The prediction of the usual solar irradiation in the Sahel using the artificial neural networks (case study: 50 MW power plant in Nouakchott)

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ABSTRACT

The development of a model for predicting meteorological variables using a physical approach was our solution for modeling a solar system, this modeling was carried out in two stages. The first step is to predict the meteorological variable (solar irradiation) at the plant level and the second step is to use a generated energy model to convert these irradiation forecasts into a forecast of the generated energy by the plant. In this study we modeled the solar irradiation curve of the Nouakchott power plant (50 MW) using artificial neural networks (ANN) which create adaptive identification methods and intelligent control laws based on the principal learning, which consists of memorizing previous results and generalizing future results, ultimately modeling the given system. The development of the curve is carried out by carrying out a series of experiments which made it possible to converge towards a methodology offering good precision, using the data measured from solar irradiation over two years at the level of the Nouakchott site. The evaluation of the solar irradiation forecasting model, by calculating the statistical parameters, made it possible to record a normalized average absolute error between 0.121 and 0.126 and a regression factor R (measures the correlation among output-target) with the aid of using 98.4% and 98.5% and the evaluation among specific present techniques in literature display the goodness of the proposed models.

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1. INTRODUCTION

The problem posed is directly linked to a need for modeling and forecasting to cover the energy demand of the Nouakchott electricity network. Thus, this contribution in this context is part of a strategy to be able to optimally manage energy resources linked to the Sahel. The strategy aims to propose a dynamic model making it possible to reproduce and anticipate the energy demand of a distribution network to compensate for part of the handicaps that we encounter, following the use of solar energy in the Sahel. For example, the data that are available are generally summarized in the form of insolation duration of a little less than 3900 hours of sunshine, with an energy per m² of the order of 5 Kwh/d considered as distribution over almost all the national territory of Mauritania and a little less than 2650 Kwh/m²/year. Not only is the existing solar data in the country and its surroundings insufficient to size solar installations on national soil. They are also insufficient to understand and predict the country's solar potential. Whereas, to carry out the sizing of photovoltaic systems, it is necessary to estimate their energy produced under continuous climatic changes. Therefore, climate changes should be predicted, in order to facilitate the control and monitoring of the PV system. But still, we must add the use of photovoltaic (PV) technology encounters the problem of the intermittency of the solar source (example: sunrise and sunset, the presence of clouds) [1], [2]. These changes, which are linked to the intermittency of the solar source, become complex if meteorological and geographical variables must be added (maximum temperature, relative humidity, duration of sunshine, cloud cover, latitude, longitude, and altitude) [3]-[5]. All this variability can make it more difficult to exploit and predict the power delivered to the electrical network. And in addition, the integration of PV energy in the energy market requires the development of accurate PV power forecasting models [4]. And finally, for AI models, studies [5], [6] reviewed artificial neural networks (ANN), fuzzy logic, genetic algorithms with a fairly complete state of the art for the part related to the prediction of sunshine data using artificial intelligence methods and more particularly by the ANN.

For all these reasons, researchers have proposed many technical methods to overcome these challenges. The first method is that of Rayleigh. It has been used by the authors of the articles for the evaluation of solar irradiation [3]-[6]. The second method is rather simple and it exploits empirical relationships between the clarity index (ratio of solar radiation on the earth's surface and that outside the earth's atmosphere) on the one hand, and the insolation ratio on the other hand. The disadvantage of these relationships is that they are valid only in the places where they were developed. For example, we find the Angstrom model [5]-[7]. The third method allows the prediction of solar radiation on the site whose data is available over time ($t + \Delta t$) from data that is known at time (t) [6]-[9]. The most recent is to use artificial intelligence techniques, such as the ANN, genetic algorithms (GA), fuzzy logic (FL) and many others will surely emerge [10].

Given the importance we wanted to give to prediction, it is essentially important to propose in this work the ANN technique, to overcome the problems mentioned above (intermittency of data and their insufficiency for dimensioning). In this context, it should be mentioned that the number of publications has experienced a significant increase in recent years, with a steady growth until 2022, when it reaches a value of more than 33 publications in 2020 [11]. This testifies to the growing interest of researchers in exploring AI in the context of all sciences where, it is possible to apply the ANN method, for example in environmental economics [3], [4] and in wind energy [12].

Besides, there are many ANN structures, such as multilayer perceptron (MLP), recurrent neural network (RNN), and radial basis function network (RBF) [4]-[7]. ANN is therefore a method that can model complex and non-linear systems due to the ability of the network to adjust flows. ANNs can be used to predict solar radiation, which can subsequently facilitate the management of the energy generated by a PV system [10]-[12]. It should be noted that significant prediction research has been conducted to have the prediction of solar energy using ANN techniques. These aspects are present in the literature, among which we find the identification of the model. Classification, function approximation, automatic control in the context of the increasing use of these ribonucleic acids or RNAs. It is possible to say that ANNs have been successfully developed to model different variables of solar radiation. Such techniques have been used for prediction which consists in predicting the solar radiation which will arrive on the sensor in the near future. This makes it possible to emphasize that these are mainly reference articles in the field of sunshine forecasting [13]-[15]. They give the RNA to generate hourly solar irradiance series [15]-[17]. These reviews give the daily clarity index, the hourly values of this same index for the previous hours, the difference between these indices and its maximum value and the time were used as input quantities of the RNA. In this sense, it is possible to achieve the integration of PV energy in the energy market by the development of accurate PV power forecasting models. Besides the prediction model, the selection of the appropriate optimizer can contribute to the increase of the accuracy of the predictions in an even larger area that affects other engineering fields [18]-[20].

Finally, in this introduction, it is possible to emphasize that the neural network can be considered, as an innovative forecasting framework, to improve the exploitation of production applications of existing solar systems on the ground. To size the photovoltaic generator, it will first be necessary to estimate its energy produced under continuous climatic changes. Therefore, climate changes should be predicted, in order to facilitate the control and monitoring of PV systems.

Therefore, in this paper, we aim to evaluate the ANN model to estimate solar irradiation data. Our main contribution in this study will be to present an approach that simultaneously estimates and forecasts solar irradiation in the Nouakchott area by means of a multi-task ANN with two outputs using the structure of the neuron network feed-forward. The multi-layer perceptron (MLP) model is optimized by an evolutionary algorithm. Indeed, the model uses an algorithm to measure the error and to evaluate the accuracy of the estimation of solar irradiation data.

2. METHOD
2.1. Neural network
ANN models appoint artificial intelligence strategies and are data driven; they examine and memorize a data structure and sooner or later simulate the structure. ANN are capable of examine key information styles inside a multidimensional information domain [21]. In a way, ANN mimic the getting to know method of a human brain and consequently do now no longer want function statistics approximately the system; instead, they examine the connection among input parameters and the output variables through analyzing formerly recorded data. This makes ANN perfect for modeling non-linear, dynamic, noisy data, and complicated systems. Further, ANN are precise for tasks involving incomplete data sets [22].

2.2. The neuron network, feed-forward, and structure
For Figures 1 and 2, the input gadgets are organized in distinct layers (reference to the vertical row of neurons) and are interconnected through weighted connections (synapses). Thus, Figure 1 suggests a feed-forward network which affords a function of its inputs and Figure 2 proposes a network of multi-layer neurons with enter gadgets and a hidden layer [23].

In addition, it is miles viable to expand a network of artificial neurons able to predicting or modelling an electricity device via network data (inputs). These data are device inputs and outputs to be expected to assist the community research the device. Thus, as shown in Figure 3, the studying of the network undergo the subsequent five steps: i) Weighting of inputs via way of means of parameters referred to as weight (W); ii) Summation of weighted inputs; iii) Calculation of neuron reaction via way of means of activation function; iv) Calculation of the error among the theoretical output and that calculated via way of means of the R.N.A; and v) Weight amendment to reduce error via way of means of a specific mathematical algorithm called learning algorithm.

In end of this part, it is far viable to mention that this activation function that became selected represents the switch characteristic to be able to join the weighted summation to the output signal. Indeed, the proposed mathematical version illustrates one of the most typically used activation functions. It is referred to as sigmoid function. It needs to additionally be referred to that in the technique of using the version through MATLAB, the weights are adjusted for you to assemble for every enter measured in the network with an output predicted. A quantity of 14 education algorithms had been invested for the improvement of the MLP network, the Levenberg-Marquardt backpropagation training algorithm (trainlm) had been used too, as shown in Figure 4.

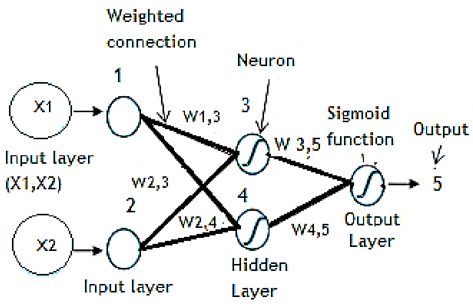

Figure 1. Three-layered feed-forward NN

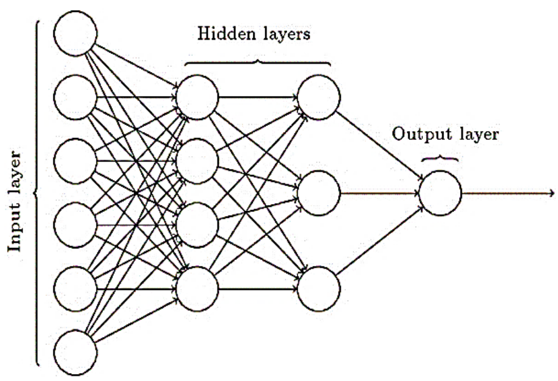

Figure 2. Network of multi-layer feed-forward NN

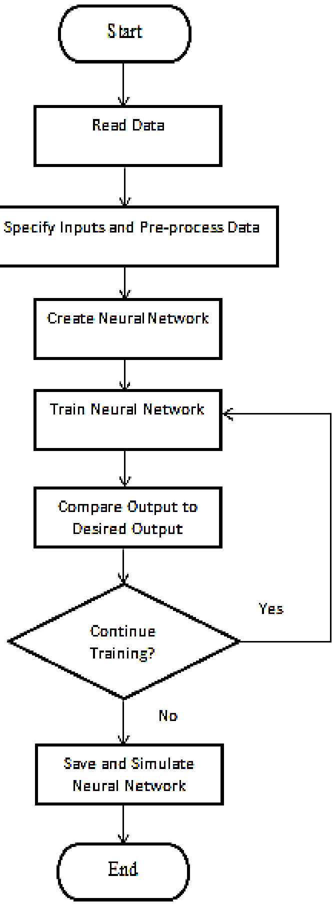

Figure 3. Flowchart of the MLP neural network implementation

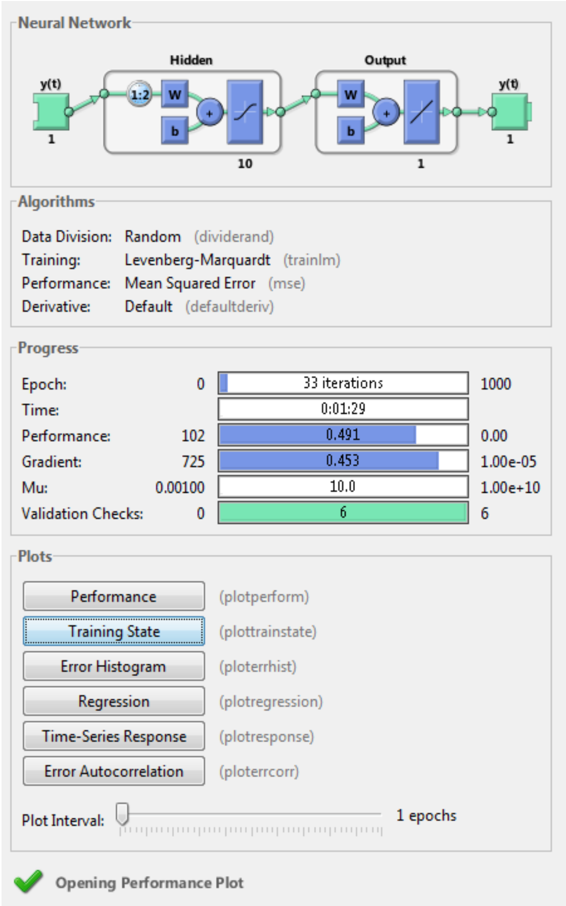

Figure 4. MLP network training window

3. DATA

Various factors can influence the production of photovoltaic panels such as temperature and humidity. Temperatures in the Sahelian region vary between 16 °C and 38 °C. The Sahelian regions are characterized by very high temperatures above 30 °C throughout the year and well above 40 °C during periods of high heat. These high temperatures combined on the one hand with a very variable relative humidity during the year and between 30% and 90% according to the seasons and with the strong ultraviolet or UV irradiation constitute restrictive operating conditions for the PV modules. Hence, in this part of the work, we presented the inputs of the model from which we can follow the evolution of temperature, humidity, and solar irradiation in the Nouakchott region during the years 2018 and 2019. The data used are provided by the National Office of Meteorology.

3.1. Temperature and humidity

From Figures 5 and 6 of the temperature variation in Nouakchott during the year 2018 and 2019, we found that during the dry season the maximum temperature varies around 30 °C, during the hot season the maximum temperature reached 35 °C in 2018 and 38 °C in 2019 and during the rainy season an increase in temperature was only observed in September (46 °C) in 2018 and 37.8 °C in 2019. And from Figures 7 and 8 which present the variation of humidity in Nouakchott during the years 2018 and 2019, we found that during the dry season, the maximum humidity reaches 74% in 2018 and 55% in 2019, during the hot season. The maximum humidity reaches 89% in 2018 and 87.5% in 2019 and during the wet season there is an increase in humidity 92% in 2018 and 85.9% in 2019.

3.2. The variation of irradiance at the 50 MW plant during the hot, wet, and dry season

Figure 9 shows us the rhythm of the intermittency of irradiation at the level of the plant during the change of seasons (hot, humid, and dry season) on a sunny and cloudy day. the variation in irradiation due to climate change which subsequently generates a variation in production, we have retained that the parameters influencing moreover the production of the plant are the temperature and the sunshine during the day, since the site of the plant is well ventilated with high humidity, and that the days with a cloudy passage (less sunshine), are the most disturbed days. We can therefore conclude that for each month and during each season, the drop in temperature and the cloudiness generates the disturbance of the power plant network.

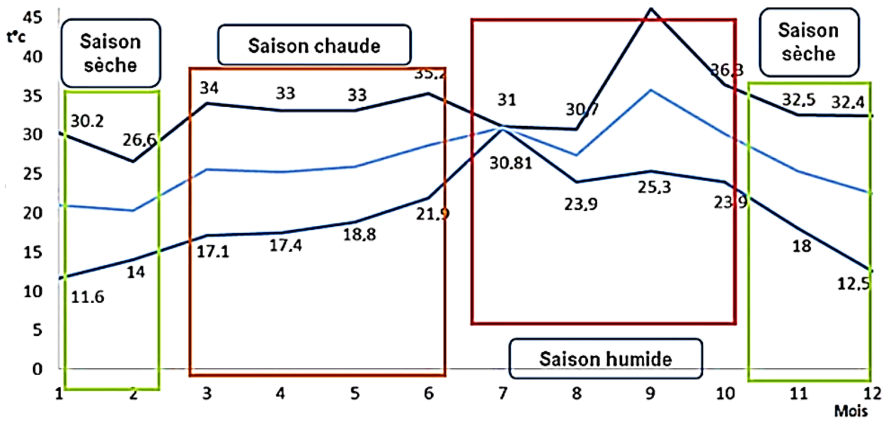

Figure 5. Temperature variation (Nouakchott-2018)

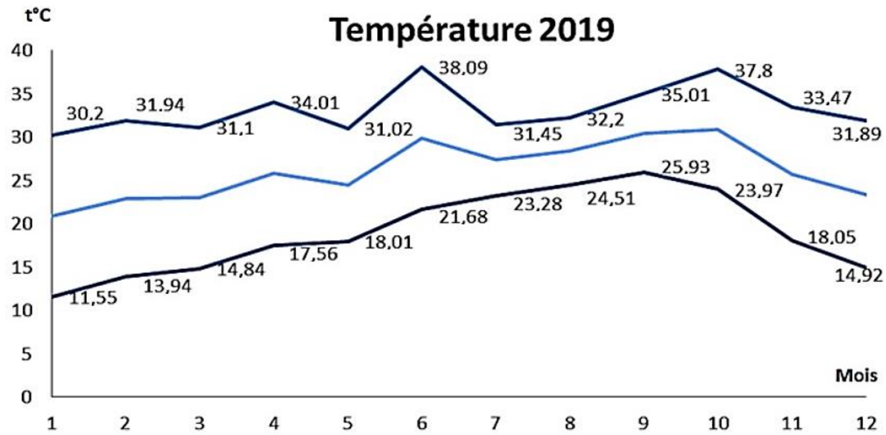

Figure 6. Temperature variation (Nouakchott-2019)

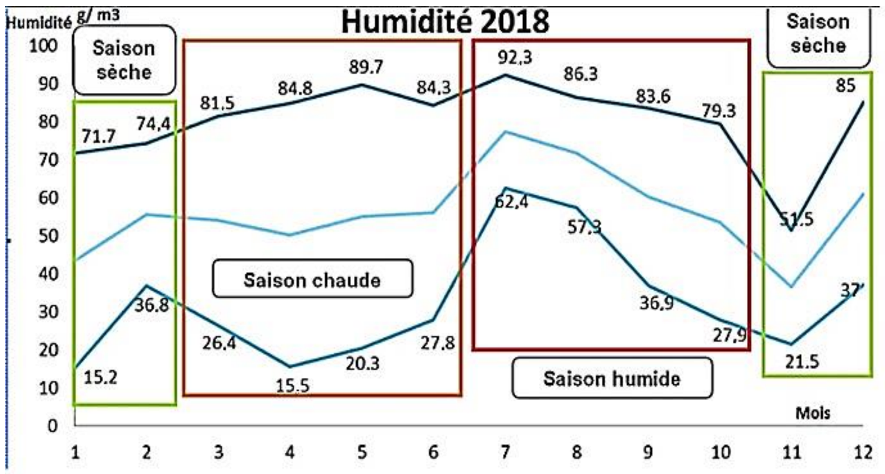

Figure 7. Humidity variation (Nouakchott-2018)

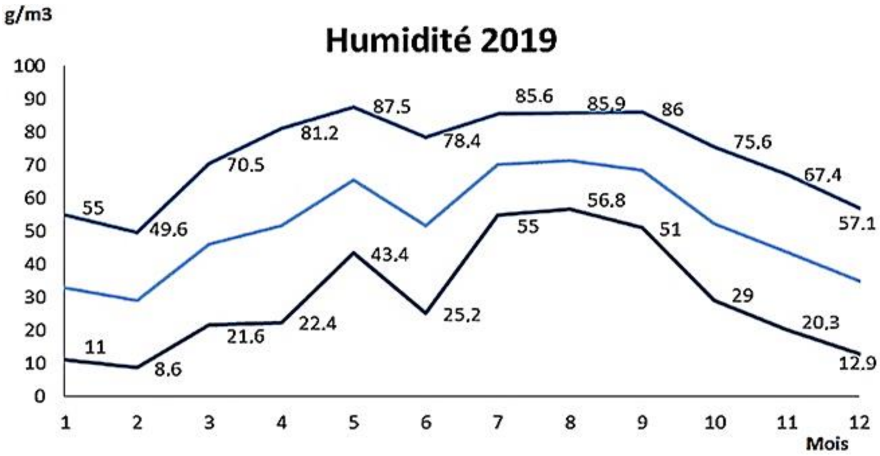

Figure 8. Humidity variation (Nouakchott-2019)

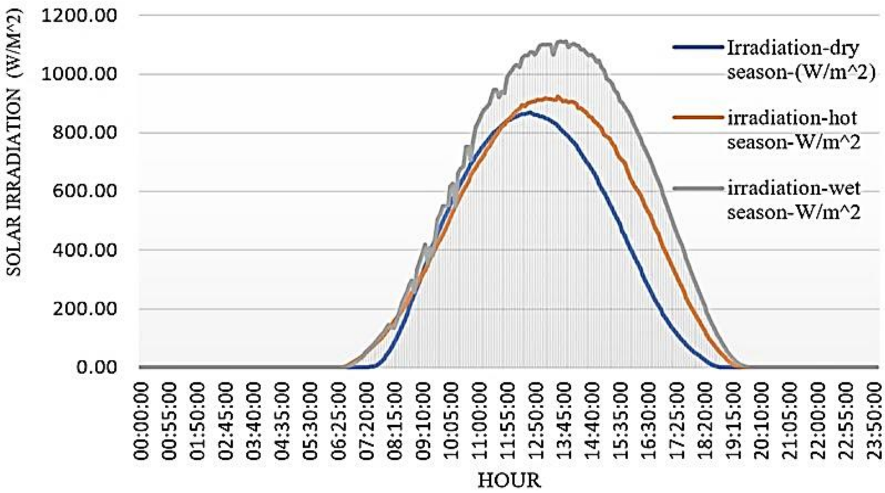

Figure 9. The variation of irradiance

4. RESULTS AND DISCUSSION

4.1. ANN prediction

First, the studies targeted on ANN models to pick out the network structure that extra as it should be simulates who paperwork the hidden layer. The statistic used for this validation is the simulated mean squared error (MSE) primarily based totally at the measured data for the equal variable. This makes it feasible to reply withinside the quick time period and withinside the long time as a way to discover a version able to fixing the hassle connected to the variety of solar production that is the principal hassle which slows down the evolution of solar systems. Within the framework of this conclusion, pointers may be drawn, following the nonlinear character which may be trapped in a neighborhood minimal in which the performances of the networks are truly beneath Neath optimal.

To keep away from this, entice in a nearby minimal, its miles proposed: i) Modify the network studying step to push the network out of the nearby minima and on the equal time, we control to modify the scale of the error zone; ii) The training of the equal network from numerous selections of preliminary weights, to then maintain best the exceptional of them; and iii) The range of neurons withinside the hidden layer become various from 1 to 10, and 600 training classes had been executed with a one-of-a-kind initialization on every occasion for every of those architectures; then we recorded the value of the synaptic weights which offers the minimal MSE primarily based totally at the training.

According to the results found by this simulation model, it can be seen that this model has achieved good accuracy in terms of estimated values of solar irradiation. Figures 10-12 which represent a comparison between the actual and predicted values of solar irradiation in the Nouakchott region during the hot, dry, and wet season, we see that the two histograms (blue and red accented) in the three graphs are almost confused with regard to the dry and wet season and a small difference with regard to the hot season which reflects the great climatic fluctuations of our country during this season.

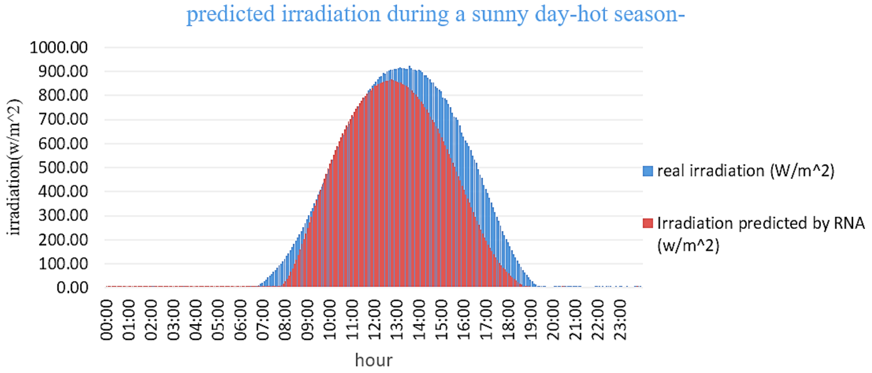

Figure 10. Comparison between the reel irradiation and the predicted (hot season)

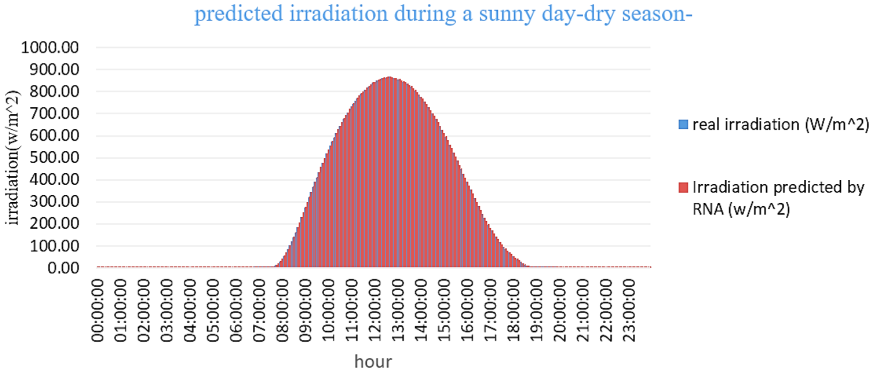

Figure 11. Comparison between the reel irradiation and the predicted (dry season)

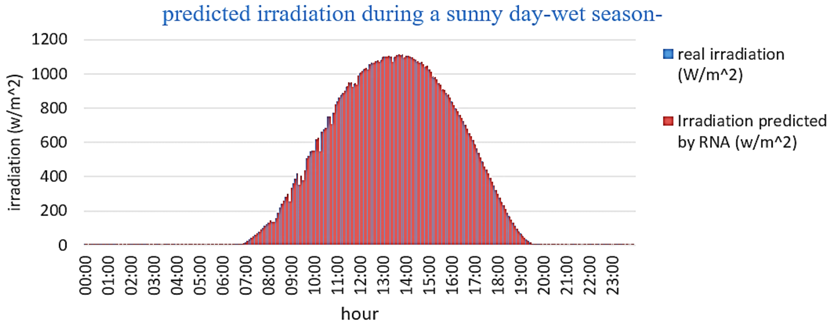

Figure 12. comparison between reel and predicted irradiation (wet season)

In addition, Table 1 illustrates the overall performance of the prediction version shown. The prediction version found out the mastering of the energy system and it allowed to generalize the unsatisfied data of the system with low mean squared error (MSE) simulation errors that attain on average for the actions (training, validation, and tests) a value which varies among 1.21% and 1.26%. This model affords the very best overall performance with maximum determination coefficient (R^2) of 0.9851 and minimal MSE 0.121. In our forecasts, global solar irradiance data from the current day and days in the back of had been used. We acquired models whose predictive overall performance has stepped forward as compared to traditional models (weighted moving average with two-day lag, linear regression, and Fourier analysis). The predictive development of ANN models is acquired while the input variable is the day of the year, due to the fact the simulation refers back to the time of year while it occurs. In this situation, it may be visible that the use of solar radiation data with more day's lag does now no longer enhance predictive conduct models. Moreover, any other manner to enhance ANN models is to apply the daily luminosity index, which is an indicator of the daily proportion of solar radiation absorbed and scattered in the atmosphere, with which the best simulation fits are obtained. compared to conventional models.

Table 1. Statistical error parameters of developed MLP

Inputs	Target values	MSE	R^2
Training	21843	0.123107	0.98483
Validation	4680	0.126829	0.98435
Testing	4680	0.121206	0.98518

4.2. Comparison

In order to assess and carry out the first-class of the proposed ANN for the hourly solar irradiation estimation model, a comparison phase is essential among the present models withinside the literature and the model proposed on this article. For this purpose, 10 models had been examined towards our model, which can be summarized in Table 2. The fundamental goal is to check the values of R^2 for different models and examine it with those who had been acquired with our model. These models we're speaking approximately are: MLP, neural network auto-regressive model with eXogenous inputs (NNARX), support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS), and radial basis function neural network (RBFNN). It is observed that for specific models, they are proposed in in [24]-[28]. On the alternative hand, for the hybrid models with algorithm optimization, they are in [29]-[33]. In this context, it needs to be stated that the R^2 value become decided on as the error measure for every model. We discover that the comparison results virtually show the robustness and quality of the proposed model for estimating the solar irradiation time series. Because, it offers an R^2 which has a value of 98.48%. This value is excessive in comparison to different models. From those results, we will conclude that the accuracy of solar radiation estimation relies upon on several factors following the hierarchy of the model through growing the extent of the layers and growing the neurons for every layer for every step with the proper gaining knowledge of the model.

Table 2. Artificial intelligence methods for prediction of solar radiation from the literature and this study

Reference	Location	Model used	Inputs used	R^2
Ozgoren *et al.* [24]	Turkey	Feed forward back propagation	Mean land surface temperature	0.9936
Mohammadi *et al.* [25]	Tabbas, Iran	ANFIS	Number of days	0.9777
Quej *et al.* [30]	Yucatán Peninsula México	SVM, ANN, ANFIS	Daily maximum and minimum air temperature, extraterrestrial solar radiation and rainfall	0.6684 0.6483 0.6478
Belaid and Mellit [32]	Ghardaïa, Algeria	SVM, MLP	Ambient temperature, maximum sunshine duration, extraterrestrial solar radiation	0.9830 0.9545
Moghaddamnia *et al.* [33]	Brue catchmet, UK	MLP, extreme learning machine artificial networks (ELMAN), NNARX, ANFIS	Hourly information of temperature, rainfall, atmospheric pressure, and wind velocity	0.7349 0.7798 0.8199 0.6948
Ağbulut *et al.* [29]	Turkey (Kırklareli, Tokat, Nevsehir and Karaman)	ANN, SVM, DL, Kernel and nearest-neighbor (k-NN)	Max and min temperature, extraterrestrial irradiation, and sunshine hours cloud cover	From 0.855 to 0.936
Woldegiyorgis *et al.* [26]	Ethiopia	Feed-forward neural network (FFNN)	Temperature, sunshine duration, wind speed, rainfall, and relative humidity	0.7998
Geetha *et al.* [31]	Tamil Nadu, India	ANN (levenberg-marquardt (LM), scaled conjugate gradient (SCG), resilient backpropagation (RP)	Wind speed temperature humidity	0.8790
Bounoua *et al.* [27]	Morocco	MLP(FFNN)	Wind speed temperature, humidity	0.9254
Dhiaeddine *et al.* [28]	Algeria	Feedforward neural networks	Clear sky and the top of atmosphere solar irradiation, temperature, sun height, and wind speed	0.9554

5. CONCLUSION

This study confirms the ability of neural networks to accurately predict solar irradiation, and the predicted data can therefore be used in the absence of measurements. The results indicate that neural network modeling seems promising for the evaluation of the potential of the solar resource as has already been indicated for the evaluation of the potential of the wind source. It became verified that feed-forward neural networks received excellent prediction accuracy of the meteorological variable (wind pace and sun irradiance). This helps meet both short-term and long-term predictions. The result which was obtained can be used in terms of energy planning by providing the previous solutions for predicting (by feed-forward neural network) the wind speed and the solar irradiation then the energy produced in the short term. term. This prediction can play a role in stabilizing the electricity network and further facilitating the insertion of renewable energies into electricity networks. Indeed, such mastery of the input parameters of the solar system will allow good prediction in the future, as it will also make it possible to increase the percentage of renewable energy injected into our country's network. It must also be said that this mastery of predicting the input parameters of the solar system will help operators to operate better, as it will help to limit electricity load shedding in the city of Nouakchott.

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