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ORIGINAL ARTICLE

A novel long term solar photovoltaic power forecasting approach using LSTM with Nadam optimizer: A case study of India

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Abstract

Solar photovoltaic (PV) power is emerging as one of the most viable renewable energy sources. The recent enhancements in the integration of renewable energy sources into the power grid create a dire need for reliable solar power forecasting techniques. In this paper, a new long-term solar PV power forecasting approach using long short-term memory (LSTM) model with Nadam optimizer is presented. The LSTM model performs better with the time-series data as it persists information of more time steps. The experimental models are realized on a 250.25 kW installed capacity solar PV power system located at MANIT Bhopal, Madhya Pradesh, India. The proposed model is compared with two time-series models and eight neural network models using LSTM with different optimizers. The obtained results using LSTM with Nadam optimizer present a significant improvement in the forecasting accuracy of 30.56% over autoregressive integrated moving average, 47.48% over seasonal autoregressive integrated moving average, and 1.35%, 1.43%, 3.51%, 4.88%, 11.84%, 50.69%, and 58.29% over models using RMSprop, Adam, Adamax, SGD, Adagrad, Adadelta, and Ftrl optimizer, respectively. The experimental results prove that the proposed methodology is more conclusive for solar PV power forecasting and can be employed for enhanced system planning and management.

KEYWORDS

long short-term memory, Nadam, photovoltaic power forecasting, photovoltaic power plant, time series forecasting

1 | INTRODUCTION

Electricity is one of the most essential facets of the life of a modern man. The rapid increase in population and industrialization has resulted in a steep rise in energy demand. Taking the case of India, despite having an enormous potential for renewable energy of around 900 GW; the country still confronts a massive electrification problem. According to International Energy Agency (IEA), approximately 25% of the total population of the country is not connected to the electrical grid.[1] Furthermore, India's energy demands are escalating and are anticipated to reach around 15,820 TWh by the year 2040 as shown in Figure 1.[2]

As India aims at becoming self-reliant on its energy demands while meeting the COP′21 (Paris Agreement) targets; it needs to tap onto its abundant renewable energy potential as shown in Figure 2.[3] Currently, it relies heavily on its conventional energy sources, but the power sector is witnessing a transition toward renewable energy sources (RES). During FY16–20, it posted a fast-paced CAGR of 17.33% with an aim to attain a renewable energy capacity of 225 GW (including the addition of 114 GW of solar and 67 GW of wind power capacity) by the year 2022.[2–9]

Solar power offers a multitude of benefits such as clean, environment-friendly, and easily accessible energy production.[10] This aids in the integration of power grids

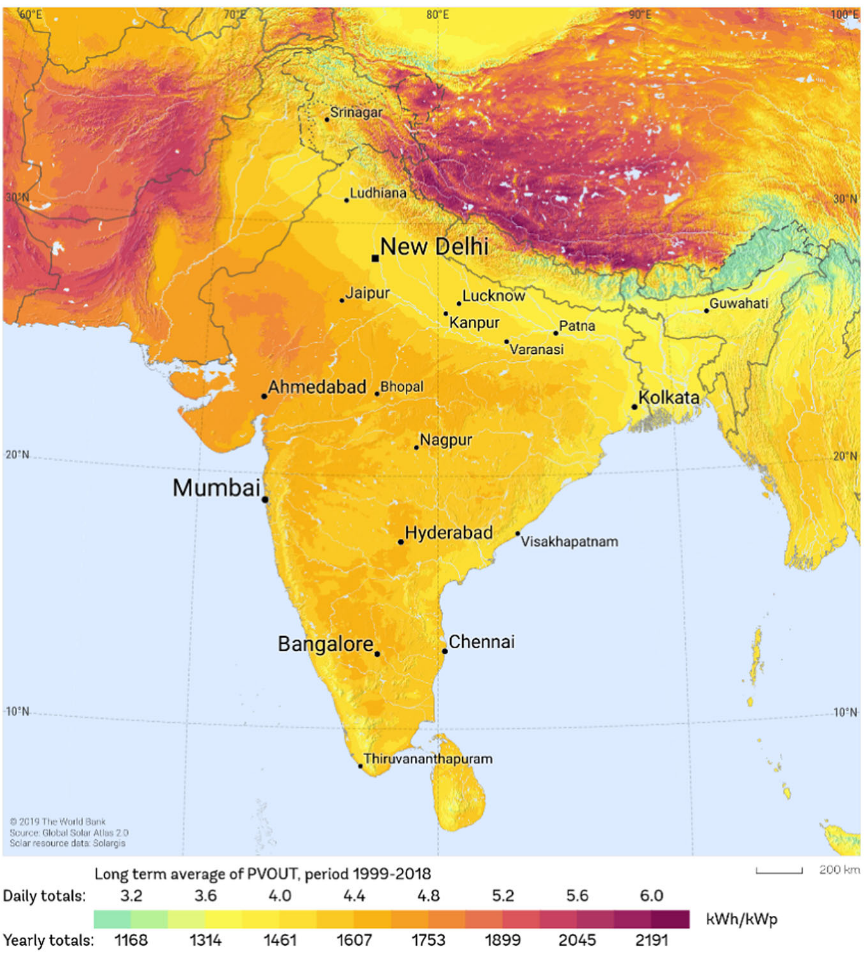
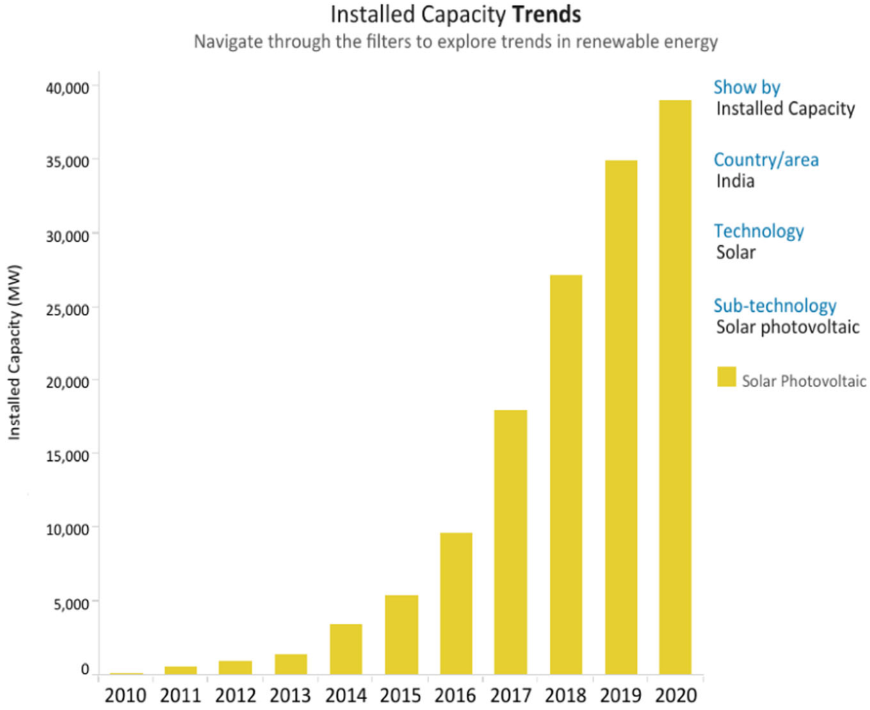


FIGURE 1 Solar photovoltaic power potential of India.[2]

FIGURE 2 Solar photovoltaic installed capacity trends in India.[3]



with RES.[11] For successful grid operation, energy management, and economic scheduling, the need for an optimal solar photovoltaic (PV) power prediction technique becomes critical.[12,13]

The salient prediction techniques like autoregressive integrated moving average (ARIMA)/seasonal autoregressive integrated moving average (SARIMA; statistical), numerical weather prediction (NWP; physical), artificial neural network (ANN; machine learning), and hybrid methods have shown modest results in their tenure. However, they can only be applied for short-term forecasts. Short-term forecasts may be adequate for primitive standalone or small PV systems, but long-term forecasts are required for the operation of modern grid-integrated PV systems. Hence, there is an immediate requirement for a much enhanced and reliable technique as the renewable power network becomes increasingly complex in structure.[12–16]

The extensive literature review conducted on the forecasting techniques suggests that most techniques employed still focus on obsolete methods for solar photovoltaic (SPV) power prediction.[17] These methods do not consider the impact of the most crucial meteorological parameters which greatly affect the accuracy of predictions and results in inefficient monitoring, maintenance, and regulation of power generated from RES.[18] Mashud et al.[19] predicted for forecasting horizon of 5–60 min. They used the best-first search algorithm with forwarding selection for the variable selection algorithm. The data set was then fed into the neural network (NN) ensemble and SVR as the univariate and multivariate data set, respectively. It provided an mean relative error (MRE) of 7.26% with an NN ensemble in the univariate model. Behera et al.[20] used a 15–60 min forecasting horizon. They used extreme learning machine (ELM) and its modifications like particle swarm optimization-extreme learning machine (PSO-ELM), craziness particle swarm optimization-extreme learning machine (CRPSO-ELM), and accelerate particle swarm optimization-extreme learning machine (APSO-ELM). Among these, APSO-ELM forecast the best result for 15 min horizon having a root mean squared error (RMSE) of 0.0178 for the 11.2 kW SPV plant.

Sonia leva et al.[21] produced a persistence model to predict the output power of a BIPVS; comprising various data processing strategies like NN modeling and error metrics analysis. Their intra-day SPV power forecasting proposal is confirmed with the help of a comparison between their error metrics with the existing standards. The total capacity of the SPV plant under consideration was only 34 kW. An RMSE of 99.98 for 120 min forecast horizon was obtained using the ANN method.

Mishra et al.[22] have produced short time-horizon SPV power forecasts (1-to-4-h time horizon) using recurrent neural networks (RNN) integrated with multitime-horizon predictions. This enabled forecasts by real-time inputs which can be employed for applications in the smart grid. The same model has been trained for data sets of various locations. For fixed as well as multitime horizon forecasts, the results for Penn State were found to be the most optimal.

Kardakos et al.[23] produced an NWP model for the power prediction of a grid-connected photovoltaic plant. The predictions have been done on an hourly basis with a SARIMA model applied for predicting the solar insolation resulting from multiple inputs using ANN. The performance of the model on both intraday and day-ahead bases was assessed using NRMSE values. The outcomes reflect the annual average NRMSE readings as 11.12% for modified SARIMA, 11.26%–11.46% for ANN, 12.89% for pure SARIMA, and 13.71% for the persistence model. Chen et al.[24] prepared a 24-h ahead forecasting model using a self-organized map (SOM) for weather data classification. This was implemented along with meteorological parameters so that their ANN–RBFN model is well trained. After testing for some days, the mean absolute percentage error (MAPE) obtained for sunny days was 9.45%, for cloudy days was 9.88%, and for rainy days was 38.12%.

Lee et al.[25] produced two long short-term memory (LSTM) models having three hidden layers. They provided a single SPV power output for hourly predictions located at the Gumi City in South Korea. Inputs like cloudiness, humidity, irradiance, atmospheric temperature, day, and month were fed to the first model whereas the seasonal data of day and month were excluded from the second model. Of all the above models, the LSTM-1 seasonal model provided the best results compared with ARIMA, SARIMA, feed-forward ANN, deep-learning ANN, and seasonal deep-learning ANN. Nasser et al. produced, trained, and tested five LSTM models with variable inputs, types of LSTM, and a number of layers for an hour-ahead SPV forecasting of a system located at Aswan and Cairo, Egypt. Model 1 (base-model) consisting of a single hidden layer having 4-LSTM cells was fed the SPV output an hour ahead of the anticipated forecast time. Model 2 differed from the first by getting SPV output values from the last 3 h-ahead time-steps as discrete input features. Model 3 transformed the last three time steps. Model 4 differed from Model 1 by employing LSTM blocks for making the network memorize the trends over various training batches. Lastly, a two-layer LSTM network was employed as Model 5. The training and testing data were in the ratio of 7:3. Training and analysis for each model were done after 20, 50, and 100 epochs. It was observed that Model 3 showed the best results with 50 epochs compared with the boosted regression trees, multiple linear regression, and feed forward neural networks.

William VanDeventer et al.[26,27] and Mehdi Seyedmahmoudian et al.[28] produced models using the genetic algorithm-based support vector machine (GASVM) model and differential evolution and the particle swarm optimization (DEPSO) technique for short-term power forecasting, respectively. The peak output of the PV system under consideration was only 3 kW situated at Deakin University, Australia. The GASVM model classifies the historical weather data using an SVM classifier initially and later it is optimized by the genetic algorithm using an ensemble technique. Experimental results demonstrated that the GASVM model outperforms the conventional SVM model by a difference of about 669.624 W in the RMSE value and 98.7648% of the MAPE error. Whereas DEPSO forecasts under three different time horizons (1-, 2-, and 4-h) gave the best results for the 1-h time horizon as the RMSE, MRE, mean average error (MAE) of the DEPSO based forecasting as 4.4%, 3.1%, and 0.03, respectively.

The work proposed in this paper is an extension of the work proposed by Nasser et al.[29] which employs only endogenous data for SPV power forecasting with different LSTM-models. The key distinction between the proposed work and Abdel-Nasser et al.[29] is that here 24-h time steps have been used as inputs compared with 1, and 2-h time-steps thus, reducing the number of steps employed. This in turn reduces the learning time of the model.[30] A summary of various solar PV forecasting methods is presented in Table 1.

1.1 | Research gaps

The various research gaps identified based on an extensive bibliometric analysis are as follows:

(i) The existing literature is mostly focused on short time-horizon power forecasting methods which are inappropriate for modern SPV plants. Thus, ample focus must be given to the long-time-horizon power forecasting of SPV systems. To impart clarity, it is essential to have a comparison between the two methods. However, literature available on the comparison between the two is also scarce.
(ii) The conventional methods can maintain the accuracy of SPV power prediction up to a few steps ahead but are unsuccessful as the step count increases.
(iii) Majority of work reported in the literature has addressed the problem of SPV plants with low capacity. The ones focusing on larger plants have adopted only short-term forecasting. However, when existing techniques are applied to large capacity plants, RMSE error becomes significantly large.
(iv) Meteorological and power data employed for forecasting is usually of exceedingly small duration and may have high inaccuracies.

Based on the research gaps, it can be assessed that there is a necessity for efficient SPV power forecasting

TABLE 1 Summary of forecasting techniques of solar PV.

Reference	Forecast horizon	Forecast resolution	Meteorological input	Forecasted parameter	Modelling technique	Site under study
Rana et al.[19]	5–60 min	5 min	GHI, T, RH, W	PV power	NN, SVR	Brisbane, Australia
Behera et al.[20]	15–60 min	15 min	GHI, T, RH, W, cloud cover	PV power	APSO-ELM	Bhubaneswar, India
de Paiva et al.[21]	120 min	15 min	GHI, RH, W, ambient temperature, atmospheric pressure	PV power	ANN	Goiania, Brazil
Mishra and Palanisamy[22]	1–4 h	1 h	GHI, solar irradiance	PV power	RNN	Boulder (CO); Bondville (IL); Desert Rock (NV); Fort Peck (MT); Goodwin Creek (MS); Sioux Falls (SD); and Penn State (PA), USA
Kardakos et al.[23]	24 h	1 h	Solar radiation	PV power	SARIMA, ANN	Greek territory
Chen et al.[24]	24 h	1 h	GHI, T, RH, W	PV power	ANN trained with NWP classified via SOM	Wuhan, China
Lee and Kim[25]	1 h	1 h	Cloudiness, humidity, irradiance, atmospheric temperature	PV power	LSTM	Gumi City, South Korea
VanDeventer et al.[26]	1 h	1 h	Solar irradiance, and air temperature	PV power	GASVM	Victoria, Australia
Seyedmahmoudian et al.[28]	1-, 2-, and 4-h	1 h	Solar irradiance, and air temperature	PV power	DEPSO	Victoria, Australia
Abdel-Nasser et al.[29]	1–2 h	1 h	-	PV power	LSTM	Aswan and Cairo, Egypt
Sophie et al.[31]	24 h	1 h	GHI, T, RH, W, pressure, rainfall, sunshine duration, and wind direction	PV power	Hybrid ANN using NWP for optimization	Cornwall, United Kingdom
	30–60 days	24 h	Solar Radiation, Atmospheric Temperature, Relative Humidity, Wind Speed	PV Power	LSTM with Nadam optimizer	Bhopal, India

techniques for a long time horizon. Competent techniques are needed for a successful and efficient setup of a practical SPV plant that will facilitate better system planning when large-scale grid integration is required.

1.2 | Contributions and organization of paper

In this paper, a new and improved SPV power forecasting model is presented that significantly improves the forecasting accuracy by effective use of optimizers. The initial study comprises of the meteorological parameters like:

- Atmospheric temperature (AT),
- Relative humidity (RH),
- Solar insolation (SR), and
- Wind speed (WS).

The above parameters greatly affect the output power from SPV panels. They are also the most frequently mentioned factors employed under relevant studies.[30,32] The data exploited for the present study contains 366 days of operational data occupied from a 250.25 kW grid connected SPV plant in the city of Bhopal, Madhya Pradesh, India. None of the studies in recent literature have considered such a large plant in their work for long-term forecasting.[12,33,34] The long-term solar forecasting is very necessary for reserve planning and operation management (for system operators) and efficient placement of renewable plants (for renewable generators). Solar power has emerged as a viable solution to cater to the growing energy demands with minimal impact on the environment. However, one of the key issues associated with the grid scale integration of solar power is its inherent variability. This hinders its prospect for large-scale deployment on the grid. To facilitate optimal planning, it is imperative that the planning of large-scale solar power plants be carried out on the basis of sound long-term forecasts. This asserts the importance of development of efficient and accurate long-term forecasting techniques.

The major contributions of the paper addressing the research gaps discussed in Section 1.1 can be listed as follows:

i. In this paper, a novel long-time-horizon power forecasting method for SPV systems using LSTM with Nadam optimizer has been developed.
ii. The proposed method can be implemented for large number of step counts.
iii. To enable an in-depth understanding, comparison of various parameters that significantly affect large capacity SPV plants has been provided.
iv. A practical case study has been conducted for long-time horizon to demonstrate the efficacy of the proposed technique. A comparison with existing work has also been presented to validate the superiority of the proposed approach.

The remaining paper is organized as follows:

In Section 2 several forecasting methods are discussed and classified. Section 3 provides the description of existing and proposed models on the current study. Section 4 is devoted to the case study executed in steps of collection, preparation, and analysis of data along with the adopted models. Section 5 discusses the results obtained by testing various models followed by a brief comparison of their performances. Section 6 draws the conclusions and the future avenues of research in solar power forecasting are briefly discussed.

2 | CLASSIFICATION OF FORECASTING METHODS

Forecasting is a statistical method used to predict a trait using historical patterns in the data. Forecasts can be made for several years ahead or for the next few minutes. Various kinds of forecasting methods can be utilized for SPV power forecasting depending upon the PV plant size, geographical location, forecasting horizon, and other climatic variations. Therefore, it is crucial to identify which method of forecasting should be utilized in different circumstances so that the risks of forecasting can be curtailed. Different classifications of SPV forecasting methods are briefly discussed in the following sections.

2.1 | Based on the forecasting horizon

The period for which the SPV power output is forecasted is called the forecasting horizon. Figure 3 shows the various kinds of solar PV forecasting methods based on time-horizon[35–37] which are further described in Table 2.

2.2 | Based on historical data

In literature, numerous forecasting methods have been developed for solar PV power forecasting as shown in Figure 4. These methods are broadly classified in Table 3.

To attain accurate results, choosing the correct forecasting method depending on the available data and required time horizon is essential. In the next section, some of the commonly used models along with the proposed model are discussed.

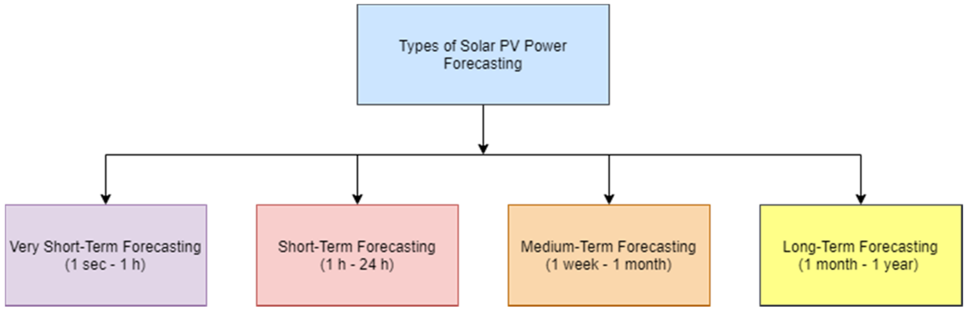


FIGURE 3 Classification of solar photovoltaic forecasting based on time-horizon.

TABLE 2 Review on solar PV power forecasting based on time-horizon.

Type of solar PV power forecasting	Time-horizon	Applications
Very short-term	1 s–1 h	Power and voltage regulation, real-time electricity dispatch, and grid stability.
Short-term	1–24 h	Grid security, power reserve management.
Medium-term	1 week–1 month	Unit commitment decisions, planning, and maintenance scheduling of the power system.
Long-term	1 month–1 year	Helps authorities in planning the generation, transmission, and distribution of electricity along with the structuring and operation of electricity markets.

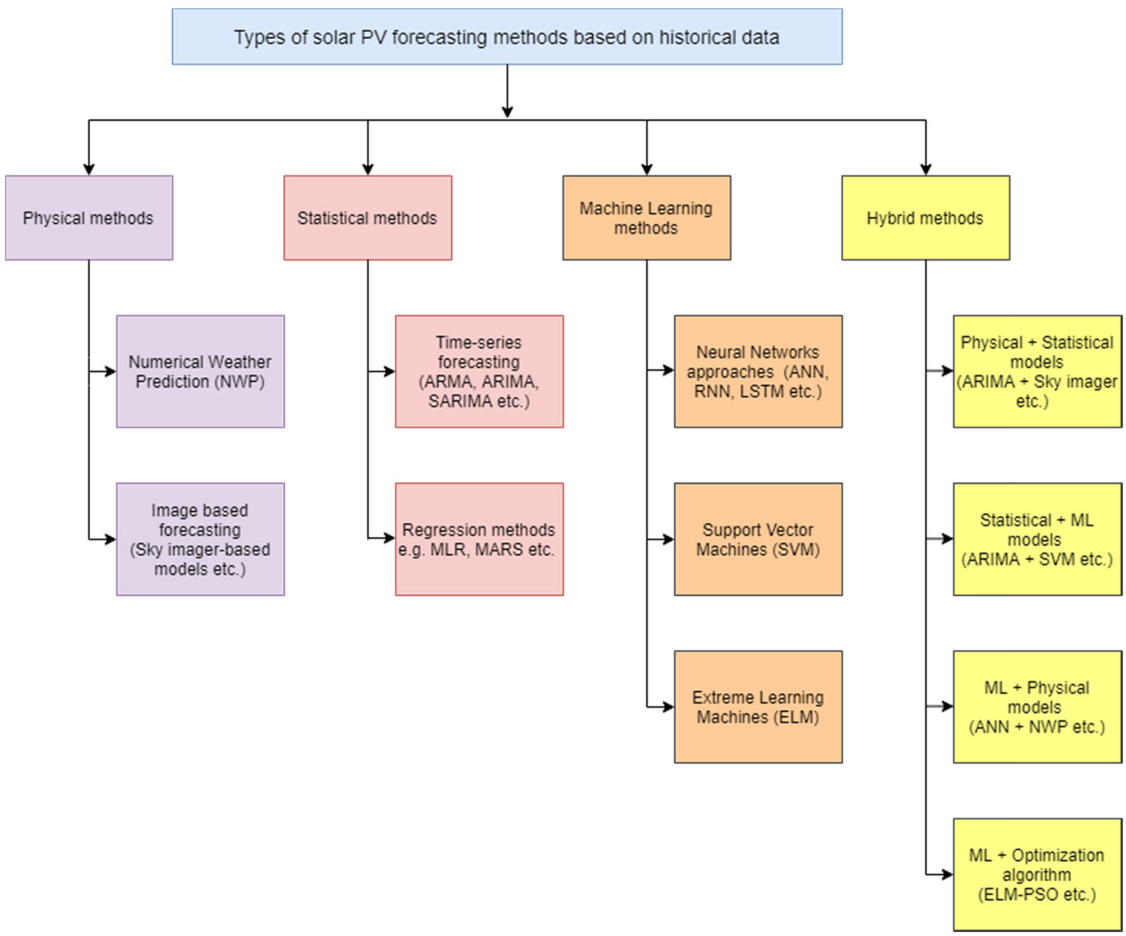


FIGURE 4 Classification of solar photovoltaic forecasting based on historical data.

TABLE 3 Review of solar photovoltaic (PV) power forecasting techniques based on historical data.

Forecasting approach	Advantages	Disadvantages
Physical models	Can be employed without historical data sets.	Sensitive to abrupt changes in the values of meteorological variables.
	Can be adapted to generate input variables for statistical models.	Requires detailed models of solar PV and local measurements.
		Difficult to get physical input data.
	More suitable for long-term forecasting than satellites.	Appropriate and frequent calibrations are required in the recording devices.
Statistical models	A reliable forecasting approach for short term as it exploits readily available meteorological data.	Requires a considerable number of past input data.
		Less accurate for long-term forecasts.
	Typically outperform physical models.	Unable to capture the intermittent behaviour of input variables.
	Easier to implement.	
Machine Learning models	Adaptable to a wide range of parameters.	Needs large training data set and optimal
	Learns through the training process (knowledge-based systems).	training algorithm.
	Ability to capture high non-linearities in PV power generation data.	Complex and difficult design.
	Can be implemented for large systems with higher accuracy.	Requires more computational memory and time to persist more information.
Hybrid models	Designed to improve the performance of physical or statistical techniques.	Generally, the temporal changes in the PV historical data are not considered.
	Outperforms all the physical models.	Requires larger memory and more time for computing multiple datasets as it combines different methods.

3 | DESCRIPTION OF EXISTING AND PROPOSED MODELS

The analysis of data in accordance with the time it was recorded (generally spaced at equal intervals), is called time series. The objectives of time series analysis are to define the course of generating the data and to predict future values. ARIMA and SARIMA are among the most popular time-series forecasting models[38] reported in the literature. However, looking into the shortcomings as discussed in Section 1.1, in this study, LSTM with Nadam optimizer is proposed. All the three models have been discussed in the following sections.

3.1 | Auto regressive integrated moving average

ARIMA modeling is one of the most popular ways to conquer time-series forecasting. It is mostly used over the nonseasonal and stationary time series. Mathematically, it consists of three terms p, d, and q which are nonnegative integers named autoregressive, integrated, and moving average, respectively. Mathematically, ARIMA (1, 1, 1) can be represented as:

$$\Delta y_t = d + \eta_t, \tag{1}$$

$$\eta_t = \phi_1 \eta_{t-1} + e_t + \theta_1 e_{t-1}. \tag{2}$$

Here, the first difference Δy_t is a zero-mean ARMA (1, 1) process η_t plus the drift term d.

By substituting $\eta_t = y_t - y_{t-1} - d$, the same ARIMA (1, 1, 1) process can be written as:

$$y_t - y_{t-1} - d = \phi_1 (y_{t-1} - y_{t-2} - d) + e_t + \theta_1 e_{t-1}, \tag{3}$$

where d is the drift term; ϕ_1 is the AR (p) coefficient; θ_1 is the MA (q) coefficient.

For the proper selection of (p, d, q), auto_arima function of pmdarima library of python has been used. AIC is used to select the values of p, d, q exactly. Lower the AIC for the given (p, d, q) higher will be the accuracy or fit.[38]

3.2 | Seasonal autoregressive integrated moving average

SARIMA modeling is adopted where a seasonal change in data is present. Thus, it has an advantage over ARIMA as it can be applied to the seasonal data as well. The mathematical equation of the SARIMA contains nonseasonal as well as seasonal terms. The representation of the SARIMA equation is done as follows:

ARIMA (p, d, q) = nonseasonal part of the model,
$(P, D, Q)_m$ = seasonal part of the model,
m = number of observations per year.

Mathematically, the equations for SARIMA (1, 0, 1) × (0, 1, 1, 12) can be represented as follows:

$$Y_t = \phi_1 y_{t-1} + \theta_1 e_{t-1} + \Theta_1 (e_{t-12} + \theta_1 e_{t-13} - D) + e_t. \tag{4}$$

In the above equation, e_t = error at a given time, y_t = value of function at a given time. Θ is the seasonal moving average. D is the seasonal difference and $m = 12$ represents that data is used to identify the seasonality over a year. Whereas ϕ is nonseasonal AR and θ represents nonseasonal moving average.

For the proper selection of $(p, d, q) \times (P, D, Q)_m$, auto_arima function of pmdarima library of python has been used. AIC is used to select the values of p, d, q, P, D, and Q exactly. Lower the AIC for the given $(p, d, q) \times (P, D, Q)_m$ higher will be the accuracy or fit.[39]

The flow diagram for implementing ARIMA and SARIMA models can be seen in Figure 5.

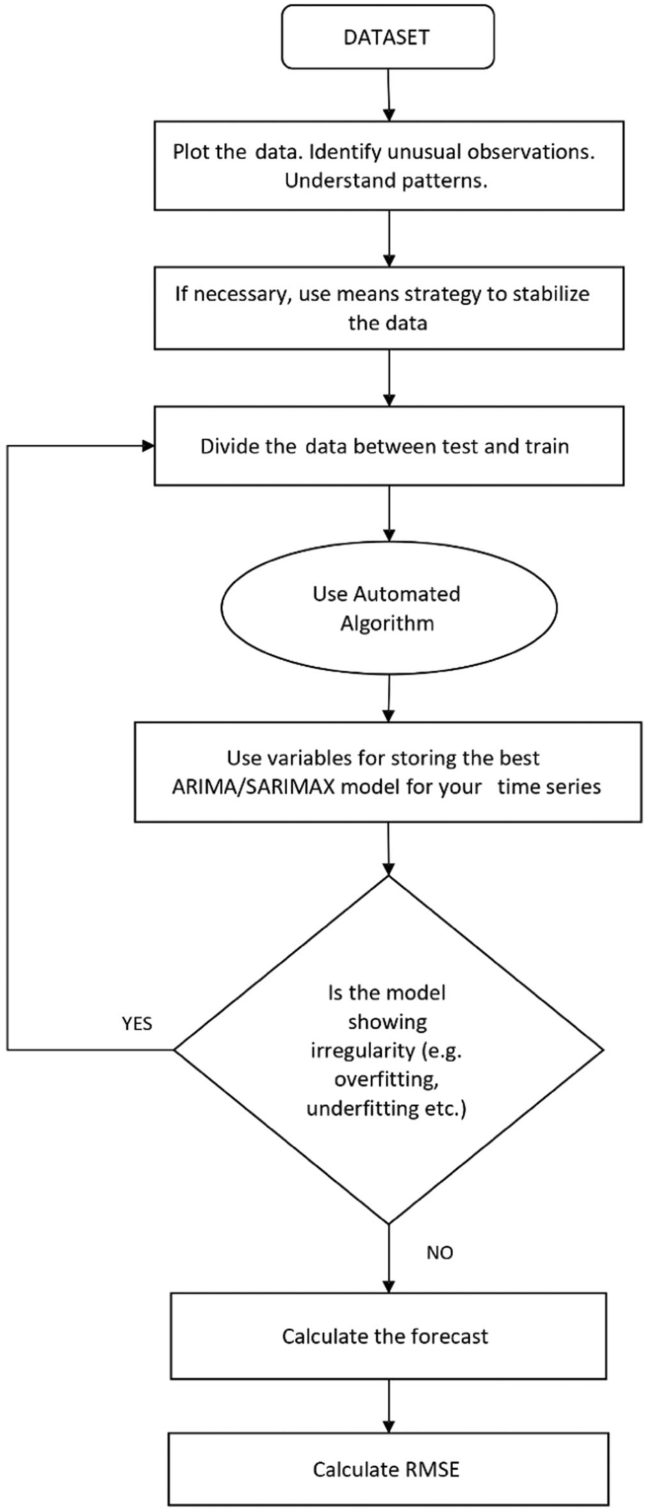


FIGURE 5 Flow diagram of ARIMA/SARIMA implementation.

3.3 | Proposed model using LSTM with nadam optimizer

The LSTM networks are a type of RNN. Before discussing LSTM, a brief discussion on RNN is necessary. RNN is a class of ANN. ANN techniques pose various advantages over the aforementioned techniques.[19,40] But, RNN has a distinctive feature that it can persist the information. It can learn the short-term dependencies, so as the data grows bigger RNN may fail to eradicate this problem. To remove this problem, LSTM is used to have a long-term learning dependency.[41]

A significant challenge faced while using a PV source is to tackle its nonlinear output characteristics. LSTM-based models are effective in understanding the nonlinear relationship between the input and output parameters of a given data set.[42] Hence, LSTM models have been employed for analyzing the effects of meteorological parameters on the solar power output.[25,43–46] The diagram of a common LSTM cell can be seen in Figure 6. The various "memory blocks" or "cells" represented as rectangular blocks are used for

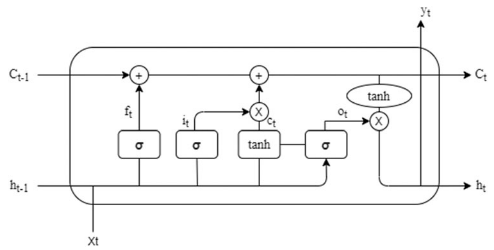


FIGURE 6 Common long short-term memory cell network.

memorizing information and can be exploited using three main mechanisms known as "gates." There are three gates, that is, input, output, and forget gate in a typical LSTM cell network. They are used to control as well as protect the cell states which are transferred toward the next cell; the hidden state and the cell state.[41]

The role of each LSTM gate and its mathematical representation is as follows:

i. Input gate (i): It determines the extent of information to be written onto the Internal Cell State.

$$\mathrm{i}_t = \sigma(w_\mathrm{i}[h_{t\text{-}1},\ x_t] + b_\mathrm{i}). \tag{5}$$

ii. Forget gate (f): It determines the extent to which the previous data is to be forgotten.

$$\mathrm{f}_t = \sigma(w_\mathrm{f}[h_{t\text{-}1},\ x_t] + b_\mathrm{f}). \tag{6}$$

iii. Output gate (o): It determines what output (next Hidden State) to generate from the current internal cell state.

$$\mathrm{o}_t = \sigma(W_\mathrm{o}[h_{t\text{-}1},\ x_t] + b_\mathrm{o}). \tag{7}$$

where i_t represents the input gate, f_t represents forget gate, o_t represents output gate, σ represents a sigmoid function, w_x is weight for the respective gate (x) neurons, H_{t-1} is the output of the previous LSTM block, x_t is input at the current timestamp, b_x represents biases for the respective gates (x).

Hence, due to these numerous advantages of LSTM networks, there has been a great shift of interest toward employing them for solar radiation as well as solar PV power predictions and forecasting. One of the main reasons for this shift has been the type of data, that is, exogenous, or endogenous being required for accurate forecasts.[29] While conventional techniques still rely on exogenous data which is very often inaccessible, uneconomic, or unreliable; LSTM can work simply fine with endogenous data as well. This quality of LSTM networks/models makes them stand out and the first choice for SPV power predictions.

Initially, the data set was set into a supervised learning format and normalized. The data set was converted into the 3D format as anticipated by LSTM (samples, time steps, features). The number of neurons taken in the first hidden layer was 50 and in the output predicting layer was 1. The model was tested for several validation sets running over 50 epochs having a batch size of 10. The flow diagram for the above work has been presented in Figure 7.

For considering the weights of the LSTM network, MAE has been used as the loss recovery method.

$$\text{Mean absolute error} = \sum_{i=1}^{n} \frac{|\hat{y}_i - y_i|}{n}, \tag{8}$$

where $\hat{y}_i$ = predicted value, y_i = actual value, and n = number of days for which the forecast is done.

Furthermore, Nadam has been used as the optimizer for the stochastic gradient descent method. Furthermore, a track of both the training and testing losses throughout the training has been kept by settling the validation data argument in the model. Nadam's one step ahead functionality over adam has reduced the RMSE error. The RMSE is evaluated as follows:

$$\text{Root mean squared error} = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}, \tag{9}$$

where $\hat{y}_i$ = predicted value, y_i = actual value, and n = number of days for which the forecast is done.

This is attributed to it being a combination of both NAG and adam. Its employability for the high curvature/noisy data makes it more useful for such unprecedented datasets. The experiments have been carried out on the following optimizers: SGD, Adamax, RMSprop, Adadelta, Adagrad, Ftrl, Adam, and Nadam.[47–53]

4 | CASE STUDY

The proper selection of input variables, forecast horizon, and climatic factors for the site under consideration greatly affects the accuracy of any model. In general, some input variables are used more frequently while developing forecasting models:

- PV power output data.
- Meteorological parameters like atmospheric temperature, relative humidity, solar radiation, wind speed, and so on.

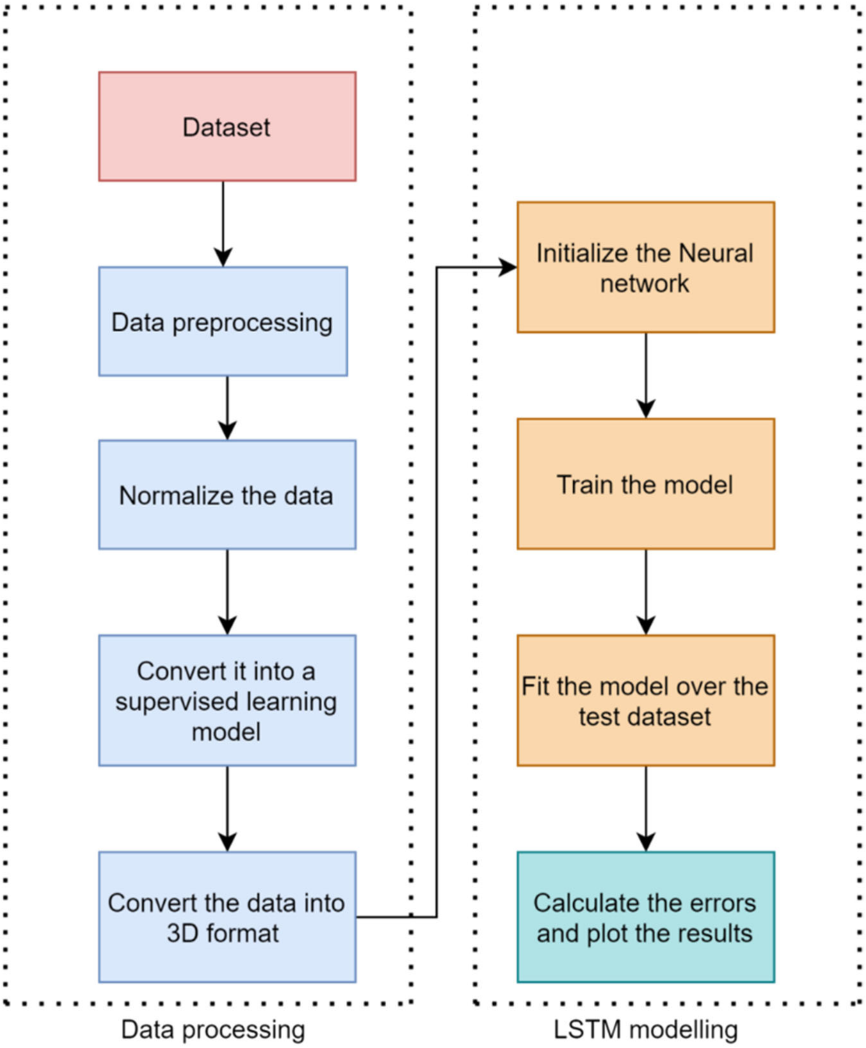


FIGURE 7 Flow diagram of the proposed model.

For demonstrating the implementation of the proposed technique, a case study has been carried out for Bhopal, India. Bhopal located at 23.2599°N; 77.4126°E is estimated to have an annual energy output of 14 kWh/m^2.[54] In this section, the procedure for implementing the proposed framework of LSTM with Nadam optimizer has been discussed. An overview of the forecasting horizons, data collection, data analysis, and parameters used in the study has been presented in the following sections.

4.1 | Data collection

The meteorological and observational solar energy output data for 12 months starting from September 2019 to September 2020 has been acquired from a weather station located at MANIT Campus, Bhopal. Some of the meteorological data has been derived from the Central Pollution Control Board (CPCB).[55] The details of the data sets are mentioned in the following sections.

4.1.1 | Solar (PV) output energy data

The Solar PV system under study for this experiment has the following details (Table 4).

The SPV power system under study consists of solar panels having a total capacity of 250.25 kW with a total of five inverters (3×66 kW and 2×25 kW), situated at MANIT, Bhopal, Madhya Pradesh, India.

4.1.2 | Meteorological (weather) parameters data

The CPCB provides historical meteorological data for different regions throughout India, consisting of several weather metrics for each hour daily for the past few years. The various weather metrics selected are atmospheric temperature, relative humidity, solar radiation, wind speed, and so on. Figure 8 shows the annual variation of all parameters.

TABLE 4 Plant specifications.

Plant details		Location details	
Plant capacity	250.25 kW	Address	Energy Centre Road, MANIT Bhopal (M.P.)
Panel make	Renewsys	Pin code	462007
Plant model	325	Coordinates	Latitude: 23.212101; Longitude: 77.406235
Temperature coefficient	−0.004	Zone	West

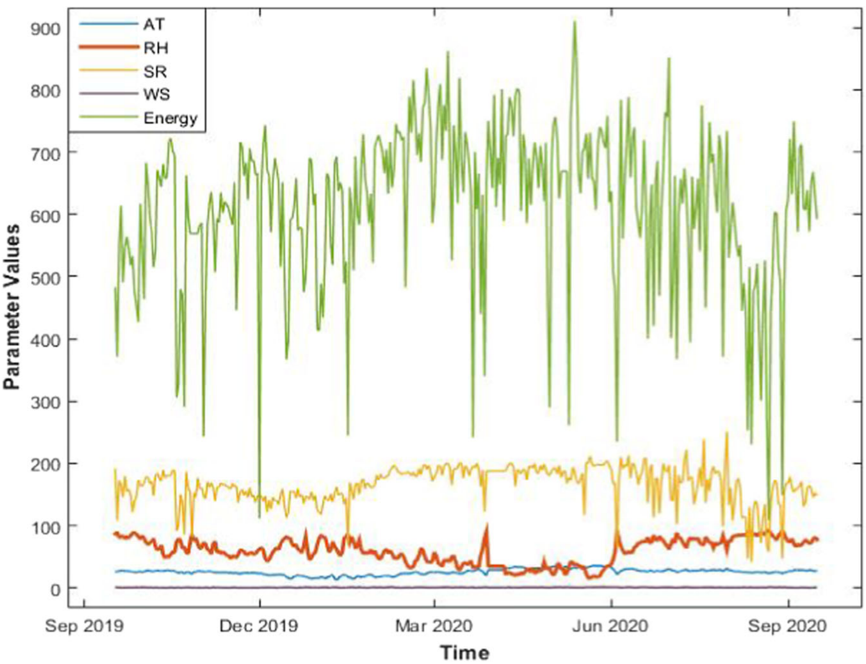


FIGURE 8 Variation of output energy and selected meteorological parameters with time.

In addition to the meteorological metrics, the specific day of the year is also included as a metric since the variable nature of daylight influences the solar intensity at any given site all over a year. The observational SPV energy data from a weather station deployed on the rooftop of the Energy Centre at MANIT has been used in this study. The angle of tilt of the PV arrays is fixed.

The SPV energy being monitored daily over our selected 12-month period, with the day-zero being September 17th, 2019, undergoes seasonal variations which can be observed in Figure 8. As anticipated, the graph reflects the SPV output energy being the least in the month of December–January close to the winter solstice {22/12/2019 for Bhopal} which rises on moving toward the vernal equinox {20/03/2020 for Bhopal} and consequently decreases with the onset of summer thereafter.[18]

4.2 | Data preparation and analysis

To have a thorough investigation of the correlation between SPV power forecasts and climate, the predictive models were made taking into consideration all the meteorological variables that may influence the SPV power output. The dependent variable was the output energy of the SPV system whereas the independent factors were normal averages of atmospheric pressure, atmospheric temperature, relative humidity, solar radiance, wind direction, and wind speed.[56] However, after initial assessments it was found that taking an unnecessarily high number of input variables (training data) makes the model more complex and increases its computational time leading to over-simplification of the data causing problems like “overfitting” and “underfitting.”[31,57] Hence, ineffective parameters, for example, wind direction, atmospheric pressure, and so on were eliminated.

Thereafter, a database entailing the day-to-day values of meteorological parameters and the energy created by the SPV system through the period ranging from 17 September 2019 to 16 September 2020 was composed. The data has been collected in a day-wise format because of the difficulties faced in dealing with the tuning of minute/hour-wise data.[58] Of the 366 days of total accessible data, 270–330 days (variable) are employed for training and the rest for testing purposes. The missing data is imputed, and noisy data is cleaned and normalized with other data sets into the range [0, 1] to forfend any alterations in the results.

The main purpose of the data analysis is to get an insight as to how the power produced by an SPV system is subject to variations with different meteorological measurements. The intricacies, thus observed by initial investigations are the core motivation for generating enhanced SPV power prediction models and their automation. Following the trends, the solar forecast was analyzed using LSTM with a Nadam optimizer. For comparing the results, similar work was carried out upon other optimizers as well as two statistical models, that is, ARIMA and SARIMA. In the upcoming sections, the different models have been introduced.

4.3 | Parameters of adopted models

In this study, three different models have been designed; the first two are based on conventional methods, that is, ARIMA and SARIMA. The third model is proposed using an LSTM network with a Nadam optimizer which overcomes the drawbacks of the first two. The different parameters and corresponding values for ARIMA, SARIMA, and LSTM are presented in Tables 5, 6, and 7, respectively.

The ARIMA model has been trained for different ratios of data set. To select the most optimum p, d, q values, the auto-ARIMA technique has been used which is able to check for the best set of (p, d, q) values.

The proposed model has been implemented using LSTM with a Nadam optimizer. It has been trained on a training set using 50 epochs to minimize the training and validation losses. The weights of the network were updated after every epoch. The batch size has been taken as 10 with a learning rate of 0.0001 with weights being regularized by mean absolute error and nadam optimizer (and aforementioned optimizers).

TABLE 5 ARIMA parameters.

Parameters	Values
p	1
d	1
q	1

Note: The SARIMA model has been trained for different ratios. It also uses the auto-ARIMA technique to check the best fit $(p, d, q) * (P, D, Q)_m$ values.

TABLE 6 SARIMA parameters.

Parameters	Values
p	1
d	0
q	1
P	0
D	1
Q	1
m	12

TABLE 7 LSTM parameters.

Network components used	Quantity/type
Hidden layer	50
Output layer	1
Activation function	Hyperbolic tangent function
Loss function	Mean absolute error
Optimizer	Nadam

5 | RESULTS AND DISCUSSION

This section represents the implementation details of the proposed methods and the result analysis. The following sections will contain model descriptions, results of the proposed method, and comparison of all the methodologies.

5.1 | Results using ARIMA

The ARIMA model having time-series methodology has been trained for a variable data set of 9–11 months. Python library "statsmodels" has been utilised to obtain the results. The model gave the best output with least MSE and RMSE for 296 days of training and 70 days of forecasting as shown in Figure 9. The RMSE value as shown in Figure 10 for all the variable days of the data set was comparable. The ARIMA error values have been presented in Table 8.

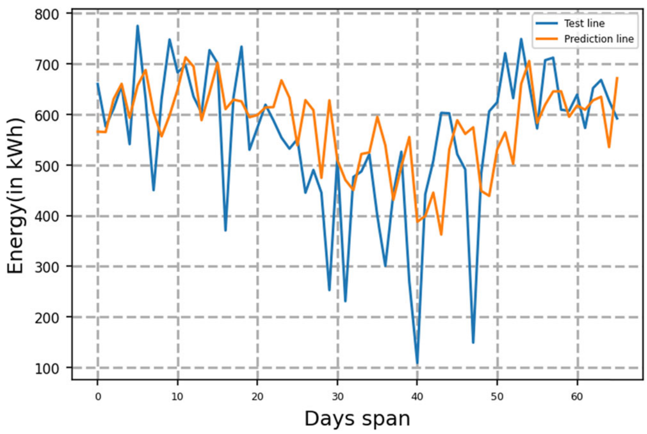


FIGURE 9 Forecast graph using ARIMA model.

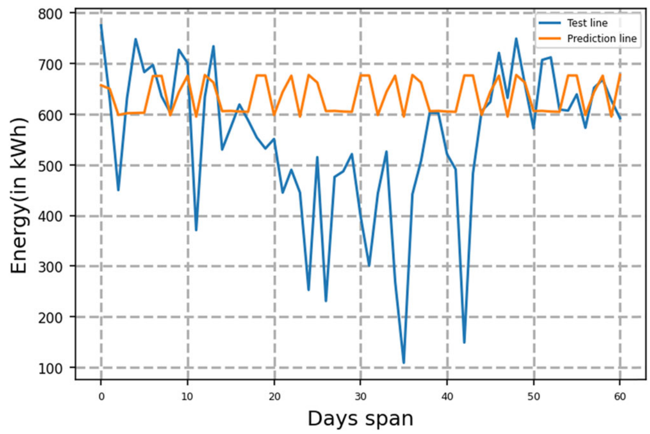


FIGURE 11 Forecast results using SARIMA model.

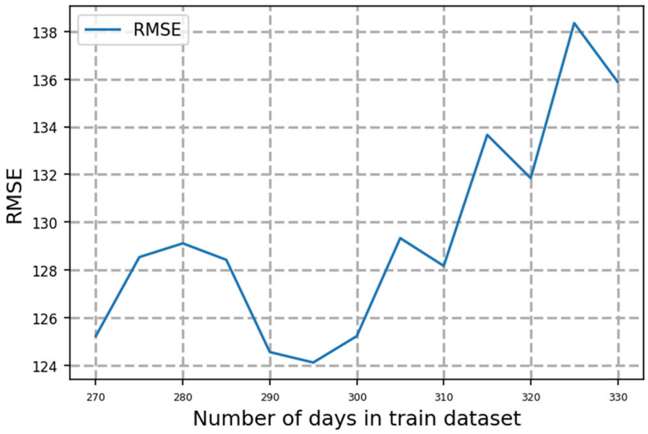


FIGURE 10 Root mean squared error values of a variable number of days in data set for ARIMA.

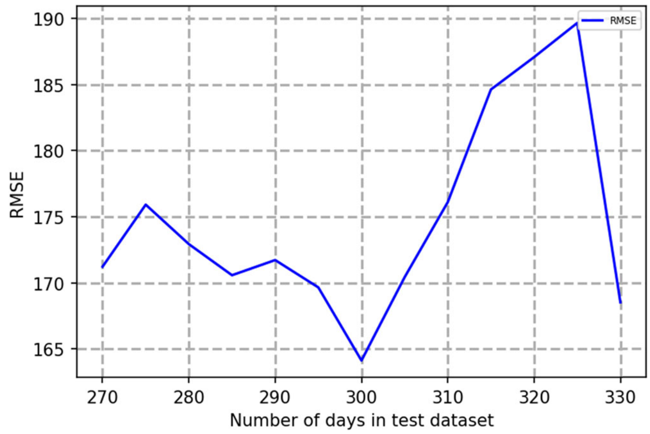


FIGURE 12 Root mean squared error values of variable number of days in the data set for SARIMA.

TABLE 8 ARIMA error values.

Error type	Amount
RMSE	124.126
MSE	15,407.301

TABLE 9 SARIMA error values.

Error type	Amount
RMSE	164.121
MSE	26,935.703

5.2 | Results using SARIMA

SARIMA also works on time-series methodology and the training data set contains 9–11 months. It has been implemented using the "statsmodel" library by making use of the seasonal parameter. The model gave the least RMSE and MSE at 301 days of training data and gave least RMSE for 65 days of forecasting as shown in Figure 11. RMSE values as shown in Figure 12 for all the variable days from the test data set were also comparable. Table 9 presents the SARIMA error values.

5.3 | Results using proposed LSTM with Nadam

LSTM model works on NN and changes the weights of neurons according to the data input. It has been implemented using "keras" library of python. Nadam optimizer has been used as the activation function for the data set. Using Nadam optimizer has enhanced the model's accuracy hence reducing RMSE and MSE. Figure 13 presents the forecast using LSTM models. Figure 14 represents the RMSE values of variable number of days in the data set in LSTM. The number of days in training

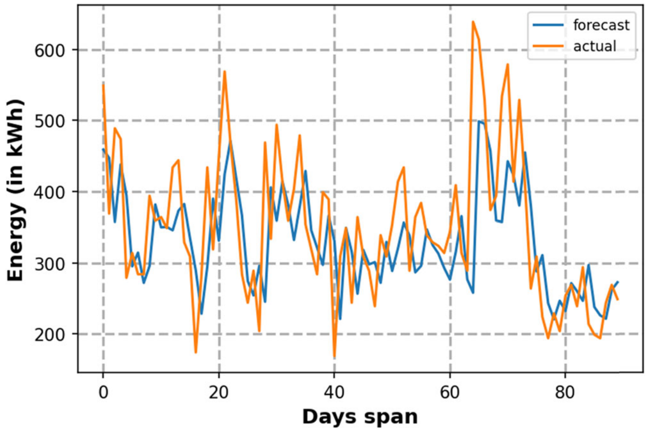


FIGURE 13 Forecast results using LSTM model.

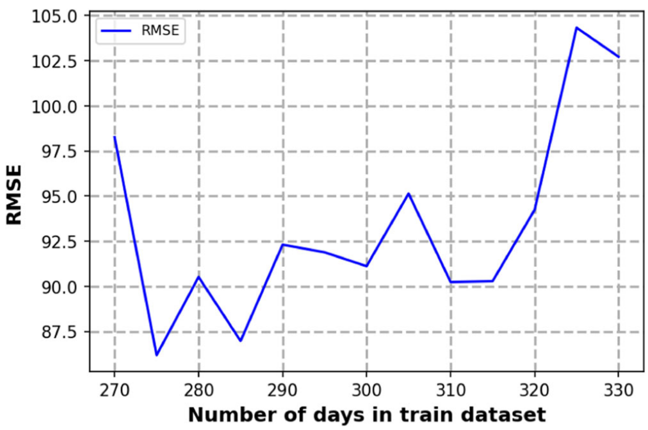


FIGURE 14 Root mean squared error (RMSE) values of variable number of days in the data set for LSTM.

TABLE 10 LSTM error values.

Error type	Amount
RMSE	86.190
MSE	7428.716

data set was taken as 275 and test data consisted of 91 days. RMSE curve for all the test data sets were in range. The LSTM error values have been shown in Table 10.

5.4 | Performance comparison

All the three models were trained on the same data set by taking into consideration the variations in all the methods being used for time series analysis. All the three models including various optimizers were trained on the data set to forecast the result for the test duration time. The LSTM network using Nadam optimiser provided the best results. The broad comparison of all the three models is presented in Figure 15.

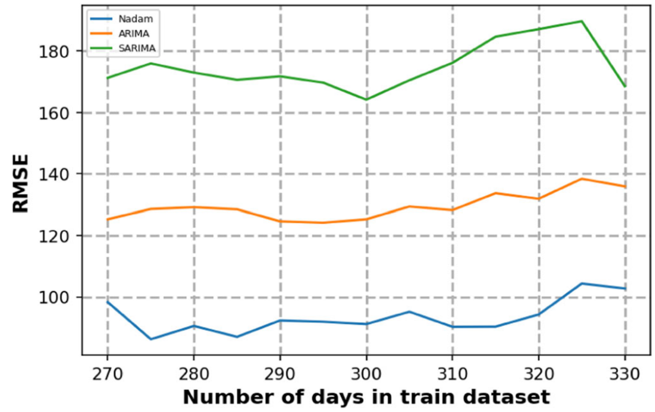


FIGURE 15 Comparison curve of RMSE values for 3 different models.

The tabulated results showing contrasting results for different optimizers based on RMSE values are presented in Table 11.

The detailed comparison covering RMSE values of all the optimizers is presented in Figure 16. Nadam's one step ahead functionality over Adadelta, Ftrl, Adagrad and SGD has reduced the RMSE error significantly while RMSprop, Adamax and Adam provided comparable results.

The Standard deviation values for the different optimizers were calculated according to (10) and can be seen in Table 12. The respective findings have been plotted on Figure 17.

$$\text{Standard deviation}\,(\sigma) = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n}}. \tag{10}$$

where n is the number of predicted days, $\bar{x}$ is the mean of predicted values, and x_i predicted value.

The uncertainty values for the different optimizers were calculated according to (11) and can be seen in Table 13. The respective findings have been plotted on Figure 18.

$$\text{Uncertainty}\,(\mathrm{u}) = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n * (n-1)}}. \tag{11}$$

6 | DISCUSSION

As shown in Sections 5.3 and 5.4 the proposed model outperforms the compared models. From the analysis made of the results of different models, it can be observed that the optimization through Nadam was the key step in improving the forecast accuracy. The actual output compared with the predicted plant output results using the proposed approach with LSTM and Nadam optimizer show significant

TABLE 11 RMSE values for different optimizers.

No. of days in train data set	Nadam	RMSprop	SGD	Adadelta	Adagrad	Adamax	Ftrl	Adam	ARIMA	SARIMA
270	98.260	98.194	102.247	251.918	108.745	94.741	227.977	99.648	125.235	171.226
275	**86.190**	91.905	102.530	258.499	107.842	95.589	220.929	**87.440**	128.546	175.917
280	90.521	97.479	**90.613**	231.395	**97.760**	91.618	215.892	94.893	129.123	172.930
285	86.976	90.679	103.465	235.886	107.718	94.268	217.378	89.165	128.433	170.580
290	92.309	89.532	104.330	267.796	104.214	91.371	216.138	92.522	124.565	171.725
295	91.886	**87.367**	101.367	214.025	110.668	95.512	218.542	90.192	**124.126**	169.657
300	91.120	90.336	102.834	260.270	105.668	94.693	211.809	90.684	125.233	**164.121**
305	95.140	94.898	101.921	256.707	110.578	90.994	213.808	89.184	129.342	170.428
310	90.240	98.024	96.909	226.316	108.877	**89.330**	**206.678**	97.293	128.177	176.109
315	90.284	95.859	98.653	212.434	114.030	93.161	207.356	97.989	133.657	184.631
320	94.240	105.029	106.914	253.982	117.986	97.855	212.973	96.694	131.843	187.079
325	104.323	102.569	111.883	**174.811**	119.173	101.071	219.389	105.706	138.345	189.664
330	102.715	101.379	117.841	244.361	126.157	104.122	219.421	103.558	135.876	168.530

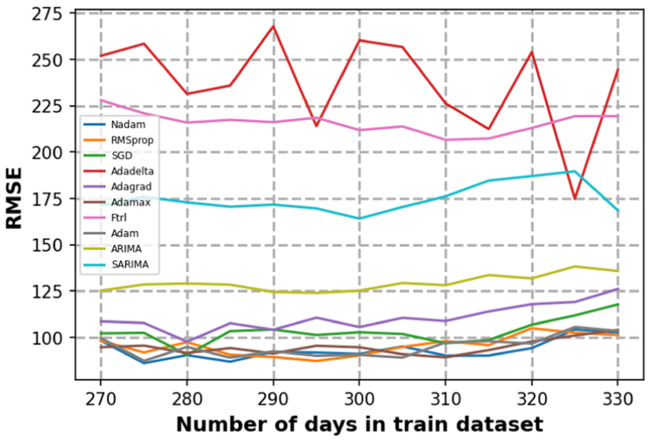


FIGURE 16 Comparison of RMSE values for 8 optimizers and 2 time-series forecasting methods.

improvement of 30.56% over ARIMA, 47.48% over SARIMA, and 1.35%, 1.43%, 3.51%, 4.88%, 11.84%, 50.69%, and 58.29% over models using RMSprop, Adam, Adamax, SGD, Adagrad, Adadelta, and Ftrl optimizer, respectively. Thus, the proposed model used to forecast the long time-horizon values of the SPV system located at MANIT, Bhopal significantly improves the accuracy of the predicted plant output. However, there are some limiting factors:

- The model requires more time and memory to train.
- Less control over the memory of the forget gate of LSTM architecture.
- Optimal removal of outliers is required to prevent overfitting.
- The efficacy of the model varies on conversion from online mode to hardware implementation depending upon the input data set.

Despite having some limitations, the proposed method can be used for the following applications:

- Optimal regulation of solar PV plants and protection from operational issues such as inverse power flow, and voltage spikes.
- Planning and installation of solar PV units based on their optimal locations and sizes.
- Grid-integration of standalone medium to large-scale solar PV plants.
- Systematic scheduling of auxiliary supplies and generators (e.g., diesel generators) with respect to the solar PV power forecasts to ensure economic operation.
- Maintenance of power controller and storage devices (e.g., batteries) for enhanced system operation.

The future work will be focused on removing the aforementioned limitations and further expanding the applications of the proposed model.

7 | CONCLUSIONS AND FUTURE SCOPE

Accurate solar power forecasting is subject to the planning and recording system of power plant design. The intermittent behavior of solar irradiance makes solar

TABLE 12 Standard deviation values for different optimizers.

No. of days in train data set	Nadam	RMSprop	SGD	Adam	Adadelta	Adagrad	Adamax	Ftrl	ARIMA	SARIMA
270	69.858	72.242	19.497	70.274	4.848	15.318	69.099	0.008	73.342	41.715
275	69.976	69.899	19.281	69.999	4.546	13.659	71.108	0.013	72.732	40.931
280	69.793	68.256	24.462	68.254	5.373	14.232	67.956	0.008	72.176	41.586
285	68.706	68.544	18.317	68.730	5.254	**8.539**	66.125	0.007	71.538	40.211
290	68.220	69.471	19.524	70.370	6.795	14.779	66.979	0.015	70.832	41.540
295	69.803	**66.984**	18.681	70.166	10.488	14.088	67.034	0.017	70.067	41.580
300	**66.280**	68.537	22.890	68.381	5.040	16.590	67.263	0.016	**69.159**	41.212
305	67.218	69.324	17.027	67.573	8.111	15.042	66.576	0.015	69.852	40.509
310	68.626	67.560	23.991	67.172	4.235	20.827	**64.869**	0.019	70.247	40.740
315	67.893	67.569	**13.790**	**65.795**	4.542	18.306	68.058	0.020	71.745	**37.924**
320	70.075	68.123	21.657	69.271	9.011	10.644	67.325	**0.005**	72.949	42.016
325	73.054	71.659	20.772	72.359	8.698	22.639	70.747	0.014	74.731	43.372
330	75.539	75.906	20.428	76.469	**3.481**	14.190	75.167	0.048	75.865	44.071

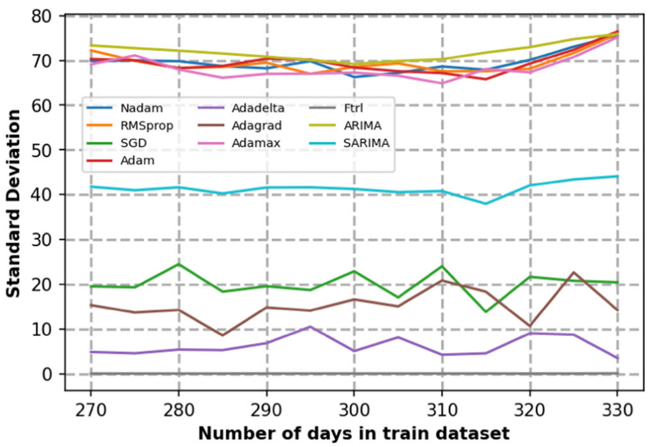


FIGURE 17 Comparison of standard deviation values for eight optimizers and two time-series forecasting methods.

forecasting one of the most essential components of system planning. Inaccurate forecasting may lead to a system design that has compromised reliability standards and poor economic viability. In this paper, an effective technique for long time horizon forecasting has been proposed. The major contributions of this study can be summarized as follows:

- A novel SPV power forecasting technique based on LSTM using Nadam is proposed. The proposed models show the variation in SPV output power with respect to the meteorological parameters under consideration.
- The performance of eight LSTM, as well as ARIMA and SARIMA time series forecasting models with different algorithms, are evaluated.
- The efficacy of the proposed technique is verified by comparing it with two extensively used SPV power forecasting methods.

The proposed method of predicting SPV power also helps in the prediction of circumventing factors, such as solar irradiance, the efficiency of the SPV module, and the impact of other meteorological parameters. The meteorological parameters that are studied for alternative modeling methods also add to the accuracy and reliability of the system.

As observed in Section 1.1, as the size of the SPV plant under consideration and the forecasting time horizon increases, the forecasting accuracy decreases significantly. The proposed model which is developed on a large-scale SPV plant of 250.25 kW for a long time horizon significantly reduces the difficulties faced in the future analysis of varied sizes of plants without conducting a comprehensive analysis between the correlations of meteorological and plant parameters. The model is simple while parameterizing based on layers used and epochs considered. The authors have emphasized more on the optimization of optimizers used in the forecasting of solar PVs. The usage of the Nadam optimizer helps in driving the predictions in the right direction considering the rolling momentum attached. Thus, the model will scale on large data sets as well as this architecture will help in creating a driving momentum for the forecasting

TABLE 13 Uncertainty values for different optimizers.

No. of days in train data set	Nadam	RMSprop	SGD	Adam	Adadelta	Adagrad	Adamax	Ftrl	ARIMA	SARIMA
270	**7.297**	7.418	2.342	**7.319**	1.483	1.831	**6.842**	0.001	5.172	3.462
275	7.577	**7.286**	2.190	7.592	0.406	**1.299**	7.210	**0.000**	5.010	**3.380**
280	7.460	7.496	**2.010**	7.361	0.583	1.534	7.368	0.002	**4.982**	3.472
285	7.587	7.500	2.141	7.661	0.627	1.665	7.573	0.001	5.103	3.586
290	8.055	8.314	2.058	7.925	0.411	1.549	7.612	0.000	5.353	3.629
295	8.509	8.300	2.460	8.636	0.917	1.344	8.066	0.001	5.764	3.794
300	8.495	8.306	2.024	8.529	**0.228**	1.904	8.450	0.002	5.516	3.968
305	8.701	8.829	2.952	8.772	0.792	2.350	8.580	0.003	6.009	4.236
310	9.122	9.145	3.052	9.212	0.359	3.670	8.983	0.001	6.178	4.708
315	9.579	9.512	3.507	9.628	1.599	2.465	9.050	0.003	6.765	4.571
320	10.326	10.229	2.515	10.244	1.340	2.955	10.083	0.004	6.931	4.993
325	11.509	11.740	4.159	11.494	0.840	2.627	11.303	0.004	7.948	5.471
330	12.633	12.795	3.494	12.563	2.297	3.844	12.651	0.003	8.756	6.314

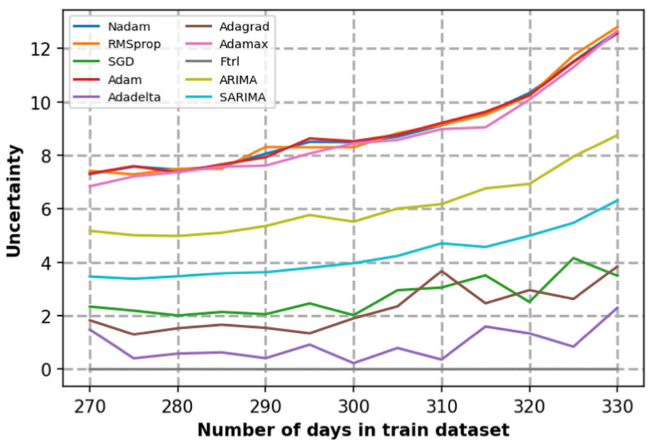


FIGURE 18 Comparison of Uncertainty values for 8 optimizers and 2 time-series forecasting methods.

curve, and the forget gate of LSTM helps retain the momentum calculated in previous steps.

None of the studies in recent literature have considered such a large plant in their work for long-term forecasts. Thus, the proposed model can also be implemented even for a smaller plant by downscaling the metrics of certain parameters while maintaining good accuracy.

However, there are some limitations to the proposed method such as less control over the memory of LSTM's forget gate, more training time as the model cannot be implemented without having minimal data set regarding a few of the weather factors including the parameters of the plant which may lead to some problems during the hardware implementation of the virtual model.

Further work may be carried out on the same model using more layers of neurons or by increasing the training data set. Newer approaches like GRU, DNN, and some hybrid models can be taken up making use of the statistical methods with NN. More input parameters like aerosol index, barometric pressure, and wind direction can be considered depending upon the correlation factor.

NOMENCLATURE

ACF	auto-correlation function
AIC	Akaike information criterion
ANN	artificial neural networks
APSO-ELM	accelerate particle swarm optimization-extreme learning machine
ARIMA	auto-regressive integrated moving average
BIC	Bayesian information criterion
BIPVS	building-integrated photovoltaics system
CAGR	compound annual growth rate
CRPSO-ELM	craziness particle swarm optimization-extreme learning machine
d	difference
ELM	extreme learning machine
GRU	gated recurrent unit
LSTM	long short-term memory
m	duration of training data set
MAE	mean average error
MAPE	mean absolute percentage error
MRE	mean relative error
N	number of input parameters

NN	neural networks
NRMSE	normalized root mean square error
NWP	numerical weather prediction
p	auto-regressive
PACF	partial auto-correlation function
PSO-ELM	particle swarm optimization-extreme learning machine
q	moving average
RES	renewable energy sources
RMSE	root mean square error
RNN	recurrent neural networks
SARIMA	seasonal auto-regressive integrated moving average
SPV	solar photovoltaic

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REFERENCES

1. World Economic Forum. New Energy Architecture India. Accessed January 20, 2021. http://reports.weforum.org/new-energy-architecture-india/
2. Indian Renewable Energy Industry Report. Accessed January 20, 2021. https://www.ibef.org/industry/renewable-energy.aspx
3. Global Solar Atlas: Photovoltaic Power Potential of India. Accessed January 20, 2021. https://globalsolaratlas.info/download/india
4. International Energy Agency (IEA), India 2020 Energy Policy Review. Accessed January 20, 2021. https://niti.gov.in/sites/default/files/2020-01/IEA-India%202020-In-depth-EnergyPolicy_0.pdf
5. Alayi R, Kumar R, Seydnouri SR, Mohammad Hossein A, Issakhov A. Energy, environment and economic analyses of a parabolic trough concentrating photovoltaic/thermal system. *Int J Low-Carbon Technol*. 2021;16(2):570-576. doi:10.1093/ijlct/ctaa086
6. Alayi R, Mohammad Hossein A, Visei AR, Sharma S, Najafi A. Technical and environmental analysis of photovoltaic and solar water heater cogeneration system: a case study of Saveh City. *Int J Low-Carbon Technol*. 2021;16(2):447-453. doi:10.1093/ijlct/ctaa077
7. Alayi R, Mohkam M, Seyednouri SR, Mohammad Hossein A, Sharifpur M. Energy/economic analysis and optimization of on-grid photovoltaic system using CPSO algorithm. *Sustainability*. 2021;13(22):12420. doi:10.3390/su132212420
8. Sari-Ali I, Rahmoun K, Chikh-Bled B, et al. Mono-crystalline silicon photovoltaic cells under different solar irradiation levels. *Optik*. 2020;223:165653. doi:10.1016/j.ijleo.2020.165653
9. Açıkkalp E, Kandemir SY, Ahmadi MH. Performance evaluation of the thermophotovoltaic-driven thermoionic refrigerator. *J Energy Resour Technol*. 2020;142(3):032001. doi:10.1115/1.4044558
10. Paliwal P. Reliability constrained planning and sensitivity analysis for solar-wind-battery based isolated power system. *Int J Sustain Energy Planning Manage*. 2020;29:109-126. doi:10.5278/ijsepm.4599
11. Paliwal P, Patidar NP, Nema RK. Probabilistic indices for analysing the impact of penetration of distributed energy resources on system reliability. *IET Renew Power Gen*. 2020;14(12):2154-2165. doi:10.1049/iet-rpg.2019.1214
12. Sharadga H, Hajimirza S, Balog RS. Time series forecasting of solar power generation for large-scale photovoltaic plants. *Renew Energy*. 2020;150:797-807. doi:10.1016/j.renene.2019.12.131
13. Basurto N, Arroyo Á, Vega R, Quintián H, Calvo-Rolle J, Herrero Á. A hybrid intelligent system to forecast solar energy production. *Comput Electr Eng*. 2019;78:373-387. doi:10.1016/j.compeleceng.2019.07.023
14. Santhosh M, Venkaiah C, Kumar DMV. Current advances and approaches in wind speed and wind power forecasting for improved renewable energy integration: a review. *Eng Rep*. 2020;2(6):e12178. doi:10.1002/eng2.12178
15. Khalid R, Javaid N. A survey on hyperparameters optimization algorithms of forecasting models in smart grid. *Sustain Cities Soc*. 2020;61:102275. doi:10.1016/j.scs.2020.102275
16. Vaziri R, Oladipo AA, Sharifpur M, Taher R, Mohammad Hossein A, Issakhov A. Efficiency enhancement in double-pass perforated glazed solar air heaters with porous beds: Taguchi-artificial neural network optimization and cost–benefit analysis. *Sustainability*. 2021;13(21):11654. doi:10.3390/su132111654
17. Zolghadri A, Maddah H, Mohammad Hossein A, Sharifpur M. Predicting parameters of heat transfer in a shell and tube heat exchanger using aluminum oxide nanofluid with artificial neural network (ANN) and self-organizing map (SOM). *Sustainability*. 2021;13(16):8824. doi:10.3390/su13168824
18. Sharma N, Sharma P, Irwin D, Shenoy P. Predicting solar generation from weather forecasts using machine learning. 2011 IEEE international conference on smart grid communications (SmartGridComm). IEEE; 2011:528-533. doi:10.1109/SmartGridComm.2011.6102379
19. Rana M, Koprinska I, Agelidis VG. Univariate and multivariate methods for very short-term solar photovoltaic power forecasting. *Energy Convers Manage*. 2016;121:380-390. doi:10.1016/j.enconman.2016.05.025
20. Behera MK, Majumder I, Nayak N. Solar photovoltaic power forecasting using optimized modified extreme learning machine technique. *Eng Sci Technol Int J*. 2018;21(3):428-438. doi:10.1016/j.jestch.2018.04.013

21. de Paiva GM, Pimentel SP, Marra EG, et al. Intra-day forecasting of building-integrated PV systems for power systems operation using ANN ensemble. 2019 IEEE Milan PowerTech. IEEE; 2019:1-5. doi:10.1109/PTC.2019.8810480
22. Mishra S, Palanisamy P. Multi-time-horizon solar forecasting using recurrent neural network. 2018 IEEE Energy Conversion Congress and Exposition (ECCE). IEEE; 2018:18-24. doi:10.1109/ECCE.2018.8558187
23. Kardakos EG, Minas CA, Vagropoulos S, Simoglou CK, Biskas PN, Bakirtzis AG. Application of time series and artificial neural network models in short-term forecasting of PV power generation. 2013 48th International Universities' Power Engineering Conference (UPEC). IEEE; 2013:1-6. doi:10.1109/UPEC.2013.6714975
24. Chen C, Duan S, Cai T, Liu B. Online 24-h solar power forecasting based on weather type classification using artificial neural network. *Sol Energy*. 2011;85(11):2856-2870. doi:10.1016/j.solener.2011.08.027
25. Lee D, Kim K. Recurrent neural network-based hourly prediction of photovoltaic power output using meteorological information. *Energies*. 2019;12(2):215. doi:10.3390/en12020215
26. VanDeventer W, Jamei E, Thirunavukkarasu GS, et al. Short-term PV power forecasting using hybrid GASVM technique. *Renew Energy*. 2019;140:367-379. doi:10.1016/j.renene.2019.02.087
27. Das UK, Tey KS, Seyedmahmoudian M, et al. Forecasting of photovoltaic power generation and model optimization: a review. *Renew Sustain Energy Rev*. 2018;81:912-928. doi:10.1016/j.rser.2017.08.017
28. Seyedmahmoudian M, Jamei E, Thirunavukkarasu GS, et al. Short-term forecasting of the output power of a building-integrated photovoltaic system using a metaheuristic approach. *Energies*. 2018;11(5):1260. doi:10.3390/en11051260
29. Abdel-Nasser M, Mahmoud K. Accurate photovoltaic power forecasting models using deep LSTM-RNN. *Neural Comput Appl*. 2019;31(7):2727-2740. doi:10.1007/s00521-017-3225-z
30. Sobri S, Koohi-Kamali S, Abd Rahim N. Solar photovoltaic generation forecasting methods: a review. *Energy Convers Manage*. 2018;156:459-497. doi:10.1016/j.enconman.2017.11.019
31. Sophie P, Remund J, Kleissl J, Oozeki T, De Brabandere K. Photovoltaic and solar forecasting: state of the art. *IEA PVPS, Task*. 2013;14(2013):1-36. https://iea-pvps.org/key-topics/photovoltaics-and-solar-forecasting-state-of-art-report-t1401-2013/
32. Antonanzas J, Osorio N, Escobar R, Urraca R, Martinez-de-Pison FJ, Antonanzas-Torres F. Review of photovoltaic power forecasting. *Sol Energy*. 2016;136:78-111. doi:10.1016/j.solener.2016.06.069
33. Gao M, Jianjing L, Hong F, Long D. Short-term forecasting of power production in a large-scale photovoltaic plant based on LSTM. *Appl Sci*. 2019;9(15):3192. doi:10.3390/app9153192
34. Adel M, Massi Pavan A, Lughi V. Short-term forecasting of power production in a large-scale photovoltaic plant. *Sol Energy*. 2014;105:401-413. doi:10.1016/j.solener.2014.03.018
35. Halpern-Wight N, Konstantinou M, Charalambides AG, Reinders A. Training and testing of a single-layer LSTM network for near-future solar forecasting. *Appl Sci*. 2020;10(17):5873. doi:10.3390/app10175873
36. Rana M, Rahman A. Multiple steps ahead solar photovoltaic power forecasting based on univariate machine learning models and data re-sampling. *Sustain Energy Grids Netwk*. 2020;21:100286. doi:10.1016/j.segan.2019.100286
37. Akhter MN, Mekhilef S, Mokhlis H, Mohamed Shah N. Review on forecasting of photovoltaic power generation based on machine learning and metaheuristic techniques. *IET Renew Power Gener*. 2019;13(72019):1009-1023. doi:10.1049/iet-rpg.2018.5649
38. Souissi A, Guidara I, Chaabene M. Dynamic forecasting-based load control of an autonomous photovoltaic installation. *Comput Electr Eng*. 2020;85:106674. doi:10.1016/j.compeleceng.2020.106674
39. Box GEP, David AP. Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. *J Am Stat Assoc*. 1970;65(332):1509-1526. doi:10.1080/01621459.1970.10481180
40. Pedro HTC, Carlos FMC. Assessment of forecasting techniques for solar power production with no exogenous inputs. *Sol Energy*. 2012;86(7):2017-2028. doi:10.1016/j.solener.2012.04.004
41. Hochreiter S, Schmidhuber J. Long short-term memory. *Neural Comput*. 1997;9(8):1735-1780. doi:10.1162/neco.1997.9.8.1735
42. He H, Hu R, Zhang Y, Zhang Y, Jiao R. A power forecasting approach for PV plant based on irradiance index and LSTM. 2018 37th Chinese Control Conference (CCC). IEEE; 2018:9404-9409. doi:10.23919/ChiCC.2018.8483960
43. Gao M, Jianjing L, Hong F, Long D. Day-ahead power forecasting in a large-scale photovoltaic plant based on weather classification using LSTM. *Energy*. 2019;187:115838. doi:10.1016/j.energy.2019.07.168
44. Li J, RunRan L, Jia YJ, Zhang ZX. Prediction of short-term photovoltaic power via codec neural network and mode decomposition based deep learning approach. *Energy Sci Eng*. 2021:1-18. doi:10.1002/ese3.1009
45. Ali A, Ahmed A, Labbadi M, El Houm Y. Short-term self consumption PV plant power production forecasts based on hybrid CNN-LSTM, ConvLSTM models. *Renew Energy*. 2021;177:101-112. doi:10.1016/j.renene.2021.05.095
46. Li Y, Yaoyu H, Zhang M. Prediction of Chinese energy structure based on convolutional neural network-long short-term memory (CNN-LSTM). *Energy Sci Eng*. 2020;8(8):2680-2689. doi:10.1002/ese3.698
47. Sutskever I, Martens J, Dahl G, Hinton G. On the importance of initialization and momentum in deep learning. International conference on machine learning. PMLR; 2013:1139-1147. http://www.jmlr.org/proceedings/papers/v28/sutskever13.pdf
48. Da K. A method for stochastic optimization. *arXiv preprint arXiv*. 2014;1412:6980. https://arxiv.org/abs/1412.6980v9
49. Hinton G, Srivastava N, Swersky K. Overview of mini-batch gradient descent. *Neural Netwk Mach Learn*. 2012;575:16-21. http://www.cs.toronto.edu/%7Ehinton/coursera/lecture6/lec6.pdf
50. Zeiler MD. Adadelta: an adaptive learning rate method. *arXiv preprint arXiv*. 2012;1212:5701. https://arxiv.org/abs/1212.5701
51. Duchi J, Hazan E, Singer Y. Adaptive subgradient methods for online learning and stochastic optimization. *J Mach Learn Res*. 2011;12(7):2121-2159. https://www.jmlr.org/papers/volume12/duchi11a/duchi11a.pdf

52. McMahan H, Brendan G, Holt D, et al. Ad click prediction: a view from the trenches. Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining; 2013:1222-1230. doi:10.1145/2487575.2488200
53. Dozat T. Incorporating nesterov momentum into adam; 2016. http://cs229.stanford.edu/proj2015/054_report.pdf
54. Shukla KN, Rangnekar S, Sudhakar K. Mathematical modelling of solar radiation incident on tilted surface for photovoltaic application at Bhopal, MP, India. *Int J Ambient Energy*. 2016;37(6):579-588. doi:10.1080/01430750.2015.1023834
55. Central Pollution Control Board; Ministry of Environment, Forest and Climate Change, Government of India. Accessed January 20, 2021. https://www.cpcb.nic.in
56. Praynlin E, Ida Jensona J. Solar radiation forecasting using artificial neural network. In 2017 Innovations in Power and Advanced Computing Technologies (i-PACT). IEEE; 2017:1-7. doi:10.1109/IPACT.2017.8244939
57. Ramsami P, Oree V. A hybrid method for forecasting the energy output of photovoltaic systems. *Energy Convers Manage*. 2015;95:406-413. doi:10.1016/j.enconman.2015.02.052
58. Srivastava R, Tiwari AN, Giri VK. Forecasting of solar radiation in India using various ANN models. 2018 5th IEEE Uttar Pradesh section international conference on electrical, electronics and computer engineering (UPCON). IEEE; 2018:1-6. doi:10.1109/UPCON.2018.8597170

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