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RESEARCH ARTICLE

Nowcasting of Weather Parameters Impacting Solar PV Output Using Grey System Model

S Uma[1]*, **S Sridhar[2]**, **S Sumathi[3]**

1 Associate Professor, Department of Computer Applications, B.M.S. College of Engineering, Bangalore, India
2 Associate Professor, Department of Electrical & Electronics Engineering, Ramaiah Institute of Technology, Bangalore, India
3 Professor, Department of Electrical & Electronics Engineering, RNS Institute of Technology, Bangalore, India

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* **Corresponding author**.

uma.mca@bmsce.ac.in

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Abstract

Objectives: To nowcast the weather parameters having a direct impact on the power output of the solar PV installations, with high prediction accuracy and a limited quantity of past data. **Methods**: In this study, the GM (1,1) model with Fourier series of error residuals has been proposed and used for forecasting the weather parameters namely Ambient temperature, Solar Photo Voltaic Module temperature, and Solar Irradiation. Real-time data has been used for showing the suitability of the proposed model to nowcast the weather parameters. The existing models like Autoregression and Double Exponential Smoothing are applied to the same data to prove the superiority of the GM (1,1) model with Fourier series of error residuals. **Findings**: It is found that the GM (1,1) model with Fourier series of error residuals is an apt model for nowcasting the weather parameters. The accuracy of the predicted result of this model on the real-time data ascertains the appropriateness of this model for nowcasting. The precision of the prediction accuracy of GM (1,1) with the Fourier series of error residuals model is verified by comparing it with other time series prediction models such as Autoregression and Double Exponential Smoothing algorithms. **Novelty**: Using GM (1,1) with the Fourier series of error residuals model for nowcasting the weather data is novel when compared with the existing algorithms because for nowcasting the weather parameters with accuracy, many of the existing algorithms require a huge volume of past data and involve complex computation. On the other hand, GM (1,1) with the Fourier series of error residuals model requires only a limited measure of past data and involves simple computation. Moreover, the accuracy of prediction is significantly higher than the other models.

Keywords: Grey Theory; Renewable Energy; PV Installation; Auto Regression; Double Exponential Smoothing

1 Introduction

With an ever-growing demand for electricity, the energy sector is moving toward renewable energy sources as a source of alternate energy. Solar energy is the most sought-after renewable form of energy. Photovoltaic technology (PV) that transforms solar radiation into electricity is considered one of the most significant sustainable energy systems[(1)]. Many countries have commissioned solar plants of higher capacity. Such huge installations are usually grid-connected. Hence, for the safe and stable function of the power system, it is essential to predict the solar power output. Also in a deregulated environment, the prediction of power output from huge installations plays a crucial role in energy trading. Now-casting of power output from renewable energy sources is essential for optimal scheduling of generation from Non-renewable sources. Solar panel output power is normally rated at standard insolation of $1KW/m^2$ at 25°C. The weather conditions have a significant impact on the capacity of solar PV power generation. The daily energy generated by PV systems is dependent on the weather such as the irradiance, the air temperature, etc., [(2)]. Since the temperature is a variable parameter, it significantly affects the power output and hence it is necessary to predict the ambient temperature, module temperature, and irradiance to which the solar cells are exposed. Time series prediction algorithms are more appropriate algorithms for now-casting of ambient temperature, module temperature, and irradiance for a specific installation as they are based on cost-effective sensor outputs.

The literature shows that many prediction algorithms are available for the now-casting of solar PV output. Ultra-short-term solar radiation prediction model using BP neural network has been proposed by the authors to forecast solar radiation in photovoltaic power stations[(3)]. Sky cameras and satellite images have been used for Nowcasting solar radiation[(4)]. Satellite images have been used to forecast global horizontal solar irradiance and are compared with the persistence model[(5,6)]. Nespoli & Niccolai[(7)] have used the sky image captured via a high-resolution camera installed on-site for the Now-casting of PV output. Nowcasting based on sky image with CNN was used in predicting 1-minute photovoltaic power by Siddiqui et al., [(8)]. For nowcasting of weather data, images captured through a sky camera need data pre-processing to extract the input. This is a time-consuming process and involves complex computation. There is also a need for high-resolution cameras for data acquisition whereas, in the current work, the input data can be acquired through low-cost sensors. When images are captured through sky cameras, there is a possibility of less accurate input data when the weather conditions are unfavourable. Also, the quality of the image is affected by pollutants in the atmosphere. These kinds of quality compromises are avoided when sensors are used in the actual locations where the PV panels are installed. Hence, in the proposed model, the input data is captured in the actual locations using sensors. A refining algorithm based on physical hybrid ANN is used for prediction by Leva et al.[(9)]. The Impact of various Irradiance Forecasting Techniques for predicting Solar Energy is analyzed[(10)]. For forecasting solar power, genetic algorithm and artificial neural network have been used[(11)]. Recurrent neural network (RNNs) has been used by authors for the hourly forecast of Solar Photovoltaic Power[(12)]. A convolution neural network for deep feature selection of short-term solar radiation forecasting is proposed in[(13)]. The hybrid method based on a self-organizing map (SOM theory) and grey wolf optimization (GWO) based general regression neural network (GRNN) has been proposed by the authors to predict the solar power output within a 24-hour time range[(14)]. In the review of nowcasting approaches for solar energy production, the authors have found that Artificial Neural Networks and Convolutional Neural Networks are the most commonly used techniques with the root mean squared error as the predominant error metric for model validation[(15)]. But, Neural Networks require a high volume of data and are computationally expensive in nature. ARMA and ARIMA models are a combination of Auto regressive, integrated, and moving average models. These models are the prevailing models in the field of time series forecasting[(16)]. Furthermore, Simple Exponential and Double Exponential Smoothing algorithms are the commonly used Time series prediction algorithms. The Autoregression model is more suitable when the data is coming from a stationary process. The moving average method generally overlooks the complex associations present in the data. But the weather data in reality is usually not stationary. Compared to Autoregression and Moving average methods the Exponential Smoothing algorithms perform well in terms of prediction Accuracy. Still, the predictions are not precise when data is present with seasonal variations. Other Neural network-based algorithms used for nowcasting require a huge volume of past data to achieve prediction accuracy. To overcome the limitations identified with the existing methods, this study proposes the Grey System modeling (GM(1,1)) and more specifically GM(1,1) with Fourier series of error residuals[(17)] for nowcasting the Ambient temperature, Solar Photo Voltaic Module temperature, and Solar Irradiation. Grey System forecasting is a highly accurate short-term forecasting model and has been applied successfully in various domains[(18)]. The reasons for proposing Grey Modeling for nowcasting weather data are as follows.

1. Grey system theory-based methodologies exhibit a notable performance characteristic on real-time data as grey predictors adjust their parameters to new situations when additional data are generated. Hence, grey Predictors are suitable when data has noise and modeling information is insufficient in contrast to conventional methods.

2. Grey models need a minimal quantity of data to predict the characteristics of new systems. Hence, there is no need of maintaining the historical data for a long period.

3. Since, the amount of data used is limited, it involves inexpensive computation and very less computational time compared to the techniques that involve neural networks.

4. The Grey model has the potential to produce predicted output with good precision

Thus, the Grey model is apt to nowcast Ambient temperature, Solar Photo Voltaic Module temperature, and Solar Irradiation using the current data. To show the efficiency of the Grey model, results of the Grey model are compared with existing time series techniques Auto Regression, and Double Exponential Smoothing (DES).

2 Methodology

This paper proposes Grey System modeling (GM(1,1)), then GM(1,1) with Fourier series of error residual to nowcast the weather data. The GM(1,1) with Fourier series of error residual uses the result of the GM(1,1) to increase the prediction accuracy. For nowcasting, the weather data, the duration of a day is divided into 4 different time slots from dawn to dusk considered on different days. The proposed algorithms have been applied to the real-time Weather sensor data published on Kaggle.com [19]. This work considers the weather data gathered from a solar plant having Plant_Id 4135001 every 15 minutes. The data is collected from the solar plant installed near Gandikotta, Andhra, India. A single array of sensors placed optimally at the plant is used for gathering ambient temperature, module temperature, and Irradiance at the plant level.

The following details have been used from the solar plant data set.

1. Date & Time: This field has the Date and time for each observation. The observations are recorded at a time interval of 15 minutes.
2. Ambient Temperature: This field represents the ambient temperature at the solar plant location.
3. Module Temperature: This field represents the temperature reading from a solar panel.
4. Irradiation: This field represents the amount of irradiation for the time interval of 15 minutes.

The Ambient Temperature, Module Temperature, and Irradiation for the next time interval are predicted based on the past four observations.

Following are the steps involved in prediction.

1. Observe the Ambient Temperature, Module Temperature, and Irradiation values for four-time slots and generate the Grey sequence for Ambient Temperature, Module Temperature, and Irradiation.
2. Formulate the grey models for Ambient Temperature, Module Temperature, and Irradiation
3. Predict the future values of Ambient Temperature, Module Temperature, and Irradiation employing the model of GM(1,1).
4. Modify the model of GM(1,1) using the Fourier series of error residuals to enhance the prediction accuracy.

The framework given in Figure 1 demonstrates the steps involved in nowcasting the weather data.

The detailed description of Grey Prediction algorithms is as follows.

2.1 Create the grey sequence for weather data

In this step, the inherent characteristic of the system is extracted by making use of the existing time series data of weather.

To generate the grey sequence from the given data, the following steps are involved.

1. Represent the actual weather sequence having n samples as

$$X^{(0)} = (X^{(0)}(1), X^{(0)}(2), X^{(0)}(3), \ldots, X^{(0)}(n)),\ where\ n \geq 4\ and\ X^{(0)}\ is\ positive \tag{1}$$

2. Smoothen the weather data with Accumulated Generating Operator (AGO) to obtain a sequence that is increasing monotonically.

The new sequence of weather data is expressed as

$$X^{(1)} = (X^{(1)}(1), X^{(1)}(2), X^{(1)}(3), \ldots, X^{(1)}(n)),\ where\ \textstyle\sum_{i=1}^{n} X^{(1)}(j) = X^{(0)}(i),\ j = 1, 2, \ldots n \tag{2}$$

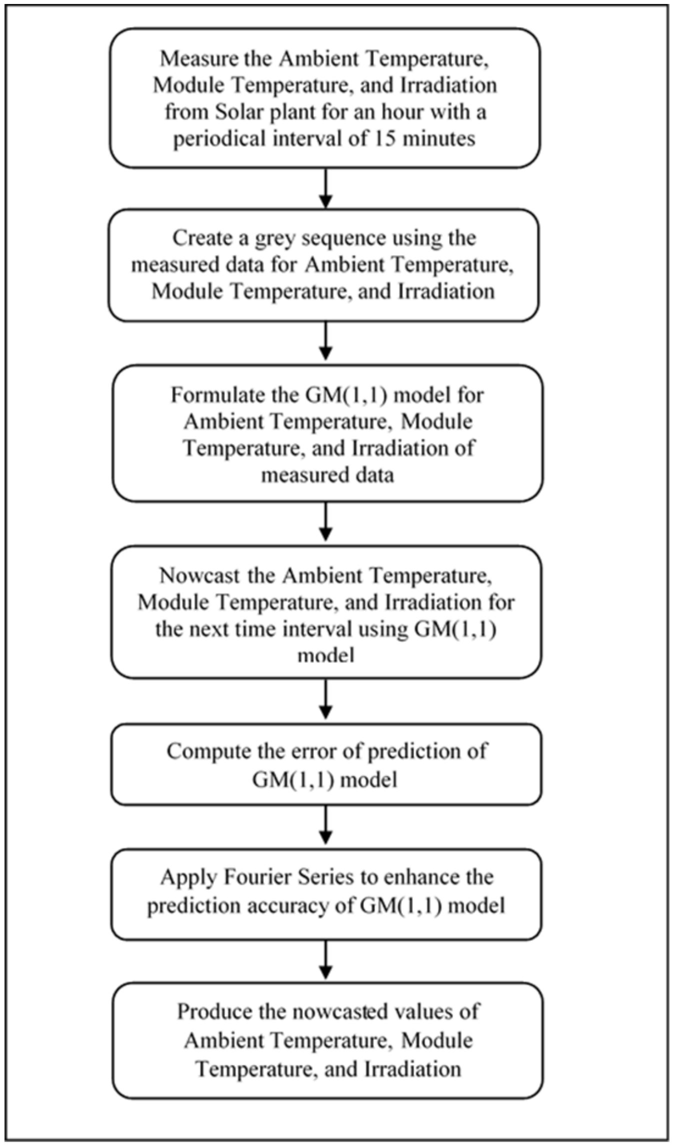

Fig 1. Framework for nowcasting weather data using GM(1,1) with Fourier series of error residual

2.2 Formulate the grey model for weather data

Devise GM(1,1) for weather data by applying a first-order grey differential equation as:

$$X^0(i) + aZ^{(1)}(i) = b, \text{ where } Z^{(1)}(i) = 1/2X^{(1)}(i) + X^{(1)}(i+1) \tag{3}$$

a and b are found using the least mean square estimation method. Calculate $[a,b]^T$ as

$$[a,b]^T = \left(B^T B^{-1}\right) B^T Y \tag{4}$$

where $B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}$

and $Y = \begin{bmatrix} X^{(1)}(2), & X^{(1)}(3), & \cdots, & X^{(1)}(n) \end{bmatrix}^T$,

$$z^{(1)}(j) = 0.5X^{(1)}(j) + 0.5X^{(1)}(j-1),\ j = 2,3,\ldots,n$$

2.3 Grey weather data Forecasting

From Equation 3, the equation for prediction $X^{(1)}(t)$ at time j is computed by applying the Inverse Accumulating Generation Operator (IAGO) as

$$X_p{}^{(1)}(j+1) = \left(X^{(0)}(1) - \frac{b}{a}\right)e^{-aj} + \frac{b}{a} \tag{5}$$

To predict the weather data at a time (j+1), determine $X_p{}^{(0)}(j+1)$ using Inverse Accumulating Generation Operator(IAGO) as

$$X_p{}^{(0)}(j+1) = \left(X^{(0)}(1) - \frac{b}{a}\right)e^{-aj}(1-e^{a}) \tag{6}$$

To predict the primitive weather data at a time (j+H),

$$X_p{}^{(0)}(j+H) = \left(X^{(0)}(1) - \frac{b}{a}\right)e^{-a(j+H-1)}(1-e^{a}) \tag{7}$$

2.4 Change GM(1,1) with Fourier series of error residuals

By Considering the actual sequence $X^{(0)}$ and the sequence predicted by GM(1,1), find out the error sequence as:

$$\varepsilon^{(0)} = \left(\varepsilon^{(0)}(2), \varepsilon^{(0)}(3), \ldots, \varepsilon^{(0)}(n)\right) \text{ where } \varepsilon^{(0)}(j) = X^{(0)}(j) - X_p^{(0)}(j), j = 2,3,\ldots,n \tag{8}$$

The error residuals of Equation 8 are represented in the Fourier series as

$$\varepsilon^{(0)}(j) \cong a_0 + \sum_{n=1}^{z}\left(a_i \cos\frac{2\pi i}{\mathrm{T}} j + b_n \sin\frac{2\pi i}{T}\mathrm{j}\right), \mathrm{j} = 2,3,\ldots\mathrm{n},\ \text{where } \mathrm{T} = \mathrm{n}-1 \text{ and } \mathrm{z} = \left(\frac{n-1}{2}\right) - 1 \tag{9}$$

Equation 9 could be written as

$$\varepsilon^{(0)} \cong PC \tag{10}$$

P and C are denoted as follows

$$P = \begin{bmatrix} 1/2 & \cos 2\frac{2\pi}{T} & \sin 2\frac{2\pi}{T} & \cos 2\frac{2\pi 2}{T} & \sin 2\frac{2\pi 2}{T} & \ldots & \cos 2\frac{2\pi z}{T} & \sin 2\frac{2\pi z}{T} \\ 1/2 & \cos 3\frac{2\pi}{T} & \sin 3\frac{2\pi}{T} & \cos 3\frac{2\pi 2}{T} & \sin 3\frac{2\pi 2}{T} & \ldots & \cos 3\frac{2\pi z}{T} & \sin 3\frac{2\pi z}{T} \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ 1/2 & \cos\frac{2\pi}{T} & \sin\frac{2\pi}{T} & \cos\frac{2\pi 2}{T} & \sin\frac{2\pi 2}{T} & \ldots & \cos n\frac{2\pi z}{T} & \sin\frac{2\pi z}{T} \end{bmatrix} \tag{11}$$

$$C = \begin{bmatrix} a_0 & a_1 & b_1 & a_2 & b_2 & \ldots & a_n & b_n \end{bmatrix}^{\mathrm{T}} \tag{12}$$

By applying the Least Squares method, solve equation 10

$$C \cong \left(P^T P\right)^{-1} P^T \varepsilon^{(0)} \tag{13}$$

The rectification for the Fourier series is computed as

$$X_{pf}{}^{(0)}(j) = X_p{}^{(0)}(j) - \varepsilon \mathrm{P}^{(0)}(j), j = 2,3,\ldots,n+1 \tag{14}$$

To prove the precision of prediction of GM(1,1) and GM(1,1) with Fourier series of error residual, the results found from the proposed models have been compared with Auto Regression and Double Exponential time series forecasting algorithms.

3 Results and Discussion

This work utilizes the weather data gathered from a solar plant having Plant_Id 4135001 every 15 minutes. To prove the correctness of the proposed algorithms for predicting the weather data, irrespective of the time of the day, 4 different periods have been considered. Python is used for implementing the proposed methodology and to make comparisons with the existing models. The details of the data gathered are shown in Table 1. The results obtained by applying Smoothing GM(1,1) & GM(1,1) with Fourier series of error residuals, on four subsets of the weather data gathered from the solar plant are provided in this section. To show the superiority of the proposed Grey model for prediction, conventional methods like Auto regression and Double Exponential have also been used for prediction and the results are compared. The Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) have been employed to find the prediction accuracy of models. The results of the prediction and corresponding error of prediction are shown in Table 2. It is very evident from the results that the Prediction accuracy is very high in the Modified GM(1,1) with Fourier series of error residuals followed by the GM(1,1) when compared to Auto regression and Double Exponential smoothing models. For instance, to predict the Ambient temperature by applying Autoregression, the error of prediction using the Mean Absolute error method and Root Mean Squared Error are 0.085125 and 0.093385 respectively. By applying Double Exponential Smoothing, the error of prediction using the Mean Absolute error method and Root Mean Squared Error are 0.229067 and 0.323966 respectively. By applying GM(1,1), the error of prediction using the Mean Absolute error method and Root Mean Squared Error are 0.080641 and 0.099466 respectively. These error values are convincingly lower than the error values of the Autoregression and Double Exponential Smoothing Models. By applying Modified GM(1,1) with Fourier series of error residuals, the error of prediction using the both Mean Absolute error method and Root Mean Squared Error is 0. This is a clear indication that the proposed Modified GM(1,1) with Fourier series of error residuals model outperforms the other existing models in terms of prediction accuracy.

Table 1. Observed values with different time periods

	Date_Time	Ambient Temperature	Module Temperature	Irradiation
	5/15/20 17:15	33.300255	35.852207	0.173899
	5/15/20 17:30	33.032122	34.338400	0.087162
Data Set - 1	5/15/20 17:45	32.311871	31.548539	0.038403
	5/15/20 18:00	31.132414	30.225331	0.022545
	5/15/20 18:15	29.243111	28.682507	0.009150
	5/16/20 14:45	32.350198	46.203597	0.514964
	5/16/20 15:00	32.436880	45.770209	0.503626
Data Set - 2	5/16/20 15:15	32.524149	45.840538	0.419736
	5/16/20 15:30	32.328025	43.170093	0.349962
	5/16/20 15:45	32.103391	39.814439	0.261409
	5/19/20 8:15	25.188797	30.107466	0.194092
	5/19/20 8:30	25.615072	33.972492	0.297789
Data Set - 3	5/19/20 8:45	25.791661	34.815735	0.273515
	5/19/20 9:00	26.121533	36.858085	0.386892
	5/19/20 9:15	26.495522	39.636977	0.424118
	5/20/20 7:45	23.921140	28.769306	0.325195
	5/20/20 8:00	24.471149	31.939571	0.390585
Data Set - 4	5/20/20 8:15	25.124652	35.992171	0.437920
	5/20/20 8:30	25.562463	38.252356	0.498368
	5/20/20 8:45	26.212557	40.396549	0.510470

To show the effectiveness of the proposed algorithms, the algorithms were applied to three more data sets. Data Set-2 includes weather data collected on 16-05-2020, between 2.45 PM to 3.30 PM at 15 minutes time intervals as input and predicts the weather at 3.45 PM. Data Set-3 uses the weather data measured on 15-05-2020, between 5.15 PM to 6.00 PM at 15 minutes time intervals as input and predicts the weather at 6.15 PM. Data Set-4 utilizes the weather data measured on 20-05-2020, between 7.45 AM to 8.30 AM at 15 minutes time intervals as input and predicts the weather at 8.45 PM. The results of the prediction and corresponding error of prediction for Data Set-2, Data Set-3, and Data Set-4 are shown in Tables 3, 4 and 5 respectively.

Table 2. Predicted Values and Error of Prediction for Data Set – 1

Prediction Method	Ambient Temperature			Module Temperature			Irradiation		
	Predicted Value	Mean Absolute Error	Root Mean Squared Error	Predicted Value	Mean Absolute Error	Root Mean Squared Error	Predicted Value	Mean Absolute Error	Root Mean Squared Error
Autoregression (AR)	28.900515	0.085125	0.093385	28.734040	0.579937	0.624064	0.011749	0.003203	0.003441
Double Exponential Smoothing (DES)	29.958853	0.229067	0.323966	28.276088	0.274693	0.307097	-0.023303	0.012030	0.012091
GM(1,1)	30.307670	0.080641	0.099466	28.102382	0.224817	0.272384	0.010096	0.002113	0.002482
GM(1,1) with Fourier	29.985109	0.000000	0.000000	29.001651	0.000000	0.000000	0.018547	0.000000	0.000000

Table 3. Predicted Values and Error of Prediction for Data Set – 2

Prediction Method	Ambient Temperature			Module Temperature			Irradiation		
	Predicted Value	Mean Absolute Error	Root Mean Squared Error	Predicted Value	Mean Absolute Error	Root Mean Squared Error	Predicted Value	Mean Absolute Error	Root Mean Squared Error
Autoregression (AR)	32.498125	0.062894	0.066710	38.738158	1.025793	1.167822	0.253465	0.024427	0.028305
Double Exponential Smoothing (DES)	32.426239	0.069801	0.076999	43.002688	0.561525	0.668501	0.303062	0.014754	0.017652
GM(1,1)	32.321133	0.047246	0.057866	42.411428	0.462263	0.567065	0.291398	0.000659	0.000805
GM(1,1) with Fourier	32.132151	0.000000	0.000000	40.562378	0.000000	0.000000	0.292460	0.000000	0.000000

Table 4. Predicted Values and Error of Prediction for Data Set – 3

Prediction Method	Ambient Temperature			Module Temperature			Irradiation		
	Predicted Value	Mean Absolute Error	Root Mean Squared Error	Predicted Value	Mean Absolute Error	Root Mean Squared Error	Predicted Value	Mean Absolute Error	Root Mean Squared Error
Autoregression (AR)	26.291776	0.076313	0.039293	37.126748	0.596165	0.674343	0.332893	0.043740	0.048532
Double Exponential Smoothing (DES)	26.299993	0.083224	0.044045	38.247619	0.423772	0.510398	0.420368	0.026648	0.029906
GM(1,1)	26.353658	0.025186	0.030782	38.212342	0.191276	0.232681	0.426237	0.022045	0.026748
GM(1,1) with Fourier	26.454401	0.000000	0.000000	38.977447	0.000000	0.000000	0.514416	0.000000	0.000000

Table 5. Predicted Values and Error of Prediction for Data Set – 4

Prediction Method	Ambient Temperature			Module Temperature			Irradiation		
	Predicted Value	Mean Absolute Error	Root Mean Squared Error	Predicted Value	Mean Absolute Error	Root Mean Squared Error	Predicted Value	Mean Absolute Error	Root Mean Squared Error
Autoregression (AR)	26.003278	0.068617	0.072869	40.568467	0.566864	0.602743	0.549479	0.006693	0.007129
Double Exponential Smoothing (DES)	26.039219	0.032520	0.036284	40.904388	0.273143	0.305622	0.554076	0.005257	0.006313
GM(1,1)	26.161331	0.037671	0.046459	42.098806	0.338640	0.423381	0.561193	0.001257	0.001455
GM(1,1) with Fourier	26.010646	0.000000	0.000000	40.744246	0.000000	0.000000	0.566219	0.000000	0.000000

It is obvious from the results that for all the Data Sets used, variation between the actual values and the predicted values are very marginal for Ambient temperature, Module temperature, and Irradiation using the GM(1,1) & GM(1,1) with Fourier series of error residual. The MAE and RMSE values computed through the GM(1,1) & GM(1,1) with Fourier series of error residual prove that the variation between the actual and predicted weather data is very low when compared to Autoregression and Double Exponential Smoothing Models.

To further strengthen our claim that GM(1,1) with Fourier series of error residual outperforms in terms of accuracy of prediction compared to the Auto regression model and Double Exponential Smoothing model, the accuracy of prediction is computed for all four data sets using Mean Absolute Percentage Error (MAPE) of prediction and are shown in the following figures. Figure 2 shows the prediction accuracy of Ambient Temperature, Figure 3 depicts the prediction accuracy of Module Temperature and Figure 4 reveals the prediction accuracy of Irradiance.

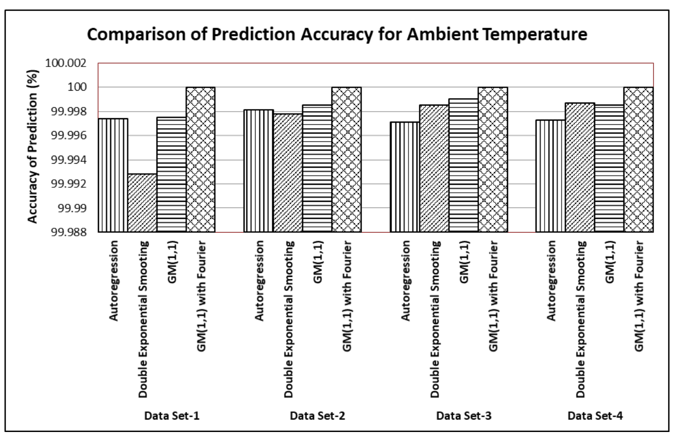

Fig 2. Prediction Accuracy of Ambient Temperature

From Figures 2, 3 and 4 , it is very obvious that the accuracy of prediction of GM(1,1) with Fourier series of error residual model is remarkably higher when compared to the Auto regression model and Double Exponential Smoothing model.

Hence, this study found that in comparison with the Auto regression model and Double Exponential Smoothing model, prediction accuracy is high in GM(1,1). However, the GM(1,1) with Fourier series of error residual outperforms the GM(1,1) in terms of accuracy of prediction.

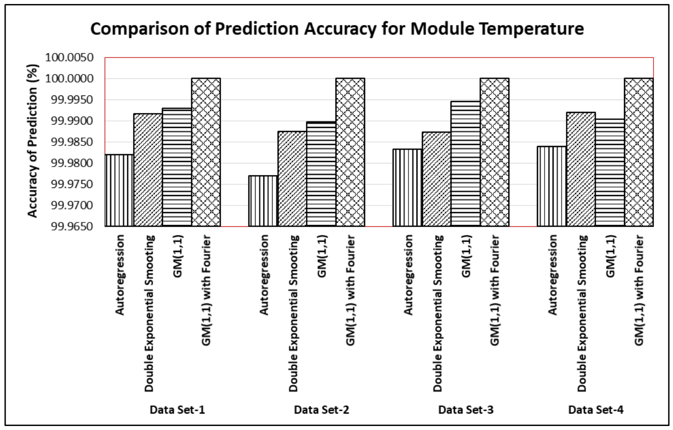

Fig 3. Prediction Accuracy of Module Temperature

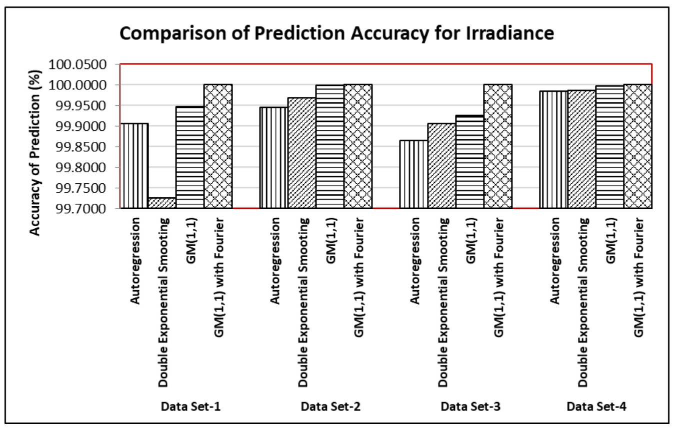

Fig 4. Prediction Accuracy of Irradiance

4 Conclusion

Nowcasting in real-time demands simple and fast computation of results. Even though many methods are existing for predicting weather parameters that affect solar output, most of these algorithms involve a complex procedure and require a huge volume of data for accurate prediction. GM (1,1), as well as GM (1,1) with Fourier series of error residuals are simple and hence require only a minimal amount of time for Prediction. Another advantage of the proposed model is that the precision of prediction is very high even with fewer measures of input data. The proposed algorithms show more accurate prediction results when compared to conventional methods like Auto regression and Double Exponential Smoothing. The accuracy of prediction of weather data (on which the solar power output depends), confirms that the GM (1,1) with Fourier series of error residuals is the most suitable method for nowcasting. As the increasing penetration of PV systems into the present power systems poses new problems for the stability of electricity grids, there is a demand for energy management methods including precise PV production forecasting which in turn depends on prevailing weather conditions. Hence, the GM (1,1) with Fourier series of error residuals shall be used as a decision aid tool for power system operators, in load dispatch centers. The future work will focus on the applicability of other variations of the Grey model and consider the additional parameters impacting the Solar PV output.

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