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Comparative Electrical Energy Yield Performance of Micro-Inverter PV Systems Using a Machine Learning Approach Based on a Mixed-Effect Model of Real Datasets

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ABSTRACT Long-term energy evaluation of PV systems that use micro-inverter configuration (micro-inverter PV systems) is currently unclear due to the lacking of sufficient longitudinal measurement data and appropriate analysis method. The poor knowledge about impact and aging of micro-inverter PV system affects the comprehension and accuracy of PV design and simulation tools. In this paper, we propose a machine learning approach based on the mixed-effect model to compare and evaluate the electrical energy yield of micro-inverter PV systems. The analyzed results using a 5-year period data of PV stations located at Concord, Massachusetts, USA showed that there is no significant difference in yearly electrical energy yield of micro-inverter PV systems under shading and non-shading condition. This finding has confirmed the advantage of micro-inverter PV system over the other PV types. In addition, our work is the first study that identified the average degradation rate of micro-inverter PV of 3% per year (95% confidence intervals: $2\% - 4.3\%$). Our findings in this study have extended substantially the comprehensive understanding of micro-inverter PV system.

INDEX TERMS Mixed-effect model, micro-inverter PV system, micro-inverter configuration, longitudinal measurement, fixed effects, random effects.

I. INTRODUCTION

Photovoltaic system (PV) plays a key role in many renewable energy development plans. According to the Global Market Outlook report, the total generated power from PV is expected to be over 1 TW by 2022 [1]. In addition, the global rooftop PV grows rapidly due to the decline of installment cost and many incentive policies from governments such as utility rebates, tax credit, or renewable energy credit [2]–[4]. From customer aspect, installing the residential PV system is the referred choice because of the self-consumption, i.e. the generated electricity can be used directly for appliances at household. The electricity from rooftop PV also feeds in energy to the distribution grid to make profit for homeowner. From utility aspect, the development of rooftop PV brings the ability to better control and manage the grid since they are distributed power generators, which helps to reduce the peak load demand. Therefore, the rooftop PV systems prove to be a cost-effective solution.

To encourage homeowner turning to PV system, many PV designing and planning tools have been released, for example PVSOL [5], PVsyst [6], PVsites [7], PVwatt [8], and Google Project Sunroof [9]. These simulation tools have successfully provided an easy-to-use method to provide sufficient outputs about energy performance rooftop PV system and also the additional information such as the Levelized Cost of Energy (LCOE) or Energy Payback period [10]–[12]. Nevertheless, the reliability of these tools is still in doubt since they focus only the details about solar panel and PV location. The challenge is how to accurately predict the energy of PV system, taking into account the impacts of inverter configurations and also the aging of PV system.

Regarding the impact of inverter configuration to energy efficiency (measured by kWh/kW) of PV system, there

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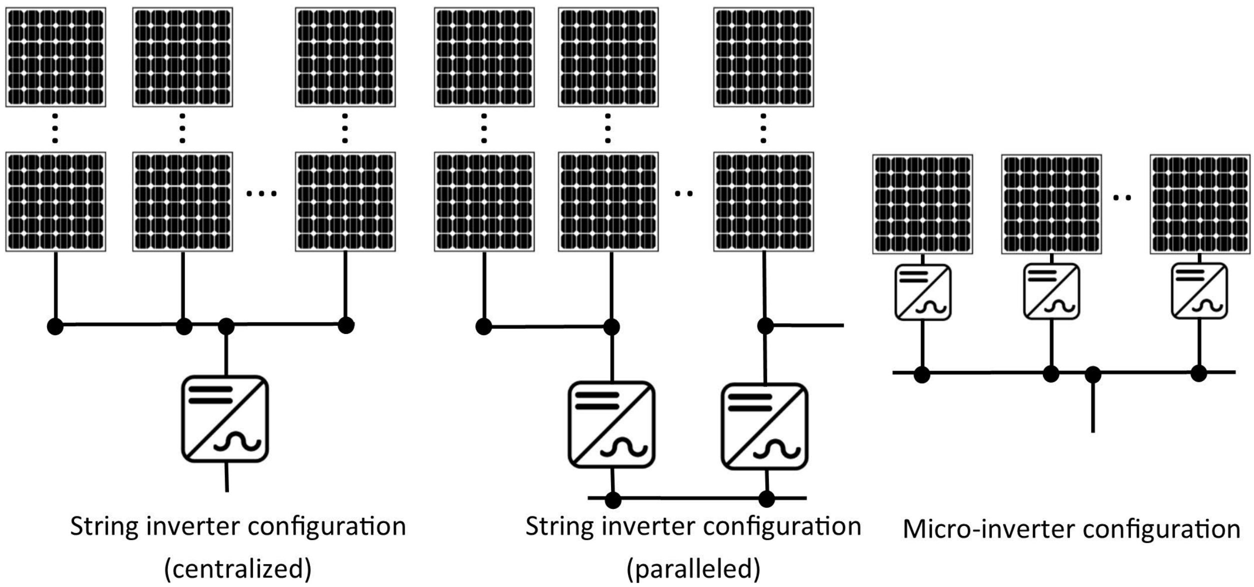

FIGURE 1. Typical inverter configurations of rooftop PV system.

are limited studies concerning about this issue. Currently, there are three common inverter configurations in rooftop PV system, named as central inverter, string inverter, and micro-inverter configuration (Fig. 1). In the two former configurations, an inverter is connected to a string PV panels to convert DC power to AC power. In the last configuration, micro-inverters are connected to single PV panel (or two PV panels) and archive maximum AC power at module level by integrating maximum power point tracker (MPPT) in individual micro-inverter. Therefore, the shading appears in a PV module does not affect to other modules in a micro-inverter PV system. Authors in [13]–[16] investigated the conversion efficiency and energy yield of micro-inverters in non-shading condition in both laboratory environment and outdoor test field. The study in [17] simulated the operation of micro-inverter based on Matlab and Simulink modeling. Those studies theoretically proved that PV system that uses micro-inverter configuration has better energy efficiency than the one using central inverter configuration. The data driven approach in [18] showed that the energy efficiency from PV station that uses micro inverter is higher than that uses central inverter configuration. However, the drawback of study is that all monitored PV systems are not in the same weather condition. Moreover, all PV stations also did not have the same orientation. The case study in [19], [20] said that in the same environment condition, the micro-inverter more quickly reaches the Levelized Cost of Energy (LCOE) than string inverter under shading effects. Although the above mentioned studies have proven the advantages of micro-inverter PV system, their proposed methods have not completely convinced the reader. The first reason is due to the lacking of longitudinal datasets of micro-inverter PV system. This type of dataset is the recorded measurements of the same system (e.g.: power, generated energy) hourly or daily. The second reason is due to the lacking of an appropriate analysis method rather than T-Test, which is only applied to compare the mean values between two independent datasets.

Regarding the aging of PV system, many existing studies only focused on the degradation rate of solar panel level, rather than the degradation at system level [21]–[28]. In string inverter configuration, the degradation of solar panel also can be represented as the degradation of PV system since the inverter usually have been operated in standard condition in the indoor condition. However, micro-inverter is integrated into individual solar panel and placed outdoor, such as on the rooftop or facade wall. Hence, it is certain that the changes in operating temperature, humidity affect to both solar panel and micro-inverter. Therefore, it is very important to identify the degradation rate of PV systems that use micro-inverter configuration.

Because most existing micro-inverter PV systems in the world have been installed recently, there are obviously no long term energy performance records yet for the most recent systems. In this study, we aim to provide a comprehensive understanding about energy efficiency to the amount of generated energy of PV stations that use micro-inverter configuration based on a real dataset. In addition, the proposed machine learning approach is conducted based on the mixed-effect model, which is a flexible and powerful machine learning tool for analyzing longitudinal data. In general, our contribution are: ***(i)*** proposing how to utilize mixed-effect model to evaluate the longitudinal PV dataset; ***(ii)*** evaluating the impact of shading condition to generated energy of micro-inverter PV system; and ***(iii)*** identifying the energy degradation rate at system level, which represents the aging of micro-inverter PV system over time. The remaining of this

TABLE 1. PV stations that use micro-inverter configuration in our study. All stations are located in Concord city, Massachusetts, USA (postcode: 01742). The distance among stations is below 1 km to ensure the climate would vary as little as possible. All stations use monocrystalline silicon panel. Shading (caused by trees, chimney, or neighbor building) is temporary but unavoidable.

Station	Name	Installed power (kW)	PV array		Inverter configuration		Orientation	Shading	Tilt degrees
			Rated power (W)	Total panel	Rated power (W)	Number of inverters			
1	Clothesline	6.48	240	27	260	27	South	No	45
2	300 Virginia Road	4.9	245	20	215	20	South	No	23
3	76 Channing	4.65	245	19	210	19	South West	No	33
4	First on Crest	8.2	265	31	215	31	South West	No	43
5	15 Pine St	10.2	255	40	215	40	South	No	1
6	58 Elsinore	4.16	260	16	260	16	South West	Yes	45
7	Acorn Cape Concord	9.36	240	39	215	39	South	Yes	45
8	Concord-DJE	6.72	240	28	240	28	South	Yes	45
9	Great Meadows	12.48	240	52	215	52	South	Yes	45
10	IQ Hill Concord	5.76	240	24	215	24	South	Yes	26
11	PV29	7.25	250	29	215	29	South	Yes	1
12	solargeeks	14.3	260	33	260	33	South West	Yes	45
13	Wiggins Solar Power Plant	4.5	250	18	250	18	South	Yes	1
14	Concord Commonwealth	4.9	175	28	190	28	South	Yes	45
15	Concord Ferg Solar	2.22	185	12	190	12	South West	Yes	45
16	Not Just Cosumer Anymore	6	250	24	215	24	South	Yes	25
17	6.5kW Great Meadows	6.5	250	26	225	26	South	Yes	22
18	Concord Cape	9.9	236	42	215	42	South	Yes	19

paper is organized as follows: Section II represents the longitudinal PV datasets that we used in our study. In Section III, we introduce the mixed effect analysis and propose two mixed-effect models to evaluate the energy efficiency of PV stations. In detail, the proposed linear model is used to evaluate the annual energy yield, while the nonlinear model is used to evaluate the monthly energy yield. Then, the analysis results and discussion are described in Section IV. Finally, Section V summarizes our findings and suggests further researches.

II. PV SYSTEMS DATASET

Table 1 shows the list of micro-inverter PV stations that are used in our study. These stations are located at Concord city, Massachusetts, USA. We collected these stations from the open source dataset PVoutput [29]. This website allowed registered user uploading every 5-minute measurement data of their PV system for academic use. The data include the power and generated energy of PV systems. The datasets are uploaded every five minutes from the registration day of system at PVoutput to the latest day. In addition, the registered informations of each PV system are the rated PV power; the brand, type of solar panel, total number and power of solar panels; the brand, total number and power of inverters; orientation; shading condition; and tilt degrees of solar panel.

The PV systems in Table 1 were chosen since we intend to analyze the impact of micro-inverter configuration to the overall energy efficiency of PV system under non-shading and shading conditions. They all used monocrystalline solar panels and the micro-inverter from Enphase manufacturater [30], ranging of rated power from 190 Watt to 260 Watt. Our dataset included 5 non-shading PV stations and 13 shading ones. Comparing to other datasets used in previous studies, the advantages of our collected dataset are that all PV stations share the same climate environment (Concord region) and the measurement data are continuously recorded from 2014 to 2018. Hence, this longitudinal measurement data is useful and reliable for analyzing the performance of PV systems.

The monthly and yearly yield of electrical energy (m and y, respectively) are chosen as the metrics to investigate the electrical energy performance of a PV system in our study. The calculations of these yields are given in (1) and (2),

$$m = \frac{\sum_{j=1}^{M} E_{day_j}}{M.P_{pv}} \; (kWh/kW) \tag{1}$$

$$y = \frac{\sum_{j=1}^{Y} E_{day_j}}{Y.P_{pv}} \; (kWh/kW) \tag{2}$$

where P_{pv} is the rated power of PV system, M is the total number of recorded days of the month m^{th}, Y is the total number of recorded days of the year y^{th}, and E_{day_j} is the total generated energy from PV system at the j^{th} day. The resulting yearly yield and monthly yield of micro-inverter PV systems in Table 1 are represented in Fig. 2 and Fig. 3, respectively.

III. THE MIXED-EFFECT ANALYSIS

The longitudinal dataset is usually a repeated measurement data of objects taken over time such as hourly, monthly, or yearly. This type of dataset is useful for the longitudinal study and provides reliable results for evaluating or comparing the difference of many observed measurement data. The common T-Test [31] is used to compare the mean values between two independent datasets when we evaluate any difference. However, this method actually is not suitable for longitudinal data since it violates the assumption about

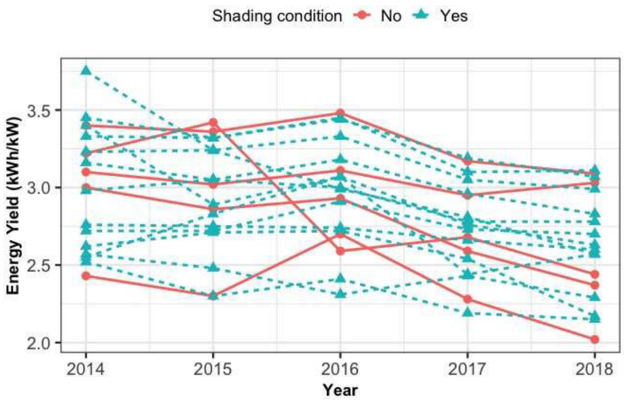

FIGURE 2. The yearly yield of micro-inverter PV systems in Table 1 from 2014 to 2018.

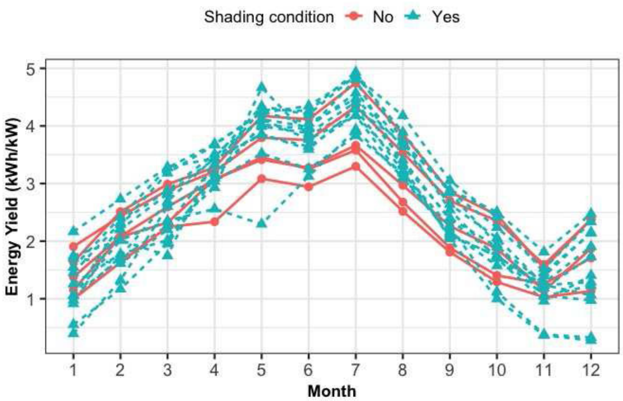

FIGURE 3. The monthly yield of micro-inverter PV systems in Table 1. The recorded measurements are from January to December, 2018.

correlation between data observing from the same object. Recently, the mixed-effect model is increasingly recognized as an effective method in case dataset is longitudinal and consists of grouped objects [32]. Each mixed-effect model is combined from two terms: fixed effects and random effects. While the former represents the trend of the general energy yield of whole PV dataset, and the latter term reflects the variability among many PV stations and the variability in many measurements of each PV station. By identifying the fixed effect terms for grouped objects, any differences among groups can be identified easily. In this study, we applied mixed-effect model to the energy yield dataset in Fig. 2 and Fig. 3 in order to evaluate the energy performance of micro-inverter PV systems under two groups: non-shading and shading.

The procedure analysis based on mixed-effect model is as follow. Further related theories and computational methods of mixed-effect model are referenced to [32]:

1) Choosing the suitable statistical model (ie.: linear model, nonlinear model) to represent the trend of longitudinal PV dataset;
2) Identifying the fixed-effects and random-effects parts in the model based on the particular grouped dataset of the comparison;
3) Fitting and estimating the coefficients of the model. Two methods that are used for parameter estimation are maximum likelihood (ML) and restricted maximum likelihood (REML) [32];
4) Assessing the precision and the significance of various terms in the model:
   - Test the significance of terms in the fixed effects part: Performed by F-Test for assessing the significance of terms [33], the resulted significance of terms is shown by P value. The F-Test is a ratio of two variances, which is a measure of dispersion, or how far the data are scattered from the mean;
   - Test the assumption on the random effects part about normal distribution. Using the diagnostic methods such as the Quantile-Quantile (Q-Q) norm plot. This is a scatter plot created by plotting two sets of quantiles against one another. If both sets of quantiles come from the same distribution, we should see the points forming a roughly straight line.
   - Test the significance difference of many models that represent subjects belonging to difference groups. This test is called as likelihood ratio test and performed by an analysis of variance (ANOVA) method [34].

From the annual energy yield in Fig. 2, we saw that the Y_i tends to decrease over years. Also in Fig. 3 it seems that the monthly generated energies are the same between two groups. Hence, the question are: is there any real difference in the yearly yield trend between two PV groups? and is there any real difference in the monthly energy yield between two PV groups?.

Shading is the main issue that causes the reduction in energy efficiency of PV system. From our literature review, the maximum power point tracker (MPPT) algorithm in micro-inverter is performed at individual PV module, hence the shading on a module does not affect other modules. Therefore, the overall energy efficiency of micro-inverter system in shading condition equals to the one of micro-inverter system in non-shading condition. Therefore, we formulate the hypothesis test of our research as below:

- The null hypothesis (H_0): There is no difference in energy yield between non-shading group and shading group. If the P value is larger than 0.05, then H_0 can be assumed;
- The alternative hypothesis (H_1): There is real difference in energy yield between two groups ($P < 0.05$).

A. THE UNCONDITIONAL LINEAR MODEL

Linear mixed-effect model has both fixed and random effects occurring linearly in the model function. It extends linear model by incorporating random effects, which can be regarded as additional error terms, to account for correlation among observations within the same group. In the unconditional model, we treat the dataset in Fig. 2 as only one group regardless of the shading conditions. The yearly yield is represented as (3):

$$y_i = \alpha_i + \beta_i t + e_i \tag{3}$$

where y_i is the observed energy yield for individual PV station $i = 1, 2, ..., 18$, measured repeatedly every year from 2014 to 2018 and represented by the index of year $t = 1, 2, .., 5$. The α_i and β_i are called the baseline yield (kWh/kW) and annual degradation rate of PV station i, respectively. The meaning of baseline yield is the initial observed yield that we obtained in 2014, and e_i is the error (or residual) between the measured value (or real value) and estimated value from model of station i. The error e_i is assumed to follow a normal distribution with zero mean and variance σ_e^2, $e_i \sim \mathcal{N}(0, \sigma_e^2)$.

Since all the PV stations in Table 1 are micro-inverter configuration and share the same environment condition, it is reasonable to imply that they all shared a common baseline yield and degradation rate. Therefore, we interpret the parameters α_i and β_i as (4),

$$\alpha_i = A + u \quad \beta_i = B + v \tag{4}$$

where A and B are the mean baseline yield and the mean degradation rate of all observed stations, respectively. The error terms u and v are assumed to follow a normal distribution with their respective variances $u \sim \mathcal{N}(0, \sigma_u^2)$ and $v \sim \mathcal{N}(0, \sigma_v^2)$.

By substituting (4) to (3), (3) is written as below

$$y_i = (A + u) + (B + v)t + e_i = (A + Bt) + (u + vt) + e_i \tag{5}$$

The term $(A + Bt)$ in (5) is called the fixed-effects part of model since it represents the general decreasing trend of annual energy yield of micro-inverter PV systems during a 5-year period. The term $(u + vt)$ is called the random-effects since it includes the variant elements in the model. This random-effects explains the variability in measured energy yield from many stations.

B. CONDITIONAL LINEAR MODEL

In this model, the PV stations in Table 1 are fomulated as same as (3). However, the PV system are grouped into non-shading and shading group since we consider to investigate there is any difference or not in annual yield between two groups. Then, the (4) is rewritten as (6) below:

$$\alpha_i = A_0 + A_1 S_i + u \quad \beta_i = B_0 + B_1 S_i + v \tag{6}$$

where A_0 and B_0 have the same meaning as A and B. The new parameters A_1 and B_1 reflect any differences in the baseline energy yield and in the degradation rate between two PV groups. The S_i equals to 0 if PV station belongs to non-shading group and to 1 if it belongs to shading group as shown in Fig. 4.

By substituting (6) to (3), then (3) is written as (7) below:

$$\begin{aligned} y_i &= (A_0 + A_1 S_i + u) + (B_0 + B_1 S_i + v)t + e_i \\ &= [(A_0 + A_1 S_i) + (B_0 + B_1 S_i)t] + (u + vt) + e_i \end{aligned} \tag{7}$$

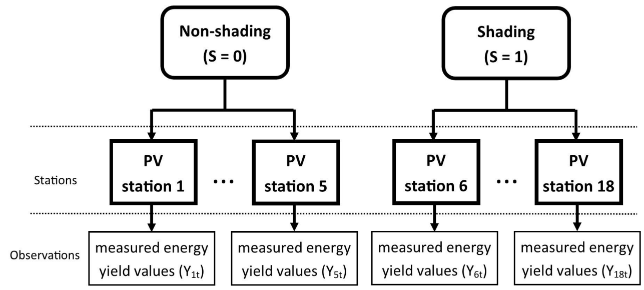

FIGURE 4. The groups of micro-inverter PV systems in Table 1. PV system which is suffered shading is coded as $S = 1$, while none-shading PV station is coded as $S = 0$.

In this case, the fix-effects term is $[(A_0+A_1S_i)+(B_0+B_1S_i)t]$. Unlike the fix-effects term in unconditional model, it now separately represents the decreasing of annual energy yield of none-shading PV stations and shading PV stations. In addition, if there exists any significant difference between two groups, then A_1 and B_1 identify how large the difference. The resulting analysis of linear mixed effects models are shown in Subsection IV-A.

C. CONDITIONAL NONLINEAR MODEL

The monthly energy yield m_i of the i^{th} PV station in Fig. 3 can be represented by the d^{th} degree polynomial function as (8) below. This nonlinear function (d^{th} degree polynomial function) was chosen as it can efficiently represent the curve which includes two peaks like those in Fig. 3 [32].

$$m_i = f(t, \boldsymbol{\psi}_i) + e_i = \sum_{j=0}^{d} \beta_{ji} t^j + e_i \tag{8}$$

where $\boldsymbol{\psi_i}$ is a d vector of coefficients of the polynomial function, The error e_i is assumed to follow a normal distribution with zero mean and variance σ_e^2, $e_i \sim \mathcal{N}(0, \sigma_e^2)$.

In a population approach, the PV stations in our dataset are assumed to be randomly sampled from a same population of individuals. Then, each individual parameter $\boldsymbol{\psi_i}$ is treated as an independent random variable and distributed normally, $\boldsymbol{\psi_i} \sim \mathcal{N}(\boldsymbol{\psi_0}, \boldsymbol{\Omega})$. The fixed effect term $\boldsymbol{\psi_0}$ is a d-vector of population parameters and $\boldsymbol{\Omega}$ is a $d \times d$ variance-covariance matrix. In this model, the least squares estimate of $\boldsymbol{\psi}_i$ is defined as (9)

$$\hat{\boldsymbol{\psi}}_i = argmin_{\psi_i} \sum_{k=1}^{12} (m_{ik} - f(t_k, \boldsymbol{\psi}_i))^2 \tag{9}$$

As mentioned in Fig. 4, there are two grouped data: non-shading and shading PV stations. We assumed that any variability in the monthly yield between two groups can be reflected by the differences in parameters of their polynomial functions. Therefore, we define the parameters of each group as (10) and (11) as follow:

For non-shading group, we imply that this group represents the population since we coded $S = 0$:

$$\boldsymbol{\psi}_i = \boldsymbol{\psi}_0 + S\boldsymbol{\psi}' + \boldsymbol{\eta}_i = \boldsymbol{\psi}_0 + \boldsymbol{\eta}_i \tag{10}$$

TABLE 2. The fixed effect results of both models.

Model	Parameter	Meaning	Value (kWh/kW)	95% CI. (kWh/kW)	P value
Unconditional model	A	Baseline energy yield	3.05	2.88 – 3.21	<0.0001
	B	Degradation rate	-0.09	(-0.13) – (-0.06)	<0.0001
Conditional model	A_0	Baseline energy yield	3.09	2.76 – 3.42	<0.0001
	B_0	Degradation rate	-0.11	(-0.18) – (-0.05)	0.0009
	A_1	Difference in baseline energy between two groups	-0.06	(-0.47) – 0.35	**0.77**
	B_1	Difference in degradation rate between two groups	0.02	(-0.05) – 0.1	**0.50**

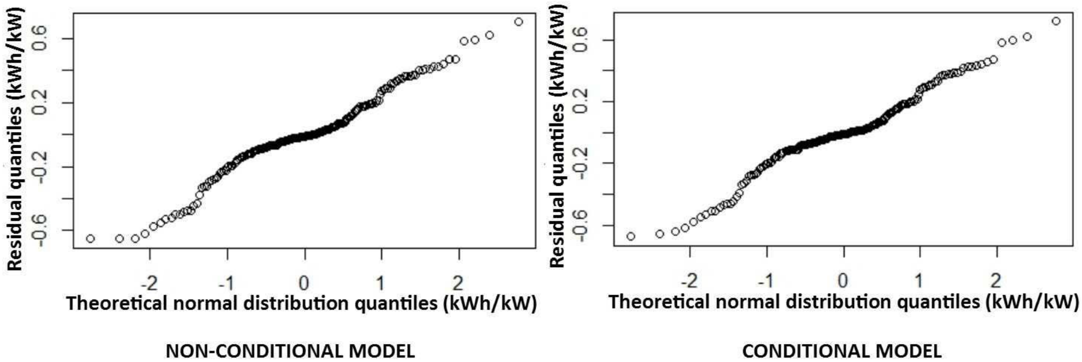

FIGURE 5. The Q-Q plots of residuals of non-conditional model and condition model in Table 2 and Table 3.

For shading group ($S = 1$):

$$\boldsymbol{\psi}_i = \boldsymbol{\psi}_0 + S\boldsymbol{\psi}' + \boldsymbol{\eta}_i = (\boldsymbol{\psi}_0 + 1\boldsymbol{\psi}') + \boldsymbol{\eta}_i = \boldsymbol{\psi}_S + \boldsymbol{\eta}_i \quad (11)$$

where $\boldsymbol{\eta}_i$ is random effect and $\boldsymbol{\eta}_i \sim \mathcal{N}(0, \boldsymbol{\Omega})$. The fixed effect $\boldsymbol{\psi}_0$ and $\boldsymbol{\psi}_S$ comparative result is shown in Subsection IV-B.

IV. ANALYSIS RESULTS

All algorithms and models were implemented using **R** programming version 3.4.0 [35] and **nlme** package [36]. The random process used the same number of generators to ensure the reproducibility.

A. YEARLY YIELD ANALYSIS

Table 2 and Table 3 show the resulting parameters of the fix effects and random effects terms of yearly energy yield modeling, respectively. From these results, the models of each PV group are rewritten as follow:

TABLE 3. The random effect results of both models.

Model	Variance	Source of variance	Std. Deviation
Unconditional model	σ_u^2	Baseline energy yield	0.34
	σ_v^2	Decline rate	0.05
	σ_e^2	Residuals	0.147
Conditional model	σ_u^2	Baseline energy yield	0.35
	σ_v^2	Decline rate	0.06
	σ_e^2	Residuals	0.147

The model for all micro-inverter PV stations is:

$$y_i = 3.05 - 0.09t \quad (12)$$

The model for non-shading PV group ($S = 0$):

$$\begin{aligned} y_i &= [(A_0 + A_1 S_i) + (B_0 + B_1 S_i)t] \\ &= [(3.09 + (-0.06)0) + (-0.11 + (0.02)0)t] \\ &= 3.09 - 0.11t \quad (13) \end{aligned}$$

The model for shading PV group ($S = 1$):

$$\begin{aligned} y_i &= [(A_0 + A_1 S_i) + (B_0 + B_1 S_i)t] \\ &= [(3.09 + (-0.06)1) + (-0.11 + (0.02)1)t] \\ &= 3.03 - 0.09t \quad (14) \end{aligned}$$

However, there is no significant difference between these models since the obtained P values of A_1 and B_1 are 0.77 and 0.50, respectively. In addition, the 95% CI. ranges of A_1 and B_1 in Table 2 also cross the zero value. Therefore, we conclude that there is no significant difference in annual energy yield of micro-inverter PV systems under shading and non-shading conditions. This means that we can use the model in (12) to represent the annual degradation yield of two PV groups. Our finding has confirmed again the advantage of micro-inverter configuration over other inverter configurations under shading condition.

Another interesting finding is that the averaged degradation rate (DR_{PV}) of micro-inverter PV systems is about -0.09 kWh/kW per year (95% CI.:-0.13 to

TABLE 4. Comparative results of the degradation rates of PV system.

Studies	Degradation rate	Methods	Remark
D. C. Jordan et al. [22]	0.77% (x-Si)	Clear sky models of sensor values	Module level
A. Limmanee et al. [25]	0.3% - 1.9%(x-Si) 1.8% - 2.1% (Thin Si) 1.7% (CIGS)	4-year period, outdoor measurement data	
J. Y. Ye et al. [24]	1% - 2%(x-Si) 6% (CIGS)	3-year period, outdoor measurement data	
I. Tetsuyuki et al. [21]	1.5% (x-Si)	3-year period, outdoor and indoor measurement data	
D. C. Jordan et al. [39]	0.8-0.9% (x-Si)	Review	
B. Marion et al. [23]	1.3% (single crystal Si) 1.4% (CdS/CdTe) 1.1% (a-Si)	12-year period, linear regression model	
IRENA [37]	0.5% (x-Si)	Surveyed from experts by International Renewable Energy Agency	Residential, system level
Australian Solar Report [38]	0.5% (x-Si)	Surveyed from experts by Australian Energy Council	
Our work	3%, 95%CI.:2%-4.3%	5-year period, analyzed from real datasets by mixed effects model	

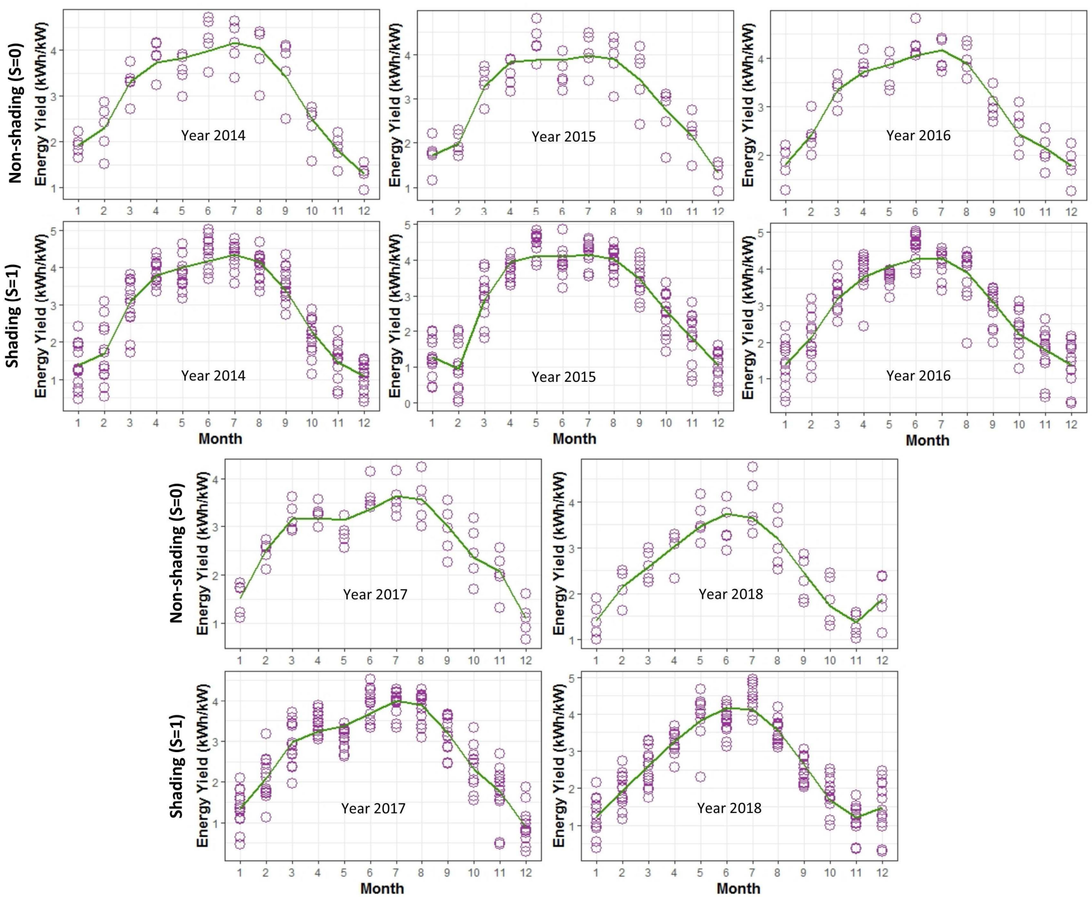

FIGURE 6. The polynomial fitting curves for monthly energy yield based on the nonlinear mixed effect model.

−0.06 kWh/kW). Counting in percentage, DR_{PV} is calculated as (15)

$$\mathrm{DR_{PV}} = -\frac{B}{A}.100 = \frac{0.09}{3.05}.100 \approx 3\% \tag{15}$$

and the 95% CI. range is calculated as (16)

$$95\%\mathrm{CI.} = -\frac{(-0.06)}{3.05}.100 : -\frac{(-0.13)}{3.05}.100 \approx 2\% : 4.3\% \tag{16}$$

Actually, our work is the first study that figures out the degradation rate of PV system analyzed from real datasets at system level of micro-inverter PV system. Comparing to other existing studies in Table 4, this degradation rate is higher than recommendations by IRENA [37] and Australian Energy Council [38] at system level, which are used for string inverter PV system. However, our result is acceptable, comparing to other studies at module level.

Finally, the Q-Q norm plot in Fig. 5 indicates that the assumption of normality of random effect term is plausible. In addition, the curves of two models are nearly identical since there are no significant difference between them.

B. MONTHLY YIELD ANALYSIS

Figure 6 shows the monthly yield during 5-year period from 2014 to 2018 and the corresponding polynomial fitting curves of monthly yields for both groups. According to [32], $d = 7$ was chosen to trade off between the minimum errors for two nonlinear models in Subsection III-C and computation load. Table 5 shows the result of likelihood ratio test (ANOVA) for model of non-shading group and model of shading group in each year. If the P value is smaller than 0.05, this indicates that the monthly yield model of non-shading PV stations is significantly different from the one of shading stations.

TABLE 5. The ANOVA analysis result of nonlinear mixed-effect models.

Year	Models	Degree of freedom	Sum of Square	F value	P value
2014	$f(\psi_0, t_k)$ $f(\psi_S, t_k)$	52 148	10.6 37.2	1.36	0.11
2015	$f(\psi_0, t_k)$ $f(\psi_S, t_k)$	52 148	10.9 38.5	1.37	0.11
2016	$f(\psi_0, t_k)$ $f(\psi_S, t_k)$	52 148	6.4 42.2	3.06	< 0.0001
2017	$f(\psi_0, t_k)$ $f(\psi_S, t_k)$	52 148	7.9 30.8	1.57	0.037
2018	$f(\psi_0, t_k)$ $f(\psi_S, t_k)$	52 148	10.7 37.8	1.37	0.10

The results in Table 5 shows that the monthly energy yield is only significantly different in 2016 and 2017 ($P < 0.05$). While the results of other years do not show any significant difference. Actually, it seems that the monthly energy efficiency of micro-inverter PV system is dependent on the shading, resulting in a lower ambient temperature and slow MPPT adaption as mentioned in [13] and [40], comparing to the non-shading one. However, we did not observe this difference in our monthly yield analysis. We recommend further study in order to reach stronger conclusion about the effect of ambient temperature to micro-inverter PV system.

V. CONCLUSION

In this study, we compared monthly and yearly yield of micro-inverter PV systems to evaluate the impact of shading. Our work has contributed further evidence that the shading issues such as trees, chimney, or neighbor building does not affect the yearly electrical energy yield of PV systems that use micro-inverter configuration. Hence, the micro-inverter PV guarantees to obtain the maximum energy efficiency in case of shading. We also found that the averaged energy yield degradation of micro-inverter PV system is 3% per year, with the 95% confidence interval from 2% to 4.3% and this degradation rate is totally independent of shading conditions. Lastly, our proposed mixed-effect model in our study have been proven as an effective method to use for the longitudinal data measurement.

In further study, we will extend our proposed mixed-effect model to verify the consistency of our findings with micro-inverter PV systems in other regions. We also plan to compare the long-term energy efficiency between micro-inverter PV and string inverter PV system in various conditions based on mixed-effect method.

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