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Predicting Performance Parameters of Polycrystalline Solar Panels using ANN

(6479)

Author's Details

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Abstract

- With a focus on sustainable development, grid-connected photovoltaic (PV) systems are increasingly being employed.
- The performance evaluations of these grid-connected PV plants can aid plant operators and the scientific community in the design, operation, and maintenance of plants for a more efficient and reliable system.
- Typically, standard statistical procedures are applied for performance evaluations. With the recent advancements in artificial intelligence, artificial neural network (ANN) based approaches are promising for forecasting and monitoring the performance of various PV systems.
- This work investigates the ANN-based model for estimating polycrystalline PV module technology's short-term performance in tropical environments at Raysan, Gujarat.
- The proposed model, trained with Levenberg-Marquardt (LM), Bayesian Regularization (BR), Resilient Backpropagation (RBP), Conjugate Gradient with Powell/Beale Restarts (CGP), Gradient Descent (GD).
- It accurately predicts the performance metrics such as final yield (YF), reference yield (YR), power produced/day (PD), performance ratio (PR), and total energy loss (ET) with a 98 percent degree of accuracy.
- Predicting solar power generation has been an important topic in renewable energy. Prediction improves the planning and operation of photovoltaic systems and yields many economic advantages for electric utilities.

Overview of work

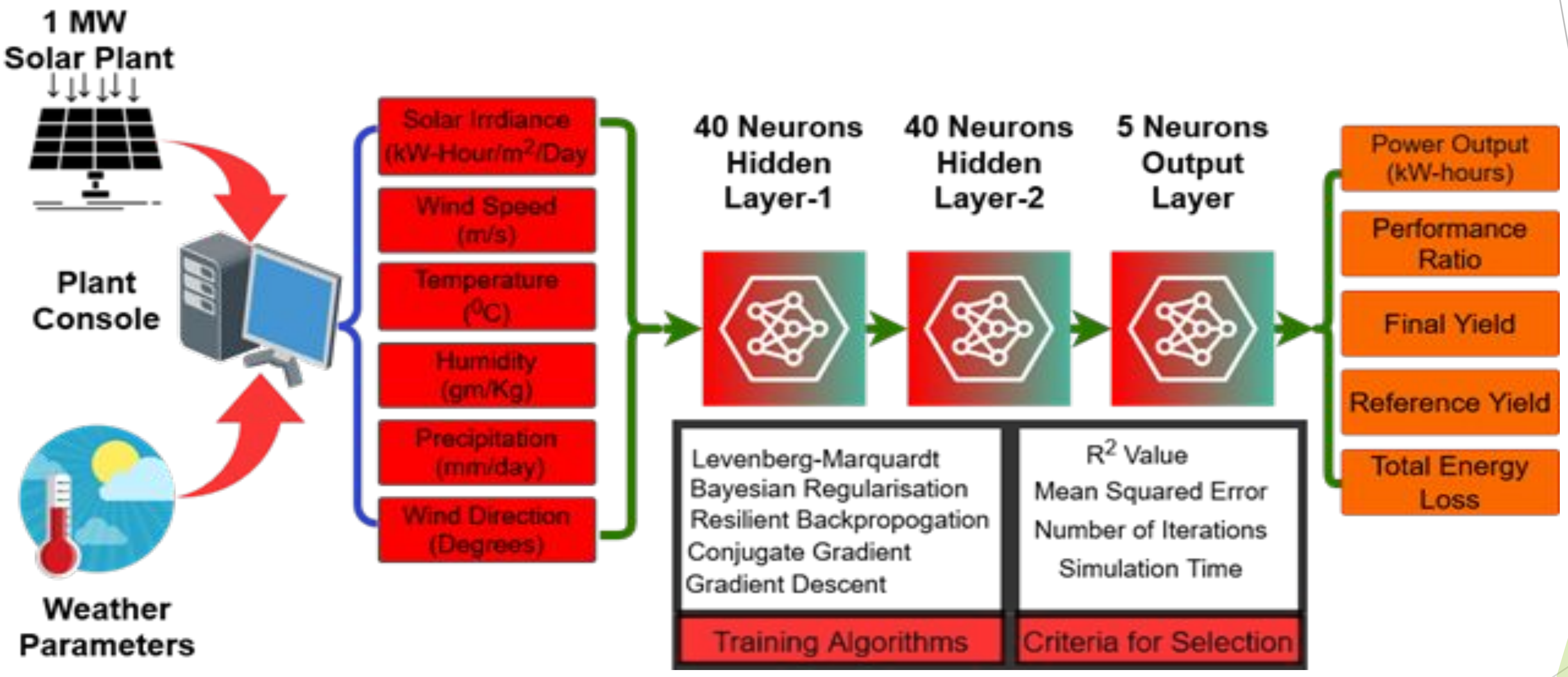

Fig. 1 Represents the overview of the work

Methodology

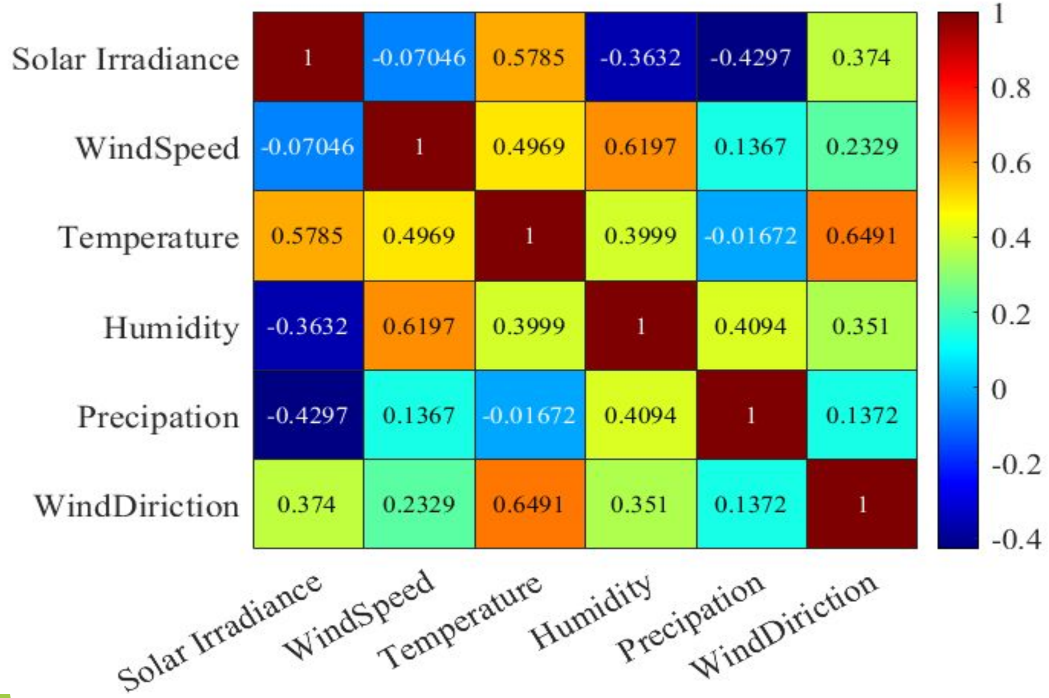

Fig. 2 Pearson's Correlation Matrix

$$Y_f = \frac{E_{AC}}{P_{PV,Rated}} \quad (1)$$

$$Y_r = \frac{H_t}{G} \quad (2)$$

$$PR = \frac{Y_f}{Y_r}.100\% \quad (3)$$

$$L_T = Y_r - Y_f \quad (4)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (5)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2 \quad (6)$$

Results

Algorithms	R-value	MSE	Time (sec)	Number of Iterations
LM	0.99195	2.5815e+03	4	11
BR	0.99383	1.8469e+03	608	1000
RBP	0.98446	4.6667e+03	5	20
CG	0.98759	3.7275e+03	6	33
GD	0.8252	1.0841e+06	4	6

Table. 1 Performance of different training algorithms.

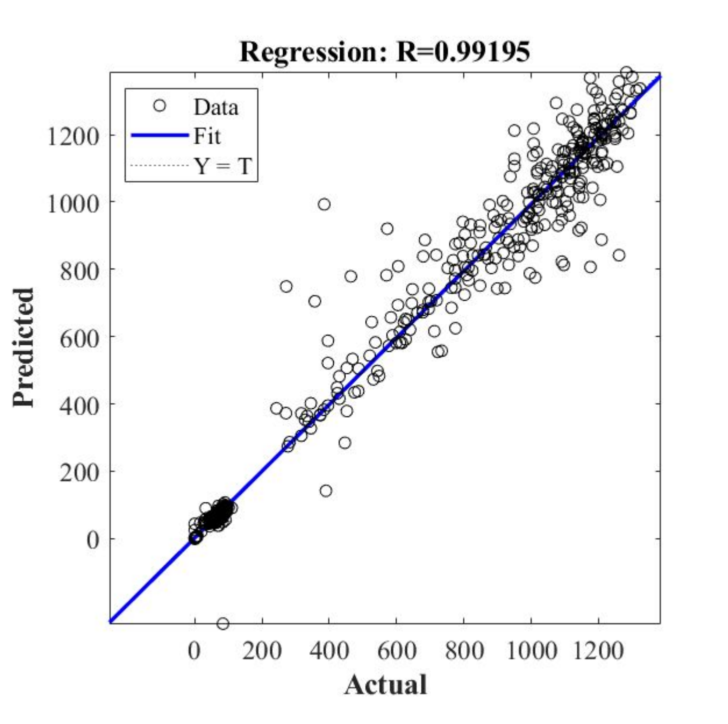

Fig. 3 Regression Plot

Power Output

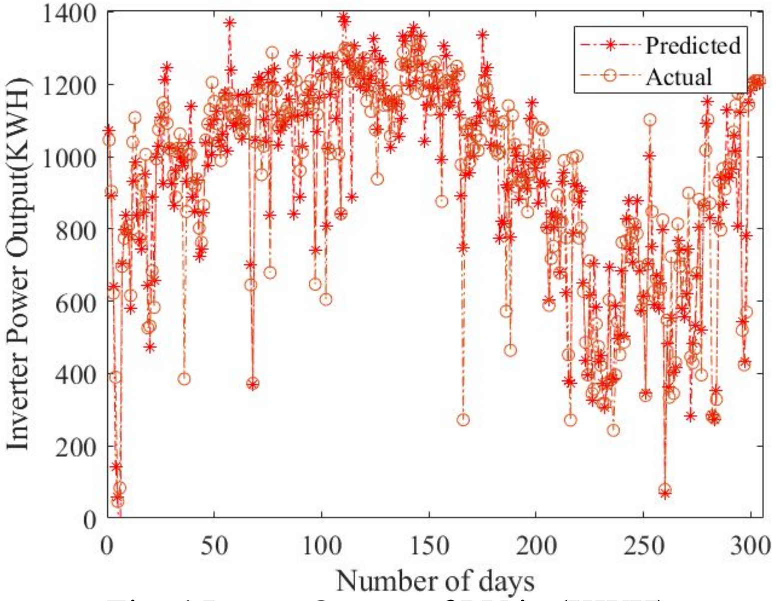

Fig. 4 Power Output of PV in (KWH)

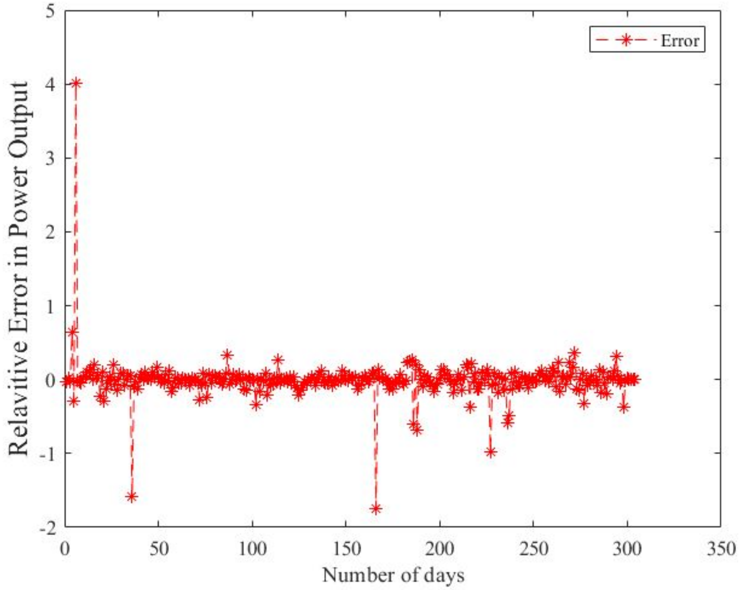

Fig. 5 Error in Power Output of PV (KWH)

- The data shows that the PV panel power production in Dec 2019 increases towards the summertime (Feb 2020- Jun 2020), and it further dips significantly during rains in July-Aug 2020.

PV Yield

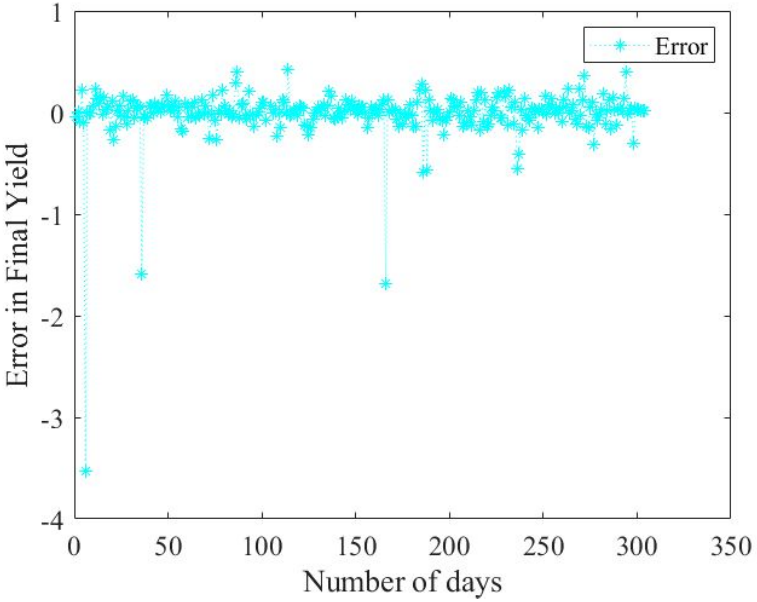

Fig. 6 Error in PV Yield (KWh/KWp, or h)

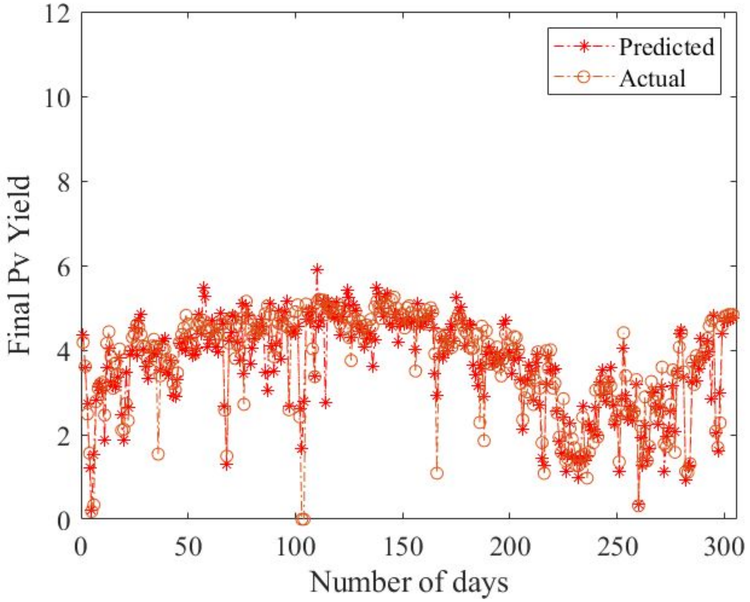

Fig. 7 Final PV Yield (KWh/KWp, or h)

- The Yf shown in the figure increases during March- June 2020 during summer and significantly falls during the rain between July-Aug 2020

Reference Yield

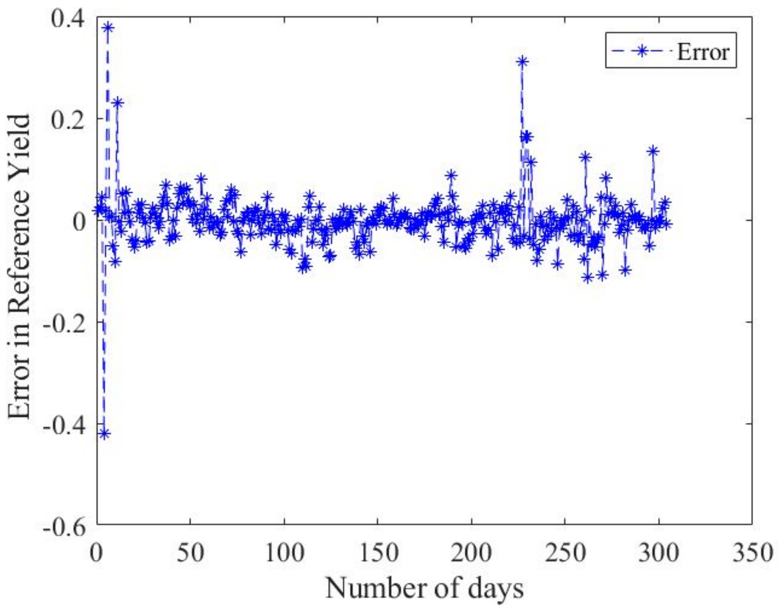

Fig. 8 Error in Reference Yield (H)

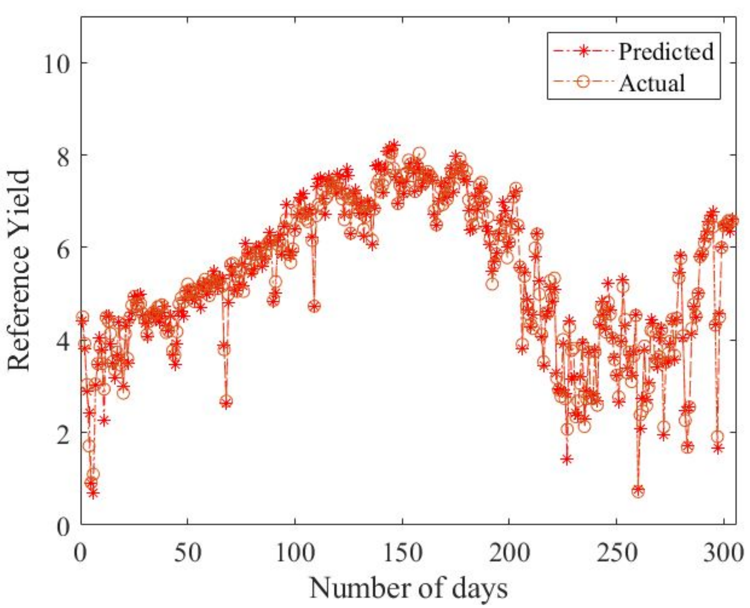

Fig. 9 Reference Yield (H)

- Shows the actual and predicted referent yield. The model predicts the Yr efficiently and follows the solar in-plane irradiance.

Performance Ratio

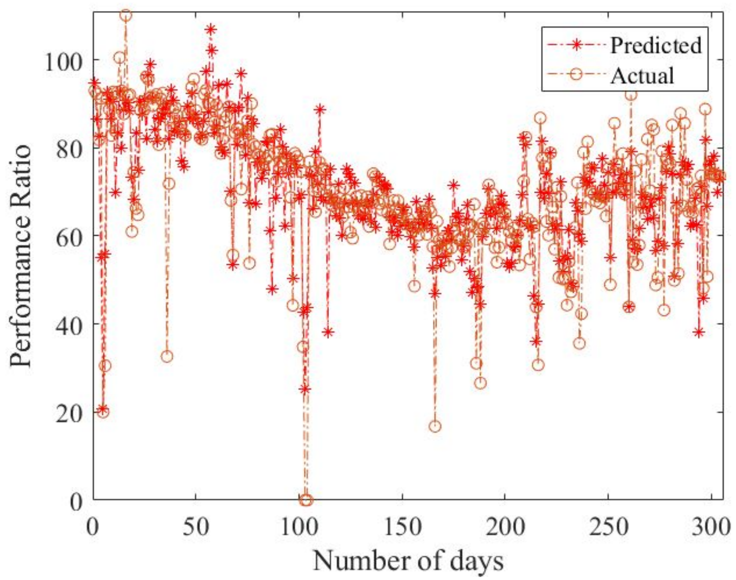

Fig. 10 Performance Ratio

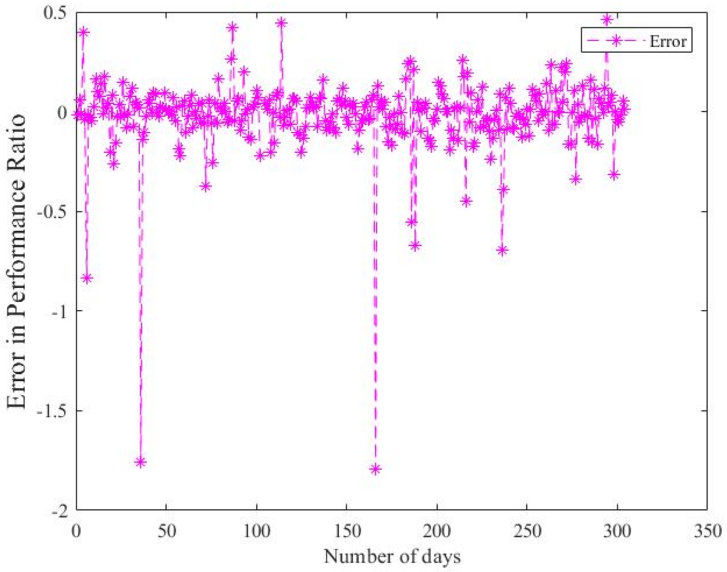

Fig. 11 Error in Performance Ratio

- Shows the performance between 80 to 90% during winters because of the negative temperature coefficient of temperature for p-Si PV panels.
- It further decreases when the surface temperature increases during the summer and remains between 60-70%.
- As soon as the surface temperature of the panel goes down, the performance ratio restores to 80 %

Total Energy Loss

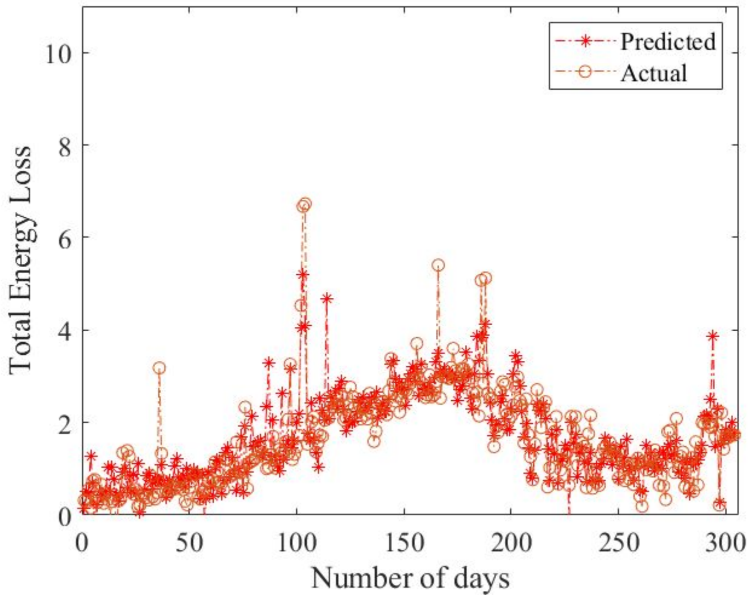

Fig. 12 Total Energy Loss KWH

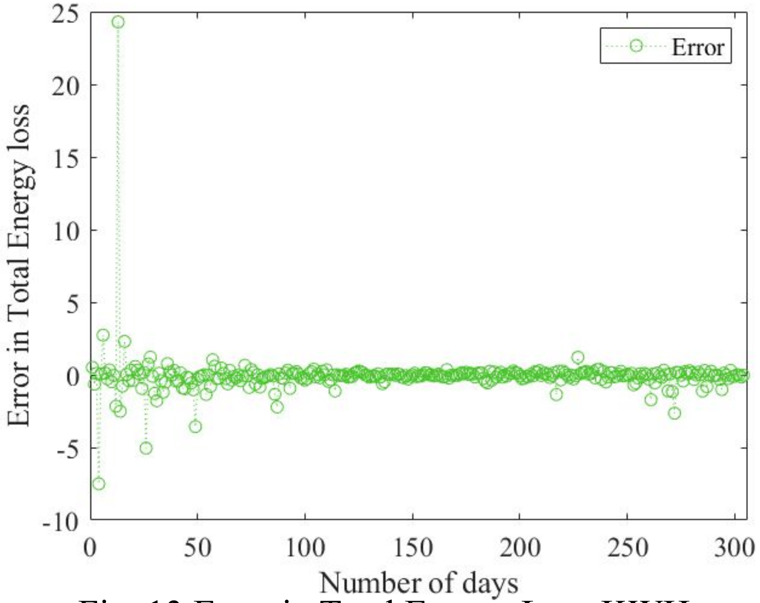

Fig. 13 Error in Total Energy Loss KWH

The proposed model makes accurate predictions and follows the actual energy loss pattern which increases during the summertime and goes down during rainy or cloudy weather conditions.

Conclusion

- Five learning algorithms were successfully used to solar PV system data from a 1-MW solar plant erected on the PDEU campus in Gandhinagar to anticipate the system's performance characteristics.
- The LM learning algorithm beat the competition with an R-value of 0.9913 and the shortest simulation time.
- Solar photovoltaic (PV) systems' performance parameters, such as Y_r, Y_f, E_t, PR, and power output, may be accurately predicted and evaluated using the suggested method.
- The proposed model can accurately estimate the performance of various solar PV systems by using a data set gathered through the extended operation.
- The authors gratefully acknowledge the support of the Solar Research Development Centre (SRDC), PDEU, Gandhinagar, Gujarat, India, for providing the operation data.

References

1. Ministry of New and Renewable Energy, “Ministry of New and Renewable Energy Annual Report 2020-21.”
2. R. Kumar et al., “Draft National Energy Policy,” Energy Policy, vol. 1, no. 5, pp. 122–140, 2018.
3. D. A. Quansah, M. S. Adaramola, G. K. Appiah, and I. A. Edwin, “Performance analysis of different grid-connected solar photovoltaic (PV) system technologies with a combined capacity of 20 kW located in a humid tropical climate,” Int. J. Hydrogen Energy, vol. 42, no. 7, pp. 4626–4635, 2017.
4. H. Maammeur, A. Hamidat, L. Loukarfi, M. Missoum, K. Abdeladim, and T. Nacer, “Performance investigation of grid-connected PV systems for family farms: Case study of North-West of Algeria,” Renew. Sustain. Energy Rev., vol. 78, no. May, pp. 1208–1220, 2017.