SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V10I9P120

Volume 10 Issue 9, 213-220, September 2023

Original Article

Teaching Learning-Based Optimization Approach for Optimal Estimation of Power and Temperature of Photovoltaic Technologies

Krupali Kanekar[1], Prakash Burade[2], Dhiraj Magare[3]

[1,2]*Department of Electrical, SOET, Sandip University, Maharashtra, India.*
[1]*Department of Electronics and Telecommunication, Ramrao Adik Institute of Technology, D. Y. Patil Deemed to be University Maharashtra, India.*
[3]*Department of Electronics, Ramrao Adik Institute of Technology, D. Y. Patil Deemed to be University Maharashtra, India.*

[1]*Corresponding Author : raut.krupali7@gmail.com*

Received: 26 July 2023 Revised: 29 August 2023 Accepted: 20 September 2023 Published: 30 September 2023

Abstract *- The operating temperature throughout the Photovoltaic (PV) module has a greater impact on the environmental performance of the PV module as it affects the module's output power. Amorphous Silicon (a-Si) and Hetero-junction with Intrinsic Thin layer (HIT) PV modules, which are placed at the National Institute of Solar Energy (NISE), Gurgaon site in India, are the two PV technologies covered by this work. It describes a new method for estimating the effects of module temperature on seasonal performance variation. For the first time in this research project, estimates of the outcomes have been made based on a method for identifying new coefficients at the site by taking into account the same reported module temperature model format, then finding the RMSE of predicted temperature using Teaching Learning-Based Optimization (TLBO) method. This estimation is also used to boost the performance of PV modules. The calculation of the module temperature model coefficients and Root Mean Square Error (RMSE) for the two technologies are also presented here. Additionally, the PV module temperature model's efficiency and output power were estimated. The RMSE between anticipated and measured power and the percentage power departure from the Standard Test Condition (STC) were assessed. HIT module was the better performing PV technology than a-Si at the NISE site when comparing the parameters of the two distinct PV technology modules in terms of efficiency and output power. The performance evaluation of solar plants around the world can benefit from the methodology outlined in this paper.*

Keywords *- Photovoltaic, Amorphous silicon, Hetero-junction with an intrinsic thin layer, Teaching Learning Based Optimization, Root Mean Square Error, Power.*

1. Introduction

Solar Photovoltaic (PV) energy is one of the most promising renewable energy sources because of its attractive advantages, including being limitless and free of carbon emissions, fuel, and noise. A PV system's fundamental components are PV cells and modules. They have a direct impact on the system's evaluation and control. Precise mathematical models must be produced to raise the evaluation and control levels. The temperature of the solar PV modules significantly impacts PV module efficiency since it lowers output power and ultimately diminishes PV system performance.

Due to the various mounting techniques used, the module temperature negatively impacts the PV system's performance. The appropriate placement of the module temperature sensor is crucial to reducing this degradation [1]. The centre of the solar PV module is the ideal location for the sensor, which aids in precise PV performance estimation.

The necessity for module temperature prediction is crucial for optimal energy output prediction as it serves to account for local environmental factors such as in-plane irradiance, wind speed and ambient temperature with daily time instance [2]. In this research, the local environmental characteristics are taken into account for estimating the module temperature model coefficient. Also, it calculates the estimated module temperature using the predicted coefficient and the module temperature after taking the provided models' coefficients for the site into account.

A weather station and separate Current-Voltage (I-V) scanners for each technology are used as examples for testing the three technologies at NISE, India, in collaboration with the

Advanced Industrial Science and Technology (AIST), Japan, at the department of New and Renewable Energy (MNRE), Government of India. The images for the technological components are shown in Figure 3. The solar array, data logger with PV analyzer, and associated software for communication and analysis are the four key elements of this PV test setup.

Many researchers have developed analytical methods to describe the behaviour of PV modules. It has the benefits of speed and simplicity. However, the accuracy of the parameters is significantly influenced by a number of distinct data points collected at the Standard Test Conditions (STC) by the PV manufacturer. Unexpected faults will result from any noise on them and differing operation conditions. Therefore, the retrieved parameters are physically impractical and erroneous due to simplification, approximation, and undue reliance on a small number of individual data points.

The Teaching-Learning-Based Optimization method is presented in this article as a means of achieving global solutions with more consistency and little calculative work. The teaching and learning concept is the foundation of the TLBO approach. The TLBO method is relayed on the teacher's teacher's-students' influence on performance in a class.

In this case, output is measured in terms of outcomes or grades. The teacher is frequently thought of as a knowledgeable somebody who gives knowledge to the students. The effectiveness of a teacher has an impact on pupils' performance. It goes without saying that a good teacher helps pupils learn in order for them to get better grades or test scores.

Additionally, learners gain knowledge through their interactions with one another, which also aids in their performance. The weather in India has several diverse seasonal patterns, making it very different from any other nation. The three main seasons are summer, monsoon, and winter, each of which uniquely impacts the spectrum. For performing detailed analysis with respect to season, in the proposed work, the monsoon season is subdivided into monsoon and post-monsoon sub-season. According to our knowledge, teaching learning-based optimization is a unique technique used to optimize parameters like temperature and output power for a-Si and HIT PV technologies by considering seasonal variation.

2. Different PV Module Technologies

Temperature Hetero-junction intrinsic thin layer technology under the promising hetero-junction category and amorphous silicon technology under the thin film category is the most widely used technology globally [3-5]. Due to the prevalence of these technologies in the PV industry, in this proposed work, the same PV technologies are considered and explained in detail with their typical structure.

2.1. Thin Film Technology

Typically, thin layers of semiconductor material are applied to glass surfaces to create thin film technology. This technology is more flexible, lighter, simpler, and easier to build than Crystalline Silicon (c-Si) technology. 15% of PV market sales worldwide are attributable to this technology. Compared to c-Si, the energy conversion efficiency is substantially lower. Their optical absorption coefficient indicates that the band gap is approximately 1.7 eV. The increased power production at high temperatures is the key benefit of employing thin film technology. This is brought on by a lower temperature coefficient value and more dispersed radiation absorption. The two main subtypes of thin film technology are multi-junction and amorphous silicon. The amorphous silicon PV module is a widely established and well-liked form of thin film technology. Figure 1 depicts the a-Si module construction and solar cell architecture. The design of the solar cell has various layers. TCO (Transparent Conducting Oxide) serves as an antireflective component. Due to its wider band gap and greater conductivity than the hydrogenated a-Si (a-Si: H) layer, hydrogenated a-Si (a-SiC: H) is deposited in this layer and employed as a p-type layer. The purpose of the p and n-doped layers is to create an electric field over the intrinsic i-type layer, which is a photo-absorbing layer, and to help with good electrical contact for the purpose of collecting electrons at the end terminals. Several layers of light-absorbing semiconductor material are placed onto a substrate, such as coated glass, to create a thin film module. Due to the very thin semiconductor layers, solar energy can be efficiently absorbed.

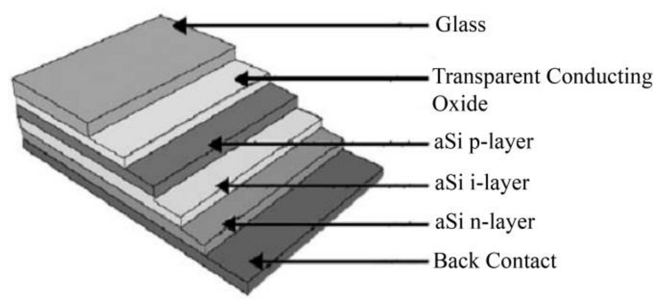

Fig. 1 Thin film a-Si module construction

2.2. Hetero-Junction Technology

The most recent emerging technology in the global solar PV market is silicon hetero-junction technology. It is highly well-liked in the industry right now because of its high-efficiency solar cells. Solar cells have an energy conversion efficiency of 21% at industrial manufacturing levels. Compared to c-Si, it exhibits a wider spectrum response and a band gap of about 1.06 eV. Due to the low-temperature coefficient of the solar cell's construction, technology can continue to operate at high temperatures while maintaining excellent energy conversion efficiency. Consequently, more energy is produced over the full day's sunny hours. When compared to competing technologies, the unique solar cell structure has better high-temperature stability [6-9].

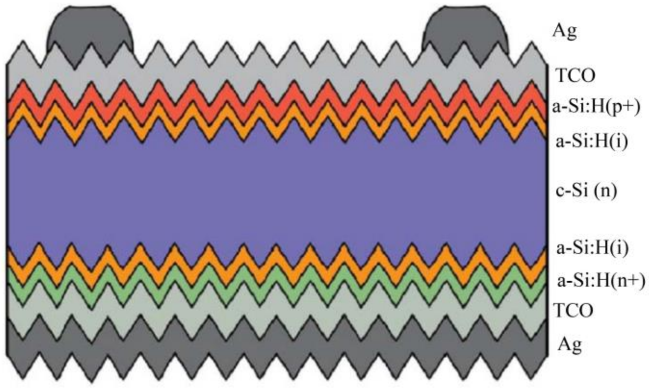

Fig. 2 Silicon hetero-junction PV modules construction

The Silicon Hetero-Junction (SHJ) PV module structure is similar to that of c-Si PV modules; however, the solar cell structure is different. Thin amorphous silicon (a-Si) layers are placed on crystalline silicon wafers to create the SJH solar cells depicted in Figure 2. The main component of this method is the metal grid contacts, a location in conventional c-Si solar cells that is highly recombination active. As a result, it inserts a wider band gap layer hydrogenated a-Si (a-Si: H) buffer layer to electrically disconnect from the absorber. Antireflective Transparent Conductive Oxide (TCO) coating is formed on top of these layers. Additionally, an intrinsic a-Si: H layer is deposited on the backside of the c-Si material, followed by n-type a-Si: H.

3. Measurement and Experimental Setup

The Temperature (T_m) of the module is a crucial factor for determining efficiency and output power. This is because it directly impacts the PV module's output performance. The photovoltaic test system consists of a solar array, a data recorder with a solar analyzer, and auxiliary software for communication and analysis.

A conceptual experimental measuring setup used in NISE is shown in Figure 2. Additionally, this place is 216 metres above sea level and may be found at 28° 37'N latitude and 77° 04'E longitude. The same area of these technologies' modules, namely a-Si, HIT, and mc-Si, is set up parallel to the sites at a slope angle of 28°.

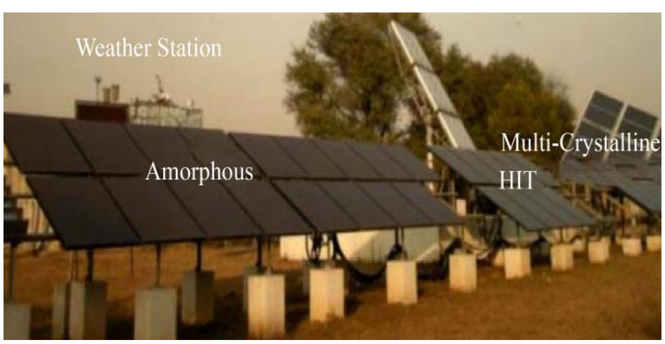

Fig. 3 Experimental setup at NISE, Gurgaon, India

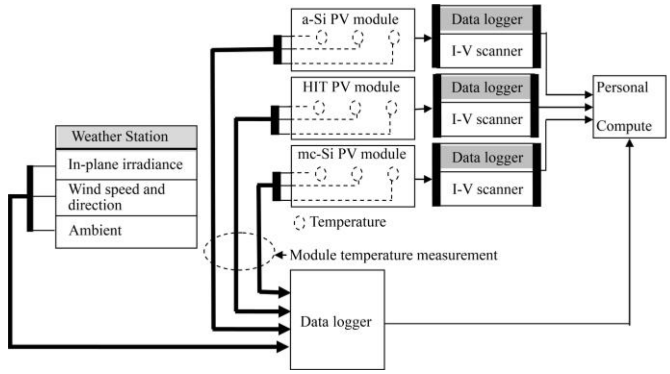

Fig. 4 Test setup of measurement system

While environmental characteristics like irradiance (G_t), wind speed (V_w), and ambient temperature (T_a) are sensed by sensors and sent to data loggers, which then send the information to a personal computer for estimation, data loggers collect information from modules and send it to computers for estimation. The solar radiation was measured by a pyranometer sensor. A wind sensor in the shape of a propeller can pick up V_w at heights of about three metres. A K-category thermocouple is considered to track the air's temperature. Real-time data, including the temperature of each solar module and information on the current and voltage, were gathered over a 10-minute period. To record solar radiation on the exterior surface of the module with a 305-2800 nm wavelength (λ) range, a Pyranometer has a resolution of 10 W/m^2. A wind sensor is used to record the speed of wind V_w with standard resolution 0.3 m/s, 3°. In order to sense and record the atmospheric temperature, a temperature sensor with a resolution of 0.2°C is used. Heuristic modelling was employed to implement this model for power deviation prediction. Important environmental factors that have an indirect and direct impact on the power of the PV module are included in the model. Irradiance has a big impact on module power. Other major environmental elements that impact module temperature are ambient temperature and wind speed. To estimate the percentage of the power departure from STC, a heuristic approach is presented in the following equation, which takes into account the inter-correlation and reliance of various environmental elements; this deviation from STC is given by (ΔP):

$$\Delta P = 100 * \left\{\frac{[P_{STC} - (E_1 * E_2)]}{P_{STC}}\right\} \tag{1}$$

Where,

$$E_1 = a_1 AG + a_2 AG \ln\left(\frac{G}{G_{STC}}\right)$$

$$E_2 = 1 + \Upsilon_m\left(\left[a_3\left(1 - \frac{P_{STC}}{G_{STC}.A}\right)G + a_4 T_a + a_5 V_w + a_6\right] - T_{STC}\right)$$

Where G_{STC}, P_{STC}, and T_{STC} denote the module's irradiance, power, and temperature under standard test conditions, respectively. The instantaneous environmental parameters G, T_a, and V_w represent the in-plane irradiance, ambient temperature, and wind speed, respectively. TLBO method can considered to formulate module temperature as a series of linear terms with variable coefficients. This formulation greatly accounts for the interdependency of various factors, as shown in Eq. (1).

4. Methodology of TLBO

Rao proposed TLBO as an easy-to-use and effective optimization technique. The teacher's impact on students' performance in a class is where the core idea comes from. For nonlinear optimization issues, it is a population-based optimization approach. The majority of TLBO is made up of the teaching phase and the learner phase. During the teaching phase, the teacher imparts knowledge to the students. In the learner phase, students benefit from one another's knowledge.

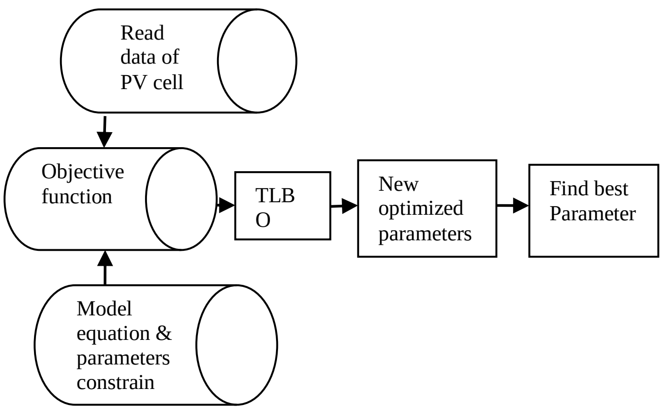

Fig. 5 Methodology of TLBO

4.1. Teacher Phase

The best learner in a class with one teacher and N_p-1 students (x_i, I = 1,...., N_p) is typically the teacher ($x_{teacher}$), who disseminates the knowledge to the students to raise the class mean. The definition of the class's mean value (x_{mean}) is,

$$X_{mean} = \frac{1}{N_p}\sum_{i=1}^{N_p} X_i \tag{2}$$

In the teaching process,

$$X_{i,new} = X_i + rand.(X_{teacher} - T_F.X_{mean}) \tag{3}$$

The i[th] updated learner is represented by $x_{i,new}$; TF is the teaching factor, and its value is either 1 or 2. Rand is a random value in the range of zero to one, and the rand is a teaching factor.

All $x_{i,new}$ are assessed in accordance with the goal function following each repetition. If $x_{i,new}$ is superior to x_i, then $x_{i,new}$ is substituted for x_i; else, x_i remains unchanged.

4.2. Learner Phase

In the learner phase, a student randomly selects another learner with whom to communicate in order to advance her or his knowledge through activities, including formal communications and dialogues. The formulation of the learning process is as follows:

$$X_{i,new} = \begin{cases} X_i + rand.\left(X_i - X_j\right), & iff(X_i) < f\left(X_j\right) \\ X_i + rand.\left(X_j - X_i\right), & Otherwise \end{cases} \tag{4}$$

Where f(x) is the value of x's objective function, and x_j is the learner distinct from x_i by the j[th] learner. Accept $x_{i,new}$ instead of x_i if $x_{i,new}$ is superior. So, to obtain the best answer, TLBO used both the instructor and learner phases. During the teaching phase, the teacher tries to help all students learn from her/him to raise the x_{mean}.

However, each learner's improvement is partially dependent on their own capacity for learning. In the learner phase, a learner x_i simply chooses a learner x_j at random to exchange knowledge with.

5. Result and Analysis

Implementing TLBO is simpler since, unlike other optimization approaches, it does not need any algorithm parameters to be tweaked. The population's current solution is changed using TLBO, which raises the convergence rate. The proposed model has been used to forecast the power deviation from STC for a-Si and HIT PV technologies modules in this part. The model's coefficients were determined via teaching learning-based optimization method analysis of measured data collected over the course of a year, together with technological specifications recommended by the manufacturer. The proposed study has used the measured module temperature to derive the model's coefficients a_3, a_4, a_5, and constant a_6. The analysis also employed these coefficients to derive the a_1 and a_2 coefficients together with the measured power deviation.

Tables 1 and 3 provide the calculated coefficients for various technology modules, namely a-Si and HIT, respectively.

Table 1. Model coefficients and constants for a-Si panel

Coeffi-cients	Monsoon	Post Monsoon	Winter	Summer
a_1	0.07	0.067	0.059	0.066
a_2	-0.001	0.018	0.003	-0.008
a_3	0.03	0.027	0.028	0.025
a_4	0.77	0.765	1.15	1.138
a_5	-1.61	-2.25	-2.22	-1.81
a_6	17.22	14.34	3.403	5.42

Table 2. Temperature and power RMSE for a-Si panel

Parameter	Monsoon RMSE	Post Monsoon RMSE	Winter RMSE	Summer RMSE
Temperature	2.2093	3.5305	3.2158	2.15
Power	4.5662	3.5042	1.40	4.7432

Table 3. Model coefficients and constants for HIT panel

Coefficients	Monsoon	Post Monsoon	Winter	Summer
a1	0.1268	0.1250	0.13	0.12
a2	-0.0136	-0.0102	-0.0072	-0.01
a3	0.0415	0.0463	0.042	0.0425
a4	0.9248	0.6686	1.0505	1.0317
a5	-1.4733	-1.6399	-2.2643	-1.3355
a6	5.9844	9.9994	1.9818	0.5174

Table 4. Temperature and power RMSE for HIT PV panel

Parameter	Monsoon RMSE	Post Monsoon RMSE	Winter RMSE	Summer RMSE
Temperature	1.5821	2.4967	2.0611	1.6479
Power	2.3490	3.9044	2.655	2.3270

Temperature-related coefficients (a_3–a_6) may vary depending on the site situation. However, such a variation would not significantly affect electricity generation due to the low value of temperature coefficients. The characteristics of the module technology would be mostly connected to the coefficients for terms a_1 and a_2 of power generation. Power would be most significantly impacted by coefficient a_1, following the efficiency trend of various technological modules. In comparison to the a_1 coefficient, other coefficients have a smaller effect.

The module temperature was initially calculated using its TLBO formula, and the root mean square error was determined for four distinct seasons: monsoon, post-monsoon, winter, and summer. Monsoon, post-monsoon, winter, and summer have temperature RMSE values of 2.2093, 3.5305, 3.2158, and 2.1457, respectively, for a-Si PV technology. The next step is to determine the power of RMSE. Power RMSE values for the monsoon, post-monsoon, winter, and summer seasons with respect to a-Si PV technology are 4.5662, 3.5042, 1.3953, and 4.7432, respectively.

Similarly, RMSE temperatures for HIT PV technology are noted as 1.5821, 2.4967, 2.0611, and 1.6479 for monsoon, post-monsoon, winter, and summer, respectively. Whereas Power RMSE values for the monsoon, post-monsoon, winter, and summer seasons with respect to HIT PV technology are 2.3490, 3.9044, 2.6553, and 2.3270, respectively.

In Figures 6 to 9, the influence of seasonal spectrum variation of a-Si thin film technology and HIT technology are depicted for temperature and output power for the specified site. When compared to module temperature, the amorphous-silicon thin film technology modules are extremely susceptible to seasonal spectrum variation. India has three distinct seasons; hence, the graphs individually show efficiency and output power for each season on a given day. Monsoon season is separated into monsoon and post-monsoon categories to undertake detailed analysis.

The results in Tables 2 and 4 demonstrate that the power deviation predicted by the model and the experimentally measured deviation correspond quite well. Despite some differences between experimental and anticipated values, RMSE has been utilized to quantify this variation, and Figures 6 to 9 use graphics to show this variation. Even if there are occasional differences between observed and anticipated values, which may be the result of approximation mistakes, their impact on overall outcomes is minimal. Due to increased noise and other minor environmental influences during outside studies, the range in experimental values is greater than predicted values. Additionally, because a-Si PV technology is more sensitive to temperature than HIT PV technology, those modules have more diversity. When using an optimization approach for a-Si technology based on teaching and learning, the graph shows that the actual and anticipated output power and temperature values are in good agreement.

Table 5. Comparative analysis with respect to the proposed method

Ref No.	PV Technology	Predicted Power RMSE
[3,4]	a-Si	5.14
	HIT	5.09
[1,5]	a-Si	5.52
	HIT	5.63
[2,6]	a-Si	4.84
	HIT	4.80
[7,8]	a-Si	5.07
	HIT	5.34
[9]	a-Si	5.18
	HIT	6.14
[2]	a-Si	5.28
	HIT	4.86
Proposed Method	a-Si	**3.55**
	HIT	**2.81**

Table 5 compares power RMSEs with power RMSEs obtained in the literature.

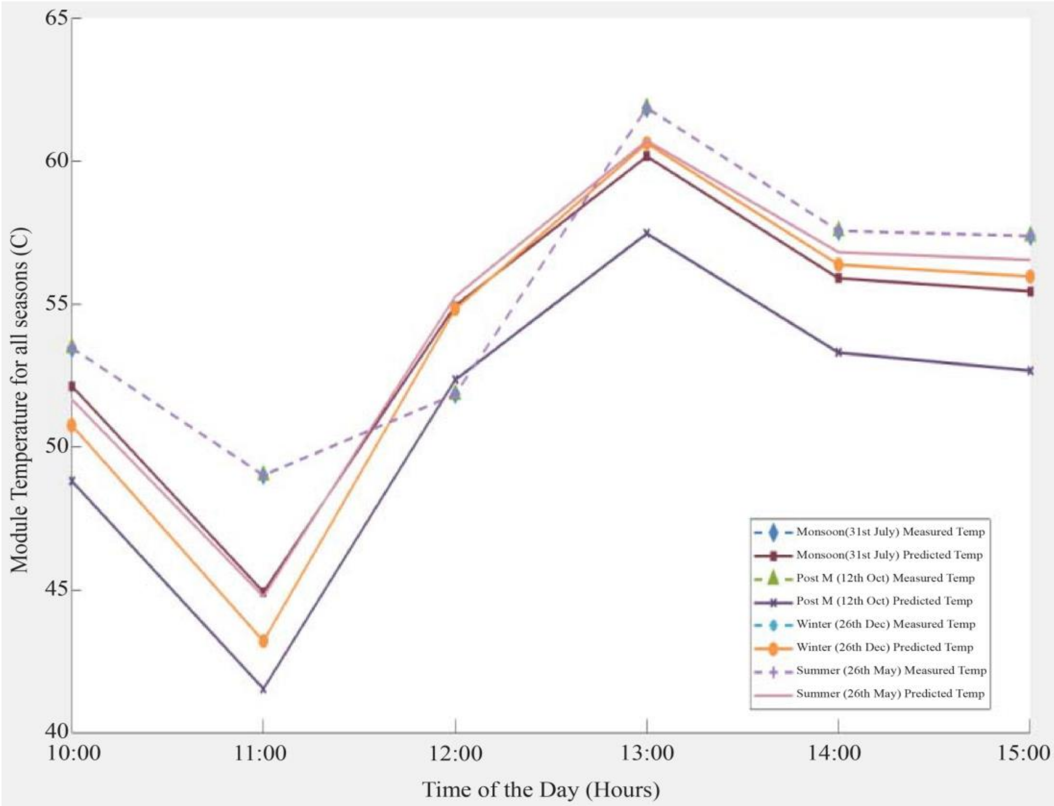

Fig. 6 Season-wise temperature variation for a-Si panel

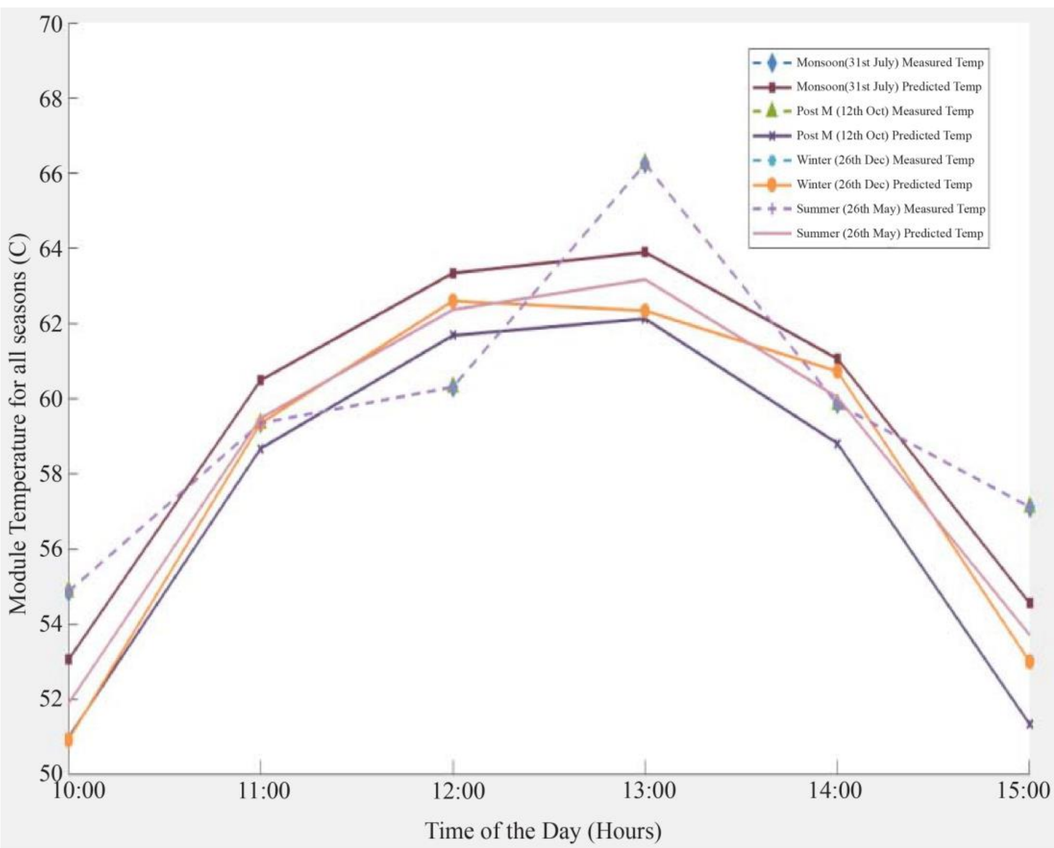

Fig. 7 Temperature variation with respect to seasons for HIT panel

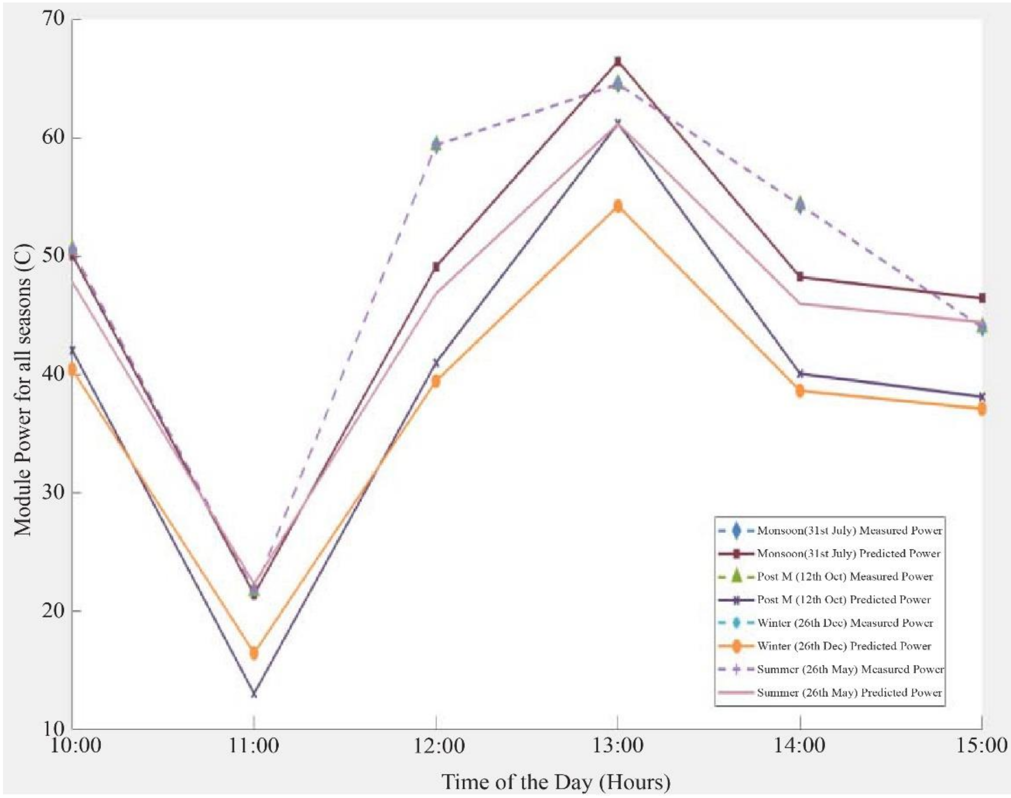

Fig. 8 Output power variations with respect to seasons for a-Si panel

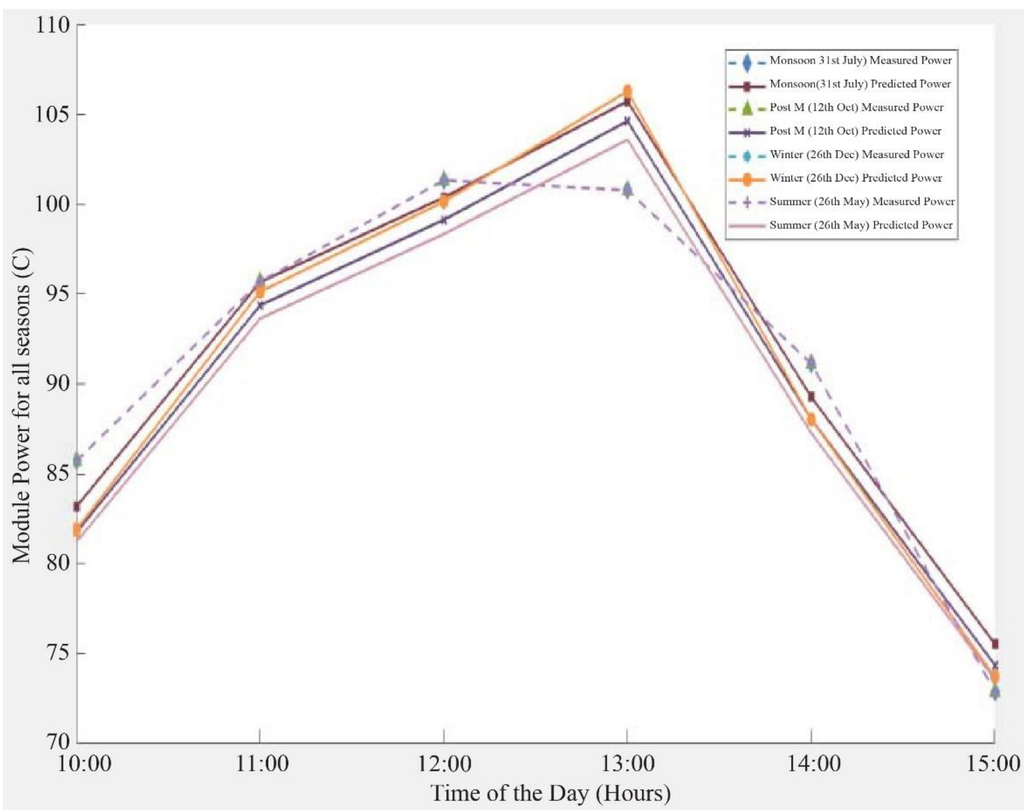

Fig. 9 Season-wise output power variation for HIT technology

Table 6. Temperature and power RMSE for the proposed method

PV Technology	Temperature RMSE by Suggested Method	Power RMSE (%) by Suggested Method
a-Si	2.78	3.55
HIT	1.95	2.81

As the power RMSE value is small compared to other methods, teaching learning based optimization method is improving over the other proposed methods. In Table 6, temperature and power RMSE values are shown. The findings demonstrated that the temperature and output power of the HIT PV module technology were functioning well at the NISE site when compared to a-Si. Its lower RMSE value in relation to temperature and power parameters is the cause of this. So, from this, the proposed work shows the performance improvement of the PV system.

6. Conclusion

The power departure from STC in this situation has been predicted using a model considering various parameters. For a-Si technology PV modules, the discrepancy between the model's anticipated results and the experimental findings was less than 2.78% with respect to temperature and 3.55% with respect to power, whereas for HIT, it is 1.95% with respect to temperature and 2.81% with respect to power, supporting the modelling technique and demonstrating its value in designing PV installations.

From the findings, we can conclude that the temperature and output power of the HIT technology were functioning well when compared to a-Si technology. Results indicate that TLBO is a successful and efficient optimization approach to other methods proposed in the literature.

The research described in this paper may offer a fresh viewpoint on how to rate PV modules for a more accurate performance evaluation.

Acknowledgment

The National Institute of Solar Energy (NISE), Gurgaon, and Japan's Advanced Industrial Science and Technology (AIST) are both to be thanked by the writers.

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