IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received June 26, 2021, accepted July 8, 2021, date of publication July 13, 2021, date of current version July 23, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3096982

Annual Degradation Rate Analysis of Mono-Si Photovoltaics Systems in Thailand Using the Mixed Effects Method

NGOC THIEN LE, WIDHYAKORN ASDORNWISED, SURACHAI CHAITUSANEY, AND WATIT BENJAPOLAKUL

Department of Electrical Engineering, Faculty of Engineering, Artificial Intelligence, Machine Learning and Smart Grid Technology (Year 2) Research Unit, Chulalongkorn University, Bangkok 10330, Thailand

Corresponding author: Watit Benjapolakul (watit.b@chula.ac.th)

This work was supported by the Ratchadapisek Somphot Fund through the Artificial Intelligence, Machine Learning, and Smart Grid Technology (Year 2) Research Unit (RU) and the Postdoctoral Fellowship, Chulalongkorn University.

ABSTRACT The annual degradation rate (DR) of photovoltaics (PV) system is a critical factor to evaluate the energy performance and the levelized cost of electricity (LCOE) during its operation lifetime. However, the DR of a particular system strongly depends on the technical configuration such as PV module and array, inverter configuration, and also the climatic conditions. Therefore, a real operation dataset of DR is necessary to PV engineer in order to estimate energy performance and the LCOE for a particular system. This article presents the annual DR for a group of PV systems in Bangkok, Thailand which share the same monocrystalline silicon (Mono-Si) solar cell and inverter brand, over a four-year period. Instead of using simple linear regression, we apply the linear mixed effects method to estimate the DR value, which is suitable to formula a time-series data. The annual DR was found about 2.7% per year, with the 95% confidence interval from 0.7% to 4.6% per year. Hence, the operation lifetime of PV system until it reaches 80% of their initial energy conversion performance is about 7 years, with the 95% confidence interval from 4 years to 28 years. The resulting DR is informative and useful for further study on PV system performance and cost of investment in tropical region. Furthermore, we are the first group in Thailand to estimate the DR of PV station at system scale based on the mixed effects method. Finally, our study has enriched the knowledge about the operation of Mono-Si PV station in real operation condition.

INDEX TERMS Degradation rate, linear decline model, levelized cost of electricity (LCOE), mixed effects model (MEM), mono-Si PV station.

I. INTRODUCTION

The annual degradation rate (DR), defined as the decrease of system efficiency over year, is a significant factor of the energy performance in order to estimate the energy yield of PV system during its operation lifetime [1]–[6] or calculate its return of investment [7]–[13]. The DR is also used to calculate the total lifetime energy produced from PV system during its operation. This amount of energy is the denominator component of the levelized cost of electricity (LCOE) equation [14]–[17]. However, DR of a particular PV system not only depends on the technical configuration, but also depends on the climatic condition. The real operation dataset of DR is thus necessary for PV engineering, PV system planning and designing.

Thailand is currently in the top tenth of the most installed PV capacity in the world, with shared about 3% of total world PV capacity [18]. One of the most concerns in PV research efforts is about estimating the DR of PV systems in Thailand's tropical condition. For example, Limmanee *et al.* [19] surveyed 5 technologies of solar module to estimate their DRs at the location of Thailand Science Park, Bangkok and reported their impact to LCOE. However, it is obviously that neither the DR at module level could not represent for PV system, nor the DR of a PV array. Furthermore, the effects of ambient temperature to reduce energy efficiency of both PV array and inverter are significant. For example, authors in [20] showed that at above 37 °C, the maximum efficiency

The associate editor coordinating the review of this manuscript and approving it for publication was Akshay Kumar Saha.

of inverter drops about 2.5%. Other PV studies in [21]–[26] focused on evaluating the energy performance of rooftop PV systems in Thailand.

Although there are some studies about DR evaluation and energy performance of PV systems located in Thailand, there is still lacking in the literature the real operation information of DR at system level rather than module or array levels and the DR evaluation of PV system that uses monocrystalline solar cell (Mono-Si). In this study, we broaden the knowledge about the DR information in Thailand by evaluating the real Mono-Si PV systems at many locations in Bangkok. Since our DR values is estimated as system level, the LCOE calculation then provides more reliable result than existing DR in literature.

In addition, the mixed effects model (MEM) is applied for estimating monthly decline rate and then interpreting the annual degradation rate of Mono-Si PV system based on linear mixed effects method instead of simple linear regression as in [19]. The mixed effects model, proposed by author [27] in statistical literature, has received attention in biological, clinical, and also in power engineering recently [28]–[31]. By utilizing this model, the decline rate is achieved by decomposing the trend of monthly energy yield of a particular PV system as the fixed term, which represents the generalized value for the whole observed systems, and the random terms, which represent the variations in trend of that PV system and between many PV systems to the fixed term. The formula of linear mixed effects then represents the monthly decline trend of Mono-Si PV systems in Bangkok, Thailand. In general, the contributions of our study are: *(i)* we are the first group in Thailand to provide the information about annual degradation rate of Mono-Si PV station at system level rather than module or array level based on the mixed effects method; and *(ii)* our study enriches the knowledge about the operation of monocrystalline silicon PV stations in real operation condition.

The article is structured as follows. Section II presents the PV systems in our study and our method analysis based on the mixed effects model. Section III provides the analysis results of annual degradation rate. Finally, Section IV summarizes our study and discusses future directions.

II. METHODOLOGY

A. PV SYSTEM DESCRIPTION

Table 1 shows the configurations of PV stations used in our study. There are 4 one-phase PV systems (residential system) and 2 three-phase PV systems (commercial system). The PV technology of all stations is Mono-Si (LG MonoX/black series) with its output warranty of maximum rated power at least 80.2% for 25 years [32]. These stations also used the same inverter brand from SMA manufacturer. In detail, the SMA Sunny Boy (maximum DC-to-AC efficiency: 97%) is used for 4 residential PV systems and the SMA Sunny Tripower (maximum DC-to-AC efficiency: 98.4%) is used for 2 commercial PV systems. Other technical specifications of inverters are mentioned from the manufacturer website [33]. The SMA inverter also supports connecting PV stations to data acquisition system on cloud via the Internet link. The parameters logged are generated power, power efficiency, peak power, peak time, and conditions. All these measurement are collected and uploaded to PVoutput website [34] every 5 minutes.

B. METHOD OF ANALYSIS

1) INPUT VARIABLE

The monthly energy yield m is chosen as a primary variable to estimate the monthly degradation rate of PV stations in Table 1. The calculation is shown in (1)

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

where P_{pv} is the rated power of PV system, M is the total number of recorded days of the m^{th} month, and E_{day_j} is the total generated energy from PV system on the j^{th} day. Those data are obtained via the published datasets at PVoutput [18].

TABLE 1. PV systems used in our study. The technology of all PV arrays is monocrystalline solar cell (Mono-Si). All PV stations are located in bangkok. The starting time of observing these PV station is January 2016. Shading does not affect to these stations.

PV station	Rated power (kW)	Orientation	Tilt degrees
One-phase			
1	3.64	North	25
2	4.68	South	30
3	3.12	South East	15
4	9.9	South	5
Three-phase			
5	25.57	South	10
6	108	South	1

Figure 1 demonstrates the monthly yields of commercial and residential PV systems in our study. In general, there is a decreasing trend in monthly yield from 2016 to 2019. Therefore, we propose a decomposition technique to extract the monthly trend and use it as a secondary variable for our proposed model.

2) TIME SERIES DECOMPOSITION TECHNIQUE

If we assume an additive decomposition, then the monthly energy yield m_i of the i^{th} PV station in Figure 1 is represented as (2),

$$m_i = t_i + s_i + e_i, \tag{2}$$

where t_i is the trend component, s_i is the seasonal variation component, and e_i is the residual (or error) component, all at the cycle of 12 months. The additive decomposition is the suitable technique if the magnitude of the seasonal variation around the trend does not change when the time series value increases [35].

The trend component of a time series is commonly calculated using a moving average filter [35], [36]. Because there

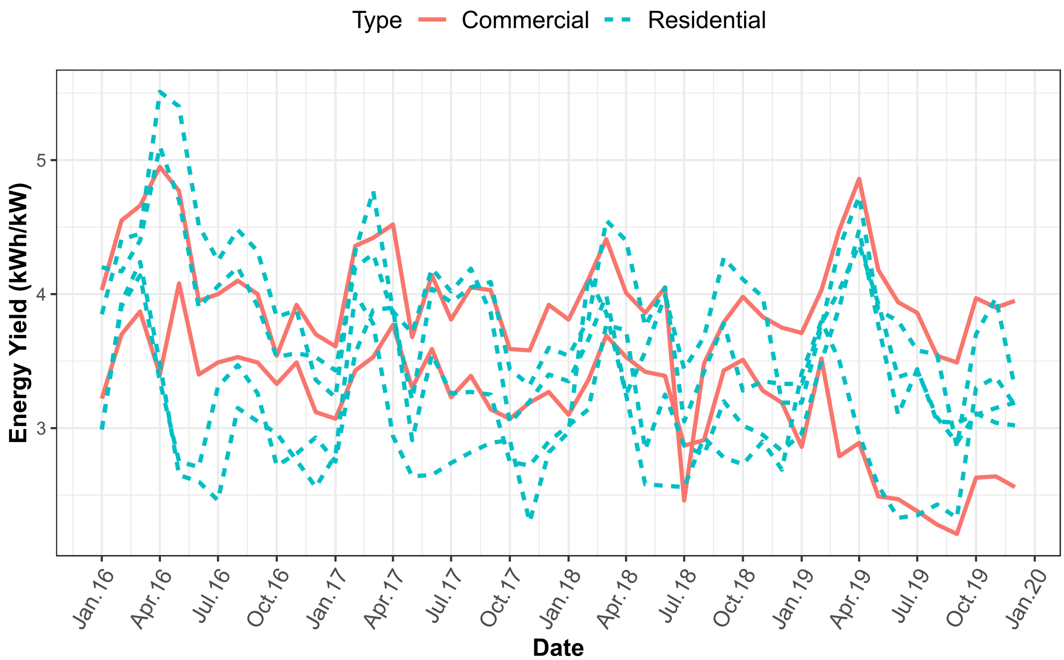

FIGURE 1. The monthly energy yield of Mono-Si PV systems in table 1 from 2016 to 2019.

are 12 months in a year we thus have to use a moving average of length twelve. This means that at each data point j (j starts at 7) is averaged by the 6 data points behind and 6 data points in front of the position j to calculate an average value for ($a = 6$). However, since the moving average is an even length, the result includes the mean of two averages as (3).

$$\begin{aligned} t_i(j) &= \frac{1}{2}[\sum_{k=-a}^{a-1}(\frac{1}{2a})m_i(j+k) + \sum_{k=-(a-1)}^{a}(\frac{1}{2a})m_i(j+k)] \\ &= \frac{1}{4a}[\sum_{k=-a}^{a-1} m_i(j+k) + \sum_{k=-(a-1)}^{a} m_i(j+k)] \end{aligned} \tag{3}$$

The result of these moving averages yields the decreasing trend of monthly energy yield from 2016 to 2019 as shown in Figure 2. The decomposition process of monthly yield of PV stations was implemented using **R** programming version 3.4.1 [37] and decomposing function in **R** statistics package. Then, the trend component $t_i(n)$ of these systems is used as a secondary variable to estimate the degradation rate based on the linear decline model based on mixed effects model.

3) LINEAR MIXED EFFECTS METHOD

This model is based on the assumption that degradation trend of monthly yields t_i in Figure 2 is linear. This assumption is worthy for PV energy studies in short time observation as mention in [1], [38], [39]. Hence, the monthly energy yield is formulated as (4):

$$t_i = A_i + B_i n + e_i \tag{4}$$

where t_i is the observed trend for the i^{th} PV station $i = 1, 2, \ldots, 6$, measured repeatedly from 2016 to 2019 and represented by the index of month n. The A_i and B_i are called the baseline yield (kWh/kW) and monthly decline rate of the i^{th} PV station, respectively. The meaning of baseline yield is the initial trend value that we observed at $n = 0$, and e_i is the residual (or error) between the measured value (or real value) and estimated value from the model of the i^{th} PV station. 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 we intend to estimate the common decline trend for any PV system installed in Bangkok, Thailand which uses Mono-Si panel and central inverter configuration. This trend is affected by the differences between many PV stations such as orientation and tilt degrees. Based on the mixed effects method, this variation is formulated as a two-level nested data model in Figure 3 and assume that A_i and B_i in (4) include two terms as follows:

- *Fix-effect terms*: The common value of baseline yield and common value of decline rate that represent for the Mono-Si PV systems using SMA inverter in Bangkok, Thailand;
- *Random-effect terms*: The variations of baseline yield and decline rate caused by the differences between many PV stations;

The parameters A_i and B_i are thus rewritten as (5) to reflect both fix-effect and random-effect terms:

$$A_i = A_0 + u \quad B_i = B_0 + v \tag{5}$$

where A_0 and B_0 are the baseline yield and common decline rate of all Mono-Si PV systems in Bangkok, Thailand; and

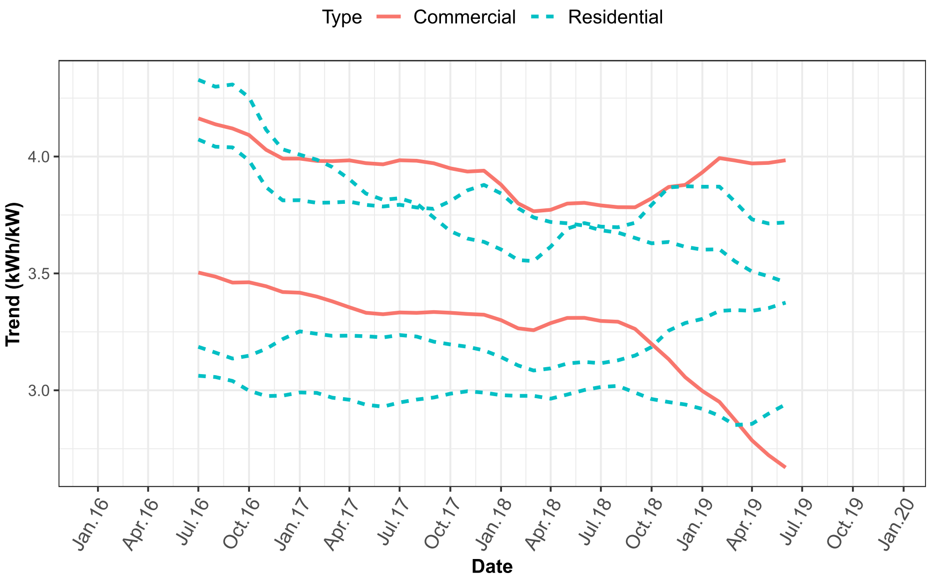

FIGURE 2. The decreasing trend in monthly yield of Mono-Si PV systems in table 1 during 4-year period from 2016 to 2019.

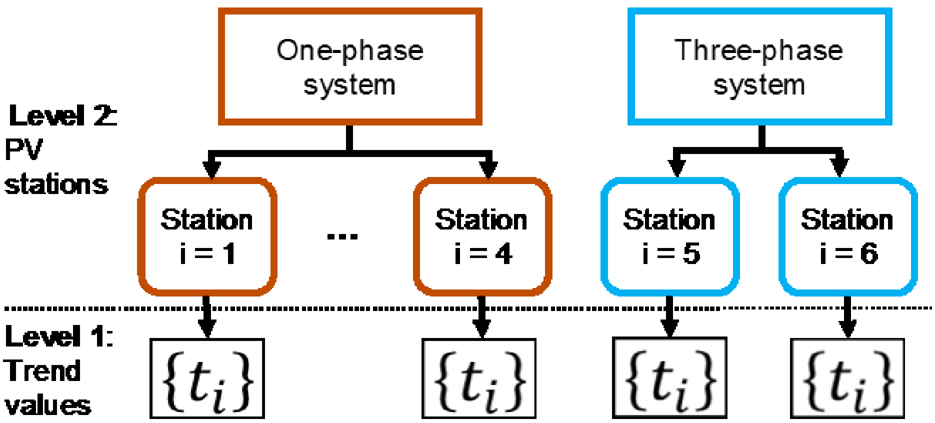

FIGURE 3. Two-level nested data of PV stations in table 1 used for linear decline model. Level 1 is the variation within PV station. Level 2 is the variation among many PV stations.

u and v represent the variation of baseline yield and common decline rate caused by the random-effect terms to a particular Mono-Si PV system. 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 (5) to (4), the (4) is written as (6) below:

$$\begin{aligned} y_i &= (A_0 + u) + (B_0 + v)n + e_i \\ &= (A_0 + B_0 n) + (u + vn) + e_i \end{aligned} \tag{6}$$

In (6), the term $(A_0 + B_0 n)$ shows the common decreasing trend of monthly energy yield for all Mono-Si PV systems in Table 1. The term $(u + vn)$ depicts the variation of decreasing trends between many PV stations, compared to the common decreasing trend. The value of monthly decline rate B_0 is our interesting result since it is interpreted the annual DR of Mono-Si PV system. The resulting analysis of linear decline model based on MEM and interpreted annual DR are shown in Section III.

III. RESULTS AND DISCUSSION

The algorithm for proposed linear decline model based on MEM was implemented using **R** programming version 3.4.1 [37] and nlme package [40]. The random process used the same number of generators to ensure the reproducibility.

A. LINEAR DECLINE MODEL BASED ON MEM

Table 2 shows the analyzed results of fix-effect term and random-effect term from proposed linear decline model based on MEM, respectively. From these results, the common decreasing trend of monthly energy yield of PV stations

TABLE 2. **The fixed-effect results of linear decline model.**

Model	**Parameter**	**Meaning**	**Value** (kWh/kW)	95%**CI** (kWh/kW)	**P value**
Linear decline model based on MEM	A_0	Initial trend	3.64	3.26 – 4.01	<0.0001
	B_0	Monthly decline rate	-8.2×10^{-3}	$(-14) \times 10^{-3}$ – $(-2) \times 10^{-3}$	0.0097

TABLE 3. **The random-effect results of linear decline model.**

Model	**Parameter**	**Source of variance**	**Variance**	**R-squared** (%)
Linear decline model	σ_u^2	Initial trend	0.32	74.4%
	σ_v^2	Decline rate	4.52×10^{-3}	
	σ_e^2	Residuals	0.11	

TABLE 4. **The resulted parameters of monthly decline model using simple linear regression in [19].**

Model	**Parameter**	**Meaning**	**Value** (kWh/kW)	**Standard error**	**P value**
Simple linear regression [19]	α	Initial trend	3.64	0.0515	<0.0001
	β	Monthly decline rate	-8.2×10^{-3}	0.0025	0.00134

in Table 1 is as (7):

$$t = A_0 + B_0 n = 3.64 - (8.2 \times 10^{-3})n \tag{7}$$

The resulted monthly decline rate B_0 is (-8.2×10^{-3}) kWh/kW. This value is statistically significant since its P value is 0.0097 (<0.05) and its 95% CI range does not cross zero. Therefore, this means that B_0 can be represented as the monthly decline rate for the whole PV stations in Table 1.

Table 3 shows the random-effect results of the linear decline model and the corresponding R-squared. This score, calculated as $(\sigma_u^2 + \sigma_v^2)/(\sigma_u^2 + \sigma_v^2 + \sigma_e^2)$, represents the proportion of variance in the degradation trend that is explained by the model. The resulted R-squared indicates that about 74.4% variation in the decline trend of PV stations can be explained by the linear decline model based on MEM.

Finally, the Q-Q plot in Figure 4 shows that all the points fall approximately along the reference line, hence we can assume normality of residuals in our proposed linear decline model based on MEM in Subsection II-B3.

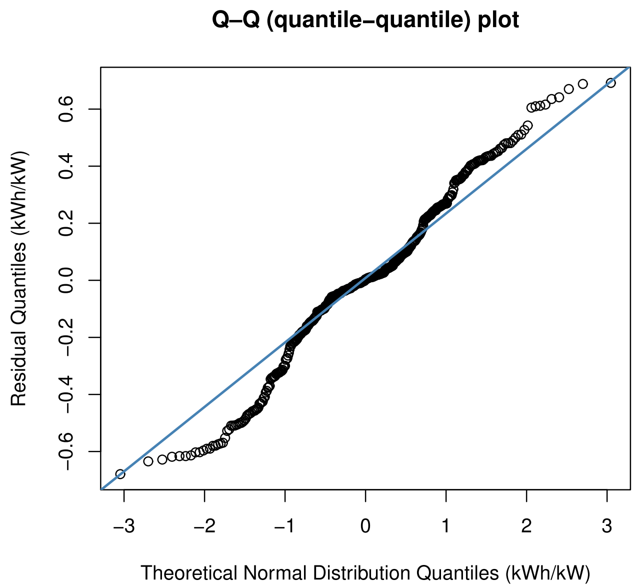

FIGURE 4. **The Q-Q plots of residuals of linear decline model based on MEM in table 2.**

B. COMPARISON WITH SIMPLE LINEAR REGRESSION MODEL

To evaluate the efficiency of proposed linear decline model, the simple linear regression model as in study [21] is applied to formulate the monthly energy yield of PV systems. The models of single linear regression is shown in (8).

$$t = \alpha + \beta n + e \tag{8}$$

The outcome t is the common monthly decline trend of PV stations. α, β, are the initial trend and monthly decline rate parameters. The variable n is the index of month.

The result analysis in Table 4 shows the same initial and monthly decline rate found by the model based on MEM in Table 2 with both P values being statistically significant (smaller than 0.05).

TABLE 5. **The goodness-of-fit comparison between our proposed models based on MEM and linear regression models.**

Model	**Mean Square Error (MSE)**	**R-squared** (%)	**AIC score**
Linear decline model based on MEM	0.148	74.4%	−321.26
Simple linear regression [19]	0.148	4.7%	206.03

The goodness-of-fit comparison between two models are shown in Table 5 based on the R-squared and Akaike information criterion (AIC) score. AIC is a method for evaluating

TABLE 6. Example LCOE calculation for residential system and commercial system in table 1. parameters are extracted from national survey report of PV power applications in Thailand 2018 [43].

Parameters	Unit	Meaning	Residential PV system	Commercial PV system
I_0	Baht/kW	Investment cost	52,000	47,000
A_c	Baht/kW	Operation cost per year (1% of I_0)	520	470
T_c	Baht/kW	Total cost, calculated as (14)	55,640	50,290
M_o	kWh/kW	Energy yield at initial year 2016	4.35	3.84
E_{pv}	kWh/kW	Total generated energy during $N = 7$ years, calculated as (15)	10,249	9,056
LCOE	Baht/kWh	levelized cost of energy, $(\frac{T_c}{E_{pv}})$	5.43	5.56

how well a model fits the dataset [41], [42]. The lower AIC score, the better the model fits the dataset. The resulted values of R-squared and AIC indicate that the linear decline model is better fit to the monthly trend of PV stations in Table 1 than the simple regression model. This is because the model based on MEM can learn across the PV station population and also learn the variation between many PV stations. In addition, the MSE scores of two methods are about the same since the MEM is actually extended from the linear regression method.

C. ANNUAL DEGRADATION RATE OF MONO-SI PV SYSTEMS

The annual DR of Mono-Si PV systems in Table 1, counted in a year in percentage, is interpreted from the monthly decline rate B_0 as (9)

$$\begin{aligned} \text{DR} &= -\frac{B_0}{A_0}\left(\frac{12 \text{ months}}{\text{year}}\right)(100) \\ &= -\frac{(-8.2 \times 10^{-3})}{3.64}(12)(100) \approx 2.7\% \end{aligned} \tag{9}$$

and its 95% CI. range is calculated as (10)

$$\begin{aligned} 95\%\text{CI.} = &-\frac{(-14 \times 10^{-3})}{3.64}(12)(100) \\ &\times \text{to} - \frac{(-2 \times 10^{-3})}{3.64}(12)(100) \approx 0.7\% \text{ to } 4.6\% \end{aligned} \tag{10}$$

Furthermore, the operation time N (years) of PV system, when it reaches 80% of their initial energy conversion efficiency, can be estimated as (11) below:

$$1 - (DR)N = 0.8 \tag{11}$$

Thus,

$$N = \frac{1 - 0.8}{DR} = \frac{0.2}{0.027} \approx 7 \text{ years} \tag{12}$$

and the 95% CI. range of N is calculated as (13)

$$\begin{aligned} 95\%\text{CI.} = &\frac{1 - 0.8}{0.046} \approx 4 \text{ years} \\ &\times \text{to } \frac{1 - 0.8}{0.007} \approx 28 \text{ years} \end{aligned} \tag{13}$$

From the 95% CI. range of N of PV systems in Table 1, the best case is that their energy conversion efficiency is still higher than 80% of their initial one after passing the warranty period of 25 years. On the other hand, the worst case is only after 4 years of operation.

D. LCOE CALCULATION

The simple method to calculate LCOE is that it equals to the total cost of PV system (T_c) divided by the total generated power (E_{pv}) over a period of time ($N = 7$ years). The T_c is calculated as (14)

$$T_c = I_0 + (A_c)N \tag{14}$$

where I_0 is the investment cost and A_c is the annual operation cost.

The total generated power E_{pv} over a $N = 7$ years (starting at year 2016) is estimated as (15) below:

$$\begin{aligned} E_{pv} &= (365)M_0 + (365)M_0[1 - (1)DR] \\ &\quad + (365)M_0[1 - (2)DR] + \cdots \\ &\quad + (365)M_0[1 - (6)DR] \\ &= (365)M_0 \sum_{i=0}^{N-1}[1 - (i)DR] \end{aligned} \tag{15}$$

where M_0 (kWh/kW) is the daily energy yield of PV systems in Table 1 at the initial year 2016. M_0 is the ratio of total generated energy in a year per kilowatt divided by the number of days in a year (365 days). From our gathered data of PV systems in Table 1, this value is about 4.35 (kWh/kW) for residential system and is about 3.84 (kWh/kW) for commercial system.

Table 6 demonstrates an example LCOE calculation for both PV types in Table 1. It should be noted that the LCOE was estimated based on the first $N = 7$ years of operation period (starting from 2016), not on the warranty period of 25 years. The resulting LCOE of residential Mono-Si PV station is about 5.43 (Baht/kWh), which is nearly the same values with the LCOE of Multi-Si and Hetero-Si PV system in [19] (5.3 (Baht/kWh) and 5.4 (Baht/kWh) respectively). Meanwhile, the retail electric price for residential

TABLE 7. Summary findings of degradation analysis of PV systems located in bangkok, Thailand.

Study	Location	Method of analysis	Interval	Level	Degradation Rate (%/year)
[19]	Thailand Science Park, Bangkok, Thailand	Simple linear regression	Monthly	Module; array	1.7 (CIGS) 1.2 (Multi-Si) 1.3 (Hetero-Si)
Our study	Different locations, Bangkok, Thailand	Linear mixed effects method	Monthly	PV system	2.7 (Mono-Si)

TABLE 8. Similar degradation analysis studies of Mono-Si PV technology in many tropical countries.

Study	Location	Method of analysis	PV panel technology	Period of study	DR (%/year)	Level
[44]	Dakar, Senegal (Tropics)	Linear regression	Mono-Si	2 years	2.96	Module and array
[45]	Singapore (Tropics)	Linear regression	Mono-Si	3 years	0.8	Module and array
Our work	Bangkok, Thailand (Tropics)	Linear mixed effects method	Mono-Si	4 years	2.7	System

user is 8.19 (Baht/kWh) in 2018 [43]. This reveals that in the future if the retail electric price does not reduce to below 5 (Baht/kWh), the owner of residential PV system will gain benefit from their PV investment.

Table 7 summarizes the findings of our study and study in [19] with many types of PV panel technologies. Actually, compared to [19] our findings is reliable and useful since we have surveyed much datasets from many PV stations across Bangkok, Thailand. It also has enriched the knowledge about operation of Mono-Si PV stations in real operation condition.

Table 8 shows the degradation rate studies of Mono-Si PV in some tropical countries. In Thailand, our study is the first one in literature surveying and estimating the degradation rate of whole PV system based on the mixed effects model in real operation condition, rather than at module or array level.

Finally, the sources of the DR differences in Table 7 and Table 8 come from the difference in the level of DR studies. Other authors ([19], [44], and [45]) have examined the DR of solar module or array only, not included the degradation rate of other components such as inverter or cable. On the other hand, our study has not only examined the DR of Mono-Si PV but also taken into account the DR of other components of PV system (at system level). Since a PV system can be integrated by many PV types (CIGS, Multi-Si, Mono-Si. etc) and inverter types (SMA, LG, SolarEdge, etc.), therefore it is impossible to obtain a DR value that can be represented for all types of PV stations located in Thailand at present. Our study has only contributed to the DR information of PV system using Mono-Si and SMA inverter. In future, if further DR studies with other PV station types are conducted, then we will obtain the represented parameter of DR and also investigate the effect of different PV configurations on DR.

IV. CONCLUSION

In this study, the annual degradation rate at system level of Mono-Si PV stations in Bangkok, Thailand during 4-year study has been performed. The resulting degradation rate was found to be about 2.7% per year, corresponding to the operation lifetime of Mono-Si PV system of about 7 years until it reaches 80% of their initial energy conversion performance. Our work has expanded the existing DR datasets of PV system, which is useful for LCOE calculation to assess the cost-effectiveness of Mono-Si PV system. In addition, our study is also useful for government to publish policy initiative or interest rate to develop PV systems in Thailand.

In further study, we will extend our proposed mixed-effects model to conduct a meta-analysis study about PV systems that use Mono-Si technology at system level in different climatic conditions.

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NGOC THIEN LE received the B.E. degree in electrical engineering from the HCMC University of Technology and Education, Vietnam, in 2006, the M.E. degree in telecommunication from the Ho Chi Minh City University of Technology, Vietnam, in 2008, and the Ph.D. degree from the Department of Electrical Engineering, Chulalongkorn University, Thailand, in 2016. His research interests include data analysis for smart grid and smart grid communication.

WIDHYAKORN ASDORNWISED received the M.Sc. degree in electrical engineering from Drexel University, in 1999, and the D.Eng. degree in electrical engineering from Chulalongkorn University, in 2005. He is currently an Assistant Professor with the Department of Electrical Engineering, Chulalongkorn University. The current projects are 5G Chula, Micro-operator, and 5G/6G Private Networks. His research interests include artificial intelligence, data mining, and artificial neural networks.

SURACHAI CHAITUSANEY received the Ph.D. degree from The University of Tokyo, Japan, with JICA Scholarship, in 2007. He is currently an Assistant Professor and the Head of Power System Research Laboratory (PSRL), Chulalongkorn University. He has more than 70 international and 60 domestic publications. His research interests include renewable energy, solar PV, distributed generation, power system planning and reliability, and smart grid regulation. In addition, he has served as a member for the subcommittee, the committee, and the working group in several professional organizations, such as the Engineering Institute of Thailand (EIT), the Energy Policy and Planning Office (EPPO), the Energy Regulatory Commission (ERC), and the Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI) Association.

WATIT BENJAPOLAKUL received the D.Eng. degree in electrical engineering from The University of Tokyo, in 1989. He is currently a Professor with the Department of Electrical Engineering, Chulalongkorn University, Thailand. He is also the Head of the Artificial Intelligence, Machine Learning, and Smart Grid Technology Research Unit, Faculty of Engineering, Chulalongkorn University. His current research interests include mobile communication systems, broadband networks, applications of artificial intelligence in communication systems, wireless networks, and applications of communication networks in smart grids.