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INCREASING PREDICTION ACCURACY OF UNIVARIATE SOLAR FORECASTING USING HOLT WINTER METHOD WITH DAMPED ADDITIVE TREND AND SEASONALITY

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Energy harvesting plays a crucial role in extending the lifespan of wireless sensor networks deployed in unattended environments such as forest fire detection and flood detection. While solar radiation stands as the most abundant energy source, its reliability is affected by seasonal fluctuations. Consequently, a dependable solar radiation forecast becomes imperative for enhanced network planning and architecture. Utilizing statistical time series for short-term predictions in energy-harvested wireless sensor networks proves to be a swift and reliable approach. To validate the results, the NREL database is employed, and various statistical time series methods, including AR, ARMA, SARIMA, and Holt Winter, are compared based on RMSE, accuracy, and MAE. The simulations are conducted using the Python framework. This paper presents a 48-hour prediction horizon for each season, allowing for the observation of the model's effectiveness. All simulation results indicate that Holt Winter with the damped additive trend and additive seasonality outperforms other models in terms of accuracy, RMSE, and rapid response.

Keyword: Holt winter method, Autoregressive Moving Average, Seasonal Autoregressive Integrated Moving Average, Energy Harvested Wireless Sensor Network, Solar energy

Introduction

In the modern age, wireless sensor networks (WSNs) play a crucial role in applications like forest fire detection, hilly road mishaps, flood detection, hazardous industrial settings, and other scenarios where they operate unattended for extended periods. Typically powered by batteries that necessitate regular replacement, WSNs face operational challenges. To overcome this, researchers have proposed networks powered by ambient energy sources such as solar energy, thermal energy, and RF energy to address prolonged unattended deployments. Among these sources, solar energy is considered the most efficient, boasting high energy density (15mW/cm2) and widespread availability. However, solar energy's variability in both time and space poses challenges for accurate prediction. Numerous prediction techniques have been proposed by researchers to tackle this issue, categorized into three main groups [1].

Statistical models: It can be a traditional time series model. The examples are Auto-Regressive Model (AR), Auto Regressive Moving Average Model (ARMA), exponentially weighted moving average (EWMA), Auto-Regressive Integrated Moving Average Model(ARIMA), Weather-conditioned moving average (WCMA), Seasonal Autoregressive

Integrated Moving Average (SARIMA) along with a machine learning technique

Physical model: Fifth-Generation Penn State/NCAR Mesoscale Model (MM5), Numerical Weather Prediction (NWP) and so-on

Hybrid models: ANN + FUZZY, ANN + WT, ANN + GA and so on

Problem Statement:

RQ1: Search for simple univariate Time Series model which gives High Accuracy and relatively fast.

RQ2: Less tuning of Hyper parameters, for ex. in ARIMA based method suitable values of P,D,Q searched by various iteration method which requires lot of training for desired accuracy.

1. Motivation

Life on Earth hinges on the quality of air and water. Unfortunately, the disposal of harmful chemicals into water bodies poses severe threats, causing diseases like diarrhea and, in extreme cases, leading to human fatalities. The World Health Organization (WHO) reports that 80% of deaths result from pulmonary diseases associated due to air pollution.

As previously mentioned, wireless sensor networks (WSN) find applications in vital areas such as forest fire detection, earthquake monitoring, and flood management. Consequently, there is a pressing need for a low-cost, standalone wireless network capable of continuously monitoring pollutant parameters. However, the battery-operated nature of WSNs introduces challenges, and despite implementing energy management processes, nodes eventually succumb.

Addressing the imperative of continuous operation involves incorporating energy harvesting technologies such as wind, solar, and thermal methods. The fusion of WSN with energy harvesting gives rise to a novel category known as Energy Harvested Wireless Sensor Network (EH-WSN), offering a promising solution to the sustainability challenge.

The first attempt at short-term energy forecasting for WSN used the exponentially weighted moving average method [2], and the energy harvested at one time is similar to the energy harvested in the same slots the day before. Later research also took into account seasonality and previously harvested profiles[3][4]. Researchers[5][6] began using statistical time series methods like AR (Auto regressive), ARMA (Autoregressive and Moving Average), ARIMA (Autoregressive Integrated Moving Average), and SARIMA, which can be seasonal or non-seasonal, because the aforementioned models could not accurately handle the non-stationary of the data. ARIMA models are basically denoted by ARIMA (P,D,Q) where ‘P’ denotes order, ’D’ refers degree of difference and ‘Q’ denotes order of moving Average and depending upon the need, one can vary either of these parameters. Author Yang proposed three ARIMA models that used global horizontal irradiance (GHI) as an input parameter with seasonal components removed, as well as another model that relates GHI with zenith angle[7], with different cloud conditions, and achieves better accuracy than the other two. Author Colak[8] found that the ARIMA(2,2,2) model has the lowest mean absolute error when compared to other models for one-hour, two-hour, and three-hour predictions. The Holt Winter approach is another trend- and seasonally-based statistical time series technique that can be applied to forecasting problems without needing stationary data. For one-day forecasting, Author Prema[9] employed exponential smoothing and multiplicative decomposition and evaluated it for various data lengths. The two-month period produces the greatest findings, with a MAPE of less than 9.28%, but error rises on overcast days, the research found. In Seoul, South Korea, the ARIMA

(1,1,2) model was discovered to be the best fit for daily prediction, whilst the ARIMA(4,1,1) model with 12 delays[10] was discovered to be the best fit for monthly prediction. The daily and monthly predictions had RMSE values of 33.18 and 104.26, respectively, with R-squared (R2) %ages of 79% and 68%. A multiplicative SARIMA model was proposed by Shadab [11], who evaluated it using NREL data spanning 37 years. They discovered that the ARIMA (1, 0, 1) (0, 1, 1) (12) model has the lowest mean %age error (MPE), and they advised future research into a hybrid model. In order to select the ideal ARIMA model, Author Atique [12] used the sum of squares and Akaike information criterion (AIC). In terms of AIC and SSE accuracy, simulation results show that ARIMA (0, 1, 2) (1, 0, 1) (30) has the highest accuracy, while MAPE was 17.70%. The SRAIMA model was used by the Author Ahzam Shadab[13] to forecast using 34 years of NREL data from Haryana, India. The following simulated results were obtained as MAPE (6.556), MAE (0.2659), R2 (0.9293), and RMSE (0.3529).

To determine the highest and lowest isolation receiving locations, he used an isolation contour. Three models for daily forecasting were investigated by the Belmahdi and his team [14] involves ARIMA model, ANN model and the hybrid of ARIMA model and ANN model. They found that for Tanger, Morocco, the hybrid combination yields the highest results in terms of R2 (0.083), RMSE (449.670), and MAPE (25.544) sun forecast for the next 5 and 60 minutes. Another researchers[15] Jaihuni and his team investigations by using three models i.e the ARIMA model, the Bi-GRU (Bi-directional gated unit) model and the hybrid (ARIMA+ Bi-GRU) model and observed for the time intervals with RMSE of 71.17 for a 5-minute prediction and RMSE of 52.64 for a 60-minute prediction. Sharadga and his team[16] employed statistical and ANN-based strategies for 1 hour forward prediction using 3640 hours of solar data from a 20 MW grid-connected solar plant in China, and discovered that NN beats statistical techniques. SAIRIMA, ARIMA, and ARMA's computed RMSE values were 1.183, 1.318, and 1.212, respectively. Another study employed with Holt winter technique[17] to predict a variety of environmental factors, including temperature and sunshine and found that the multiplicative method performed 4% better than the additive method in terms of MAPE., Sharma and his colleagues[18] carried out the investigated by using NREL data from the year 2010 to 2015, which has been tested in 2016. Using the machine learning methods FoBA, leap Forward, Spikeslab, Cubist, and bagEarthGCV, they simulated the entire data set into four seasons and employed the R programming interface to mimic the result.

2. Materials and Methods

Solar dataset description

The data utilized in this study originated from the NREL Solar Radiation Research Laboratory, employing the CMP22 and AMSL measuring systems, with coordinates at 39.742° North, 105.18° West, and an elevation of 1828.8 meters. The dataset covers the years 2015 to 2021. Despite minute-by-minute sampling, hourly averages were computed for data collected between 7:00 AM and 5:00 PM, excluding nighttime data to mitigate noise impact, as illustrated in Fig 1. This reduction in sample frequency aimed to address noise effects but resulted in memory-constrained WSN nodes due to a reduced memory system.

Sensor nodes within Energy Harvested Wireless Sensor Networks (EHWSN) face limitations in both memory and performance. The implementation of multivariate machine learning techniques in such constrained environments proves power-intensive. Given that existing literature predominantly focuses on predictions for solar power plants, transferring the same implementation to EHWSN is impractical and necessitates a shift toward simpler univariate predictions.

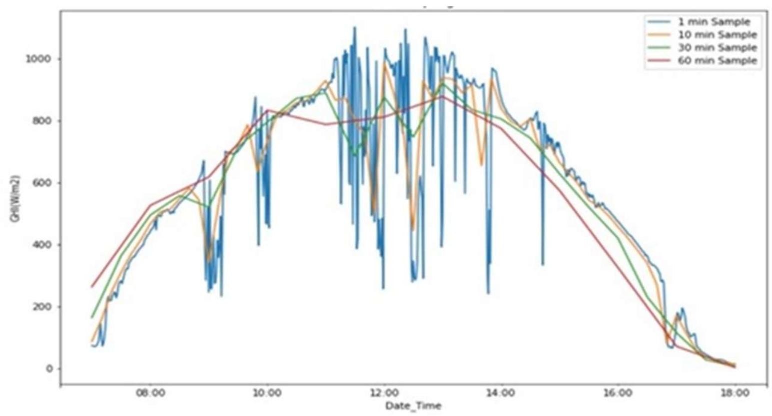

Fig 1. Noise Sampling Effect

The two techniques, EWMA and WCMA, employed in Energy Harvested Wireless Sensor Networks did not yield satisfactory results concerning seasonal variation. Despite some exceptions, time series methods outperformed machine learning models in univariate modeling and short-term prediction. To forecast solar irradiance for a 48-hour horizon and evaluate model performance based on parameters such as RMSE and prediction accuracy, various time series approaches were applied in the proposed work.

The dataset was categorized into four seasons for a more nuanced analysis, with a unique model applied to each season. Prediction accuracy and RMSE were subsequently examined using the Sharma Methodology. The Proposed Methodology, depicted in Fig 2, was adopted for the current investigations, demonstrating consistent performance across all seasons.

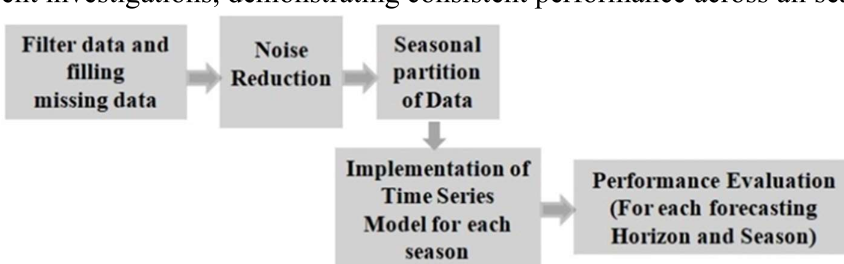

Fig 2 Process of new model

The new model compromises of following steps:

- Filter Downloaded data and fill missing value
- Sampling and discarding night data to reduce number of samples.
- Seasonal Partition of Data.
- Verification of Time series Techniques for each season in terms of various performances metrics.

Statistical Time series Forecasting models

Data must be stationary in time series forecasting, can be indicated by ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots. If the variance and mean are fixed between two equidistant points, the data is said to be stationary. In Python, the

Augmented Dicky-Fuller test library, which is based on the unit root Hypothesis test, can be used to determine stationarity.

AR Model

This is an Auto regression model that forecasts future data using a linear combination of lagged values, with the number of lagged values represented by order p.

$$Y_t = \mathrm{C} + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots \emptyset_p Y_{t-p} + \epsilon_t \quad (1)$$

Here C is constant, $\emptyset_1$, $\emptyset_2$are lag coefficients ,and it can goes to order of p.ϵ_t is a Noise.In order to apply AR model time series must be stationary.

ARMA model

When moving average (MA) and autoregressive parts (AR) are combined, the model is known as the ARMA model. When this linear combination of lag errors is combined with the model, then the order of the model is specified as (p, q). For instance, the AR (1) model equation is written as

$$Y\_t = C + \emptyset\_1 \, Y\_(t-1) \in \_t \quad (2)$$

And MA (1) model in term of lagged errors written as:

$$Y_t = U + \theta_1 Y_{t-1} \quad (3)$$

Here U is Expectation of Y_t which is assumed to be zero, θ_1 is moving average (MA) coefficient.

Combining Eq (1) and Eq (2) gives ARMA model. This model is used when no trend components or stationary data are required.

$$Y_t = U + \theta_1 Y_{t-1} \quad (3)$$

ARIMA model

When moving average (MA), autoregressive parts (AR) and Differencing are combined, then model is known as the ARIMA model[6]. When this linear combination of lag errors is combined with the model, then the order of the model is specified as (p, d, q). Model equation is written as

$$Y_t = \Delta^d y_t = (1-B)^d y_t \quad (5)$$

$$Y_t = \delta + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + .. + \emptyset_p Y_{t-p} + \epsilon_t - \theta_1 \, \epsilon_{t-1} - \theta_2 \, \epsilon_{t-2} \dots \dots - \theta_q \, \epsilon_{t-q} \quad (6)$$

Here Δ^d represents order of differencing for the parameters $\Delta y_t = y_t - y_{t-1}$, $\Delta^2 y_t = \Delta y_t - \Delta y_{t-1}$ and so on. AR and MA terms in the ARIMA model can be determined manually using PACF and ACF, respectively. If there is a sharp drop after lag K in PACF, the AR-K model is used, and if there is a gradual decrease, the MA model is suggested. Reading the AR and MA terms from the graph by hand frequently yields misleading values; however, the optimum value of p, d, and q can be determined using the grid search method. The Python pyramid ARIMA library can be used as a grid search algorithm.

SARIMA Model

SARIMA model is usually used when there is a trend and seasonal variations in data.[18] Additional parameters (P, D, and Q) in this model specify seasonal regression, differencing, and moving average. In this, model is denoted by ARIMA (p, d, q)* (P, D, Q)

$$\emptyset_P(B)\varphi_P(B^S)(1-B)^d Y_t = \theta_q(B)\vartheta_\theta(B^S)E_t \quad (7)$$

In this case, $\emptyset_P$ and $\theta_q$represents AR and MA terms in the non-seasonal case, and φ_P and ϑ_θ in the seasonal case, where B represent the Backshift operator.

Holt winter Method with damped additive trend and additive seasonality

The Holt winter method is based on label, trend, and seasonality in data and is also known as the triple Exponential Smoothing method. It is based on a weighted average of past observations, where the weight decays exponentially with past samples and is affected by three smoothing parameters (α, β, ϒ), but if the trend is damping, it is affected by an additional parameter ϕ.

There are nine Exponential methods that can be used depending on whether the trend is none, additive, or damped additive, and whether the seasonal components are none, additive, or multiplicative. In this paper, we tested all Holt winter methods, and the results show that Holt Winter with the damped additive trend and additive seasonality outperforms other models. The forecast equation is written as

$$y_{t+h}|t = l_t + \emptyset_h b_t + S_{t+h-m(k+l)}$$

(8)

The Level equation is written as

$$l_t = \alpha y_t + \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + \emptyset b_{t-1})$$

(9)

The Trend Equation is written as

$$b_t = \beta^* \times (l_t - l_{t-1}) + (1-\beta^*)\emptyset b_{t-1}$$

(10)

The Seasonality Equation is written as

$$s_t = \gamma(y_t - l_{t-1} - \emptyset b_{t-1)} + (1-\gamma)s_{t-m}$$

(11)

Here l_t= level estimates b_t= trend estimates, α is a smoothing factor for the level with a range is,$0 < \alpha < 1$ and β represents the trend smoothing factor with a range of $0 < \beta < 1$. The factors α, β, γ and ∅ are smoothing parameters.

Results and Discussions

A one-minute sampled dataset was obtained from the NREL laboratory for seven years spanning between 1st January, 2015 to 31st December 2021, to investigate the afore mentioned models. The first six years of data were used for training, and the remaining data were used to test the model. The data is then divided into four sets based on the four seasons (winter, spring, summer, and monsoon). Each set contains data from the same month across all years. As an example, if the date of August 25, 2021, must be predicted, the dataset contains August data from 2015 to 2021. The collected data is then filtered and re-sampled for 1 hour to remove noise from the data. In the simulation, for all-season daily data from 07:00 AM to 06:00 PM was considered, with no night data; both methods reduced their length of data, which was necessary for memory-constrained wireless sensor nodes.

To test the model, one day from each season was chosen for solar prediction i.e 11th March 2021 for spring; 25th June 2021 for summer; 30th August 2021 for monsoon and 31st December 2021 for winter. Fig.3 shows the measured solar radiation for these days, and it is seen that the data for March shows smooth variation, whereas the data for June shows a lot of fluctuation in solar radiation. In the month of December, there is once again smooth variation. Table 1 summarizes the comparison of all four Time Series models for four different days of the season.

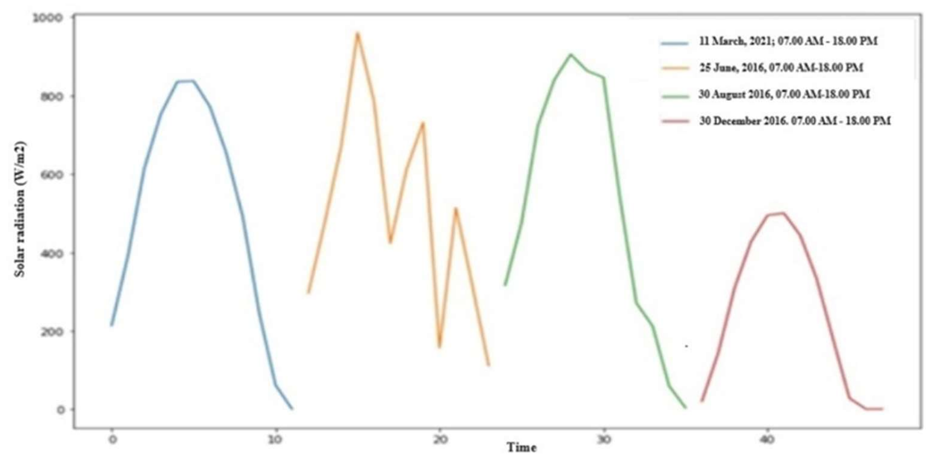

Fig 3 Solar radiation measurement taken on specific days

Table 1 Comparison Results of Four Time Series Models

Methods	Metrics	11th Mar 2021	25th June 2021	30th Aug 2021	31st Dec 2021
AR Method	**RMSE**	124.4	163.3	187.3	151.0
	MAE	154.2	189.1	141.0	166.6
	Prediction Accuracy %	75.4	62..5	74.9	73.9
ARIMA Method	**RMSE**	152.4	237	169.5	76.7
	MAE	125.4	192.9	130.2	58.3
	Prediction Accuracy %	76.5	72.6	78.54	79.8
SARIMA Method	**RMSE**	155.4	217.8	172.9	65.8
	MAE	114.1	175.0	126.0	42.8
	Prediction Accuracy %	82.5	77.1	82.3	81.9
Holt Winter Method	**RMSE**	151.7	196.9	185.2	40.1
	MAE	89.8	163.5	142.1	26.9
	Prediction Accuracy %	86.88	80.26	87.5	88.53

In the present investigation, the various data were collected using a CMP-22 pyrometer from Renewable Energy Laboratory (NREL) for solar radiation measurements. Historical data of the year 2015-2021 used for training the model, and year 2021 data is used for testing. Data so collected is called Time series data, which can be Stationary or Non-stationary data exhibits trend or seasonality, and it must be stationary for the Time series model to function properly. Data stationary can be manually checked by observing trends and seasonality in a graph or by running the Augmented Dickey-Fuller test (ADF test). The ADF test is a unit root test that checks the value of p; if p>.05, the process has a unit root and is non-stationary; if p.05, the process has no roots and is stationary. When the ADF test was used for the 25th February to 27th March of the year 2015-2021, the value of p obtained was 3.06×10 -16; 2.74×10-13 for the 10th June to 10th July (2015-2021), 1.60×10-12 for the 15th August to 14th September (2015-2021), and 1.90×10-12 for the 16th December to 15th January (2015-2021).

In the field of statistical time forecasting, When the Classical ARIMA model is used, PACF can be used to calculate AR (p), and ACF plots can be used to calculate MA(q). The number of lags following a sharp drop in PACF yields AR(p) terms, while the number of lags following a sharp drop in ACF yields MA (q) terms. The p and q values observed from the graph may be misleading or incorrectly interpreted, so in the present experiment, it has been used the “pmdarima” library of python to predict the correct p, d, and q values.Fig.4 & Fig.5 shows the ACF and PCF of data of each season.

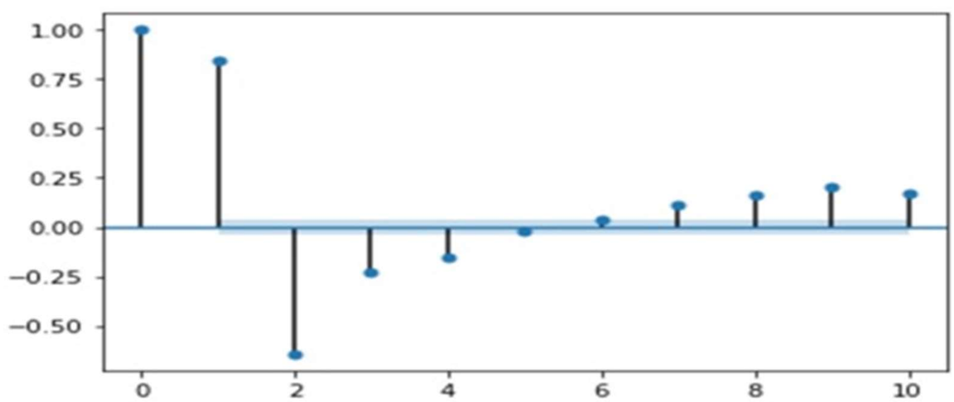

Fig 4 Autocorrelation

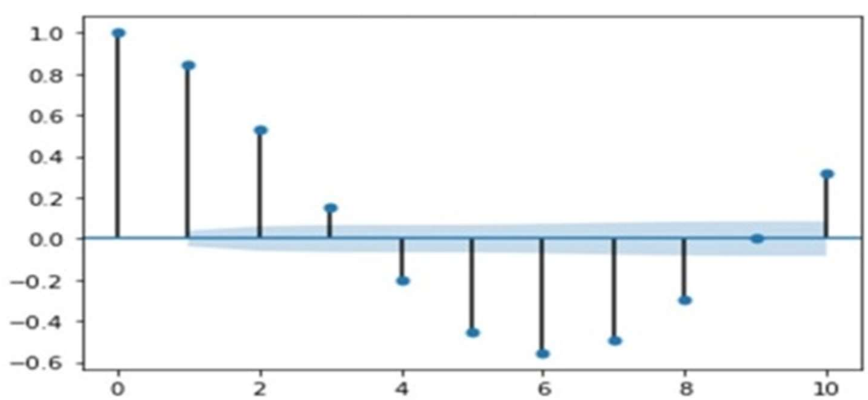

Fig 5 Partial Autocorrelation

March Forecasting (11-03-2021, 7:00AM to 6:00PM)

48 Hour Ahead Prediction: The Holt Winter method achieves a maximum prediction accuracy of 86.88% and an RMSE of 151.7. The historical data from 25th February to 27th March, 2015-2021 used for training, and the data from 25th February to 10thth March 2021, 6:00 PM 2021 was used for testing the model. At 11:00 AM and 12:00 mid noon the solar radiation drops abruptly. Due to this reason, all the models deviate, but after some time, it again starts following the actual data. The prediction results of solar radiation are shown in Fig 6 for March 2021.

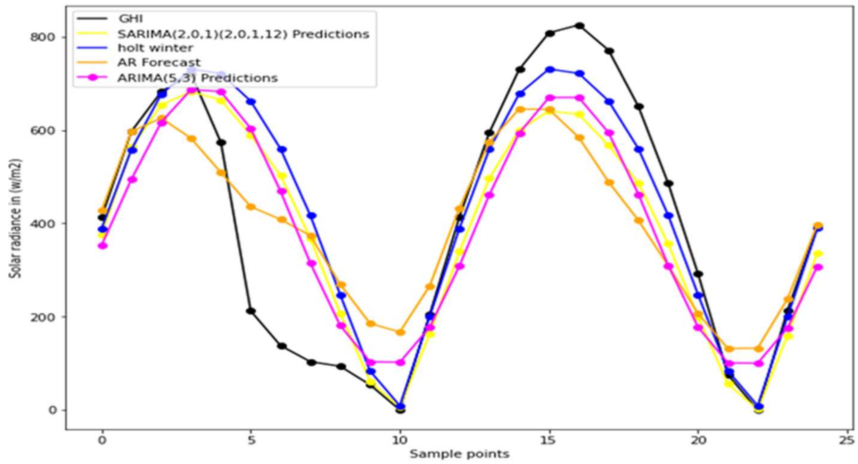

Fig 6 Solar radiation data on 11th March 2021: 48 Hour ahead Forecasting

June Forecasting (25 -06-2021, 7:00AM to 6:00PM)

48 Hour Prediction: In 48-hour forecasting, the maximum accuracy of 80.26 % and RMSE of 196.6 were obtained for 25th June. The historical data from 1th June to 10th June, 2015-2021used for training, and the data from 10th June to 24th June, 6:00 PM 2021 was used for testing the model. The high RMSE indicates that there is a significant difference between measured and predicted data. The prediction results of solar radiation are shown in Fig 7 for June 2021.

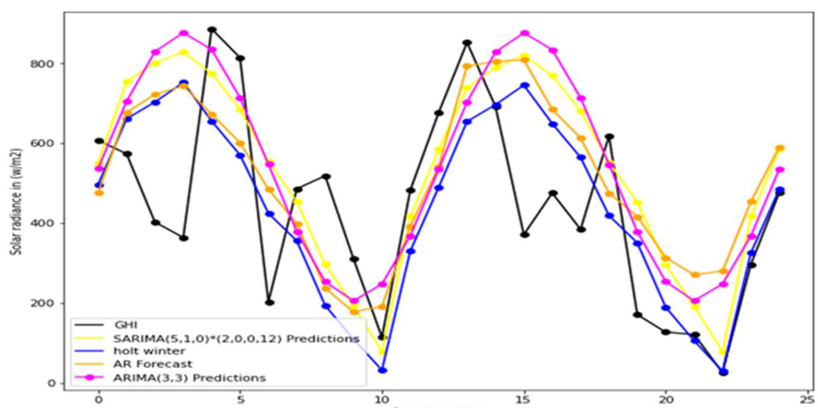

Fig 7 Solar radiation data on 25th June 2021: 48 Hour ahead Forecasting

August Forecasting (30 -08-2021, 7:00AM to 6:00PM)

48 Hour Prediction: In this Forecasting Horizon SARIMA (2, 0, 0) (1, 0, 1, 12) model achieves the highest accuracy of 87.3%, while the ARIMA MODEL (3, 3) achieves the lowest RMSE of 169.57. The historical data from August 1st to September 14th, 2015-2021 used for training,

and the data from August 16th to August 29th 2021 was used for testing the model. The prediction results are shown in Fig 8.

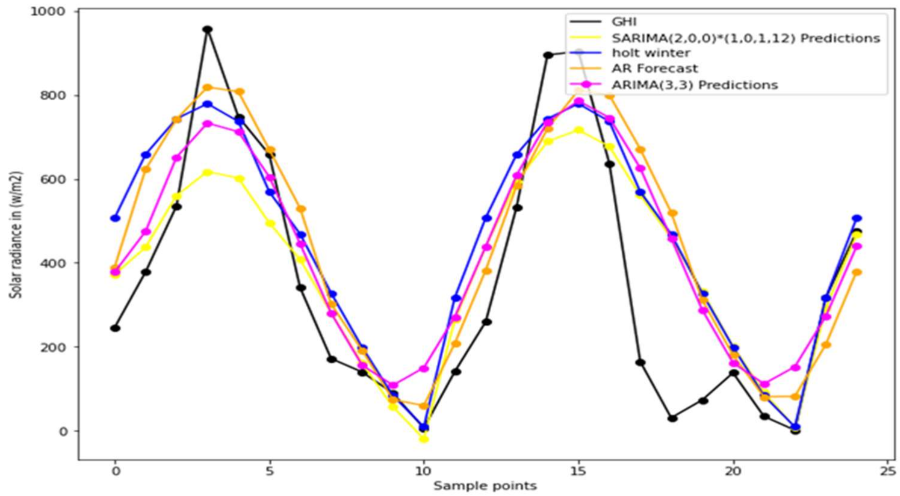

Fig 8 Solar radiation data on 30th August 2021: 48 Hour ahead Forecasting

December Forecasting (31-12-2021, 7:00AM to 6:00PM)

48 Hour Prediction: In this Forecasting Horizon perform best with the Accuracy of 88.53 and achieve lowest value of RMSE of 40.1. In Second place SARIMA occupies a position with the accuracy of 81.9 and RMSE of 65.8. The historical data from 1st December to 15th January, 2015-2021 used for training, and the data from 16th January to 30th December 2021 was used for testing the model. Following testing, the model is retrained for the entire dataset (Training Testing) and predictions are made 48 hours ahead of time. The future results from all four types of time series models are shown in Fig. 9, which shows the relationship between real global horizontal irradiance (GHI) and expected sun radiance.

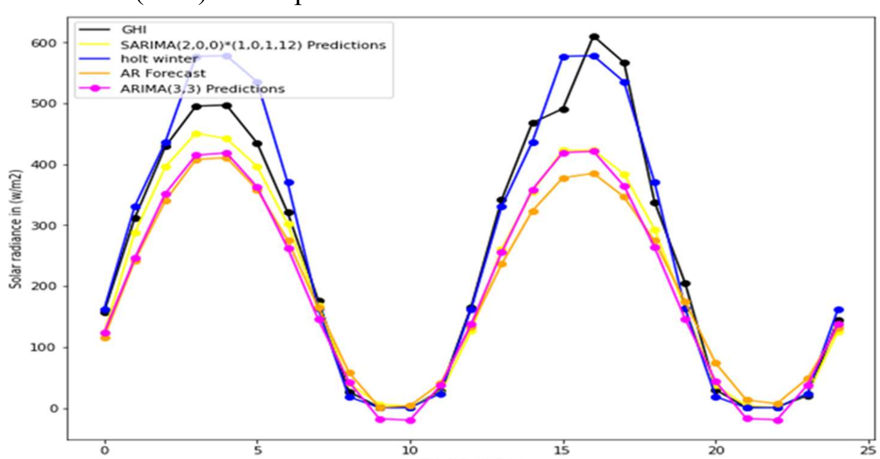

Fig 9 Solar radiation data on 30th December: 48 Hour ahead Forecasting

Conclusions

The Python framework is used in this research paper to test four-time series models, including AR, ARIMA, and SARIMA, as well as the Holt Winter Method, on real-time data obtained from NREL. Data is re-sampled for one hour to reduce the number of sample points, noise, and memory resources in EHWSN; this is not the best technique, but it is beneficial for memory-constrained devices. To evaluate the seasonality effect, four days from each season were chosen: 11th March of spring, 25th June of summer, 25th August of Monsoon, and 31st December of winter in the years 2015-2021. The simulation is used to investigate a variety of performance measures, including MAE, RMSE, and accuracy. The findings obtained from the simulation graph clearly demonstrate that the Holt winter technique performs better than any other time series models in terms of RMSE and accuracy. According to the Holt winter approach, the prediction accuracy and RMSE for the 11th of March are 86.88 % and 151.7, respectively. For the 25th of June, the prediction's accuracy and RMSE are 80.26% and 196.9 respectively. The prediction accuracy and RMSE of 30th August are 86.5% and 185.26 respectively. For 31st December, the forecast accuracy and RMSE are 88.53 % and 40.1 respectively. Better approaches are required for future research in the month of June because of the large variation in solar radiation during this month.

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