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Prosumer solar power and energy storage forecasting in countries with limited data: The case of Thailand

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ABSTRACT

Forecasts of distributed energy resource deployment are becoming increasingly important in electric power purchase plans and difficult for countries with limited data. This study utilizes the Customer Adoption Model to forecast the deployment of behind-the-meter distributed solar photovoltaics and battery energy storage systems until the year 2050 and Thailand is used as a case study of the countries with limited data. Comparing methods and results from this study with those used in past studies shows that methodological choices can produce diverging results that shape investment plans and the estimated cost of power supplies. Several input variables of the Customer Adoption Model are discussed that will require continuous refinements as more data become available. The results show that pairing solar systems with batteries could in principle accelerate solar deployment and carbon emissions reduction but the high cost of batteries lengthens the payback period, raising questions about forecasting methodologies that rely mainly on the payback period. The methodological contribution points to a "chicken-and-egg" problem between forecasting and policy uncertainties: accurate forecasting depends on policy certainty, but getting policy right depends on accurate forecasting. Integrated scenario construction and the determination of a specific timeframe for achieving the adoption goal can help policymakers understand the impacts of different policy designs on distributed energy resource deployment and overcome this problem.

1. Introduction

Globally, electricity consumers have shown increasing interest in producing their own electricity using solar photovoltaic generation systems to reduce their electricity bills and lower the climate impact of their consumption [1]. Furthermore, declining energy storage costs have enabled consumers to enhance their savings and increase their consumption of solar power. Together, distributed solar PV (DPV) and battery energy storage systems (BESS) enable a new type of electricity stakeholder, known as the prosumer [2], and are transforming electricity systems and disrupting the planning processes and investments of utilities.

However, policymakers, planners and electric utilities in many developing countries are not well-equipped to project this trend into the future and incorporate it into investment and policy decisions. Adoption of DPV and BESS is difficult to predict, as it is dependent

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on a variety of factors both economic and non-economic factors [3–9]. Misforecasting DPV adoption can drive up utility system costs [10]. The increase of DPV and BESS installations behind the meter adds complexity to electric power procurement and investment planning. The projection of the uptake of DPV and BESS is an important component of planning and investment because they significantly reduce daytime electricity consumption from the grid and hence lower the need to expand conventional power plant capacities. Underestimation of the growth of DPV and BESS can result in excessive generation capacities that are locked in over the long term and place an unnecessary burden on ratepayers, especially in power markets with a lack of competition in the generation sector. Conversely, their overestimation can result in power shortages. Furthermore, when low- or zero-carbon power generation becomes a goal for planners, DPV and BESS deployment forecasting is critical for charting cost-effective and secure pathways to carbon emissions reduction targets.

We selected Thailand as a case study due to its relatively mature solar market, a high potential for significant solar capacity growth, and being located in a region with one of the highest forecast economic growth rates in the world for 2023–2024 [11]. In addition, Thailand has experienced the challenge of a high reserve margin caused by long-term contracts with fossil fuel plants [12]. This situation is a barrier to the energy transition in the short term, but also an opportunity to delay investment in new centralized generation and explore more extensive deployment of DPV. Therefore, the Thai case is of particular interest for the study of forecasting behind-the-meter DPV and BESS for power system planning purposes.

In this study, we provide an overview of DPV adoption forecasting methodologies. We address the following research questions: (1) Which forecasting methodology is the most suitable for countries with limited data (such as Thailand)? (2) How do varying economic and regulatory conditions affect the annual deployment of behind-the-meter DPV (in MW) and BESS (in MW/MWh) from 2019 to 2050, and? (3) What are the implications of our findings for forecasting, policy and regulations? These questions are also applicable to other countries where limited research has been carried out and/or limited data are available.

The novelty of our methodology is *the integration of BESS into the Customer Adoption Model and the evaluation of the impact of rate growth, rate restructuring, and the timing of rate restructuring on DPV and BESS deployment, as well as pointing out the chicken-and-egg problem between accurate forecasting and policy certainty*. Though rate restructuring has become a key regulatory approach to the duck curve [13] in countries or jurisdictions with high PV penetration, its potential impact has not been considered as a predictive element in the forecast of DPV and BESS penetration. Therefore, our scenarios better capture the two-way dynamics between market growth and regulatory feedback. We adopt the Customer Adoption Model [14,15], *to forecast DPV and BESS adoption* to the year 2050 based on four scenarios to understand the impacts of different policies on the forecasting results.

Our methodological contribution also points to the "chicken-and-egg" problem between the need for accurate forecasting and the need for policy certainty. Without a clear policy and the timeline for when the full market potential should be realized, the forecasting cannot be accurate. Based on the existing literature [16–21], the impact of many policy instruments, such as feed-in tariffs, capital subsidies, and tax incentives, can be accurately captured in forecasting models because they predict consumers' response based on the feasibility of DPV installation (e.g. payback period). Since the Customer Adoption Model relies on the payback period as a key parameter for forecasting solar adoption, its forecasting accuracy is highly sensitive to policy changes. On the other hand, policy formulation also relies on accurate forecasting of technology adoption. Because many policy instruments draw on large government budgets, particularly in the early stage when consumers' demand is to be stimulated, it is important to predict their effectiveness to justify the use of funds. Therefore, as implied in some studies [22–24], a valid projection of the uptake of technologies is an essential first step for analyzing the effects of enacted or forthcoming policy actions. This chicken-and-egg problem can be overcome by scenario construction, which can help policymakers and regulators understand the impacts of different policy designs on the speed and level of deployment. Well-crafted scenarios can capture potential policy changes that will result in different trajectories of technology uptakes.

2. Literature on methods for prosumer forecasting

2.1. Methods in the literature

A variety of DPV forecasting methodologies have been developed over the past two decades [15], each using different predictive factors as summarized in Fig. 1. The Customer Adoption Model is the most comprehensive approach to DPV forecasting [15,25–29] and

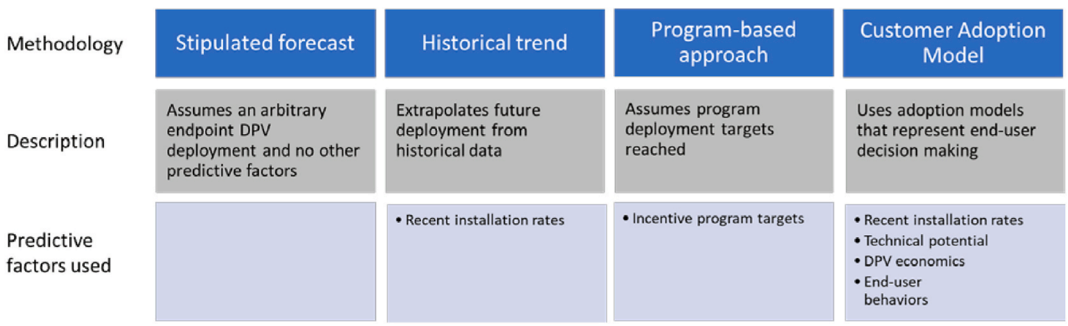


Fig. 1. Predictive factors used by various methodologies to forecast DPV adoption [15].

has recently been improved to include the pairing of DPV with energy storage [30]. This methodology requires a substantial amount of data since it can take into account the preferences of various consumers and directly reflect their reactions to policy and regulatory changes, such as rate restructuring, net energy metering (NEM) phase-out or cancellation, and changes in levels of incentives such as feed-in tariffs and tax credits. Importantly for the purposes of this study, the Customer Adoption Model can be adjusted over time as more data become available. However, significant groundwork must be done to create the inputs required for the Customer Adoption Model, including surveys on customers' willingness to adopt DPV and energy storage.

The Customer Adoption Model postulates that each customer's decision to adopt DPV depends on the economics of the adoption and that there is a diversity of customer perceptions of the acceptable economic thresholds. If the economics is acceptable to a particular category of customers because it is above a certain economic threshold (e.g., payback period or net present value), then that group of customers will become the early adopters. As the market dynamic changes due to variables such as technology cost, retail electricity price, support policies, word of mouth, and customer awareness, new groups of customers with higher economic thresholds will follow suit. Over the years, the level of adoption will follow a path known as an S-curve.

The Customer Adoption Model estimates yearly DPV and energy storage adoption in three steps. *In the first step*, the technical potential of DPV or DPV paired with BESS is calculated for a specific geographical area. Different methods for estimating technical potential are listed in Table 1. *In the second step*, willingness to adopt determines the ultimate share of consumers that will adopt DPV (as a percentage of the technical potential). In this step, the model uses an evidence-based willingness-to-adopt curve, which describes the ultimate adoption level (in %) as a function of an economic variable (e.g., payback period, net present value) [14,15]. Each geographic area has a unique willingness-to-adopt curve because the consumers have different economic thresholds. For this reason, the selection of the willingness-to-adopt curve is drawn from the existing literature or customer surveys for a specific geographical area. The ultimate adoption or the maximum market size does not specify how soon and how fast the adoption will occur. This lack of a time dimension necessitates *the third step*, which relies on the Bass Diffusion Model [31], depicted in an S-curve. The Bass Diffusion Model is widely used in solar adoption forecasting [32–34]. In this third step, an S-curve is selected, showing the percentage of adoption that occurs each year. The selection of the S-curve is thus specific to a geographical area and depends on previous empirical studies that drew conclusions for the two parameters that shape the S-curve for that area [15]. These two parameters are the co-efficient of innovation (p) and the co-efficient of imitation (q). The resulting S-curves can vary significantly in terms of how fast the DPV market starts to take off and how soon it becomes saturated [15].

While the original Customer Adoption Model relies on other studies for inputs such as technical potential and customer preferences, a more advanced approach modifies Step 1 by predicting the technical potential using a bottom-up agent-based approach. NREL's Distributed Generation Market Demand Model (dGen) is an example of this latter approach [37,41]. The dGen model simulates

Table 1
Steps in customer adoption modeling and different methods.

Steps and explanation	Method	Examples of studies
1. Estimation of the total technical potential feasible amount of rooftop solar systems that can be installed based on suitable roof spaces, regardless of economic considerations	**Top-down:** Share of appropriate roof area out of the total available roof area (m^2) multiplied by solar DPV power density (kWdc per m^2)	[14,35]
	Top-down: Finding a relationship between population and rooftop areas in urban and rural areas based on a sample of districts in those areas and extrapolate the relationships to estimate the total rooftop area for the whole country.	[36]
	Bottom-up: Use of national land-use database to distinguish between residential, commercial, and industrial land use in each grid. Then use these locations as potential agent locations to be sampled from by the dGen model.	[37]
2. Willingness-to-adopt curve The ultimate share of the consumers who will adopt DPV if the economics becomes better than their economic threshold (e.g., payback period)	Use of historical DPV adoption data to generate a function of payback period and market share. Then fit a curve to this historical trend to create the willingness-to-adopt curve.	[38] cited in [15]
	Estimate the uptake of DPV based on a net positive return on investment for the DPV, subject to constraints, including a maximum of 20% of total households and 65% of businesses in each region that can deploy solar energy.	[39]
	Calculate the total maximum market potential in each year based on the payback period realized by the customer in each year.	[14]
3. Market diffusion (S-curve) The annual estimates of DPV deployment	Use of historical DPV adoption data and extrapolate the future trend by considering current growth rates, known projects in queue, and planned projects by customers.	[40]
	Use of historical DPV adoption data as a starting point. Assume a maximum market share of DPV adoption in the end of the analysis period. Derive the maximum market share based on the payback period in each year. Derive the realized annual adoption using the Bass Diffusion Curve, which resembles an S-curve. The variables that affect the shape of the curve is derived from empirical data or literature.	[36]

different agents who represent unique clusters of customers and forecast their adoption of DERs to 2050. It requires detailed geospatial data to form the agents, such as load profiles, solar generation potential, retail rates, number of households in each area. The current version of the dGen model draws input data from databases in the U.S. and pre-generates nearly 350,000 agents. The assessment of the technical potential is done as the agents are created and associated with factors that affect the technical potential including location, solar resource, and solar siting considerations. Customer preferences can either be represented by a pre-selected S-curve or generated based on the historical adoption trend. Due to the requirement for high-resolution datasets, this method can only be applied to countries that build the required databases to link to the model.

In recent years, BESS have experienced continuous growth, researchers have incorporated distributed ESS into the Customer Adoption Model by pairing it with the DPV system [30]. The technical potential of the distributed ESS is capped as a fraction of the optimal DPV system for each specific customer group.

2.2. Methods in past studies on Thailand

Forecasts of prosumers are becoming increasingly important as solar DPV adoption increases in Southeast Asian nations. However, forecasting studies of prosumers in this region are uncommon and data is limited. We chose to include a case study of Thailand to demonstrate the challenge of integrating DPV and BESS into long-term power procurement plans since Thailand has some DPV adoption forecast research [36,42–44] and the history of Thailand's policies to support DPV market development is quite well documented [13,45–48]. Thailand experienced a 543% increase of DPV between 2014 and 2020 [49,50]. Most (82%) of this capacity growth is attributable to "parallel customers" who do not join any incentive program, and this group accounts for future growth due to the Thai government's lack of policy and incentives for DPV. Despite the rapid growth of prosumer-driven behind-the-meter PV, Thailand's latest Power Development Plan (PDP 2018 revision 1) did not include projections of DPV in its analysis [51].

There are currently four DPV adoption forecast studies on Thailand, as shown in Table 2. The methodologies used by the IEA [36] and EPPO [43] are summarized here since these two studies originally conduct technical potential assesements and forecasts of DPV. However, the studies by Chaianong et al. [42] and EPPO et al. [44] refer to the methodology as conducted by the IEA and consider some other factors in their studies.

The study by IEA (2018) [36] estimates the technical potential of DPV in Thailand by examining the relationship between roof area and population. 100 sub-district samples were randomly selected and then classified into two groups based on high and low population density. Next, the relationship between population and roof area with proper rooftop orientation for each population density was determined to estimate a rooftop solar potential. This resulted in the identification of the maximum potential, which was greater than the actual technical potential since the methodology did not consider roof age, shading, structural strength, and technical constraints of distribution grid. The maximum economic potential for each customer group was calculated by using a relationship between the willingness of technology adoption and payback period [14]. The payback period of each customer group in each year of the study period needs to be known in order to calculate the maximum market share of the technical potential, which was the number of customers of each group, for that particular year. Next, annual additional DPV adoption was determined using a technology penetration curve, or the "Bass Diffusion Model" [31].

EPPO (2019) estimated the technical, economic and market potential of DPV adoption. The study estimates rooftop area of Thailand based on a statistically representative stratified sample of vector Geographic Information System (GIS) maps and representative topologies of buildings in a function of population density and building density. This results in the total rooftop area for Thailand, to which the researcher applied a factor of 0.50, which was derived by experts using visual interpretation from high-resolution satellite and aerial photographs along with GIS tools, to include only appropriate rooftops for solar installations. The economic potential was determined by creating a model to predict intention based on a survey on attitudes and factors that influence DPV installation decisions. For market potential, the study considered the constraints of grid codes of distribution utility and grid capacity.

3. Scenarios, methods, and data inputs

3.1. Scenario development

We constructed four main scenarios with a total of six sub-scenarios based on varying economic and regulatory conditions and calculated the total estimated annual deployment of behind-the-meter DPV (in MW) and BESS (in MW/MWh) from 2019 to 2050. None of the six sub-scenarios include an incentive or compensation mechanism for DPV excess generation to reflect the current policy trajectory. The DPV and BESS systems were optimally sized for self-consumption of the site host. The six sub-scenarios, as summarized in Table 3, were varied on three key parameters: the addition of BESS, the rate structure, and the growth rate of the retail tariff and detailed scenarios are described in Appendix 1. The BESS considered in this study was a stationary lithium battery. However, in the future, the utilization of BESS with DPV could include the batteries of electric vehicles (EVs) in line with the concept of vehicle-to-X where the battery of an EV can supply electricity to the grid or be utilized for other energy and power applications [52,53].

We varied the rate structure since it is one of the key regulatory approaches to align the interests of DPV-plus-BESS customers with the broader power system [54]. High solar PV penetration creates the duck curve situation that can be mitigated through rate restructuring, which in turn incentivizes BESS deployment [55,56]. The duck curve is the net system load curve with high contribution of solar power during the daytime, which significantly meets daytime load and causes a sharp increase demand on the grid in the early evening hours when solar production ends. The steep increase in demand could create a need for peaking natural gas or diesel plants to

Table 2
Comparison of Thai forecasts of the technical and economic potential of DPV.

Papers	Total forecasted MW	Timeframe	Notes
IEA (2018) [36]	Maximum technical potential: 380,000 MW Economic Potential: 24,614 MW-36,787 MW in 2036	2018–2036	The authors added 10% to the maximum technical potential to arrive at an estimate technical potential of 38,000 MW.
EPPO (2019) [43]	Technical potential: 208,409 MW in 2019 226,373 MW in 2037 Economic potential: 9794 MW in 2037 Market potential: 9267 MW in 2037	2019–2037	The economic potential determined by a behavioral intention prediction model must not exceed the technical potential. The market potential was calculated based on the economic potential not overloading grid capacity.
Chaianong et al. (2019a) [42]	Economic potential: 24,614 MW-36,605 MW in 2036	2018–2036	The methodology was the same as [36], but some assumptions are different, such as export rate of excess DPV generation.
EPPO et al. (2018) [44]	Economic potential: 32,828–36,787 MW in 2036 (for the case of without grid constraints) 20,798–20,801 MW in 2036 (for the case of with grid constraints)	2018–2036	The study referred to Ref. [36]'s economic potential but reduced the potential by grid constraints.

Table 3
Scenarios of DPV and BESS adoption to 2050.

Technology	Retail tariff structure	Growth rate of retail tariffs	Scenario
DPV only	Current	Low	**Scenario 1**: Static policy
	Current	High	**Scenario 2**: Testing the sensitivity to higher retail tariff growth
DPV with Battery	Current	Low	**Scenario 3**: Testing whether batteries can succeed under current trajectory
	New tariff structure applied in 2031	Low	**Scenario 4.1**: Testing the impacts of early tariff structure but lower retail tariff growth
	New tariff structure applied in 2031	High	**Scenario 4.2**: Testing the impacts of early tariff structure and higher retail tariff growth
	New tariff structure applied in 2036	High	**Scenario 4.3**: Testing the impacts of late tariff structure and higher retail tariff growth

ramp up. For this reason, some jurisdictions with high solar penetration such as California have phased in retail rate restructuring by moving the peak hours of the TOU rate to the early evening hours to incentivize the use of energy storage to meet the evening load. For Thailand, according to the modelling by the IEA [36], the high renewables scenarios exert the demand for gas turbines to meet the steep ramping during the peak evening hours. The current and proposed restructure retail tariffs used in this study are summarized in Appendix 2. The proposed restructuring of retail tariffs differentiates between customer groups. This structure incentivizes the consumers to store solar electricity during the daytime for discharge during the high-price peak hours.

3.2. Methods for estimating DPV and BESS deployment

We used the Customer Adoption Model to estimate the deployment of DPV and BESS by year, by rate class, and by region in the following steps, as illustrated in Fig. 2.

In the first step, existing data on the technical potential of DPV in Thailand from Ref. [36] was utilized. *In the second step*, to assess the economic potential, due to the lack of existing research on customers' willingness to adopt DPV and energy storage, the willingness-to-adopt curve from Ref. [14] was used to assess the market potential for the year 2019–2050. Though this willingness-to-adopt curve does not reflect the real consumer preferences in Thailand, the curve represents the medium level of adoption and was used by studies for two geographic areas including Arizona [14] and Northern California [57]. Two financial inputs that would affect the economics of solar DPV were varied: retail rate and DPV system prices. The retail rate is projected to increase at an annual rate of 1.6% for a low-rate growth and 4.6% for a high-rate growth based on the retail rate trend of Thailand. The DPV system prices are projected to decline in the future at rates comparable to the conservative scenarios of U.S. Department of Energy's projected annual energy technology baseline for each respective class of customers [58].

REOpt Lite API[1] was adopted to search for the optimal sizes of DPV and battery. With these optimal sizes, yielded payback periods are then fed into the equation from Ref. [14], as shown in Eq. (1) to calculate the maximum market share (willingness-to-adopt) in that particular year. Eq. (1) was adopted to both DPV-only and DPV-battery scenarios.

[1] REopt Lite API is a web-based tool that evaluates the economic viability of distributed generation and microgrids and recommends optimal sizes for the distributed generation systems. It is developed and managed by the U.S. National Renewable Energy Laboratory (NREL).

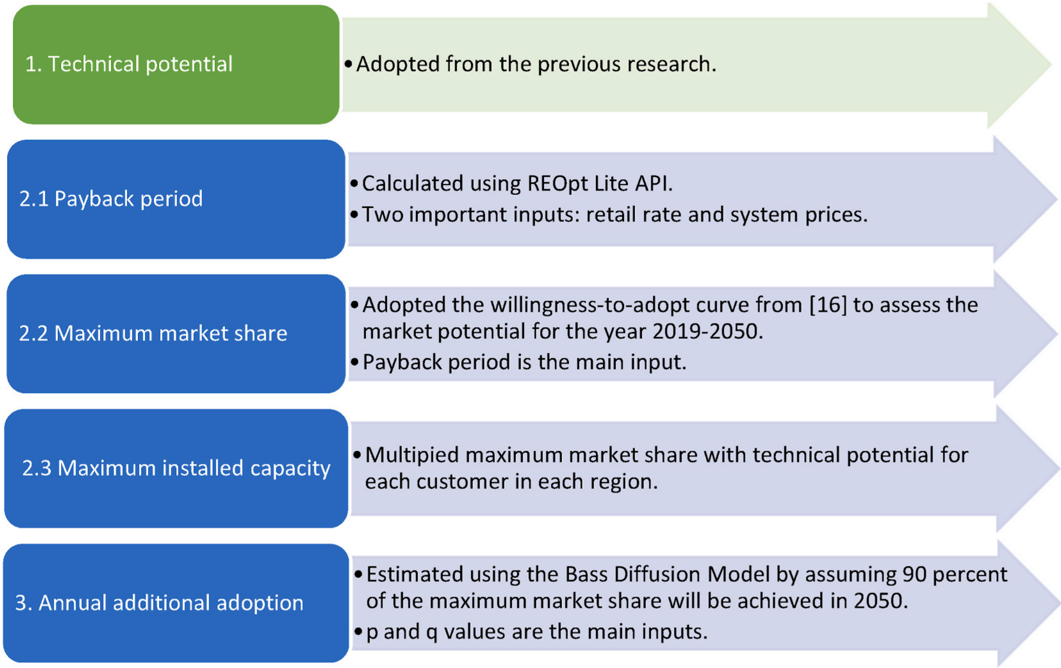


Fig. 2. Methodological framework for estimating DPV and BESS economic potential. The green box represents the step related to the technical potential, while the blue boxes are our main method in this paper.

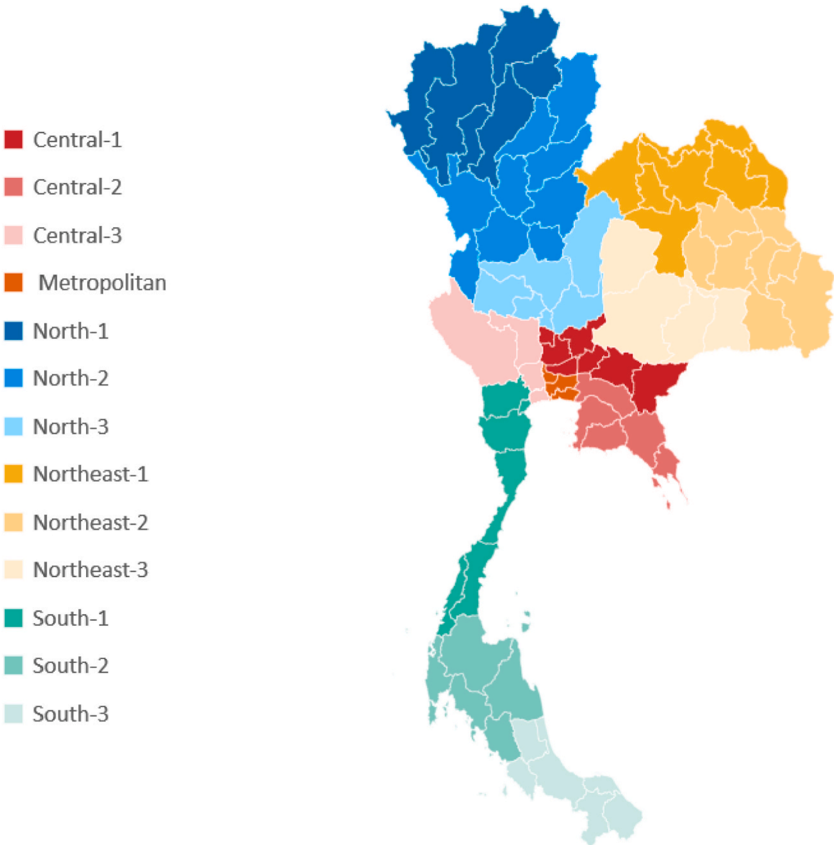


Fig. 3. The 13 sub-areas associated with each load profile for each rate class in Thailand.

$$\text{Maximum market share} = e^{(-0.3 \text{ x payback period})} \quad \text{Eq.(1)}$$

Next, the maximum installed capacity of each customer in each region was calculated by multiplying the maximum market share from previous step with the technical potential from Ref. [36],.[2] *In the third step*, the annual DPV adoption was estimated using a technology penetration curve, the "Bass Diffusion Model" (see Eqs. (2) and (3)). It was assumed that 90% of the maximum market share will be achieved in 2050. This is because the technology diffusion curve cannot be fully (100%) saturated. The p and q values were assumed to be 0.003 and 0.5, respectively, in line with existing research [36,59,60]. The current DPV installation for self-consumption in the country as of 2018 (about 464 MW [49]) was taken as the starting point.[3]

$$\mathrm{F}(t) = \frac{1 - pe^{-(p+q)^t}}{1 + \frac{q}{p}e^{-(p+q)t}} \tag{2}$$

$$\mathrm{f}(t) = \left\{ \begin{matrix} F(t), t = 1 \\ F(t) - F(t-1), t > 1 \end{matrix} \right\} \tag{3}$$

where:

f(t) is annual (additional) PV installation at time t.

F(t) is cumulative PV installation at time t.

p is innovation (external) coefficient (such as advertising – in the case without social influence).

q is imitation (internal) coefficient (such as word-of-mouth).

3.3. Data inputs

Data inputs on electric load profiles, retail tariffs, and baseline DPV system prices are specific to Thailand. However, the rates of price decline for DPV and BESS to 2050 are based on the U.S. Department of Energy's Annual Technology Baseline [58]. Detailed description of these data inputs is provided in Table 4 and Appendix 2.

4. Results

4.1. Total DPV deployment and diffusion paths

Our Customer Adoption Model charts the diffusion of Thailand's DPV deployment in different scenarios as illustrated in Table 5, Fig. 4, and Fig. 5. Peak deployment occurs in 2028, and cumulative deployment plateaus around 2038 in all scenarios. The ultimate levels of adoption range from 4155 MW to 7852 MW, depending on the scenario. For all scenarios, large general service (LGS) customers contribute the largest share of adoption, followed by medium general service (MGS), residential with consumption exceeding 150 kWh/month (RES > 150), small general service (SGS), and residential with consumption not exceeding 150 kWh/month (RES < 150), respectively. The deployment by region for all scenarios can be found in Appendix 3–8.

Due to the longer payback periods of PV with BESS scenarios in most years, compared to the PV-only scenarios, the cumulative deployment is higher in the PV-only scenarios. However, the optimal size of individual PV systems in PV with BESS scenarios is higher than in PV-only scenarios, as shown in Fig. 6(a) and (b) and Fig. 7(a) and (b).

4.2. Scenario impacts on DPV deployment

4.2.1. Impacts of retail tariff growth rate when installing PV only

Retail tariff could increase from internal factors, such as energy policies on power generation mix, or external factors such energy crisis. Considering the installation of PV only, the condition that favors high DPV deployment is the high retail tariff growth rate. When deploying PV alone under the current rate structure, a higher growth rate of the retail tariffs results in greater savings and hence shorter payback periods for all rate classes (Fig. 8(a) and (b)).

4.2.2. Impacts of installing BESS

Compared to DPV alone (Scenario 1), pairing of BESS with DPV (Scenario 3) results in larger optimal DPV sizes and hence greater decarbonization potential. However, the underlying financial conditions of our scenarios do not result in a higher aggregate DPV deployment when paired with BESS due to the longer payback period that comes with the addition of BESS. In Fig. 8(a) and (c), although the addition of batteries enables greater utilization of solar electricity even with the current retail tariff structure and low retail growth rate, it also causes longer payback periods due to the higher investment costs, compared with DPV alone. This suggests

[2] Originally, this technical potential was aggregated for the whole country. We adopted percentage of energy sale in 2017 from National Statistical Office (http://statbbi.nso.go.th/staticreport/page/sector/th/13.aspx.) to determine the technical potential by customer group and region.

[3] Same as above footnote, we adopted percentage of energy sale from National Statistical Office (http://statbbi.nso.go.th/staticreport/page/sector/th/13.aspx.) to determine 2018 DPV installation by customer group and region.

Table 4
Data inputs used in this study.

Data input	Description
Electricity load profiles	We acquired 2017 hourly load profiles of a representative customer for each rate class from the MEA and PEA[a], which are divided into 13 sub-areas (Fig. 3). Both the MEA and PEA have five rate classes, which include residential with electricity consumption less than 150 kWh per month (RES $\leq$ 150), residential with electricity consumption over than 150 kWh per month (RES > 150), small general service (SGS), medium general service (MGS), and large general service (LGS). Load profiles are also different from month to month.
Retail tariffs	We assumed that RES and SGS customers would automatically switch to TOU tariff as past studies [13,48] have shown that the TOU tariff is better for the economics of solar self-consumption for RES and SGS customers. Furthermore, TOU tariffs are default rates for MGS and LGS customers, so they are used in the modeling for these groups of customers.
Retail tariff growth	We considered two growth rates: 1.6% per year for a low-rate growth based on the 2002–2021 historical trend and 4.6% per year for a high-rate growth based on the increased rate in 2022[b].
DPV system prices and price projection	We used 2019 DPV system prices from Ref. [49], which derived data from industry survey. Starting from the 2019 base year, we projected the yearly price decline of DPV until 2050 using the trends for residential and commercial customers from NREL's Annual Technology Baseline [58].
BESS prices and price projection	The rates of price decline for BESS to 2050 are based on the U.S. Department of Energy's Annual Technology Baseline [58]
Sizing of PV and BESS for each respective rate class	REOpt Lite API was adopted to search for the optimal sizes of DPV and battery that give the highest net present value [61] for each customer class in each sub-area in each year. Since REOpt Lite adds a battery when it yields the highest NPV, compared with DPV-only and no DPV, it is possible that some customers may experience the highest NPV from PV and Battery but also a longer payback period compared to installing DPV alone.

[a] Thailand has two distribution utilities: the Metropolitan Electricity Authority (MEA) and the Provincial Electricity Authority (PEA). MEA, "Load profile study," [Online]. Available: https://www.mea.or.th/home. [Accessed November 1, 2021]. PEA, "Load Research of PEA. Power Economics Division," [Online]. Available: http://peaoc.pea.co.th/loadprofile/en/. [Accessed November 1, 2021].

[b] Based on the increased rate in 2022 from Yuthana Praiwan, "Power bills poised to rise 4.6% in early 2022," 2021. [Online]. Available: https://www.bangkokpost.com/business/2218539/power-bills-poised-to-rise-4-6-in-early-2022. [Accessed December 1, 2021].

Table 5
Comparison of cumulative PV adoption (from 2019 to 2050) across scenarios and areas.

Cumulative PV adoption (MW)		Scenario 1	Scenario 2	Scenario 3	Scenario 4.1	Scenario 4.2	Scenario 4.3
Scenario description	**Technologies:**	PV only	PV only	PV and BESS	PV and BESS	PV and BESS	PV and BESS
	Rate structure:	Current	Current	Current	Restructured in 2031	Restructured in 2031	Restructured in 2036
	Retail tariff growth:	Low	High	Low	Low	High	High
Metropolitan[a]		617	829	473	486	442	436
Central		1090	1458	825	873	796	774
North		1457	1900	1236	1242	1123	1103
Northeast		1566	2176	1374	1307	1139	1087
South		1096	1489	846	846	770	755
Total		5826	7852	4754	4754	4270	4155

[a] MEA or Metropolitan area includes three provinces: Bangkok, Nonthaburi, and Samut Prakan.

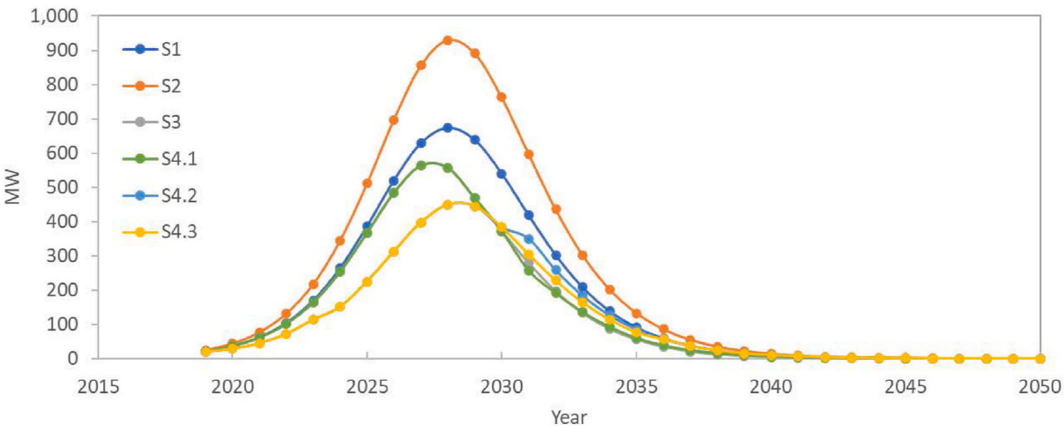


Fig. 4. Annual PV deployment under different scenarios.

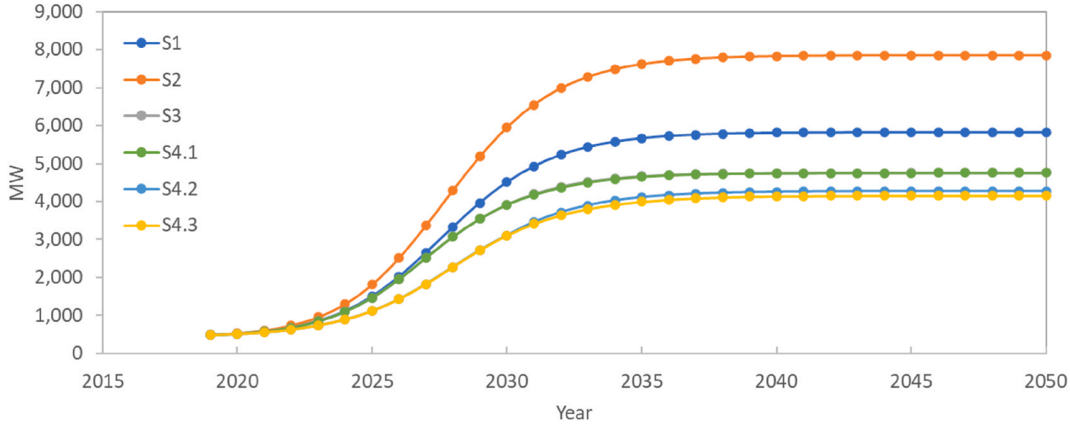


Fig. 5. Cumulative PV deployment under different scenarios.

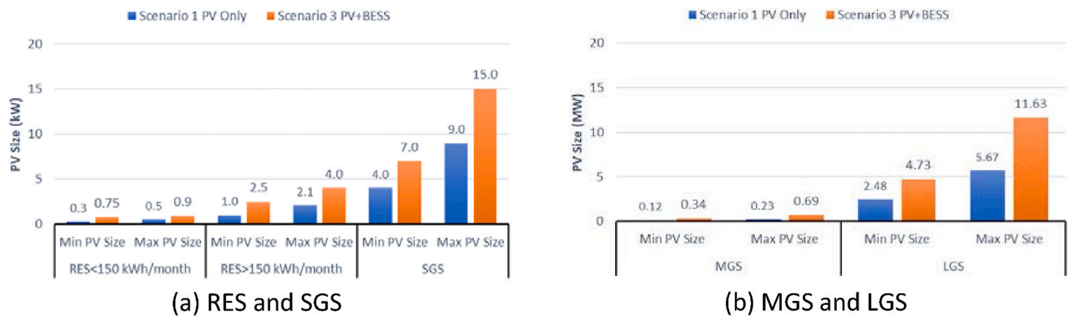


Fig. 6. Comparison of PV sizes between scenario 1 and scenario 3 in 2050 for (a) RES and SGS and (b) MGS and LGS.

Fig. 7. Comparison of PV sizes between scenario 2 and scenario 4.2 in 2050 for (a) RES and SGS and (b) MGS and LGS.

the need for some form of subsidy to lower the investment cost of batteries to maximize the use of solar electricity and reduce greenhouse gas emissions.

4.2.3. Impacts of rate restructuring on DPV and BESS installation

When the retail tariff growth rate is low (Figs. 8(c) and 9(a)), rate restructuring in 2031 (Scenario 4.1) produces detrimental outcomes for SGS and RES customers. Specifically, early rate restructuring drastically increases the payback period in the early years of restructuring for SGS and RES customers while only slightly lowering the payback period for the LGS and MGS customers and hence resulted in higher aggregate DPV capacity in these two groups. In the later years (approaching 2050), however, rate restructuring appears to slightly lower the payback period for SGS and RES customers, but this is too long after the peak adoption period to make a difference. The introduction of rate restructuring in the year 2031 does not result in higher DPV adoption since the peak of DPV adoption occurs before 2031, and after 2031 annual DPV adoption slows down.

Rate restructuring also produces different decisions on DPV and BESS sizing for different customer groups. Under lower retail growth rate condition, rate restructuring does not cause the LGS and MGS customers to increase their PV and battery sizes but

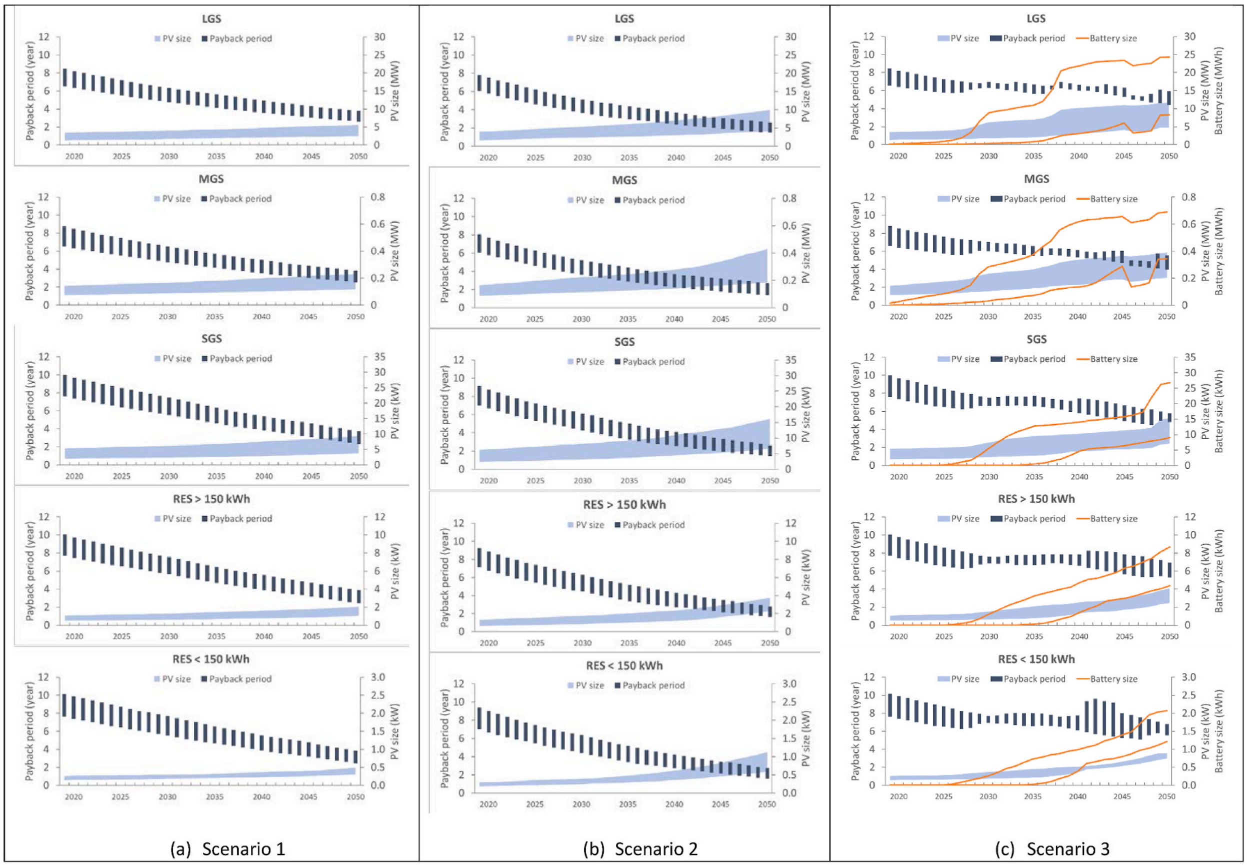


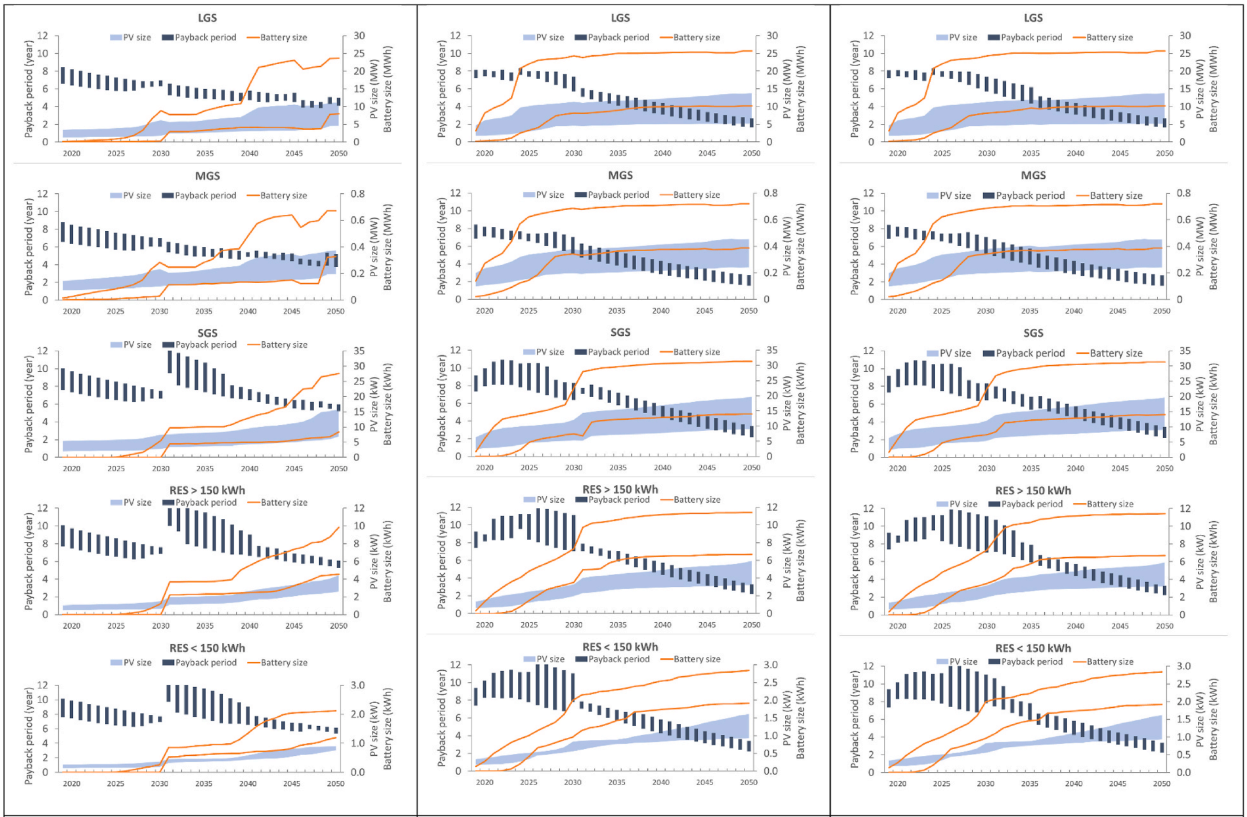
Fig. 8. Payback period and DPV size by customer group and year of (a) Scenario 1 and (DPV only, current rate structure, low tariff growth rate), (b) Scenario 2 (DPV only, current rate structure, high tariff growth rate) and (c) Scenario 3 (DPV + BESS, current rate structure, low tariff growth rate).

significantly stimulate the RES customers to increase their PV and pair it with much larger BESS in the years immediately following restructuring. However, in aggregate, the benefits from rate restructuring are not significantly observed since the demand charge is already applied for the LGS and MGS. On the other hand, the demand charge, which has not been applied for SGS and RES before, accelerates the decision of these customer groups to install batteries but also lengthens their payback periods.

Fig. 9(a) and (b) compare the impact of retail tariff growth rate when rate restructuring happens in the same year (Scenario 4.1 and Scenario 4.2). Higher retail tariff significantly increases the sizes of DPV and BESS for all customer classes. These larger DPV and BESS sizes result in higher NPV but longer payback periods in the years prior to the peak of adoption (before rate restructuring). This leads to lower PV adoption of Scenario 4.2, compared to Scenario 4.1. In the context of high retail tariff growth rates, the imposition of rate restructuring appears to help improve the economics of DPV with BESS for RES customers by immediately lowering the payback period in the year of restructuring. The opposite trend occurs under the condition of low retail tariff growth rates (Scenario 4.1) since rate restructuring appears to penalize SGS and RES customers by lengthening the payback periods as discussed above.

The impact of earlier restructuring under the condition of high retail tariff growth is assessed (Scenario 4.2 and Scenario 4.3). When the rate restructuring is moved to an earlier year (2031 compared to 2036), the long-term impact to cumulative DPV deployment is only slightly improved. In Fig. 9(b) and (c), earlier restructuring in 2031 immediately reduces the payback period for the RES groups in that year but only slightly shortens the payback period for other groups. Over the long term, however, the ranges of payback periods experienced by each group are similar in the two scenarios, hence there is only a minor increase in cumulative DPV installed capacity in Scenario 4.2 compared to Scenario 4.3.

To summarize, the impact of a higher retail tariff growth rate produces a stronger impact on cumulative DPV deployment when considering DPV only. BESS deployment can increase the sizes of DPV but higher costs of the combined DPV and BESS systems cause a lower deployment than the DPV only scenarios. Rate restructuring has mixed impacts, depending on the growth rate of the retail tariff, customer class, timing of rate restructuring and other factors. Rate restructuring alone may not be effective at inducing a high DPV deployment and may need to be designed differently for different customer groups. Our form of rate restructuring does not induce higher deployment or even lower the deployment of DPV under scenarios with high retail price growth rates. This is because the rate restructure is applied in the year that diffusion levels of DPV adoption almost off or market is almost saturated.



(a) Scenario 4.1 | (b) Scenario 4.2 (Rate restructuring in 2031) | (c) Scenario 4.3 (Rate restructuring in 2036)

Fig. 9. Payback period and PV size by customer groups and year of (a) Scenario 4.1 (DPV + BESS, restructured rate in 2031, low tariff growth rate) and (b) Scenario 4.2 (DPV + BESS, restructured rate in 2031, high tariff growth rate), and (c) Scenario 4.3 (DPV + BESS, restructured rate in 2036, high tariff growth rate).

5. Discussion

The estimate of DPV deployment in this study can be considered a lower bound of estimates. As discussed previously, all the data inputs are conservative, including the lack of incentive for deployment, the lack of payment for excess generation, retail tariff growth rate based on historical trends, and the rate of PV prices decline. Even so, the total estimated DPV deployment is significant enough to be used to offset the need to dispatch or build several large-scale fossil fuel-based power plants. For example, for our business-as-usual scenario (Scenario 1), using a capacity factor of 18% for solar and 80% for natural gas turbine plants, energy generation from approximately four 300 MW of gas-fired plants can be avoided during daylight hours in 2050.

Our analysis also confirms the limitations of the Customer Adoption Model, which have previously been discussed in Mills et al. [15]. Though the Customer Adoption Model is comprehensive, the input variables can be derived using different methodologies (Table 1), causing the results from different studies of the same market to diverge. For Scenario 1, our estimated total economic potential of 5826 MW by 2050 is much lower than previous forecasts for Thailand. Compared to the IEA study [36], several factors contribute to our finding of lower economic potential, including sizing of DPV systems, rate of DPV system price decline, projected growth rate of retail tariffs, and assumed DPV technical potential. The rest of this section discusses the importance of several key input variables and suggests a way of standardizing the methods within the Customer Adoption Model.

5.1. Key data for customer adoption model

In developing countries, to forecast DPV and BESS adoption using the customer adoption model, it is necessary to acquire relevant data as inputs to the model. First, technical potential is a critical input factor since it is the “entry point” for the customer adoption model, which is used to calculate total market share. Therefore, this estimate should be standardized and continuously enhanced for a given jurisdiction. There are several methods for estimating the technical potential of DPV, each of which yields vastly different estimates; however, the method chosen is contingent on the data at hand.

Second, necessary information for payback period calculation—such as solar irradiation for each region or capacity factor, system cost, and installed capacity—need to be as accurate as possible. The accuracy of the payback period affects the estimation of the ultimate share of DPV adoption, as the payback period is its primary input of the simplified method we have chosen. Once other economic and non-economic factors on customers' motivations for DPV adoption are investigated further in the country context [62–65], the estimation of ultimate adoption shares can be improved by incorporating these multiple key factors, not only payback period.

Third, the forecasting model requires a baseline of current DPV and BESS installations. It is important to set up an effective and convenient registration system, which DPV and BESS customers are able to enter their systems with relevant information (such as installed capacity, and monthly electricity consumption (to represent load profiles)). This registration system might belong to the power utility company and data should be anonymized and publicly available for non-commercial use.

As customer meter readings increasingly become digitalized in the future, planners will be able to collect a larger number of load samples. A rollout strategy for smart meters is crucial for collecting end-use data in greater detail. In addition to measuring energy consumption, the smart meters are essential for demand side management and grid operation as distributed renewable energy technologies and electric vehicles proliferate. This would allow for a more bottom-up approach to characterize a fuller spectrum of the load profiles.

5.2. *Influential aspects of DPV adoption estimation*

From our scenario analysis, we found that selection of representative customers, willingness-to-adopt curve and parameters for the diffusion model (p and q parameters) are essential for estimating DPV adoption and required based on each country's specific environment.

5.2.1. *The selection of representative customers*

The selection of representative customers can greatly impact the estimates of adoption through several factors that affect the decision to invest in DPV and BESS by those customers. Two key factors that shape customer characteristics include the load profiles and PV sizing. In the Customer Adoption Model, there is no standardized way of selecting the customers to represent future deployment. In this study, the load profile for each customer class was taken from the load profiles of a small number of customers drawn from distribution utilities' data from each sub-area [66].

PV sizing approaches range from selecting load profiles and assigning installation sizes for each class of customer[4] [36], optimizing for the size with the greatest savings in each year (this study), specifying typical sizes observed to be purchased in the market [39]. Comparing IEA (2018) [36] and this study, the larger sizes of PV assigned for RES (5 kW), SGS (5 kW), MGS (100 kW), and LGS (1000 kW) customer groups in the IEA study, compared to the median sizes of each corresponding group in this study, is one of the factors that causes the larger potential in the IEA study. Appendix 9 illustrates the distribution of the optimal PV sizes in Scenario 2 (the scenario with the highest economic potential).

Moreover, an agent-based model such as dGen can better represent the customers by sampling from unique agents in each geographical grid, each one with a unique location, system capacity, and electricity consumption. Using random sampling, the dGen model extracts attributes of agents in each grid and create agents based on statistical prevalence of those attributes. This way, the agents are expected to be statistically representative of each geographical grid [37]. The agents also cover a broader base of customers that are more closely linked to geographical grid and hence provide a more precise representation compared to the traditional Customer Adoption Model.

5.2.2. *The ultimate share of customers adopting DPV (willingness-to-adopt)*

Another factor that limits potential adoption of DPV is the ultimate share of adoption in each year, derived from the Willingness-to-Adopt Curve. In this study, the R.W. Beck's equation [14] is used to estimate the ultimate shares in each year. We found that using the Beck's equation has limitations due to its sole reliance on the payback period. As shown in our study, the combined DPV and BESS system can yield significantly higher NPV than DPV alone but due to longer payback periods, the equation will force a lower level of adoption for DPV with BESS scenarios compared to DPV-only scenarios. This suggests that the payback period alone may not be adequate for determining deployment, especially in situations where policy or regulations such as rate restructuring causes the customers to deploy the combined DPV and BESS system to achieve bill savings.

5.2.3. *DPV diffusion curve*

DPV diffusion curves represent the realized installations of DPV and BESS, which are derived from the ultimate shares from technical potential. The shape and magnitude of the curves are derived solely from the co-efficient of innovation (p) and co-efficient of imitation (q) values (Eqs. (1) and (2)). These values are geographically specific and can be unique for each rate class. So, to be consistent, researchers working on the same geographical area should select the same method for deriving the diffusion curve or generate their own curve using consumers' willingness-to-pay surveys, instead of adopting the same equation to all rate classes and regions.

Past studies have pointed only to the importance of the year when the DPV market starts taking off [15]. Our study uncovers that the end year of the analysis also affects the shape of the S-curve because the Bass Model would allocate annual capacities to form an

[4] IEA (2018) [36] assigned the following solar DPV sizes for different rate classes: 5 kW for RES, 5 kW for SGS, 100 kW for MGS, and 1000 kW for LGS and then multiply the number of customers from each class and percentage of maximum market share from Beck's equation to the selected size in order to get the total DPV installation in each year.

S-curve within the analysis timeframe. In our methodology, it is assumed that 90% of the maximum market share will be achieved in 2050. If we were to shorten this analysis timeframe, the Bass Diffusion Model will allocate more annual capacities. This finding has an important implication for the timing of a policy to enable market expansion of DPV and BESS. In other words, the DPV adoption rate depends on setting a timeframe of achieving a solar capacity target.

5.3. Forecasting and policy uncertainties

As discussed earlier, our methodological contribution also points to a “chicken-and-egg” problem between forecasting and policy uncertainties. The effort to generate the input variables discussed above can be harmonized as part of an integrated planning process, involving relevant stakeholders such as policymakers, regulators, utilities, the private sector, and customer groups. The integrated planning would incorporate DPV, BESS, EVs, and demand response, as well as conventional resources, and models what resource mix can meet future decarbonization scenarios. Scenario construction can help policymakers and regulators understand the impacts of different policy designs on the level of deployment. The scenarios do not provide precise forecasts, but they can be used to analyze qualitatively the decision-making risks associated with various paths [67].

Through this process, a key input variable discussed above, namely the ultimate share of customers who adopt DPV and BESS, can be specified through an iterative exercise aiming at a decarbonization outcome. In short, by specifying a DPV and BESS target through modeling in an integrated planning process, the chicken-and-egg problem can be overcome.

6. Policy and regulatory recommendations

The results of this study show long payback periods for investing in DPV and longer payback periods when BESS is added to the DPV system, especially in early years. In later years when prices of both systems significantly decline, there is still no immediate payback for any customer, resulting in low adoption compared with previous forecasts. This finding suggests that policymakers interested in accelerating low-carbon technology deployment should consider reevaluating the DPV and BESS support framework. Higher compensation excess DPV generation has proven to rapidly increase the adoption of DPV in many jurisdictions, including in California, Germany, and Vietnam. Higher compensation shortens the payback periods for DPV under different compensation schemes for excess generation [45,48]. Furthermore, to accelerate market deployment of BESS a strong subsidy to bring down the high upfront cost of must be implemented, at least in the short term when the prices of BESS remain high. As discussed in Chaianong et al. [68], optimal battery sizing and investment subsidies can reduce DPV grid integration costs, which will happen when DPV excess generation needs to be sent back to the grid without charging to the battery.

This finding also implies an additional benefit of carbon emission reduction from the avoidance of running fossil-fuel based peaking power plants. The forecasts of behind-the-meter DPV and BESS are important for low-carbon and cost-effective power procurement plans, but the methodologies are still currently in flux, especially in Southeast Asia. Methodology refinement is a crucial part of their policy and regulatory process to strengthen the forecasts of DPV and BESS capacity and enable comparisons across studies. There are certainly no accurate forecasts but a full range of low, medium, and high deployment scenarios will better equip planners to develop alternative procurement options. Furthermore, setting an end year for the full realization of DPV market potential will provide a good framework for both modeling and the design of targeted policy support schemes.

Our results also demonstrate the risk of continuing the current policy and regulatory trajectory for achieving carbon emission reduction goals. The lack of a compensation mechanism for DPV, the lack of a subsidy to jumpstart the energy storage market, and delayed cost-reflection of electricity ratemaking[5] in combination cause an unfavorable environment for the deployment of DPV and BESS systems and hence a delay in carbon emissions reduction. Policy uncertainties and unstable support schemes that have undergone multiple changes in the past decade in Thailand, as documented by Junlakarn et al. [45], are also critical factors that deter the deployment of DPV.

The testing of retail tariff impacts in this study depends on speculating about future unknown conditions, including how fast the retail tariff will grow and when rate restructuring should happen from the system perspective. Further research can be informed by the implementation of more comprehensive studies by involving the modeling of system impacts resulting from the integration of solar PV systems, BESS systems, EVs and demand response mechanisms [69]. Such integrated planning will help overcoming the chicken-and-egg problem of forecasting by informing the level of investment needed, hence how fast the retail tariff will increase, and the appropriate year for implementing rate restructuring, allowing iterations in the forecasting process until a desirable carbon emission reduction target is achieved.

7. Conclusions

This study uses the Customer Adoption Model to forecast DPV and energy storage adoption in countries with limited data, using Thailand as a case study. We constructed several scenarios based on economic and regulatory conditions (retail tariff structure and

[5] The current base retail tariffs have been in place since 2015. The base tariffs are reflective of the costs of investment in generation, transmission, and distribution systems, operation and maintenance, and expected fuel costs. Actual divergences from the expected fuel costs are adjusted by adding the variable component, or Ft, to the base tariffs. The Ft has been artificially capped to prevent the exposure of customers to real prices, thereby resulting in the recent low retail tariff growth rate.

growth rate of retail tariffs). From our modeling, the DPV adoption ranges from 4155 MW to 7852 MW in 2050, depending on the scenario. The cumulative DPV deployment peaks in 2028 and reaches a saturation point in 2038. Our results constitute a lower bound of the market potential of behind-the-meter DPV that can be realized in Thailand.

Considering scenario impacts, the high retail growth rate strongly impacts cumulative DPV deployment since it leads to a lower payback period. Although the pairing of DPV and BESS results in optimal DPV size, its financial feasibility is lower than DPV-only systems due to the high costs of BESS. Additionally, the rate restructuring has mixed impacts, depending on the retail growth rate, customer class, timing of rate restructuring, and other factors. Thus, this regulatory change alone might not be enough to foster DPV deployment.

To overcome the chicken-and-egg problem between forecasting and policy uncertainties, we recommend deployment scenarios with integrated assessment of PV, BESS, EVs, and demand response which can be used in targeted policy and regulatory design to build DPV and BESS markets in a more predictable way. Specifically, policymakers should set a specific timeframe for achieving DPV and BESS market potential and work with forecasters to develop adequate data collection framework as well as deliberate on a desirable scenario through an extensive stakeholder engagement process.

8. Limitation

Though the model is comprehensive and systematic, its use must be accompanied by standardized methodologies to allow for comparisons across studies within the same region. First, the selection of representative customers should better represent the customers in each area, such as those done in the agent-based dGen model. Second, the willingness-to-adopt curve should not rely only on the payback period because it is not enough to determine the adoption rate. Lastly, the co-efficient of innovation and imitation values in the Bass Diffusion Model should be geographically specific to each customer group. As a result, future researches can build on this study by using the standardized methods that we suggest and varying the input assumptions to be less conservative and to explore a full range of future scenarios.

In this study, we merely examine the effect of shifting hours in the rate structure, as this is one of the most important regulatory approaches for aligning the interests of DPV-plus-BESS customers with the bulk power system. However, electric rate design is a complex topic guided by several rate design principles, such as reflecting costs and addressing customer requirements [70,71]. Investigating the impact of rate design on DPV-plus-BESS deployment would be a pertinent area of inquiry for future research.

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials (Appendix).

CRediT authorship contribution statement

Sopitsuda Tongsopit: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Siripha Junlakarn:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Aksornchan Chaianong:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis. **Indra Overland:** Writing – review & editing, Validation. **Roman Vakulchuk:** Writing – review & editing, Validation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Sopitsuda Tongsopit reports financial support was provided by Norwegian Institute of International Affairs.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e23997.

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