Attaining Grid Parity: LCOE Analysis for Grid-Connected PV Systems of Utility Scale Across Selected ASEAN Countries

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Abstract: Historically, ASEAN countries are dependent on conventional energy resources due to their abundance, which in turn explains renewable energy's slow progress. With the existing government plans, various reports predict that only 17% renewable energy share can be achieved by 2025. Geothermal, Hydro and Bioenergy being limited to regional availability and with the declining cost of Solar PV, it is important to predict future Levelized Cost of Electricity (LCOE) for Solar PV systems in this region. Hence, unlike earlier research articles this paper focuses on evaluating Levelized Cost of Electricity (LCOE) for PV (equal 1 MW) technology across selected five ASEAN member states, i.e. Indonesia, Malaysia, Thailand, Vietnam and Philippines till 2040 while considering capital cost of sub-system components within a typical PV system, i.e. PV module, Inverter, Mounting Structure and Balance of System (BoS) distinctly to generate unique Learning Curves (LCs) for individual countries. Sensitivity analysis was conducted with regard to discount rate, solar irradiation and CAPEX to identify impact on LCOE values and attainment of grid parity.

***Keywords*:** LCOE, Learning Curve, Grid Parity, ASEAN, PV,WALCO, Solar PV

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1. Introduction

Historically, ASEAN countries are dependent on conventional energy resources due to their abundance. (ACE.2017) highlights on existing status and future estimates of energy across ASEAN countries. It classified its analysis into three scenarios. Business-As-Usual (BAU) scenario assumed that no significant changes will be introduced from past practices while AMS Target Scenario (ATS) assumed all energy-related policies and national targets across all ASEAN nations will be fully attained. ASEAN Progressive Scenario (APS) assumed an optimistic future with regard to Renewable Energy and Energy Efficiency improvement. BAU scenario is based on the current progress of RET (Renewable Energy Technology), latest national power development plans, and primary production of fossil fuels and refineries. Hence, it is more realistic to assume BAU scenario for the rest of this article. ASEAN countries have rich and largely untapped renewable energy sources. Countries like Myanmar, Indonesia and few other lower Mekong countries have potential to one of the best hydropower in the world. Global horizontal irradiation- in the region is one of the highest among the world with an annual average of 1.5-2.0 MWh/m^2 (IRENA.2018a). As compiled from (IRENA.2018), the cumulative installed capacity of PV systems across ASEAN countries is provided in Figure 1. Hence, it can be documented that Thailand, Malaysia, Indonesia, Philippines and Singapore are the pioneers in PV installations among ASEAN nations. Due to the introduction of the FiT

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scheme in most of these countries and constant decrease in solar PV cost, PV installation has increased substantially in recent years.

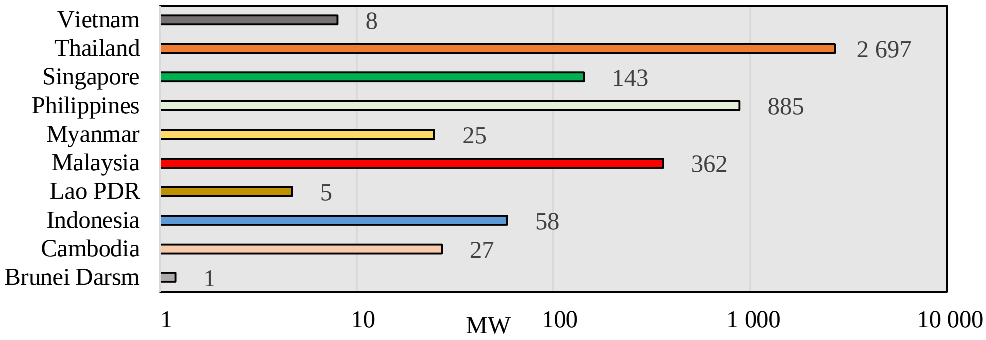

Figure 1 Solar PV Cumulative Installed Capacity, (IRENA.2018)

1.1. Literature Review

A comprehensive literature review has been conducted to identify previous research methodologies and progress attained in estimating future Levelized Cost of Electricity (LCOE) in ASEAN countries in case of renewable energy technologies, especially utility- scale solar PV systems.

1.1.1. LCOE of Renewable Energy Technology (RET)

(Zhao and Zhang.2018) focused on estimating PV installation capacity along with LCOE projection using Learning Curve (LC) between 2015-2030. It also investigated the effect of local government subsidy on LCOE predictions along with identifying 17 factors affecting PV installation capacity. Many LCOE projection studies have been conducted and reports have been published for solar PV and other Renewable Energy Technologies (RET) for European countries. Forecasting LCOE of various RET in Germany till 2035 was highlighted by (Fraunhofer Institute for Solar Energy Systems ISE.2018). Researches solely focusing on solar PV was also conducted in Europe. (Energiewende.2015) aimed at forecasting solar PV capital cost and BoS separately for Germany till 2050 to project LCOE using LC. While (Ayompe, Duffy et al.2010) focused on estimating LCOE for a 1.72 kWp system in Dublin using LC attained through estimating solar PV capital cost dynamics untill 2055.It also estimated the amount of CO_2 reduction. Differently, (Breyer and Gerlach.2013) focused on comparing grid parity with LCOE of solar PV in more than 150 countries using Learning Curve methodology to predict future LCOE. It also considered LC for inverter and BoS cost projection. (Vartiainen, Masson et al.2015) & (Vartiainen, Masson et al.2015a) focused on LCOE projection of solar PV till 2030 and 2050 consecutively. However, (Vartiainen, Masson et al.2015a) emphasized on Weighted Average Cost of Capital (WACC) as the most important parameter guiding LCOE projections. It used data from the International Energy Agency (IEA) and Bloomberg New Energy Finance (BNEF) in the model. Apart from solar PV systems, some researchers have also used LC methodology to predict LCOE for CSP systems. (Parrado, Girard et al.2016), (Hernández-Moro and Martínez-Duart.2013) & (Breyer, Afanasyeva et al.2017) focused on long term LCOE projection for both Solar PV and CSP systems using LC methodology. However, (Parrado, Girard et al.2016) also focused on identifying the possible effect of a change in molten salts in Thermal Energy Storage (TES) on LCOE in Chili. Similar research was conducted for South America, North America and Australia by (Köberle, Gernaat et al.2015) where two scenarios were considered namely, fast learning and slow learning using Learning Curves. Another forecasting methodology that has been widely used is Expert Elicitation. Expert Elicitation method was used by (Wiser, Jenni et al.2016) to predict LCOE of energy systems and it also showed that results are congruent with LC methodology. Research with LC methodology is not only limited to grid-connected energy systems. (Zou, Du et al.2017)used LC to estimate energy cost of grid-connected and off-grid solar PV system in 5 cities of China. For studying the effect of government policies on solar PV market, (Talavera, Muñoz-Cerón et al.2016) conducted a study taking into consideration 12 laws and Royal Decrees.

1.1.2. LCOE of Other Technologies

LCOE projection through Learning Curve method is not only limited to RET. Few researches have already been conducted wherein both conventional and non-conventional energy technologies have been considered. LCOE was projected for China till 2035 using LC for coal, gas, wind, solar PV and nuclear power systems in (Miao.2015). (West.2012) focused on similar methodology, however; it was focused on OECD countries.

1.1.3. LCOE of RET in ASEAN

Focusing ASEAN countries, few studies have already been conducted. (Pratama, Purwanto et al.2017) aimed to foretell LCOE of solar PV in Indonesia between 2011 & 2050 with a 5-year interval using LC. However, it considered global average cost data published by IEA and IRENA. While (Finenko and Soundararajan.2016) considered floating solar, roof-top solar PV and BIPV systems and identified LCOE till 2030 for Singapore by LC method. Apart from LC method, few researchers used TIMES and TEEP model wherein LCOE was estimated for articulating long term least cost energy mix scenarios as depicted by studies conducted by (Tanoto, Handoyo et al.2015) & (Zou, Du et al.2017) focusing on Philippines and Java (Indonesia) consecutively.
It is therefore, admissible that, Learning Curve (LC) method is a powerful tool for technological cost reduction and LCOE estimation. To the best of authors' knowledge, almost all of the research article utilized average global data of PV system cost to predict LCOE evolution for specific countries or region. Besides, research articles are very limited which takes into consideration sub-systems of solar PV i.e. Solar PV module, Inverter, Mounting Structure and BoS cost separately to generate distinctive Learning Curves based on local i.e. country/region-specific data.

Hence, authors intend to develop ASEAN country-wide LC of solar PV sub-systems individually to predict LCOE till 2040 with 2020 as the reference year.

1.2. Measuring Cost of Renewables

According to (IEA/NEA.2018), cost of electricity can be categorized into three different levels; Plant-level costs, Grid-level system costs and External or Social costs outside the electricity system. Plant-level cost is commonly referred to as technology cost described as Levelized Cost of Electricity (LCOE), which represent lifetime costs divided by electricity production. Grid-level system costs concern the costs at the level of the electricity system, linked through the transmission and distribution grid. The third category includes items that impact the well-being of individuals and communities outside the electricity sector.

2. Method

In the previous section, by deep diving into technology cost and system cost analysis approaches, how 'costs' of renewables are calculated and how it can be different depending on the parameters and the power systems are presented. Even when considering the cost within the power system, in an accounting sense, there can be a huge diversity in implications of the cost assessment results depending on how analysts set the assumptions and parameters. However, this study focuses on the plant-level economic aspect of renewable energy, namely the Levelized Cost of Electricity (LCOE) of variable renewable electricity i.e. grid-connected solar PV systems to simplify the argument. Thus, the purpose of this modeling study is to first construct the LCOE models for selected ASEAN Member States.

2.1. LCOE Calculation Formulae

LCOE calculations mainly depend upon fixed cost (capital cost), variable cost (operation, maintenance & replacement cost) of systems and the electricity generated by the project over its lifetime. In this section, methodology used to derive capital cost, variable cost and the amount of electricity generated over the project lifetime are described. Levelized Cost of Electricity is the ratio of NPV of all discounted cost incurred during the project life to the total electricity generation capacity (kWh) of the project. LCOE is essentially expressed in $/kWh. The significance of LCOE is that it provides a fair idea regarding generation cost of electricity and can be used to compare between technologies to identify the least cost solution. Many research works by (Hoffmann.2010), (IRENA.2012) & (Branker, Pathak et al.2011) have considered LCOE for comparing various technologies in terms of grid parity.

By neglecting the carbon cost and decommissioning costs, LCOE can be expressed as follows (U.S. DOE.2004):

$$\sum_{n=0}^{n} \frac{LCOE \times E_n}{(1+r)^n} = \sum_{n=0}^{n} \frac{Costs_n}{(1+r)^n} \tag{1}$$

Re-arranging the above equation, we get

$$LCOE = \frac{\sum_{n=0}^{n} \frac{Costs_n}{(1+r)^n}}{\sum_{n=0}^{n} \frac{E_n}{(1+r)^n}} \tag{2}$$

Eq. (2) resembles LCOE which is the sum of all the discounted cost incurred during project life divided by the units of discounted energy produced from the system. While calculating, it has to be noted that all initial costs of the project occurs at n = 0 year and should not be discounted. Hence, initial cost needs to be separated from Eq. (2) and all other parameters in Eq. (2) should be discounted starting from year 1. Initial cost plays a vital role in LCOE calculation as it encounters for 80% of PV system costs as observed by (Hoffmann.2010). Initial Cost (I) can be divided into Capital Cost (C) and Land Cost (L). On the other hand, Annual Cost (OPEX) is comprised of Operation, Maintenance & Replacement Cost, which occurs over the project lifetime and hence required discounting. Next, we considered energy generated from a PV system over its lifetime. Energy produced from PV systems is related to available Solar Resource i.e. irradiation (S), Solar PV Performance Factor (PF) and Solar PV annual degradation factor (d). Hence, Energy Generated (E_n) annually can be illustrated as:

$$E_n = \mathrm{S} \times \mathrm{PF} \times (1 - \mathrm{d}) \times 365 \tag{3}$$

Notably, both Energy Generated (E_n) and Costs must be calculated in kWh/W and $/W to derive LCOE in $/kWh. Combining and re-arranging Eq. (2) & (3)

$$LCOE = C + \{L \times (1+p)^{x-y}\} + \frac{\sum_{n=1}^{n} \frac{OPEX \times (1+p)^n}{(1+r)^n}}{\sum_{n=1}^{n} \frac{S \times PF \times (1+d)^n \times 365}{(1+r)^n}} \tag{4}$$

Where,

- p=Inflation rate (%)
- x= Year of installation
- y= Year of data source
- r= Discount rate

- S= Solar Irradiation (kWh/m^2/day)
- PF= Performance Factor of Solar PV system (%)
- d= Annual degradation of PV module
- n= Project Life i.e. 25 Yrs.
- C= Capital Cost
- L= Land Cost
- *OPEX*= Operation, Maintenance & Replacement Cost

Notably, mathematical model for calculating Levelized Cost of Electricity (LCOE) is developed based on Eq.4.

2.2. Evolution of the LCOE using the Learning Curve (LC) approach

As derived in Eq. (4), LCOE calculation requires cost parameters as input to the model. Hence; it is essential to derive cost data with regard to Capital Cost (C), Land Cost (L) and OPEX. For LCOE estimation from 2020-2040, feeding of future cost parameters into the LCOE model is required. Deriving future costs, associated with solar PV system requires estimation of Capital Cost (C) that an investor would encounter while installing a solar PV project in the future. Various past research has been published wherein Learning Curves (LC) approach was used to identify the evolution of cost in terms of economy of scale. LCOE of various renewable energy technology until 2035 was calculated using Learning Curves by (Energiewende.2015). Similarly, (Hernández-Moro and Martínez-Duart.2013) aimed at projecting Capital Cost (CAPEX) for PV and CSP plants based on Learning Curves until 2030. (Hernández-Moro and Martínez-Duart.2013) also described Learning Curve (LC) as a method which derives cost of systems as a function of cumulative installed capacity. Hence; Learning Curve (LC) methodology has been used to predict future CAPEX for solar PV systems. The LC is plotted as the straight line in log-log space and the slope of these curves are related to Learning Rate (LR) which indicates cost reduction per cumulative doubling of installed capacity and can be expressed as follows:

$$Log[C(t_2)] = -b \times [Log[Q(t_2)] - Log[Q(t_1)]] + Log[C(t_1\ )] \tag{5}$$

or,

$$\frac{C(t_2)}{C(t_1)} = [\frac{Q(t_2)}{Q(t_1)}]^{-b} \tag{6}$$

The exponent –b in Eq. (6) represents the slope of the straight line in log-log space and is called the Learning Rate (LR). LR can be described as:

$$1 - LR = 2^{-b} \tag{7}$$

Using Eq. (6) & (7), capital cost between two comparing time periods can be derived based on relevant cumulative install capacity data. Combining Eq. (6) & (7),

$$\frac{C(t_2)}{C(t_1)} = [\frac{Q(t_2)}{Q(t_1)}]^{\frac{Log(1-LR)}{Log(2)}} \tag{8}$$

As articulated in Figure 2, historical data retrieved from research articles and reports along with the cumulative installation capacity plans of each of the countries are fed into the LC model to derive distinctive LCs. These LCs are then used to derive the future cost of solar PV sub-systems.

2.3. Purchasing Power Parity

Purchasing goods in one country may be less or more in another country. Adjusting the cost with inflation rate overlooks the effect of purchasing power and price index. According to (Piyasil.2012),

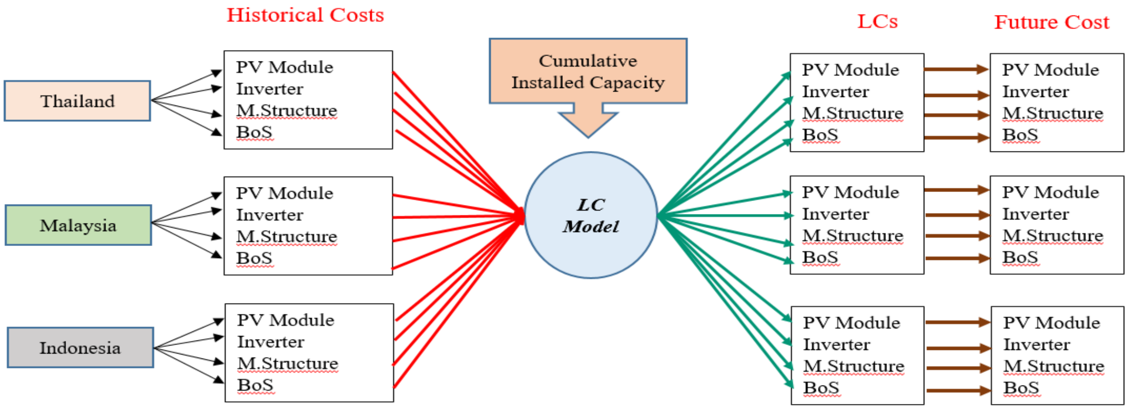

Figure 2 Learning Curve Approach

$$PPP\ index\ of\ \mathrm{X}\ \ to\ \mathrm{Y} = \frac{PPP\ index\ of\ Y}{PPP\ index\ of\ X}$$

Cases wherein publicly available cost data was unavailable, PPP theorem was utilized to convert cost data of one country to other as described in (Piyasil.2012).

2.4. Assumed Parameters

2.4.1. Capital Cost

Capital Cost of equipment works as a vital catalyst in LCOE model. Most of the earlier studies like (Fraunhofer Institute for Solar Energy Systems ISE.2018, Energiewende.2015, Ayompe, Duffy et al.2010) considered Capital Cost of the PV system as a whole while others (Breyer and Gerlach.2013) considered PV module cost and Inverter Cost separately. Moreover, earlier research works utilized global average cost data. On the contrary, this research work has segregated PV system costs into four sub-systems namely, Solar PV cost, Inverter cost, Mounting Structure cost and BoS (Balance of System) cost enabling better understanding of implications injected by individual sub-system cost on LCOE. A sample of Capital Cost is provided in Table 1.

2.4.2. Land Cost

Estimating land cost is the most difficult part as it varies in wide range due to geographical attributes. PV plants use 10-50 km^2 /GW (U.S. DOE.2004). Land Cost (L) of 30$/kW has been considered based on previous research works of (Hernández-Moro and Martínez-Duart.2013). Notably, country-specific inflation rates have been considered while adjusting Land Cost to present and future cost.

2.4.3. Operation & Maintenance Costs

Solar PV plants encounter costs for its successful operation and maintenance over its life-time. As prescribed by (Hernández-Moro and Martínez-Duart.2013), operation and maintenance cost for solar PV mainly comprises of regular cleaning of PV modules, monitoring of performance and inverter replacement costs and amounting it as 1.5% of the capital cost. On the other hand, (ACE.2016) highlighted a variation of O&M cost within ASEAN countries ranging between 1-2%.

2.4.4. Solar Resource

Solar resource, S, stands for the average annual energy per unit area (kWh/m^2/day) based on the location of the country where the systems will be installed. Solar PV systems utilize both direct and diffuse radiation for its electricity generation. Based on the solar resource data collected from (NASA.2018), average solar energy incident on fixed structure tilted solar PV for sample countries is compiled in
Figure 3.

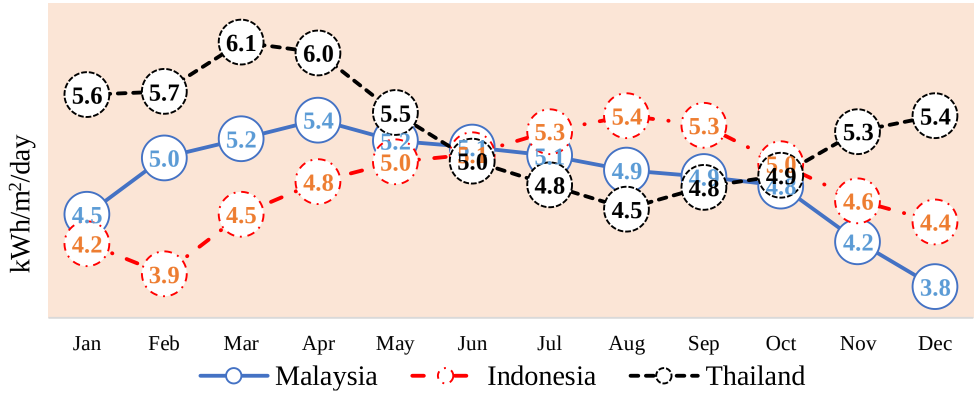

Figure 3 Solar Resource at Tilted PV Module

Variations in solar resource have been evaluated in the sensitivity analysis to replicate country-wide fluctuations in LCOE for each country. This also provides an indication regarding regions of lowest LCOE with highest potential for solar PV system dissemination.

2.4.5. Performance Factor

Eq. (3) describes energy output from solar PV. However, the real output of solar PV when exposed to sunlight decreases due to various factors and losses. Since, electricity produced from solar PV is DC in nature, it requires to be converted to AC before evacuating to the grid. However, the conversion is done with an efficiency of 93-95% as noted by (Ayompe, Duffy et al.2010, Zahedi.2009). In addition, PV module performance decreases with increase in temperature from their standard testing condition linearly as mentioned by (Tian, Mancilla-David et al.2012). Taking all these losses, the real Performance Factor (PF) ranges between 75-85% as suggested by (Hernández-Moro and Martínez-Duart.2013) & (Zahedi.2009). Hence, Performance Factor of 75% has been considered in this study.

2.4.6. Degradation Factor

Solar PV modules' performance tends to degrade yearly due to its exposure to ultraviolet radiation throughout its lifetime. It has been noted in previous studies that PV modules' performance degrade at the rate of 0.6%/ year which is highlighted in (Branker, Pathak et al.2011).However, 1% and 1.21% has been considered in our work based on the recent research outcome as published in (NREL.2018).

2.4.7. Discount Rate

In terms financial aspect, one of the most important parameters that guides the outcomes of LCOE model is the discount rate. Discount rate not only takes into account inflation rate but also technological risk. (ACE.2016) considered discount rate of 10% and hence, a similar discount rate has been considered.
A comprehensive literature review was done and relevant data was collected for LC and LCOE modeling. Apart from this, various assumptions were made to complete the research work.

Details of assumption and data used in this research work is tallied in Table 2

Table 1 Details of Capital Cost

Year	**Country**	**Component**	**$/W in 2018**	**Source of Data**	**Notes**
2016	Thailand	Solar PV	0.60	(SEDA.2017)	• All values are adjusted to reference year (2018) with average relevant inflation rates. • For 2011, exchange rates collected from (Malaysia.2018) (accessed on 17/11/2018) were used. • For 2014 & 2016, exchange rates as mentioned in (SEDA.2017, SEDA.2015) were used.
		Inverter	0.14		
		M. Structure	0.28		
		BoS	0.54		
2014		Solar PV	0.79	(SEDA.2015)	
		Inverter	0.21		
		M. Structure	0.40		
		BoS	0.69		
2011		Solar PV	1.87	(Mahyudin and Malek.2012)	
		Inverter	0.40		
		M. Structure	0.82		
		BoS	1.00		
2015	Malaysia	Solar PV	0.68	(IEA.2016)	• 2015 data related % share of sub-system in capital cost, was used to extract 2013, 2014 costs . • All values are adjusted to reference year (2018) with average relevant inflation rates. • For 2013, 2014 & 2015, exchange rates as mentioned in (IEA.2016, IEA.2015) were used.
		Inverter	0.16		
		M. Structure	0.16		
		BoS	0.47		
2014		Solar PV	0.73	(IEA.2015)	
		Inverter	0.17		
		M. Structure	0.17		
		BoS	0.56		
2013		Solar PV	1.22	(IEA.2014)	
		Inverter	0.28		
		M. Structure	0.28		
		BoS	0.81		
2016	Indonesia	Solar PV	0.55	(SEDA.2017)	• Power Parity Theorem utilized for conversion • All values are adjusted to reference year (2018) with average relevant inflation rates. . • For 2014 & 2016, exchange rates as mentioned in (SEDA.2017, SEDA.2015) were used.
		Inverter	0.13		
		M. Structure	0.25		
		BoS	0.49		
2014		Solar PV	0.74	(SEDA.2015)	
		Inverter	0.20		
		M. Structure	0.37		
		BoS	0.64		
2011		Solar PV	1.21	(Nippon Koei Co. and ORIX Corporation.2012)	
		Inverter	0.26		
		M. Structure	0.53		
		BoS	0.65		

Table 2 Assumed Parameters

Parameters			Source Data (Value)	Data Used in Calculation (Value)	Source of Data
Solar PV Annual Performance Degradation	1^{st} year of operation		0.4% & 1.5%	1.0%	(NREL.2018)
	2^{nd} year and onwards		1.41-1.45% &	1.21%	
Irradiation (kWhr/m^2/day	Malaysia		4.84	4.84	(NASA.2018)
	Thailand		5.30	5.30	
	Indonesia		4.79	4.79	
Project Lifetime	All countries		25 Years	25 Years	(Hernández-Moro and Martínez-Duart.2013)
Land Cost (L)			30 $/kW	30 $/kW	
Discount rate (r)			10%	10%	(ACE.2016, Taylor.2010)
O&M Cost (OPEX)	Malaysia		1.5% of C	1.5% of C	(ACE.2016)
	Thailand		1.3% of C	1.3% of C	
	Indonesia		1.2% of C	1.2% of C	
Inflation rate (%)	Malaysia	Land Cost (L)	2.6%	2.6%	(World Bank.2018)
		OPEX	3.9%	3.9%	
	Thailand	Land Cost (L)	1.91%	1.91%	
		OPEX	0.67%	0.67%	
	Indonesia	Land Cost (L)	5.7%	5.7%	
		OPEX	3.8%	3.8%	

3. Results

3.1. Cumulative Installed Capacity

In order to generate Learning Curves for individual system components of Solar PV, Cumulative Installed Capacity of Solar PV for every 5 years of increment till 2040 with a base case of 2020 is required. Since, ASEAN member states have different targets, cumulative installed capacity of solar PV varies within 2020-2040 for different member states. Cumulative Installed Capacity of Malaysia, Thailand and Indonesia has been compiled and estimated with relevant information as depicted in (IRENA.2018) & (APERC.2016) in Figure 4.

3.2. Learning Rates (LR)

It was suggested by (Schaeffer.2004) that the experience curve projections were generally more accurate than optimistic engineering predictions found in the literature. It was proved by (Alberth.2008) that having more data sets reduces biasness of LC in terms of predicting technological cost reductions. Availability of accurate and sufficient data set has been an issue in ASEAN countries which led to the fact that only 3 sets of complete data were found available for few countries and may have limited the accuracy of LC estimation. Nevertheless, LC can be used as an unbiased estimator of future technology costs as mentioned by (Alberth.2008). Deriving Learning Rate (LR) requires developing Learning Curves (LC). A typical utility scale

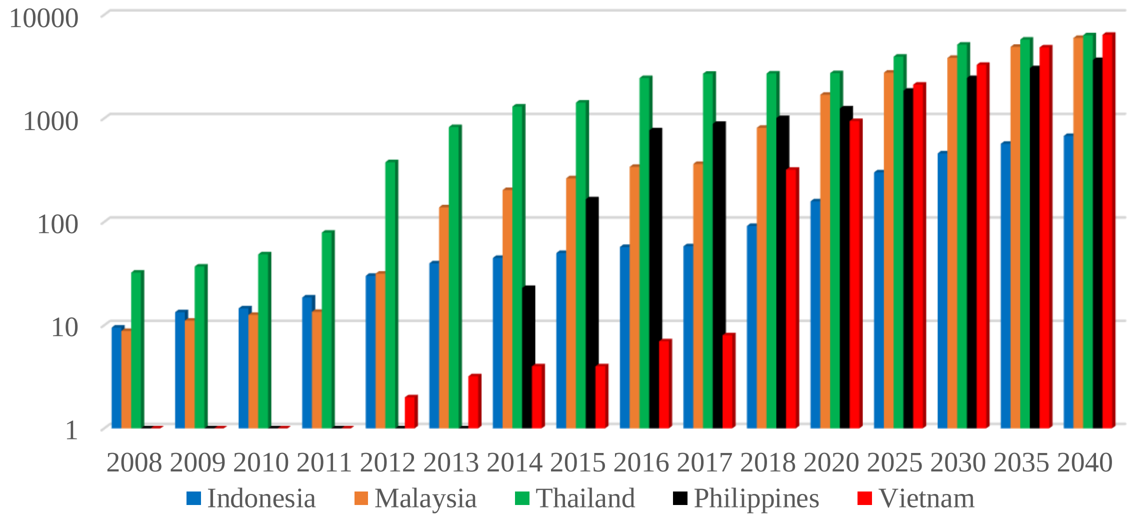

Figure 4 Comparison of the Cumulative Installed Capacity

Solar PV project capital cost can be divided into four main sections i.e. Solar PV cost, Inverter cost, Mounting Structure cost and BoS (Balance of System) costs. BoS cost comprises of grid integration, licensing, cables, profit and installation. Hence, deriving Learning Rate (LR) requires developing Learning Curves (LC). Hence, 4 × Solar PV sub-system LC × 5 countries (Malaysia, Thailand, Indonesia, Vietnam, Philippines) = total 20 LCs were developed. Learning Rates (LR) derived from these curves were used to estimate future evolution of capital costs as described in Figure 2. Learning Rate (LR) for different components for sample countries are noted in Table 3

Table 3 Learning Rates

Country	Sub-System	Slope value (-b)	Progress Ratio (PR)	Learning Rate (LR)
Malaysia	Solar PV	0.38	0.77	0.23
	Inverter	0.29	0.82	0.18
	M. Structure	0.13	0.92	0.08
	BoS	0.18	0.88	0.12
Thailand	Solar PV	0.56	0.68	0.32
	Inverter	1.055	0.48	0.52
	M. Structure	1.055	0.48	0.52
	BoS	0.92	0.53	0.47
Indonesia	Solar PV	0.59	0.66	0.34
	Inverter	0.52	0.70	0.30
	M. Structure	0.13	0.92	0.08
	BoS	0.19	0.88	0.12

3.2.1. Malaysia

With a cumulative installed PV system capacity of only 362 MW till 2017 as mentioned in Figure 4, Progress Ratio (PR) of solar PV modules in Malaysia has been derived as 77% expounding that the cost has been reduced by 23% (LR) in contrast to the global average of 20.9% as identified by (Zhao and Zhang.2018). PR is defined as (1-LR) in (Hernández-Moro and Martínez-Duart.2013). In spite of having low cumulative installation capacity, notable cost reductions in Malaysia may be attributed to its evolution as one of the major PV system manufacturing country in recent years. With regard to progress in inverter cost reductions, comparative slow progress is observed with a PR of 82% (18% cost reduction) owing to the fact that inverters used in Malaysia are mostly imported and inverter price reduces with increase in volume. Since, Malaysia's cumulative installation is lower compared to other pioneers i.e. Thailand, a slow Progress Ratio has been observed. BoS and Mounting Structure are mostly locally procured, developed and constructed. Cost of installation, grid integration, license, infrastructure, cables and wire are included in BoS. Grid integration cost varies with the distance between the project site and nearest transmission substation along with capacity of the project. As derived in this work, BoS and Mounting Structure has a PR of 88% and 92%, respectively. Notably, cost reductions in BoS and Mounting Structure are dependent on the availability of cheap, skilled human resource and cumulative installed capacity. Lower PR of BoS and Mounting Structure may be owed to the fact that Malaysia has less PV system installed in terms of capacity and high labor cost.

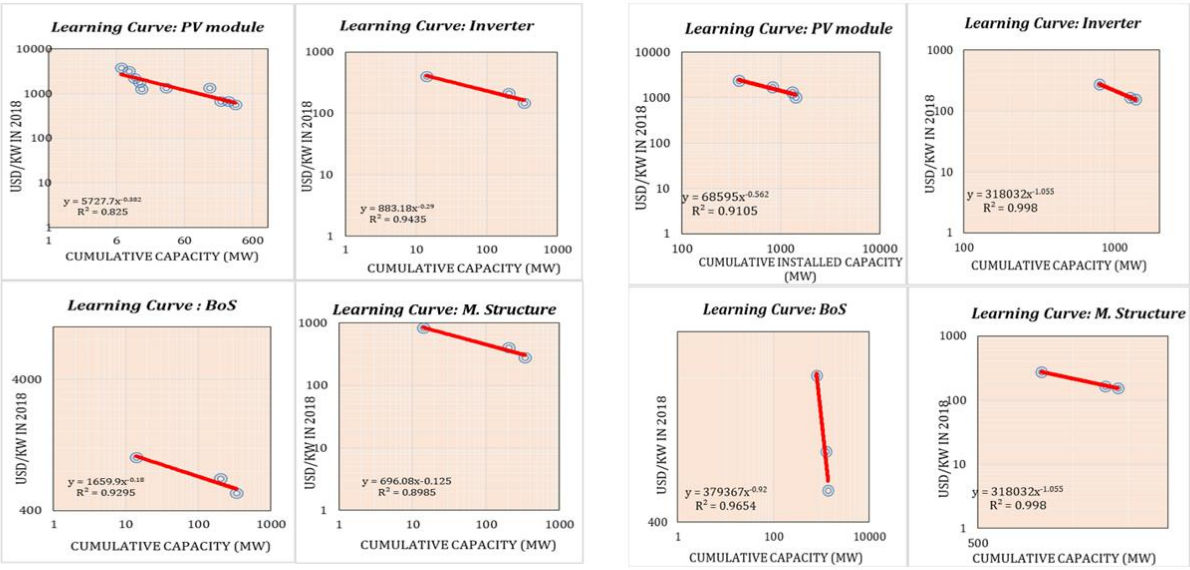

Figure 5 Learning Curves for Malaysia & Thailand

3.2.2. Thailand

As per Eq. (8), cost reductions depend upon both cumulative installed capacity as well as LR. As seen from the LCs of PV system installed in Thailand, a PR of 68 % is achieved meaning that solar PV module cost has reduced by 32% (LR) due to doubling of capacity installation in the reference period. Higher LR in contrast to the global average of 20.9% as derived in (Fraunhofer Institute for Solar Energy Systems ISE.2018) may be owed to the fact that PV installations in Thailand is highest among ASEAN countries. Among all the sub-system, cost of inverter has dropped to 48% followed by cost of BoS and cost of solar PV modules. Though, Thailand is considered as one of the pioneers in implementing solar PV projects in ASEAN, cost reductions of solar PV module is not the highest. The reason may be inherited due to the absence of local manufacturers. (Tongsopit, Chaitusaney et al.2015) highlighted the existence of 3 solar PV module manufacturer having annual capacity of >180 MW. Moreover, ratio of reduction of solar PV cost was not as progressive as the cumulative installation during this period and as mentioned in LC theorem, PR depends not only on cost reductions but also cumulative installation during reference period.

3.2.3. Indonesia

Cost reductions in Indonesia has been much higher compared to the annual capacity installation. This may be owed to the fact that solar PV installation has been increasing in recent times in

Indonesia and it is youngest among the countries in terms of solar PV adaptation. Congruently, solar PV system cost has been lowest globally in recent times.

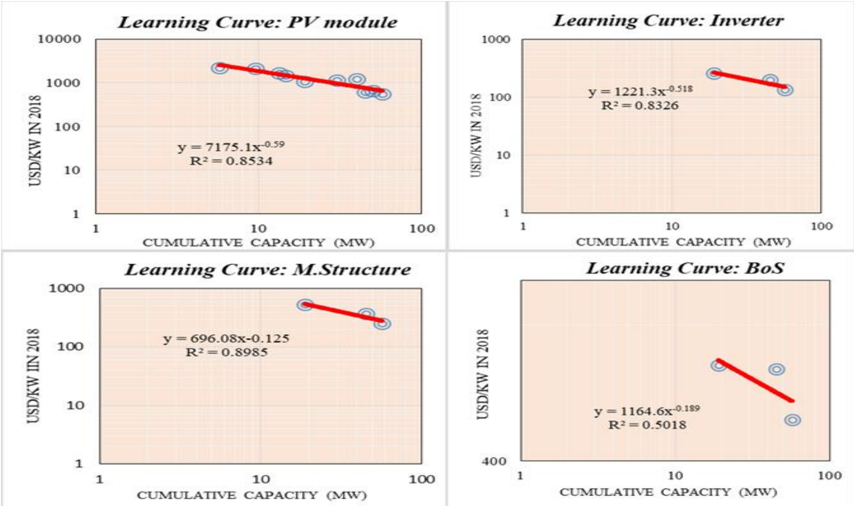

Figure 6 Learning Curves for Indonesia

4. Discussions

4.1. Levelized Cost of Electricity (LCOE)

4.1.1. Simple LCOE

The simple Solar PV Levelized Costs of Electricity (LCOE), that is, LCOEs without the carbon cost and decommissioning costs, were calculated based on the findings detailed in Section 3.2. As shown in Figure 7, simple LCOEs for all countries reduces from the reference period till 2040. In 2020, Philippines will have the highest LCOE. In 2040, LCOE of Philippines is predicted to remain highest and Thailand generating electricity at the lowest 0.074$/kWh. LCOE for Philippines remains highest among three countries due to the higher capital cost as derived from data sets. CAPEX in the future is predicted to be lowest in Indonesia followed by Thailand, Vietnam and Malaysia. However, LCOE evolves to be lowest in Thailand followed by Indonesia, Vietnam & Malaysia. This opposite evolution can be explained by the fact that Thailand inherits the highest solar irradiation resource, lowest labor cost and land cost among the comparing countries.

Impact of various sub-system costs on LCOE can be observed in Figure 8. As noted, cost of solar PV module contributes highest (30%~48%) on LCOE in Thailand and Philippines followed by BoS costs. On the other hand, BoS costs account for more than 30% on LCOE in Malaysia, Indonesia & Vietnam followed by cost of Solar PV module. Hence, it can be concluded that LCOE can be drastically reduced if special consideration is provided on project site selection. Projects installed adjacent to existing substation will have reduced BoS cost and subsequently lower LCOE. Besides, the utilization of locally manufactured PV modules also rduces LCOE as seen in the case of Malaysia. Lastly, it is also apprehensive that the absolute value of component-wise share shrinks over the years, regardless of their % share of contribution on LCOE.

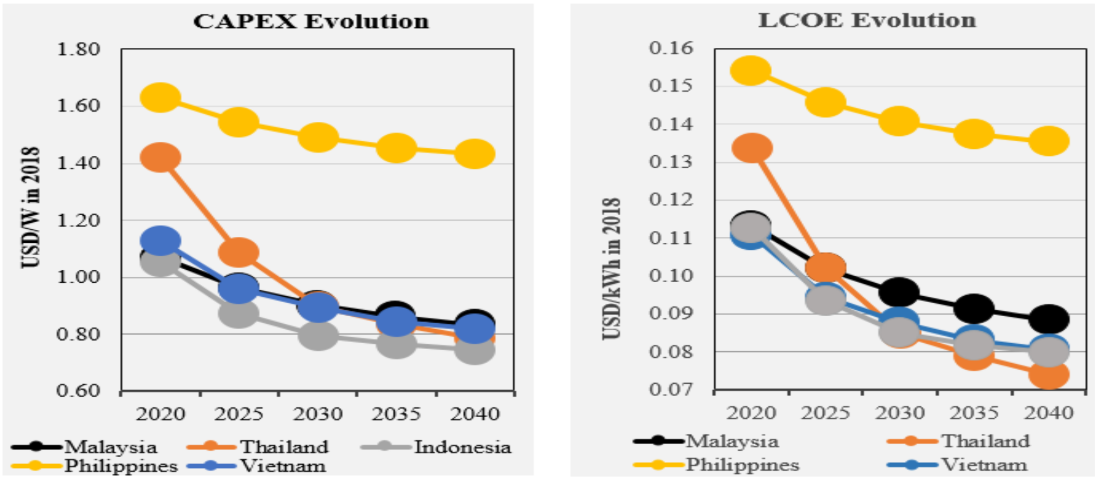

Figure 7 CAPEX & LCOE Evolution

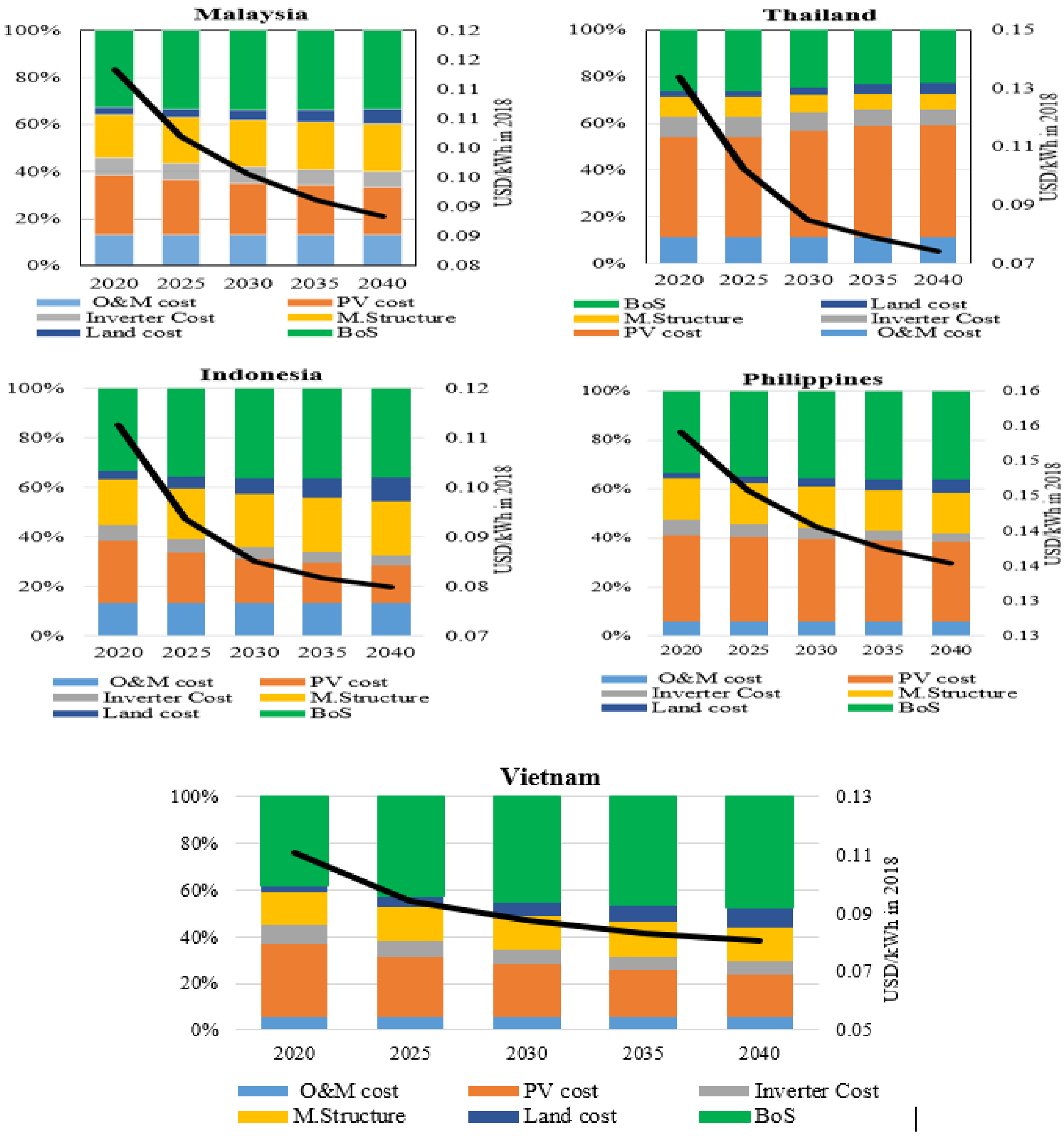

Figure 8 % Share of Costs in LCOE

4.1.2. Country-wide Weighted Average LCOE

In the aim of aiding policy-makers, the Weighted Average LCOEs (WALCOEs) were also calculated. Since PV module's performance degrades, it is expected that PV systems installed in 2020 will gradually produce less electricity and hence additional PV systems will be required to mitigate loss in electricity generated in previous year. Reduction in output also affects actually attainable LCOE of solar PV in a particular year. Reduction in generation from previously installed systems, triggers an additional installation of PV systems having lower LCOE in forthcoming years. As seen from Figure 9, WALCOE is higher than simple LCOE in all countries throughout the evaluation period.

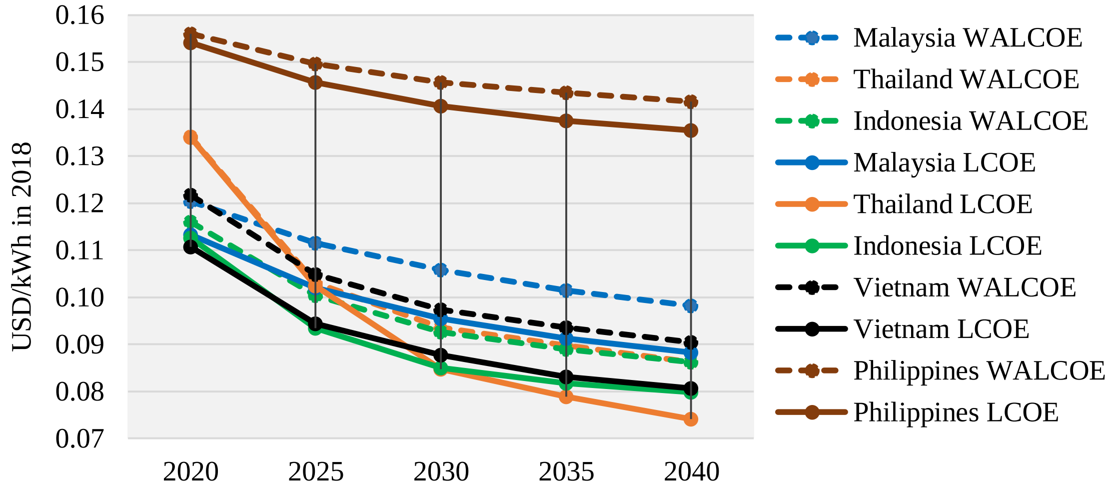

Figure 9 Comparison between WALCOE & LCOE

4.1.3. Sensitivity Analysis

Among selected countries, Thailand retains the best geographical location in terms of solar irradiation (5.3 kWh/m^2/day) at tilt angle (14°). Solar irradiation plays a vital role in dictating LCOE calculation. Hence; sensitivity analysis was conducted keeping solar irradiation constant at maximum 5.3 kWh/m^2/day for three countries. As seen from Figure 10, LCOE of all countries decreases as electricity generation increases due to increased solar irradiation. This leads to LCOE of Indonesia evolving as the lowest in 2040.

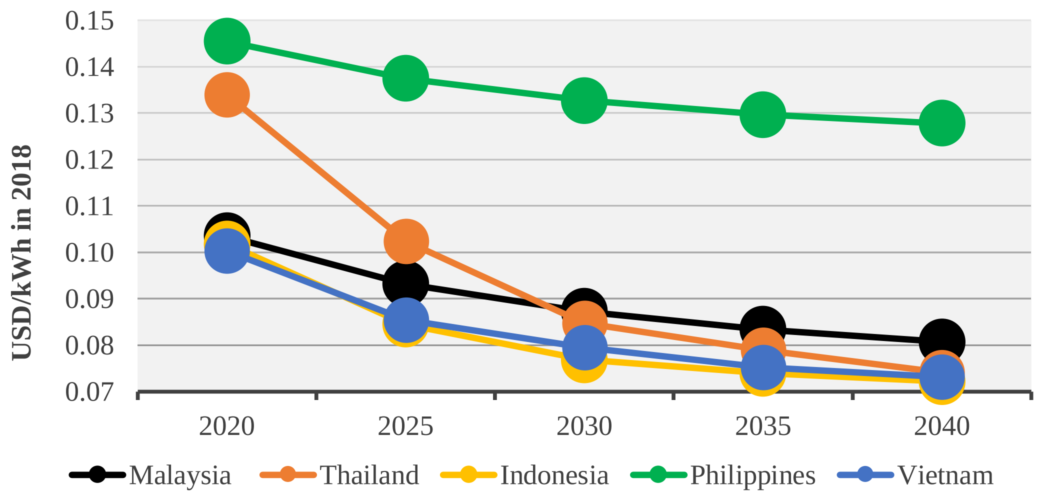

Figure 10 LCOE Evolution at 5.3 kWh/m^2/day

Furthermore, except Thailand, other countries are geographically dispersed requiring sensitivity within the country in terms of variation in solar irradiation. Hence, sensitivity analysis was concluded for few countries by varying irradiation while keeping other factors constant. As seen from Figure 11 to Figure 13, variation is observed within each of the country from regions with highest LCOE to lowest.

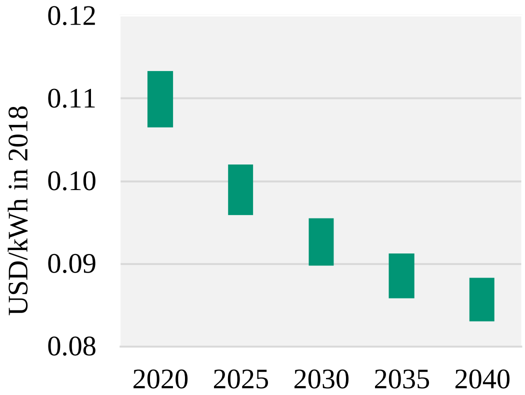

Figure 11 Regional LCOE Range (Malaysia)

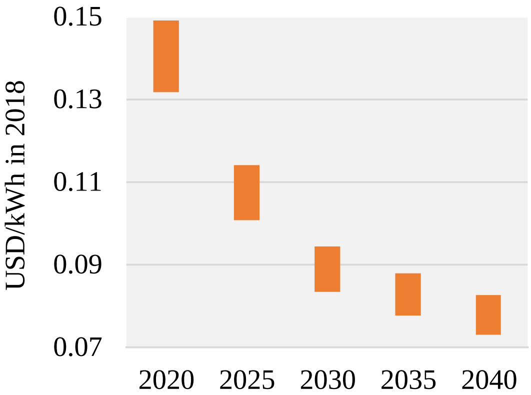

Figure 12 Regional LCOE Range (Thailand)

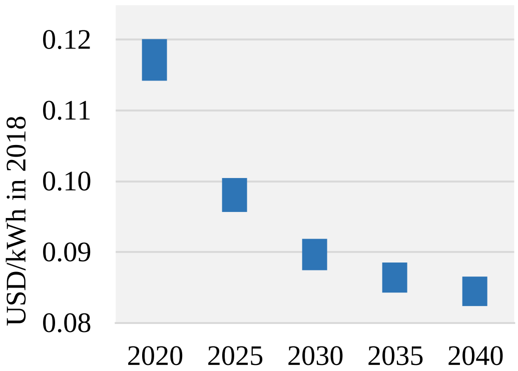

Figure 13 Regional LCOE Range (Indonesia)

4.2. Policy Implications

With the existing government plans, ASEAN countries may only succeed to attain 17% of energy share through renewable sources by 2025. However, with declining Solar PV cost, it is important to predict future attainment of grid parity across ASEAN. Future projections shown in Section 4 infer that Philippines has the highest LCOE of 0.15 $/kWh in 2020 while LCOE being lowest in Thailand with 0.074 $/kWh in 2040.
The authors also projected simplistic future LCOE for conventional energy based on the data gathered from (ACE.2016) & (Khanh and Development Centre 2017) with further adjustment in cost of fuel for each of the member states. The estimations were based on the predicted prices of fossil fuel (coal, oil and LNG). The LCOEs of Solar PV and conventional electricity at the generation level are compared in Figure 14.

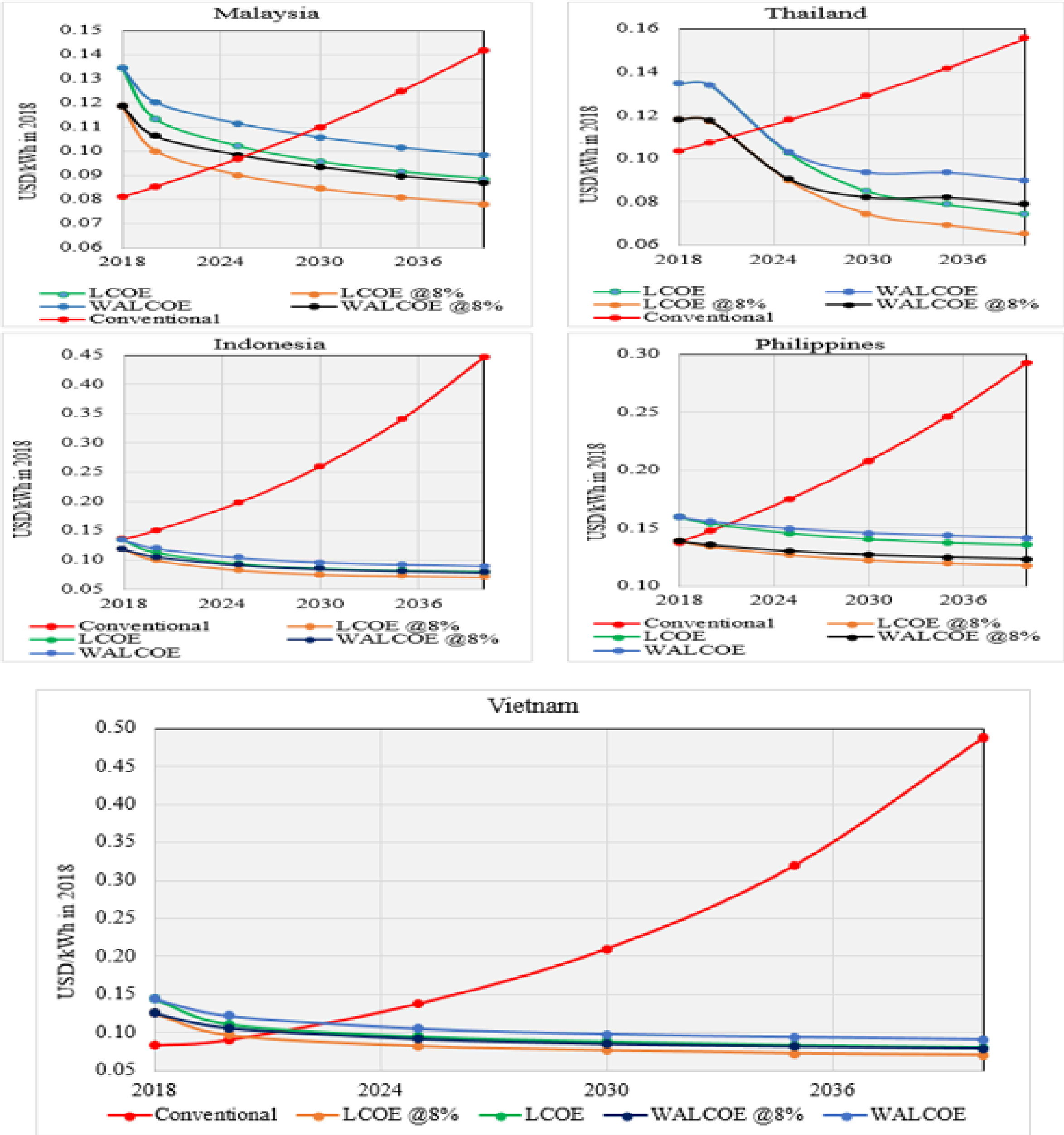

Figure 14 Grid Parity

The results predict that utility PV systems has already attained Grid Parity in Indonesia & will be achieved in Philippines, Vietnam, Thailand & Malaysia subsequently.

5. Conclusion

This research work provides a future estimation of LCOE of grid-connected PV systems across selected ASEAN countries. It is well understood that the accuracy of LC methodology increases with more number of data set. However, due to the scarcity of publicly available data, this work has been conducted based on few data points and hence may lead to inaccuracies in the estimation. LCOE estimation of solar PV systems as provided in (ACE.2016), may be compared with the outcome of this research work for validation. (ACE.2016) calculated LCOE

of PV systems in Indonesia and Malaysia as 0.145 USD/kWh and 0.15 USD/kWh consecutively. However, these results are based on data sets of 2014. On the contrary, our research work identified LCOE of 0.112 USD/kWh and 0.113 USD/kWh for Indonesia and Malaysia consecutively for the year 2020. If compared, variation may be owed due to the fact that capital cost has decreased from 2014 till today and tend to decrease further in 2020 and hence resulting in plummeting of LCOE in 2020 and beyond. Besides, it is also notable that LCOE in Malaysia and Indonesia as mentioned in (ACE.2016) is marginally dissimilar, which is also reflected in our research work.
Cost of PV module and BoS affects generation cost of solar PV systems mostly and hence, effective measure in terms of developing in-house supply chain of equipment, especially PV modules must be developed to accelerate future LCOE reduction. As mentioned earlier, grid injection of electricity generated from PV systems requires additional infrastructure, which alternatively affects LCOE outcomes. For instance, BoS costs comprised more than 35% share in generating one unit of electricity in Indonesia. Geographical dispersion of the locality and grid integration point may be attributed to such high BoS cost in Indonesia. Besides, Indonesia being rich in natural resources is currently undergoing an infancy stage in implementing renewable energy technologies and hence, a shortage of skilled labor as well as knowledge-gap may also have influenced increased BoS costs. This is to be noted that estimation conducted in this research is based on PV systems with a capacity equivalent to 1 MW. Implementation of larger capacity systems will trigger attainment of grid parity earlier in these countries. Attaining grid parity can also be accelerated by installing systems in regions with high solar irradiation. Higher solar irradiation will generate more energy with lower LCOE (Figure 11, Figure 12, Figure 13) and acceleration in grid parity will be realized

Funding: This research was conducted as a part of the project of Economic Research Institute for ASEAN and East Asia (ERIA) ‘Renewable Development Strategy for ASEAN 2030: A Dynamic Multilateral Scenario Analysis ’. The authors are deeply indebted to the members of this project for their invaluable suggestions. The opinions expressed in this paper are the sole responsibility of the authors and do not reflect the views of ERIA.

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