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An experimental cum computational economical approach for evaluation of performance loss rate or degradation rate for realistic roof-top PV plant in south India

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Abstract. Degradation rate in Solar photovoltaic systems is truly an important factor affecting economic feasibility. A linear drop in performance is typically assumed during the operational life-time of the PV system. However, the operational ground performance data reveal that the degradation rate for PV- module based systems is often non-linear similar to the present investigation. This, if neglected, can cause financial uncertainty. So, this paper presents an experimental field estimation coupled with an analytical model-based approach for prediction of degradation of Solar PV systems. A section of 380 kWp PV system is considered for the present work. Furthermore, comparison of regressors encompassing non-linearities like random forest and decision tree-based are attempted for model formulation. The work is also supported with a comprehensive review on modelling approaches for assessment of degradation-based failure modes in Solar PV system. The experimental average value of degradation rate of the 380 kWp PV system is 7.78% or 0.0778. The reported analytical models possess a close match with the experimental results which are quantified by MPE whose value ranges from a minimum of 1.79% to a maximum of 10.4%. The annual performance ratio of the considered system for study is as less as 0.4 indicating and justifying the occurrence of failure effects in the system.

1 Introduction

India's renewable energy installations are on rise in the overall energy mix with 10,226 MW of capacity contributed by it in 2021-22. Among the renewable energy installations, Solar photovoltaic systems contribute amounting to 9068 MW [1]. Beyond installation of plant units, its societal acceptance in delivering the instantaneous demand lies important. Renewable energy installations have become a fit and forget model. The genuine operation of these systems is not investigated seriously by the investors or the plant owners. Degradation or failure rate or performance loss rate [2] is the one of most vital parameters for assessing the useful life-time of the PV plant. An indicator when considered as a universal comparator /benchmark should provide accurate information on a plant's energy

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generation, operational losses and incorporate attributes relating to the field conditions. Inverters in a solar system are believed to work efficiently, operating with an average conversion ratio of 93-96%. So, major failure loss is injected due to PV module operation. Information on the failure metric is also essential for deciding the levelized cost of electricity produced. So, a realistic cost-effective quantification-based approach for estimation of degradation rate / power loss rate for PV systems is essential.

The major modes of failure observed as degradation are PV module decolourization, module cracks, hot spots, encapsulant browning, Potential Induced Degradation, Light Induced degradation, soiling loss etc [3]. These impact the remaining useful life of the power plant eventually reducing its performance ratio. So, the loss in power output due to degradation effects should be quantified which further provides information on the cost priority number. The CPN should be as low as possible benefiting the plant owner.

This paper presents an analytical model derived from on-field experimental investigation. The model is derived based on error minimization approaches for computing the degradation rate of an operational Solar PV module system. Furthermore, a review on model-based estimation methodologies available for the assessment of failure rate is also carried out.

2 Reported quantification based approaches

The estimation of failure-based degradation rate is broadly classified based on the mode of estimation as Indoor / Accelerated based experimental evaluation and outdoor mode or on-field based evaluation [4]. Furthermore, analytical based model approaches act as derived methods from experimental procedures. As the current scope of work attempts to derive an analytical tool/ model for failure rate estimation, this section includes the review of model-based estimation techniques for assessment of failure rate or degradation rate of Solar PV systems. Spataru et al. (2015) [5] has performed a dark current degradation test in an environmental chamber which resulted in modelling the degradation aspect of potential induced degradation as a function of relative humidity and temperature.

$$P_{max}/P_{max0}= 1-A\exp(-E/kT)\,(RH)^{B}\, t\text{^}2 \qquad (1)$$

Where A and B are model co-efficients. E- activation energy obtained from accelerated field test. RH -Relative humidity;

Belluardo et al.(2015) [6] proposed a simple linear model for determining the performance loss rate of PV system on-field. The corrected peak power output is estimated by applying least square criterion based fit applied to a time-series of monthly averages of peak power output. This model is widely used to estimate degradation rate. However, an underlying fact of degradation rate appearing non-linear remains true on-ground. Theristis et al. (2020) [7] reported a non-linear model for estimation of photovoltaic degradation rate for performance ratio. Non-linear time -series based forecasting using facebook prophet algorithm (from python library) based approach is trained for a 1 kWp grid connected PV systems. These systems incorporated mono-crystalline PV modules. The input to the model was irradiance and the output was the degraded performance ratio. The degradation percentage varied from a minimum of -0.45 %/ year to -2.80%/year. Quansah et al. (2020) [8] estimated the realistic degradation rate in maximum power for 65 silicon based crystalline PV module erected at twenty-nine (29) different locations across the country of Ghana. The estimation was characterized using in-situ voltage and current curves, thermal imaging technique and visual field inspection. Annual module performance based degradation rates occurred in the range of 0.8% to 7%, 1.1% to 2.4% and 0.55% to 2.07% for PV modules located in various climate sub -categorizations namely humid, dry and sub-humid respectively. Kaaya et al. (2019) [9] attempted to propose a mathematical model for estimating maximum power output incorporating degradation precursors like hydrolysis, photo-degradation and thermo-mechanical degradation. An exponential model for deducing degradation rate using thermo-mechanical degradation aspects and hydrolysis-based photo-degradation were reported as represented mathematically in equation (2 -3).

$$k_h = A\,(RH)\,exp\,(\,E_H / k_b\,T_m) \tag{2}$$

$$kp = A\,(UV)^x\,(1+RH)\,exp\,(\,E_p / k_b\,T_m) \tag{3}$$

Kaaya et al. (2021) [10] attempted to formulate a model for predicting performance loss over a time horizon by applying a self-regulated multi-step algorithm. Here a multiple linear model for estimation of performance loss rate employing the time-series trend of performance ratio is proposed. The performance loss rate of crystalline modules varied from -1.3%/year, whereas for thin film modules varied between -0.6 % and -2.4%/year. The form of the model is as provided below. Cariget et al. (2021) [11] quantified the long-term performance degradation of silicon PV modules using outdoor and indoor measurement. The outdoor measurements included parameters like irradiance, DC voltage, DC current and DC power. The rate of degradation was determined by formulating a linear regression of P_{mp} over time. The author has considered the rate of degradation to be linear.
Analytical based degradation approaches possess advantages as enlisted:

- Non-dependence of field test procedures for model usage at different field scenarios.
- Economical computation, as it does not require cost effective equipment such as higher spectral response based thermal imager, electroluminescence tester and solar curve tracer.
- Consideration of actual field conditions for degradation rate estimation ensuring accuracy of the proposed estimation.

3 Solar V-I curve tracer based on-field experimentation for assessment of actual failure rate

The system of investigation included panels of 325 W_p each amounting to 380 kWp roof-top system. 41 panels were selected for the proposed research after visual investigation. The system is located in our erstwhile transit campus, NITTE Meenakshi Institute of Technology, Bengaluru, Karnataka situated at latitudinal and longitudinal angle of 12.97^0N and 77.59 ^{0}E. The computed performance ratio was as low as 0.41 indicating the occurrence of degradation-based failure modes.

A visual inspection is carried out well before covering the field. Though the visual inspection method is limited in detection of minute failure defects, other defects like decolorization, snail trails and visible cracks can be detected. The modules possessing these failure defects are majorly considered, to ensure that the measured output embodies the degraded conditions. This inspection is performed in accordance with the standard of IEC 61215-1. After visual inspection, an on-field test methodology based on Solar V-I curve tracer [12-14] was carried out for a short-term duration for formulation of a cost effective design tool for estimating performance loss rate or degradation rate. An on-field Solar IV curve tracer, PV 200 was employed for measurement. This device traces the output voltage, output current and power output at maximum power point. The test is performed as per the International Electrotechnical Commission standard of 60904-1. The actual field input conditions like plane of array irradiance, module temperature and tilt angle are also recorded. Figure 1 illustrates the on-field /quantitative testing methodology for determining the output voltage, output current and series resistance employing Solar V-I curve tracer at Solar noon.

Figure .1. Solar I-V Curve tracer connected to actual PV system under field conditions.

The experiments are carried out close to solar noon approaching standard test conditions (STC). However, the field-based output values correspond to actual module temperature. This is then corrected to STC. Equation (4) is employed for experimental evaluation of failure rate or degradation rate of the considered Solar PV system.

$$R_{d(actual)} = P_{actualc}/P_{rated} \tag{4}$$

$P_{actualc}$- Measured power output using Solar V-I curve tracer corrected to STC conditions; P_{rated} - Power output at STC.

4 Analytical based degradation rate model formulation and validation

The model formulation encompasses true factor identification, training using experimental data sets and testing /validation. Input factors like global irradiance at tilt or plane of array irradiance, module temperature and series resistance are identified as significant factors affecting degradation rate. The coefficients are derived on the basis of error minimization. The Pearson's coefficient (p-value) is as less as 0.05% for the incorporated model input's justifying the same.

The model coefficients of model-1 are estimated by employing non-linear least square criterion technique, involving sum of squares of error for all the experimental observations. This ensures least error or improved accuracy. The model coefficients are evaluated subjected to the condition as specified in the equation (5)

$$Error = (Rd\ (est) - Rd\ (act)) \tag{5}$$

$d\ (error)/\ dA = 0;\ d\ (error)/\ dB = 0;\ d\ (error)/\ dC = 0;\ d\ (error)/\ dD = 0;$

So estimation of R_d using model-1 is shown in equation (6)

$$R_d = 0.02468-(3.6e\text{-}5\times A)+(7.8e\text{-}3\times B)-(0.076\times C)-(1.12\ e\text{-}4\times D) \tag{6}$$

The derived model coefficients a, b, c, d and e are 0.0247, -3.6e-4, 0.0078, -0.0762 and 1.12 e-3 respectively. A comparison between the actual and the estimated value is as seen in Figure 2 (a). The agreement between the predicted and actual parameters are quantified

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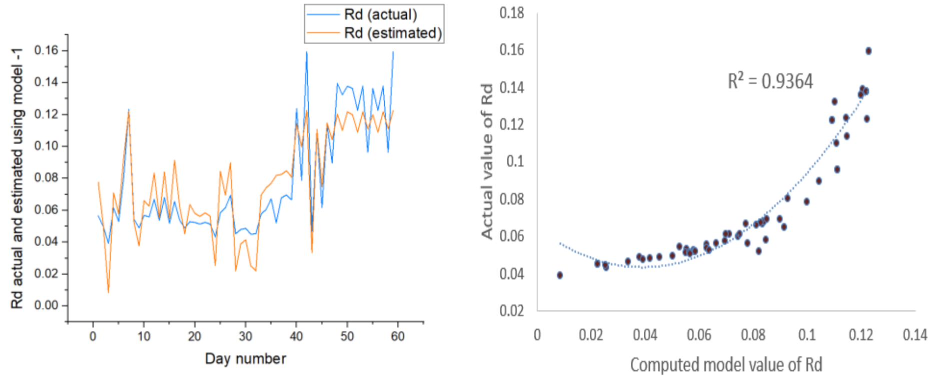
by the value of absolute average bias error to be as least as 0.0136 with R^2 of 0.9364 as indicated in Figure 2 (b).



(a) (b)

Figure 2. The estimated and actual value of degradation rate (R_d) for 14 Solar PV panels of 325 W_p

Secondly, a random forest-based regression modelling approach [15], designated as model-2 is also attempted. This method evaluates the model coefficients employing bagging based ensembling technique. Bagging also known as boot strap aggregation operates with row and feature sampling. Retraining of ensemble-based models with row sampling and replacement of the training data set is performed for evaluation of coefficients of the model. The agreement between the predicted and actual degradation rate during the training and testing phase is illustrated in Figure 3 (a) and (b).

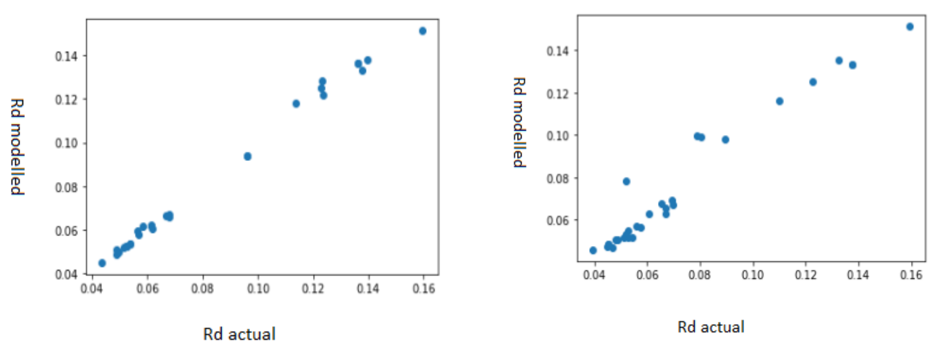


Figure 3. Comparison of R_d during training (a) and testing phase (b) respectively using random forest regressor

Model-3 employs a decision tree based evaluation approach [15]. Comparison of performance loss rate employing decision tree during the training and testing phase is as shown in Figure 4. The agreement between the experimental and the estimated value is quantified to be 0.9674.

Furthermore, a time-series based model with delay states incorporating dynamic variation of inputs such as series resistance, irradiance and module temperature are provided. The weight adjustment is based on backward progressive iteration of weight gradients. The model incorporates two delay states with three inputs. There are 10 neurons in the hidden layer.

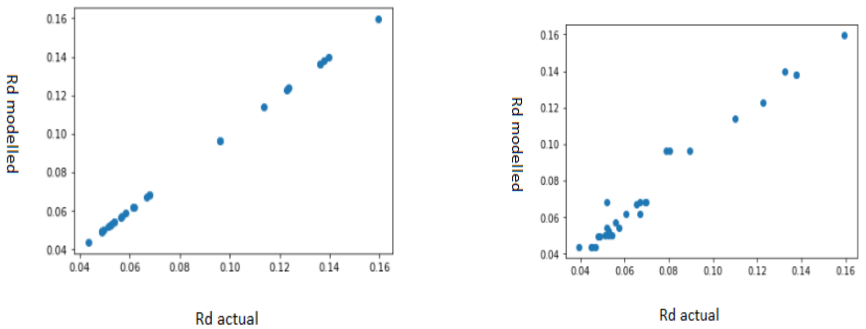


Figure 4. Comparison of R_d during training and testing phase respectively using decision tree regressor

Model- 4 for degradation rate : $O_h=f\ (b_1+x_i\ (t\text{-}2)\ w_i\ )$ *(7)* ; $Y=\sigma\ (b_2+\sum(j=1:n)\ O_h\ \times W_j)$ *(8)*

where O_h is the output of the hidden -layer ; b_1, b_2 are the bias of the input to hidden and hidden to output respectively ; w_i, w_j represent the weights of input to hidden and hidden to output connection.

Table.1. Comparison of the proposed models with R^2

S.No	Nature of model and Model name	Model name	R^2 during training and validation	MPE
1	Multiple linear regression- Model 1	Model 1	0.936	9.10%
2	Random forest regressor -Model 2	Model 2	0.974	2.39%
	Decision tree regressor -Model 3	Model 3	0.964	1.79%
3	Non-linear estimation model using predictors-Model 4	Model 4	0.73	10.4%

As seen from Table 1, the value of R^2 encompassing the entire experimented duration is highest for model-2 operating on random forest regressor amounting to 0.974. However, the mean percentage error rendered by Decision tree based regressor is as least as 1.79%. The accuracy rendered by a model is always better acceptable during the training phase than the testing phase. So, model -2 and model -3 are better adaptable for non-linear variations in Rd. So, the proposed analytical model derived from experimental procedures ensuring minimal error can act as a design tool leading to a cost-effective measure in estimating failure or degradation rate.

5 Conclusion

An economical and a tool devoid of complexity and time-consuming experimental procedure for estimation of degradation or failure or performance loss rate is proposed. A true non-linear nature of degradation rate on-field obtained from short-term experimental investigation is considered for model formulation. The considered system is also a realistic PV plant operating at an annual performance ratio of 0.4 which is relatively lower than the widely accepted value of 0.8. Four different model approaches incorporating the trend or time series-based variation in inputs are considered for design tool or model formulation. Among the proposed evaluation tools for R_d decision tree and random forest based regressor are considered adaptable to field conditions. Moreover, a review of approaches available for estimation of degradation rate is discussed with limitations. The formulated computational tool possesses an MPE of 1 % to 2% which falls between the acceptable variation of MPE and is derived from experimental investigation. This suggests the employability of the proposed tool for estimation of degradation rate of PV systems.

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