Advances in Energy Research, *Vol. 6, No. 2 (2019) 131-143*
DOI: http://doi.org/10.12989/eri.2019.6.2.131

A novel SARMA-ANN hybrid model for global solar radiation forecasting

Rachit Srivastava*, A. N. Tiwari[a] and V. K. Giri[b]

Department of Electrical Engineering, Madan Mohan Malaviya University of Technology, Gorakhpur 273010, Uttar Pradesh, India

(Received April 25, 2019, Revised July 25, 2019, Accepted July 31, 2019)

Abstract. Global Solar Radiation (GSR) is the key element for performance estimation of any Solar Power Plant (SPP). Its forecasting may help in estimation of power production from a SPP well in advance, and may also render help in optimal use of this power. Seasonal Auto-Regressive Moving Average (SARMA) and Artificial Neural Network (ANN) models are combined in order to develop a hybrid model (SARMA-ANN) conceiving the characteristics of both linear and non-linear prediction models. This developed model has been used for prediction of GSR at Gorakhpur, situated in the northern region of India. The proposed model is beneficial for the univariate forecasting. Along with this model, we have also used Auto-Regressive Moving Average (ARMA), SARMA, ANN based models for 1 – 6 day-ahead forecasting of GSR on hourly basis. It has been found that the proposed model presents least RMSE (Root Mean Square Error) and produces best forecasting results among all the models considered in the present study. As an application, the comparison between the forecasted one and the energy produced by the grid connected PV plant installed on the parking stands of the University shows the superiority of the proposed model.

Keywords: global solar radiation; Box-Jenkin's model; ANN; SARMA; hybridization

1. Introduction

Among different renewable energy technologies, Solar Energy technology has been considered as the fastest growing. The technological developments and cost effectiveness of this plays before its global acceptance. (Hosenuzzaman *et al.* 2015, Salcedo-Sanz *et al.* 2014). Forecasting of GSR may help in optimal operation of SPPs (Yadav and Chandel 2014). Such forecasting also renders help to SPP developers in energy bidding process. Effective management of power production form conventional sources and that from SPPs may directly or indirectly helps in management of fossil fuel reserve, which can be achieved by forecasting of GSR, as by forecasting of solar radiation, the utility can predict how much electricity will be generated from a solar power plant in future and how much power share will be required in the next hour, day, week or month (Marquez and Coimbra 2011). Solar radiation forecasting can be performed by two approaches: multivariate

*Corresponding author, Student, E-mail: srivastava.rachit94@gmail.com
[a]Professor, E-mail: amarndee@rediffmail.com
[b]Professor, E-mail: girivkmmm@gmail.com

http://www.techno-press.org/?journal=eri&subpage=7 ISSN: 2287-6316 (Print), 2287-6324 (Online)

and univariate. Multivariate models are helpful where solar radiation data and some other related variables are available, in case, only solar radiation data are available, univariate models are applicable. Univariate forecasting is pursued in the present work.

Various univariate prediction models for GSR forecasting are discussed well in various publications (Reikard 2009). Plenty of publications are available in literature, where forecasting is performed using Box-Jenkin's and Artificial Intelligence based models (Amrouche and Le Pivert 2014, Boualit and Mellit 2017, Hassan 2014, Ji and Chee 2011, Khashei and Bijari 2011). Some authors have used these models for prediction of GSR at different geographical locations of the world, for short, medium and long term forecasting (Perez *et al.* 2010). Different time series models, such as Exponential Smoothing, Moving Average and Decomposing models have been presented in (Prema and Uma Rao 2015) and used for forecasting of GSR. One-day-ahead GSR prediction model has been presented in (Mellit and Pavan 2010) and has been used for GSR prediction at a location in Italy. ANN based model has been used for short-term prediction. A comparison among various time series prediction models for prediction of GSR is presented in (Reikard 2009). Some authors have compared the prediction performances of Regression, Auto-Regressive Integral Moving Average (ARIMA), Unobserved Components Model *(*UCM), ANN, Transfer Function and their hybrid models. ANN based prediction models have been used for forecasting of GSR and the performance outcomes are compared with various other time series models such as; Bayesian Interface, ARIMA, K-Nearest Neighbor and Markov Chain models (Paoli *et al.* 2010). Box-Jenkins, ANN and their hybrid model for GSR forecasting have been presented in (Gairaa *et al.* 2016). One author has used ARMA and ANN models for GSR prediction at two locations of Algeria (Assas *et al.* 2014).

In this paper, some time series models, ANN model, and novel Hybrid models are presented to predict GSR for the site location of Gorakhpur, situated in the northern region of India. Time series prediction models are appropriate for linear data, whereas the ANN model is good for non-linear data. As GSR data have both linear and non-linear properties, hence hybrid model has been developed. Since, solar radiation data has seasonality in them, so we have proposed a hybrid SARMA-ANN model addressing non-linearity and seasonality in the data. For the present work we have used RStudio 8.1 and various associated packages of it (Team 2016) (Hyndman and Khandakar 2008)(Di Narzo *et al.* n.d.).

This paper is divided into six sections. Second section contains the details of Solar Radiation Data used for the forecasting in present work. In the third section, we have presented a brief discussion on different linear and nonlinear prediction models along with various statistical indicators used for the comparison of prediction outcomes. In section four, we have presented the forecasting outcomes obtained from different models used in the present work and comparative analysis extracted out of them. In fifth section we have used forecasting results for estimation of power production. Finally, sixth section concludes the paper.

2. Description of data set

For the present analysis, one year GSR Radiation Data have been collected from the Solar Radiation Resource Setup installed by National Institute of Wind Energy (NIWE), which is an autonomous R&D institution under the Ministry of New and Renewable Energy (MNRE), Government of India. The setup is commissioned at Madan Mohan Malaviya University of

Fig. 1 Pictorial view of measuring system used which records the solar radiation

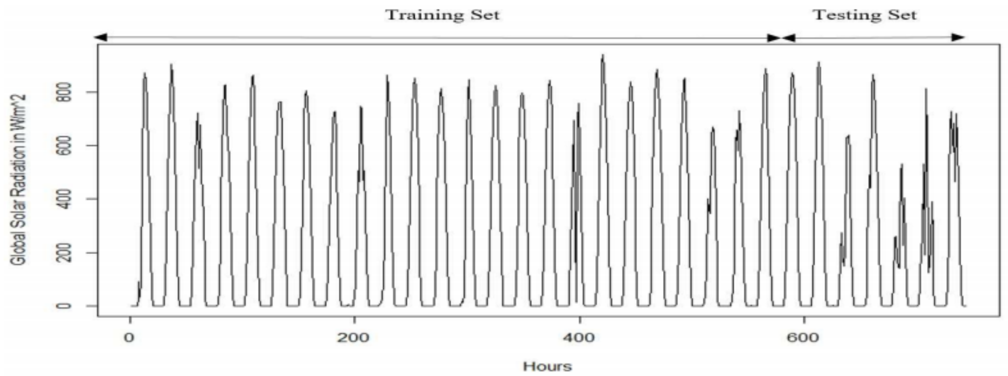


Fig. 1 Pictorial view of measuring system used which records the solar radiation

Technology, Gorakhpur, India (“CWETSolar” n.d.). Pictorial view of the Setup is shown in Fig. 1. One year GSR data (from January 2017 to December 2017) have been used in this case study. Details and standards of the setup can be seen from (Kumar *et al.* 2013). The Solar Radiation Resource Setup measures minute wise data. As model fitting of such large dataset is tedious, that’s why minute-wise dataset have been converted into hour-wise dataset by addition operation. Month-wise, 1 to 6-day-ahead hourly forecasting have been done in this case study. For this purpose, the observations of starting days of a month is used to train the model and observations of last days of a month is used for testing the models. For an example, for 6-days-ahead forecasting for the month of July, observations on 1st- 24th July is used for training of the models whereas observation on 25th- 30th July is used for testing of the models. Fig. 2 shows the graphical representation of the selection of training and testing set for 6-day-ahead solar radiation forecasting for month of July.

In recent years, many techniques have been developed for solar radiation prediction, we can classify them into two broader categories which are cloud imagery combined with physical models and the machine learning models. The choice is mainly based on the time horizon for which the forecasting is required. For short term forecasting (up to 6 hour-ahead) extrapolation and statistical processes using satellite images or measurements on the ground level and sky images are generally suitable (Paulescu *et al.* 2013). Numerical Weather Prediction (NWP) model is the combination of post-processing modules and real-time measurements or satellite data. NWP model is suitable for up to two days ahead or beyond forecasting (Perez *et al.* 2010). Time series models (such as ARMA and SARMA) also have been used in various literature for solar radiation forecasting and presents suitable results but the main cons of these models are that they are not able to consider non-linearity in the data.

3. Methodology

3.1 Box-Jenkin's model

Box and Jenkin presented various linear time series prediction models in their book (Box *et al.* 1994). These models are useful in predictions in field of economics, metrology and energy. Out of various models, ARMA and SARMA models are used in this paper as these models are most suitable for solar radiation forecasting.

3.1.1 ARMA Model

ARMA model is the combination of Auto-Regressive (AR) and Moving Average (MA) models. This model is represented as ARMA (p,q) where p represents the order of AR process and q represents the order of MA process. In the AR model, the present value X_t of series is expressed as the function of past values x_{t-1}, x_{t-2} …, x_{t-p} where p is the order required to predict the present value. AR model is denoted as AR (p). It can be formulated as

$$x_t = C + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \cdots + \beta_p x_{t-p} + c_t \tag{1}$$

where, C and $\beta 1 \ldots, \beta_p$ are parameters and c_t is white noise.

In the MA model, past prediction errors e_{t-1}, e_{t-2} …, e_{t-q} are used to calculate the present value x_t of the series. Where q is the number of required past errors required. MA model is denoted as MA (q). It can be formulated as

$$x_t = C + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_p e_{t-q} + c_t \tag{2}$$

where, C and $\theta_1 \ldots \theta_p$ are constants and e_{t-1}, e_{t-q} are past errors.

By combining AR and MA models ARMA (p, q) model can be written as

$$x_t = C + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \cdots + \beta_p x_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_p e_{t-q} c_t \tag{3}$$

It is very important to identify the correct order of the ARMA (p,q) model means appropriate values of p and q must be identify to choose the best model to be fitted. For this, Akaike Information Criterion (AIC) has been used in this case study (Posada and Buckley 2004). The model having the least AIC value provide the best results.

3.1.2 SARMA Model

SARMA model is an extended version of the ARMA model. It stands for Seasonal Auto-Regressive Moving Average Model. SARMA model is used where seasonality is present in the dataset means dataset follow a regular pattern after a certain time period. SARMA model is represented by SARMA $(p,q)\times(P,Q)_s$. Where, P represents order of seasonal Auto-Regressive, Q represents order of seasonal Moving Average and s represents seasonal period length. To find the best orders of SARMA model, Autocorrelation Function (ACF) and Partial Autocorrelation

Function (PACF) tests are performed (Crawley 2012).

3.2 ANN model

Artificial Neural Network (ANN) is an Artificial Intelligence approach used for non-linear data forecasting (Zhang *et al.* 1998). ANN model is applicable for both univariate and multivariate data. ANN gives good results among all nonlinear models. The advantage of the ANN model is that in this model, no prior assumptions are required. For univariate analysis, feed forward neural network is generally used. The relation between the current value x_t and past values $x_{t-1}, x_{t-2} \ldots, x_{t-p}$ is represented by

$$x_t = \alpha_0 \sum_{j=1}^{q} \alpha_{jg} (\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} x_{t-1}) + \varepsilon_t \tag{4}$$

where, α_{jg} and β_{0j} are the connection weights, p is the numbers of input layers and q is the number of hidden layers. Hidden layer transfer functions can also be expressed as

$$g(x) = 1 + \frac{1}{1+\exp(-x)} \tag{5}$$

From eq. (4) current value and past values can presented as

$$x_t = f(x_{t-1}, x_{t-2}, \ldots, x_{t-p}, W) + \varepsilon_t \tag{6}$$

where, W is the vector of all parameter and f is the function which is determined through structure and weights. Hence, ANN model represents non-linear prediction model.

3.3 Hybridization

ARMA and SARMA models are linear prediction models and ANN is the non-linear prediction model. If we apply hybrid ARMA-ANN or SARMA-ANN approach then the model will give better results as the hybrid prediction model would be able to identify linear as well as the non-linear property of the data. In this analysis, Zang hybridization (Zhang 2003) technique has been used. According to the Zang hybridization model, present value X_t can be written as

$$x_t = L_t + N_t \tag{7}$$

where, L_t is the linear component and N_t is the non-linear component. For hybrid SARMA-ANN model, firstly SARMA model has been applied which is a linear model then residual for SARMA forecasting has been calculated which give non-linear relationship at a time t. Error e_t of the SARMA model can be represented as

$$e_t = x_t - \hat{L}_t \tag{8}$$

where, $\hat{L}_t$ denote forecasted value at the time t by the linear model (SARMA), e_t contains a non-linear pattern in the data at the time. Now the non-linear (ANN) model has been applied on n error terms (e_t). ANN model has been applied as

$$e_t = f(e_{t-1}, e_{t-2} \ldots, e_{t-n}) \varepsilon_t \tag{9}$$

where, f is the non-linear function which will be calculated through the ANN and ε_t is the random error. If $\hat{N}_t$ denote forecast value through eq. (9) then forecasted present value $\hat{x}_t$ can be represented as

$$\hat{x}_t = \hat{L}_t + \hat{N}_t \tag{10}$$

Hence, by this technique, both SARMA and ANN has been applied in a single model for forecasting. This will contain linear forecasting property of SARMA model and non-linear forecasting property from ANN model. This will improve the forecasting results.

3.4 Model evaluation

For comparing various models, various statistical indicators were used in this case study. These indicators help to judge how well these models are fitted and how much accurate prediction outcomes are obtained through the models. In this analysis, Mean Bias Error (MBE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are considered. These errors terms are formulated as follows

$$\mathrm{MBE} = \sum_{k=1}^{n} e_k / n \tag{11}$$

$$\mathrm{RMSE} = \sqrt{\sum_{k=1}^{n} e_k^2 / n} \tag{12}$$

$$\mathrm{MAE} = \sum_{k=1}^{n} |e_k| / n \tag{13}$$

where, e_k represents difference between the true value and predicted value and n is the number of observations.

4. Results and discussions

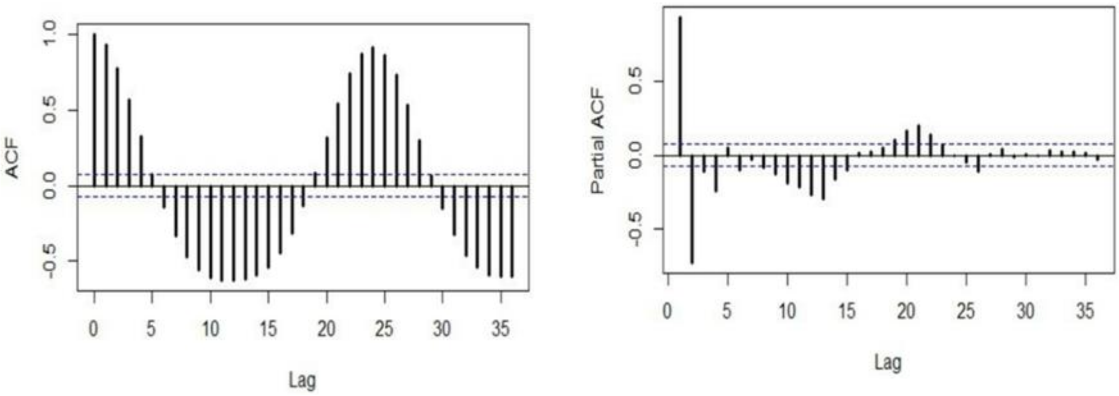
4.1 ARMA model results

Firstly, the ARMA (p, q) model is applied then Auto Correlation Function (ACF) and Partial Autocorrelation Function (PACF) tests are done on the dataset. Fig. 3 represents the ACF and PACF plot for month of May data for 4-day-ahead forecasting. From Fig. 3, we can observe that ACF is continuing in nature and not decaying and PACF has maximum value on lag 1. To identify the most appropriate values of p and q least Akaike Information Criterion (AIC) method has been used.

By applying ARMA model, we have observed that this model does not provide good results because it is not able to trace seasonality effects present in the dataset. So, we further move to the SARMA model.

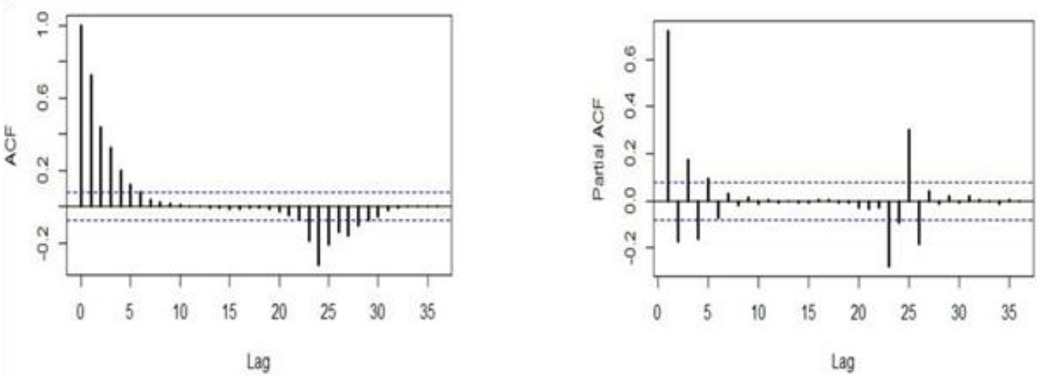
4.2 SARMA model results

As the Solar Radiation repeats its cycle after 24 hours, ACF and PACF tests have been done for the lag 24. Fig. 4 shows the ACF and PACF test. From Figure 4, it can be observed that the highest value of ACF is found at lag 1 and decaying rapidly and the next highest value is found at lag 24. PACF also shows the same characteristic as in ACF. Hence, the value of the seasonal parameter (s) is selected as 24. From the minimum AIC method, best order of SAMRA has been selected.



(a) (b)

Fig. 3 (a) ACF and (b) PACF test graph of May 2017 Month Data for 4-day-ahead forecasting



(a) (b)

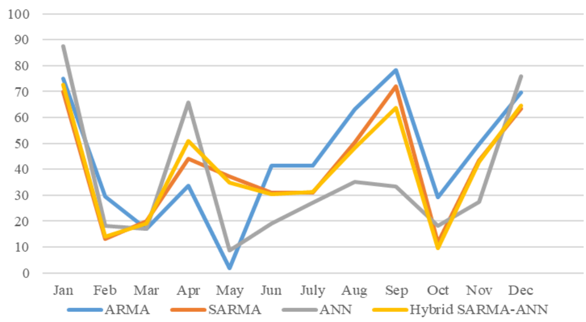
Fig. 4 (a) ACF and (b) PACF test graph with lag 24 of May 2017 Month Data for 4-day- ahead forecasting

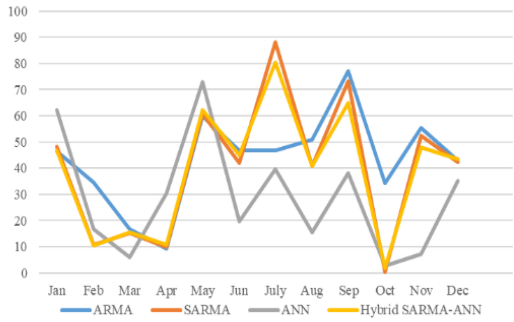
It has been observed that SARMA model is able to predict up to 6-day-ahead forecasting with satisfactory results. But SARMA model is a linear model so, we further move towards non-linear model (ANN).

4.3 ANN model results

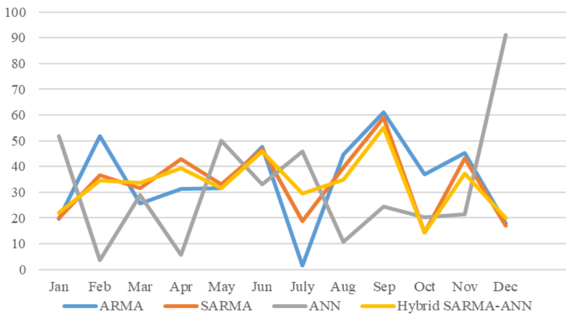
Univariate ANN model is applied to the GSR data for non-linear analysis. Non-linear auto-regression ANN model has been applied for forecasting. From the analysis, it has been found that in most of the cases, ANN model having 3 input layers, 3 hidden layers and 1 output layer having 16 weights provide optimal results. The model has been optimized using the BFGS method (Liu and Nocedal 1989). In some cases, the ANN model is not able to predict accurately because univariate ANN model is not able to fit seasonal graph accurately.

It has been found that the ANN model is also able to predict up to 6-day-ahead forecasting with satisfactory results. ANN model is a non-linear model. To facilitate both linear and non-linear properties we further move towards the proposed hybrid SARMA-ANN model.



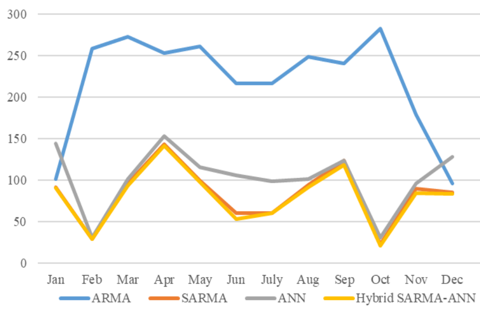


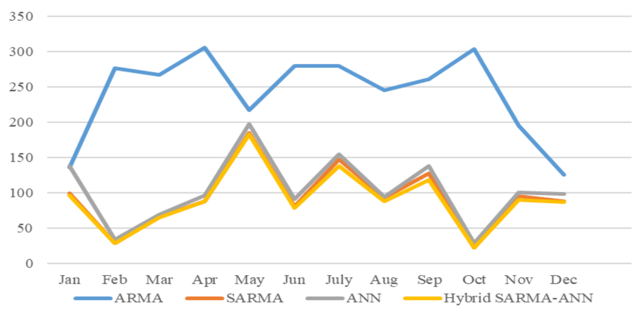
(a) (b)



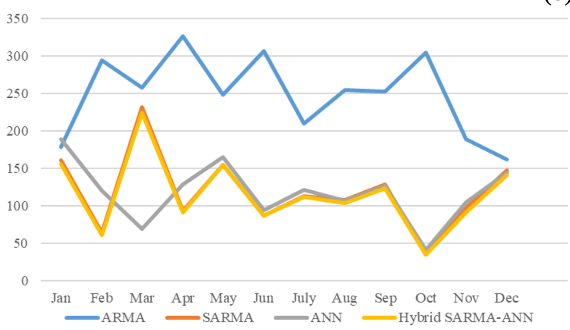
(c)

Fig. 5 Mean bias error in (a) 1-day-ahead, (b) 3-day-ahead and (c) 6-day-ahead forecasting





(a) (b)



(c)

Fig. 6 Root mean square error in (a) 1-day-ahead, (b) 3-day-ahead and (c) 6-day-ahead forecasting

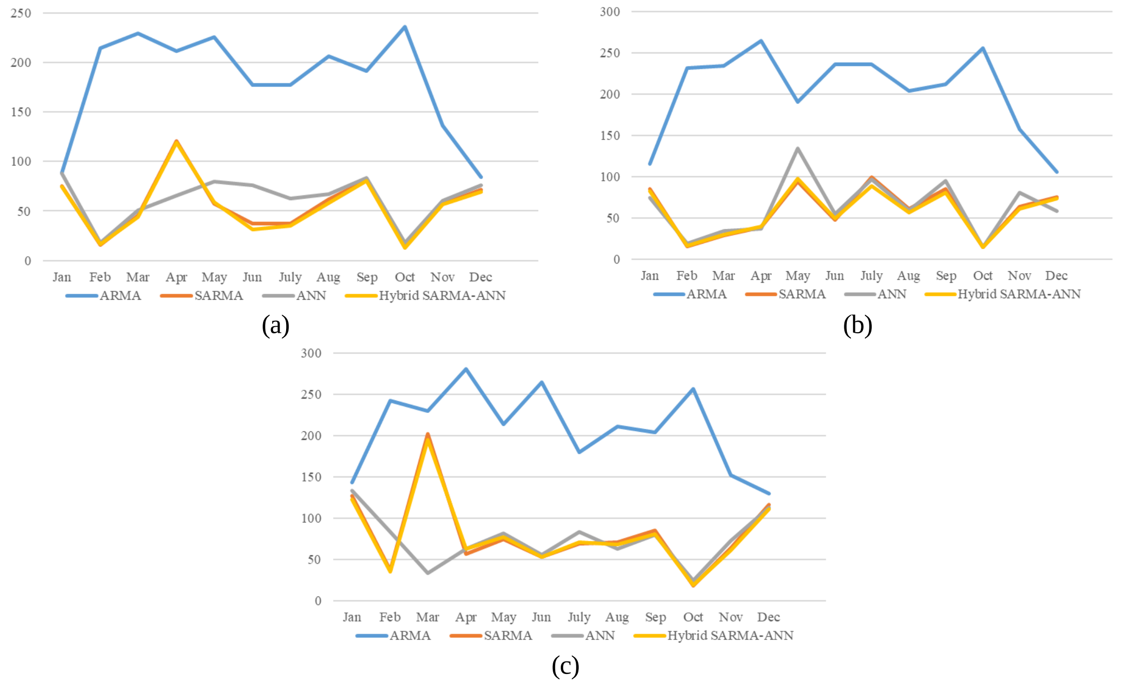


Fig. 7 Mean absolute error in (a) 1-day-ahead, (b) 3-day-ahead and (c) 6-day-ahead forecasting

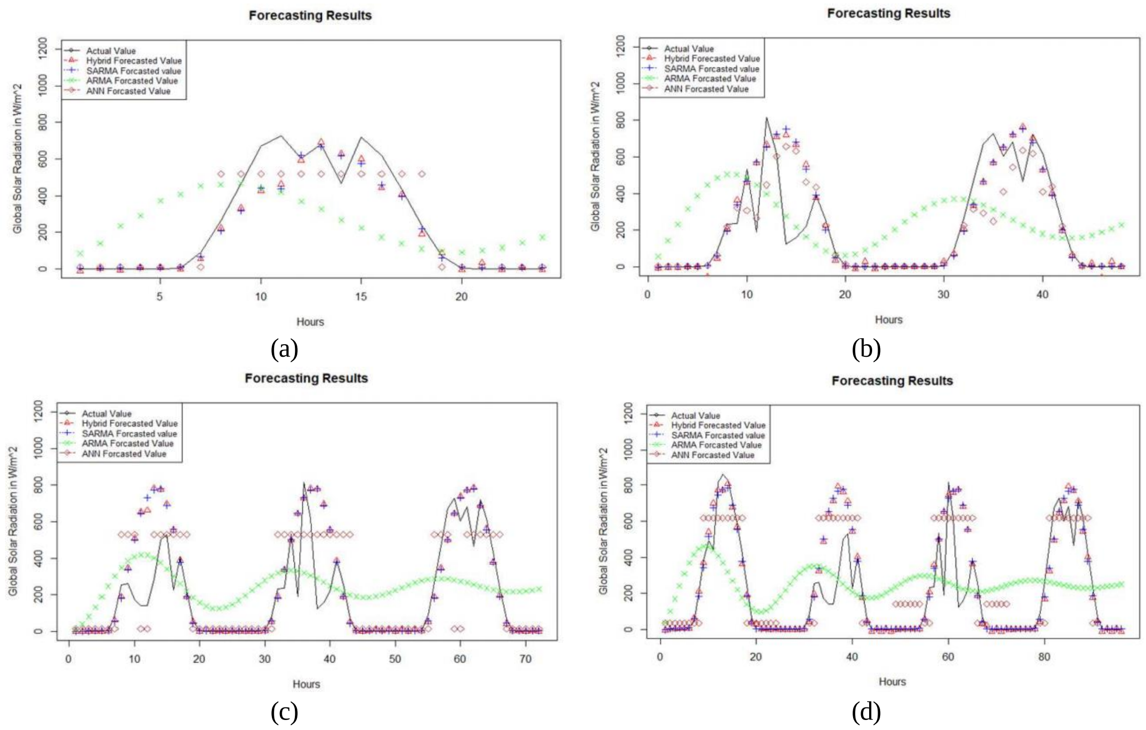
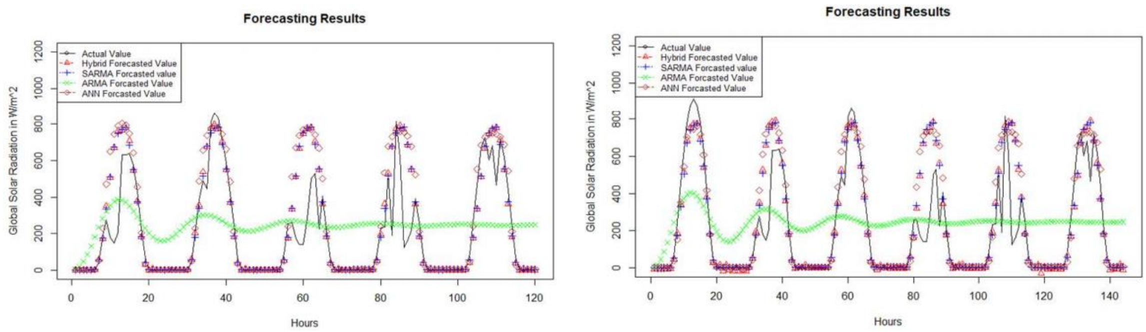


Fig. 8 (a) 1-day-ahead, (b) 2-day-ahead, (c) 3-day-ahead, (d) 4-day-ahead, (e) 5-day-ahead and (f) 6-day-ahead Forecasting Comparison of various Models for May 2017 Month Data



(e) (f)

Fig. 8 Continued

4.4 Hybrid model results

Now, SARMA-ANN hybrid model has been implemented on the GSR data. For this, firstly SARMA model has been applied and residuals from SARMA model have been calculated. After that, the ANN model has been applied to residuals data. The resultant from ANN is summed with the SARMA results.

It has been found that the proposed Hybrid SARMA-ANN model is also able to predict up to 6-day-ahead forecasting with satisfactory results.

4.5 Discussion

In order to find out the best model, comparisons of the models have been done on the basis of RMSE, as RMSE is the key parameter to judge the model. Figs. 5, 6 and 7 represent MBS, RMSE and MAE graph associated in various month for 1-day, 3-day and 6-day-ahead forecasting respectively. Fig. 8 represents actual and forecasted result graphs for May month of 1-day, 2-day, 3-day, 4-day, 5-day, and 6-day-ahead forecasting. From the Figs. 5-8, it has found that Hybrid SARMA-ANN model presents the best results among all models in all the cases. Worst performance has been found from the ARMA model where the SARMA model presents better result than ANN.

5. Application of forecasting and validation

In order to evaluate the effectiveness of the models, the solar radiation forecasting results were used to calculate electricity generation from 50kW solar power plant commissioned at the same location of solar radiation resource setup (Parking integrated 50kW PV plant at Madan Mohan Malaviya University of technology, Gorakhpur, India). Validation has been done on the basis of 6-month day wise power output data from the solar plant. Forecasted solar radiation results have been converted into expected plant power output using the following formula

$$E_{day} = \sum_{h=1}^{24} G_h \times PC_{PV} \times R_{p(month)}/1000 \tag{14}$$

where, E_{day} is total estimated electricity in a day, G_h is predicted solar radiation in an hour, PC_{PV} is PV plant capacity or rating and $R_{p(month)}$ is average performance ratio of that month.

Table 1 Overall % error in solar power estimation

Day-ahead Span	Models			
	ARMA	SARMA	ANN	Hybrid
1 Day-ahead (Avg. Jul-Dec)	22	16.958	20.638	13.64
2 Day-ahead (Avg. Jul-Dec)	12.673	11.343	12.82	5.46
3 Day-ahead (Avg. Jul-Dec)	24.38	22.31	25.41	16.6
4 Day-ahead (Avg. Jul-Dec)	27.34	19.49	25.32	25.67
5 Day-ahead (Avg. Jul-Dec)	29.9	25.29	28.02	21.34
6 Day-ahead (Avg. Jul-Dec)	31.8	27.98	30.25	32.65
Average	24.682	20.562	23.743	19.23

From this, actual solar power output has been compared with expected power from 1 to 6-day-ahead GSR forecasting results. Table 1 represents overall % errors in solar power estimation for all day-ahead spans. From Table 1, we can observe that all the models are showing good results. Among all models, hybrid model is presenting best results having just 19.23% error in solar power estimation.

By this, we can say that hybrid SARMA-ANN model is a good option to predict solar radiation where only GSR data are available. It could be beneficial to the solar power plant to hourly bid (up to 6 days advance) to sell their power to the grid with high level of certainty.

6. Conclusions

GSR forecasting is very important for the prediction of future electricity generation by any SPP. In this study, medium-term hourly solar radiation forecasting has been performed for the site location of Gorakhpur, India. One year solar radiation forecasting has been done through ARMA, SARMA, ANN and novel hybrid SARMA-ANN models. We have presented month-wise, 1 to 6-day-ahead forecasting in the present work. From the analysis, it has been found that the proposed hybrid model shows the best results amongst all the models considered for the present study, as it contains linear as well as non-linear properties. It also found that the proposed Hybrid model presents good results up-to 6-day-ahead forecasting. Results produced by SARMA model is somewhat inferior as this model cannot address non-linearity in data. ANN model presents poor results than SARMA model whereas ARMA model presents the worst results among all the models. This paper presents solar radiation forecasting on hourly basis which is certainly beneficial in the estimation of available solar power during every hour of a day. Along with this, validation of the results has also been carried out by calculating expected power output from the nearby solar power plant and compare it with actual power output for the plant. Such forecasting results are certainly beneficial for Independent System Operators (ISO) (POSOCO in India) in there bidding process. This forecasting is beneficial for the site where only solar radiation data are available and no other data is available.

References

Amrouche, B. and Le Pivert, X. (2014), “Artificial neural network based daily local forecasting for global solar radiation", *Appl. Energy*, **130**, 333-341. https://doi.org/10.1016/j.apenergy.2014.05.055.

Assas, O., Bouzgou, H., Fetah, S., Salmi, M. and Boursas, A. (2014), "Use of the artificial neural network and meteorological data for predicting daily global solar radiation in Djelfa, Algeria", *Proceedings of the 2014 International Conference on Composite Materials & Renewable Energy Applications (ICCMREA)*, Sousse, Tunisia, January.

Boualit, S.B. and Mellit, A. (2017), "SARIMA-SVM hybrid model for the prediction of daily global solar radiation time series", *Proceedings of the 2016 International Renewable and Sustainable Energy Conference*, Marrakesh, Morocco, November.

Box, G.E.P., Jenkins, G.M. and Reinsel, G.C. (1994), *Time Series Analysis: Forecasting & Control*, Prentice-Hall, Englewood Cliffs, New Jersey, U.S.A.

Crawley, M.J. (2012), *Time Series Analysis, The R Book*, John Wiley & Sons.

CWETSolar. (n.d.), http://www.cwetsolar.com/.

Di Narzo, A.F., Aznarte, J.L. and Stigler, M. (n.d.), tsDyn: Time series analysis based on dynamical systems theory. R Package Version 0.7.

Gairaa, K., Khellaf, A., Messlem, Y. and Chellali, F. (2016), "Estimation of the daily global solar radiation based on Box-Jenkins and ANN models: A combined approach", *Renew. Sust. Energy Rev.*, **57**, 238-249.h ttps://doi.org/10.1016/j.rser.2015.12.111.

Hassan, J. (2014), "ARIMA and regression models for prediction of daily and monthly clearness index", *Renew. Energy*, **68**, 421-427. https://doi.org/10.1016/j.renene.2014.02.016.

Hosenuzzaman, M., Rahim, N. A., Selvaraj, J., Hasanuzzaman, M., Malek, A.B.M.A. and Nahar, A. (2015), "Global prospects, progress, policies, and environmental impact of solar photovoltaic power generation", *Renew. Sust. Energy Rev.*, **41**, 284-297. https://doi.org/10.1016/j.rser.2014.08.046.

Hyndman, R.J. and Khandakar, Y. (2008), "Automatic time series forecasting: The forecast package for R", *J. Stat. Softw.*, **27**(3), C3-C3. https://doi.org/10.18637/jss.v027.i03.

Ji, W. and Chee, K.C. (2011), "Prediction of hourly solar radiation using a novel hybrid model of ARMA and TDNN", *Solar Energy*, **85**(5), 808-817. https://doi.org/10.1016/j.solener.2011.01.013.

Khashei, M. and Bijari, M. (2011), "A novel hybridization of artificial neural networks and ARIMA models for time series forecasting", *Appl. Soft Comput.*, **11**(2), 2664-2675. https://doi.org/10.1016/j.asoc.2010.10.015.

Kumar, A., Gomathinayagam, S., Giridhar, G., Mitra, I., Vashistha, R., Meyer, R., Schwandt, M. and Chhatbar, K. (2013), "Field experiences with the operation of solar radiation resource assessment stations in India", *Energy Procedia*, **49**, 2351-2361. https://doi.org/10.1016/j.egypro.2014.03.249.

Liu, D.C. and Nocedal, J. (1989), "On the limited memory BFGS method for large scale optimization", *Math. Program.*, **45**(1-3), 503-528. https://doi.org/10.1007/BF01589116.

Marquez, R. and Coimbra, C.F.M. (2011), "Forecasting of global and direct solar irradiance using stochastic learning methods, ground experiments and the NWS database", *Solar Energy*, **85**(5), 746-756. https://doi.org/10.1016/j.solener.2011.01.007.

Mellit, A. and Pavan, A.M. (2010), "A 24-h forecast of solar irradiance using artificial neural network: Application for performance prediction of a grid-connected PV plant at Trieste, Italy", *Solar Energy*, **84**, 807-821. https://doi.org/10.1016/j.solener.2010.02.006.

Paoli, C., Voyant, C., Muselli, M. and Nivet, M.L. (2010), "Forecasting of preprocessed daily solar radiation time series using neural networks", *Solar Energy*, **84**(12), 2146-2160. https://doi.org/10.1016/j.solener.2010.08.011.

Paulescu, M., Paulescu, E., Gravila, P. and Badescu, V. (2013), *Weather Modeling and Forecasting of PV Systems Operation. Green Energy and Technology*. Springer Science & Business Media.

Perez, R., Kivalov, S., Schlemmer, J., Hemker, K., Renné, D. and Hoff, T.E. (2010), "Validation of short and medium term operational solar radiation forecasts in the US", *Solar Energy*, **84**(12), 2161-2172. https://doi.org/10.1016/j.solener.2010.08.014.

Posada, D. and Buckley, T.R. (2004), "Model selection and model averaging in phylogenetics: Advantages of akaike information criterion and bayesian approaches over likelihood ratio tests", *Syst. Biol.*, **53**(5), 793-808. https://doi.org/10.1080/10635150490522304.

Prema, V. and Uma Rao, K. (2015), "Development of statistical time series models for solar power prediction", *Renew. Energy*, **83**, 100-109. https://doi.org/10.1016/j.renene.2015.03.038.

Reikard, G. (2009). "Predicting solar radiation at high resolutions: A comparison of time series forecasts", *Solar Energy*, **83**(3), 342-349. https://doi.org/10.1016/j.solener.2008.08.007.

Salcedo-Sanz, S., Casanova-Mateo, C., Pastor-Sánchez, A. and Sánchez-Girón, M. (2014), "Daily global solar radiation prediction based on a hybrid coral reefs optimization-Extreme learning machine approach. *Solar Energy*, **105**, 91-98. https://doi.org/10.1016/j.solener.2014.04.009.

Team, Rs. (2016), RStudio: Integrated Development for R. [Online] RStudio, Inc., Boston, MA URL http://www. Rstudio. Com, RStudio, Inc., Boston, MA. https://doi.org/10.1007/978-81-322-2340-5.

Yadav, A.K. and Chandel, S.S. (2014), "Solar radiation prediction using artificial neural network techniques: A review", *Renew. Sustain. Energy Rev.*, **33**, 772-781. https://doi.org/10.1016/j.rser.2013.08.055.

Zhang, G., Patuwo, B.E. and Hu, M.Y. (1998), "Forecasting with artificial neural networks: The state of the art", *Int. J. Forecasting*, **14**(1), 35-62. https://doi.org/10.1016/S0169-2070(97)00044-7.

Zhang, G.P. (2003), "Time series forecasting using a hybrid ARIMA and neural network model", *Neurocomputing*, **50**, 159-175. https://doi.org/10.1016/S0925-2312(01)00702-0.

CC