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The Impacts of Maintenance Weather and Aging on Solar Power Generation Forecasting and Prediction

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Abstract— **Solar energy forecasting has seen tremendous growth by using weather and photovoltaic (PV) parameters. This study presents new approach that predicts solar energy production by using the scheduled, unscheduled maintenance activities and weather data. The dataset is obtained from the 1MW solar power plant of PDEU (our university), which has 12 structured columns and 1 unstructured column with manual text entries about different scheduled and unscheduled maintenance activities, and weather conditions on the daily basis. The unstructured column is used to create new features by using Hash-Map, flag words and stop words. The solar power generation forecasting is formulated as a vector auto regression (VAR) optimization problem and total power generation forecasting is presented with the results of four different cases. The results have shown that the root mean square percentage error (RMSPE) in total power generation forecasting is less than 10% for different lag (p) values. The vector auto regression can forecast the unscheduled maintenance activities like *Grid failure, Inverter Failure,* scheduled maintenance activity like *module cleaning,* weather activity like *cloudy* along with total power generation forecasting for effective and efficient management of solar power plants. The power generation decay is different for all the PV sets which show the variations in the impacts of weather, aging and maintenance on the solar power plant. This research work has proven that the peaks of total power generation forecasting and prediction can be tracked in a better way by using daily unscheduled, scheduled maintenance activities and weather conditions.**

Keywords—Forecasting, Prediction, Vector auto regression, maintenance, weather

I. INTRODUCTION

Solar energy forecasting is an emerging area over the last decade by using historical time series data collected through a weather station (such as weather variables wind speed and direction, solar irradiance, and temperature). The scheduled and unscheduled maintenance activities are carried out frequently for efficient and effective management of solar power plant. Another important parameter that contributes slowly but effectively is the age of the Solar PV module. The degradation of PV modules is further impacted by the conditions such as High temperature, solar cell shedding, discoloration, and delamination, etc. India has been endowed with non-depleting renewable energy resources like solar, hydro, geothermal, and wind and it is currently ranked no. 3rd globally in the renewable energy market. According to MNRE sources, about 5,000 trillion kWh of energy is falling on India's land mass annually, with the majority receiving between 4 and 7 kWh per square meter per day. This is going to be one of the fastest-developing industries to boost rural electrification as well as the economy. Currently, there are more than 35 solar power plants in India. These plants are managed and operated by various government organizations. The operational expenditure of MW to GW solar photovoltaic power plants imposes a huge cost. Artificial Intelligence based solutions such as forecasting and recommendation-based systems can provide fruitful insights to reduce such expenditure.

II. LITERATURE REVIEW

Solar energy forecasting has remained an active area of research across the globe. Several studies and novel mechanisms have been presented on the number of platforms to show their accuracy. However, a comprehensive approach that considers all the aforementioned factors (event analysis, age and weather) has not been considered in studies. AI fuzzy logic and genetic algorithms are used to predict and model solar irradiance, performance, and control of photovoltaic (PV) systems in [1]. Multi-step solar forecasting is proposed using Ensemble of deep ConvNets in [2], which results in 22.5% RMSE. Solar power generation forecasting is proposed for a short period of time by using Mycielski-Markov approach, which results in 32.65% RMSE. Two step solar power generation prediction is proposed for a short period of time in [4] which results in 98.70 average RMSE, first step is feed forward neural network-based solar irradiance prediction and second step is LSTM-based solar power generation forecasting. Solar power generation forecasting is achieved by using long short-term memory (LSTM), gated recurrent unit (GRU), Auto encoder LSTM (Auto-LSTM), and Auto-GRU based ensemble approaches in [5] without considering any maintenance activities. The 10MW solar power plant as well as one hundred inverters of three different technology brands are used to evaluate generic fault/status prediction and specific fault prediction by unsupervised clustering and neural networks in [6]. This model is able to predict generic faults up to 7 days in advance with 95% sensitivity and specific faults some hours to 7 days in advance [6]. Intra-hour, short-term, medium-term, long-term, ramp forecasting, and load forecasting are proposed for variable renewable energy like wind and solar energy in [7]. Solar power generation is reduced by 17.4% per month because of dust on solar collectors in [8]. In [9], they performed day-ahead forecasting of a 1MW solar power plant for American Southwest with 10.3% to 14% RMSE. Neural network models like LSTM, MLP, LRNN, feed-forward, ARMA, ARIMA, and SARIMA are proposed for solar power generation forecasting by using 3640 hours of data of a 20 MW power plant in [10]. Autoregressive model based six-hour-ahead solar power forecasting is proposed at residential and medium voltage substation levels in [11], which results in 8% to 10% improvements. In [12], a two-step probabilistic solar PV forecasting is proposed, in which the first step forecasts solar irradiance and the second step forecasts PV generation, thus minimizing loss and maximize daily profits in the energy market. Solar power forecasting is proposed by using robust Auto-Encoder-Gated-Recurrent-Unit (AE-GRU) models for 24-hour, 48-hour, and 15-day periods in [13]. Solar power forecasting is proposed at 1 h 15 min resolution using a sparsity enhancing LASSO-VAR structure and the Alternating Directional Multiplier Method (ADMM), yielding a forecast improvement of 11% in [14]. A probabilistic solar PV forecast is proposed and compared with the autoregressive method of [15], yielding RMSEs of 8% to 12%. A nonlinear autoregressive neural network is proposed to predict the solar power generation with an extrinsic input model, Levenberg-Marquardt, Bayesian regularization, scaled conjugate gradients, and the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm, in [16]. The 5-minute forecasts are generated for 22 wind farms in Australia with point and probability forecasting capability as well as calibration using sparse vector auto regression in [17]. A LASSO vector autoregressive model is proposed in [18] for very short-term wind power forecasting. A vector autoregressive weather model has been proposed to forecast power supply and demand before 6 hours with reduced RMSE in [19]. Graph-Convolutional Long Short-Term Memory (GCLSTM) and Graph-Convolutional Transformer (GCTrafo), two new graph neural network models are used for multi-site PV power forecasting, each with NRMSE of 12.6% and 13.6% [20]. Solar PV forecasting includes global horizontal irradiance (GHI), direct normal irradiance (DNI), and photovoltaic (PV) functions with naive persistence models for 1-6 hours, 15-360 minutes in [22, 23]. Autoregressive integrated moving average (ARIMA) model is proposed for 5, 15, 30, and 60-minutes solar power generation forecasting using average GHI in [24]. Seasonal autoregressive integrated moving average (SARIMA) model and average GHI features are proposed to achieve 20 minutes solar power generation forecasting in [25, 42]. Auto regressive, auto regressive moving average (ARMA) models and GHI features are used to achieve 1-day solar power generation forecasting in [26-29]. ARMA with exogenous variables (ARMAX) and weather features are proposed for 1 hour solar power generation forecasting in [30]. ARIMA, VAR, Autoregressive conditional heteroscedasticity (ARCH), generalized ARCH (GARCH) and nonlinear regression models with GHI, Spatial-temporal parameter GHI and hourly solar irradiance features are used to achieve approximately 1 or 2-hours solar power forecasting in [31-34]. A K-NN model has been proposed in [35] for one-month solar power forecasting using average solar radiation. A Markov chain model was proposed in [36] for the daily solar power forecast using solar irradiance. Naive Bayes, ensemble learning models with GHI, weather and solar PV data features are proposed for 1-hour solar power forecasting in [37, 38]. Auto encoder, LSTM and ANN models with numerical weather prediction and global horizon solar radiation are proposed for 1-2 days and 1-hour solar power forecasting in [39, 40].

III. Solar Power Generation Parameters and Data Pre-processing

Pandit Deendayal Energy University (PDEU), Gandhinagar and Gujarat Energy Research and Management Institute (GERMI) has set up 1 MW Solar Power plant in 2012. The dataset is obtained from this solar power plant and it has daily entries of 13 columns from year 2012 to year 2020. The solar plant consists of five sets of PV modules, three out of these five sets are “poly-crystalline” based and each has capacity of approximately 250KW. The remaining two sets of PV modules are “thin film amorphous silicon” and “Concentrate Photovoltaic” based with the capacity of approximately 250 KW and 15 KW respectively. In total, there are four sets of PV modules and each of the sets has approximately 250KW capacity. The fifth set of PV modules has approximately 15KW capacity.

A. Attribute Description

According to the literature work carried out, it has been noted that most of the work in the field of solar energy forecasting has been done using only weather data. The features that have been extensively used for the same are: “Global Solar Radiation”, “Temperature”, “Sunshine Hours”, and “Humidity”. Though some of the research work conducted at the international level also considers “Cloud Cover”, “Wind Pressure”, “wind speed” etc. The degradation in solar modules may happen due to several environmental conditions and Maintenance activities such as Wind Speed, PV Cell shedding, cleaning through hard water, elevated air temperature, high humidity, and extreme ambient temperature. Other stress-causing factors include ultraviolet (UV) radiation, temperature, wind, hail, high voltages in the system, and factors such as broken connections, hot spots, corrosion, discoloration of potting materials, and delamination [43].

The weather attributes include global solar radiation, temperature, sunshine hours, humidity, cloud cover, wind pressure, wind speed, and ultraviolet (UV) radiation. Solar PV panel aging factors include PV cell shedding, cleaning through hard water, elevated air temperature, high system voltages, broken interconnects, hot spots, corrosion, encapsulant, discoloration, delamination. As per the study carried out by Kim et al. [43], in India, this degradation happens at the approximate rate of 1.3%-1.4% because of high cell temperature, humidity, air temperature, and high irradiance. There are scheduled and unscheduled maintenance activities at the solar power plant which affect solar power generation. The list of scheduled activities are module cleaning, transformer maintenance, cable and fuse maintenance, plant shutdown, battery maintenance and list of unscheduled activities are grid failure, inverter failure, transformer replacement, cable fault, internet, no module cleaning, and module cleaning by rain.

B. Dataset Description

The dataset has five columns for power generation from five sets of PV modules and the other columns are “date”, “Total power generation (KWH)”, “aggregate meter reading (KWH)”, “difference”, “Seeds data (KWH)”, “insolation”, “PR (%)” and “any issues/problems observed”. As discussed above, there are 13 columns in this data set and it is semi structured because the last column “any issues/problems observed" has text data which include day wise manually entered weather information, maintenance issues, grid failure, module cleaning information etc. from 2012 to 2020.

C. Data Pre-processing

The first and most important research challenge is to create the different features from the last column "any issues/problems observed". This research challenge was addressed by creating a nested hash map with different rules. The hash map key contains the possible feature label as a text and its value is a 2 × m-dimensional array. One of the row has possible values of the targeted m labels and second row has stop words that prevent overlapping and duplication of the maintenance issues or problem observed or weather condition. Each key is the new feature (maintenance or problem observed or weather condition) column, and the value is tokenized as a 1 if the new feature is present on a particular day. Using the above approach, new feature vectors created are "Grid Failure", "Inverter Failure", "Module Cleaning", "Rainy Day", "No Module Cleaning", "Transformer Replacement and Maintenance", "Cable and Fuse Maintenance", "Plant Shutdown", "Internet", "Battery", "Cloudy day", "Module Cleaning by Rain". There are only five columns "Total generation (KWH)", "Grid Failure", "Inverter Failure", "Module Cleaning", "Cloudy" that have been used in the final dataset based on the correlation and causality analysis. A vector autoregressive (VAR) model is chosen for concurrent forecasting of the total power generation and the features, as it is interdependent time series data.

IV. Methodology

The proposed work intends to establish a complex yet very useful mathematical relationship between the parameters as shown in equation (1).

$$S = f(M(x_1, x_2, \dots, x_n), A, E(z_1, z_2, \dots, z_n)) \qquad (1)$$

Where, S is solar power generation, $M(x_1, x_2, \dots, x_n)$ is maintenance activities performed at solar power plant, $E(z_1, z_2, \dots, z_n)$ is environmental factors such as rains, cloud cover, temperature, humidity, insolation, wind pressure etc., A is Age of the solar panel as calculated using degradation function, In this paper, solar power generation is forecasted using maintenance activities and environmental factors. The power generation prediction is formulated as a multivariate regression problem on time series data. The labels of processed dataset have been used to feed the regression model, and the future maintenance variable has been considered as test data. Random Forest Regression is applied to this data set, and it has been observed that the maintenance issues can be used as variables to forecast the power generation. A VAR model treats each variable as a linear combination of its own past lag as well as the past lags of other variables. In this work, we have considered five variables *Total Generation (KWH) Grid failure, Inverter Failure, Module Cleaning, and Cloudy*. The novelty here is to not only forecast the total power generation but also the prediction of maintenance activities. Let $Z_t = \{Z_{1,t}, Z_{2,t}, Z_{3,t} \dots\dots, Z_{n,t}\}$ denote a $n \times 1$ vector of time series model. The VAR (p) model where p is the lag, has the form as shown in equation (2)

$$Z_t = \alpha + \beta_1 Z_{t-1} + \beta_2 Z_{t-2} + \cdots + \beta_p Z_{t-p} + \epsilon_t \qquad (2)$$

Where t = 1…T, β_i are $(n \times n)$ coefficient matrix and ϵ_t is an $n \times 1$ K-dimensional white noise process with time-invariant positive definite covariance matrix. Suppose we have bivariate variables Z1 and Z2 and we need to predict the values of these variables at time (t). To calculate Z1 (t), VAR uses past values of both Z1 and Z2. Similarly, the past values of both Z1 and Z2 are used to calculate Z2 (t). For example, the system of equations for a VAR model with two time series (variables 'Z1' and 'Z2') looks like equation (3).

$$\begin{aligned} Z_{1,t} &= \alpha_1 + \beta_{11,1} Z_{1,t-1} + \beta_{12,1} Z_{2,t-1} + \varepsilon_{1,t} \\ Z_{2,t} &= \alpha_2 + \beta_{21,1} Z_{1,t-1} + \beta_{22,1} Z_{2,t-1} + \varepsilon_{2,t} \end{aligned} \qquad (3)$$

In more generic form, equation (3) can be represented using matrices of equation (4), where lag value is 1.

$$\begin{bmatrix} Z_1 \\ Z_2 \end{bmatrix}_t = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} Z_1 \\ Z_2 \end{bmatrix}_{t-1} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \qquad (4)$$

To model the propose work, we consider a multivariate system considering five variables, Total Generation (TG-target variable), Grid Failure (GF- unscheduled maintenance activity), Inverter Failure (IF- unscheduled maintenance activity), Module Cleaning (MC- Scheduled maintenance activity), Cloudy (CC- Environmental variable). The revised equation can be written for our proposed multivariate system as per equation (5).

$$\begin{bmatrix} TG \\ GF \\ IF \\ MC \\ CC \end{bmatrix}_t = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \cdots & \beta_{15} \\ \vdots & \ddots & \vdots \\ \beta_{51} & \cdots & \beta_{55} \end{bmatrix} \begin{bmatrix} TG \\ GF \\ IF \\ MC \\ CC \end{bmatrix}_{t-1} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{bmatrix} \qquad (5)$$

Akaike information criterion (AIC) has been computed to find the optimal value of lag (p) day using data. Optimal AIC was derived for the specific lag days to fit the VAR model and the model with acquired lag day, the coefficient matrix is computed for each of the equations. Now, there would be ten predictors on the right side of each equation (5), five lag 1 term and five lag 2 terms by assuming the value 2 for lag days. The lag value depends on the distribution of different features of the dataset and it plays a crucial role in the power generation forecasting. Now, equation (5) is formulated for the AIC based optimum lag (p) value of 12. The optimization problem of equation (6) is solved to compute the value of target variables using vector auto regression.

$$\min_{\alpha,\beta,\varepsilon} \frac{1}{N} \sum_{i=1}^{N} (\hat{T}_i - T_i)^2 \qquad (6)$$

Where $\hat{T} = \begin{bmatrix} TG \\ GF \\ IF \\ MC \\ CC \end{bmatrix}_{t,Predicted}$ and $T = \begin{bmatrix} TG \\ GF \\ IF \\ MC \\ CC \end{bmatrix}_{t,actual}$

To check the interconnected time series dependencies, Granger casualty has been performed. Here all five variables are used as the endogenous attribute. Forecasting results with multiple periods of days will give us the understanding of how power generation varies as well as the probability of the various positive and negative peaks.

A. Simulation of different cases

Weather and maintenance features are considered in the solar power generation forecasting. The maintenance activities do not last for the whole day, so the total power generation forecasting is done without considering the time duration of maintenance activities. Currently, the duration of maintenance activities is used in the model to predict total energy production. Vector auto regression can forecast solar power generation as well as the maintenance and weather activities simultaneously. Work flow diagram of simulation is shown in fig.1.

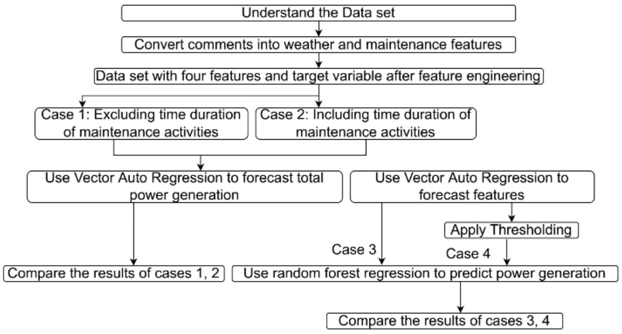

Fig. 1. Simulation flow of four cases.

There are only five columns "Total generation (KWH)", "Grid Failure", "Inverter Failure", "Module Cleaning", "Cloudy" in the final dataset after feature engineering. "Grid Failure" and "Inverter Failure" are unscheduled maintenance activities for some duration of the day. "Grid Failure" and "Inverter Failure" are kept as binary variables with values 1 and 0, excluding the duration of their occurrence in case 1. "Grid Failure" and "Inverter Failure" are kept as binary variables with values 1 and 0, including the duration of their occurrence in case 2. Vector auto regression is used to forecast the solar power generation for cases 1, and 2, so the performance can be compared. Solar power generation can be predicted through regression but the future values of the features "Grid Failure", "Inverter Failure", "Module Cleaning", and "Cloudy" are not known. The vector auto regression model is used to forecast the future values of these features. Now these values are used to predict the total power generation in cases 3 and 4. Thresholding is used to convert the values of features into 0 and 1. By default, 0.5 is used as threshold value to convert values of features into either 0 or 1. In case 4, thresholding values are used according to number of occurrences of maintenance activities. The total power generation is predicted using random forest regression so the performance of cases 3 and 4 can be compared.

V. Results

The processed dataset has best four features and target variable. Results are generated by simulating four cases of

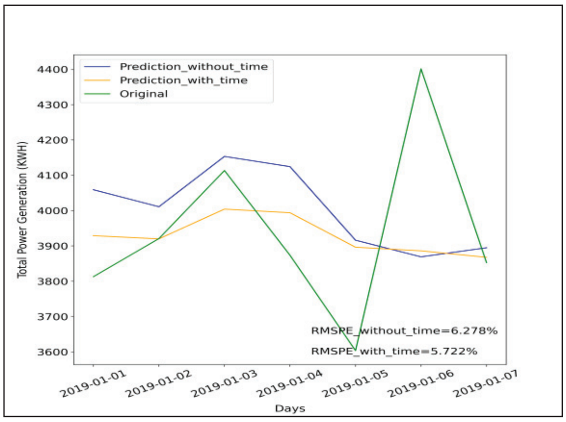

Fig. 2. Comparison of original and forecasted total power generation values without as well as with time duration of maintenance activities for p=7

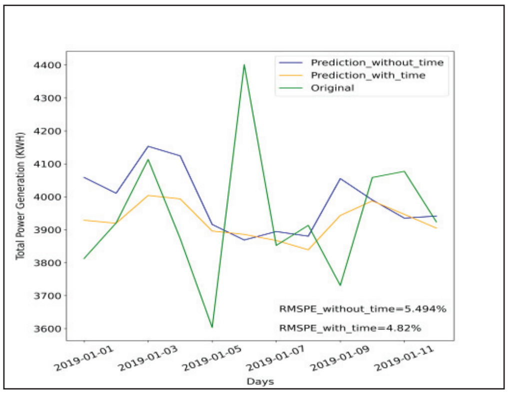

Fig. 3. Comparison of original and forecasted total power generation values without as well as with time duration of maintenance activities for p=12.

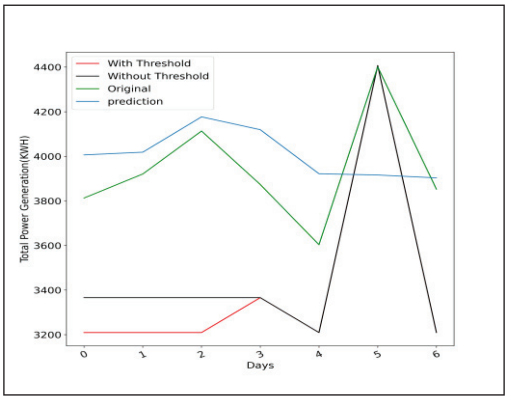

Fig. 4. Comparison of original and forecasted total power generation values without as well as with threshold of maintenance activities for p =7.

fig.1. Fig. 2 and fig. 3 show comparison of original and forecasted total power generation values without as well as with time duration of maintenance activities (cases 1 and 2) for p=7 and p=12 respectively.

The original power generation of figures 2, and 3 have high and low peaks, which are mainly due to environmental factors, maintenance activities and aging of the solar panels. The plant shutdown is considered as the outlier in all the results. Fig. 4, and fig. 5 show comparison of original and forecasted total power generation values without as well as with threshold on maintenance activities (cases 3 and 4) for p=7, and p=12 respectively.

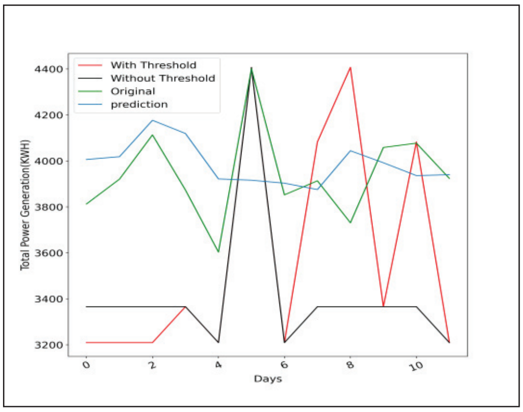

Fig. 5. Comparison of original and forecasted total power generation values without as well as with threshold of maintenance activities for p =12.

The RMSE and MAE values of cases 1 and 2 are shown in Table I for lag values of 7, 10 and 12. The lag value of 12 results into lowest RMSE for both cases.

TABLE I. RMSE OF CASES FOR DIFFERENT LAG VALUES

Lags (p)	*Error for case 1*		*Error for case 2*	
	RMSE	***MAE***	***RMSE***	***MAE***
7	253.774	207.842	236.442	167.091
10	235.562	187.288	211.428	152.727
12	218.91	169.183	196.728	139.724

Power generation decay is shown in fig. 6 for three sets of poly-crystalline PV modules, one set of thin film amorphous silicon PV modules, and one set of Concentrate Photovoltaic (Tracker) PV modules.

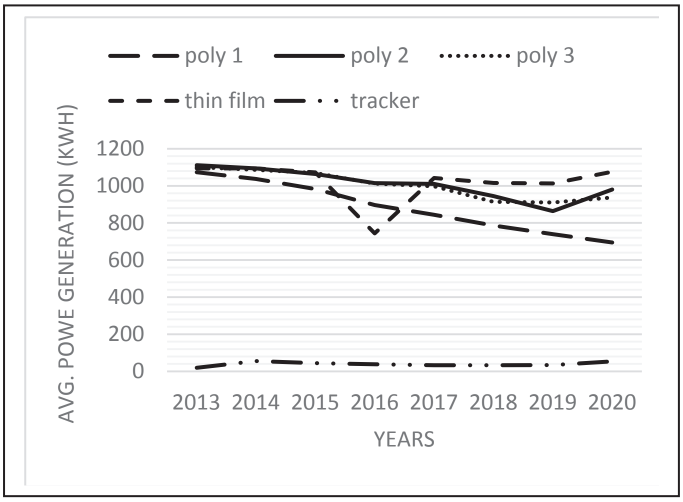

Fig. 6. Yearly decay in power generation for five sets (poly1, poly2, poly3, thin film, tracker) of PV modules

VI. CONCLUSIONS AND FUTURE WORK

The maintenance activities like "grid failure", "inverter failure", "module cleaning" and the weather parameter "cloudy" have huge impact on the solar power generation forecasting and prediction. The optimum value of lag p=12 results in lowest RMSPE, RMSE and MAE for different cases. The error is reduced due to inclusion of duration for maintenance activities in this model for case 2. The VAR model used in this work is capable of forecasting all the four features as well as power generation target variable simultaneously. The predicted power generation is able to follow the trends of original power generation when the thresholding is applied to the predicted values of maintenance features (activities). The results have shown that the root mean square percentage error (RMSPE) in total power generation forecasting is less than 10% for different lag (p) values for all cases. The vector auto regression can forecast the unscheduled maintenance activities like *Grid failure, Inverter Failure,* scheduled maintenance activity like *module cleaning,* weather activity like *cloudy* along with total power generation forecasting which result in effective and efficient management of solar power plant. The power generation decay is different for all the PV sets which show the variation in the impacts of weather, aging and maintenance on the solar power plant. The effects of aging, dust and other environmental factors can be considered in the model as a future scope to improve the solar power generation forecasting and prediction.

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