Tree-based ensemble approaches for desert grid-tied solar module temperature prediction

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Abstract - *A key factor in a grid-tied PV station's performance and a significant factor in the efficiency of the PV system is the temperature of the PV modules. Using tree-based ensemble approaches, such as random forest and boosted decision tree, we are interested in forecasting the module temperature of a grid-tied photovoltaic system in this study. In order to compare the outcomes of tree-based ensemble approaches, the linear least squares method and the artificial neural network method were utilised. To increase accuracy, avoid overfitting, and optimise the model's parameters, the tree ensemble approach was hyper-tuned. The accuracy of each produced model was comparable throughout training, and they are all equally useful for forecasting PV module temperature. The findings demonstrated that, during testing, the tree-based ensemble approaches maintained their accuracy with R2 over 0.98. The value of the tree-based ensemble over the traditional technique, notably the ANN, is demonstrated by the declining accuracy of other methods.*

Key Words: Grid-tied PV station, Photovoltaic tree, Module temperature, Photovoltaic cell, Optimization

1. INTRODUCTION

Photovoltaics are crucial to combating global warming and building an eco-friendly economy (Bouraiou et al. 2020).

The conversion efficiency of the PV module can be affected by PV technologies (Edalati, Ameri, and Iranmanesh 2015), PV array tilt angles (Saber et al. 2014), dust accumulation on photovoltaic panels (Abderrezzaq et al. 2017b; Mostefaoui et al. 2018, 2019), partial shading on PV modules (Dabou et al. 2017), and an array tilt angle that is too steep (Abderrezzaq et al. 2017a; Dabou et al. 2016). However, the PV module temperature is the main factor that significantly affects efficiency (Franghiadakis and Tzanetakis 2006; Necaibia et al. 2018; Skoplaki and Palyvos 2009b), output power (Ba, Ramenah, and Tanougast 2018), and energy yield (Correa-Betanzo, Calleja, and De León-Aldaco 2018), as well as energy and power output (Ogbonnaya, Turan, and Abeykoon 2019).

Due to these considerations, various researchers attempted to construct a thermal model to compute and forecast PV module temperatures using explicit and implicit connections between PV module temperature and metrological data (Santiago et al. 2018). Skoplaki and Palyvos 2009a; Coskun et al. 2017; Obiwulu 2020).

Using climatic factors such ambient temperature, irradiance, and wind speed, several research predicted PV solar module operating temperatures using linear and nonlinear regression (Huang et al. 2011; Kamuyu et al. 2018; Rawat, Kaushik, and Lamba 2016; Skoplaki and Palyvos 2009a; Tuomiranta et al. 2014). The government urges everyone to promote the greatest and most efficient inventions to reduce carbon emissions to ensure a sustainable and environmentally friendly future. Improved immunity from solar energy aids in reducing the spread of infectious diseases in people (Shah et. al., 2021, Shah et. al., 2020, Shah et. al., 2021).

In ref, a thermal model simulates and experiments on how wind speed, direction, orientation, and inclination impact PV module temperature (Kaplani and Kaplanis 2014).

Kamuyu et al. used two models, one with and one without water temperature, to anticipate photovoltaic module temperature for floating PV power production (Kamuyu et al. 2018). Mahjoubi et al. developed a real-time analytical model to evaluate photovoltaic water pumping system cell temperature (Mahjoubi et al. 2014). Solar panel temperatures have been measured experimentally using thermal imaging and modelling (Irshad, Jaffery, and Haque 2018). Despite these studies, module temperature forecast accuracy may still be improved considering its importance in PV system diagnostics. Tree-based machine learning techniques can improve prediction accuracy. Photovoltaics can play important role in technology such as prosthetic arms which is very well described by (Pawar & Mungla, 2022) and (Pawar & Bhatt, 2019).

Tree-based algorithms successfully predicted PV system behaviour and characteristics. Combining decision tree classifiers to create ensemble approaches can also improve their performance.

Ahmad, Mourshed, and Rezgui (2018) used boosted decision trees to anticipate semi-arid solar radiation components and extra trees and random forests to estimate photovoltaic system output (Rabehi, Guermoui, and Lalmi 2018). Assouline et al. used Random Forests and GIS data processing to calculate rooftop PV potential (Assouline, Mohajeri, and Scartezzini 2018). Gradient boost decision tree forecasts short-term solar power (Wang et al. 2018).

The first is the bootstrap-aggregated random forest. Bootstrap aggregation reduces volatility and overfitting (Assouline, Mohajeri, and Scartezzini 2018). Gradient boosting improves tree choice regression. This improvement may minimise bias and variance (Ahmad, Mourshed, and Rezgui 2018).

These two approaches predict the module temperature of a 7kWp grid-tied PV system in a desert climate using 2017 experimental irradiance and ambient temperature data. The method's accuracy and precision are compared to linear least squares and neural networks to evaluate it.

2. TECHNIQUE AND MATERIALS

2.1. THE SETUP FOR THE EXPERIMENT

Photovoltaics are crucial to combating global warming and building an eco-friendly economy (Bouraiou et al. 2020).

The conversion efficiency of the PV module can be affected by PV technologies (Edalati, Ameri, and Iranmanesh 2015), PV array tilt angles (Saber et al. 2014), dust accumulation on photovoltaic panels (Abderrezzaq et al. 2017b; Mostefaoui et al. 2018, 2019), partial shading on PV modules (Dabou et al. 2017), and an array tilt angle that is too steep (Abderrezzaq et al. 2017a; Dabou et al. 2016). However, the PV module temperature is the main factor that significantly affects efficiency (Franghiadakis and Tzanetakis 2006; Necaibia et al. 2018; Skoplaki and Palyvos 2009b), output power (Ba, Ramenah, and Tanougast 2018), and energy yield (Correa-Betanzo, Calleja, and De León-Aldaco 2018), as well as energy and power output (Ogbonnaya, Turan, and Abeykoon 2019).

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2.2. PREDICTING TECHNIQUES

A decision assistance tool that uses a decision tree-based method represents a group of options graphically as a tree.

The numerous options are positioned at the branches' ends (the "leaf" of the tree), and they are chosen based on the selections made in each individual situation. A decision tree is a technology that is employed in several industries, including data mining, security, and medical. A strategy based on using a decision tree as a nonparametric predictive model is known as decision tree learning. We employed random forest and boosted decision trees as prediction methods for module temperature among ensemble tree approaches for decision trees. The decision tree may be modified by meta-algorithm to generate an ensemble of a decision tree.

2.2.1. RENDOM FOREST

Leo Breiman's Bootstrap aggregating or bagging approach underpins the random forest, a decision tree classifier ensemble (Breiman 1996). Bagging reduces decision tree classifier variance. Thus, the goal is to randomly build subsets of the training sample with replacement (Tin Kam Ho 2003). Each subset data set trains their decision trees to produce a random forest (Tin Kam Ho 1998, 1995). We have an ensemble of parallel models. According to Ziane et al. (2021), regression employs the average of all predictions from numerous trees, which is more trustworthy than using a single decision tree classifier. Classification depends on a majority vote on classification findings (Tin Kam Ho 2002).

This method can maximise accuracy and minimise variation without overfitting the training data set (Tin Kam Ho, 1998). The random forest can also improve unstable classifiers that vary drastically with little data set changes.

2.2.2. IMPROVED DECISION TREE

Gradient boosting underpins the enhanced decision tree. Gradient boosting combines weak learning techniques into a powerful learner for regression and classification tasks. Weak learning algorithms only slightly outperform random guesses (Breiman 1997; Friedman 1999; Mason et al. 1999).

Leo Breiman introduced gradient boosting. He said boosting may be used to optimise a cost function (Breiman 1997). Friedman invented explicit regression gradient boosting algorithms (Friedman 1999, 2002). Llew Mason and colleagues expanded their functional gradient boosting perspective (Mason et al. 1999).

Most boosting methods train a weak learner model on a training dataset and compute its error on each dataset. Later, the Adaboost method weights and creates a new adjusted training dataset to give higher prediction error data more weight. The weighted dataset generates new trees and models. Gradient boost develops a new model from estimated errors. The goal is to split a loss function optimally (Zhang and Haghani 2015). Each improved tree depends on the one before it, unlike random forests. Benefits include lower susceptibility to severe alteration (Zounemat- Kermani et al. 2017).

Table-1: PV module specs

Parameter	Specification
Type of module	Mono-Crystalline
STC Power (Pmax)	250 W
Voltage maximum (Vmp)	30.75 V
Current Max (Imp)	8.131 A
Open Circuit Voltage (Voc)	36.99 V
Short Circuit Current (Isc)	8.768 A
Efficiency	15.3%
Dimension (m3)	0.990*1.65*0.040 m
Weight	19.5 kg
Temperature	- 40 to + 90
Thermal Power(%/°C)	−0.416%/°C

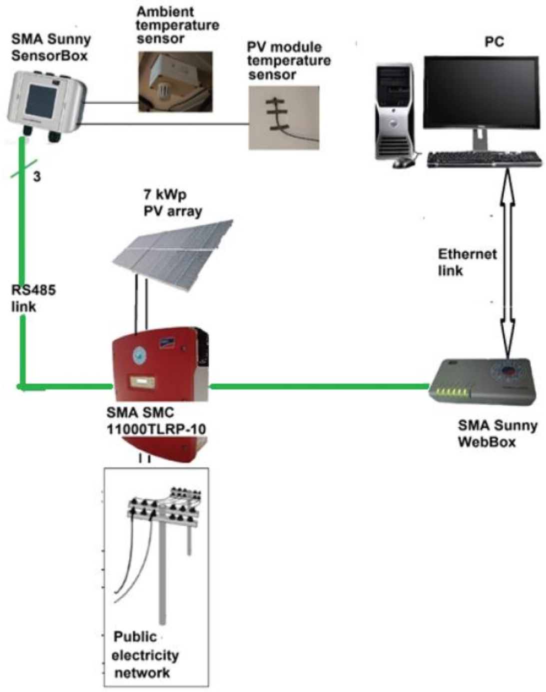

Fig- 1: PV system at URER.MS, Algeria

Table-2: Ambient temperature sensor specs

Parameter	Specification
Width x height x depth	100 mm × 52 mm × 67 mm
Measuring shunt	PT 100
Mounting location	Outdoors
Ambient temperature	−30°C + 80°C
Defendability	IP65
Tolerance	Max ±0.7°C (class B)
Scale	−30°C + 80°C

2.2.3. LINEAR LEAST SQUARE

Linear regression plots the "best-fit line" on a graph to evaluate the connection between two variables. The least-squares approach minimises the squared error for each point.

Simple hardware is needed to calculate this approach. An artificial neural network and linear least square frame this work.

Table-3: Module temperature sensor specification.

Parameter	Specification
Measuring resistor	Platinum sensor (PT100)
Defendability	IP62
Cable length	2.5 m
Scale	−20°C + 110°C
Precision	± 0.5°C
Resolution	0.1°C

Table-4: Integrated solar radiation sensor specification

Parameter	Specification
Pv cell type	PV cell, amorphous silicon (a-Si)
Scale	0 W/m2 1500 W/m2
Precision	± 8%
Resolution	1 W/m2

2.2.3. NEURAL NETWORK

Artificial neural networks use biological neurons and statistical methods. Algorithms learn, recognise patterns, classify, and decide (Westreich, Lessler, and Funk 2010). (Elsheikh et al. 2019): formal neuron inputs = 1,2,..., n, weighting parameters, activation function (non-linear, sigmoid, etc.), and output (Figure 2). An activation function regulates a formal neuron's weighted sum of external inputs (Abiodun et al. 2018).

2.3. EVALUATION STRATEGY

Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Relative Absolute Error (RAE), Relative Squared Error (RSE), and Determination Coefficient R2 were used to evaluate the models and compare regression approaches.

2.3.1. MEAN ABSOLUTE ERROR (MAE)

MAE is the test sample's mean absolute difference between the forecast and the observation, weighted equally. The mean absolute error averages absolute errors.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|M_i - P_i| \quad (1)$$

2.3.2. RELATIVE ABSOLUTE ERROR (RAE)

RAE is a ratio of the absolute error to the measurement size and relies on both. The measured value or absolute error determines the relative error.

$$RAE = \frac{\sqrt{\sum_{i=1}^{N}(M_i - P_i)^2}}{\sqrt{\sum_{i=1}^{N} M_i^2}} \quad (2)$$

2.3.3. ROOT MEAN SQUARED ERROR (RMSE)

Regression analysis yields R2. R2 indicates the regression model's contribution to dependent variable variance. Thus, the coefficient of determination is the square of the correlation (r) between anticipated and actual y scores.

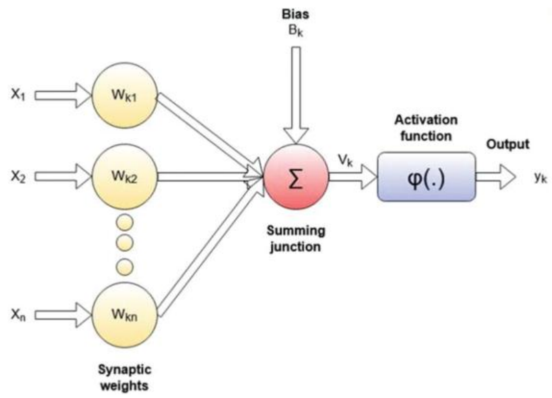

Fig-2: A nonlinear model of a neuron

$$RMSE = \sqrt{\sum_{i=1}^{N}\frac{(M_i - P_i)^2}{N}} \quad (3)$$

2.3.4. RELATIVE SQUARED ERROR (RSE)

RSE normalises total squared error by dividing by the average observed value. RSE can compare models with different error units, unlike RMSE.

$$\boldsymbol{RSE} = \sqrt{\frac{\sum_{i=1}^{N}(M_i - P_i)^2}{N}} \quad (4)$$

2.3.5. COEFFICIENT OF DETERMINATION (R2)

Regression analysis yields R2. R2 indicates the regression model's contribution to dependent variable variance. Thus, the coefficient of determination is the square of the correlation (r) between anticipated and actual y scores.

it ranges from 0 to $1. R2 \in [0,1]$ and it is defined by:

$$1 - \frac{\sum_{i=1}^{N}(M_i - P_i)^2}{\sum_{i=1}^{N}(M_i - M_{moy})^2} \quad (5)$$

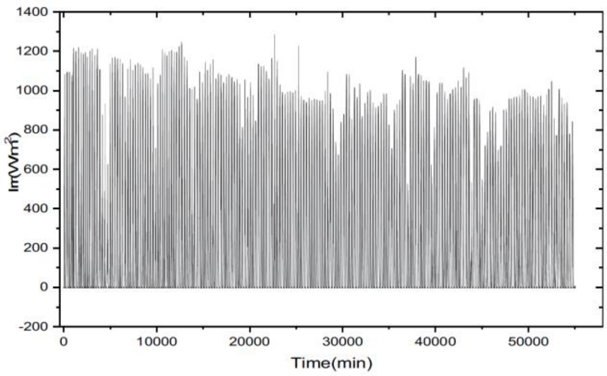

Fig-3: 2017 global irradiance.

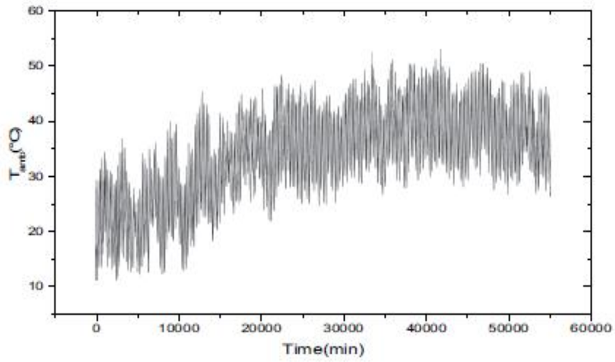

Fig-4: 2017 ambient temperatures

3. RESULTS AND DISCUSSION

We utilised global irradiance and ambient temperature data from 01/01/2017 to 30/09/2017 with a 5-minute gap between measurements to train ensemble tree models and neural networks. Damaged or partial measurements are sorted out.

Figures 3 and 4 show global irradiance and ambient temperature, which are inputs.

Figure 3 indicates that the observed irradiance exceeds 1300 W/m2 and the ambient temperature ranges from 10°C to 50°C at the experimental setup site (Blal et al. 2020).

Module temperature (Figure 5) is model training data. The chart shows that global irradiance and ambient temperature affect module temperature.

3.1. HYPER-PARAMETERS TUNING (RANDOM FOREST REGRESSION)

Four hyper-parameters define Random Forest regression. To get the optimal model, change m, dmax, n, and smin. We used grid search to find the optimised parameters. Table 5,6,7, 8 shows how the number of trees (m), maximum depth of decision trees (dmax), number of random splits per node (n), and minimum number of samples per leaf node (Smin) affect the predicted results, while the other parameters are fixed at the maximum value. As seen in Table 5, increasing the number of decision trees in the ensemble increases coverage and improves outcomes. However, it also increases training time.

The depth of the tree and number of random splits per node plays an important role, they can widen the model and make it more inclusive for all observed data, the increase of both parameters increase the accuracy but only to a limit after that the model will fell in overfitting as shown in Tables 6 and 7.

To recreate a rule in a tree structure, the minimum sample per leaf is required. The minimal value is 1, hence only one observed value may be ruled. Table 8 shows that increasing the threshold for generating new rules, which may enhance the regression tree model.

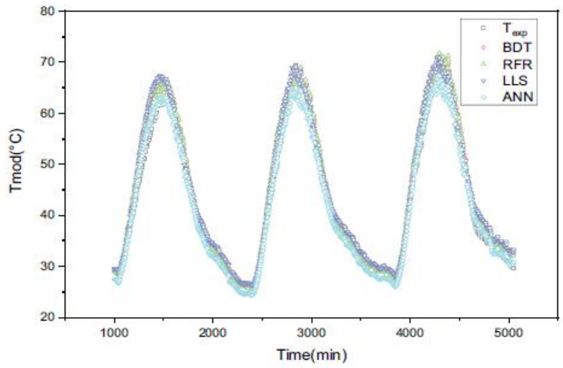

Fig-5: Comparing four approaches with three-day experimental data.

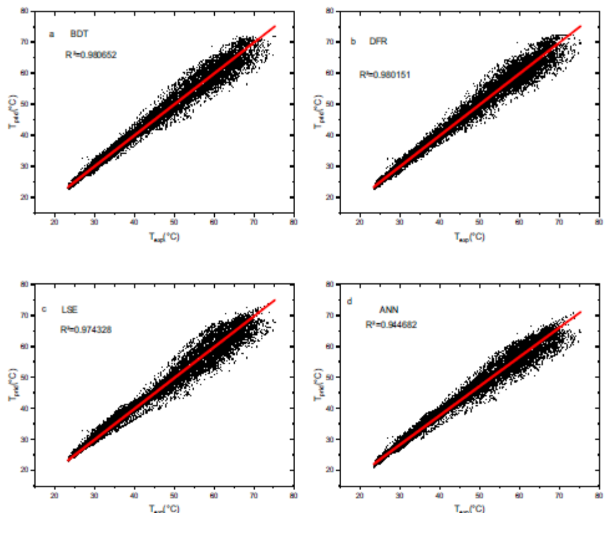

Fig-6: BDT, RFR, LLS, and ANN module temperature predictions against measurements.

The ideal BDT parameters are m = 32, dmax = 16, n = 128, an d Smin = 16.

The parameters for the RFR technique are m = 500 k = 32, imi n = 10, and r = 0.025.

Figure 7 depicts a comparison of the findings from the four ap proaches and the experimental data for three days in 2017.

The graph illustrates that, despite the fact that all methods pr oduce satisfactory results, both tree-based ensemble models overestimate the module temperatur e and the predicted values are superior to the measured data, particularly for high temperatures, whereas the ANN model u nderestimates the module temperature, resulting in predicte d values that are inferior to the observed values.

In Figure 7 a-c and d, the projected values for BDT, RFR, LLS, and ANN techniques were displayed against the observe d data for further investigation.

The predicted values have a high correlation with the measur ed values for all methods ($R2 = 0.98$ for tree-based ensemble methods, $R2 = 0.97$ for LLS, and $R2 = 0.94$ for the ANN). The BDT method achieves the best results, with a high coefficient of determination and a slightly better variance than the RFR method.

Figure 7 further illustrates that for lower temperature values, especially in the absence of sun irradiation, the four approac hes have a high degree of accuracy, however the accuracy dec reases as the temperature increases.

4. CONCLUSION

The module temperature of grid-tied solar systems was predicted in this work using the tree-based ensemble techniques, and their performance was assessed. As a case study, a PV installation in Adrar, Algeria's desert was examined. The outcomes demonstrated the value of hyper-tuning in achieving high performance and guarding against overfitting. The LLS method has agreeable results with less computational demand, whereas the ANN, although training gave good results, the accuracy dropped significantly for testing. Tree-based ensemble methods have high performance, the coefficient of determination remains above 0.98 for training and testing for ensemble tree methods, and they are feasible in predicting the module temperature of grid-tied PV stations. Overall, all of the approaches showed high training accuracy; however, the key distinction is seen during the testing phase.

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