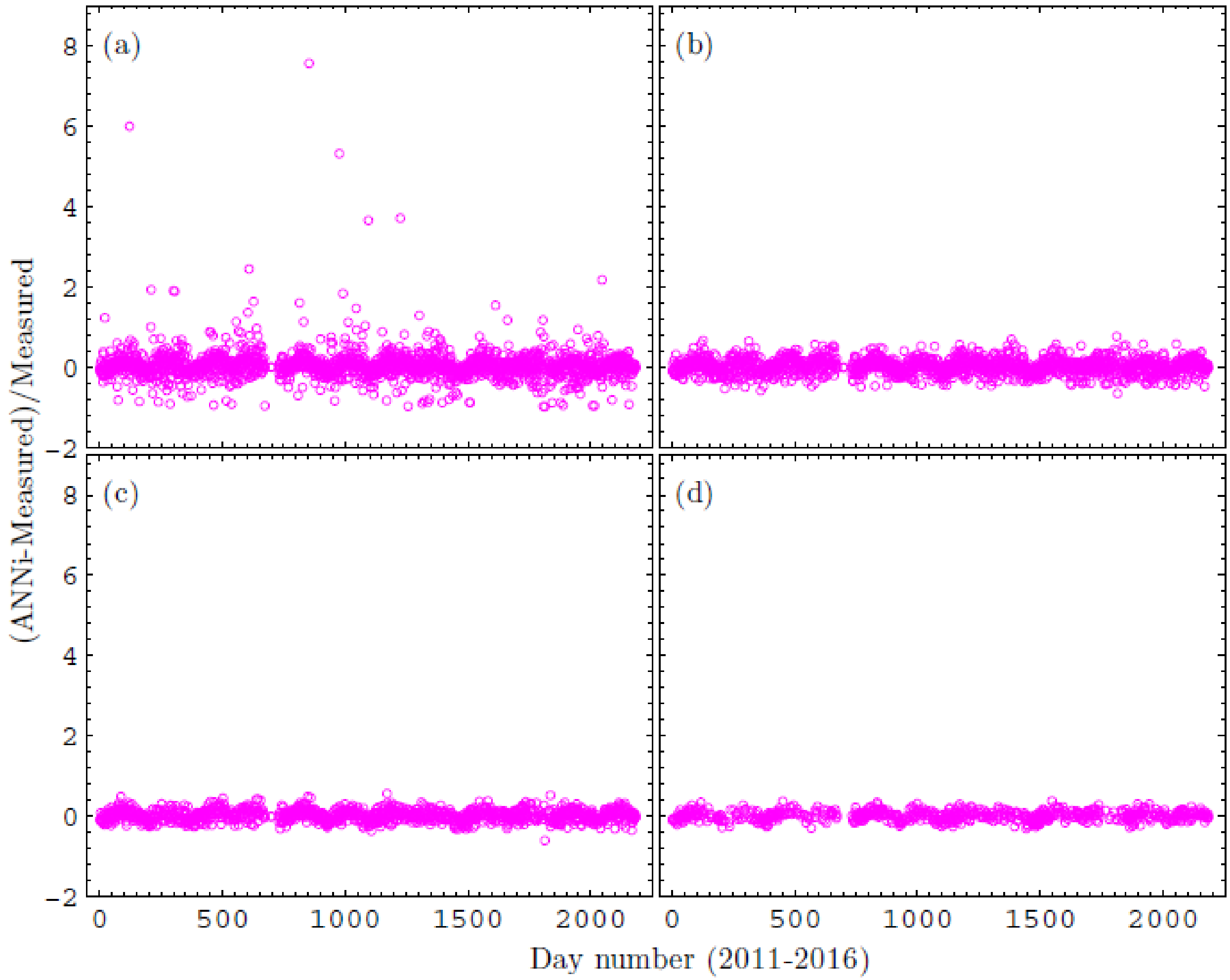

Figure 5. Relative difference plots for days in period 2011-2016 of: (a) all measured sunshine hour values. (b) sunshine hour values above 3 hr. (c) sunshine hour values above 5 hr (d) sunshine hour values above 7 hr

For the all-sunshine hours (SH) category, the minimum RD, maximum RD, and mean bias values were -0.987, 7.563 and 0.0434, respectively. The predicted sunshine hours which had a relative difference in the range -10% to 10% were 44.2%. It was observed from Table 2 that the category of SH > 7 had the highest number of data points that had a relative difference of 63.7% in the range -10% to10%. This implied the model works well for high values of sunshine hours. Also Figure 5(d) that shows relative differences for SH > 7 indicates that the model predicted the sunshine hours better than for other sunshine hour categories given in Figures 5(a), 5(b), and 5(c). Figures 5(b) and 5(c) are for relative differences for sunshine hour (SH) categories of SH > 3, and SH > 5 hour, respectively. The percentage RD values for SH above 3 hours and above 5 hours between -10% and 10% are 47.9% and 56.6%, respectively. As seen in Table 2, as SH increased from 3 hours to 7 hours the model performance improved. Furthermore, in Table2, it was observed the minimum RD values decreased from -0.657 for SH > 3 to -0.31 for SH > 7 and the maximum RD values decreased from 0.7604 for SH > 3 to 0.377 for SH > 7. The ANNi algorithm performance presented in Figures 5(b) and 5(c) indicates improvements for days of higher SH values, which are generally less cloudy days.

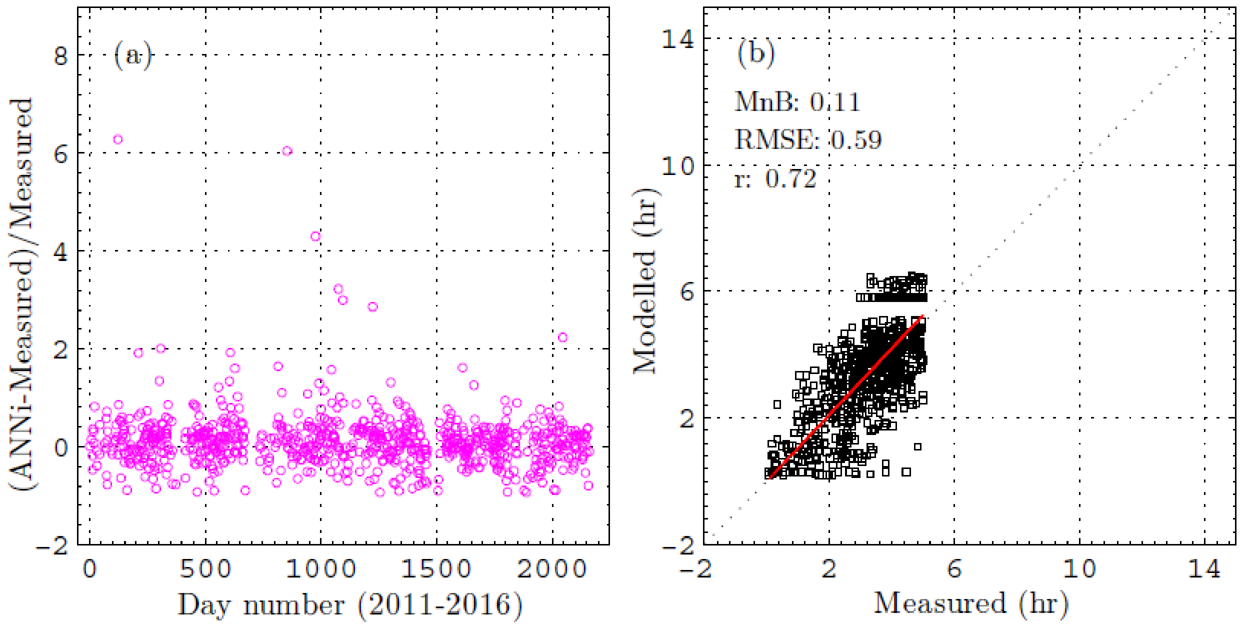

Figure 6. (a) Relative difference plots for days of measured sunshine hour values less than 5 hr. (b) Scatter plots for days of measured sunshine hour values less than 5 hr. Figure 7: (a) Relative difference plots for days of measured sunshine hour values between 3 and 7 hr. (b) Scatter plots for days of measured sunshine hour values between 3 and 7 hr

Figure 5(d) is a graph of RD for days with measured sunshine hour values above 7. For 784 data points which represent 63.8% of the data, the percentage RD values ranged between -10% and 10%. Thus, the performance of the model improves with an increase in sunshine hours. The minimum and maximum values of RD were -0.307 and 0.377, respectively, and the mean RD was 0.0096. This means that error margins were much reduced for the category. The ANNi algorithm performance characteristics are summarised in Table 2. The mean bias decreased from 0.0169 for SH > 3 to 0.0096 for SH > 7.

The last two categories in Table 2 investigated were; one for low sunshine hour values which was SH < 5, and moderate sunshine hour values which was 3 < SH < 7. It was observed from Table 2 that for low sunshine hours, SH < 5, the mean bias, minimum RD, and maximum RD values were 0.114, -0.937, 6.29, respectively. For moderate sunshine hours, 3 < SH < 7, the mean bias, minimum RD, and maximum RD were 0.029, -0.574, and 0.712, respectively.

Figure 6(a) shows the relative differences of sunshine hour category SH < 5 and we observed that 95% of the RD were in the range -0.8 to 0.8. The MnB, RRMSE and correlation coefficient (r) were 0.11, 0.59, and 0.72, respectively as shown in Figure 6(b). Only 20.4% of the data points had percentage RD values between -10% and 10% (Table 2). Figure 7(a) shows the relative differences of sunshine hour category 3 < SH < 7 and we observed that 95% of the data had RD in the range -0.2 to 0.2. The MnB, RRMSE and *r* were 0.029, 0.21, and 0.73, respectively as indicated in Figure 7(b). It should be noted that only 35% of the total number of data points had percentage RD values between -10% and 10% was 35%,

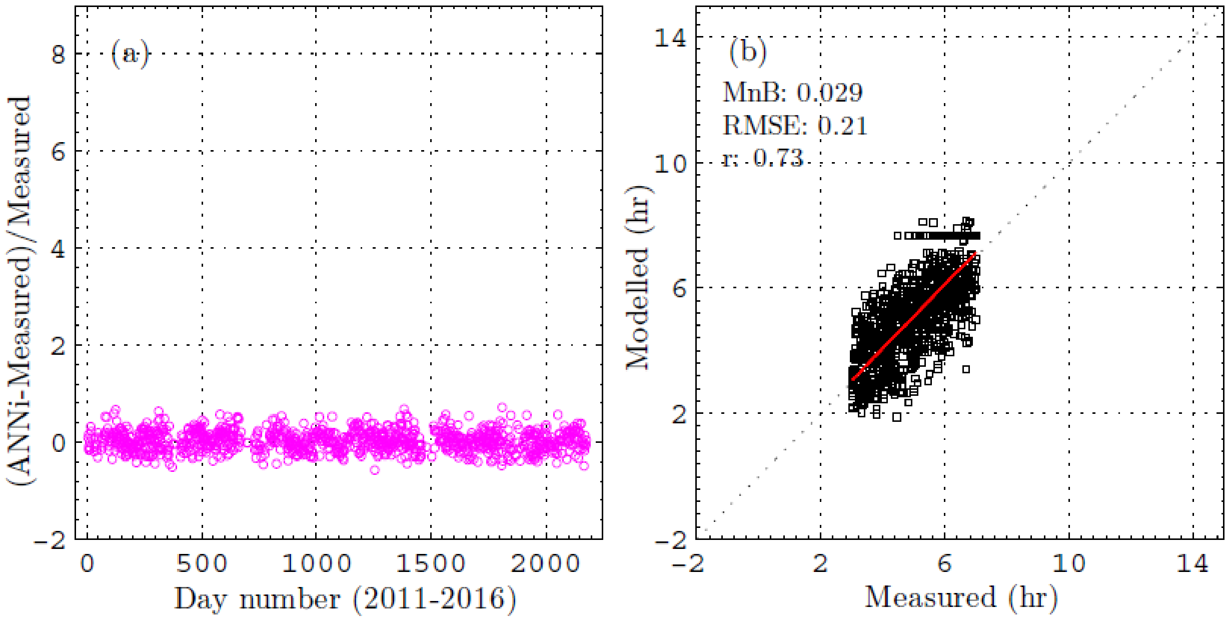

Table 2. Percentage of the values in the range -10% to 10% of the relative difference (RD) for the six categories investigated

Category (hr)	MnB	Min(RD)	Max(RD)	-10% ≤ RD ≤ 10%
All SH	0.0434	-0.9867	7.5629	44.2
SH > 3	0.0169	-0.6569	0.7604	47.9
SH > 5	0.0161	-0.6103	0.5597	56.6
SH > 7	0.0096	-0.3070	0.3770	63.7
SH < 5	0.1141	-0.9370	6.2883	20.4
3 < SH < 7	0.0293	-0.5736	0.7117	35.0

Correlation Coefficients for Four Categories of Sunshine Hour Values

Linear regressions were also conducted to determine correlation coefficients (r), RRMSE and MnB for the 4 categories of measured sunshine hour values and the findings are presented in Figure 8. Figure 8(a) for all measured sunshine hour values (0 - 12 hours) produced a correlation coefficient between the ANNi predicted and sensor measured sunshine hour values of 0.92, with RRMSE and MnB of 0.39 and 0.043, respectively. Figures 8(b), 8(c) and 8(d) were for measured sunshine hour values greater than 3, 5 and 7, respectively. The correlation coefficient for those categories were 0.90, 0.85, and 0.74, respectively. The corresponding RRMSE values were 0.184, 0.14 and 0.12, respectively and the MnB values were 0.043, 0.016 and 0.0096, respectively. The RRMSE and MnB values show improved ANNi algorithm performance for categories with days of high sunshine hour values. However, the corresponding correlation coefficient values fell.

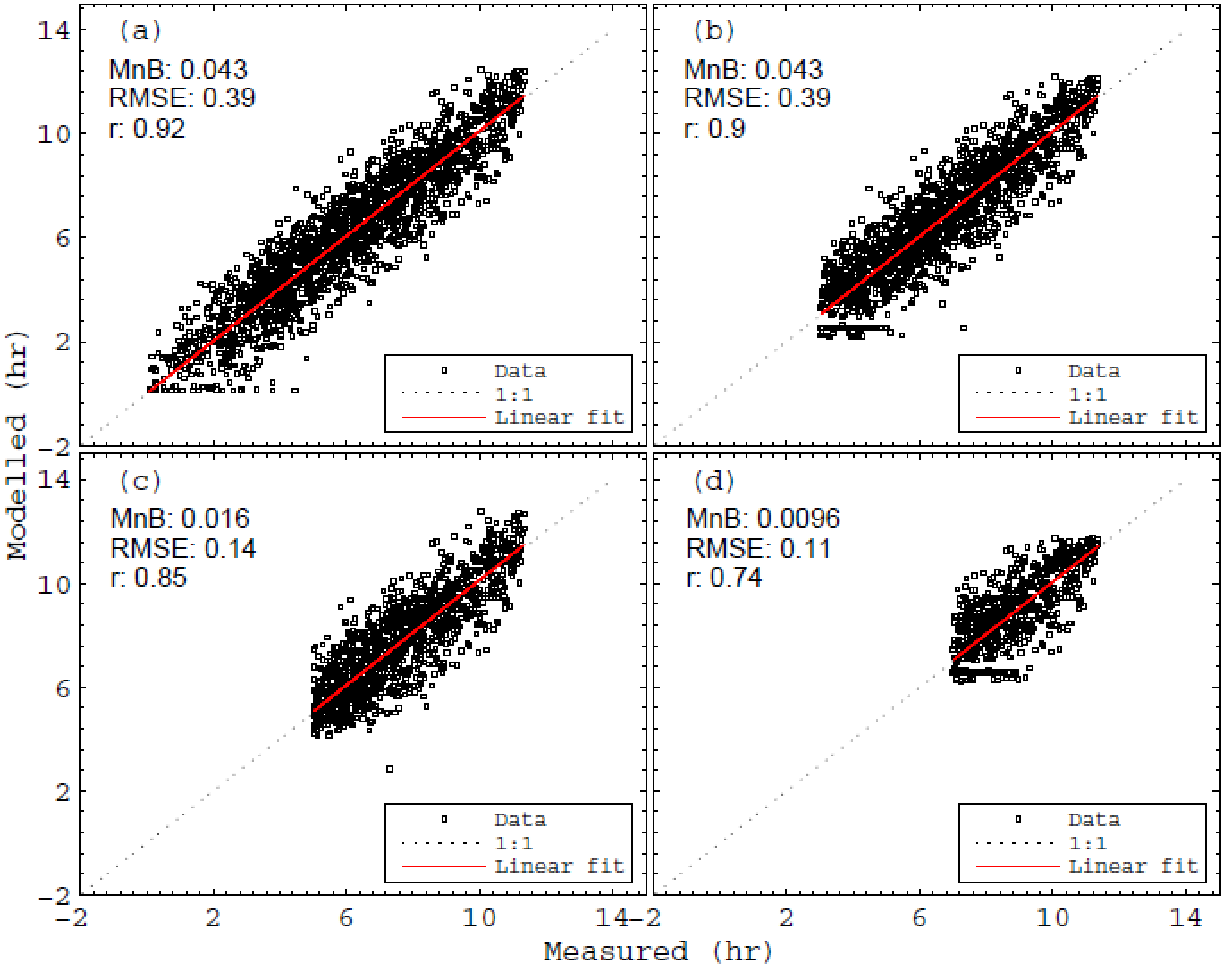

Figure 8. Scatter plots of ANNi modelled sunshine hour values against those measured by the sunshine duration censor for: (a) all measured sunshine hour values. (b) sunshine hour values above 3 hr. (c) sunshine hour values above 5 hr (d) sunshine hour values above 7 hr

Discussion

The performance of Artificial Neural network model using RBF as the training function

The RBF-NN was trained starting with 2 up to 200 neurons in the RBF layer. The input vector was the sunshine hour values and the output vector was the global horizontal solar irradiation. The number of data points used to train the forward ANN was 1879. We found an agreement between the predicted and measured values with a relative root mean square error (RRMSE), mean bias (MnB) and correlation coefficient (r) values of 10.7%, 0.002 and 0.934, respectively. The correlation coefficient in this study is slightly lower than that of Angela *et al.*, (2011) by 0.029. Angela *et al.*, (2011) had a mean bias error and root mean square error of 0.055 MJm^{-2} and 0.521 MJm^{-2}, respectively. These values are higher than the mean bias and relative root mean square values in this study. Angela *et al.*, (2011) used artificial neural network to predict global solar irradiation using sunshine hours but they used monthly averages of global solar irradiation and in this study, daily averages of global solar irradiation were used.

The Mubiru & Banda (2008) six-parameter ANN model gave a correlation coefficient of 0.974 between the predicted and pyranometer measured global horizontal solar irradiation values. The better performance of the several-parameter ANN models could be due to the fact that one weather parameter, sunshine hours, fed into the RBF-NN as input is less likely to describe, entirely, the non-linearity nature of global horizontal solar irradiation (Angela *et al.*, 2011).

The RBF-NN performance was comparable to those of Chen *et al.*, (2011) and Shamshirband *et al.*, (2015). The monthly average of daily solar irradiation was estimated from measured temperatures at Chongqing, China using Support Vector Machines by Chen *et al.*, (2011). They obtained a relative root mean square error (RRMSE) and coefficient of determination (r^2) of 9.00% and 0.969, respectively. The daily global horizontal solar irradiation for Bandar Abass, Iran was estimated using kernel extreme learning machine by Shamshirband *et al.*, (2015). They obtained a relative root mean square error and correlation coefficient of 11.25% and 0.9057 respectively.

The performance of the inverse artificial neural network model using fminseach function

Figure 2(b) is a scatter plot of sunshine hour values predicted by the ANNi against those measured by the sensor and a positive mean bias of 0.043 combined with high positive correlation of 0.92 between the ANNi predicted and sunshine duration sensor measured values indicated that the model performed well. A relative difference (RD) analysis between the RBF- predicted and the pyranometer measured values, presented in Figure 3, revealed that about 70% of the data points are in the range of -6% to 6%. This indicated that the difference between predicted and measured sunshine hours for most data points is small.

It was observed that whenever measured sunshine hours were low, the model showed an overestimation of the sunshine hours. This can be observed in Table 2, the higher the sunshine hours the lower the mean bias and the higher the number of sunshine hours data points that have lower relative difference. In Table 2, 63.7% of the data points for sunshine hours greater than 7 hours had relative difference between -10% and 10%. The lower sunshine hours mainly occur on cloudy days and on rainy days. The algorithm in this study fails to appropriately predict sunshine hour values for low values of global horizontal solar irradiation, which could be due to high levels of cloudiness. Clouds are known to produce intense scattering of radiation passing through them causing the radiation to diminish rapidly as the geometrical thickness of the clouds increases.

Conclusion

A new fast inverse algorithm that retrieves one meteorological parameter, sunshine hours, based on global horizontal solar irradiation was developed. The algorithm was tested using solar data measured at Makerere University, Uganda over a period of six years and it retrieved data with a correlation coefficient of 0.923 between the algorithm predicted and CSD 3 sunshine duration sensor measured data. We obtained an average value of 1.043 for the ratio of predicted to measured values, MnB and RRMSE of 0.043 and 0.394, respectively. The developed model predicts sunshine hours very well for days with higher solar irradiation, and this implies that the model developed works well for clear sky days. This showed that the algorithm is reliable, thus can facilitate determining sunshine hour values cheaply where it is not available, provided global horizontal solar irradiation can be obtained. From this study, it is recommended that similar algorithms be developed which retrieve sunshine hour values for days with global solar irradiation less than 10 MJm^{-2} to cater for cloudy day conditions.

Acknowledgement

Our deepest appreciation goes to the staff at the Department of Physics, Makerere University, Uganda for providing the solar irradiation and sunshine hours data. We highly appreciate Michael Musoke, a senior laboratory technician at the Department of Physics, Makerere University for his efforts in managing the equipment and downloading solar data measurements that were used in the study, and the German Academic Exchange Service (DAAD) for sponsoring the study programme.

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