Nano World Journal

https://doi.org/10.17756/nwj.2023-s5-058

Research Article

Open Access

Solar Irradiation Forecasting with the Application of Nanotechnology

Priti Sharma[1], Govind Murari Upadhyay[2*], Shalendra Kumar[3], Rakhi Chawla[3] and Pramod Kumar Soni[2]

[1]*Department of IT, JIMS-VK, Guru Gobind Singh Indraprastha University, Delhi, India.*
[2]*Department of Computer Applications, Manipal University Jaipur, Jaipur, Rajasthan, India*
[3]*Department of Computer Science, NDIM, Guru Gobind Singh Indraprastha University, Delhi, India*

[*]Correspondence to:
Govind Murari Upadhyay
Department of Computer Applications,
Manipal University Jaipur,
Jaipur, Rajasthan, India.
E-mail: govind.upadhyay@jaipur.manipal.edu

Received: October 20, 2023
Accepted: December 22, 2023
Published: December 28, 2023

Citation: Sharma P, Upadhyay GM, Kumar S, Chawla R, Soni PK. 2023. Solar Irradiation Forecasting with the Application of Nanotechnology. *Nano World J* 9(S5): S319-S325.

Published by United Scientific Group

Abstract

In the last three decades, the human population has rapidly increased and continues to do so leading to a severe impact on the requirement of energy needs. Nanotechnology is a technology of opportunity that offers a wide variety of resources to address the issues associated with energy as smaller than 100 nm components and appliances present new opportunities for energy capture, storage, and exchange. The high energy demand has started a quest for alternative renewable sources of energy, especially solar energy can satisfy the growing power demands without exhausting conventional resources. Different types of nanomaterial are used to harness solar energy to meet the required needs and solar irradiance (SIR) is a crucial component of solar applications. The precise forecasting of SIR helps in the efficient management of solar energy systems and is of prime importance task. In this study, different technology that harnesses SIR with the help of nanomaterials has been discussed and further, a deep learning (DL) based model is designed to forecast the amount of solar energy that will be produced at a given site. This study uses NASA's solar irradiation historical data (from the date 1/1/2010 to 31/12/2021) of India's North Central Region (NCR). The experiment results depict the higher performance of the proposed hybrid model as compared to the ML (machine learning), LSTM and GRU individually on different parameters such as MSE (mean squared error), RMSE (root mean squared error), MAE (mean absolute error) and R^2.

Keywords

Nanotechnology, Nanomaterial, Solar irradiation, Deep learning, LSTM, GRU, Machine learning

Introduction

SIR performs a vital role in maintaining the ecology of the earth. The alteration in ecology will trigger a chain of amendments in atmospheric and external temperature, hydrological life cycle, and carbon sequestration. These variations in the atmosphere will impact the overall socio-economic development of society. SIR is the principal source of the sun's energy on our planet, and it is a clean, renewable source of energy like solar power which has tremendous potential for reducing our dependence on fossil fuels as well as our role in climate change. Solar power was predicted to increase the global renewable energy capacity by 133 GW (+19%) in 2021 [1], a total of 849 GW, this represents 28% of the sustainable energy portfolio and as per international energy global photovoltaic (PV) of 1370 TWh in 2022 with an increase of 270 TWh (26%). The non-dispatch ability or unreliable nature of PV generation, which is reliant on meteorological factors, most notably cloud dynamics, poses several challenges to the operation of electricity networks with substantial penetrations of PV generation. Given that variable PV generation can result in power flow inversion, which results in voltage and frequency changes as well as an imbalance among both energy supplies. The rising cost of fossil fuels and the declining cost of PV system integration has been accelerated by increased PV panel production [2].

The phrase "nanotechnology" is the partition, amalgamation, and distortion of material by one molecule/atom and in terms of size particles having features as large as 100 nm are considered nanoscales as shown in figure 1. Nanotechnology provides ways to develop new industries that are cost-effective and lead to sustainable growth. In the energy sector, nanotechnology has the potential to contribute significantly to utilizing the energy generated from the sun in storing and generating efficiently. Solar cells are considered mainstream renewable energy resources as they are available at less cost as compared to other resources. Solar cell technology can be used to harness solar radiation with greater efficacy and satisfy the global clean energy requirements. The nanoparticles have played a greater role in harnessing solar energy and this development is shown in figure 2.

One of the most important sources of renewable energy is PV systems which are simply solar-powered frames that generate electricity from sunlight [4].

Role of nanotechnology in harvesting solar energy

Nanotechnology can play a significant role in hosting the solar system to fulfill the sustainable energy requirements with respect to preservation, storage, etc. Nanotechnology can be used to achieve the following objectives. Modifying the interface of light with materials and assisting the uses of low-cost semiconductors in devices such as PVs. Designing effective photocatalysts for the transformation of the sun's energy into chemical fuels. Conversion of various forms of energy to improve power consumption and reduce wastage.

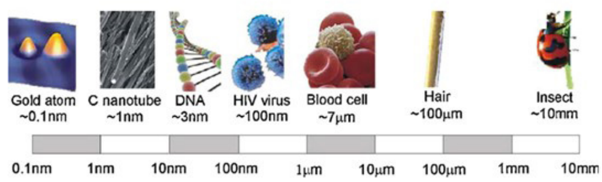

Figure 1: Length of real material and nanomaterial [3].

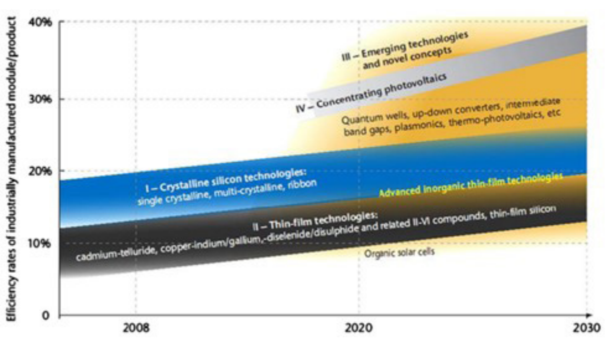

Figure 2: Development in solar cell technology [5].

Use of nanotechnology in designing solar cells

Nanotechnology is widely used in various phases of solar systems such as active and passive solar systems and storage systems. Active solar systems convert the energy from the sun into the different forms of energy for which they use electrical or mechanical equipment. Solar collectors are active solar cells that are based on nanofluids such as carbon nanotubes, Al_2O_3 and water-TiO_2 for the effective transmission of heat. It has been observed that there is an improvement of 28.3% in efficacy as of water.

Fuel cells (type of active solar cell) have low emission and high efficacy and are based on electro-catalyst or membrane materials such as proton exchange membrane fuel cells, methanol fuel cells, and Nafion membrane. Solar PV is one of the most popular active solar cell types which directly converts solar energy into either heat or electricity at the same time. The solar PVs are designed using semiconductor materials and nanofluids for cooling systems. A hybrid PV system is designed using $P_3HT/Cds/CSDE/TiO_2$ nanorod cell array.

Forecast of solar energy for solar cells using SIR

The output of PV can be forecasted using SIR using various predictive modeling techniques described in figure 1. The forecasted output can be utilized to enhance power grid management and planning for supporting various applications [6]. To effectively manage energy reserves and follow loads, forecasts of solar irradiation over the next several hours are required.

The SIR time series data can be used for quantitative forecasting, and we can utilize historical information to anticipate future samples. On average, SIR is believed to be consistent for instance, in any given year, summer has the highest monthly average solar irradiation while winter has the lowest. Yet the time series data is inherently unpredictable and strongly influenced by the passing of clouds [7] and other atmospheric factors. The expansion of renewable resources and the necessity of upgrading the current electric system are both prompted by the uncertainty of the price and availability of fossil fuels and the public's increasing awareness of the dangers of climate change. The use of renewable energy sources has the potential to provide numerous monetary and societal gains. However, problems, such as intermittent, sometimes arise when trying to incorporate these sources into the electric power grid. As a result, forecasting methodologies can help reduce the intermittent nature of the services by providing consumers with insight into future trends and enabling them to take precautions accordingly [8].

Direct measurement of SIR is the oldest and most accurate method for SIR acquisition, but its uses are limited by the cost of instruments and large landscape area [9]. Along with these instruments, different types of computing methods are also used for determining SIR namely, physical, statistical, empirical, ML and DL based models as shown in figure 3. The physical models are based on representing local physical characteristics by correlation equations and achieve high accuracy but require many parameters that are hard to obtain [10, 11].

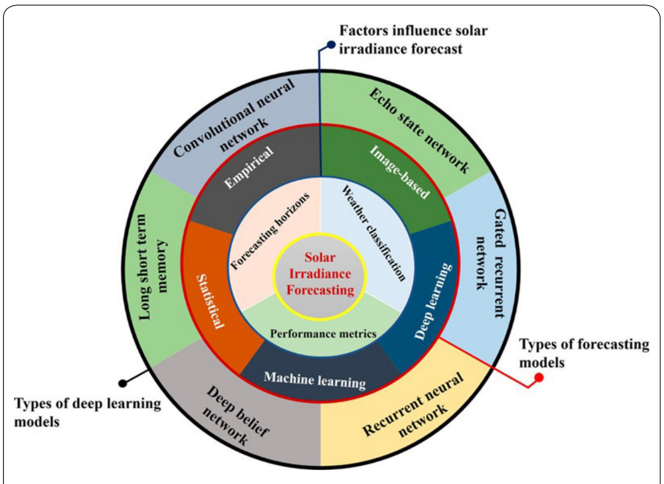

Figure 3: Models used for prediction of SIR [2].

The empirical methods utilize geographical meteorological parameters individually or in combination [12] to model the SIR data. The various researchers are motivated to combine internal and external inputs to improve the prediction performance for SIR by the significant correlation between SIR and some meteorological indicators. Most of them, however, make their decisions regarding exogenous input data intuitively, either by experimenting with different input variable combinations and selecting the one that results in the lowest amount of forecasting error or by using constrained methodologies like Pearson's coefficient of correlation, that essentially only recognizes linear relationships among variables. The main parameters used by researchers to establish the empirical relation include temperature [13], sunshine [14], and cloudiness [15]. The performance of empirical models hampers due to regional factors which degrade their performance. The information about SIR can also be forecasted using high-resolution remote sensing images [16, 17]. The major advantage of remote sensing image-based SIR forecasting is their coverage of large areas and cloud information, but the image-based method suffers from issues such as the availability of high-resolution remote sensing images and computational overhead in image processing tasks.

In recent years due to enhancements in computation facilities ML techniques have gained popularity and surpassed the model discussed above over time because of their superior capacity to identify nonlinear associations. ML-based SIR forecasting studies have been designed by various researchers which include support vector machine (SVM), artificial neural network, Random Forest, etc. The SVM-based regression (SVR) model is built to predict the daily SIR furthermore the performance of different kernel functions of SVR is analyzed in the prediction of SIR [18]. However, this method suffers from the issue of overfitting which is resolved by a hybrid approach using fuzzy regression functions along with SVR [19]. The artificial neural network-based framework is designed to predict an hourly solar radiation-based prediction system in Trabzon province it is based on a cause-effect relationship [20].

In the last 5 years, deep neural networks have gained popularity as these networks have excellent feature extraction capabilities as compared to ML-based techniques. Furthermore, the DL can handle the noise from irrelevant data and establish non-linear connections. A deep neural networks-based model named SIPNet is proposed for the prediction of SIR, it uses features of the LSTM model to handle the unsteadiness of PV output [21]. A hybrid model of CNN and LSTM model is designed to predict SIR of different time stamps and the model performs better than ML-based techniques [22, 23]. DL and adaptive portfolio theory-based technique is used to predict the SIR from 12-year hourly interval data [24]. Similarly, a hybrid framework consisting of CNN and GRU is designed to predict SIR [25]. A CNN model is used to delineate cloud features which in turn are used to predict SIR and results are more promising than direct methods [26].

By extensive literature survey, it has been observed that DL-based method has promising results as compared to ML and other traditional methods. But the DL-based model also suffers from the issues of (i) Handling 1-D data directly as data is collected from different geographical sites and features. (ii) Difficulty in generalization of the model to fit the data. In this work, to resolve these challenges a novel framework based on stacking of LSTM and GRU is proposed to predict the levels of radiation. The major objectives of the proposed work are as follows: (i) Highlight the importance of nanotechnology in the development of sustainable development of energy resources (ii) Development of a hybrid model based on DL technologies to forecast the SIR of the NCR region of India using historical data of 10 years. (iii) The hybrid model used data from multiple cities of NCR regions across the span of ~250 km (iv) The performance of the model is accessed on different evaluation metrics. The remainder of the paper is structured as follows, the material and methodology used for the study are described in Section 2. The experimental results are described and discussed in Section 3 and finally, the work is concluded in Section 4.

Materials and Methods

In this section, the dataset, methodology, and parameters used to evaluate the performance are described. The proposed method is divided into three stages namely data-collection, pre-processing of the data, designing of a hybrid deep learning model to produce reliable predictions or forecasts of SIR, and finally performance evaluation. The flow chart of the proposed approach is described in figure 4.

Data collection and description

The dataset used in this work is obtained from website (https://power.larc.nasa.gov/data-access-viewer/) [27] for the seven cities (Faridabad, Ghaziabad, Gurgaon, New Delhi, Panipat, Rohtak, and Sonipat) of NCR of India. The data is comprised of 30681 rows and 20 columns as features, and every feasible criterion is computed after the data is collected. For the prediction of SIR precisely, the proposed hybrid model is trained on time series data collected for the period of 01/01/2010 to 31/12/2021. The dataset consists of various features such as WS2M, PS, Prectotcorr, QV2M,

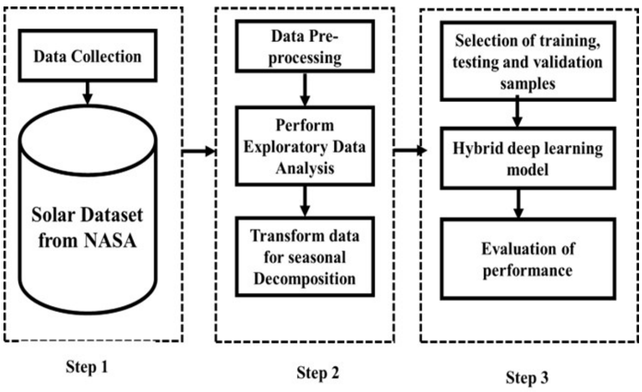

Figure 4: Proposed methodology.

RH2M, T2MWET, T2M, ALLSKY_KT, ALLSKY_SFC_SW_DWN, CLRSKY_SFC_SW_DWN, TS, T2MDEW, ALLSKY_SFC_UVB, ALLSKY_SFC_UV_INDEX, ALLSKY_SFC_UVA, and WS10M, the description of these features along with their unit of measurement is presented in table 1 and correlation between various features in shown in figure 5.

Data pre-processing

Data preprocessing involves filtering of data, detection, and elimination of null, nan values, and missing values [28]. This method uses a statistical technique to calculate the average value (the middle point) in a set of data. The data will be first sorted ascendingly, and then the median is found from there [29].

$$\text{Median} = \frac{(n+1)}{2}\text{th value} \tag{1}$$

The number of observations, denoted by n. To find the middle number, one must first arrange the data from least to greatest.

Furthermore, the dataset also suffers from outliers which is a data point that is noticeably higher than or lower than its neighbours and the rest of the data points in the dataset. This can be eliminated by using a quartile which can be obtained by dividing the total number of pieces of data into four approximately equivalent halves, the third quartile statistical method can be used to exclude outliers from the data.

Proposed hybrid framework

In this work, we employ a stacked framework consisting of (LSTM and GRU-based neural networks trained on time series data for SIR prediction, drawing inspiration from both recurrent neural networks and simple dense networks. Our proposed model makes use of a hybrid approach, incorporating LSTM shown in figure 6 and GRU shown in figure 7 into a structure comprised of dense layers and Activation functions.

Recurrent Neural Network (RNN) models such as LSTM [30], 1D-CNN, and GRU [31] perform well on time series data to forecast and predict accurately over a period. LSTM network comprises input, output, and hidden layers and its basic cell structure is shown in figure 7. The time-variant input features $I(t) \in R^{FxX}$ are processed by the hidden layer that has an input, output, and forget gate. The input features and memory blocks are updated by X time and generate the current state vector $R(t) \in R^{n}$. The output vector $Y(t) \in R^{n}$ depends on the earlier step state vector $R(t-1) \in R^{N}$ and $Y(t) \in R^{N}$. At forget layer sigmoid function is used to decide to update the current cell vector which can be represented as follows:

Table 1: Features details.

Name	Description	Unit of measure
WS2M	Wind speed at 2 meters	(m/s)
PS	Surface pressure	(kPa)
PRECTOTCORR	Precipitation corrected	(mm/day)
QV2M	Specific humidity at 2 meters	(g/kg)
RH2M	Relative humidity at 2 meters	(%)
T2MWET	Wet bulb temperature at 2 meters	(C)
T2M	Temperature at 2 meters	(C)
ALLSKY_KT	All sky insolation clearness index	(dimensionless)
ALLSKY_SFC_SW_DWN	All sky surface shortwave downward irradiance	(kW-h/m²/day)
CLRSKY_SFC_SW_DWN	Clear sky surface shortwave downward irradiance	(kW-h/m²/day)
TS	Earth skin temperature	(C)
T2MDEW	Dew/frost point at 2 meters	(C)
ALLSKY_SFC_UVB	All sky surface UVB irradiance	(W/m²)
ALLSKY_SFC_UV_INDEX	All sky surface UV index	(dimensionless)
ALLSKY_SFC_UVA	All sky surface UVA irradiance	(W/m²)
WS10M	Wind speed at 10 meters	(m/s)

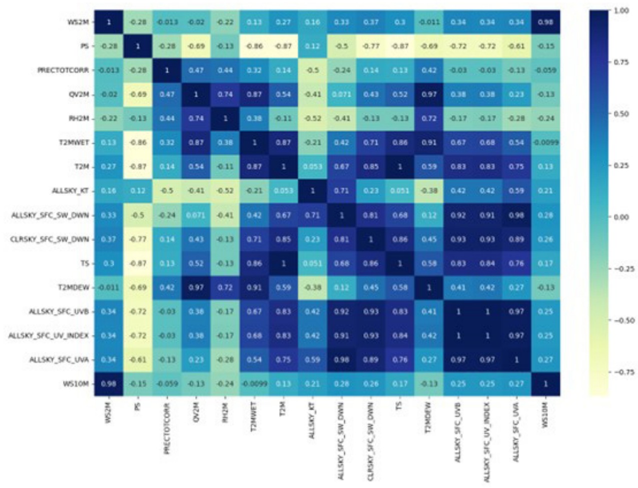

Figure 5: Correlation analysis of SIR and features.

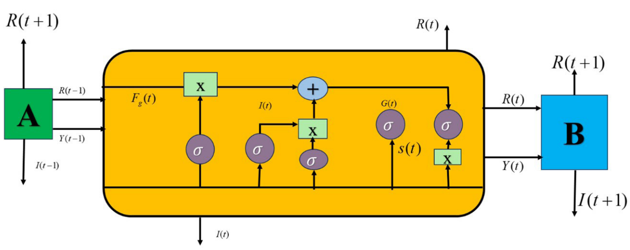

Figure 6: Architecture of cell of LSTM.

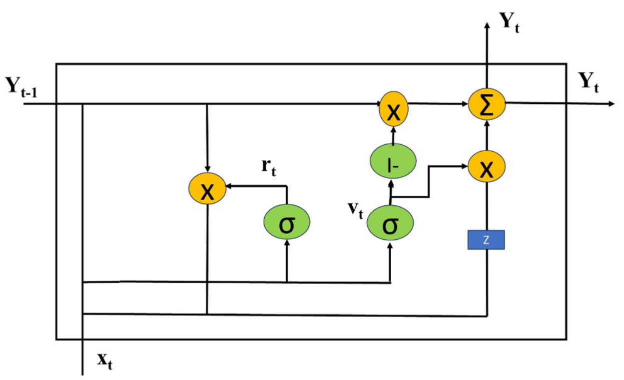

Figure 7: Architecture of cell of GRU.

$$I_g(t) = \sigma\left[\omega I(t) + \mu Y(t-1) + b\right] \tag{2}$$

The output of the intermediate cell is calculated at the thin layer (φ) as,

$$s(t) = \varphi\left[\omega I(t) + \mu Y(t-1) + b\right] \tag{3}$$

Where, $P_t = \sigma\left[W_p\left(Y_{t-1}x_t\right) + b_p\right]$ and b is the weight metric and bias input to forget gate.

LSTM eliminates the issue of a vanishing gradient, and the sigmoid function is multiplied by each of these gates individually. Whenever the value of a gate is 0, it is assumed that the data does not contain any useful information and is thus discarded.

Whereas the GRU [32] is like LSTM but computationally efficient as a single state vector is used instead of both and can store and modify information stored in two gates (update and reset). This reduces the matrix multiplications are makes it computationally efficient when we have large training data. The basic GRU cell is shown in figure 8. At time t, when current state input (R_t) and previous state output (Y_{t-1}) are used to calculate the update gate as:

$$P_t = \sigma\left[W_p\left(Y_{t-1}x_t\right) + b_p\right] \tag{4}$$

and the reset gate (r_t) obtained by merging of forget and input gate is obtained as:

$$r_t = \sigma\left[W_r\left(Y_{t-1}x_t\right) + b_r\right] \tag{5}$$

The candidate state (h_t) is computed as $h_t = \tanh\left[W_h - \left(r_t Y_{t-1}\right)x_t + b_h\right]$ where σ(.) is the sigmoid function, W_j and b_j $j \in (p, r, h, y)$ are corresponding weighed matrix and bias. Which (p_t) X_t the reset gate uses current state input (X_t) to find the data stored in the previous state (h_{t-1}) can be avoided to calculate candidate state (h_t) and the output of GRU is calculated as:

$$Y_t = \left(1 - p_t\right)Y_{t-1} + p_t.h_t \tag{6}$$

This work proposed a hybrid approach of LSTM and GRU model to address this issue. Both traditional and cutting-edge deep learning methods were utilized due to the time series and regression components of our dataset. To enhance the SIR forecast accuracy and decrease prediction time, in this work a hybrid model based on stacking of LSTM -GRU is proposed. The architecture of the proposed model is shown in figure 8. The proposed model consists of four hidden layers two for each LSTM and GRU each layer has 100 neurons. The output of the first two LSTM layers is passed to GRU during training. The large number of parameters generated by LSTM layers are reduced by GRU layers and makes the model computationally efficient. The hyperparameters (learning rate, optimizer, loss function etc.) used by the proposed hybrid model are presented in table 2.

Performance evaluation metrics

The performance of the proposed hybrid model is evaluated on different statistical parameters such as MSE, RMSE, MAE, and R^2 all of which are determined by comparing the difference between an anticipated result and an actual value [33]. These metrics can be calculated as follows:

$$MAE = \frac{1}{z}\sum_{m=1}^{z}\left|y_m - \hat{y}_m\right| \tag{7}$$

$$MSE = \frac{1}{z}\sum_{m=1}^{z}\left|y_m - \hat{y}_m\right|^2 \tag{8}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{z}\sum_{m=1}^{z}\left|y_m - \hat{y}_m\right|^2} \tag{9}$$

$$R^2 = 1 - \frac{\frac{1}{z}\sum_{m=1}^{z}\left(y_m - \hat{y}_m\right)^2}{\frac{1}{z}\sum_{m=1}^{z}\left(\left|y_m - \hat{y}_m\right|\right)^2} \tag{10}$$

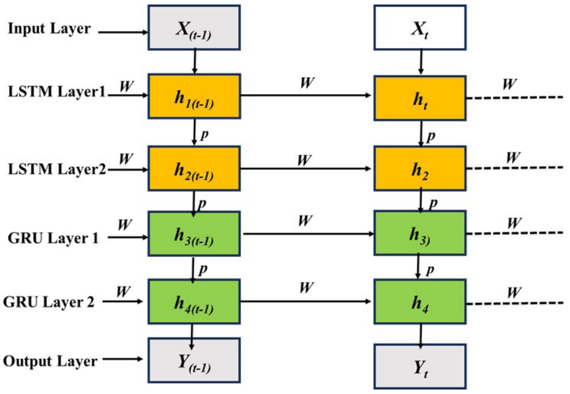

Figure 8: Architecture of proposed hybrid model.

Where, $y_m, \hat{y}_m$, and Z is the real SIR, predicted SIR and total number of samples of SIR.

Results and Discussion

The experiments are performed in Google Colob's environment using Karas with TensorFlow in the backend and Adam as an optimizer on GPU NVIDIA 1650 GTX with 16 GB of RAM. The experiments are performed on historical data collected from different cities of the NCR region. The proposed model first uses two LSTM layers and has a large number of parameters then the model superimposes two GRU layers which increase the performance of the proposed hybrid model by reflecting prediction accuracy, computational time and multiple factors expansively. The training data is divided into training and validation samples using the k-fold validation technique. The performance of the proposed hybrid model is compared with different DL models.

Comparison with DL models

To assess the efficiency of the proposed hybrid model, the empirical results are matched with other RNN-based DL models such as LSTM and GRU and the results are summarized in table 3. The LSTM and GRU model with the dense layer having 100 neurons and hyperparameters are the same as used in the proposed hybrid constant as presented in table 2 are implemented for performing intuitive comparison. The proposed hybrid model has obtained the best results as compared to LSTM and GRU models in all evaluation metrics. In the MSE parameter the proposed model has obtained 0.0611 as compared to 0.0892, 0.0987 of LSTM and GRU respectively and the LSTM model has performed worst. The hybrid model has an RMSE of 0.2437 which is far better than the LSTM of 0.2987 and GRU of 0.3142. Similarly, the proposed model has obtained the best results in MAE and R^2 metrics as compared to counterpart models and the GRU model has obtained the worst results in MAE and R^2. The loss occurring during the training and validation phase of the proposed model and counterpart models is shown in figure 9.

By investigating the experimental results, it has been observed the proposed hybrid model has outperformed the traditional ML and DL models. The proposed hybrid model has observed better performance in all evaluation metrics for SIR forecasting.

Table 2: Hyper parameters used.

Name	Type of parameter
Model	Sequential
Type	Recurrent neural network
Approach	Hybrid (LSTM + GRU)
Neurons	150,100,1
Activation	Relu
Learning rate	0.00001
Loss	MSE
Optimizer	Adam

Table 3: Comparative assessment of DL models with the proposed hybrid model for SIR forecasting.

Models	MSE	RMSE	MAE	R^2
LSTM	0.089	0.2987	0.2415	0.9942
GRU	0.099	0.3142	0.2501	0.9937
Hybrid model	0.061	0.2437	0.1957	0.9956

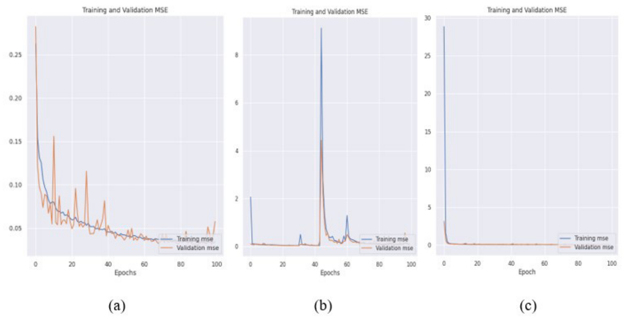

Figure 9: MSE loss during training of DL models **(a)** LSTM model, **(b)** GRU model, and **(c)** Proposed hybrid model.

Conclusion

In this work, the role of nanotechnology in harnessing solar irradiance to meet sustainable energy needs is discussed. Furthermore, a hybrid deep neural network method to forecast near-term SIR. The performance of the hybrid models is compared with the existing DL models on different evaluation metrics. The proposed model has obtained better performance as compared to ML techniques such as SVM, random forest, and XG-boost. Furthermore, the hybrid model obtained better performance as compared with individual deep learning frameworks LSTM and GRU. In future studies focus on analyzing and contrasting the efficacy of a wide variety of DL techniques, including RNN, GAN, CNN, and Bi-LSTM, as well as a few optimization strategies, including genetic algorithms and PSO.

Acknowledgements

None.

Conflict of Interest

No potential conflict of interest was reported by the authors.

References

1. El Mghouchi Y. 2022. On the prediction of daily global solar radiation using temperature as input. An application of hybrid machine learners to the six climatic Moroccan zones. *Energy Convers Manage* 13: 100157. https://doi.org/10.1016/J.ECMX.2021.100157
2. Kumari P, Toshniwal D. 2021. Deep learning models for solar irradiance forecasting: a comprehensive review. *J Clean Prod* 318: 128566. https://doi.org/10.1016/J.JCLEPRO.2021.128566
3. Serrano E, Rus G, Garcia-Martinez J. 2009. Nanotechnology for sustainable energy. *Renew Sust Energ Rev* 13(9): 2373-2384. https://doi.org/10.1016/j.rser.2009.06.003
4. Galván IM, Huertas-Tato J, Rodriguez-Benitez FJ, Arbizu-Barrena C, Pozo-Vazquez D, et al. 2021. Evolutionary-based prediction interval estimation by blending solar radiation forecasting models using meteorological weather types. *Appl Soft Comput* 109: 107531. https://doi.org/10.1016/j.asoc.2021.107531
5. Abdin Z, Alim MA, Saidur R, Islam MR, Rashmi W, et al. 2013. Solar energy harvesting with the application of nanotechnology. *Renew Sust Energ Rev* 26: 837-852. https://doi.org/10.1016/J.RSER.2013.06.023
6. Ali M, Prasad R, Xiang Y, Khan M, Farooque AA, et al. 2021. Variational mode decomposition based random forest model for solar radiation forecasting: new emerging machine learning technology. *Energy Rep* 7: 6700-6717. https://doi.org/10.1016/j.egyr.2021.09.113
7. Ali-Ou-Salah H, Oukarfi B, Bahani K, Moujabbir M. 2021. A new hybrid model for hourly solar radiation forecasting using daily classification technique and machine learning algorithms. *Math Probl Eng* 2021: 6692626. https://doi.org/10.1155/2021/6692626
8. Zhou H, Liu Q, Yan K, Du Y. 2021. Deep learning enhanced solar energy forecasting with AI-driven IoT. *Wirel Commun Mob Comput* 2021: 9249387. https://doi.org/10.1155/2021/9249387
9. Li C, Zhang Y, Zhao G, Ren Y. 2021. Hourly solar irradiance prediction using deep BiLSTM network. *Earth Sci Inform* 14: 299-309. https://doi.org/10.1007/s12145-020-00511-3
10. Kasten F, Czeplak G. 1980. Solar and terrestrial radiation dependent on the amount and type of cloud. *Sol Energy* 24(2): 177-189. https://doi.org/10.1016/0038-092X(80)90391-6
11. Zhang Q, Huang J, Yang H. 2002. Development of the typical and design weather data for Asian locations. *J Asian Archit Build Eng* 1(2): 49-55. https://doi.org/10.3130/jaabe.1.2_49
12. Hassan GE, Youssef ME, Mohamed ZE, Ali MA, Hanafy AA. 2016. New temperature-based models for predicting global solar radiation. *App Energy* 179: 437-450. https://doi.org/10.1016/J.APENERGY.2016.07.006
13. Bristow KL, Campbell GS. 1984. On the relationship between incoming solar radiation and daily maximum and minimum temperature. *Agric For Meteorol* 31(2): 159-166. https://doi.org/10.1016/0168-1923(84)90017-0
14. Mecibah MS, Boukelia TE, Tahtah R, Gairaa K. 2014. Introducing the best model for estimation the monthly mean daily global solar radiation on a horizontal surface (Case study: Algeria). *Renew Sust Energ Rev* 36: 194-202. https://doi.org/10.1016/j.rser.2014.04.054
15. Chen JL, He L, Yang H, Ma M, Chen Q, et al. 2019. Empirical models for estimating monthly global solar radiation: a most comprehensive review and comparative case study in China. *Renew Sust Energ Rev* 108: 91-111. https://doi.org/10.1016/j.rser.2019.03.033
16. Alonso J, Batlles FJ. 2014. Short and medium-term cloudiness forecasting using remote sensing techniques and sky camera imagery. *Energy* 73: 890-897. https://doi.org/10.1016/j.energy.2014.06.101
17. Hammer A, Heinemann D, Hoyer C, Kuhlemann R, Lorenz E, et al. 2003. Solar energy assessment using remote sensing technologies. *Remote Sens Environ* 86(3): 423-432. https://doi.org/10.1016/S0034-4257(03)00083-X
18. Guermoui M, Abdelaziz R, Gairaa K, Djemoui L, Benkaciali S. 2022. New temperature-based predicting model for global solar radiation using support vector regression. *Int J Ambient Energy* 43(1): 1397-1407. https://doi.org/10.1080/01430750.2019.1708792
19. Baser F, Demirhan H. 2017. A fuzzy regression with support vector machine approach to the estimation of horizontal global solar radiation. *Energy* 123: 229-240. https://doi.org/10.1016/j.energy.2017.02.008
20. Çevik S, Çakmak R, Altaş İH. 2017. A day ahead hourly solar radiation forecasting by artificial neural networks: a case study for Trabzon province. In International Artificial Intelligence and Data Processing Symposium, Malatya, Turkey.
21. Golam M, Akter R, Lee JM, Kim DS. 2021. A long short-term memory-based solar irradiance prediction scheme using meteorological data. *IEEE Geosci Remote Sens Lett* 19: 1003705. https://doi.org/10.1109/LGRS.2021.3107139
22. Ghimire S, Deo RC, Casillas-Pérez D, Salcedo-Sanz S, Sharma E, et al. 2022. Deep learning CNN-LSTM-MLP hybrid fusion model for feature optimizations and daily solar radiation prediction. *Measurement* 202: 111759. https://doi.org/10.1016/j.measurement.2022.111759
23. Jalali SM, Ahmadian S, Kavousi-Fard A, Khosravi A, Nahavandi S. 2021. Automated deep CNN-LSTM architecture design for solar irradiance forecasting. *IEEE Trans Syst Man Cybern Syst* 52(1): 54-65. https://doi.org/10.1109/TSMC.2021.3093519
24. Lima MA, Carvalho PC, Fernández-Ramírez LM, Braga AP. 2020. Improving solar forecasting using deep learning and portfolio theory integration. *Energy* 195: 117016. https://doi.org/10.1016/j.energy.2020.117016
25. Afrasiabi M, Mohammadi M, Rastegar M, Kargarian A. 2019. Multi-agent microgrid energy management based on deep learning forecaster. *Energy* 186: 115873. https://doi.org/10.1016/j.energy.2019.115873
26. Zhao X, Wei H, Wang H, Zhu T, Zhang K. 2019. 3D-CNN-based feature extraction of ground-based cloud images for direct normal irradiance prediction. *Sol Energy* 181: 510-518. https://doi.org/10.1016/j.solener.2019.01.096
27. Power Data Access Viewer. [https://power.larc.nasa.gov/data-access--viewer] [Accessed December 27, 2023]
28. Huang CJ, Ma Y, Chen YH. 2020. Solar radiation forecasting based on neural network in Guangzhou. In International Automatic Control Conference, Hsinchu, Taiwan.
29. Yan X, Abbes D, Francois B. 2014. Solar radiation forecasting using artificial neural network for local power reserve. In International Conference on Electrical Sciences and Technologies in Maghreb, Tunis, Tunisia.
30. Jung G, Choi SY. 2021. Forecasting foreign exchange volatility using deep learning autoencoder-LSTM techniques. *Complexity* 2021: 6647534. https://doi.org/10.1155/2021/6647534
31. Faisal AF, Rahman A, Habib MT, Siddique AH, Hasan M, et al. 2022. Neural networks based multivariate time series forecasting of solar radiation using meteorological data of different cities of Bangladesh. *Results Eng* 13: 100365. https://doi.org/10.1016/J.RINENG.2022.100365
32. Jaihuni M, Basak JK, Khan F, Okyere FG, Sihalath T, et al. 2022. A novel recurrent neural network approach in forecasting short term solar irradiance. *ISA Trans* 121: 63-74. https://doi.org/10.1016/J.ISATRA.2021.03.043
33. Alluhaidah BM, Shehadeh SH, El-Hawary ME. 2014. Most influential variables for solar radiation forecasting using artificial neural networks. In IEEE Electrical Power and Energy Conference, Calgary, AB, Canada.