

SOLAR RADIATION PREDICTION IN PV POWER SYSTEMS: A COMPARISON OF DEEP LEARNING MODELS USING BIG DATA

Fatma Didem Alay^{1✉}, Nagehan İlhan¹,
Mehmet Tahir Güllüoğlu²

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Abstract

Photovoltaic (PV) energy systems are one of the most significant renewable resources, requiring efficient solutions for solar power generation and maintenance. Accurately predicting PV energy generation and solar radiation is essential for managing grid maintenance and making energy market decisions. This study proposes prediction models based on the use of deep learning, including convolutional neural networks (CNN) and long short-term memory (LSTM) networks, to fill the gap in big data analysis as more renewable energy data is collected. These models will be compared with traditional machine learning methods including Artificial Neural Networks (ANN) and Support Vector Regression (SVR). Data from the GAPYENEV Centre at the University of Harran is used to implement predictive models. Several prediction error metrics such as MAE, MSE, RMSE, R^2 and accuracy are used to evaluate the predictive ability of the models.

Key words: solar radiation forecasting, deep learning, big data, CNN, LSTM

Introduction. Energy consumption is growing due to population and industrial development, leading towards the need for alternative energy sources such as solar power. PV energy systems transform solar power into electrical energy,

providing clean, non-polluting, and reliable energy [1]. Solar energy has potential in preventing climate change by reducing harmful emissions [2]. PV energy is abundant, cost-effective, environmentally friendly, and accessible, making it a promising solution for future energy needs.

Solar radiation forecasting is essential for predicting the power output of PV systems. Research in solar radiation forecasting for PV systems underscores the importance of precise and reliable predictions for optimizing energy generation, grid integration, and overall system efficiency. Various studies have proposed different methods for forecasting solar radiation, which, in turn, aids in predicting PV power output. These models use data processing techniques to generate a prediction framework, categorized into physical, statistical, and hybrid methods [3]. Techniques such as machine learning, metaheuristics, binary trees, factor analysis, and deep neural networks have been utilized for accurate solar radiation prediction [4–6]. These methods significantly enhance the accuracy of PV power forecasts, ensuring the successful integration of solar power into the electrical grid [7]. Furthermore, the integration of big data analysis in solar radiation forecasting has gained traction [8]. Big data technologies offer the capability to process vast amounts of data efficiently, which is crucial for handling the complex and diverse data sources involved in solar radiation prediction [9].

Deep learning is a sophisticated machine learning method that uses multiple layers for abstraction and processing to learn from raw data representation [10,11]. This method, which automatically uncovers and learns characteristics from raw data, has gained significant attention in various research areas such as medicine, industry, robotics, image processing, object detection, and finance. For instance, HUANG and KUO [12] proposed a multiple-input deep convolutional neural network model for short-term PV power forecasting, incorporating meteorological data and historical PV system output. ASLAM et al. [13] investigated deep learning models for long-term solar radiation forecasting, underlining the significance of accurate predictions for assessing PV panel energy potentials. The amalgamation of big data analytics with deep learning models can further improve the accuracy of solar radiation forecasting in PV power systems [14]. Time series forecasting systems rely on data from past and present states, utilizing statistical techniques for linear correlation and stationarity. However, these techniques struggle to identify intricate patterns in time-series data, necessitating the use of deep neural networks to develop reliable prediction models [15].

Moreover, analyzing the forecast accuracy of solar radiation is vital for the future operation of power systems, particularly concerning frequency regulation and generation reserve estimation. Accurately predicting solar radiation not only impacts the immediate power output of PV systems but also influences the overall stability and reliability of the power grid.

This study presents prediction performance comparison of the forecasting models based on deep learning methods such as Convolutional Neural Network

(CNN) and Long Short-Term Memory (LSTM) network with typical machine-learning models such as Support Vector Regression (SVR) and Artificial Neural Network (ANN). The comparison with existing machine-learning models highlights the proposed deep learning model's higher performance and efficacy, notably in extracting temporal patterns and informative properties from solar plant data. This study advocates using a high-performance computer environment for big data analysis in the development of solar radiation forecasting models, with the goal of filling a content gap in solar radiation forecasting.

Methodology. A particular form of machine learning technology known as deep learning simulates how the human brain observes, assesses, learns, and renders decisions on complicated issues. As top-level features are taken from lower-level features to create a hierarchical representation, deep learning is structured around learning several feature levels or representations of data. A substantial amount of data is processed in mathematical structures that occur in layers by this representation, which learns from numerous levels that correspond to various levels of abstraction [11]. When such an intense processing procedure is included in a deep learning framework, high performance computers should be employed [16].

The most popular deep learning models are CNN and LSTM. CNN is a specialized type of multilayer neural network that can extract attributes from input data powerfully and is supported by several reliable sources [17]. The input data's features are automatically retrieved via the convolution process and passed along to the following layers. As illustrated in Fig. 1, the fundamental levels of the CNN multilayered structure are an input layer, convolution layer, pooling layer, fully connected layer, and output layer [18, 19].

LSTM was developed in the context of Recurrent Neural Network (RNN) in the late 1990s as a particular type of method for modelling sequential data. Long-term dependencies can be learned by LSTM, which is a substantial gain over previous RNN designs. This capacity enables it to properly consider input from past time periods, overcoming the gradient disappearance problem inherent in standard RNNs. The claim that the architecture of LSTM performs learning that takes into account information from previous time periods is supported by the fact that LSTM is specifically designed to capture and utilize long-term dependencies in sequential data [20].

In this study, our primary goal in comparing deep learning models such as CNN and LSTM is to take advantage of their features in order to create an effective model for forecasting solar radiation.

Data and preprocessing. In this study, we present a methodology for developing and comparing prediction models for existing PV systems. Our data is sourced from the solar power plant and meteorological station at the GAPYENEV Center, Harran University in Sanliurfa, Turkey. The dataset encompasses historical weather and solar energy data from the solar power plant (Harran GES) and the GAPYENEV Center's meteorological station. The solar power plant has

an installed capacity of 5314.32 kWp and includes 5 inverters (ABB PVS800-57-1000kW-C) along with 16104 PV panels (LG Electronics LG330N1C-A5). The dataset contains 245 692 records, capturing data on solar radiation, energy production and consumption, temperature, module temperature, humidity, and wind speed at 5-minute intervals from 2018 to 2020. For our prediction models, we allocate 70% of the data for training and 30% for testing.

Data preprocessing is critical and involves cleaning the dataset by handling missing values, correcting noise, identifying outliers, and resolving inconsistencies. These steps ensure the dataset is well-prepared for subsequent data mining techniques.

Development of the prediction models. The deep learning forecasting models are developed including CNN and LSTM networks, moreover, two experimental models are performed to evaluate the performance of the deep learning models including SVR model and ANN model. The assessment of each data-driven model involved comparing its consistency with the experimental data across both training and test datasets. The proposed models are then compared based on various predictive performance criteria, (shown in Table 1), including mean absolute error (*MAE*), mean squared error (*MSE*), root mean squared error (*RMSE*), coefficient of determination (R^2) score, and accuracy (*ACC*).

T a b l e 1
Performance evaluation metrics

Model	Equation
Root Mean Square Error	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$
Mean Absolute Error	$MAE = \frac{1}{n} \sum_{i=1}^n y_i - \hat{y}_i ^2$
Mean Squared Error	$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$
Coefficient of determination	$R^2 = 1 - \frac{ss_{res}}{ss_{tot}}$
Accuracy	$ACC = \frac{TP + TN}{TP + TN + FP + FN}$

The *ACC* metric measures forecasting model accuracy by dividing the number of successful positive and negative forecasts by the total number of predictions (including erroneous ones). The following acronyms reflect the events that occurred throughout the forecasting process and are utilized to compute the *ACC* (Table 1):

TP = True Positive (true positive forecast, the flare will occur)
 TN = True Negative (negative event forecast, there will be no flare)
 FP = False Positive (positive forecast error)
 FN = False Negative (negative event forecast error)

The prediction model process is demonstrated in Fig. 1. The process of solar radiation forecasting is divided into three main stages: Data Input, Data Preprocessing, and Forecasting. The parameter settings for all prediction models are as follows: for the LSTM model, 200 units and 32 neurons are used. The CNN model utilizes filters of 32 with a stride of 2, and filters of 64 with a stride of 2. It also employs max pooling with a value of 2, 100 units, and 32 neurons. The SVR model is configured with a C value of 1.0, an RBF kernel, and a tolerance of 10^{-3} . The ANN model uses neurons set at 200, 100, and 50, with F values of 3, 6, and 12. In total, there are 500 training and validation epochs in the LSTM and CNN models. The adaptive moment estimation algorithm (ADAM) is used to optimize the models, with a batch size of 128 and a mean-squared loss function.

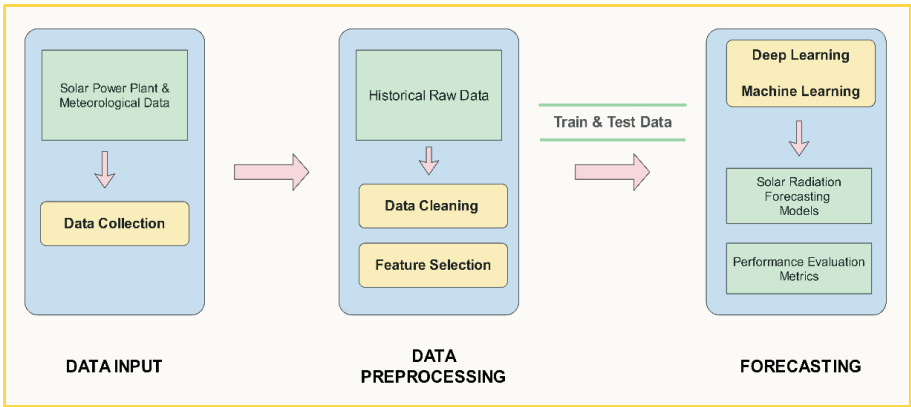


Fig. 1. Solar radiation prediction model process architecture

Experimental results. Powerful computers are essential for processing the vast amount of PV data and for enabling deep learning methods to handle large datasets efficiently. The attributes of big data, such as numerous examples, diverse class types, and high dimensionality, contribute to longer processing times and increased model complexity. Due to the sheer volume of data, it is generally impractical to train deep learning algorithms using a central processor and storage, making distributed computing frameworks with parallel programming capabilities necessary.

Recent developments have aimed to overcome the challenges posed by high data volumes. Innovative models now utilize clusters of CPUs or GPUs to accelerate training speeds while maintaining accuracy. For this study, experimental results were generated using the hardware and software resources of the High-Performance Computing Center (Harran HPC) at GAPPYENEV. The implemen-

tation code for the deep learning models was written in Python 3.9, using the TensorFlow 2.3.0 framework and the Keras 2.4.3 library, while the Scikit-learn library was employed for implementing machine learning models.

The proposed models, comprising deep learning models including CNN, LSTM, and machine learning models including SVR and ANN were assessed for their forecasting performance by comparing them with experimental data on both training and test sets. The forecasting results of these proposed models are presented in Table 2. The CNN model performed the best predictive ability, with a *MSE* of 0.0039, a *MAE* of 0.0205, a *RMSE* of 0.0039, a R^2 score of 0.986, and an *ACC* of 85.035% for the testing dataset.

T a b l e 2
Performance comparison of the forecasting models

No	Model	<i>MSE</i>	<i>MAE</i>	<i>RMSE</i>	R^2	<i>ACC</i> (%)
1	LSTM	0.003992	0.018272	0.003992	0.986271	84.162
2	CNN	0.003954	0.020554	0.003954	0.986401	85.035
3	SVR	0.009635	0.079486	0.009635	0.966864	82.894
4	ANN	0.004872	0.028651	0.004872	0.983243	83.516

Figure 2 shows the regression graph of the CNN model showing the best prediction performance. As seen in the graph, the relationship between prediction data of the CNN model and the expected (test) data provide important information about the model success.

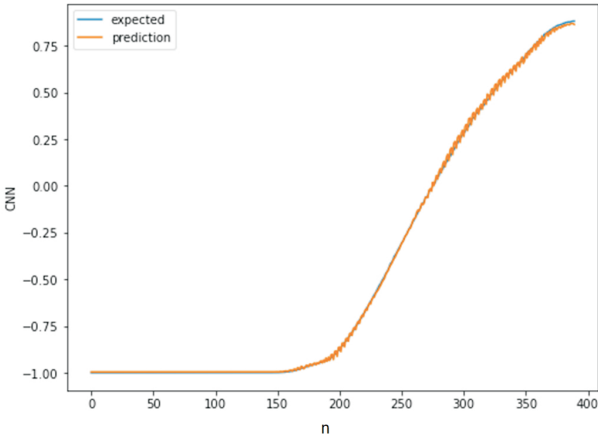


Fig. 2. Regression chart of the CNN forecasting model

Conclusions. The integration of deep learning models and advanced prediction techniques significantly enhances the accuracy and efficiency of solar radiation forecasting for PV power systems, ultimately contributing to improved energy

management and sustainability. This study highlights the importance of big data analysis and high-performance computing environments for solar radiation forecasting, utilizing distributed computing frameworks with parallel programming capabilities. The CNN model, which outperforms other deep learning and machine learning forecasting models like LSTM, SVR, and ANN, is used to improve the precision and efficacy of solar energy forecasting, thereby enhancing renewable resource competitiveness. Given the vast amount of solar radiation data from solar power plants, training deep learning algorithms with a central processor and storage is often impractical. Therefore, it is necessary to employ distributed computing frameworks with parallel programming capabilities.

REFERENCES

- [1] KABIR E., P. KUMAR, S. KUMAR et al. (2018) Solar energy: Potential and future prospects, *Renew. Sustain. Energy Rev.*, **82**, 894–900, <https://doi.org/10.1016/j.rser.2017.09.094>.
- [2] SHAHSAVARI A., M. AKBARI (2018) Potential of solar energy in developing countries for reducing energy-related emissions, *Renew. Sustain. Energy Rev.*, **90**, 275–291, <https://doi.org/10.1016/j.rser.2018.03.065>.
- [3] ALAY F. D., N. İLHAN, M. T. GÜLLÜOĞLU (2024) A Comparative Study of Data Mining Methods for Solar Radiation and Temperature Forecasting Models, *JUCS – J. Univers. Comput. Sci.*, **30**, 847–877.
- [4] BENALI L., G. NOTTON, A. FOUILLOY et al. (2019) Solar radiation forecasting using artificial neural network and random forest methods: Application to normal beam, horizontal diffuse and global components, *Renew. Energy*, **132**, 871–884, <https://doi.org/10.1016/j.renene.2018.08.044>.
- [5] MELLIT A., A. PAVAN, E. OGLIARI et al. (2020) Advanced Methods for Photovoltaic Output Power Forecasting: A Review, *Appl. Sci.*, **10**(2), 487.
- [6] LAI C. S., C. ZHONG, K. PAN et al. (2021) A deep learning based hybrid method for hourly solar radiation forecasting, *Expert Syst. Appl.*, **177**, 114941.
- [7] LOGANATHAN A. K., A. A. STONIER, Y. U. MAHESWARI (2021) Performance enhancement of a photovoltaic module using solar functional coatings, *J. Mater. Sci. Mater. Electron.*, **32**, 1242–1257, <https://doi.org/10.1007/s10854-020-04897-0>.
- [8] EL HENDOUZI A., A. BOUROUHO (2020) Solar photovoltaic power forecasting, *J. Electr. Comput. Eng.*, 8819925.
- [9] ASSUNÇÃO M. D., R. N. CALHEIROS, S. BIANCHI et al. (2015) Big Data computing and clouds: Trends and future directions, *J. Parallel Distrib. Comput.*, **79–80**, 3–15.
- [10] NAJAFABADI M. M., F. VILLANUSTRE, T. M. KHOSHGOFTAAR et al. (2015) Deep Learning Applications and Challenges in Big Data Analytics, *J. Big Data*, **2**(1), <https://doi.org/10.1186/s40537-014-0007-7>.
- [11] GOODFELLOW I., Y. BENGIO, A. COURVILLE (2016) *Deep Learning*, MIT press.
- [12] HUANG C-J., P-H. KUO (2019) Multiple-input deep convolutional neural network model for short-term photovoltaic power forecasting, *IEEE access*, **7**, 74822–74834.

- [13] ASLAM M., J-M. LEE, H-S. KIM et al. (2019) Deep learning models for long-term solar radiation forecasting considering microgrid installation: A comparative study, *Energies*, **13**, 147.
- [14] KIM H., S. PARK, H-J. PARK et al. (2023) Solar Radiation Forecasting Based on the Hybrid CNN-CatBoost Model, *IEEE Access*, <https://doi.org/10.1109/ACCESS.2023.3243252>.
- [15] GUERMOUI M., S. BENKACIALI, K. GAIRAA et al. (2022) A novel ensemble learning approach for hourly global solar radiation forecasting, *Neural Comput. Appl.*, 1–23.
- [16] MATHEW A., P. AMUDHA, S. SIVAKUMARI (2021) Deep learning techniques: an overview. In: *International conference on advanced machine learning technologies and applications*, 599–608.
- [17] WANG K., S. CHEN, L. LIU et al. (2019) Dynamic Soft Sensor Development Based on Convolutional Neural Networks, *Ind. & Eng. Chem. Res.*, **58**(26), <https://doi.org/10.1021/acs.iecr.9b02513>.
- [18] RAWAT W., Z. WANG (2017) Deep Convolutional Neural Networks for Image Classification: A Comprehensive Review, *Neural Comput.*, **29**, 2352–2449.
- [19] GU J., Z. WANG, J. KUEN et al. (2018) Recent advances in convolutional neural networks, *Pattern Recognit.*, **77**, 354–377, <https://doi.org/10.1016/j.patcog.2017.10.013>.
- [20] LIU Z., A. JERRESAND, M. DIAMANT et al. (2023) Application of Smart Way-side Object Controllers to Railway Signalling Systems for Decarbonisation, *Proc. Inst. Mech. Eng. Part F J. Rail Rapid Transit*, **238**(3), <https://doi.org/10.1177/09544097231159701>.

¹*Department of Computer Engineering, Harran University,
Osmanbey Campus, 63300, Sanliurfa, Türkiye
e-mails: fdidemogretmen@harran.edu.tr, nagehanilhan@harran.edu.tr*

²*Department of Electrical and Electronics Engineering, Harran University,
Osmanbey Campus, 63300, Sanliurfa, Türkiye
e-mail: mtahir@harran.edu.tr*