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Modeling of solar photovoltaic power using a two-stage forecasting system with operation and weather parameters

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ABSTRACT

The integration of solar photovoltaic (SPV) system to the grid has introduced a new source of intermittency in the grid, and the grid has to react smartly to the changes that occur in the penetration of SPV power. Accurate modeling of weather-dependent SPV power will be helpful in forecasting the penetration of SPV power into the grid. An SPV power output forecasting model has been developed based on artificial neural network (ANN) approach. Two forecasters, namely ANN forecaster and two-stage hybrid-ANN forecaster, are developed with operational and weather parameters. The historical data of SPV power (P), hours of operation of SPV system (t_o), daily global solar radiation (H), and ambient temperature(T) are used as modeling parameters. The combination of modeling parameters {P, H, T, t_o} is identified as the best combination that influences the forecasting of day-ahead power output. A relative root mean square error (RRMSE) of 5.74% was obtained with the combination of {P, H, T, t_o}. An RRMSE of 6.04% was observed with the combination of {P, H, T} as inputs, and the hours of operation of the SPV plant could be ignored in the model. The historical power data of the SPV plant is identified as the crucial parameter in the SPV power forecast model and has given an RRMSE of 7.25%. The models developed with temperature and radiation as modeling parameters have resulted in good forecasting accuracy, which could be best suitable for feasibility studies of SPV plant at a particular location. Solar radiation prediction models are used in the development of hybrid-ANN forecaster. It has produced an RRMSE of 7.35% with four inputs. The hybrid-ANN forecaster with predicted radiations as modeling input will eliminate the need of a costly pyranometer. The models developed in the present study have utilized readily available parameters as modeling parameters, thereby cost of the forecasting system has been decreased. The developed models will be useful for energy scheduling and energy management in the smart grid.

Abbreviations: GSR, Global Solar Radiation; ANN, Artificial Neural networks; SPV, Solar Photovoltaics; MAPE, Mean Absolute Percentage Error; RRMSE, Relative Root Mean Square Error; MSE, Mean Square Error.

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Introduction

In recent times, the consumption of energy from conventional sources has been increased, which causes the rapid depletion of fossil fuel-based resources. The emission of greenhouse gases has increased because of the utilization of conventional sources over the past few decades (Fikru and Gautier 2015). In addition to that, the energy demand has been increasing enormously in both developed and developing countries due to the increase in population, urbanization, and

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industrialization. The portion of this energy demand can be met by renewable energy sources (RES) such as wind and sun. Solar energy can be captured by installing solar collectors, solar ponds, solar chimneys, and solar photovoltaics (SPVs). Out of all these installations, the SPV installation growth rate has increased enormously. The generation of electricity using SPV is widely accepted (Larson, Nonnenmacher, and Coimbra 2016). PV power generation is eco-friendly because it produces no toxic emission, of low maintenance, of noiseless operation, and it is abundantly available (Yan et al. 2021). Up to now, several thousands of SPV systems of 1 kW to several hundreds of megawatts have been installed and integrated into the grid worldwide (Tina, Scavo, and Gagliano 2020). The integration of SPV systems to the grid has introduced a new resource of intermittency in the grid (Sepasi et al. 2017). This is due to the sensitivity of the SPV system to local weather conditions and variation in solar radiation availability. The SPV power output is uncertain since the parameters like irradiance level, ambient temperature, surface temperature of the panel, dust deposits, wind speed, cloud cover, and relative humidity etc., will have an impact on the SPV power generation. Accurate modeling of SPV power is required by the utilities to control the high instabilities of the electric grid due to unpredictable PV power penetrations (Wan et al. 2015).

In modern days, 'smart grid' has grabbed the attention and the development of accurate forecasting models, which will be much needed to meet the secure and reliable integration of renewable energy sources, especially, SPV systems into the smart grid. The changes in the SPV power production will be analyzed to schedule and manage the grid operations in the smart grid environment. SPV power forecasting is also an important factor for planning the operations of the SPV system. Accurate forecasting of solar power is essential for secure, economic, and reliable operation of the smart electrical grid (Bouzerdoum, Mellit, and Massi Pavan 2013).

Power forecasting involves an accurate prediction of the power at different time steps like 1 h ahead (Ozbek, Yildirim, and Bilgili 2021), 2 h ahead, 1 day ahead (Clements, Hurn, and Li 2015), and 2 days ahead in the future (Larson, Nonnenmacher, and Coimbra 2016). Intra-hour (5 min, 10 min, 15 min, etc.) forecasting will be used in power smoothening and power system dynamic analysis. Intra-day (1 h ahead, 2 h ahead, etc.) will be used for unit commitment, economic load dispatch problems, and electricity trading. Day ahead values will be used for power system scheduling, maintenance, storage system management, transmission scheduling, and day-ahead markets.

Forecasting can be done either with deterministic models (Pedro and Coimbra 2017) or with probabilistic models (Ramakrishna et al. 2019). PV generation forecast methods can be mainly classified into artificial intelligence (AI) approach, physical modeling approach, and hybrid modeling approach. AI approach will utilize machine learning (ML) methods like artificial neural networks (ANNs), adaptive neuro-fuzzy interface systems (ANFIS), and support vector regression (SVR) to construct the solar forecast models. ANNs will use environmental and operational parameters as modeling parameters in order to estimate the SPV power output. Historical data of the SPV power can also be used as one of the modeling parameters in the development of forecast models with ANNs (Izgi et al. 2012). Historical SPV power means the power data recorded until the current time 't.' Physical models are based on the numerical weather prediction (NWP) that predicts the solar irradiance; irradiance will be used to predict the PV generation. The physical models will include mathematical relations that are derived from regression analysis and statistical analysis. Finally, hybrid approaches are a combination of AI models and physical models. Many researchers focused on providing a forecasting tool to predict SPV power prediction with good accuracy.

The PV power can be predicted using physical prediction approach based on solar irradiance on a surface. Irradiance models will play a major role in the prediction of SPV power (Cui et al. 2019). A regional SPV power forecasting model can be better modeled using historical power data, irradiance, earth declination angle, temperature, and solar time (Zhang et al. 2019). Aerosol index data can also be better used in the development of SPV power forecasting models with great accuracy (Liu et al.

2015). Solar power forecasting model can be developed based on weather-type classifications using the ANN approach, and the accuracy of the forecast model can be enhanced further by incorporating suitable modeling parameters (Chen et al. 2011).

The review study of Barbieri et al. (Barbieri, Rajakaruna, and Ghosh 2017) highlighted the role of AI techniques for photovoltaic applications. The study concluded that AI techniques were best suitable for forecasting, modeling, and sizing of photovoltaic systems. The study also emphasized the importance of forecasting horizon, solar cell temperature, and irradiance in the forecasting models. Razaet al. published a review study on the forecast of PV output power, highlighting the need for accurate PV power forecast models (Raza, Nadarajah, and Ekanayake 2016). A wide range of forecast time horizons can be considered in the modeling stage to analyze the performance of the models. The study also reported that regressive models, artificial intelligence-based forecast models and, hybrid techniques were popularly used techniques. Antonanzas et al. perceived that the statistical approach and machine learning techniques were extensively used by the researchers due to accurate performance (Antonanzas et al. 2016). The literature also revealed that the time horizon of day-ahead is much needed for a large number of applications. The assessment of forecasting techniques was done by Pedro et al. for solar power production with no exogenous inputs for 1 MWp, PV power plant, and the findings showed that the performance of the ANN-based forecasting models dominates the other forecasting techniques (Pedro and Coimbra 2012). The models were developed with only historical power data but mentioned that the accuracy of the models strongly depends on seasonal characteristics of solar variability. Ding et al. developed an SPV power forecast model for 24-hour ahead using an ANN approach with the improved back-propagation (BP) learning algorithm and reported a mean absolute percentage error of 10.09% (Ding, Wang, and Bi 2011). Twenty-seven SPV power data points of a similar day were used for training the ANN, but no information was provided regarding the selection of input parameters. In addition to the artificial intelligence forecast models, time series models (Cococcioni, D'Andrea, and Lazzerini 2011) were also developed by Cococcioni et al. to forecast the energy production in SPV systems for 1 day ahead using irradiation and sampling hour as modeling variables.

SPV power forecasting models based on NWP information were developed by Fernandez et al. using different statistical learning algorithms, Auto-Regressive Integrated Moving Average (ARIMA), k-nearest neighbors, neural networks, and adaptive neuro-fuzzy models (Fernandez-Jimenez et al. 2012). The modeling parameters used for the development of the models were forecast values of weather variables, as well as past values of hourly energy production. Out of all the models, a multilayer perceptron ANN model was identified as the best forecasting model. Leva et al. developed an artificial neural network forecast model for photovoltaic plant energy forecasting, and the accuracy of the method was related as a function of the training data sets and error classifications (Leva et al. 2017). The study also reported that the accuracy of the method was related to the historical data pre-processing steps and the quality of the historical dataset used for the training step. The study suggested that further improvements can be made in SPV power forecasting models with the help of accurate weather forecasting models and proper pre-processing of the raw data to train the network.

Liu et al. (Liu et al. 2015) developed a model to forecast the next 24-hour SPV power using the BP-ANN model. The 6 months' hourly data of wind speed, temperature, humidity, and the aerosol index had been collected for a location in China and used as modeling parameters. Aerosol index data had been collected using remote sensing technology, which make the forecasting model as not economically viable, and the gains acquired with accurate forecasting will be vanished by the costly forecasting system.

Malvoni et al. (Malvoni, De Giorgi, and Congedo 2014) considered different time horizons for developing forecasting model with Elmann ANN approach. A regression approach was implemented to analyze the effect of modeling parameters. Forecasting error distribution revealed that high error values at low time horizon and low error values at high time horizon, which highlighted the selection of time horizon, decides the accuracy of the model. Muhammad Aslam et al. (Aslam et al. 2021) developed forecasting models by considering the wide range of SPV plants ranging from 100 and 8500 kW in Germany with a data of 990 days. Long short-term memory neural network (LSTM-NN) is a deep learning technique used with humidity, temperature, solar radiation, albedo, and snowfall as modeling parameters. A two-stage attention mechanism was proposed to identify the role of input parameters in the modeling of SPV power, but the data collection of all the modeling parameters for every location makes the model cumbersome. Hossain et al. (Hossain and Mahmood 2020) developed SPV power forecasting model with a convolution neural network approach for a location in Florida. LSTM-NN was used with six years' data of solar irradiance and the type of sky for modeling of power output. The models resulted in high MAPE values ranging from 22.31% to 79.26%, which were not in the acceptable range of forecasting values. Sangrody et al. (Sangrody, Zhou, and Zhang 2020) collected two years data of temperature, dew point, humidity, wind speed, and SPV power output from University of New York-Binghamton. A forecasting model was developed using ANN with a similarity-based approach. The low temporal resolution of modeling parameters was used to predict SPV power of high temporal resolution, which lead to forecasting errors.

It is observed from the above literature that the forecasting models are much needed in the planning and modeling of renewable energy sources. The SPV power output has to be modeled with appropriate modeling parameters. Various SPV power forecast models were presented in the literature. They required measured modeling parameters that will not be available before the installation of SPV plants. It was also observed that the performance of AI techniques dominates the other techniques and also identified that day-ahead forecasting is much needed in load scheduling and system planning. ANN-based forecasting models perform better than the other forecasting techniques. The accuracy of the forecasting models depends strongly on the seasonal characteristics of solar variability. These variations can be tracked accurately with the inclusion of suitable modeling parameters in modeling. Moreover, a little study is available on the prediction of SPV power in hot and humid climatic countries like India. India is receiving an annual mean global solar radiation (GSR) ranging from 4 to 7 kWh/m^2-day with 250–300 sunny days. India has installed a 4 GW capacity of SPV systems (Wang et al. 2019), both grid integrated and standalone systems to capture the solar radiation resources. The PV penetration into the grid has been creating issues to energy management, system planning, electricity trading, and load management due to uncertainties in SPV power output. These key objectives in the smart grid [12] will be achieved with the accurate modeling of SPV power output with suitable modeling parameters.

The objectives of the present work are to develop a day-ahead SPV power forecasting models based on AI approach and a two-stage hybrid approach. AI approach has utilized an ANN to derive forecasting models, and the models are named as ANN forecaster. The ANN forecaster has used measured radiation data in the modeling stage, and such data has not been available for many locations in India (Kdv, Premalatha, and Naveen 2018). Two-stage forecasting models are also developed to address these issues and named as hybrid-ANN forecaster.

The novelty of the work is that the effect of operational and weather parameters on forecasting of SPV power output was not much discussed by the researchers, and it has been addressed in the present study. The best ANN architecture suitable for day ahead forecasting is also proposed. The seasonal characteristics of solar radiation variability (with the help of sunshine duration data and temperature data) was not included in previous studies for Indian locations, and it has been included in the design stage of forecasting models. The inclusion of seasonal variations has made the forecasting models as adaptive models and will be able to analyze the uncertainties in SPV power output. Models are benchmarked with different statistical indices to propose the best model. The performance of the developed forecast models has been compared with the existing SPV power forecast models to validate the performance of the developed models.

Table 1. Details of the SPV power forecast models.

Forecast type	Short-term forecasting
Forecast time horizon	1-day ahead
Forecast model type	Sunshine-based models, Temperature-based models, ANN models
Forecast model input parameters	Historical SPV power, measured daily GSR, predicted daily GSR, ambient temperature, hours of operation of SPV plant

Methodology

SPV power is forecasted using the AI technique. A time horizon of 1 day is selected. A day ahead SPV power forecast models based on AI approach are developed. AI approaches utilize the ANN to construct the SPV forecast models. A two-stage forecasting model is also developed by using weather prediction models.

Procedure for SPV power forecaster design

Day-ahead power output forecasting models developed with the input variables, namely daily temperature (T), measured daily GSR (H_m), predicted daily GSR (H_p), hours of operation of SPV plant (t_o), and historical SPV power (P) output data. SPV forecast models are developed by following two cases.

Case-1: Only measured data such as radiation, temperature, historical power, and time of operation of SPV plant are used as input variables to the ANN and named as ANN forecaster.

Case-2: A two-stage forecasting model is developed. In the first stage, the daily GSR is predicted from the solar radiation prediction models. Solar radiation models are developed using sunshine duration as a modeling parameter, which is named as sunshine-based model. Solar radiation models are developed using daily average temperature as a modeling parameter, which is named as temperature-based model. The output of the first stage is used as input to the second stage with the combination of measured variables such as temperature, historical power, and time of operation and named as hybrid-ANN forecaster. The forecast model details are shown in Table 1.

Test conditions followed in SPV power forecaster design

A multilayer perceptron (MLP) network is designed with back-propagation algorithm (BP-MLP network) and is shown in Figure 1. TRAINLM (trained with Levenberg-Marquardt optimization) is used as a training function for the MLP with LEARNGDM (learn with gradient descent momentum)

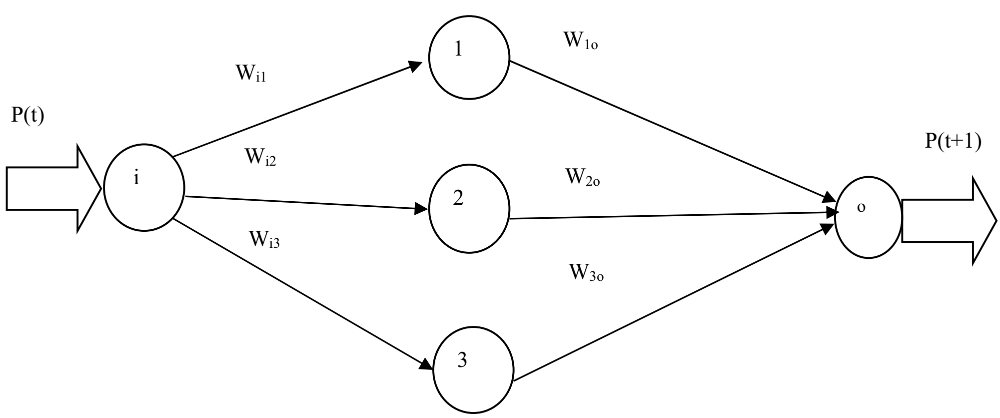

Figure 1. A functional diagram of back-propagation multilayer perceptron (BP-MLP) network.

as an adaptive learning function. The network has been trained until the performance is improved by minimizing the mean square error (MSE). The number of hidden neurons and appropriate transfer functions are identified with trial and error method.

The input neuron is given by 'i' node and present day 't' input parameter is applied to the 'i' node. The 'i' node is interconnected to hidden neurons, and it is modeled with an active function. Wi_1, W_{i2}, and W_{i3} are weights associated with the input node 'i' to corresponding hidden neurons 1, 2, and 3, respectively. The output neuron is given by 'o' node. The hidden neurons are interconnected to output node 'o' with proper weights and biased and modeled with a suitable activation function. W_{1o}, W_{2o}, and W_{3o} are weights associated with the hidden neurons 1, 2, and 3 to output node 'o', respectively. The output of the node 'o' is day ahead value 't + 1.' The activation function for neurons can be linear or nonlinear. Total three transfer functions namely log sigmoid, tan-sigmoid, and pure-lin are used in ANN modeling and are given by Eq.1 to Eq.3 The best transfer function is identified with the trial and error method for the present application. The training of the ANN architecture has been continued until the minimum value of mean square error (MSE) is attained.

Two-year data sets are used to train the ANN, and the one-year data set is used to test the developed ANN architectures. The number of neurons in the hidden layer is identified from the trial and error method. The method has been started with one neuron in the hidden layer. The number of neurons has been increased until the minimum value of MSE is obtained. The transfer function between the input to the hidden layer and the hidden to output layer has been changed with all possible types of transfer functions by fixing the optimum number of neurons in the hidden layer. The suitable transfer function is identified for the design of SPV power forecast models. The transfer functions used in the present study are given by Eq.1–3.

Log sigmoid transfer function,

$$f(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

Tan-sigmoid transfer function,

$$f(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \tag{2}$$

Pure-lin transfer function,

$$f(x) = x \tag{3}$$

Where x is the input to the activation function and $f(x)$ is the output of the activation function.

The selected inputs and target output to the ANN have large ranges in value, and the datasets has to be brought into a defined range. This process is called normalization of datasets, and it will impart robust characteristics to the non-linear datasets (Alaraj et al. 2021). The normalization process will convert a parameter into a unit less quantity. The normalization (Eq.4) and de-normalization (Eq.5) equations are given by

$$B_n = \frac{B_{actual} - B_{\min}}{B_{\max} - B_{\min}} \tag{4}$$

$$B_{actual} = B_n(B_{\max} - B_{\min}) + B_{\min} \tag{5}$$

Design of ANN forecaster (Case-1)

The SPV system operating environment will have an effect on the PV power output. These conditions will be included in the models by considering the daily GSR and the temperature data of a location in the modeling stage.

ANN-forecaster-4	{P, H_m, T, t_o}	Hybrid-ANN forecaster-S4	{P, H_{pS},T, t_o}	Hybrid-ANN forecaster-T4	{P, H_{pT}, T, t_o}

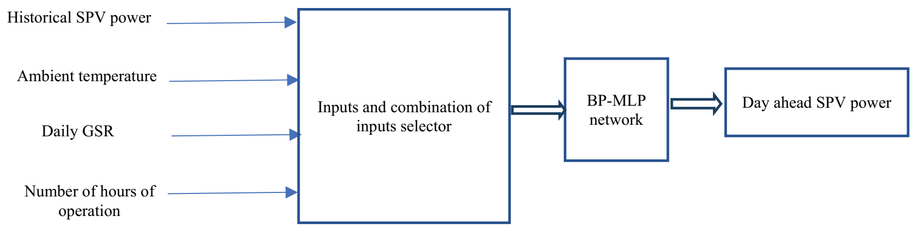

Figure 2. ANN forecaster with different inputs and combination of inputs.

Table 2. Input parameters and the combination of input parameters used in the design of ANN forecaster and hybrid-ANN forecaster.

Model name	Input parameters	Model name	Input parameters	Model name	Input parameters
ANN forecaster-1	H_m T P	Hybrid-ANN forecaster-S1	H_{pS}	Hybrid-ANN forecaster-T1	{H_{pT}}
ANN forecaster-2	{H_m, T} {T, P} {H_m, P}	Hybrid-ANN forecaster-S2	{$H_{p,S}$, T} {P, H_{pS}}	Hybrid-ANN forecaster-T2	{H_{pT}, T} {P, H_{pT}}
ANN forecaster-3	{H_m, T, t_o} {H_m, T, P}	Hybrid-ANN forecaster-S3	{P, H_{pS}, T} {$H_{p,S}$, T, t_o}	Hybrid-ANN forecaster-T3	{P, H_{pT}, T} {H_p, T, t_o}
ANN forecaster-4	{P, H_m, T, t_o}	Hybrid-ANN forecaster-S4	{P, H_{pS},T, t_o}	Hybrid-ANN forecaster-T4	{P, H_{pT}, T, t_o}

The effect of GSR and cell temperature on PV power output will be given by following (Eq.6.) relation (Idoko, Anaya-Lara, and McDonald 2018):

$$P(t) = Y_{pv}.f_{pv}.\left(\frac{H_m(t)}{H_{STC}}\right).\left[1 + \alpha_p\left(T_c(t) - T_{c,STC}\right)\right] \tag{6}$$

The ANN model has been developed with the modeling parameters such as the daily temperature (T), measured daily GSR (H_m), hours of operation of SPV plant (t_o), and historical SPV power (P) data, which is named as ANN forecaster (Figure 2). The effect of each parameter and a combination of various parameters on the performance of the forecaster are identified by developing various forecasting models. The input parameters and the combination of parameters used in the design of ANN forecaster are shown in Table 2. The forecaster utilizes one parameter as modeling parameter named as ANN forecaster-1 and, similarly, ANN forecaster-2, ANN forecaster-3, and ANN forecaster-4. The ANN forecaster-4 as a function of four input variables is given in Eq.7.

$$P(t+1) = f(P(t), H_m(t), T(t), t_o(t)) \tag{7}$$

Where t is the present instant and $t + 1$ is the future instant (prediction step: 1-day ahead).

Design of hybrid-ANN forecaster (Case-2)

The SPV power output will change with daily GSR availability. The radiation availability at a particular location is needed in ANN forecaster, and the lack of radiation data makes the ANN forecaster unusable. This is overcome by developing a two-stage forecast model. Daily GSR is predicted in the first stage of the model development. The predicted daily GSR is used as modeling parameter in the second stage of the forecasting model, and it is named as a hybrid-ANN forecaster. The hybrid-ANN forecaster also utilizes the same inputs and same combination of inputs as that of ANN forecaster. The former uses predicted daily GSR (H_p) as an input, and the latter uses measured daily GSR (H_m) as an input.

Prediction of solar radiation can be done with empirical models. Solar radiation availability at a location is modeled as sunshine-based (Kdv, Premalatha, and Naveen 2018) and temperature-based (Siva Krishna Rao, Premalatha, and Naveen 2017) solar radiation models. The models were developed for the selected Indian conditions and are given by Eq.8 and Eq.9. Equation.8. is a sunshine-based daily GSR prediction mode,l and Eq.9. is a temperature-based daily GSR prediction model, and they are given by

$$H_{pS}(t) = H_o\left(0.81 + 0.14\left(\frac{S_a}{S_o}\right)\right) - \left(-0.01\phi^2 + 0.435\phi - 3.3936\right) \tag{8}$$

$$H_{pT}(t) = 0.3019H_o(T_{\max} - T_{\min})^{0.5} \tag{9}$$

Where H_o (kWh/m^2-day) is given by Eq.10.

$$H_o = \frac{24}{\pi}I_{sc}\left[\cos\phi\cos\delta\sin\omega_s + \frac{\pi}{180}\omega_s\sin\phi\sin\delta\right]\left[1 + 0.033\cos\left(\frac{360n}{365}\right)\right] \tag{10}$$

The daily GSR predicted from the sunshine-based solar radiation model (Eq.8.) is used as one of the inputs to the hybrid-ANN forecaster. It is given by Eq.11 and named as hybrid-ANN forecaster-S1. The GSR predicted from the temperature-based solar radiation model (Eq.9) is used as one of the inputs to the hybrid-ANN forecaster. It is given by Eq.12 and named as hybrid-ANN forecaster-T1. A two-stage forecasting model is shown in Figure 3. The input parameters and the combination of input parameters used in the design of hybrid-ANN forecaster are given in Table 2.

$$P(t+1) = f\left(H_{pS}(t)\right) \tag{11}$$

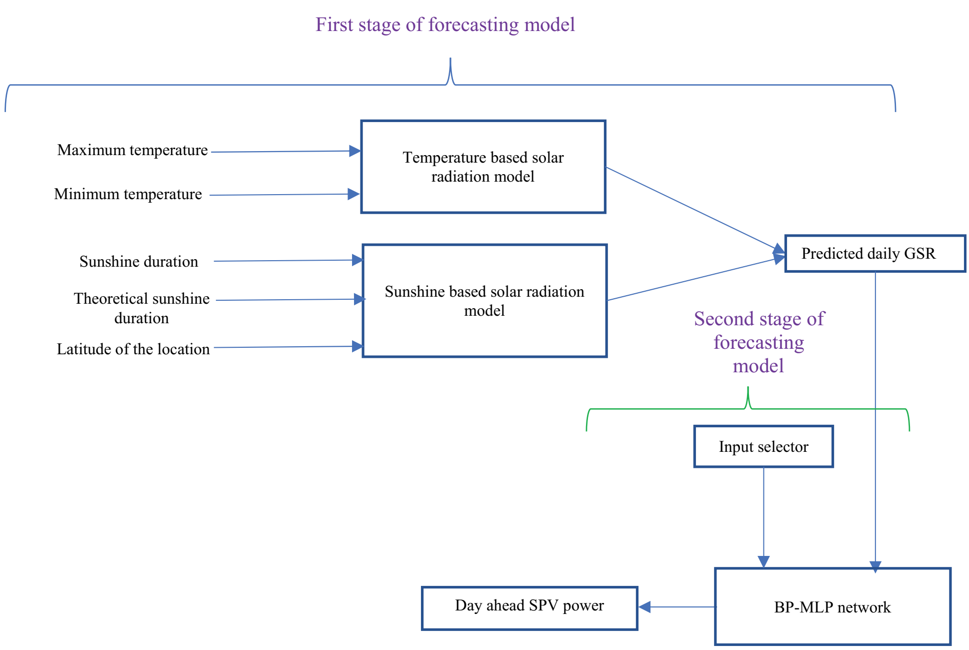

Figure 3. A two-stage forecasting model (hybrid-ANN forecaster).

$$P(t+1) = f\left(H_{pT}(t)\right) \tag{12}$$

Similarly, other hybrid ANN forecasters such as S2, S3, and S4 are developed using predicted radiation by sunshine-based models, as one of the modeling inputs. Other hybrid ANN forecasters such as T2, T3, and T4 are developed using predicted solar radiation by temperature-based models as one of the inputs, where 1, 2, 3, and 4 represents the number of input variables. For example, the hybrid-ANN forecaster-T4 as a function of four input variables is given in Eq.13.

$$P(t+1) = f\left(P(t), H_{pT}(t), T(t), t_o(t)\right) \tag{13}$$

Nine ANN forecast models and 12 hybrid-ANN forecast models are developed with various inputs and input combinations. A total of 21 forecast models are developed to forecast SPV power output with various modeling parameters.

Data collection

A grid-connected 100kW$_p$ SPV system is established in an educational institute, and the data collected from this setup is considered to develop and validate the forecast models. Daily GSR on a horizontal surface is continuously measured using a pyranometer along with the ambient temperature and SPV power output. International Electro-Technical Commission standards (IEC 61724.998) are followed for data collection and monitoring of the SPV system. A recording interval of 5 minutes is considered for the data measurements, which has resulted in 288 data points per day.

Data corresponding to 3 years (2014, 2015, and 2016) is used for the development of forecast models. The details of SPV power system along with the specifications of the measuring instruments are presented in Table 3. A total of 315,360 (3 years' x 365 days' x 288) data points are collected from the setup. Out of which, 210,240 data points (2 years) are used for model development and 105,120 (1 year) data points are used for model validation. Full cloudy days are excluded from the model development and validation. (During this period, SPV power plant is not connected to the grid.)

Statistical tools considered to assess the performance of the models

Statistical tools such as the mean absolute percentage error (MAPE) and relative root mean square error (RRMSE) are used to analyze the performance of the forecast models. Model's performance is described based on the ranges of RRMSE values (Li et al. 2013). The equation for MAPE is given by Eq.14, and the equation for RRMSE is given by Eq.15.

$$MAPE(\%) = \frac{1}{p}\sum_{i=0}^{p}\left|\frac{M_{i,e} - M_{i,m}}{M_{i,m}}\right| \times 100 \tag{14}$$

Table 3. The details of SPV power system along with the specifications of the measuring instruments.

Instrument used	Specifications	
Plant details	Model of the PV panels: L20220, Capacity of each panel: 240Wp, Number of panels: 432 panels, I_{sc} = 8.3A; V_{oc} = 36 V, Tilt angle = 11° Invertor model: 110 kVA, 3-phase, 415 V, 50 Hz, Invertor Efficiency>94%	
Location	Latitude: 10.79° N, Longitude: 78.70° E	
Temperature sensor	Range	−40 to + 60°C
	Resolution	0.10°C
	Accuracy	± 0.20°C
Pyranometer	Spectral range	360 to 1120 nm
	Response time	Less than one milli-second
	Error due to clouds	± 10 to 15%

$$RRMSE(\%) = \frac{\sqrt{\left(\frac{1}{p}\sum_{i=1}^{p}\left(M_{i,e} - M_{i,m}\right)^2\right)}}{\frac{1}{p}\sum_{i=1}^{n} M_{i,m}} \times 100 \tag{15}$$

Where, $M_{i,e}$ is the ith data point estimated value, $M_{i,m}$ is the ith data point measured value, and p is the number of data points.

RESULTS AND DISCUSSIONS

Two forecasters are developed using ANN with different inputs and the combination of modeling parameters. The performance of the developed forecasting models is compared with the literature models.

Development of ANN model

The development of ANN model involves identification of an optimum number of neurons in the hidden layer and a suitable transfer function. The ANN architecture with appropriate transfer function and an optimum number of neurons and identified by the trial and error method. The parameters namely {H_m, T, and t_o} are used as inputs for the above said purpose, and a day ahead SPV power is used as an output to the ANN. The optimum number of neurons in the hidden layer is identified with the trial and error method by considering the tan-sigmoid function as a transfer function. The developed ANN architectures are tested with the new data, and statistical analysis has been performed. This process is repeated until the optimum number of neurons is identified. The performance of the statistical tools with increasing order of neurons is presented in Table 4. Six ANN architectures are developed starting from 3-1-1 to 3-6-1. It is observed that by increasing the number of neurons in the hidden layer, there is no significant improvement in the forecast model's performance. Here, three neurons in the hidden layer are identified as an optimum number. Since a greater number of neurons in the hidden layer does not show any significant improvement (Table 4) in the performance rather making the ANN model tedious with a greater number of weights and biases corresponding to each neuron. The suitable transfer function for the present application is identified by considering ANN models with all possible combinations of transfer functions between the inputs to the hidden layer and hidden to the output layer. The number of neurons in the hidden layer is fixed as three (optimum number) with {H_m, T, t_o} as inputs to the ANN. The models are tested with new datasets to analyze the performance of the models. The performance study with all possible combinations of transfer functions is presented in Table 5.

It is observed that a linear transfer function between the input and hidden layer and log sigmoid transfer function between the hidden and output layer are most suitable and showed superior performance (Table 5). It is identified from Table 4and Table 5 that three neurons in the hidden layer with linear and log-sigmoid as transfer functions are the most suitable ANN architecture parameters for the development of forecast models. An optimum ANN architecture is identified, and this architecture is used for the design of ANN forecaster and hybrid-ANN forecaster.

Table 4. Trial and error method for identification of an optimum number of neurons.

Inputs	Transfer function	Number of neurons	MAPE (%)	RRMSE (%)	Result
{H_m, T, t_o}	Tan sigmoid – Tan sigmoid	1	11.63	14.54	Good
		2	10.55	13.65	Good
		3	**10.23**	**13.18**	Good
		4	11.25	13.76	Good
		5	10.82	13.40	Good
		6	10.20	12.96	Good

Table 5. Trial and error method for identification of transfer function.

Inputs	Number of neurons	Transfer function	MAPE (%)	RRMSE (%)	Result
{H_m, T, t_o}	3	Tan-Tan	10.79	13.78	Good
		Log-Log	10.75	13.86	Good
		Lin-Lin	10.15	12.65	Good
		Log-Tan	10.61	13.18	Good
		Tan-Log	10.66	13.77	Good
		Log-Lin	10.57	13.32	Good
		Tan-Lin	11.02	13.81	Good
		Lin-Tan	10.19	12.71	Good
		Lin-Log	09.83	12.41	Good

Performance of ANN forecaster

The effect of input parameters in the forecasting of the day ahead SPV power is identified by developing different ANN forecasting models with various input parameters and the combination of input parameters. ANN forecaster-1 to ANN forecaster-4 are developed with different inputs and combinations of inputs. The outputs of neuron-1, neuron-2, and neuron-3 (neurons shown in Figure 1) are given by Eq.16–18. The forecasted output P(t + 1) is given by Eq.19 and Eq.20. The weights and biases are substituted in Eq.20 along with the historical data of SPV power to forecast SPV power, and forecasting accuracy is tested with the new datasets. Likewise, a performance study is made for all the other input parameters and the combination of input parameters. The performance of the ANN forecaster with different inputs and a combination of input parameters are shown in Figure 4. The actual SPV power and forecasted SPV power on each day of a particular month are given in Figure 7a-d.

Output of neuron-1,

$$n_1 = W_{i1}P(t) + b_1 \tag{16}$$

Output of neuron-2,

$$n_2 = W_{i2}P(t) + b_2 \tag{17}$$

Output of neuron-3,

$$n_3 = W_{i3}P(t) + b_3 \tag{18}$$

$$P(t+1) = \frac{1}{1 + e^{-[W_{1o}n_1 + W_{2o}n_2 + W_{3o}n_3 + b_o]}} \tag{19}$$

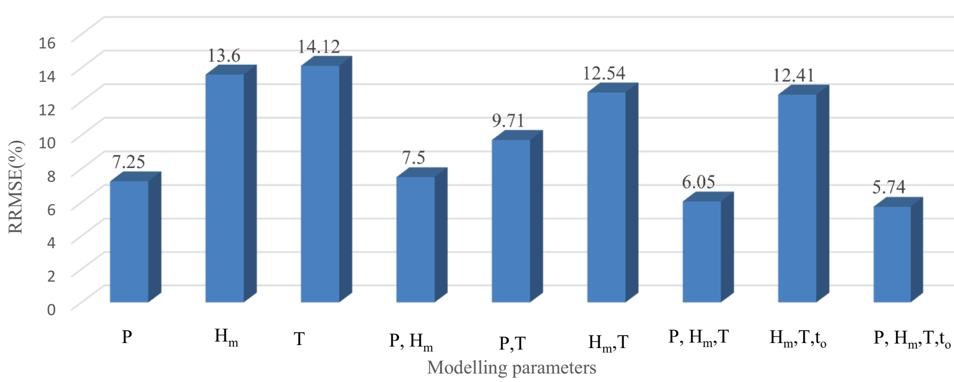

Figure 4. Performance of ANN forecaster with different inputs and combination of input parameters.

$$P(t+1) = \frac{1}{1 + e^{-[W_{1o}(W_{i1}P(t)+b_1)+W_{2o}(W_{i2}P(t)+b_2)+W_{3o}(W_{i3}P(t)+b_3)+b_o]}} \tag{20}$$

Where n_1, n_2, and n_3 are the output of the hidden neurons 1, 2, and 3, respectively, , b_2, and b_3 are biases of the hidden neurons 1, 2, and 3, respectively, and b_o is the bias of the output neuron.

The performance of the models given in Table 2 has been discussed here. **ANN forecaster-1**: The forecast model with{P} as input has shown an excellent performance with an RRMSE of 7.25% compared to the other two individual weather parameters {H_m} and {T}. The performance indices have revealed the significance of the historical power data in the day ahead forecasting of SPV power output. The variations in actual SPV power has been tracked by ANN forecaster-1 with {P}, and it has been observed from Figure 7d. **ANN forecaster-2**: The combination of inputs {P, H_m} has shown superior performance with an RRMSE of 7.5% compared to the other two combinations {P, T} and {H_m, T}. The combination of {H_m, T} as inputs has also shown good performance, and this model could be used if historical SPV power data is unavailable. In such cases, the combination of {H_m, T} will play a significant role in day-ahead forecasting. **ANN forecaster-3**: The forecast model with the combination of {H_m, T, t_o} has produced a higher error value than the combination of {P, H_m, T}. It has been observed that the inclusion of historical SPV power output data in place of hours of operation of the SPV plant has produced an improvement in model accuracy. It could be concluded that the hours of operation of the SPV plant do not have a significant effect on the day ahead forecasting of SPV power. **ANN forecaster-4**: This forecaster considers all four parameters as inputs and has shown the least RRMSE value compared to all the other forecast models. The variations in actual SPV power has been tracked by ANN forecaster-4 with {P, H_m, T, t_o}, and it has been observed from Figure 7a. If the measured values of all the input parameters are readily available for the location of the interest, then the ANN forecaster-4 model will be used in day ahead forecasting due to its great accuracy. It is observed from Figure 4 that the models with the historical SPV power as one of the input parameters have resulted in excellent RRMSE values. It could be concluded that the historical data of SPV power has a significant role in the forecasting of day ahead SPV power. The historical SPV power data at a particular location is unavailable before the installation of the SPV plant; in such cases, the weather parameters could be used as modeling inputs to the SPV power forecast models.

It is observed from Fig.4 that the models with the historical SPV power as one of the input parameters have resulted in excellent RRMSE values. It could be concluded that the historical data of SPV power has a significant role in the forecasting of day ahead SPV power. The historical SPV power data at a particular location is unavailable before the installation of the SPV plant, in such cases, the weather parameters could be used as modeling inputs to the SPV power forecast models.

The performance of ANN forecaster-1 with historical SPV power as input is superior to ANN forecaster-2 and ANN forecaster-3 (with H_m, T, t_o as input combination). If historical SPV power data (P) is readily available, {P} can be considered in addition to {H_m, T}, since 50% improvement was observed with ANN forecaster-3 with {P, H_m, T} as inputs compared with ANN forecaster-2 with {H_m, T} as inputs.

Performance of hybrid-ANN forecaster

The predicted radiation (H_p) is used as input instead of measured radiation (H_m) in the design of a two-stage forecasting model. It will eliminate the need for measured radiation data, which is not readily available for so many locations in India. Sunshine-based model (Eq.6) and temperature-based (Eq.7) model are used to predict the daily GSR on a horizontal surface. The forecaster that used daily GSR predicted (H_{pS}) from the sunshine-based model is named as hybrid-ANN forecaster-S, and daily GSR predicted (H_{pT}) from the temperature-based model is named as hybrid-ANN forecaster-T.

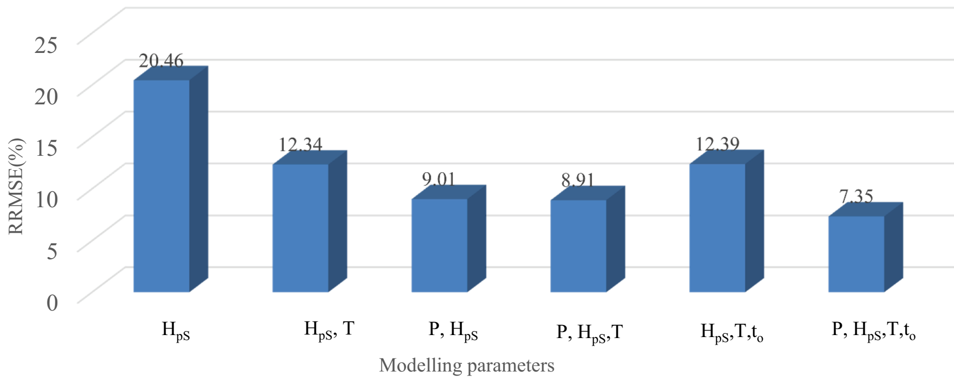

Figure 5. Performance of hybrid-ANN forecaster-S with different inputs and combination of inputs.

Performance of hybrid-ANN forecaster-S

The hybrid-ANN forecaster-S1 with H_{pS} as input is given by Eq.21.The performance of hybrid-ANN forecaster-S with different inputs and combinations of input parameters is shown in Figure 5. The hybrid-ANN forecaster-S4 has resulted in the best performance. The variations in actual SPV power have been tracked by ANN forecaster-S4 with {P, H_{pS}, T, t_o}, and it has been observed from Figure 7.b.

$$P(t+1) = \frac{1}{1+e^{-\begin{bmatrix} W_{1o}\left(W_{i1}\left(H_o\left(0.81+0.14\left(\frac{S_a}{S_o}\right)\right)-\left(-0.01\phi^2+0.435\phi-3.3936\right)\right)+b_1\right)+ \\ W_{2o}\left(W_{i2}\left(H_o\left(0.81+0.14\left(\frac{S_a}{S_o}\right)\right)-\left(-0.01\phi^2+0.435\phi-3.3936\right)\right)+b_2\right)+ \\ W_{3o}\left(W_{i3}\left(H_o\left(0.81+0.14\left(\frac{S_a}{S_o}\right)\right)-\left(-0.01\phi^2+0.435\phi-3.3936\right)\right)+b_3\right)+b_o \end{bmatrix}}} \quad (21)$$

The hybrid-ANN forecaster-S1 with H_{pS} as input has given maximum error in comparison with all the models, but this value lies within the acceptable error ranges. This maximum error could be due to the two stages of the model. The daily GSR is predicted with the sunshine duration of a given location, and uncertainties in the measurement of sunshine duration have caused the errors in the prediction of GSR in the first stage of the model. This predicted daily GSR is used as a modeling parameter to the second stage, which further increases the model error. The combination of weather parameters {H_{pS}, T} has shown good accuracy (12.34%), and it could be concluded that these parameters have a good correlation with the SPV power output of a particular location.

Performance of hybrid-ANN forecaster-T

The performance of hybrid-ANN forecaster-T with different inputs and combinations of input parameters is shown in Figure 6. The hybrid-ANN forecaster-T1 has developed with {H_{pT}} as input is given by Eq.22. Eq.22 along with the derived weights and biases is tested with the new data to forecast the P(t + 1), and it has shown good performance with an RRMSE value of 18.12%, whereas ANN forecaster-1 with {H_m} as an input gave an RRMSE of 13.60%. The higher value of RRMSE is obtained with hybrid-ANN forecaster-T1, and it could be due to the prediction error of {$H_{p,T}$}. The error produced due to the single input parameter {$H_{p,T}$} has been minimized by 27% with the inclusion of historical SPV power as input along with {$H_{p,T}$} (Hybrid-ANN forecaster-T2). The combination of weather parameters {H_{pT}, T} has resulted in good accuracy and does not demand measured GSR data of the location and the data of sunshine duration, the ambient temperature of the location is needed.

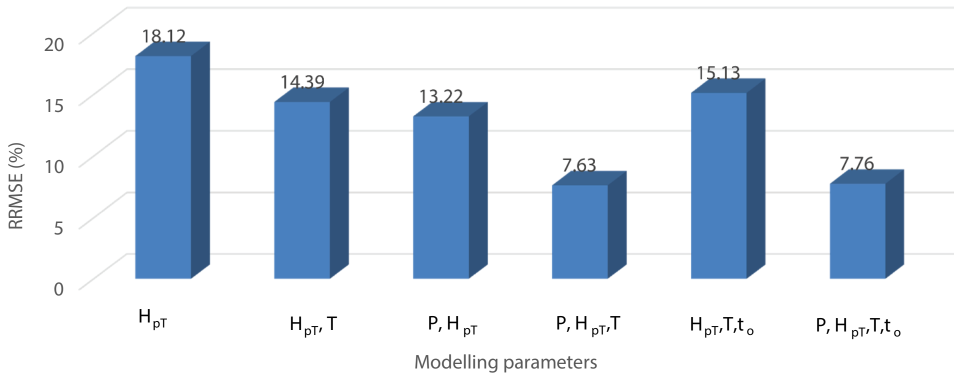

Figure 6. Performance of hybrid-ANN forecaster-T with different inputs and combination of input parameters.

$$P(t+1) = \frac{1}{1 + e^{-\left[\begin{array}{l} W_{1o}\left(W_{i1}\left(0.3019H_o(T_{\max}-T_{\min})^{0.5}\right)+b_1\right)+ \\ W_{2o}\left(W_{i2}\left(0.3019H_o(T_{\max}-T_{\min})^{0.5}\right)+b_2\right)+ \\ W_{3o}\left(W_{i3}P\left(0.3019H_o(T_{\max}-T_{\min})^{0.5}\right)+b_3\right)+b_o \end{array}\right]}} \tag{22}$$

The hybrid-ANN forecaster-T3 with {P, H_{pT}, T} and hybrid-ANN forecaster-T4 have shown similar performance with great forecasting accuracy (RRMSE about 7%). The variations in actual SPV power have been tracked by ANN forecaster-T4 with{P, H_{pT}, T, t_o}, and it has been observed from Figure 7.c.

Comparison between ANN forecaster and hybrid-ANN forecaster

A total of 21 SPV power forecast models with various input parameters are developed, and one of the forecast models can be chosen in the day ahead forecasting of SPV power depending upon the availability of the input parameters. The graphs in Figure 7.a-d revealed that the variation in actual power generation on each day has been tracked accurately by the developed forecasted models. The deviations between the actual and forecasted values are quantified with error analysis. The forecast model with four inputs, i.e., ANN forecaster-4, has shown superior performance than all the other forecast models. The recommended ANN architecture is 4-3-1, which has the highest accuracy (MAPE = 5.74%), besides the model can precisely forecast the uncertainties in power generation. The hours of operation of the SPV system could be ignored in the modeling of forecasting model. The ANN architecture 3-3-1 can also be used as a forecast model with {P, $H_{m,}$ T} as inputs since the combination has resulted in second-best accuracy (MAPE = 6.05%). The ANN-forecaster associated with {H_m} is accurate than the hybrid-ANN forecaster associated with {H_p}; nonetheless, it demands the measured daily GSR as a modeling parameter to the model. The hybrid forecaster associated with {H_p} reduces the cost of the forecasting system.

It could be concluded that the accuracy of the forecast models varied with the number of inputs and selection of influenced parameters. These findings are in line with the recommendation of (Yildiz, Bilbao, and Sproul 2017). The performance comparison of ANN forecaster with hybrid-ANN forecaster is shown in Figure 8. The MAPE limits of the ANN forecaster are in a range between 4.18% and 6.08%. The MAPE limits of hybrid ANN forecaster-S are in a range between 5.98% and 16.91%. The MAPE limits of hybrid ANN forecaster-T are in a range between 5.21% and 15.59%. Out of all models, the majority of the models have produced an error of less than 10%. The models associated with predicted daily GSR as one of the inputs, i.e., hybrid-ANN-forecaster, had resulted in error values of

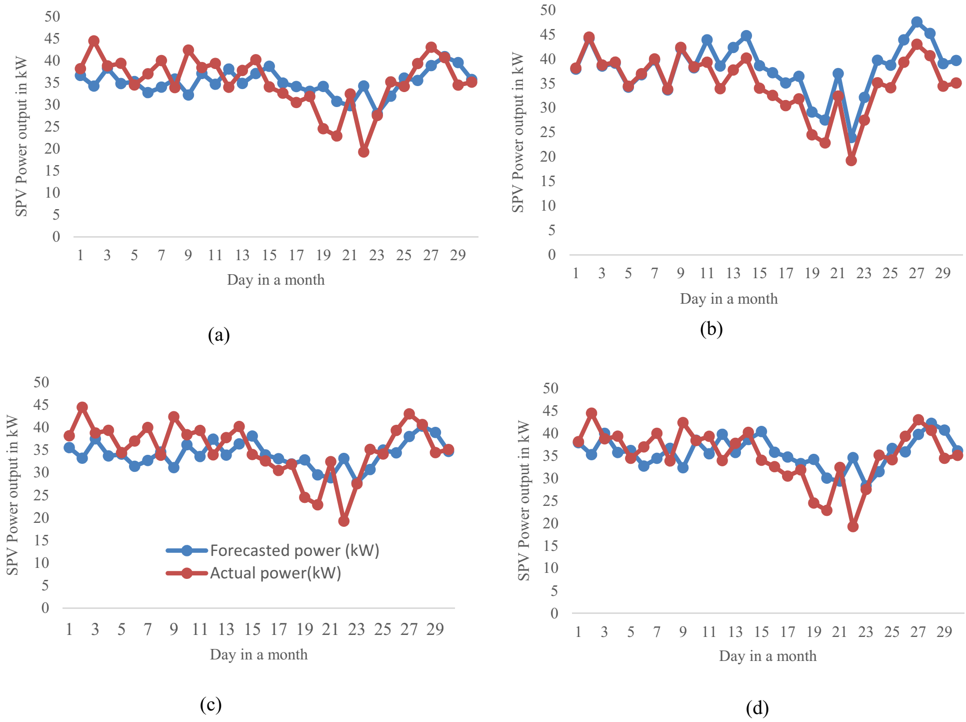

Figure 7. Comparison of actual PV power (kW) output with forecasted PV power (kW) output.

more than 10%. Since the hybrid-ANN forecaster is a two-stage model. Stage 1 had an error due to the prediction of daily GSR on a horizontal surface. The output produced from stage 1 had been used as input to stage 2, which enhance the error values further.

Performance comparison of SPV power forecast models with literature models

The performance of the developed model is compared with the literature models and is shown in Table 6. Muhammad Aslam model (Aslam et al. 2021) had utilized an AI approach that considered LSTM-NN method in solar PV power forecasting.

The model had reported good accuracy, but it considered a wide range of modeling parameters, and data collection of more number of modeling parameters is a setback for the model. Hossain model (Hossain and Mahmood 2020) was also considered LSTM-NN method along with the recurrent neural network approach but produced large error values. ANN approach was implemented in the Sangrody model (Sangrody, Zhou, and Zhang 2020) with an error of 18.7%, which had produced moderate accuracy. Liu model (Liu et al. 2015) had considered 20 modeling parameters, which had increased the model complexity with not much improvement in accuracy (MAPE range: 6.38%–8.27%).

The ANN forecaster-4 in the present study has considered four readily available parameters as modeling variables, which resulted in an MAPE value of 4.18%. The models developed in the present study are best suited for the day ahead forecasting with the minimum number of inputs. It could be observed from the literature models that the historical power data is an important parameter in the design of accurate SPV power forecasting models. The operational parameters like historical power data and hours of operation of SPV system data measurements will not be available prior to the installation of the SPV system. The weather parameters like daily GSR and ambient temperature could be used as a modeling parameters in such conditions.

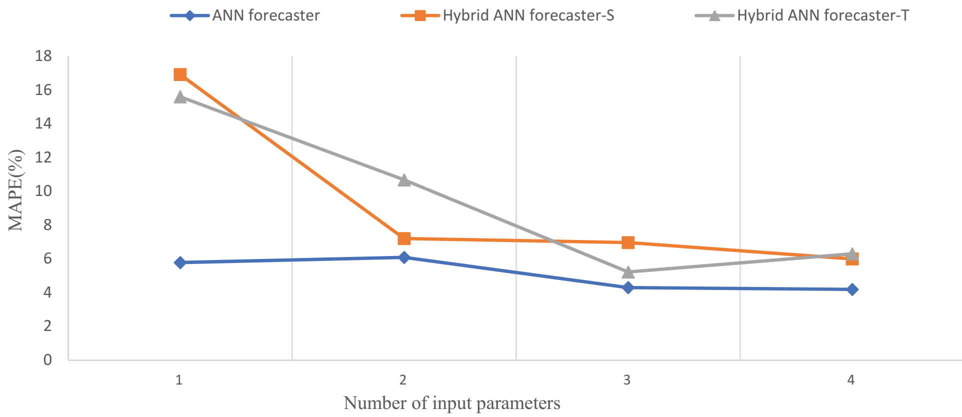

Figure 8. The performance comparison of ANN forecaster with hybrid-ANN forecaster.

(a) ANN forecaster- 4 (b) hybrid-ANN forecaster- T4 (c) hybrid-ANN forecaster- S4 (d) ANN forecaster- 1 with {P} as input.

Conclusion

A day ahead SPV power forecast models are developed by using ANN approach. Daily GSR (H_m, H_p), ambient temperature, hours of operation of SPV system, and historical data of SPV power are used as input parameters in the modeling of the day ahead forecast models. The trial and error method has revealed that the ANN model with three neurons in the hidden layer with linear-log-sigmoid transfer function has shown the best performance.

The effect of each parameter and the combination of parameters on the model accuracy is identified by developing various forecast models, and a total of 21 forecast models are developed. Out of the 21 developed forecast models, ANN forecaster-4 with the combination of inputs {P, H, T, t_o} has shown the best performance. The combination has shown a strong influence on the SPV power output. The MAPE of 4.18% and the RRMSE of 5.74% are derived with 4-3-1 ANN architecture. Historical data of measured power is the best suitable modeling parameter to predict the SPV power. Historical power measurements will not be available before the installation of the SPV system, and in such cases, ANN forecaster-2 with {H_m, T} could be used as a forecast model.

Measured daily GSR data has also played a crucial role in the development of the forecast model. Pyranometer will be used to measure the daily GSR on a horizontal surface but which is uneconomical to install in every location. In such cases, daily GSR can be predicted by using sunshine-based models and temperature-based models. A two-stage forecasting model (hybrid-ANN model) has been developed by using daily GSR prediction models to decrease the cost of the forecasting system. The daily GSR predicted with the sunshine-based model is used as input to the hybrid-ANN forecaster, and the forecaster has resulted in an MAPE of 16.91%. The daily GSR predicted with the temperature-based model is used as input to the hybrid-ANN forecaster, and the forecaster has resulted in an MAPE of 15.59%. However,

Table 6. Performance comparison of SPV forecast models with other literature models.

Name of the model	Model details
ANN Forecaster-4 (Present study)	MAPE = 04.18%
Muhammad Aslam model (Aslam et al. 2021)	MAPE = 03.78%
Hossain model (Hossain and Mahmood 2020)	MAPE = 28.79%
Sangrody model (Sangrody, Zhou, and Zhang 2020)	MAPE = 18.70%
Liu model (Liu et al. 2015)	MAPE = 06.38%

ANN forecaster used measured daily GSR as input has shown a MAPE of 10.45%. This difference in error is caused due to the uncertainty in the prediction of daily GSR. This error will be further decreased by improving the performance of sunshine-based and temperature-based solar radiation prediction models.

The developed models have shown excellent performance in the forecasting of day-ahead SPV power output. It is useful for energy traders and energy service providers for economic scheduling, energy trading, and security assessment. They are also useful for planning the operations of the SPV systems in the smart grid. AI techniques are proved as the best alternative for forecasting problems with great accuracy.

In future work, various time horizons can be implemented to forecast the SPV power. The modeling parameters suitable for various time horizons can be identified. Deep learning techniques will be tested to enhance the performance of the models. Models will be developed by classifying the modeling data with respect to the distinct weather and seasonal conditions. Hybrid ANN forecaster performance can be further enhanced by developing accurate solar radiation predictions models.

Nomenclature

B_n	normalized value of the considered parameter without units.
B_{actual}	actual value of the parameter to be normalized in the given dataset with SI units.
$B_{\min}$	minimum value of parameter in the given dataset.
$B_{\max}$	maximum value of parameter in the given dataset.
Y_{pv}	rated capacity of PV array.
f_{pv}	derating factor of PV array.
$H_m(t)$	measured daily GSR on a horizontal surface at current time step (kWh/m^2-day).
$P(t)$	power output (kW) at current time step.
$T_c(t)$	PV cell temperature (^{o}C) at current time step.
H_{STC}	GSR at standard test condition (kWh/m^2-day).
$T_{c,STC}$	PV cell temperature (^{o}C) standard test condition.
α_p	temperature coefficient.
$t\neg_o$	hours of operation of SPV plant.
$T(t)$	daily average ambient temperature on 't' day.
$t_o(t)$	hours of operation of SPV plant on 't' day.
$H_{pS}(t)$	predicted daily global solar radiation on a horizontal surface (kWh/m^2-day) using sunshine based model.
$H_{pT}(t)$	predicted daily global solar radiation on a horizontal surface (kWh/m^2-day) using temperature-based model.
S_o	maximum possible sunshine duration (hours) in a given day.
S_a	approximate bright sunshine duration (hours)in a given day.
$T_{\max}$	maximum ambient temperature (^{o}C) measured in a given day.
$T_{\min}$	minimum ambient temperature (^{o}C) measured in a given day.
H_o	theoretical daily global solar radiation on a horizontal surface (kWh/m^2).
I_{sc}	solar constant (W/m^2).
ϕ	latitude of the location.
ω_s	hour angle.
n	day in a year.
δ	declination angle.

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