



Forecasting the solar power generation by modified time series model for Cyber-Physical power system

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Abstract—Increasingly high penetration of photovoltaic generation arises in cyber-physical power system. Solar power is intermittent and variable, as the solar source at the ground level is highly dependent on atmosphere parameters. The inherent variability of large-scale solar generation introduces significant challenges in the development of cyber physical power system. Accurate forecasting of solar power is critical to secure economic operation of the power grid. This paper proposes a modified time series model to forecast the short term solar power generation forecasting for Cyber-Physical systems applications. The performance metrics are Root Mean Square Value, Mean Absolute Deviation and Mean Absolute Percentage Error are compared with the literatures.

I. INTRODUCTION

A Cyber Physical system is the combination of physical systems and cyber systems. Modern grids are integrated with lot of smart sensors that provided the required information to the system to ensure the grid is reliable on time. While modeling the cyber physical power grid, the power source plays a vital role to meet the demand. But in renewable energy case, the power generation from the sources is not reliable because of variable solar radiation and wind velocity [1, 2]. This paper addresses the forecasting of solar power generation from the installed solar photovoltaic (PV) power plant.

Normally, solar power generation forecasting models fall into three categories i.e., physical, time-series statistical and ensemble models [3, 4]. In time-series model, the past meteorological data are used to forecast. Under time-series model, Artificial Neural Network (ANN) [5-7], Support Vector Machine (SVM) [8, 9], Markov Chain [10, 11], Autoregressive [12, 13] and Regression [14] discussed in the literature. In physical models, Numerical weather prediction [15, 16] and Sky imagery [17-19] also discussed in literature. Cooperative and Competitive ensemble are discussed in [20]. Out of all types, the time-series model have easiest way to forecast and in that Holt's Winter method have less Root Mean Square Value (RMSE) identified from the literature.

II. TIME SERIES MODEL

In time series model, a set of statistical data are collected for particular time period and the measurements may be taken with the time horizon may be every hour, day, week, month and year. If data are purchased, data mining is essential because it has large set of data. As a result of data mining, the required time horizon may be obtained and used for our study. In our

work, R software is used and it is free software programming for data mining and also for forecasting.

Time series models are classified into two types, it includes- parametric and non parametric time series models [21]. In all time series models, first step is to find the Moving Average (MA), followed by Centre Moving Average (CMA). Trend, Level and Seasonal component are calculated by using the formula. Finally, decomposition model are developed to forecast the next day data. In the proposed modified time series model, decomposition stage gets differed; here hybrid decomposition is used, which is the sum of level and trend component and resultant to be multiplied with seasonal component.

III. MODIFIED TIME SERIES MODEL

In modified time series model, the forecasting equation consists of following parameters such as level component, trend component and seasonal component. For decomposition, the level and trend components are summed and multiplied with seasonal components. The hybrid forecasting formula is given in the equation (1).

$$F_{t+n} = (L_t + xb_t)S_{t+x-s} \quad (1)$$

where, F_{t+n} is the forecasted value

L_t is the level component for the time period of t .

b_t is the trend component for the time period of t .

S_{t+x-s} is the seasonal trend component for the time period of $t+x-s$, x is the length of seasonal cycle.

The level, trend and seasonal components are calculated by using the equation (2, 3 and 4).

$$L_t = \theta(y_t - S_{t-s}) + (1 - \theta)(L_{t-1} + b_{t-1}) \quad (2)$$

$$b_t = \vartheta(L_t - L_{t-1}) + (1 - \vartheta)b_{t-1} \quad (3)$$

$$S_t = \tau(y_t - L_t) + (1 - \tau)S_{t-s} \quad (4)$$

for $0 \leq \theta \leq 1, 0 \leq \vartheta \leq 1$, and $0 \leq \tau \leq 1$

where,

θ is level somoothing component

ϑ is trend smoothing component

τ is sesonal smoothig compontent

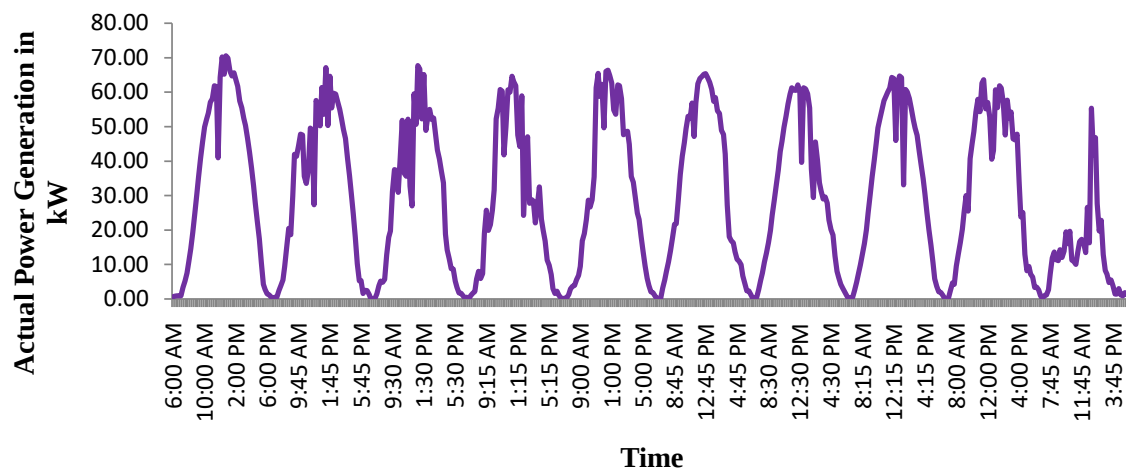


Fig.1. Actual Power Generation of 1st January 2018 to 10th January 2018

Table 1

Results comparing moving average and centre moving average for different intervals on 1st January 2018

Time	Actual Power Generation (kW)	MA interval = 3	MA interval = 5	MA interval = 7	CMA on MA interval = 5
8:00 AM	10.71	-	-	-	-
8:15 AM	14.52	-	-	-	-
8:30 AM	19.28	-	-	-	-
8:45 AM	24.72	14.84	-	-	-
9:00 AM	30.34	19.51	-	-	-
9:15 AM	35.38	24.78	19.91	-	22.38
9:30 AM	40.78	30.15	24.85	-	27.47
9:45 AM	45.60	35.50	30.10	-	32.73
10:00 AM	49.89	40.58	35.36	25.10	37.88
10:15 AM	52.17	45.42	40.40	30.09	42.58
10:30 AM	53.93	49.22	44.76	35.14	46.62
10:45 AM	57.13	52.00	48.47	39.84	50.11
11:00 AM	58.11	54.41	51.74	44.01	53.00
11:15 AM	61.88	56.39	54.25	47.84	55.45
11:30 AM	61.64	59.04	56.64	51.09	57.59
11:45 AM	40.94	60.54	58.54	54.10	57.24
12:00 PM	64.31	54.82	55.94	56.39	56.66
12:15 PM	70.19	55.63	57.38	55.12	58.58
12:30 PM	65.19	58.48	59.79	56.85	60.12
12:45 PM	70.55	66.56	60.45	59.17	61.34
1:00 PM	69.86	68.64	62.24	60.32	65.13
1:15 PM	66.16	68.53	68.02	62.10	68.20
1:30 PM	64.74	68.85	68.39	63.24	67.84
1:45 PM	65.63	66.92	67.30	63.88	67.34
2:00 PM	63.80	65.51	67.39	67.28	66.71
2:15 PM	61.68	64.72	66.04	67.47	65.22
2:30 PM	57.45	63.70	64.40	66.56	63.53
2:45 PM	55.53	60.98	62.66	66.06	61.74
3:00 PM	52.41	58.22	60.82	64.19	59.50
3:15 PM	50.36	55.13	58.17	62.14	56.83
3:30 PM	46.64	52.76	55.48	60.18	53.98
3:45 PM	42.51	49.80	52.48	58.12	50.98
4:00 PM	37.96	46.50	49.49	55.41	47.73

4:15 PM	32.81	42.37	45.97	52.37	44.01
4:30 PM	27.75	37.76	42.05	48.98	39.79
4:45 PM	22.50	32.84	37.53	45.46	35.12
5:00 PM	17.48	27.69	32.71	41.49	-
% error	-	2.7%	1.0%	3.5%	-

IV. DATA USED

The data used for this study is obtained from the sunnyportal of SMA inverters installed in Karunya Institute of Technology and Sciences (Deemed to be University) for 95kW solar photovoltaic grid connected power plant. The data recorded with the time interval of 15 minutes and for our study, ten days data, 1st January 2018 through 10th January 2018, were considered to forecast the 11th January 2018. The results are compared with the state-of-art methods. The solar irradiance being almost nil for 12 h in a day, 50% of the data points account for zero value and given in Fig.1. With these zero values, forecasted values are more sprinkled from the actual values for the regression model. Hence, the analysis is done by exclusive of zero values and the models are developed to predict the irradiance one day ahead.

V. EVALUATION OF PROPOSED TECHNIQUE FOR FORECASTING

The precision of solar forecasting highly depends on two major factors i.e., geographic locations and forecast horizons. The classical statistical indicators are Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). MAE is defined as the average distance between the measured value and forecasted model. The formula for calculating the MAE is given in the equation (5).

$$MAE = \frac{1}{N} \sum_{i=1}^N |P_{pred} - P_{meas}| \quad (5)$$

RMSE is to measure the global error during the entire prediction period and the formula is given in the equation (6).

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_{pred} - P_{meas})^2} \quad (6)$$

MAPE is used to evaluate the uniform prediction error and formula is given in the equation (7).

$$MAPE = \frac{100}{N} \sum_{i=1}^N \left| \frac{P_{pred} - P_{meas}}{P_o} \right| \quad (7)$$

VI. RESULTS AND DISCUSSIONS

For current analysis, the solar power generations from the solar PV power plants are taken into account in the time period of 01.01.2018 to 10.01.2018. In the modified time series model, the moving average (MA) models were tested under various time intervals and their values are given the table 1. From the table, it is observed that is the MA is 5, the maximum error percentage is less (Error means difference between the actual power generation and predicted power

generation). The trend pattern is obtained from the centre moving average (CMA) and it is given in the Fig2.

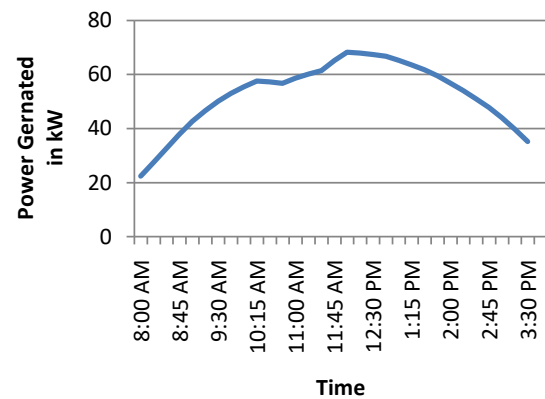


Fig.2. CMA for Power Generated on 1st January 2018

The smoothing parameters for proposed time series forecasting model are given in the Table.2. The predicted value is compared with the actual values and the deviations are calculated.

Table 2
Smoothing parameters for the proposed model

Sl no	Model	θ	ϑ	τ
1	Forecast- 1 day	0.9051	0	0.1992
2	Forecast- 5 days	0.8841	0	0.1241
3	Forecast- 9 days	0.7936	0	0.0564

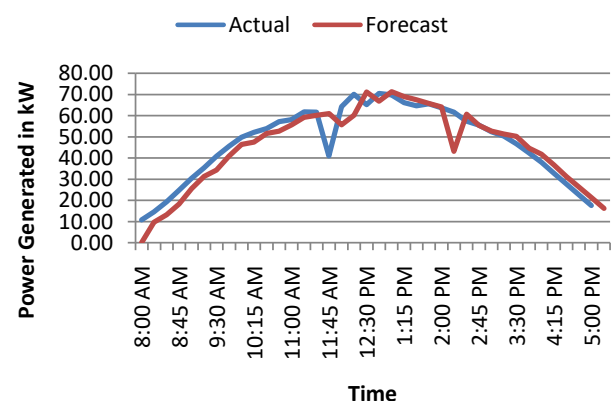


Fig.3. Plot for forecast values of 1 day

The decomposition model is analyzed for three different time periods, such as 1st January 2018, 1st

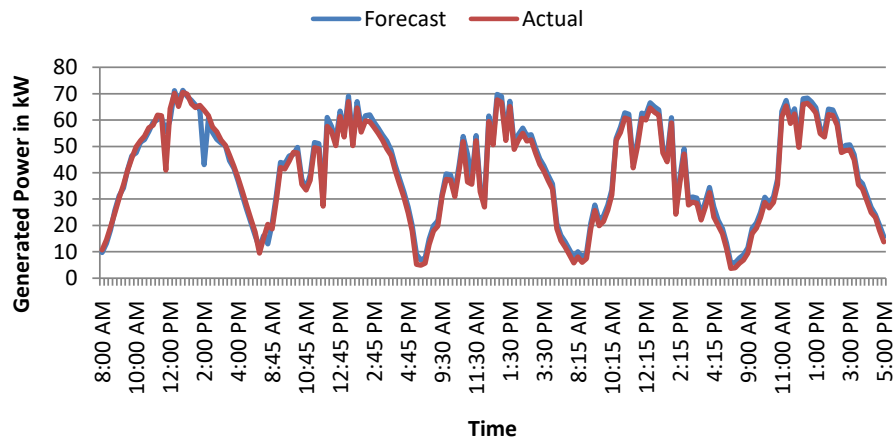


Fig.4. Plot for forecast values of 5 days

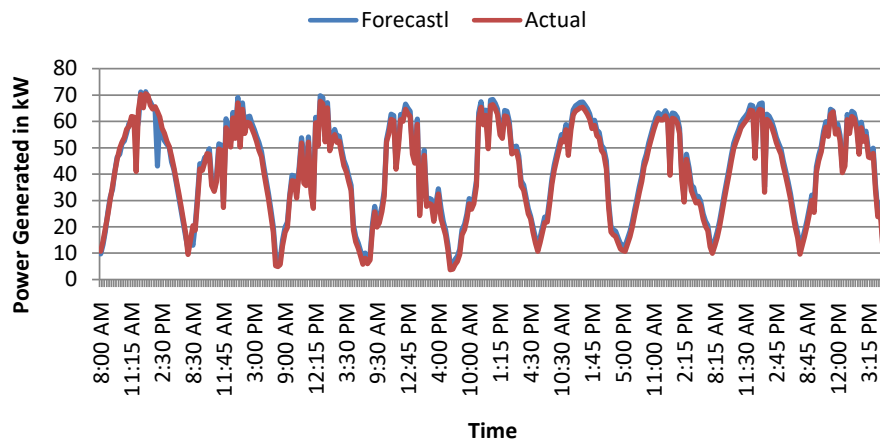


Fig.5. Plot for forecast values of 9 days

January 2018 to 5th January 2018 and 1st January 2018 to 9th January 2018. The forecast plots for three time horizon are given in the Fig.3, Fig.4, and Fig.5. The correlation between the actual and forecast for three horizons is given in the Fig.6.

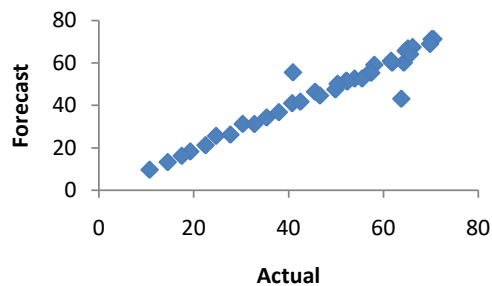


Fig.6. Correlation between Actual and forecast for 1st January 2018

A comparison of the developed time series model for three time horizons and also comparison with state-of-art methods are given in Table.3.

Table.3

Comparison of errors for three time horizons			
Date Duration	MAE (kW)	RMSE (kW)	MAPE (%)
1 day	16.12	12.17	9.09
5 days	18.62	13.56	10.11
9 days	20.42	15.62	12.23

VII. CONCLUSION

By using techniques in Microsoft excel and R software, short term prediction of solar power generation for a day ahead is carried out. The work started with the moving average and centre moving average model which is the simplest time series model. Thus, exponential smoothing models and decomposition models were tested. The developed models can forecast the solar power generation for next day. The hybrid decomposition model was developed for different data duration and prediction done for three different time horizons. It is found that MAE, RMSE

and MAPE for short duration i.e. 1 day are 16.12 kW, 12.17% and 9.09 kW respectively.

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REFERENCES

- [1] Ilge Akkaya, Yan Liu, and Edward A. Lee, "Modeling and Simulation of Network Aspects for Distributed Cyber-Physical Energy Systems", Springer-Verlag Berlin Heidelberg 2015.
- [2] Ceeman B. Vellaithurai, Saugata S. Biswas, Ren Liu, and Anurag Srivastava, "Real Time Modeling and Simulation of Cyber-Power System", Springer-Verlag Berlin Heidelberg 2015.
- [3] Monteiro, C., K. Keko, R. Bessa, et al. (2009). "Quick Guide to Wind Power Forecasting: State-of-the-Art 2009", Argonne National Laboratory. ANL/DIS-10-2.
- [4] Can Wan, Jian Zhao, et.al, "Photovoltaic and Solar Power Forecasting for Smart Grid Energy Management", CSEE Journal of Power and Energy Systems, Vol. 1, No. 4, December 2015.
- [5] Yadav AK, Chandel S. "Solar radiation prediction using Artificial Neural Network techniques: a review". *Renew Sustain Energy Rev* 2014;33:772–81.
- [6] Ogliari E, Grimaccia F, Leva S, Mussetta M. Hybrid predictive models for accurate forecasting in PV systems. *Energies* 2013;6:1918–29.
- [7] Zhu H, Li X, Sun Q, Nie L, Yao J, Zhao G. A power prediction method for photovoltaic power plant based on wavelet decomposition and artificial neural networks. *Energies* 2015;9:11.
- [8] Mohammadi K, Shamshirband S, Tong CW, Arif M, Petković D, Ch S. "A new hybrid support vector machine-wavelet transform approach for estimation of horizontal global solar radiation". *Energy Convers Manage* 2015;92:162–71.
- [9] Olatomiwa L, Mekhilef S, Shamshirband S, Mohammadi K, Petković D, Sudheer C. "A support vector machine-firefly algorithm-based model for global solar radiation prediction". *Sol Energy* 2015;115:632–44.
- [10] Hocaoglu FO, Serttas F. "A novel hybrid (Mycielski-Markov) model for hourly solar radiation forecasting". *Renew Energy* 2016.
- [11] Bhardwaj S, Sharma V, Srivastava S, Sastry O, Bandyopadhyay B, Chandel S, et al. "Estimation of solar radiation using a combination of Hidden Markov Model and generalized Fuzzy model". *Sol Energy* 2013;93:43–54.
- [12] Diagne M, David M, Lauret P, Boland J, Schmutz N. "Review of solar irradiance forecasting methods and a proposition for small-scale insular grids". *Renew Sustain Energy Rev* 2013;27:65–76.
- [13] Box GE, Jenkins GM, Reinsel GC, Ljung GM. "Time series analysis: forecasting and control". John Wiley & Sons; 2015.
- [14] Fumo N, Biswas MR. "Regression analysis for prediction of residential energy consumption". *Renew Sustain Energy Rev* 2015; 47:332–43.
- [15] Monteiro C, Santos T, Fernandez-Jimenez LA, Ramirez-Rosado JJ, Terreros-Olarte MS. "Short-term power forecasting model for photovoltaic plants based on historical similarity". *Energies* 2013;6:2624–43.
- [16] Lorenz E, Heinemann D. "Prediction of solar irradiance and photovoltaic power". *Comprehen Renew Energy* 2012;1:239–92.
- [17] Tuohy A, Zack J, Haupt SE, Sharp J, Ahlstrom M, Dise S, et al. Solar forecasting: methods, challenges, and performance. *IEEE Power Energy Mag* 2015;13:50–9.
- [18] Urquhart B, Kurtz B, Dahlin E, Ghonima M, Shields J, Kleissl J. Development of a sky imaging system for short-term solar power forecasting. *Atmosph Meas Techn Discuss* 2014;7:4859–907.
- [19] Yang H, Kurtz B, Nguyen D, Urquhart B, Chow CW, Ghonima M, et al. Solar irradiance forecasting using a ground-based sky imager developed at UC San Diego. *Sol Energy* 2014;103:502–24.
- [20] Dong Z, Yang D, Reindl T, Walsh WM. "Satellite image analysis and a hybrid ESSS/ ANN model to forecast solar irradiance in the tropics". *Energy Convers Manage* 2014;79:66–73.
- [21] V. Prema, K.Uma Rao, "Development of statistical time series models for solar power prediction", *Renewable Energy* 83 (2015) 100–109.

