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

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Abstract: *Countries of the Association of Southeast Asian Nations (ASEAN) have been dependent on conventional energy resources because of their abundance, which explains the slow progress of renewable energy. The ASEAN Centre for Energy predicts that a 17% share of renewable energy can be achieved by 2025. Geothermal, hydro, and bioenergy are restricted by regional availability. With the declining cost of solar photovoltaic (PV) equipment, it is important to predict the future levelised cost of electricity (LCOE) for solar PV systems in this region. Hence, unlike earlier research articles, this paper focuses on evaluating the LCOE for PV technology (equal to 1 megawatt) across selected three ASEAN Member States – Indonesia, Malaysia, and Thailand – until 2040, while considering the capital cost of subsystem components within a typical PV system – PV module, inverter, mounting structure, and balance of system distinctly – to generate unique learning curves for individual countries. Sensitivity analysis was conducted to identify the impact on LCOE values and attainment of grid parity.*

Keywords: LCOE, learning curve, grid parity, ASEAN, PV, WALCO, solar PV

JEL Classification: E37, Q42, Q47, Q48

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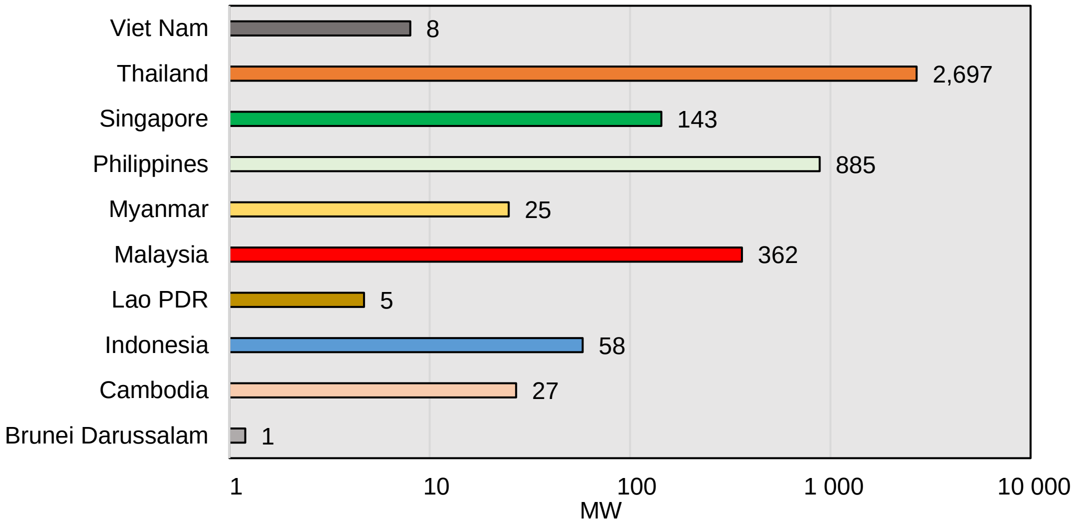
1. Introduction

The Association of Southeast Asian Nations (ASEAN) Member States (AMS) are dependent on conventional energy resources because of their abundance. The ASEAN Centre for Energy (ACE, 2017) highlighted the existing status and future estimates of energy across ASEAN countries. It classified its analysis into three scenarios: (i) the business-as-usual (BAU) scenario assumed that past practices would not change significantly, (ii) the AMS target scenario assumed that all energy-related policies and national targets across ASEAN nations would be fully attained, and (iii) the ASEAN progressive scenario assumed an optimistic future with regard to renewable energy and energy efficiency improvement. The BAU scenario is based on the current progress of renewable energy technology (RET), the latest national power development plans, national plans for the primary production of fossil fuels, and future expansion of refineries. Hence, it is more realistic to assume the BAU scenario for the rest of this article.

1.1. Current Status of Solar PV in ASEAN

AMS have rich and largely untapped renewable energy sources. Myanmar, Indonesia, and a few other lower Mekong countries have the potential to evolve as global leaders in generating hydropower. Global horizontal irradiation in the region is one of the highest in the world, with an annual average of 1.5–2.0 megawatt-hours per square metre (MWh/m^2) (International Renewable Energy Agency (IRENA), 2018a). The cumulative installed capacity of solar photovoltaic (PV) systems across ASEAN countries, compiled from IRENA (2018b), is shown in Figure 1. Thailand, Malaysia, Indonesia, the Philippines, and Singapore are pioneers in PV installations amongst ASEAN nations. PV installation has increased substantially in recent years because of the introduction of the feed-in-tariff scheme in most of these countries and the constant decrease in the cost of solar PV.

Figure 1: Solar PV Cumulative Installed Capacity

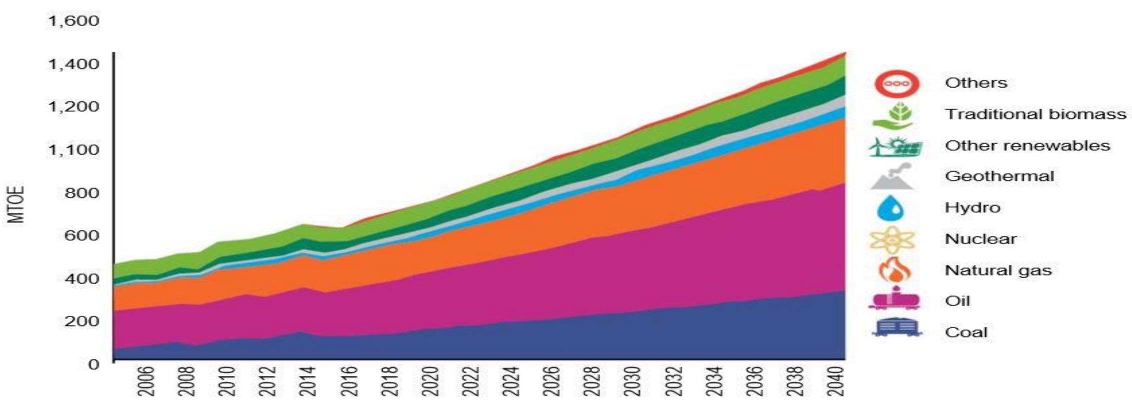


Lao PDR = Lao People's Democratic Republic, MW = megawatt, PV = photovoltaic.
Source: International Renewable Energy Agency (IRENA 2018b).

1.2. Prospects for Solar PV in ASEAN

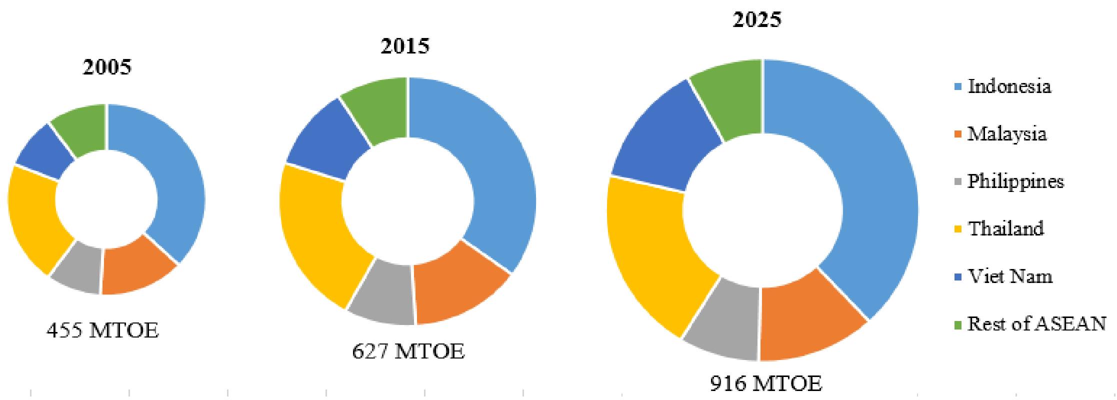
According to ACE (2017), 78.6% of the total primary energy supply across all ASEAN countries was from conventional energy sources in 2015, with oil constituting around 35% of the share (Figure 2). However, projections to 2040 show a rapid increase in renewable energy, with a compound annual growth rate of 4%. Indonesia, Thailand, Malaysia, the Philippines, and Viet Nam account for more than 90% of the energy share (Figure 3). Keeping this in mind, this research work focuses on Indonesia, Thailand, and Malaysia for further analysis.

Figure 2: Total Primary Energy Supply Shares in ASEAN



ASEAN = Association of Southeast Asian Nations, MTOE = million tons of oil equivalent.
Source: ACE (2017).

Figure 3: Country Shares



ASEAN = Association of Southeast Asian Nations, MTOE = million tons of oil equivalent.
Source: ACE (2017).

2. Literature Review

This study conducted a comprehensive literature review to identify previous research methodologies and progress attained in estimating the future levelised cost of electricity (LCOE) in ASEAN countries in the case of RETs, especially utility-scale solar PV systems.

2.1. LCOE of Renewable Energy Technology

Zhao and Zhang (2018) focused on estimating PV installation capacity and LCOE, using learning curves, during 2015–2030. They also investigated the effect of local government subsidies on LCOE predictions and identified 17 factors affecting PV installation capacity. Many LCOE projection studies have been conducted, and reports have been published for solar PV and other RETs for European countries. The Fraunhofer Institute for Solar Energy Systems (Fraunhofer ISE, 2018) forecast the LCOE of various RETs in Germany until 2035. Research focusing exclusively on solar PV has also been conducted in Europe.

Fraunhofer ISE (2015) forecast the solar PV capital cost and balance of system (BOS) separately for Germany until 2050 to project the LCOE, using learning curves. Ayompe et al. (2010) focused on estimating the LCOE for a 1.72 kilowatt-peak system in Dublin (Ireland), using learning curves attained through estimating solar PV capital cost dynamics until 2055; they also estimated the amount of carbon dioxide (CO_2) reduction. Breyer and Gerlach (2013) focused on comparing grid parity with the LCOE of solar PV in more than 150 countries, using learning curve methodology to predict the future LCOE; they also considered learning curves for inverter and BOS cost projections. Vartiainen, Masson, and Breyer (2015a, 2015b) focused on the LCOE projection of solar PV until 2030 and 2050. However, Vartiainen, Masson, and Breyer (2015a) emphasised the weighted average cost of capital as the most important parameter guiding LCOE projections, using data from the International Energy Agency (IEA) and Bloomberg New Energy Finance in the model.

Apart from solar PV systems, some researchers have also used learning curve methodology to predict the LCOE for concentrated solar power (CSP) systems. Parrado et al. (2016); Hernández-Moro and Martínez-Duart (2013); and Breyer et al. (2017) focused on long-term LCOE projections for both solar PV and CSP systems, using learning curve methodology. However, Parrado et al. (2016) also identified the possible effect of a change in molten salts in thermal energy storage on LCOE in Chile. Köberle, Gernaat, and van Vuuren (2015) conducted similar research for South America, North America, and Australia, considering two scenarios – fast learning and slow learning – using learning curves.

Another widely used forecasting methodology is expert elicitation, where the opinions of experts on a particular topic which is uncertain and lacks sufficient data are represented collectively. Wiser et al. (2016) used the expert elicitation method to predict the LCOE of energy systems and showed that the results are congruent with learning curve methodology. Research with learning curve methodology is not limited to grid-connected energy systems. Zou et al. (2017) used learning curves to estimate the energy cost of grid-connected and off-grid solar PV systems in five Chinese cities. Talavera et al. (2016) studied 12 laws and royal decrees to assess the effect of government policies on the solar PV market.

2.2. LCOE of Other Technologies

Projecting the LCOE through learning curve methodology is not limited to RETs. Some research has also been conducted considering both conventional and non-conventional energy technologies. Miao (2015) projected the LCOE for China until 2035 using learning curves for coal, gas, wind, solar PV, and nuclear power systems. West (2012) focused on similar methodology in the countries of the Organisation for Economic Co-operation and Development (OECD).

2.3. LCOE of RET in ASEAN

Few studies have focused specifically on ASEAN countries. Pratama et al. (2017) projected the LCOE of solar PV in Indonesia during 2011–2050, with a 5-year interval, using learning curves. However, they considered global average cost data published by the IEA and IRENA rather than using national data. Global cost data reflect an average value which is derived from data collected from different countries with or without in-country equipment manufacturing facilities of solar PV systems. Moreover, countries vary in terms of import and consumption taxes and other socio-geopolitical aspects which directly or indirectly influence equipment costs. Thus, the utilisation of global cost data may trigger underestimation or overestimation of cost reductions in learning curve approximation. Finenko and Soundararajan (2016) considered floating solar, rooftop solar PV, and building-integrated PV systems; and identified the LCOE until 2030 for Singapore using the learning curve method. A few researchers have used The Integrated MARKAL/EFOM System (TIMES) and Tool for Electricity Energy Planning models, which estimate the LCOE to articulate the long-term least-cost energy mix scenarios, e.g. Tanoto, Handoyo, and Sutjiadi (2015) and Zou et al. (2017) focused on the Philippines and Java (Indonesia), respectively.

The learning curve method is therefore a powerful tool for technological cost reduction and LCOE estimation. To the best of the authors' knowledge, almost all the previous research has used the average global data of PV system costs to predict LCOE evolution for specific countries or regions. Few research articles have considered the subsystem costs of solar PV separately – solar PV modules, inverters, mounting structures, and BOS – to generate distinctive learning curves based on local (country/region-specific) data. Hence, the authors intend to develop an ASEAN countrywide learning curve of solar PV subsystems individually to predict the LCOE until 2040, with 2020 as the reference year.

3. Measuring the Cost of Renewables

Renewable energy is one of the major options to mitigate greenhouse gas emissions and is expected to grow significantly in importance throughout the coming decades. Many countries have introduced support schemes for renewable electricity, such as feed-in tariffs or renewable portfolio standards, as mentioned in Hirth (2013). In such policymaking processes, it is reasonable to assume that policymakers are usually informed of the costs and benefits of increasing renewable energy in the power system. However, a wide range of information, sometimes conflicting, is available on the costs and benefits of increasing renewable energy. For example, some analysts conclude that increasing renewables will bring overall benefits to the power system as a result of fuel savings and other benefits, while others conclude that increasing renewables will bring overall costs to the power system because of the higher initial investment.

According to the OECD and NEA (2018), the cost of electricity can be categorised into three different levels: plant-level costs, grid-level system costs, and external or social costs outside the electricity system. The plant-level cost is commonly referred to as the technology cost, described as the LCOE, which represents the lifetime costs divided by the electricity production. Grid-level system costs concern the costs at the level of the electricity system, linked through the transmission and distribution grids. The third category includes items that impact the well-being of individuals and communities outside the electricity sector.

3.1. Technology Cost

The LCOE is a commonly used metric to represent this level of cost. One of the attractions of the LCOE methodology is its transparency and straightforward computation. As described in IEA and NEA (2015), the LCOE calculation begins with the equation below expressing the equality between the present value of the sum of discounted revenues and the present value of the sum of discounted costs, including payments to capital providers. The subscript *t* denotes the year in which the sale of production or the cost disbursement takes place. The summation extends from the start of construction preparation to the end of dismantling, which includes the discounted value at that time of future waste management costs. All variables are real, i.e. net of inflation. The discounted sum of benefits is on the left, while the discounted sum of costs is on the right:

$$\Sigma \mathrm{P_{MWh}} * \mathrm{MWht} * (1\ +\ \mathrm{r})^{-\mathrm{t}}$$
$$= \Sigma(\ \mathrm{Capital_t} + \mathrm{O\&M_t} + \mathrm{Fuel_t}\ + \mathrm{Carbon_t} + \mathrm{D_t})(1\ +\ \mathrm{r})^{-\mathrm{t}}$$

Where P_{MWh} is the constant lifetime remuneration to the supplier for electricity; MWh_t is the amount of electricity produced in year *t* in MWh; $(1 + r)^{-t}$ is the discount factor for year *t* (reflecting payments to capital); $Capital_t$ refers to the total capital construction costs in year *t*; $O\&M_t$ are the operation and maintenance

(O&M) costs in year *t*; $Fuel_t$ are the fuel costs in year *t*; $Carbon_t$ are the carbon costs in year *t*; and D_t refers to the decommissioning and waste management costs in year *t*.

Because P_{MWh} is a constant over time, it can be brought out of the summation, and this equation can be transformed into:

$$\mathrm{LCOE} = \Sigma[(\mathrm{Capital_t} + \mathrm{O\&M_t} + \mathrm{Fuel_t} + \mathrm{Carbon_t} + \mathrm{D_t})(1 + \mathrm{r})^{-\mathrm{t}} / \mathrm{MWh_t}(1 + \mathrm{r})^{\mathrm{t}}]$$

Where this constant, P_{MWh}, is defined as the LCOE (IEA and NEA, 2015).

One of the weaknesses of the LCOE approach is that it does not account for some important aspects of power generation, particularly the timing, location, inter-temporal aspects, and operational characteristics of the technology. Therefore, according to IEA (2018a) temporal availability – the intermittency of solar and wind resources – triggers variability and uncertainty in the power output of solar PV and wind projects. The integration of variable renewable energy (VRE) such as solar PV and wind into the electric grid causes other peak load conventional power plants connected to the same grid to operate on part load with less efficiency, requiring more fuel. In addition, speeding conventional power plants up and down to complement VRE output consumes time and additional fuel. Since the integration of VRE into the grid causes these effects, LCOE evaluation of VRE – additional metrics that account for the effects (e.g. the ramp effect and part load operation) caused by VRE on the rest of the power system – may be employed.

3.2. System Cost

As IEA (2018a) notes, adding VRE will trigger two different groups of economic effects in the power system:

(i) **Increase in some costs**. This includes the cost of VRE deployment (i.e. the LCOE), costs for additional grid infrastructure, and/or increased costs for providing balancing services. This group can be termed system costs or additional costs.

(ii) **Decrease in other costs**. Depending on the circumstances, cost reductions might occur because of the reduced fuel costs for conventional generators, reduced CO_2 and other pollutant emissions costs, a reduced need for additional generation capacity, a reduced need for transmission infrastructure, and/or reduced transmission system losses. This group can be termed benefits or avoided costs.

VRE technologies have specific characteristics that affect their contribution to power system operation and investment compared with conventional generation technologies, as suggested in IEA (2018a). Three properties are perhaps the most relevant:

(i) **Variability** – the available power output fluctuates with the availability of the primary resource (wind or sun).

(ii) **Location constraints** – the resource quality differs by location and the primary resource cannot be transported.

(iii) **Uncertainty** – the exact availability profile of the resource can only be predicted with high accuracy in the short term.

These properties affect the interaction of VRE power generation with the electrical system. It is possible to define three corresponding cost categories: profile costs, grid costs, and balancing costs (Ueckerdt et al., 2013; Hirth, Ueckerdt, and Edenhofer, 2015).

(i) **Profile costs**. These describe the effects associated with the temporal pattern of VRE generation in the medium term, particularly the non-availability of VRE when demand is close to the available generation capacity, possible periods of surplus VRE generation, and a reduction in the utilisation of other power plants.

(ii) **Grid costs**. These reflect additional costs required for connecting the system to existing electrical substations or transmission grids. They are associated with transmission constraints and losses, and incurred because of the location of generation in the power system.

(iii) **Balancing costs**. These are associated with the short-term uncertainty of VRE generation, which involves deviations from generation schedules, e.g. the cost of balancing forecast errors of VRE, the cost of providing reserves, and start-up and shutdown costs to accommodate VRE.

Calculating these different cost categories requires defining a reference technology to which VRE impacts are compared and then quantifying the difference between the reference and the VRE case. This is highly complex and requires making a number of ad hoc assumptions. The resulting system costs depend directly on the choice of benchmark technology. Examining system costs for VRE alone does not provide useful information in itself, as prescribed in IEA (2018a).

3.3. External Costs

Apart from the direct costs incurred during the construction and operation of a power system, various indirect costs and benefits outside the system emerge and are usually borne by someone else. This is well established conceptually, but is very difficult to measure accurately in practice. These costs and benefits include (i) climate change impacts, (ii) air pollution, (iii) the cost of major accidents, (iv) land-use change and natural resource depletion, (v) the security of energy and electricity supply, (vi) employment, and (vii) the impact of energy innovation on economic performance and growth.

4. Methodology

The previous section dove into technology and system cost analysis approaches to show how the cost of renewables is calculated and how it can differ depending on the presentation of parameters and power systems. Even considering the cost within the power system, in an accounting sense, can create huge diversity in 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 – the LCOE of VRE, i.e. grid-connected solar PV systems – to simplify the argument. Thus, the purpose of this modelling study is first to construct the LCOE models for selected AMS.

4.1. LCOE Calculation Formulae

LCOE calculations mainly depend on the fixed cost (capital cost) and variable cost (the operation, maintenance, and replacement cost) of systems and the electricity generated by the project over its lifetime. This section describes the methodology used to derive the capital cost, variable cost, and amount of electricity generated over the project lifetime. As described in Section 3.1, the LCOE is the ratio of the present value of all discounted costs incurred during the project life to the total electricity generation capacity (kilowatt-hours (kWh)) of the project. It is expressed in United States dollars ($) per kWh. The significance of the LCOE is that it provides a reasonable estimation of the generation cost of electricity and can be used to compare technologies to identify the least-cost solution. Research works by Branker, Pathak, and Pearce, (2011) and IRENA (2012) have considered the LCOE to compare various technologies in terms of grid parity.

By excluding the carbon and decommissioning costs, the LCOE can be expressed as follows (United States Department of Energy, 2004):

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

(1)

Rearranging the above equation, we obtain:

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

(2)

Equation 2 resembles the LCOE, which is the sum of all the discounted costs incurred during the project life divided by the units of discounted energy produced from the system. While calculating, all initial costs of the project occur at n = 0 year and should not be discounted. Hence, the initial costs need to be separated from equation 2 and all other parameters in equation 2 should be discounted starting from year 1. The initial costs (I) can be divided into capital cost (C) and land cost (L). The annual costs (OPEX) comprise operation, maintenance, and replacement costs. Annual costs are incurred over the project lifetime and hence required discounting. Next, we considered the energy generated from a PV system over its lifetime. The energy produced from PV systems is related to the available solar resource, i.e. solar irradiation (S), the solar PV performance factor (PF), and solar PV annual degradation factor (d). Hence, the energy generated (E_n) annually can be illustrated as:

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

(3)

Notably, both the energy generated (E_n) and the costs must be calculated in kWh per watt and $ per watt, respectively, to derive the LCOE in $/kWh. Combining and rearranging equations 2 and 3, the LCOE can be finally derived as:

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

(4)

Where p is the inflation rate (%); x is the year of installation; y is the year of the data source; r is the discount rate; S is the solar irradiation (kWh/m^2/day); PF is the performance factor of the solar PV system (%); d is the annual degradation of the PV module; n is the project life, i.e. 25 years; C is the capital cost; L is the land cost; and OPEX is the annual costs (operation, maintenance, and replacement costs).

4.2. Evolution of the LCOE Using the Learning Curve Approach

As derived in equation 4, the LCOE calculation requires cost parameters as input to the formula. Hence, it is essential to derive cost data with regard to the capital cost (C), land cost (L), and OPEX. The LCOE estimation from 2020 to 2040 requires future cost parameters to be fed into the LCOE model. Deriving the future costs associated with a solar PV system requires an estimation of the capital cost (C) that an investor would encounter when installing a solar PV project in the future. Various past research has used the learning curves approach to identify the evolution of cost in terms of economies of scale. Fraunhofer ISE (2015) calculated the LCOE of various RETs up to 2035 using learning curves. Similarly, Hernández-Moro and Martinez-Duart (2013) aimed at projecting the capital expenditure (CAPEX) for PV and CSP plants based on learning curves until 2030. Hernández-Moro and Martinez-Duart (2013) also described the learning curve as a method that derives the cost of systems as a function of the cumulative installed capacity. Hence, the learning curve methodology has been used to predict the future CAPEX for solar PV systems. The learning curve is plotted as the straight line in log-log space; and the slope of these curves is related to the learning rate, which indicates the cost reduction per cumulative doubling of installed capacity and can be expressed as follows:

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

(5)

or,

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

(6)

The exponent $-b$ in equation 6 represents the slope of the straight line in log-log space and is called the learning rate. The learning rate can be described as:

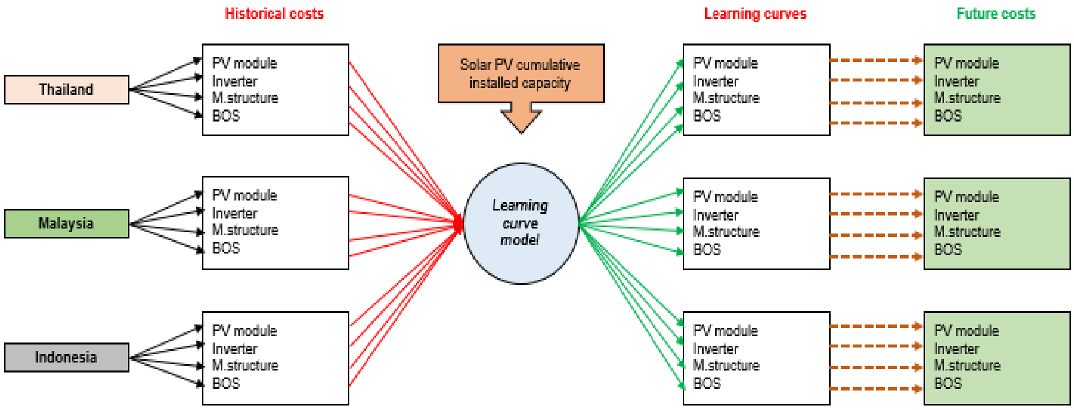
$$1 - LR = 2^{-b}$$
(7)

Using equations 6 and 7, the evolution of capital cost between two time periods can be derived based on relevant cumulative installed capacity data. Combining equations 6 and 7,

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

As articulated in Figure 4, historical data retrieved from research articles and reports – along with the cumulative installation capacity plans of each country – are fed into the learning curve model to derive distinctive learning curves. These learning curves are then used to derive the future cost of solar PV subsystems.

Figure 4: Learning Curve Approach



BOS = balance of system, LC = learning curve, M. structure = mounting structure, PV = photovoltaic.
Source: Authors.

4.3. Purchasing Power Parity

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

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

Malaysian data have been used to estimate Indonesian data for the purchasing power parity theorem because of the unavailability of public data on utility-scale PV system costs in terms of subsystem costs.

5. Estimated Parameters

5.1. Capital Cost

The capital cost of equipment is a vital catalyst in influencing the outcome of the LCOE model. Most of the earlier studies considered the capital cost of the PV system as a whole (Ayompe et al., 2010; Fraunhofer ISE, 2015, 2018) while others considered the PV module cost and inverter cost separately (Breyer and Gerlach, 2013). Moreover, previous research works used global average cost data. This research work has segregated PV system costs into four subsystems: solar PV cost, inverter cost, mounting structure cost, and BOS cost. This approach has provided a better understanding of the implications of individual subsystem costs on the LCOE outcome. Details of the capital costs are in Table 1.

Table 1: Details of the Capital Cost

Year	Country	Component	RM/W	$/W in 2018	Source of Data	Notes
2016	Malaysia	Solar PV	2.56	0.60	(SEDA, 2017)	• All values are adjusted to the reference year (2018) with the relevant average inflation rates. Different exchange rates were used to convert local currency to US dollars. • For the 2011 data, exchange rates collected from Malaysia (2018) were used. • For the 2014 and 2016 data, exchange rates from SEDA (2015, 2017) were used.
		Inverter	0.62	0.14		
		M. structure	1.18	0.28		
		BOS	2.29	0.54		
2014		Solar PV	3.00	0.79	(SEDA, 2015)	
		Inverter	0.80	0.21		
		M. structure	1.50	0.40		
		BOS	2.60	0.69		
2011		Solar PV	4.84	1.87	(Nippon Koei Co., Ltd. and ORIX Corporation, 2012)	
		Inverter	1.03	0.40		
		M. structure	2.12	0.82		
		BOS	2.61	1.00		
Year	**Country**	**Component**	**B/W**	**$/W in 2018**	**Source of Data**	**Notes**
2015	Thailand	Solar PV	22.00	0.68	(DEDE, 2016)	• Data for 2015 were separated well in terms of subsystems. However, 2014 and 2013 data only had the overall system cost rather than subsystems. Hence, the subsystem cost percentages as derived from 2015 data were used to derive subsystem costs for 2014 and 2013. • All values were adjusted to the reference year (2018) with the relevant average inflation rates. • For the 2013, 2014, and 2015 data, exchange rates were taken
		Inverter	5.00	0.16		
		M. structure	5.00	0.16		
		BOS	15.00	0.47		
2014		Solar PV	23.40	0.73	(DEDE and KMUTT, 2015)	
		Inverter	5.32	0.17		
		M.	5.32	0.17		

		structure				from DEDE and KMUTT (2014) and (DEDE and KMUTT, 2015).
		BOS	17.98	0.56		
2013		Solar PV	37.45	1.22	(DEDE and KMUTT, 2014)	
		Inverter	8.51	0.28		
		M. structure	8.51	0.28		
		BOS	24.84	0.81		
Year	**Country**	**Component**	**Rp/W**	**$/W in 2018**	**Source of Data**	**Notes**
2016	Indonesia	Solar PV	7,352	0.55	(SEDA, 2017)	• Data related to utility-scale grid-tied solar PV projects were not publicly available. Most previous research is based on off-grid solar PV systems. Extracting data from off-grid systems would not be prudent since these are smaller capacity systems and the cost of technology reduces with economies of scale. Hence, Malaysian cost data were used and converted to Indonesian cost data based on the purchasing power parity theorem. • All values are adjusted to the reference year (2018) with the relevant average inflation rates. • Exchange rates from BI (2018) were used.
		Inverter	1,780	0.13		
		M. structure	3,389	0.25		
		BOS	6,576	0.49		
2014		Solar PV	8,213	0.74	(SEDA, 2015)	
		Inverter	2,190	0.20		
		M. structure	4,107	0.37		
		BOS	7,118	0.64		
2011		Solar PV	11,964	1.21	(Nippon Koei Co.,Ltd. and ORIX Corporation, 2012)	
		Inverter	2,546	0.26		
		M. structure	5,245	0.53		
		BOS	6,444	0.65		

B = baht, BOS = balance of system, M. structure = mounting structure, PV = photovoltaic, RM = ringgit, Rp = rupiah, US = United States, W = watt.

Sources: Bank Indonesia (2018), Foreign Exchange Rates. https://www.bi.go.id/en/moneter/informasi-kurs/transaksi-bi/Default.aspx (accessed 11 November 2018); Bank Negara Malaysia (2018), Exchange Rates. http://www.bnm.gov.my/index.php?ch=statistic&pg=stats_exchangerates&s=1D6972B042AE1A64C938282A2EB181C87F7E9212 (accessed 23 November 2018); DEDE (2016); DEDE and KMUTT (2014); DEDE and KMUTI (2015); Nippon Koei Co., Ltd. and ORIX Corporation (2012); SEDA (2015, 2017).

5.2. Land Cost

Estimating the land cost is the most difficult part, as it varies widely for geographical reasons. PV plants use 10–50 square kilometres per gigawatt (United States Department of Energy, 2004). A land cost (L) of $30 per kilowatt (kW) has been considered based on previous research by Hernández-Moro and Martinez-Duart (2013). Country-specific inflation rates have been considered while adjusting the land cost to present and future costs.

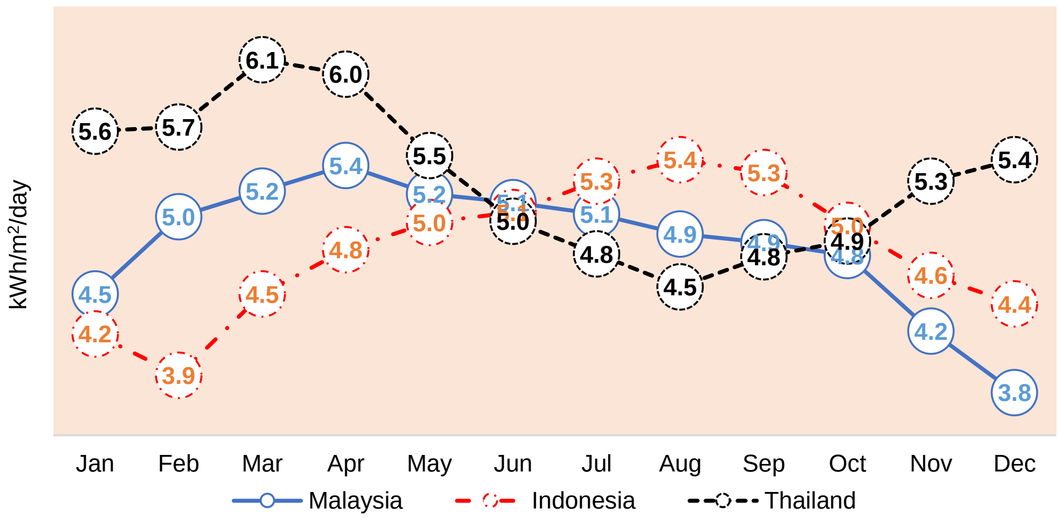
5.3. Operation and Maintenance Costs

Solar PV plants encounter costs for successful O&M over their lifetime. As prescribed by Hernández-Moro and Martinez-Duart (2013), the O&M cost for solar PV mainly comprises regular cleaning of PV modules, monitoring of performance, and inverter replacement costs; and is 1.5% of the capital cost. On the other hand, ACE (2016) highlighted a 1%–2% variation in the O&M cost within ASEAN countries.

5.4. Solar Resource

The 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 use both direct and diffuse radiation for their electricity generation. Based on the solar resource data collected from the United States' National Aeronautics and Space Administration (NASA, 2018), energy generated by fixed-structure tilted solar PV for different countries is compiled in Figure 5. The solar resources of the geographical location shown in Figure 5 are those of the capital cities of each country. However, variations in solar resources have been evaluated in the sensitivity analysis to replicate countrywide fluctuations in the LCOE for each country. This also pinpoints regions with the lowest LCOE.

Figure 5: Solar Resources at Tilted PV Module



kWh/m²/day = kilowatt-hour per square metre per day, PV = photovoltaic.
Source: Created by authors based on NASA (2018).

5.5. Performance Factor

As prescribed in equation 3, the energy output from solar PV can be expressed as:

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

However, the real output of solar PV decreases because of various factors and losses. Since the electricity produced from solar PV is direct current (DC), it must be converted to alternating current (AC) before evacuating to the grid. An inverter is used, which converts DC electricity from solar PV to AC. However, the conversion has an efficiency rate of 93%–95% (Zahedi, 2009; Ayompe et al., 2010). In addition, PV module performance decreases with the increase in temperature from standard testing conditions (Tian et al., 2012). Thus, the performance factor of 75%–85% (Zahedi, 2009; Hernández-Moro and Martínez-Duart, 2013) has already been considered in earlier research. A performance factor of 75% has been considered in this study.

5.6. Degradation Factor

The performance of solar PV modules tends to degrade over years of operation because of exposure to ultraviolet radiation. Previous studies have suggested that the performance of PV modules degrades at a rate of 0.6% per year, as in Branker, Pathak, and Pearce (2011). However, 1.00% in the first year of operations and 1.21% from the second year onwards has been considered in our work, based on the recent research outcome published in the National Renewable Energy Laboratory (2018).

5.7. Discount Rate

In financial terms, the discount rate is one of the most important parameters guiding the outcomes of the LCOE model. The discount rate not only takes into account the inflation rate but also the technological risk. ACE (2016) considered a discount rate of 10%, so a similar discount rate has been considered in this study. A comprehensive literature review was done, and relevant data were collected for learning curves and LCOE modelling. Apart from this, various assumptions were made to complete the research work. Details of the assumptions and data used in this research work are in Table 2.

Table 2: Assumed Parameters

Parameters			Source Data (Value)	Data Used in Calculation (Value)	Source of Data	Notes
Solar PV annual performance degradation (%)/year	1st year of operation		0.4% and 1.5%	1.0%	NREL (2018)	
	2nd year and onwards		1.41%–1.45% and 0.94%–1.03%	1.21%		
Irradiation (kWh/m^2/day	Malaysia		4.84	4.84	NASA (2018)	Taken from NASA (2018) for tilted surface
	Thailand		5.30	5.30		
	Indonesia		4.79	4.79		
Tilt angle with coordinates	Malaysia (19°)		(Lat: 4.960; Long:102.111)		-	-
	Thailand (14°)		(Lat: 14.073; Long:100.639)		-	-
	Indonesia (21°)		(Lat: –6.117; Long:106.79)		-	-
Project lifetime	All countries		25 Years	25 Years	Hernández-MoroandMartinez-Duart (2013)	-
Land cost (L)			30 $/kW	30 $/kW		
Discount rate (r)			10%	10%	IEA (2010, ACE (2016)	
O&M cost (OPEX)	Malaysia		1.5% of capital cost	1.5% of capital cost	ACE (2016)	-
	Thailand		1.3% of capital cost	1.3% of capital cost		
	Indonesia		1.2% of capital cost	1.2% of capital cost		
Inflation rate (%)	Malaysia	Land cost (L)	2.6%	2.6%	World Bank (2018)	Inflation rates used for land cost and OPEX are different for different countries
		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%		

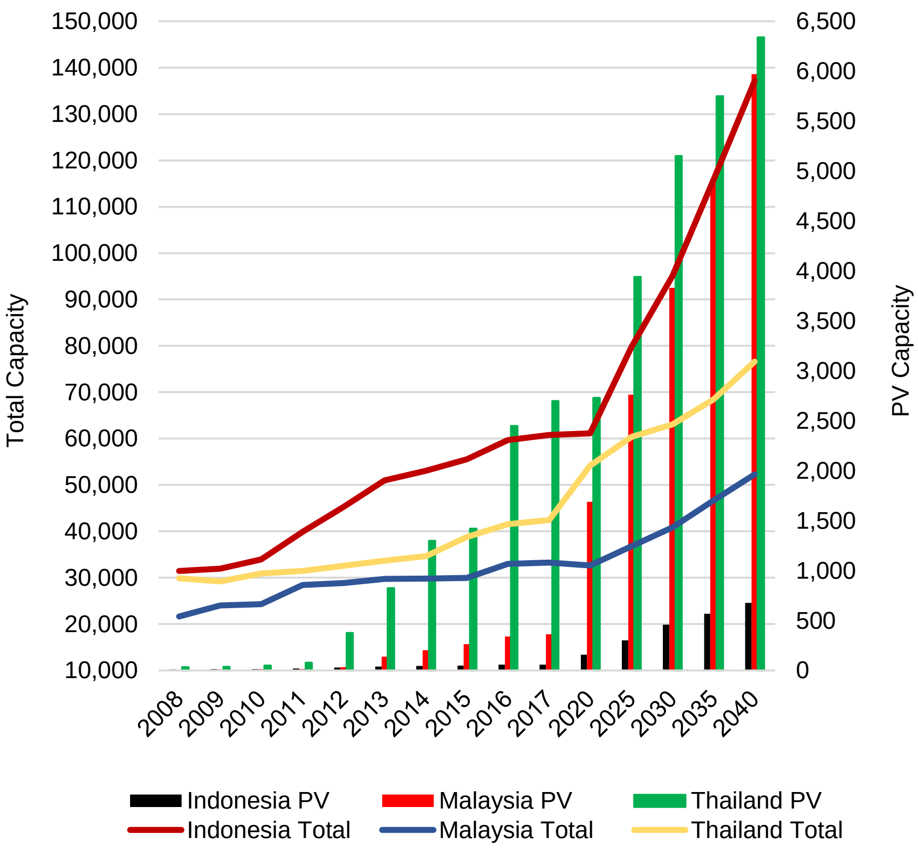
kW = kilowatt, kWh = kilowatt-hour, Lat = latitude, Long = longitude, m^2 = square metre, O&M = operation and maintenance, OPEX = annual costs, PV = photovoltaic,
Source: Compiled by authors from ACE (2016); Hernández-Moro and Martínez-Duart (2013); IEA (2010); NASA (2018); National Renewable Energy Laboratory (2018); and World Bank (2018), Indicators, Agriculture and Rural Development. https://data.worldbank.org/indicator/ (accessed 23 October 2018).

6. Estimation Results

6.1. Cumulative Installed Capacity

To generate learning curves for individual system components of solar PV, the cumulative installed capacity of solar PV for every 5 years of increment until 2040 with a base case of 2020 is required. Since AMS have different targets, the cumulative installed capacity of solar PV varies during 2020–2040 for different member states. The cumulative installed capacity of Malaysia, Thailand, and Indonesia has been compiled and estimated with relevant information from IRENA (2018b), the Asia Pacific Energy Research Centre (APERC, 2016), Indonesia's Ministry of Energy and Mineral Resources (MEMR, 2018), the Electricity Generating Authority of Thailand (2019), and the Malaysia Energy Information Hub (2019) in Figure 6.

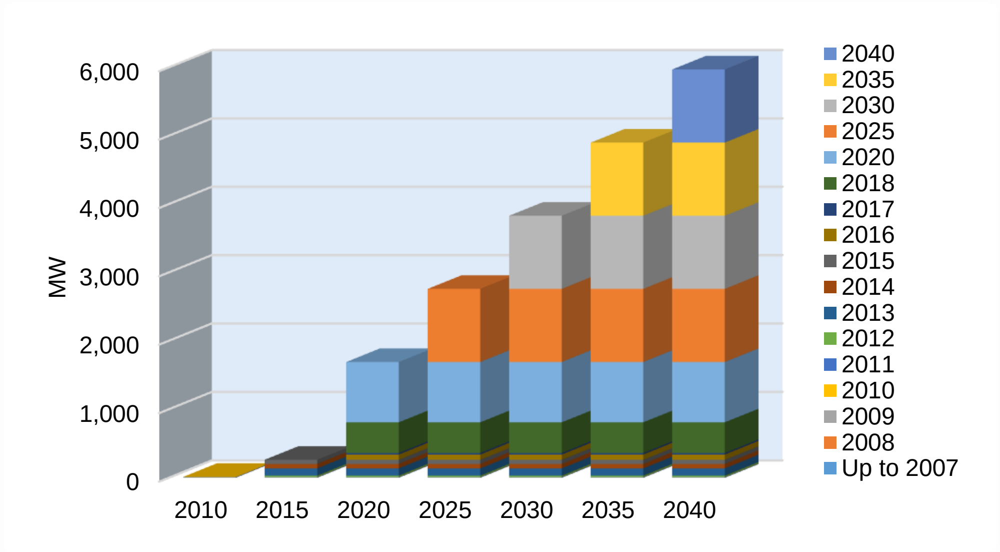
Figure 6: Comparison of the Cumulative Installed Capacity (MW)



MW = megawatt, PV = photovoltaic.
Source: Created by authors based on APERC (2016); IRENA (2018b); Electricity Generating Authority of Thailand (2019); Malaysia Energy Information Hub (2019); and MEMR (2018).

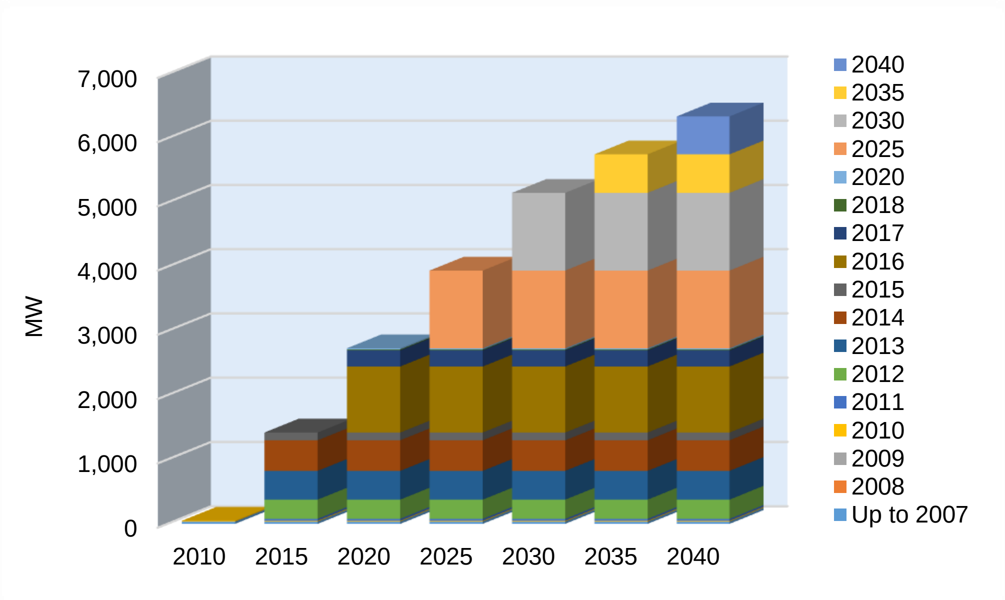
The historical installation and projections of solar PV by country are detailed in Figure 7, Figure 8, and Figure 9. These results are tabulated in Table 3.

Figure 7: Cumulative Solar PV Capacity (Malaysia)



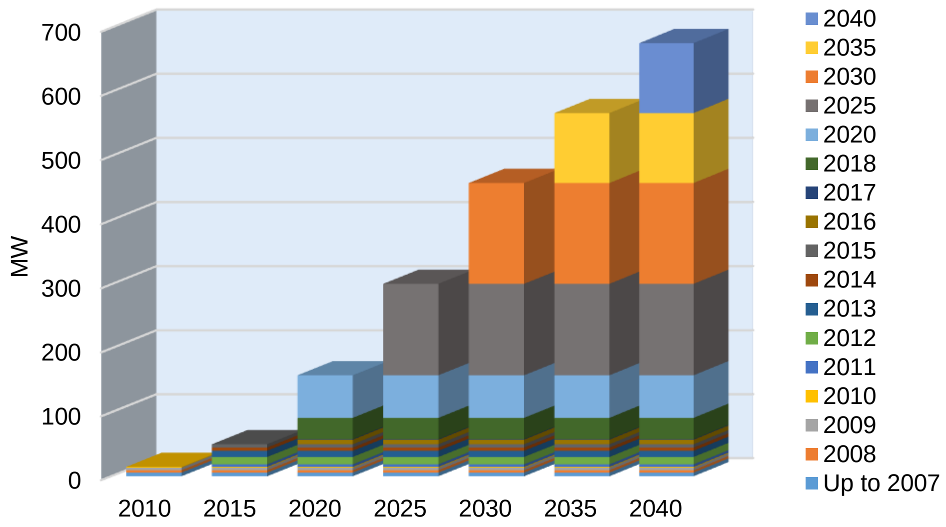
MW = megawatt, PV = photovoltaic.
Source: Created by authors based on APERC (2016) and IRENA (2018b).

Figure 8: Cumulative Solar PV Capacity (Thailand)



MW = megawatt, PV = photovoltaic.
Source: Created by authors based on APERC (2016) and IRENA (2018b).

Figure 9: Cumulative Solar PV Capacity (Indonesia)



MW = megawatt, PV = photovoltaic.
Source: Created by authors based on APERC (2016) and IRENA (2018b).

Table 3: Solar PV Installation Capacities, Cumulative and by Year

(a) Cumulative (MW)

Country	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2020	2025	2030	2035	2040
Indonesia	9.5	13.4	14.6	18.6	30.1	39.8	44.9	50.1	57.2	58.1	91.4	158.0	300.8	458.0	567.0	676.0
Malaysia	8.8	11.1	12.6	13.5	31.6	138.1	202.9	263.3	339.7	362.2	810.0	1,690.0	2,760.0	3,830.0	4,900.0	5,970.0
Thailand	32.4	37.0	48.6	78.7	376.7	823.5	1,298.5	1,419.6	2,446.1	2,697.3	2,710.0	2,730.0	3,940.0	5,150.0	5,750.0	6,340.0

(b) Per Year (MW)

Country	Up to 2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2020	2025	2030	2035	2040
Indonesia	5.7	3.8	3.9	1.2	4.0	11.5	9.7	5.1	5.2	7.1	0.9	33.3	66.6	142.8	157.2	109.0	109.0
Malaysia	7.0	1.8	2.3	1.5	0.9	18.1	106.5	64.8	60.4	76.4	22.5	447.8	880.0	1,070.0	1,070.0	1,070.0	1,070.0
Thailand	32.3	0.2	4.6	11.6	30.1	298.0	446.8	475.0	121.1	1,026.5	251.2	12.7	20.0	1,210.0	1,210.0	600.0	590.0

MW = megawatt, PV = photovoltaic.
Source: Created by authors based on APERC (2016); IRENA (2018b); Electricity Generating Authority of Thailand (2019); Malaysia Energy Information Hub (2019); and MEMR (2018).

6.2. Learning Rates

Schaeffer (2004) suggested that experience curve projections were generally more accurate than optimistic engineering predictions found in the literature. Alberth (2008) proved that having more data sets reduces the bias of the learning curve in terms of predicting technological cost reductions. The availability of an accurate and adequate data set has been an issue in ASEAN countries – only three sets of complete data were available for a few countries, which may have limited the accuracy of the learning curve estimation. Nevertheless, the learning curve can be used as an unbiased estimator of future technology costs, as argued by Alberth (2008).

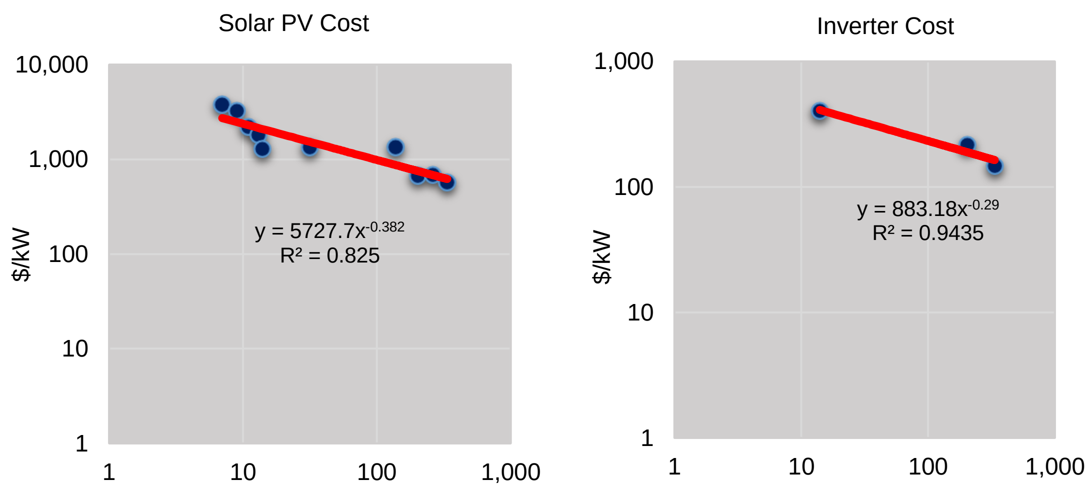
Deriving the learning rate requires developing learning curves. A typical utility-scale solar PV project capital cost can be divided into four main sections: solar PV cost, inverter cost, mounting structure cost, and BOS cost. The BOS cost comprises grid integration, licensing, cables, profit, and installation. Hence, deriving the learning rate requires developing learning curves. Therefore, four solar PV subsystem learning curves for three countries (Malaysia, Thailand, and Indonesia) were developed, totalling 12 learning curves. Learning rates derived from these curves were used to estimate the future evolution of capital costs, as described in Figure 4. The learning rates for different components and the above-mentioned three countries are noted in the following sections. The learning curves generated for Malaysia and Thailand were completed based on previous data collected from various sources: Nippon Koei Co., Ltd. and ORIX Corporation, 2012; Thailand's Department of Alternative Energy Development and Efficiency (DEDE) and King Mongkut's University of Technology Thonburi (KMUTT), 2014; DEDE and KMUTT, 2015; Sustainable Energy Development Authority (SEDA), 2015; DEDE, 2016; and SEDA, 2017. All subsystem costs – along with cumulative solar PV installation capacity for grid-tied solar PV systems of utility scale in Malaysia, Thailand, and Indonesia – are plotted in log-log scale (Figures 10, 11, and 12). Because of the absence of publicly available reliable and relevant utility-scale PV module costs, inverter costs, mounting structure costs, and BOS costs for Indonesia, Malaysian data were considered with appropriate adjustments and conversions based on the purchasing power parity theorem described in Section 0.

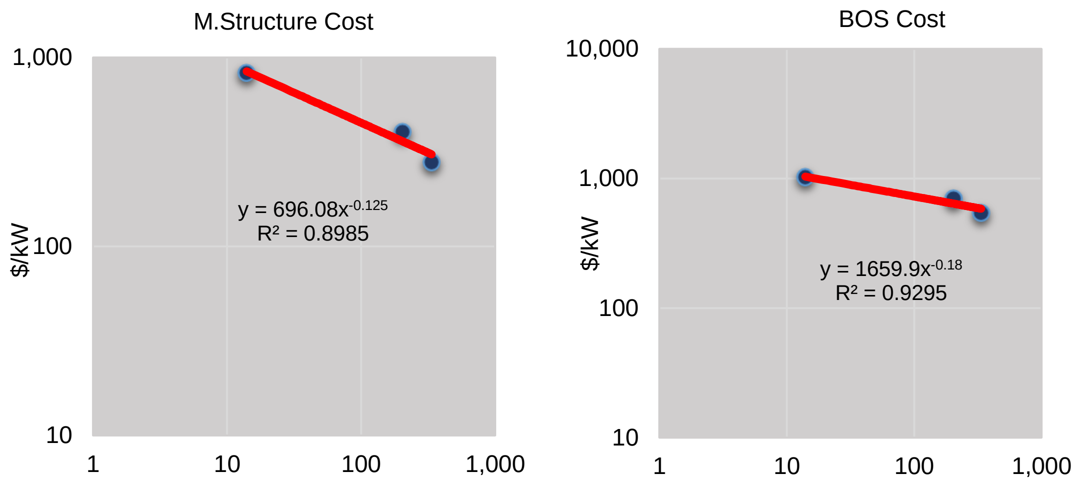
Malaysia

With a cumulative installed PV system capacity of only 362 megawatts (MW) until 2017 (Figure 7), the progress ratio of solar PV modules in Malaysia derived from the learning rate (Figure 10) is 77% – showing that the cost has been reduced by 23% (learning rate) in contrast to the global average of 21% (Zhao and Zhang, 2018). In the literature, comparisons between different learning curves are described by doubling the cumulative installations. In addition, the corresponding change in cost is referred to as the progress ratio. It is also referred to as the ratio of the final to the initial cost because of the doubling of the cumulative installation. Based on equation 6, the progress ratio can be defined as (1-learning rate) (Hernández-Moro and Martinez-Duart, 2013), which means that if the cumulative solar PV installation doubles, the price based on the learning curve theory should be reduced to 77% of the present value.

Figure 10: Learning Curves for Malaysia – Cumulative Capacity, 2018

(MW)





BOS = balance of system, kW = kilowatt, M. structure = mounting structure, MW = megawatt, PV = photovoltaic.
Source: Authors.

Table 4: Progress Ratio and Learning Rates for Malaysia

Country	Subsystem	Slope value (-b)	Progress ratio	Learning rate
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

BOS = balance of system, M. structure = mounting structure, PV = photovoltaic.
Source: Authors.

Despite having a low cumulative installation capacity, notable cost reductions in Malaysia may be attributed to its evolution as one of the major PV system manufacturing countries in recent years. With regard to progress in inverter cost reductions, comparatively slow progress is observed – a progress ratio of 82% (18% cost reduction) – since the inverters used in Malaysia are mostly imported and inverter prices reduce with increased volume. Since Malaysia's cumulative installation is lower than that of other pioneers such as Thailand, a slow progress ratio has been observed. The BOS and mounting structures are mostly procured, developed, and constructed locally. The costs of installation, grid integration, licenses, infrastructure, cables, and wire are included in the BOS. The grid integration cost varies with the distance between the project site and the nearest transmission substation, along with the capacity of the project. As estimated, the BOS and mounting structure costs have progress ratios of 88% and 92%, respectively. Cost reductions in the BOS and mounting structure are dependent on the availability of cheap, skilled human resources, and cumulative installed capacity. The lower progress ratio of the BOS and mounting structure may be because Malaysia has less PV system installed in terms of capacity and high labour costs.

The cost of the PV module is also expected to decrease in the coming years based on the learning curve. This may be because of the following factors, based on IEA (2018b):

(i) The consumption of polysilicon had a decreasing trend of 35% from 2008.

(ii) Additional investment in new production facilities will trigger production cost reductions.

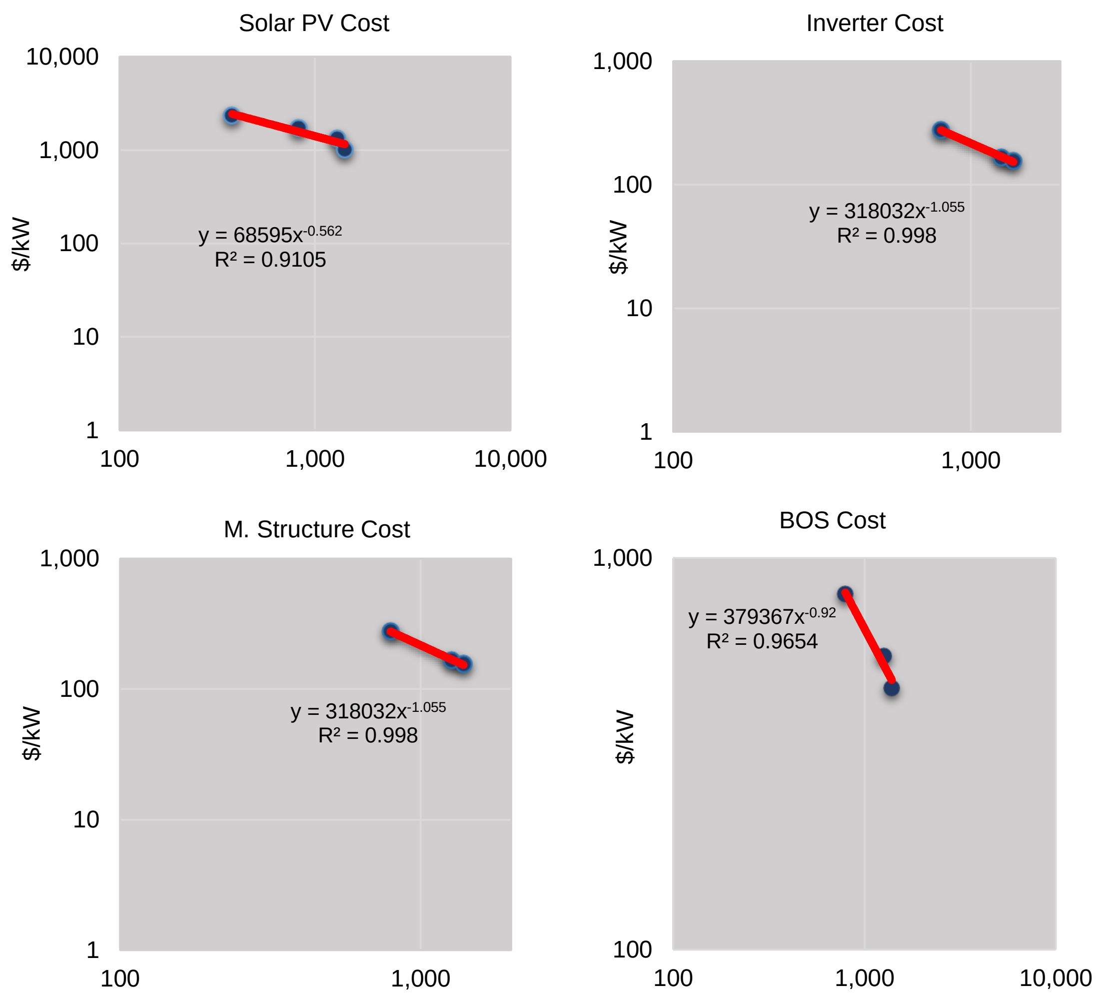
(iii) The diamond wire saw process to produce wafer has been used, which reduces the processing time and improves efficiency.

(iv) A 12% reduction in energy consumption has been reported since 2009 in polysilicon production.

Thailand

As seen from the learning curves of the PV system installed in Thailand (Figure 11), a progress ratio of 68% (Table 5) is achieved – meaning that the solar PV module cost has reduced by 32% (learning rate) as the capacity installation doubled in the reference period. A higher learning rate than the global average of 20.9% (Fraunhofer ISE, 2018) may be because PV installations in Thailand are amongst the highest in ASEAN countries. Of the subsystem costs, the cost of inverters has dropped to 48%, followed by the cost of the BOS and the cost of solar PV modules. Although Thailand is considered one of the pioneers in implementing solar PV projects in ASEAN, its solar PV module cost reductions are not the highest, perhaps because of the absence of local manufacturers.

Figure 11: Learning Curves for Thailand – Cumulative Capacity, 2018 (MW)



BOS = balance of system, kW = kilowatt, M. structure = mounting structure, MW = megawatt, PV = photovoltaic.
Source: Authors.

Table 5: Progress Ratio and Learning Rates for Thailand

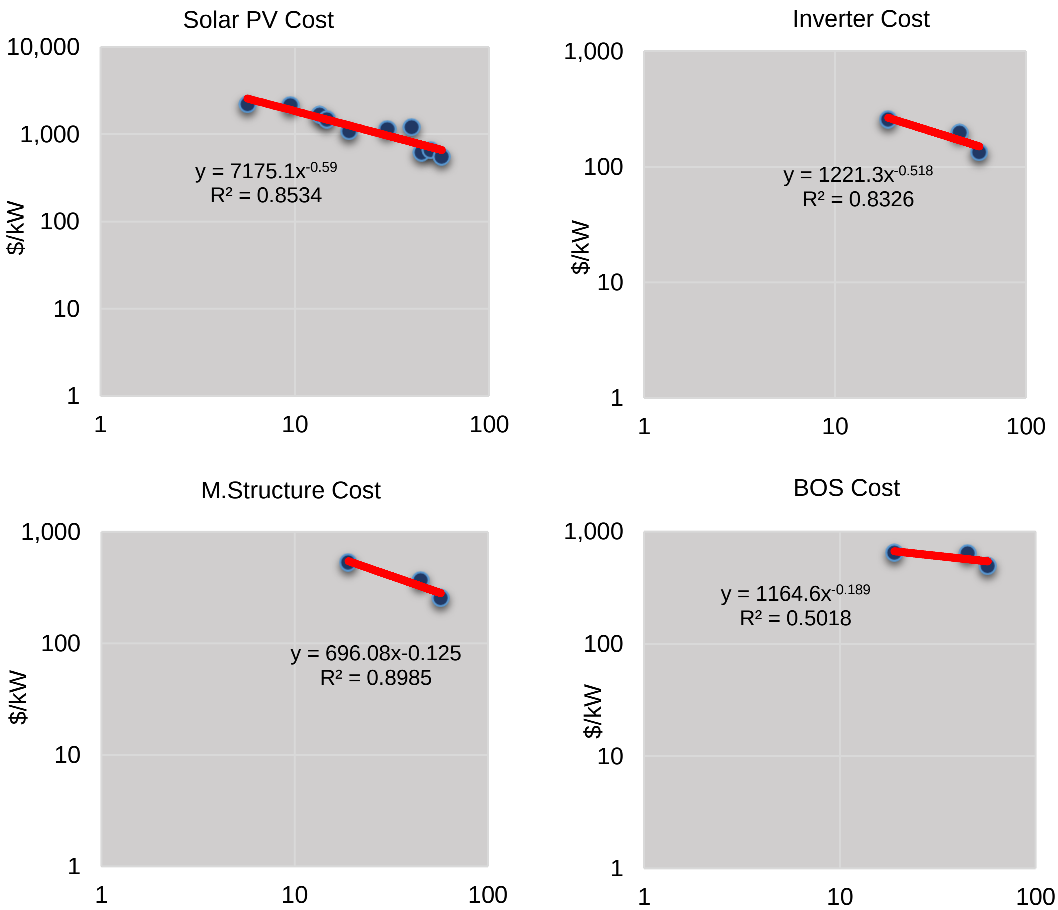
Country	Subsystem	Slope value (-b)	Progress ratio	Learning rate
Thailand	Solar PV	0.56	0.68	0.32
	Inverter	1.06	0.48	0.52
	M. structure	1.06	0.48	0.52
	BOS	0.92	0.53	0.47

BOS = balance of system, M. structure = mounting structure, PV = photovoltaic.
Source: Authors.

Indonesia

Figure 12 refers to reductions in the subsystem cost of utility-scale solar PV grid-tied projects in Indonesia. As shown in Table 6, cost reductions in Indonesia have been much higher than the annual capacity installation. This may be because solar PV installation has been increasing since 2014 in Indonesia, which is one of the newest of the AMS to adopt solar PV. Congruently, the overall solar PV system cost has been decreasing drastically since 2010 (IRENA, 2018c).

Figure 12: Learning Curves for Indonesia – Cumulative Capacity, 2018 (MW)



BOS = balance of system, kW = kilowatt, M. structure = mounting structure, MW = megawatt, PV = photovoltaic.
Source: Authors.

Table 6: Progress Ratio and Learning Rates for Indonesia

Country	Subsystem	Slope value (-b)	Progress ratio	Learning rate
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

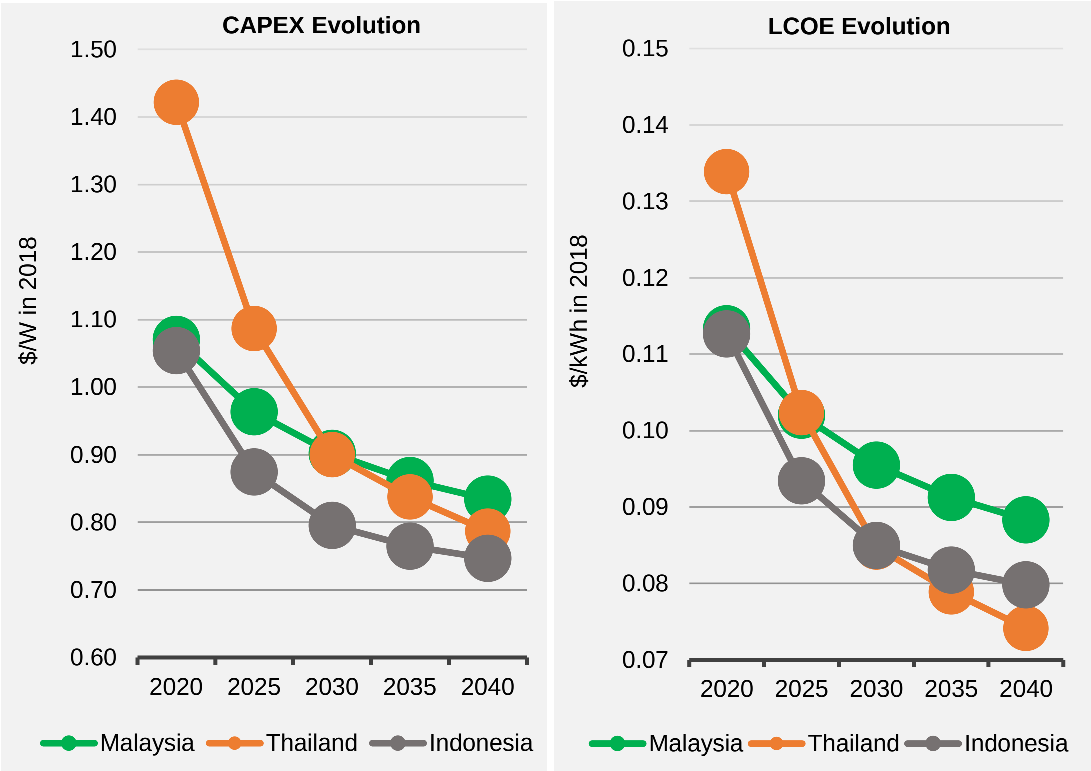
BOS = balance of system, M. structure = mounting structure, PV = photovoltaic.
Source: Authors.

7. Levelised Cost of Electricity

7.1. Simple LCOE

The simple solar PV LCOEs, i.e. without the carbon and decommissioning costs, were calculated based on the findings detailed in Section 6.2. As shown in Figure 13, simple LCOEs for all three countries reduce from the reference period until 2040. In 2020, Thailand will have the highest LCOE while solar PV systems in Malaysia and Indonesia will generate electricity at lower LCOEs compared with Thailand. In 2040, Malaysia's LCOE is predicted to be the highest, while Thailand's cost of electricity generation will be the lowest at $0.074/kWh. Malaysia's LCOE remains the highest of the three countries because of the higher capital cost, as derived from data sets. OPEX is also highest in Malaysia (Table 2). CAPEX is projected to be lowest in Indonesia, followed by Thailand and Malaysia. However, the LCOE evolves to be lowest in Thailand, followed by Indonesia and Malaysia in 2040. This opposite evolution may be because Thailand has the highest solar irradiation resource and the lowest labour costs among the selected AMS countries.

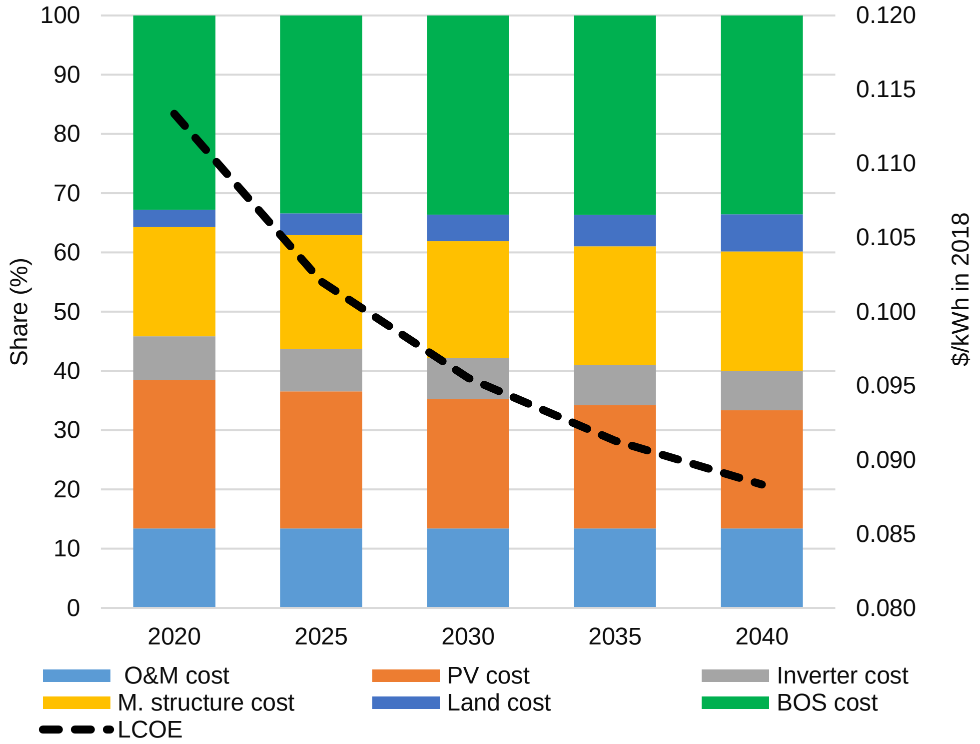
Figure 13: CAPEX and LCOE Evolution



CAPEX = capital expenditure, kWh = kilowatt-hour, LCOE = levelised cost of electricity, W = watt.
Source: Authors.

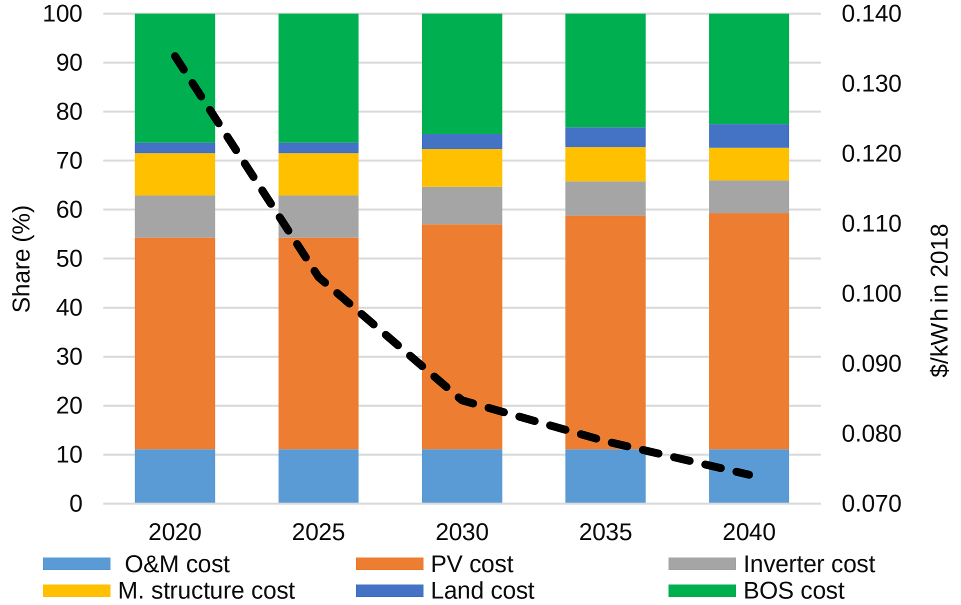
The impact of various subsystem costs on LCOE can be observed in Figure 14, 15, and 16. As noted, the cost of the solar PV module contributes the most (43%~48%) to the LCOE in Thailand, followed by BOS costs. On the other hand, BOS costs account for more than 30% of the LCOE in Malaysia and Indonesia, followed by the solar PV module costs. Hence, it can be concluded that the LCOE can be drastically reduced if special consideration is provided to the selection of project sites. Projects installed adjacent to existing substations will have a reduced BOS cost and subsequently lower LCOE. The use of locally manufactured PV modules also reduces the LCOE, as seen in the case of Malaysia. Lastly, it can also be comprehended that the absolute monetary value of the individual cost components shrinks over the years, regardless of its increase/decrease in percentage share within LCOE estimates.

Figure 14: Share of Costs in Simple LCOE (Malaysia)



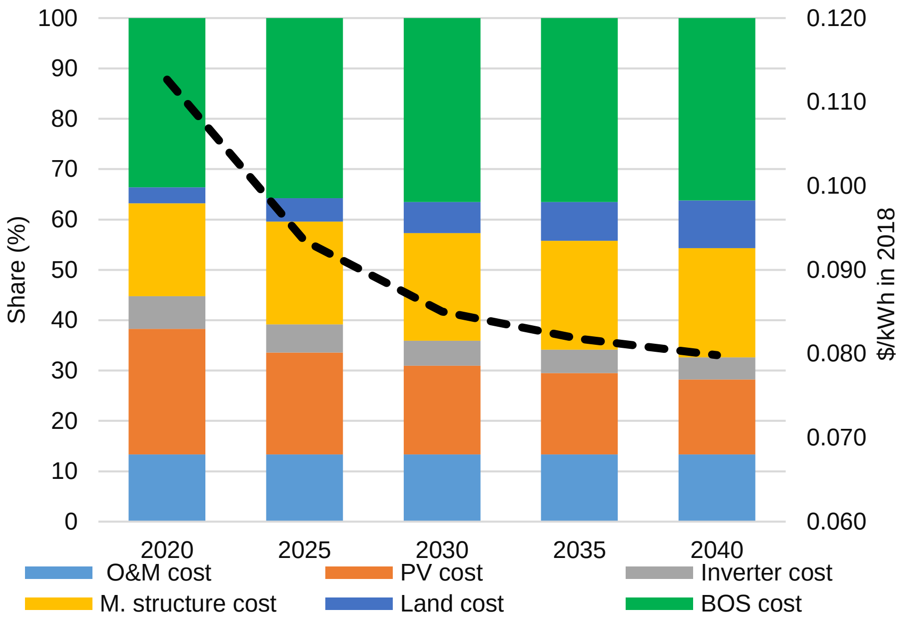
BOS = balance of system, kWh = kilowatt-hour, LCOE = levelised cost of electricity, M. structure = mounting structure, O&M = operation and maintenance, PV = photovoltaic.
Source: Authors.

Figure 15: Share of Costs in Simple LCOE (Thailand)



BOS = balance of system, kWh = kilowatt-hour, LCOE = levelised cost of electricity, M. structure = mounting structure, O&M = operation and maintenance, PV = photovoltaic.
Source: Authors.

Figure 16: Shares of Costs in Simple LCOE (Indonesia)



BOS = balance of system, kWh = kilowatt-hour, LCOE = levelised cost of electricity, M. structure = mounting structure, O&M = operation and maintenance, PV = photovoltaic.
Source: Authors.

The calculated CAPEX and LCOEs of solar PV showed significant differences between the three countries. This variance can be attributed to the following factors.

According to IEA (2018b), Malaysia was the third largest manufacturer of PV modules in 2017 – accounting for 6% of global production. In-country demand for PV modules is met by its own production sources, so the cost is lower.

According to the Indonesian Solar Module Manufacture Association (APAMSI), Indonesia has nine manufacturers with an annual capacity of less than 250 megawatt-peak (MWp) (Hamdi, 2019). According to the Asian Development Bank (ADB, 2015), these companies assemble PV modules using predominately imported components from countries such as China and Taiwan. Indonesian PV module manufacturers also form the main contingent of PV system installation contractors, and such installation works have to date been a strong driver for their PV manufacturing activity. This affects the financial planning of engineering, procurement, and construction contractors that are also manufacturers to plan their supply chain efficiently based on demand.

The Indonesian PV market has relied primarily on imported PV modules or locally assembled PV modules made from imported module components. The growth of solar PV, with regard to its potentiality, is sluggish and can be adequately supplied by domestic manufacturers. These factors have resulted in a CAPEX comparable with that of Malaysia.

According to Tongsopit et al. (2015), Thailand only has three module manufacturers. Hence, undersupply from local manufacturers persists in triggering the import of PV modules. According to DEDE (2016), Thailand imports most of its PV modules from China, Germany, Japan, and Taiwan. According to DEDE (2013), 45% of imported PV modules were from Taiwan while 27% were from Japan. Various studies have noted the higher prices of PV modules from Japan, Germany, and Taiwan compared with those from China. This may be the reason behind the higher solar PV cost in Thailand compared with the other countries.

7.2. Countrywide Weighted Average LCOE

With the aim of aiding policymakers, the weighted average LCOEs (WALCOEs) were also estimated (Table 7). Since the performance of PV modules degrades, it is expected that PV systems installed in 2020 will gradually produce less electricity and additional PV systems will be required to mitigate the loss in electricity generation in the previous years. The reduction in output also affects the attainable LCOE of solar PV in a particular year. A reduction in generation from previously installed systems triggers the additional installation of PV systems with lower LCOEs in forthcoming years.

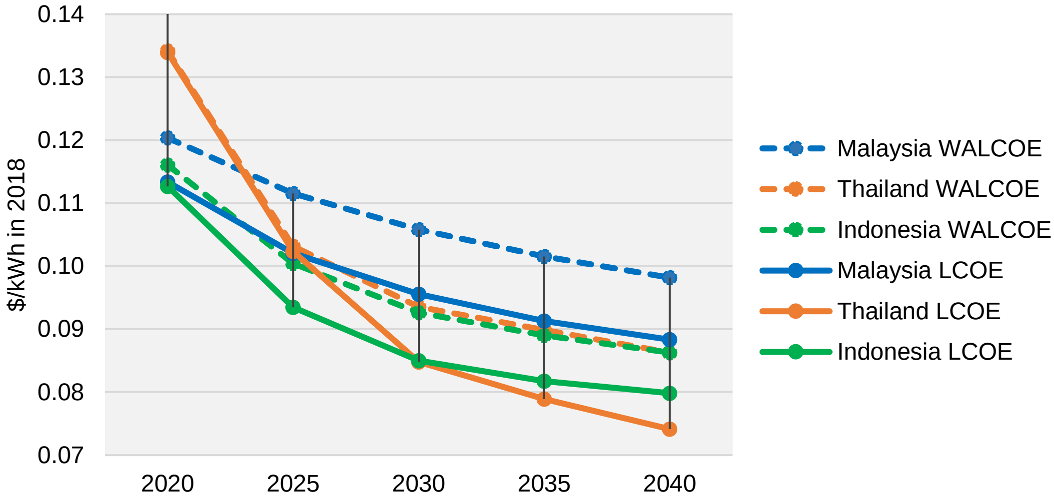
Table 7: Breakdown of the WALCOE

Malaysia	2020		2025		2030		2035		2040	
	$/kWh	Share (%)	$/kWh	Share (%)	$/kWh	Share (%)	$/kWh	Share (%)	$/kWh	Share (%)
O&M cost	0.016	13.4	0.015	13.4	0.014	13.4	0.014	13.4	0.013	13.4
PV cost	0.031	26.1	0.028	24.8	0.025	23.8	0.023	23.0	0.022	22.3
Inverter cost	0.009	7.5	0.008	7.4	0.008	7.2	0.007	7.1	0.007	7.0
M. structure	0.022	17.9	0.021	18.5	0.020	18.9	0.020	19.2	0.019	19.4
Land cost	0.003	2.7	0.003	3.1	0.004	3.6	0.004	4.0	0.004	4.6
BOS	0.039	32.3	0.037	32.8	0.035	33.0	0.034	33.2	0.033	33.3
Thailand	$/kWh	Share (%)	$/kWh	Share (%)	$/kWh	Share (%)	$/kWh	Share (%)	$/kWh	Share (%)
O&M cost	0.015	11.1	0.011	11.1	0.010	11.1	0.010	11.1	0.010	11.1
PV cost	0.058	43.1	0.047	45.8	0.044	46.7	0.042	47.0	0.041	47.3
Inverter cost	0.012	8.7	0.008	7.7	0.007	7.4	0.006	7.2	0.006	7.1
M. structure	0.012	8.7	0.008	7.7	0.007	7.4	0.006	7.2	0.006	7.1
Land cost	0.003	2.1	0.003	3.0	0.003	3.5	0.003	3.8	0.004	4.2
BOS	0.035	26.3	0.025	24.6	0.022	23.9	0.021	23.6	0.020	23.3
Indonesia	$/kWh	Share (%)	$/kWh	Share (%)	$/kWh	Share (%)	$/kWh	Share (%)	$/kWh	Share (%)
O&M cost	0.016	13.3	0.014	13.3	0.013	13.3	0.012	13.3	0.012	13.3
PV cost	0.032	26.4	0.024	23.0	0.020	20.9	0.018	19.8	0.017	18.7
Inverter cost	0.008	6.8	0.006	6.1	0.005	5.7	0.005	5.4	0.005	5.2
M. structure	0.021	17.7	0.020	19.2	0.019	20.1	0.019	20.4	0.018	20.7
Land cost	0.004	3.0	0.004	3.9	0.005	4.8	0.005	5.5	0.006	6.4
BOS	0.039	32.7	0.036	34.4	0.034	35.2	0.033	35.5	0.032	35.6

BOS = balance of system, kWh = kilowatt-hour, M. structure = mounting structure, O&M = operation and maintenance, PV = photovoltaic, WALCOE = weighted average levelised cost of electricity.
Source: Authors.

As shown in Figure 17, the WALCOE is higher than the simple LCOE in all countries throughout the evaluation period. This is mainly due to the yearly gradual reduction in PV output, which is compensated by additional solar PV installation in the proceeding years.

Figure 17: Comparison of WALCOE and LCOE

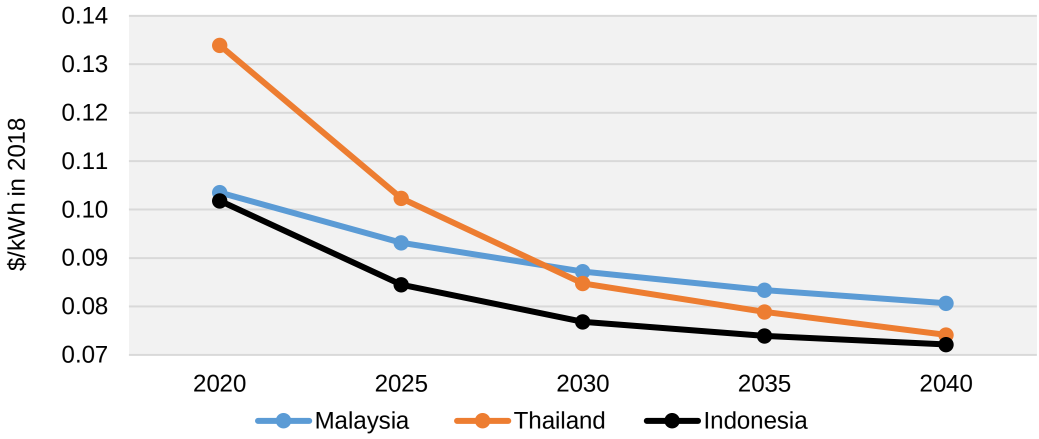


BOS = balance of system, kWh = kilowatt-hour, LCOE = levelised cost of electricity, WALCOE = weighted average levelised cost of electricity.
Source: Authors.

7.3. Sensitivity Analysis

Amongst the selected countries, Thailand retains the best geographical location in terms of solar irradiation (5.3 kWh/m^2/day) at a tilt angle of 14°. Solar irradiation plays a vital role in dictating the LCOE calculation. Hence, a sensitivity analysis was conducted, keeping solar irradiation constant at a maximum of 5.3 kWh/m^2/day for all three countries. As seen from Figure 18, the LCOE of Malaysia and Indonesia decreases as electricity generation increases because of increased solar irradiation. This leads to the LCOE of Indonesia evolving as the lowest in 2040.

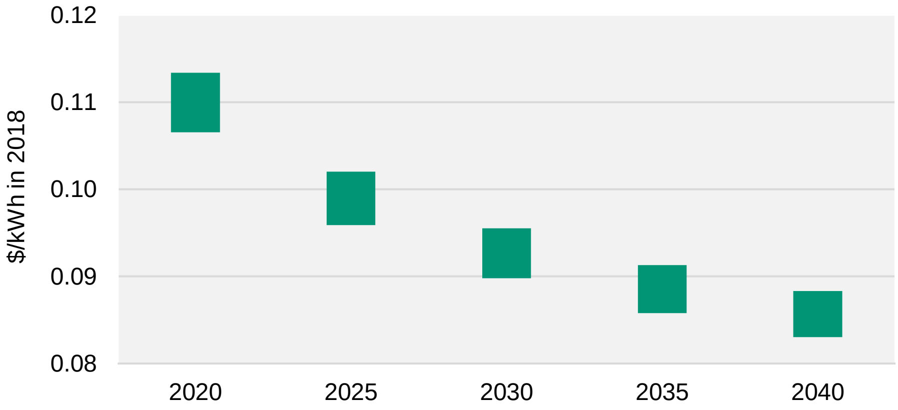
Figure 18: LCOE Evolution at 5.3 kWh/m²/day



kWh = kilowatt-hour, LCOE = levelised cost of electricity, m^2 = square metre.
Source: Authors.

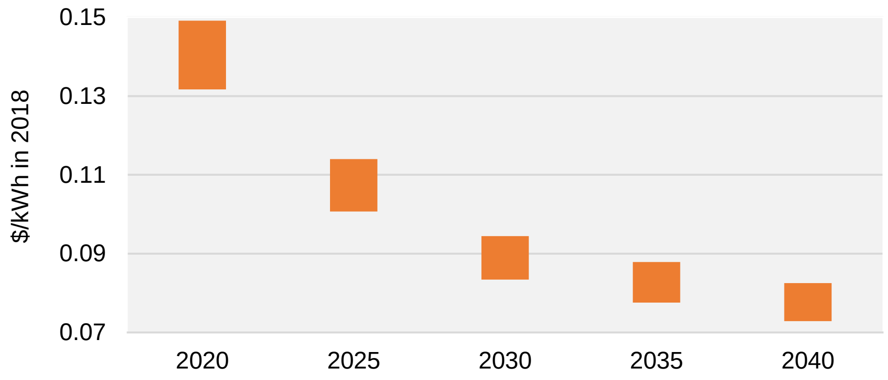
Furthermore, except Thailand, the other countries (i.e. Indonesia and Malaysia) are geographically dispersed – requiring regional sensitivity analysis in terms of variations in solar irradiation. Hence, sensitivity analysis was concluded for each of these countries by varying irradiation while keeping other factors constant. As seen from Figure 21, a wide range exists in the LCOE estimates, with a decreasing trend in the long term (i.e. 2020–2040) within each selected AMS.

Figure 19: Regional LCOE Range (Malaysia)



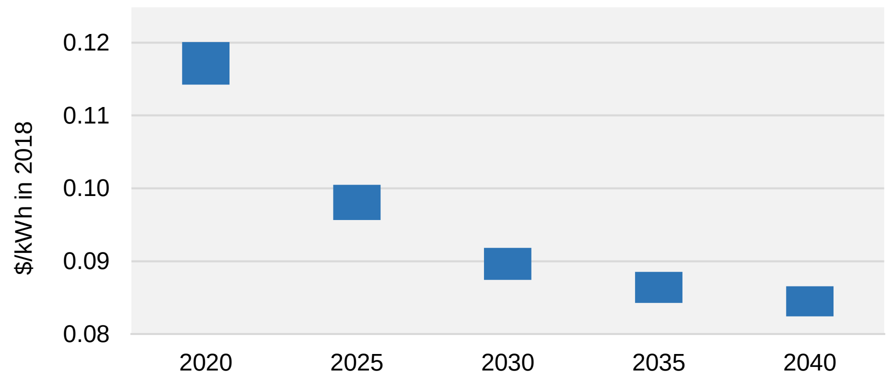
kWh = kilowatt-hour, LCOE = levelised cost of electricity.
Source: Author.

Figure 20: Regional LCOE Range (Thailand)



kWh = kilowatt-hour, LCOE = levelised cost of electricity.
Source: Authors.

Figure 21: Regional LCOE Range (Indonesia)



kWh = kilowatt-hour, LCOE = levelised cost of electricity.
Source: Authors

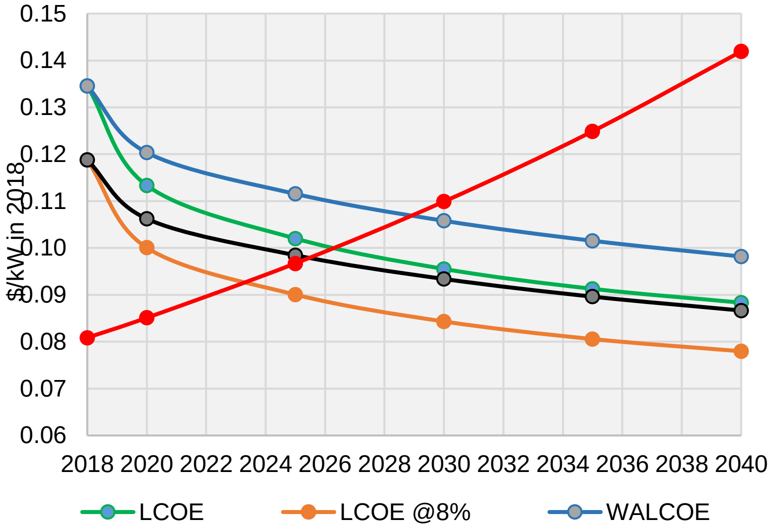
8. Policy Implications

With the existing government plans, ASEAN countries may only succeed in attaining 17% of the energy share through renewable sources by 2025. However, with the declining solar PV cost, it is important to predict the future attainment of grid parity across ASEAN. Future projections (Section 7) infer that Malaysia will have the highest LCOE at $0.10/kWh in 2020, while Indonesia will have the lowest LCOE at $0.08/kWh in 2040.

The authors also projected simple future LCOEs for conventional energy based on data gathered from Dong and Baruya (2015), MEMR (2018), and Malaysia's Energy Commission (2017), with further adjustments in the cost of fuel for each of the member states. The estimations were based on the predicted prices of fossil fuels (coal and natural gas). Improvements in generation technologies for conventional power sources were not considered.

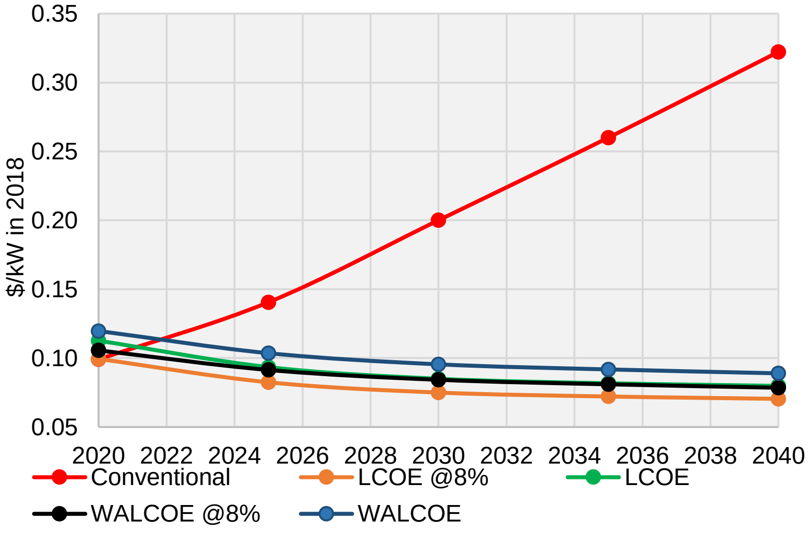
The LCOEs of solar PV and conventional electricity at the generation level are compared in Figures 22-24.

Figure 22: Forecast Grid Parity of Solar PV in Malaysia



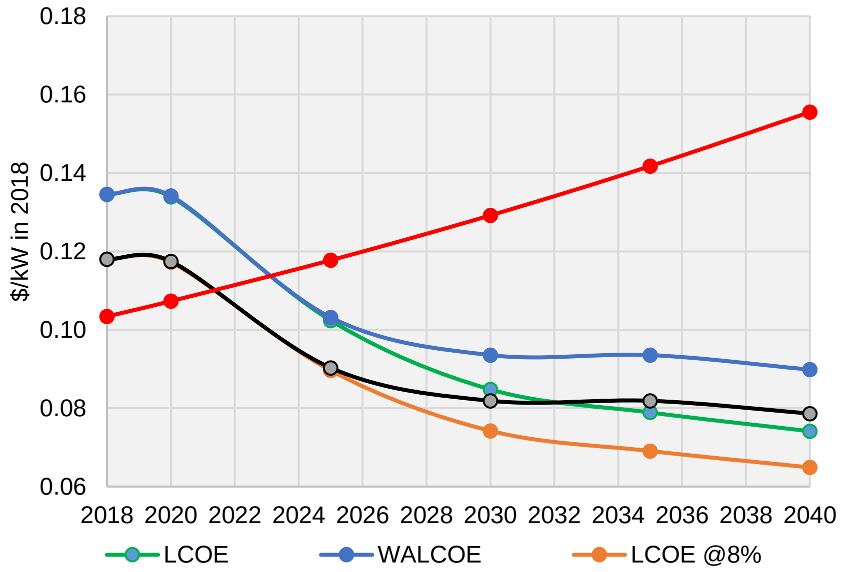
kW = kilowatt, LCOE = levelised cost of electricity, PV = photovoltaic, WALCOE = weighted average levelised cost of electricity.
Source: Authors.

Figure 23: Forecast Grid Parity of Solar PV in Indonesia



kW = kilowatt, LCOE = levelised cost of electricity, PV = photovoltaic, WALCOE = weighted average levelised cost of electricity.
Source: Authors.

Figure 24: Forecast Grid Parity of Solar PV in Thailand



kW = kilowatt, LCOE = levelised cost of electricity, PV = photovoltaic, WALCOE = weighted average levelised cost of electricity.
Source: Authors.

The results predict that utility PV systems will attain grid parity in Indonesia, Malaysia, and Thailand in 2021, 2026, and 2023, respectively.

9. Conclusion

This research study estimates the LCOE of grid-connected PV systems across selected ASEAN countries. The accuracy of learning curve methodology increases with more data sets. However, because of the scarcity of publicly available data, this work has been conducted based on a few data points, which may lead to inaccuracies in the estimation. The LCOE estimation of solar PV systems provided in ACE (2016) may be compared with the outcome of this research work for validation. ACE (2016) calculated the LCOE of PV systems in Indonesia and Malaysia as $0.145/kWh and $0.150/kWh, respectively. However, these results are based on 2014 data sets. Our research identified LCOEs of $0.112/kWh and $0.113/kWh for Indonesia and Malaysia, respectively, for 2020. The variation may be because the capital cost has decreased from 2014 to 2019 and will tend to decrease further in 2020 – resulting in a plummeting LCOE in 2020 and beyond. It is also notable that the LCOE in Malaysia and Indonesia, as mentioned in ACE (2016), is comparable to the current research outcome.

The costs of the PV module and BOS mostly affect the generation cost of solar PV systems. Hence, effective measures to develop in-house equipment supply chains, especially for PV modules, are needed to accelerate future LCOE reductions. BOS costs comprised a share of more than 35% in generating one unit of electricity in Indonesia. Geographical dispersion of localities and grid integration points may cause such high BOS costs. Besides, Indonesia is rich in natural resources and relies vastly on these for its energy supply, causing the RET market to flourish slowly compared with its ASEAN counterparts. Hence, a shortage of skilled labour as well as knowledge gaps may have influenced increased BOS costs. The outcome of this research predicts that utility PV systems will attain grid parity in Indonesia, Thailand, and Malaysia in 2021, 2023, and 2026, respectively. However, it should be noted that the estimation conducted in this research is based on PV systems with a capacity equivalent to 1 MW.

This study did not consider the potential instability of electrical grids caused by the introduction of large-scale solar PV. As mentioned earlier, grid transmission of electricity generated from PV systems requires additional infrastructure, such as electrical energy storage or batteries, which affect LCOE outcomes. This point will be further analysed quantitatively in our future studies.

A multidimensional ecology must be developed to accelerate further cost reductions. In terms of policy, the cost of health hazards, CO2, and subsidies must be added to conventional power plants during decision making or when providing carbon credits to solar PV systems as cash incentives from conventional power producers. Since solar PV systems are capital-intensive, implementers often use external financial support. The availability of green financing schemes with low interest rates will further reduce LCOEs. The import of PV modules is duty-free in Indonesia, while local assemblers must pay duty on accessories for assembling PV modules locally. To nurture and develop in-house capacity and technology, governments should focus on the exemption of duty on imported accessories and hardware. The implementation of larger capacity systems will trigger the attainment of grid parity earlier in these countries. As mentioned in Indonesia's National Energy Council (2017), the unit cost of larger capacity power plants is lower than that of smaller capacity power plants because of economies of scale. The proportionality factor in the economies of scale has been historically considered as 0.6 (National Energy Council, 2017). Hence, it is proposed that individual power producers opt for larger capacity systems to lower LCOEs. Attaining grid parity can also be accelerated by installing systems in regions with high solar irradiation, which will generate more energy with lower LCOEs (Figures 19, 20, and 21) and realise acceleration in grid parity.

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