INTRODUCTION

Global installed capacity for solar power has seen an exponential growth over the past decade in developed and developing countries due to a collective effort from the research and development and government policies that encourage power generation from renewable energy sources. In the present scenario, India is expanding its solar power capacity under the Jawaharlal Nehru National Solar Mission. The national solar mission encompasses a target solar photovoltaic (PV) installation of 40 GW rooftop installation and 60 GW large and medium scale grid connected solar PV projects by the year 2022. By achieving this ambitious target, India will become one of the largest solar energy producers in the world.

In a PV system, the performance of module is influenced by different factors such as solar cell technology, configuration of module installation, instantaneous meteorological parameters, and cell temperature. However, the performance of PV module is most influenced by cell temperature after irradiance. As it is difficult to access solar cell in a module
due to practical limitations, module temperature \( (T_m) \) measured at the rear surface has been considered analogous to cell temperature.\textsuperscript{8–10} Therefore, the impact of temperature on field performance of PV module is generally analyzed with respect to \( T_m \).

Estimation of \( T_m \) in the field conditions plays an important role in performance assessment of PV systems.\textsuperscript{5,11–13} In a country like India, most of the regions experience hot climatic conditions for a significant portion of the year; therefore, estimation of \( T_m \) with appropriate temperature correlation facilitates more accurate evaluation of power generation and energy yield. Since large number of correlations already exists in the literature which uses different approaches to formulate physical relationship between module temperature and meteorological parameters, the emphasis of this work is to cater the need for assessment of different correlations. The basic approach to derive temperature correlation between \( T_m \) and meteorological parameters utilizes the concept of energy conservation.\textsuperscript{6,9,14}

Other approaches to estimate \( T_m \) include regression analysis or heuristic approach.\textsuperscript{4,12,15–17} Different correlations available in the literature which uses different approaches to formulate physical relationship between module temperature and meteorological parameters, the emphasis of this work is to cater the need for assessment of different correlations. The basic approach to derive temperature correlation between \( T_m \) and meteorological parameters utilizes the concept of energy conservation.\textsuperscript{6,9,14}

The correlations given in Table 1 are implicit and the major difference is in the approximations used for modeling the overall thermal heat loss coefficient \((U)\) and heat transfer coefficient \((h)\).

The correlations given in Table 1 are commonly used to estimate \( T_m \) under operating conditions of the field. Prior assessment of these correlations is important for better estimation of PV module operating temperature in different climatic regions, as these correlations have been obtained by utilizing a particular set of resources.\textsuperscript{3,8,21–25} Acknowledging this, Jakhrani et al\textsuperscript{21} compared the effectiveness of temperature correlations for a site in Malaysia. The variation in correlations’ efficacy to estimate monthly mean \( T_m \) was observed due to difference in climatic conditions, set of variable parameters, configuration of PV module technology, and approach used. Almaktar et al\textsuperscript{22} formulated a different correlation for poly c-Si and mono c-Si PV module in hot and humid climatic conditions using regression analysis which used hourly global solar irradiance \((G)\), ambient temperature \((T_a)\), relative humidity \((RH)\), wind speed \((v)\) to estimate hourly, and daily average \( T_m \). On the contrary, the accuracy of temperature correlations can also be improved by using the available in situ field data to re-estimate the coefficients of the correlation. However, due to unavailability of long-term field data, Koehl et al\textsuperscript{24} proposed that one-month data can be sufficient to re-estimate the coefficients. The effectiveness of this approach was demonstrated by estimating \( T_m \) in different climatic regions with good accuracy. Schwingshackl et al\textsuperscript{8} utilized the assessment of different correlations to

### Table 1

| Name         | Correlation                                                                 |
|--------------|-----------------------------------------------------------------------------|
| Explicit     |                                                                             |
| Standard     | \( T_c = T_a + \frac{\alpha}{\gamma_{NOCT}} (T_{NOCT} - T_{NOCT}) \)       |
| King\textsuperscript{a} | \( T_m = T_a + G T e x p (a + b \times w) \)                           |
| Faiman\textsuperscript{b} | \( T_m = T_a + \frac{\alpha}{\gamma_{NOCT}} \)                                       |
| Implicit     |                                                                             |
| Duffie       | \( T_m = \frac{T_a + \frac{\alpha}{\gamma_{NOCT}} (T_{NOCT} - T_{NOCT}) \left\{ 1 - \frac{\alpha}{\gamma_{NOCT}} \left( \frac{1 + \beta}{1 + \beta_{STC} T_{STC}} \right) \right\}}{1 - \frac{\alpha}{\gamma_{NOCT}} \left( \frac{1 + \beta}{1 + \beta_{STC} T_{STC}} \right)} \) |
| Skoplaki\textsuperscript{c} | \( T_m = T_a + k G T \left\{ \frac{1}{\gamma_{NOCT}} \left( T_{NOCT} - T_{NOCT} \right) \left\{ 1 - \frac{\alpha}{\gamma_{NOCT}} \left( \frac{1 + \beta}{1 + \beta_{STC} T_{STC}} \right) \right\} \right\} \) |
| Skoplaki 1   | \( h = 5.7 + 3.8v \)                                                      |
| Skoplaki 2   | \( h = 8.91 + 2.0v \)                                                     |
| Mattei       | \( T_m = \frac{U T_a + G T (e x p - \beta_{STC} T_{STC} - \beta_{STC} T_{STC})}{(e - \beta_{STC} T_{STC}) G T} \) |
| Mattei 1     | \( U = 26.6 + 2.3v \)                                                     |
| Mattei 2     | \( U = 24.1 + 2.9v \)                                                     |

\( \alpha = -3.56, b = -0.075 \)

\( a_{Si} - U_0 = 27.8, U_1 = 3.59; HIT - U_0 = 28.3, U_1 = 4.47; mc-Si - U_0 = 23.8, U_1 = 3.51 \)

\( \alpha = 1 \)
demonstrate that wind speed ($v$) obtained from numerical weather prediction models can be used as an alternative for in situ wind measurements without significantly compromising on the accuracy of $T_m$ estimation.

The different approaches to estimate $T_m$ in the field conditions assist in understanding implications of temperature on different aspects of PV module performance. Correa-Betanzo et al.\textsuperscript{23} illustrated that accurate $T_m$ estimation can reduce uncertainty in energy estimation. Moreover, the application of explicit and implicit temperature correlations is not limited to performance assessment of PV systems only. The temperature correlations also facilitate performance evaluation of PV-Thermal (PVT),\textsuperscript{26,27} building integrated PV (BIPV),\textsuperscript{3,28} concentrated PV (CPV)\textsuperscript{29} bifacial PV\textsuperscript{30} and floating PV (FPV) systems\textsuperscript{25,31}; however, such installations are very less in comparison with ground installations for which these temperature correlations have been reported. For a BIPV system operational at a site in Thailand, Trinurku et al.\textsuperscript{3} compared the effectiveness of two correlations and found that the heat exchange between module and environment is greatly influenced by air gap and tilt angle between the rear surface of PV module and roof. Such type of improvements in temperature correlations for above cases can be made by including modified heat transfer aspect. After identifying the deviation from standard situation, application-specific modifications in temperature correlations may lead to better estimation of module temperature. Like in FPV application, modules are near to surface of water body, which would influence the heat exchange. Kamuyu et al.\textsuperscript{25} proposed regression analysis-based explicit correlations for estimating module temperature of FPV system. The higher accuracy obtained from these correlations in comparison with the existing correlations in the literature can be attributed to the incorporation of water heat exchange effect. Coherently, for extending application of temperature correlations to bifacial PV modules,\textsuperscript{30} modifications can be made to include the effect of higher elevation, tilt, and packaging aspect. Here, accommodating correct wind speed and wind directional model could improve the estimation.

The comparison among different temperature correlation is required to choose appropriate correlation toward practical application. Since a lot of temperature correlations are available in literature and there was a strong need to assess them in a systematic way on same scale for their effective use. This work mainly caters the need of such comparison among different correlations. In this work, different explicit and implicit module temperature correlations have been assessed for India. Measured data over a long duration for three very different PV module technologies have been used to categorize module temperature into low, mid, and high temperature ranges, based on their frequency of occurrence. The variation in module temperature and frequency of occurrence under different temperature ranges has been explained on the basis of technology and module parameters. Effectiveness of correlations has been compared under different temperature ranges for different PV module technologies to assess the suitability. This assessment in real field conditions would be beneficial for a more accurate estimation of large PV system's performance, which have been installed or are in planning stage under very large Jawaharlal Nehru National Solar Mission. The assessment of different correlation under different temperature ranges will also be helpful in evaluating effectiveness of correlations in different regions.

## 2 | METHODOLOGY

The explicit and implicit correlations given in Table 1 have been employed for different technology PV module and their effectiveness has been compared under different temperature ranges. The three different technology PV module installed in the test bed are single junction amorphous silicon (a-Si), hetero-junction with intrinsic thin layer (HIT), and multicrystalline silicon (mc-Si). The temperature coefficient of power ($\gamma$), efficiency ($\eta_{STC}$), and other specifications of these PV modules are given in Table 2. These three distinct PV module technologies have been chosen for this study to encompass different cases of parameter's combinations. In the category of thin-film PV module technology, a-Si conforms to low $\gamma$ and low $\eta_{STC}$. On the other hand, HIT which is basically a combination of Si-wafer-based technology and thin-film technology has been chosen due to its very high $\eta_{STC}$ compared to a-Si and slightly large $\gamma$. The mc-Si is a wafer-based

| PV Technology | Amorphous Silicon (a-Si) | Hetero-junction Intrinsic Thin layer (HIT) | Multicrystalline Silicon (multi-c-Si) |
|---------------|--------------------------|------------------------------------------|-------------------------------------|
| Type          | Glass-polymer            | Glass-polymer                            | Glass-polymer                       |
| $T_{NOCT}$    | 44                       | 48                                       | 47                                  |
| Module Efficiency $\eta_{STC}$ (%) | 7.1                      | 18.8                                     | 16.3                                |
| Temperature coefficient of power $\gamma$ (%/K) | $-0.3$                    | $-0.33$                                  | $-0.49$                             |

\textbf{Table 2} Parameters of a-Si, HIT, and mc-Si PV module technology
technology which has been chosen because of its large share in the field deployment and it covers the case of very high \( \gamma \) compared to other two technologies, and \( \eta_{\text{STC}} \) is in between these technologies.

The measured data from the test bed of 2 years consist of instantaneous module temperature (\( T_m \)) which has been measured from the rear surface, meteorological parameters: irradiance (\( G \)), ambient temperature (\( T_a \)), and wind speed (\( v \)). The \( T_m \) frequency of occurrence has been analyzed for mc-Si, HIT and a-Si technology module to categorize different temperature ranges. Under these temperature ranges, the frequency distribution of change in \( T_m \) with respect to \( T_a \) has also been analyzed for all the PV module technologies. The variation in \( T_m \) and frequency of occurrence has been explained on the basis of technology and module parameters. The measured meteorological parameters at the site have been used to estimate \( T_m \) of a-Si, HIT, and mc-Si technology PV module. The effectiveness of correlations in different temperature ranges has been compared on the basis of statistical parameters; mean bias error (MBE) and root-mean-square error (RMSE). On the basis of MBE and RMSE, most effective correlation has been obtained under different temperature ranges. The standard deviation (SD) and average values of RMSE have been obtained to further analyze the variation in accuracy of correlations under different temperature ranges for each PV module technology, whereas in a constant temperature range, these SD and average values of RMSE have also been used to analyze the accuracy of correlations for different PV module technology.

### 3 | EXPERIMENTAL SETUP

The test bed comprising of a-Si, HIT, and mc-Si PV module and weather station is installed at National Institute of Solar Energy (NISE), Gurgaon, India, which is located at latitude 28°37’ N, longitude 77°04’ E at an elevation of 216 m above sea level. The modules in the test bed are mounted in an open rack configuration at fixed tilt angle of 28° (equal to the latitude of the site). All the modules have comparable area, similar module packaging (glass-cells-tedlar). The characteristic parameter values of installed PV modules are given in Table 3. The electrical parameters of these modules have been measured using I-V Scanner (Kernel System, PVC01802). The \( T_m \) has been measured by T-type thermocouples (calibrated by Kernel System) at three different locations (top, middle, and bottom) on the rear surface of the modules. Irradiance in the horizontal plane (\( G \)) and tilted plane (\( G_T \)) of PV module was measured by using thermopile-based pyranometer and the \( T_a \) was measured by Pt100 temperature sensor. The wind sensor has been used for measurement of \( v \) at a height of around 3 m. The specification and description of sensing instruments used in weather station are given in Table 3. All the weather parameters have been logged by data logger (Campbell Scientific, CR-1000). The experimental setup recorded the meteorological parameters and module temperature of a-Si, HIT, and multi-c-Si modules from 7 am to 7 pm, at an interval of 10 minutes for 2 years.

| Sensor type          | Maker   | Model   | Accuracy   | Mounting          |
|----------------------|---------|---------|------------|-------------------|
| Pyranometer          | EKO     | MS-802  | 10 W/m²    | Leveling fixture  |
| Wind sensor          | Young   | 05103   | 0.3 m/s    | Pole mount        |
| Temperature sensor   | Vaisala | HMP 155 | 0.2°C      | PV module rear surface |

### 4 | RESULTS AND DISCUSSION

In the following section, the \( T_m \) frequency of occurrence of mc-Si, HIT, and a-Si has been used to categorize different temperature ranges. In different temperature ranges, the change in \( T_m \) with respect to \( T_a \) has been analyzed and the variation in module temperature and frequency of occurrence have been explained on the basis of technology and module parameters. The accuracy of different correlations has been compared to estimate the most suitable correlation.

#### 4.1 | Analysis of module temperature \( (T_m) \) frequency distribution

The \( T_m \) frequency of occurrence for mc-Si, HIT, and a-Si PV module has been analyzed by sorting measured data from the field. The histogram of \( T_m \) frequency of occurrence shown in Figure 1 illustrates that the percentage frequency of occurrence gradually increases to a maximum and then decreases for all PV module technologies. This trend in frequency distribution is like a Gaussian curve; therefore, the concept of full width at half maximum (FWHM) was used to categorize module temperature into low, mid, and high temperature ranges. The low and high temperature ranges have low frequency of occurrence and the mid-temperature ranges has the highest frequency of occurrence. The FWHM of a-Si and HIT PV module was same and the mid-temperature range extended from 30°C to 60°C, whereas the frequency distribution of mc-Si PV module was negative skewed due to which its FWHM was greater compared to a-Si and HIT, and the
mid-temperature range extended from 30°C to 65°C. The test bed is located in a hot climatic region; therefore, maximum temperature up to 75°C has been observed. Also, the highest frequency of occurrence for mc-Si, HIT, and a-Si PV module has been obtained in the temperature range of 40-45°C.

4.2 | Frequency distribution of change in module temperature ($T_m$)

The measured data of three different PV module technologies were sorted on the basis of estimated change in $T_m$ with respect to $T_a$. The frequency of occurrence obtained corresponding to each group has been used to analyze the applicability of same temperature correlation for different technology PV modules in same temperature ranges. The cumulative frequency of occurrence is plotted against the difference of $T_m$ and $T_a$ in Figure 2A, B, and C for low, mid, and high temperature ranges, respectively, for mc-Si, HIT, and a-Si modules. It can be seen from Figure 2A that under the low temperature range, all PV module technologies show nearly identical variation of cumulative frequency of occurrence, which indicates similar heat exchange between module and the surrounding. This indicates that single module temperature correlation with uniform coefficients can be equally effective for all technology PV modules. In Figure 2B corresponding to the mid-temperature range, different technology PV modules show significant variation. The steeper slope of HIT compared to a-Si in the range of 2.5°C to 27.5°C shows that a-Si PV module exhibits more occurrences at higher $T_m$. The mc-Si PV module shows a similar trend that is intermediate of other two technology PV modules. The higher number of occurrences at low $T_m$ for HIT compared to others is because of its highest $\eta_{STC}$ and low $\gamma$. The slightly higher number of occurrences in mc-Si at lower $T_m$ compared to a-Si can be attributed to its high $\eta_{STC}$. Broadly the variation in cumulative frequency indicates that single module temperature correlation accommodating the difference in technology parameters can be equally effective for all technology PV modules. Figure 2C illustrates that the HIT and a-Si PV module show a similar trend in variation of frequency of occurrence under the high temperature range. The relatively steep slope of HIT and a-Si compared to mc-Si indicates that mc-Si exhibits more occurrences at higher $T_m$ due to high $\gamma$ and high $T_{NOCT}$. Similar to the case in Figure 2A, the variation in cumulative frequency indicates that single module temperature correlation with uniform coefficients can be equally effective for all HIT and a-Si PV modules.

4.3 | Assessment of correlation for different technology PV module

In this section, the effectiveness of different temperature correlations given in Table 1 has been analyzed separately for a-Si, HIT, and mc-Si PV module.

4.3.1 | Estimation of a-Si module temperature ($T_m$)

The pie chart in Figure 3 illustrates the frequency of occurrences corresponding to a-Si PV module in different temperature ranges. It shows that frequency of occurrence in the low, mid, and high temperature ranges is 15.42%, 74.87%, and 9.71% of total occurrences, respectively. In the low temperature range, it was observed that $G_T$ was less than 400W/m$^2$ during 88% of occurrences, whereas in the high temperature range, it was observed that $G_T$ was greater than 600W/m$^2$ during 92% of occurrences. On the other hand, mid-temperature range comprising of highest frequency of occurrence showed a wide variation in irradiance conditions.

The MBE of different correlations under low, mid, and high temperature range is shown in Figure 4 for a-Si PV module. It can be seen from the figure that in low temperature range, correlations give negative MBE, which reflects the average trend observed for majority of data points and the magnitude of MBE value indicates extent of $T_m$ overestimation. On the hand in the mid and high temperature ranges, positive MBE has been obtained for nearly all the correlations. Figure 4 shows that in the low temperature range, all correlations give nearly same accuracy, as SD in MBE for different correlation is very less compared to other ranges and lowest MBE obtained for King correlation ($-2.2^\circ$C) was close to the average MBE of the temperature range. Compared to the low temperature range, significant variation in MBE has been observed in the mid-temperature range. In this temperature range, MBE of Standard and Faiman correlation has been obtained close to zero while the MBE of other correlations was between 1°C and 4°C. On the contrary in the high
temperature range, largest MBE values have been obtained for all correlations which reflect a major decline in accuracy of temperature estimation. Lowest MBE in this temperature range has been estimated for Standard correlation (3.4°C), whereas the MBE of other correlations was between 3.7°C and 9.3°C which shows highest underestimation of $T_m$.

The histogram of RMSE obtained under low, mid, and high temperature ranges corresponding to different correlations is shown in Figure 5 for a-Si PV module. Figure shows that highest RMSE for all the correlations has been obtained in the high temperature range. Similar to the observed trend in MBE under the low temperature range, the SD in RMSE of different correlations was found to be very less due to which lowest RMSE of 4.5°C obtained for King correlation was close to the average RMSE. It can be seen from Figure 5 that the RMSE of all correlations in mid-temperature range was lesser compared to other ranges, except for King, Duffie, and Skoplaki correlations. The lowest RMSE of 4.3°C in this range was given by Faiman and Mattei 2 which suggests that these correlations are more effective. The highest SD and average of RMSE corresponding to different correlations estimated in the high temperature range indicate significant variation and decline in accuracy of correlations. Lowest RMSE in this temperature range has been obtained for Faiman (6.2°C), while the average RMSE for all correlations is 7.9°C. Since the occurrences of high temperature are mostly found during noon when the solar insolation is high, the underestimation and low accuracy can lead to significant offset in energy yield estimation. Results show that as the frequency of occurrence in the low temperature ranges was very less compared to the combination of mid and high temperature ranges, the Faiman correlation seems a better choice for accurate $T_m$ estimation.

4.3.2 | Estimation of HIT module temperature ($T_m$)

The pie chart in Figure 6 illustrates the frequency of occurrences corresponding to HIT PV module in different temperature ranges. It shows that the low, mid, and high temperature ranges had 16.4%, 77.7%, and 5.9% of total occurrences, respectively. It was observed that in the low temperature range, $G_T$ was less than 400W/m² during 84% of occurrences and
in the high temperature range $G_T$ was greater than 600W/m² during 93% of occurrences.

The MBE of different correlation under low, mid, and high temperature ranges is shown in Figure 7 for HIT PV module. It can be seen from the figure that Standard correlation consistently gives negative MBE in all temperature ranges. In low and mid-temperature ranges, the Standard correlation gives negative MBE of $-4^\circ$C, which also indicates largest overestimation. However, in the low temperature range, average MBE of all correlations excluding Standard was $-2.1^\circ$C, which is comparatively low and lowest MBE has been obtained for Mattei 1 ($-1.4^\circ$C). Similarly, in the mid-temperature range MBE for Duffie and Faiman was obtained close to zero, whereas the average MBE of other correlations (excluding Standard correlation) is 2.3°C. In the high temperature range, the Standard correlation gives lowest MBE of $-1^\circ$C, whereas for other correlations, MBE was obtained between 4°C and 9°C.
The histogram of RMSE obtained under low, mid, and high temperature ranges corresponding to different correlations is shown in Figure 8 for HIT PV modules. It can be seen from the figure that except Standard and Faiman, other correlations have a monotonically increasing trend in RMSE, which indicates that accuracy of correlation decreases from low temperature range toward high temperature range. The SD in RMSE of different correlations estimated for all temperature ranges shows that the variation in accuracy of different correlations is less for low and mid-temperature ranges compared to high temperature range. In the low temperature range, average RMSE of 4.1°C was estimated, while lowest RMSE of 3.4°C was obtained for Mattei 1 correlation. In the mid-temperature range, average RMSE of 4.8°C was estimated, while lowest RMSE of 4.1°C was obtained for Faiman correlation. Similar to a-Si PV module, it has also been found that Faiman correlation gives lowest RMSE in the mid-temperature range, compared to its corresponding values in low and high temperature ranges. Compared to a-Si PV module, the average RMSE value of correlations in the high temperature ranges is relatively high for HIT. The average RMSE of correlations in this temperature ranges has been estimated 8.4°C, while the lowest RMSE of 6.4°C was obtained for Standard correlation.

4.3.3 | Estimation of mc-Si module temperature ($T_m$)

The pie chart in Figure 9 illustrates the frequency of occurrences corresponding to HIT PV module in different temperature ranges. It shows that the low, mid, and high temperature ranges had 14.39%, 81.12%, and 4.5% of total occurrences, respectively. It was observed that in the low temperature range, $G_T$ was less than 400W/m² during 91% of occurrences, and in the high temperature range, $G_T$ was greater than 600W/m² during 96% of occurrences.

The estimated MBE of different correlation under low, mid, and high temperature range is shown in Figure 10 for mc-Si PV module. It can be seen from the figure that the general trend in MBE is similar for all PV module technologies. In the low temperature range, Standard and Faiman correlations give relatively higher MBE close to $−3°C$ compared to the average MBE of other correlation ($−1.1°C$). On the other hand, in the mid-temperature range Standard and Faiman correlations give MBE close to zero, whereas the average MBE of other correlations was $4.8°C$. In the high temperature range, Standard and Faiman correlations give lowest MBE of $3.6°C$ and $4.1°C$, whereas for other correlations, the average MBE value was $10.9°C$. Results show that the change in MBE from low to high temperature range is very large in case of mc-Si, compared to other PV module technologies.

The histogram of RMSE obtained under low, mid, and high temperature ranges corresponding to different correlations is shown in Figure 11 for mc-Si PV module which is most widely used technology in the field. It can be seen from the figure that, excluding Faiman, all correlations show a monotonically increasing trend in RMSE which indicates that accuracy of correlation decreases from low temperature range toward high temperature range. Similar to a-Si and HIT PV module, the estimated SD in RMSE of different correlation was very less in the low temperature range. As a result, in this temperature ranges the minimum RMSE obtained for King and Mattei 1 (3.5°C) was close to the average RMSE of all correlations (3.9°C). It can be seen from Figure 11 that Faiman correlation gives lowest RMSE of 4.2°C and 6.6°C in the mid and high temperature range, respectively. Results show that similar to a-Si and HIT PV module technologies, the RMSE of Faiman in the mid-temperature range is lowest compared to its corresponding values in low and high temperature ranges, which
indicates better suitability. Moreover, similar to a-Si PV module, Faiman correlation also gives lowest RMSE in the high temperature range. Based on the estimated SD and average of RMSE under the mid and high temperature range, it has been found that for mc-Si PV module, the accuracy of correlations was relatively low, and variation in accuracy was also very high. As the frequency of occurrence in the low temperature ranges was very less compared to the combination of mid and high temperature ranges, the Faiman correlation appears to be most suitable choice for \( T_m \) estimation.

5 | CONCLUSION

This work presented assessment of different explicit and implicit correlations of module temperature for India, under different temperature ranges based on frequency of occurrence. Primary analysis shows that module temperature frequency of occurrence follows a Gaussian like distribution, which has been used to categorize module temperature in low, mid, and high temperature ranges from the field data of 2 years. As expected, frequency of occurrence was less within low and high temperature ranges as compared to mid-temperature range which had 78%, 75%, and 81% occurrences for a-Si, HIT, and mc-Si PV technology module, respectively. Different technology modules have been analyzed under different temperature ranges, and their frequency of occurrence and temperature variations have been explained on the basis of technological and module parameters.

It has been observed that accuracy of correlations decreases from low module temperature range toward high module temperature range for all technology modules, except in case of Faiman correlation, which gives highest accuracy in mid-temperature range, that also has highest frequency of occurrences. Under the low temperature range, lowest RMSE of 3.5°C and 3.4°C has been obtained for mc-Si and HIT technology PV modules, respectively, by Mattei 1 correlation, whereas for a-Si, lowest RMSE of 4.5°C was obtained by King correlation, which is close to that of Mattei 1 correlation (4.8°C). Overall, Mattei 1 correlation represents most suitable for low temperature range, whereas Faiman correlation was most effective under the mid-temperature range for all technology modules, which has given lowest RMSE of 4.2°C, 4.1°C, and 4.3°C, for mc-Si, HIT, and a-Si modules, respectively. Under the high temperatures range, lowest RMSE was obtained by Faiman correlation for mc-Si and a-Si of 6.6°C and 6.2°C, respectively. However, in case of HIT technology, the Standard correlation gives lowest RMSE of 6.4°C compared to 7°C of Faiman correlation. Due to very low number of occurrences in the low temperature range, compared to the combination of mid and high temperature ranges, Faiman correlation comes out to be the best choice of module temperature estimation by any single correlation. Among all the PV technology modules, the variation in accuracy under different temperature ranges was highest for mc-Si, which is most widely used PV technology in the field.

The comprehensive analysis and discussion presented in this work enhance the knowledge of correlation’s effectiveness and their applicability in field conditions for different technology PV modules, especially from an Indian perspective. This work helps to choose appropriate correlation for module temperature estimation from large pool of available correlations, which can improve performance assessment of large solar PV plants, that have been installed or in the planning stage under a very large national solar mission. The assessment of different correlation in different temperature ranges can also help to evaluate effectiveness of correlations in different regions.
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