

Predictive Linear Regression Model for Microinverter Internal Temperature

Mohammad A. Hossain^{*}, Timothy J. Peshek^{**}, Yifan Xu^{***}, Yang Hu^{**}, Liang Ji^{****}, Alexis R. Abramson^{*}, and Roger H. F.

^{*}Department of Mechanical and Aerospace Engineering, Case Western Reserve University, Cleveland, Ohio, 44106

^{**}Department of Material Science and Engineering, Case Western Reserve University, , Cleveland, Ohio, 44106

^{***}Department of Epidemiology and Biostatistics, Case Western Reserve University, Cleveland, Ohio, 44106

^{****}Underwriters Laboratories, LLC., Bollingbrook, Illinois

Abstract—A predictive linear regression model was developed to predict the microinverter internal temperature operating under real-world conditions on dual-axis trackers. The predictive model is a function of statistically significant variables: ambient temperature, photovoltaic (PV) module temperature, irradiance and AC power data. Time-series environmental, temperature and power data were analyzed in a statistical analytical approach to identify the statistically significant variables. The adjusted r -squared value of the predictive model is 0.9793. The dominant contributor to the microinverter temperature is the PV module backsheet temperature.

Index Terms—microinverters, temperature prediction, reliability, photovoltaic systems.

I. INTRODUCTION

PV modules equipped with microinverters have become very common in PV system now a days, especially in residential PV market where a microinverter equipped PV system can offer individual maximum power point tracking (MPPT), no single point failure, absence of high voltage DC line and higher design flexibility compared to the traditional string inverter system. Reliability of microinverters in harsh and extreme real-world outdoor operating conditions has always been a critical concern for the growth of microinverter equipped PV systems. Early microinverters showed poor reliability performance in real-world operating conditions even after passing successfully in accelerated tests in lab [1]. The Solar Durability and Lifetime Extension (SDLE) SunFarm at Case Western Reserve University has an unique testbed for study the PV system and components under real-world operating conditions. 24 microinverters connected to 8 different brands of PV modules on dual-axis trackers were analyzed from July through October 2013 in SDLE SunFarm and a prediction model was developed to predict the microinverter backsheet temperature connected to the different brands of PV modules.

II. BACKGROUND

Microinverters convert the DC power output of the PV module to AC power and supply the AC power to the grid. A microinverter consists of several critical components: MOSFETs, capacitors, inductors, diodes, transformers, circuit boards, etc. The lifetime of commonly used electrolytic capacitors is strongly dependent upon the operation temperature. A

high operating temperature evaporates the aqueous component electrolytes, and leads to an increase in equivalent series resistance (ESR) [2]. This introduces more dissipative heat inside the capacitors which in turn accelerates the evaporation rate and reduces the capacitance. Since the ripple current amplitude increases with the reduction of capacitance, a higher ripple current may result, causing greater Joule heating, and pushing the microinverters towards capacitor dry out failure. MOSFET failure can occur due to rapid heat build up on the die package as observed in the case of insulated-gate bipolar transistor (IGBT) during the power cycling [3,4]. Heat build up in the die degrades the die attachments and causes failures such as wire bond breakage. Additionally a sudden inrush of current through the inductor or a blocking voltage surge in the inductor can induce an avalanche failure of the MOSFET. High speed diodes are also sensitive to thermal stressors. Although limited studies have been conducted in microinverters as a system to date, thermal stress is selected as the most common cause of failure from the component study. Therefore, a predictive model for microinverter temperature given the operating conditions will provide critical insights to the long term performance of microinverters.

In real-world operation, thermal stress in microinverters is developed from several heat/energy sources. The typical DC to AC power conversion efficiency of microinverter is approximately 96%, and remaining 4% energy loss converts into heat. This energy loss is typically considered as one of the major sources of thermal stress for microinverter. Another important source of thermal stress for microinverter can be the PV module backsheet temperature. PV modules warm up by absorbing the solar insolation and the warm backsheet of the PV module radiates heat energy. The microinverters, located beneath the PV modules, receive the PV module backsheet radiated heat and eventually develops the thermal stress in the microinverter. Ambient temperature, wind speed and mounting of PV modules are some other important factors behind the development of thermal stress that will be studied herein. Wind speed determines the convection cooling rates of the PV module and microinverter. The convection cooling rate is different for different types of PV module mounting systems. For example, wind access to the fixed rack roof top PV system

is very limited compared to the PV system in the dual-axis trackers. Therefore, more thermal stress will be developed in the microinverters at fixed rack mounted roof top PV system compared to the microinverters in dual-axis trackers.

III. EXPERIMENTAL

24 Enphase M215 microinverters were analyzed in this study. The microinverters are connected to 24 PV modules from 8 different brands. The baseline power of different brands of PV modules are listed in Table 1. Baseline power was measured by the SPIRE4600 solar simulator [5].

TABLE 1

Baseline power of different brands of PV modules [5]

Brand	Baseline power (W)	Standard deviation (W)
K.t6	225.19	2.59
L.t6	231.02	4.12
O.t12	241.14	1.65
P.t12	231.75	0.95
Q.t12	212.86	4.98
R.t14	231.375	1.53
S.t14	230.95	1.03
T.14	232.20	2.47

The insolation data were measured by the Kipp&Zonen CMP11 pyranometer and environmental data were collected by the Vaisala WXT520 weather transmitter. PV module backsheet temperature and microinverter backsheet temperature were measured by the T-type thermocouples from Omega Engineering Inc. The thermocouples were attached by using adhesive tape to the hottest point in the backsheet of the PV modules and microinverters. The hottest point was determined from IR images when the microinverter was near its power rating. The pyranometer, weather transmitter and the thermocouples are connected to the Campbell CR1000 data loggers and multiplexers. The data loggers collect every minute by minute data and store all the data in the central database every two hours [5]. Enphase microinverters use a power line communication technology to report the power data: DC voltage and current, AC power, frequency and microinverter’s internal temperature; to Enphase Envoy device. The Envoy device reports the data to the Enphase website every 5 minutes. Using a Java Selenium webdriver package, the power data were automatically acquired from the Enphase website and ingested into our informatics and analytics infrastructure, known as energy-CRADLE™.

IV. DATA ANALYSIS

Raw environmental, temperature, and power time-series data were validated by sensor cross-checks. Then the time stamp of the different sensors were checked with cross correlation functions (ccf) to determine the lag in time stamps. The time-series data were slewed according to their lags to match their time formats. Multivariate graphical Exploratory Data Analysis (EDA) processes were employed on the raw time-series data and correlation coefficients were determined among the variables. Fig. 1 shows the pairs plot, histogram and correlation coefficient for the microinverters connected with

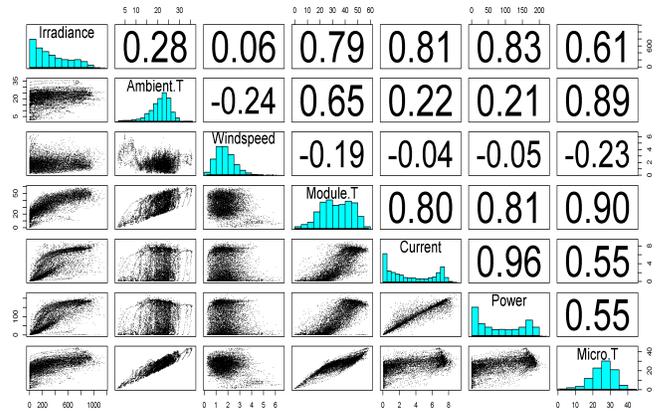


Fig. 1. Pairs plot, histogram and correlation coefficients for the microinverters connected to Q PV modules. Pairs plot are in bottom-left triangle, histograms are in the diagonal boxes, and top-right triangle represents the correlation coefficients between variables. ²

the Q.t12 brand of PV modules from the EDA analysis where the diagonal boxes represent the histogram of the data, top-right triangle represents the correlation coefficients between the variables, and bottom-left triangle shows the pair plots between different variables [7]. From Fig. 1, the microinverter temperature is strongly correlated with ambient temperature and PV module temperature. In addition, AC power, DC current and irradiance are also moderately correlated with the microinverter temperature. The wind speed shows no correlation with the microinverter temperature. In case of PV module temperature, it shows stronger correlation with DC current, AC power and Irradiance, and moderate correlation with ambient temperature. Wind speed do not show any correlation with PV module temperature.

The wind speed is measured by the weather transmitter which is placed on top of a pole on the SDLE SunFarm. However, the wind flow may be more turbulent or at least different at the location of various dual-axis tracker platforms due to height variations and obstructions. That’s why the wind speed show poor correlation with PV module temperature and microinverter temperature. The microinverters are shaded by the PV modules and do not have a direct interaction with irradiance. Thus irradiance is more strongly correlated with the PV module temperature compared to the microinverter temperature.

While an analysis of the full data set is insightful, segregating the data into distinct data sets corresponding to specific time ranges can also reveal other important information about the thermal behavior of the microinverters. Therefore, the time format of the data was transformed into local solar time and the full data set was divided into two subsample data sets: morning and noon time. These two subsample data sets were created to isolate and observe the thermal characteristics under

²Ambient.T = Ambient temperature, Wind speed = 5 point moving average wind speed, Module. T = PV module temperature, Current = DC Current, Power = AC Power, Micro. T= Microinverter Temperature

TABLE 2

List of Correlation Coefficients of different variables with Microinverter Temperature

	Irradiance	Ambient.T	Wind speed	Mod.T	DC Current	AC Power
Full data	0.60	0.89	-0.23	0.90	0.55	0.55
Morning Hours	0.34	0.97	-0.01	0.85	0.20	0.19
Noontime	0.60	0.90	-0.32	0.92	0.58	0.58

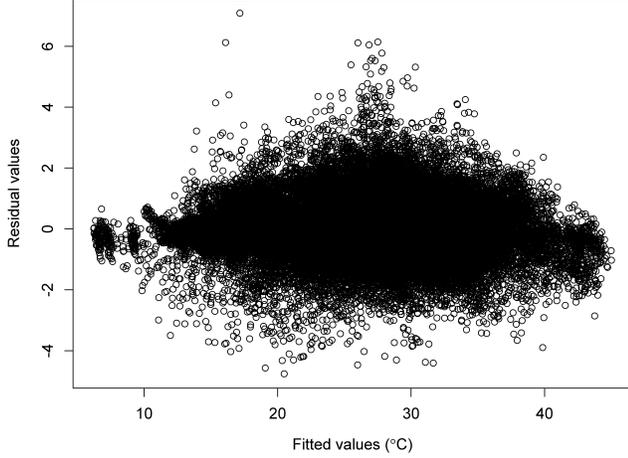


Fig. 2. Residual plot for linear regression prediction model for microinverter connected to L.t6 PV modules.

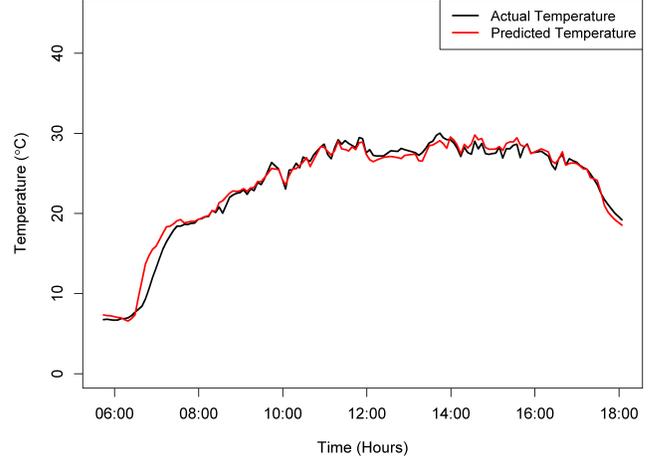


Fig. 3. Comparison of predicted microinverter temperature with actual microinverter temperature in a sunny day for microinverter connected to L.t6.2 PV modules.

low and high irradiance conditions. Morning time is defined as local solar time from 5 AM to 6:30 AM, and the noon time data set is defined between local solar time from 11 AM to 1 PM.

Table 2 represents the correlation coefficients of different variables with microinverter temperature in different times. Ambient temperature is the strongest influencing factor under conditions of low irradiance in morning hours. Due to the low irradiance of morning hours, the temperature rise in PV modules is very small and the AC power output of the system is very low. As a result, the microinverters' temperature is not influenced greatly by either PV modules' temperature or AC power. At solar noon time, the microinverter's temperature is strongly correlated with ambient temperature and PV module backsheet temperature. Irradiance, AC power and DC current are also in moderately and similarly correlation with microinverter temperature. The correlation coefficient of microinverter's temperature with AC power and DC current is similar as AC power is directly proportional to DC current. Hence it may be more advantageous to the long term performance of the microinverter to expand the saturation power limit to higher powers even if the CEC efficiency is reduced, since tracking off of the maximum power point due to inverter saturation will increase the temperature of the PV module.

V. PREDICTION LINEAR REGRESSION MODEL

A predictive model for the microinverter backsheet temperature connected to any of the studied 8 PV module brands was developed using multiple linear regression analysis. First,

various linear regression models were formulated using different variables with all possible variable combinations. Then, the Akaike Information Criterion (AIC) value for each models was determined. Using domain knowledge and AIC value, the final model was selected as the predictive model. The residual plot of the selected model was then checked for the appropriateness and degree of validation of the model. In the predictive model, continuous response variable (microinverter temperature) is predicted using two types of predictor variables: continuous and categorical. Ambient temperature, PV module temperature, AC power and irradiance are the continuous predictors and PV module brand is the categorical predictors. Contrast was set on the categorical predictors so that the thermal behavior of microinverters connected to different brands of Pv module can be compared.

$$\begin{aligned}
 Micro.T_i = & \beta_0 + \sum_{j=1}^7 \beta_{0j}x_{ij} + (\beta_1 + \sum_{j=1}^7 \beta_{1j}x_{ij})Ambient.T_i \\
 & + (\beta_2 + \sum_{j=1}^7 \beta_{2j}x_{ij})Module.T_i + (\beta_3 + \sum_{j=1}^7 \beta_{3j}x_{ij})Irradiance_i \\
 & + (\beta_4 + \sum_{j=1}^7 \beta_{4j}x_{ij})AC.Power_i + \varepsilon_i \quad (1)
 \end{aligned}$$

Equation 1 represents the multiple linear regression predictive model equation. $i = 1$ to 8 represents the 8 different brands of PV modules and ε_i represents the errors associated with

TABLE 2

Coefficient values for the predicted models					
	Intercept	Ambient.T	Mod.T	Irradiance	AC Power
	β_0	β_1	β_2	β_3	β_4
Mean Model	-0.232	0.676	0.365	0.002	-0.010
	β_{0j}	β_{1j}	β_{2j}	β_{3j}	β_{4j}
L.t6	0.033	0.011	-0.017	0.000	0.001
K.t6	0.256	-0.030	0.023	-0.002	0.008
P.t12	0.240	-0.052	0.048	-0.000	0.000
O.t12	-0.045	0.014	-0.015	0.000	0.003
Q.t12	-0.155	0.025	-0.024	0.001	-0.003
R.t14	-0.185	-0.013	0.009	0.001	-0.003
S.t14	-0.403	0.040	-0.29	0.001	-0.005

the predictive model for each brands. The adjusted r-squared value of the regression model 0.9793 with residual standard error of 0.9064. β_0 , β_1 , β_2 , β_3 and β_4 are the coefficients for intercepts, ambient temperature, PV module temperature, irradiance and AC power for the mean model. β_{0j} , β_{1j} , β_{2j} , β_{3j} and β_{4j} represent the variation in coefficients of intercepts, ambient temperature, PV module temperature, irradiance and AC power from the mean model for different brands of PV module. The coefficient x_{ij} is the dummy variable for different brands in the predictive model. $x_{ij} = 1$ when $i = j$ or $x_{ij} = 0$ otherwise. The value of the coefficients are listed in table 3. In Table 3, coefficients are listed for 7 brands of PV modules. For the 8 th brand (T.t14), the coefficients of the predictive model can be calculated like these: $\beta_{08} = -(\sum_{j=1}^7 \beta_{0j})$, $\beta_{18} = -(\sum_{j=1}^7 \beta_{1j})$, $\beta_{28} = -(\sum_{j=1}^7 \beta_{2j})$, $\beta_{38} = -(\sum_{j=1}^7 \beta_{3j})$, $\beta_{48} = -(\sum_{j=1}^7 \beta_{4j})$. Form the coefficients of the mean model, we can observe that, the microinverter temperature is strongly influenced by ambient temperature and PV module temperature. The influence of power on microinverter is less significant than PV module temperature The coefficients of irradiance is very small and very similar for all the 8 brands of PV modules.

Fig. 2 represents the residual vs. fitted plot for the linear regression model of microinverter's temperature connected to three brand L.t6 PV modules. All the residual values are scattered randomly; do not show any specific pattern. This indicates that the predictive model is a good fit. Fig. 3 shows the comparison between actual and predicted microinverter temperature of the microinverter connected to the L.t6.2 PV module on a bright sunny day (2013-09-17). The predicted model predicts the temperature fairly well throughout the day. Over prediction of microinverter is observed in the morning time. The absolute temperature difference between the actual and predicted temperature of this microinverter on a sunny day (2013-09-17) is between 0.03°C to 0.35°C with 95% confidence interval. Fig. 4 compares the predicted and actual temperature of the microinverter on a cloudy day (2013-08-06). In cloudy day, sudden irradiance change is observed due to the cloud movement. As a result, the power output also changes very sharply. However, the predicted model can not deal with this sudden irradiance change. The predicted model over or under predicts when there is a sharp change

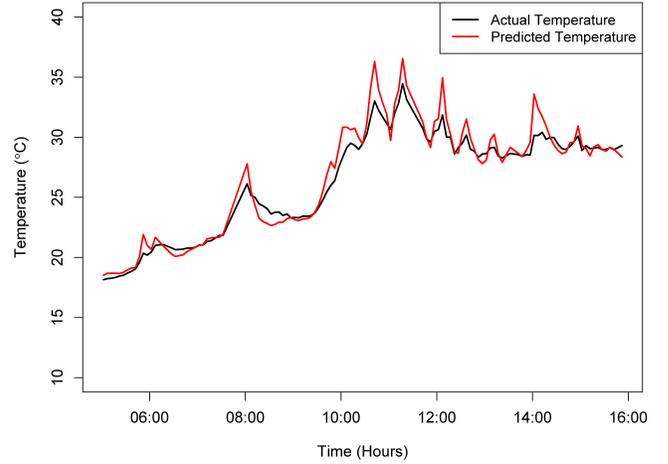


Fig. 4. Comparison of predicted microinverter temperature with actual microinverter temperature in a cloudy day for microinverter connected to L.t6.2 PV modules.

of irradiance occurs. The model under predicts when there is a sudden cloud cover over the PV module and the model over predicts when the cloud cover the PV module is begin to fade. Thermal diffusivity of the microinverter materials can be the reason for the over or under prediction behavior of the predicted model. The change in irradiance due to cloud cover is very sharp but due to thermal diffusivity of the microinverter material, the change in microinverter temperature can not be that rapid.

VI. FUTURE WORKS

The developed predictive model can predict the microinverter temperature operating on dual-axis trackers. The study will be further pursued to study the thermal behavior of microinverters in fixed-rack system and roof top systems which will allow us to compare the thermal characteristics of microinverters in different setup. SDLE SunFarm is a part of a global SunFarm network [5, 6]. Under this SunFarm network, similar experiment will be setup in different SunFarms of different climate zones. This will provide us the opportunity to gather insights about the thermal behavior of microinverters.

The predictor variables in the predicted model are considered as independent. The interactions between different predictor variables require further study.

VII. SUMMARY

A multiple linear regression predictive model for microinverter temperature has been developed for the microinverters connected to different brands of PV modules installed in dual-axis trackers. The predictive model is a function of ambient temperature, PV module temperature, AC power and irradiance; the statistically significant variables related to the microinverter temperature. An unbiased statistical analytical approach has been followed to find out these statistically significant variables. The analytic approach and prediction model methodology can also be expanded to predict the microinverters' temperature in fixed rack or roof setup. Due to these results we uncover that at high irradiance the PV module backsheet temperature, which is determined by the difference between absorbed solar power and maximum DC electrical power loading the module, is the dominant predictor of microinverter temperature. It is thus more advantageous to match the power handling capability of the inverter to the module instead of allowing the inverter to enter a power saturation state.

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