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Profitability of commercial and industrial photovoltaics and battery projects in South-East-Asia

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HIGHLIGHTS

- Assesses photovoltaics and battery project at commercial and industrial customers.
- Studies applications in three industries and three South-East Asian countries.
- Finds that profitable photovoltaic and battery investments exist already today.
- Shows that adding a battery often reduces profitability vis-à-vis photovoltaic only.
- Derives policy advice to foster the deployment of photovoltaic and battery projects.

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ABSTRACT

Solar photovoltaics and batteries are key technologies to enable a rapid decarbonization of electricity systems. Commercial & industrial consumers are an important market for these technologies due to their fast growing electricity demand, particularly in emerging economies. However, it remains unclear if photovoltaics and battery installations are profitable for commercial & industrial applications in an emerging country context. Assessing the profitability of investments in photovoltaics and battery projects, however, is much more complex than for standalone photovoltaics projects, and strongly depends on the regulatory regime. These regimes are often complex and can be inconsistent. Hitherto decision makers lack models which are suitable for detailed assessments and which can serve as basis to adjust the regime. Here, we develop a techno-economic optimization model for commercial & industrial photovoltaics and battery projects, which returns a profit-maximizing storage dispatch and system design. We investigate three South-East Asian countries (Vietnam, Thailand, and Malaysia) and three different industries (Textile, Consumer Goods, and Electronics). The results show that profitable investment opportunities in photovoltaics and battery projects exist already today, even though a battery typically reduces profitability vis-à-vis standalone photovoltaics projects. We discuss how reducing investment risks, building local industries, and shifting existing support schemes towards batteries could support battery deployment in South-East Asia and thereby contribute to the decarbonization of electricity systems in the region.

1. Motivation and research question

Rapid decarbonization of global electricity production relies on additional deployment of renewable energy technologies (RET) [1,2]. Emerging and developing economies are of particular importance, because electricity demand is increasing rapidly in many of these countries, and RET deployment could serve to avoid locking-in carbon-intensive electricity generation technologies, such as coal-fired power stations [3,4]. Commercial and industrial (C&I) consumers are a key group driving the growth in electric load in these countries. At the same time, solar photovoltaic (PV) plants are well suited to satisfy the additional demand: Their modularity makes them technically viable to serve C&I loads within geographical proximity, e.g., by installing them on C&I consumers' rooftops, "behind-the-meter". The cost of PV plants have decreased significantly in recent years, making them the least-cost option in many instances [1,5,6]. Accordingly, since 2012 many emerging and developing countries started adding PV capacity to their grid [7]. Nevertheless, deployment has so far mainly focused on utility-scale projects, whereas behind-the-meter installations have lagged behind [8]. Reasons are manifold [9], including subsidized grid electricity

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[10], high perceived investment risks[11], as well as inconsistent regulatory regimes[1] [12]. PV's intermittency poses an additional challenge: Its integration into the electricity system needs to be actively managed, especially in emerging and developing economies where grid infrastructure is typically weaker compared to in high-income countries [13]. Batteries present a possible solution to this challenge. However, to date it remains unclear if C&I PV and battery projects are profitable in emerging economies and how different regulatory regimes influence the profitability. To address this gap, we develop a novel techno-economic optimization model for C&I PV and battery projects, which returns a profit-maximizing storage dispatch and system design and apply it to compare three emerging economies in South-East-Asia.

Existing literature has examined in detail how regulatory regimes influence economics and deployment of behind-the-meter (both residential and C&I) standalone PV (without battery) projects, including in emerging economies. For example, Ossenbrink (2017) conceptualizes various operational strategies and system designs depending on PV project investment cost, electricity tariffs and PV remuneration in California and Germany [14]. In addition, specific case studies on individual emerging economies have been presented, such as by Tongsopit and colleagues, who assess the profitability of PV self-consumption for residential and C&I customers in Thailand [15]. In addition to conceptual and empirical findings, open-source techno-economic models exist for policy makers and private decision makers to assess profitability of standalone PV projects [16,17], including in emerging economies [18]. These models are easily adaptable to different geographies and regulatory regimes, as typically no optimization is necessary but simple spreadsheet-based cash-flow models do suffice. However, these models do not consider battery storage. For C&I PV and battery projects, the complexity of such assessments is much higher and – to our knowledge – no comprehensive analysis and open-source model exist for decision makers to assess a project's viability and the relevant influencing factors. Tariff designs are usually more intricate for C&I customers, including time-variant prices, charges for peak power demands, and other design elements. Furthermore, the battery adds flexibility to the operating and design strategies of developers. A battery enables consumers to tap into multiple value streams [19] that need to be co-optimized to achieve an overall optimal result. Several studies assess project economics without applying a comprehensive optimization framework, which limits wider applicability (Residential and C&I in Germany [20], C&I in Germany [21], Residential, C&I and Grid in Germany [19]). Pena-Bello and colleagues (2019) provide an open-source model to optimize PV and battery projects, however focus on residential consumers in the United States (Texas) and Switzerland [22]. Von Appen and colleagues (2015) compare residential PV and battery systems design and their impact on the distribution grid in Germany and Australia [23]. Khalilpour and Vasallo (2016) provide an integrated optimization framework to both size and optimally dispatch residential PV and battery projects [24]. Other studies provide assessments of single case studies, which do neither compare regulatory regimes across countries, nor do they make the developed model accessible to decision makers (e.g., Germany Residential [25], Germany C&I [26] Australia [27], United Kingdom C&I [28], United Kingdom Residential [29], United States C&I [30] Hungary C&I [31]. Furthermore, none of the reviewed C&I PV and battery studies focus on the specific issues in emerging economies.

Hence, we apply our model to three emerging economies in South-East Asia, a region with plentiful solar resources, strongly increasing electricity demand, and a large and growing C&I sector. More specifically, we analyze Vietnam, Thailand, and Malaysia, which strongly differ in their regulatory regimes. Furthermore, we include three archetypical load profiles that represent different industries: textiles production, consumer goods production, and electronics manufacturing. To analyze the effects of the further decreasing investment cost of PV and battery systems, we perform the analysis using current values (invest in 2018, operate from 2019) and values as projected to 2030 drawing on learning curve-based projections. To account for the financing costs of different firms in different countries, we conduct a sensitivity analysis of the applied discount rate. Moreover, we discuss the various levers available to policymakers in the respective countries to efficiently and effectively foster deployment of battery systems.

The remainder of this study is structured as follows. Section 2 describes the selected cases in detail. Section 3 introduces our methodology and the data used in the study. In Section 4, we present our results, and in Section 5, we discuss the results and their implications for policymakers and the private sector. Section 6 concludes the study and lays out potential avenues for further research.

2. Case description

In this section, we describe the regulatory regimes in the three selected countries and the load profile archetypes of the three selected industries. Concerning countries, we selected three emerging economies in South-East Asia, because the region's electricity demand is rapidly growing (meaning the deployment of RET can contribute greatly to mitigating global climate change), and because the high solar resources allow for PV installations. We chose three large countries - Malaysia, Thailand, and Vietnam - which strongly differ in their regulatory regimes, hence allowing to study the impact of various electricity-sector and PV-specific regulations. All three countries have a growing C&I sector.

Concerning the regulatory regimes, we focus on (i) design elements that influence how electricity flows are remunerated or what their costs are, and (ii) on which electricity flows are allowed at all. In Vietnam and Thailand, C&I consumers can utilize time-dependent electricity prices in the energy-related part of their bill (measured per kWh), whereas in Malaysia, uniform prices are applied. The price differential in Vietnam and Thailand allow consumers to charge a potential battery system at low electricity prices and occasionally discharge into their load at higher electricity prices. Peak demand charges (i.e., electricity prices for the capacity-related part of the bill, measured per kW) are applicable in Thailand and Malaysia, but not in Vietnam. These charges allow consumers to reduce their typical peak loads in a period either directly by consuming electricity generated by the PV system or by charging the battery system during periods of lower demand and discharging it during peak load times. Policies that support PV-generated electricity in Vietnam and Malaysia provide a Feed-in-Tariff (FiT) and a Net Metering scheme (NEM), respectively. Only in Vietnam is it possible to sell electricity on the wholesale market. In both Thailand and Malaysia, PV projects incur license fees, adding to projects' operational expenditures. In addition, it is important to highlight which electricity flows related to the electricity grid are permitted. In Vietnam and Malaysia, PV and battery system operators have the highest degree of flexibility because they are allowed to directly feed-in electricity from the PV system, and charge and discharge batteries through the grid. Conversely, in Thailand, only electricity consumption is allowed so that consumers cannot feed-in electricity from a PV system. An overview of the countries' characteristics is provided in Fig. 1:

To understand the influence of load profile archetypes, it is important to consider total consumption in kWh per year, simultaneity of PV generation and consumer load, and the shape of the load curve (e.g., to what extent the monthly load peak deviates from the monthly average consumption). In the textile industry and in electronics manufacturing, the load archetypes are characterized by comparatively high annual electricity consumption at about 8 GWh and 6 GWh,

[1] The regulatory regime summarizes all elements that influence the economics of behind-the-meter PV and battery projects and that can be influenced by public policy. Specifically, we consider policies in support of RET and battery deployment, regulations influencing the electricity tariff, and the design of the electricity market.

	VIETNAM	THAILAND	MALAYSIA
Country info			
Population:	96m	68m	31m
GDP/ capita 1):	2,300	6,600	9,900
Power cons./ capita 2):	1,600	2,500	4,700
Regulatory Regime			
Energy Tariff:	Time of Use	Time of Use	Uniform
Peak demand charges:	No	Yes	Yes
Net Metering:	No	No	Yes
FiT:	Yes	No	No
Wholesale:	Yes	No	No
Energy flows			
PV into grid:	Yes	No	Yes
Battery into grid:	Yes	No	Yes
Battery from grid:	Yes	Yes	Yes

1) in USD
2) in kWh/year

Fig. 1. Overview of countries with their respective regulatory regimes. General country information is based on CIA World Factbook; regulation-related information is based on desk research (analysing relevant policy documents, schemes and legislation) and has been confirmed via interviews with project developers active in the three countries. All data for 2019 or the latest available year.

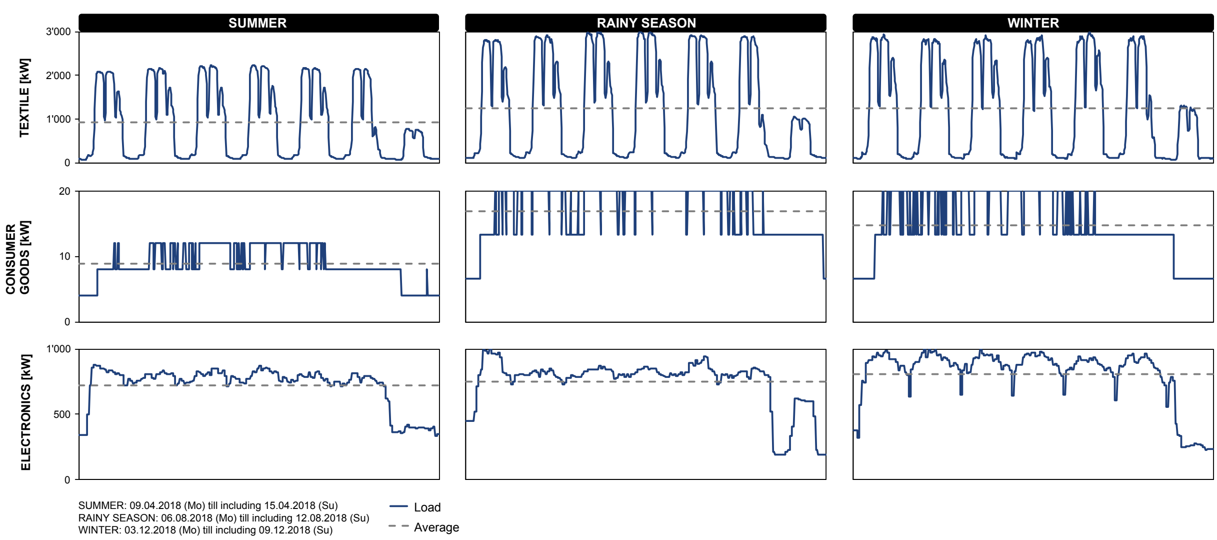

Fig. 2. Overview of industries and their respective load profile archetypes. Power in kW on the vertical axis every quarter hour per week starting at Monday on the horizontal axis. These load profile archetypes in quarter-hourly resolution are based on measured load curves from respective businesses that have been provided by a single C&I PV project developer active in the three countries in an anonymized way.

respectively. In the consumer goods industry, the load archetype has an annual consumption of only about 72 MWh. An overview of the various shapes of the load profile archetypes is provided in the Fig. 2.

3. Methodology

This section describes the new PV-STOR model that was developed to perform techno-economic assessments of PV and storage projects. We first introduce the overall framework, before explaining its two components: the battery dispatch optimization model and the financial model.

3.1. Modeling framework

The analysis of the profitability of PV and storage projects requires the combination of two independent models: a battery dispatch model and a financial model.[2] Investigating the profitability of battery storage requires programming the optimization routines in battery dispatch models. Such models aid the assessment of battery revenues from combining multiple applications, considering degradation impacts and the optimal sizing of a battery. To evaluate the net present value (NPV)

[2] The PV-STOR model is available to the reader upon reasonable request to the authors

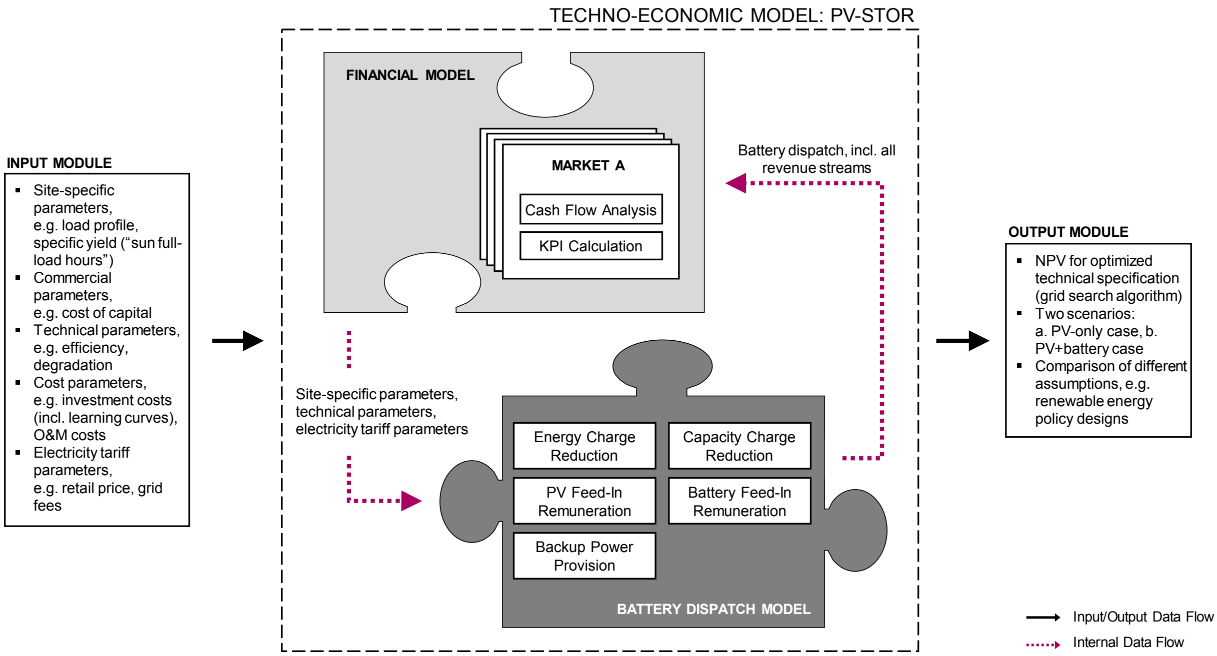

Fig. 3. General framework of the PV-STOR model.

of the PV and battery projects, the derived optimal battery dispatch is fed into a financial model. A graphical summary of both models and their respective interfaces are provided in Fig. 3.

The techno-economic model PV-STOR is fed various sets of input data (compare Section 3.3.3 *and Appendix* Tables A1–A3), such as site-specific, commercial, technical, and cost parameters, as well as information about electricity tariffs and the specific period that is simulated. The battery dispatch model then co-optimizes the battery schedule across the various revenue sources to maximize the project's NPV. This so-called "revenue stacking" approach assesses the battery's capability to perform multiple energy and power services simultaneously [19]. Thus, the model determines the NPV-optimal battery schedule that simultaneously reduces the consumers energy charge (paid per kWh consumed, reduced by e.g., utilizing time-of-use tariffs or consuming electricity generated from PV directly), reduces the capacity charge (paid per kW of peak demand, reduced by e.g., shaving peaks in the consumer load vector), generates revenues from feeding PV electricity into the grid (e.g., by obtaining Feed-In-Tariffs), generates revenues from feeding electricity from the battery into the grid (e.g., by selling electricity on the wholesale market), and provides backup power in the case of a grid outage. The optimized battery dispatch is then fed back to the financial model, where its implications for the project's cash flow are derived by offsetting the resulting electricity bill against the status quo, in which neither a PV nor a storage system is installed. The resulting energy and capacity charge savings are considered battery revenues and added to the revenues that result from the PV feed-in, direct battery feed-in, and backup service provision (as is common practice in assessments of behind-the-meter PV and battery projects [21–23], we will refer to both revenues and avoided costs as "revenue streams" in the following). Based on these stacked revenue streams, project's capital and operational expenditures (CAPEX and OPEX) and the investor's discount rate, the NPV is calculated. In addition, the NPV of the PV system without battery is calculated, which serves as a benchmark in answering the question of whether adding storage capacity would benefit the project's profitability. In addition to the NPV-optimal operation of a given PV and battery system, the NPV-optimal system sizes are derived by simulating a grid of different setups (differing PV system power in kWp, battery power in kW, and battery capacity in kWh).

3.2. The battery dispatch model

3.2.1. PV and battery representation

3.2.1.1. System design parameters. Regardless of the specific application, the model is defined by a set of three fundamental parameters: *rated power*, *energy capacity*, and *roundtrip efficiency*. Particular battery technologies or even non-battery electricity storage options can be analyzed by numerical variations of these three parameters [32].

The definition of rated power and energy capacity might be a given in specific projects. However, to answer the research question at hand, these parameters are subject to optimization. This fact is important because project revenues typically increase with increasing battery sizes that theoretically allows for the reduction of energy and capacity costs to the global minimum. However, in most cases, the costs of the battery required to leverage such reductions would far exceed the potential savings on an electricity bill. Therefore, the optimization of the battery dispatch to must always be paired with sizing methods to find the optimum between battery revenues and costs. Here, we apply a grid search algorithm by which the same project is simulated using predefined system designs, i.e., differing values for battery power, battery capacity, and PV capacity, to construct a three-dimensional grid. As a result, the sizes of the PV and battery system are determined by the parameter combination that yields the highest overall NPV for the integrated system.

The roundtrip efficiency indicates how much of the electricity used in charging can be retrieved from the battery during discharging. In charging, less energy enters the device than is extracted from the grid or the PV system. Similarly, in discharging, less energy is derived from the battery than the amount that was stored. Hence, for the purpose of optimization, we split the roundtrip efficiency into losses from charging activities and losses from discharging activities. We propose to achieve this split geometrically, as typically done in other studies defining battery dispatch as linear programming problem [e.g.,33]. As a further simplification, we assume an average roundtrip efficiency across operating modes and thereby neglect its dependence on the actual charge and discharge power applied [34].

3.2.1.2. Implementation of regulatory regime and system design constraints. The battery dispatch solution space is constrained by both

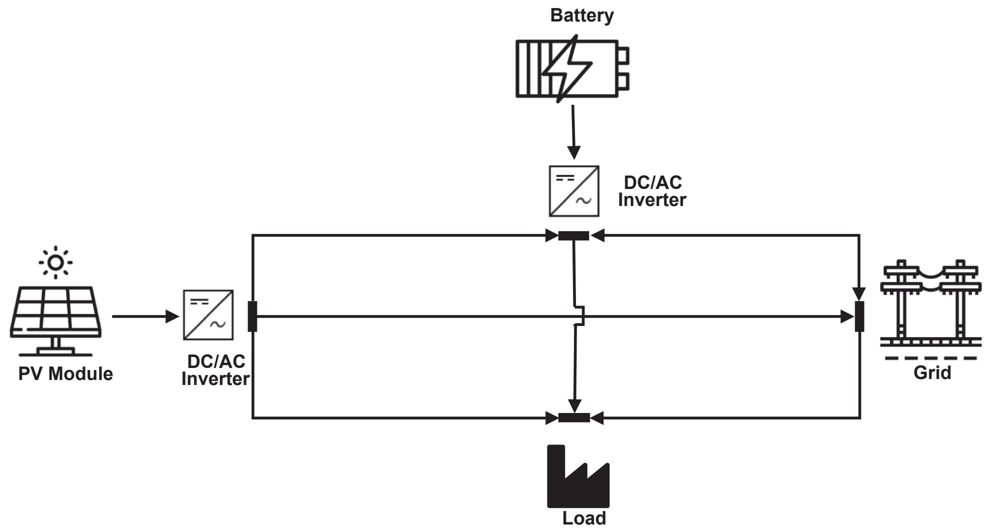

Fig. 4. System layout of an AC coupled PV and battery system. The arrows indicate the direction of energy flow. Other technical components (e.g., transformer, meter, circuit breaker, and control units) are not depicted.

technical feasibility and the regulatory regime. The energy flows that are technically possible and therefore need to be considered in the optimization depend on the system's design. In this study, an "AC-coupled" system (battery with separate inverter, instead of DC connection to PV system) in which the PV and battery systems each include inverters is used (Fig. 4). This topology is considered easier to retrofit to existing PV plants and more flexible to provide multiple services with a battery. In turn, this setup typically yields lower system efficiencies, due to the additional power conversion step [35]. The regulatory regime can be implemented by allowing or forbidding certain energy flows depicted in Fig. 4. For example, in Thailand the PV system is not allowed to feed electricity into the grid.

3.2.1.3. Degradation. Battery degradation needs to be considered in both system design and operation. For computational efficiency, the battery dispatch is optimized for a single year instead of running a simulation over the life of the project. Thus, the battery's nameplate properties must be adjusted for degradation. Degradation is assumed to be linear over its lifetime, which is expected to end before the dominant aging mechanism changes to lithium plating, resulting in the typical "aging knee" [36,37].

In order to determine the battery lifetime (and thereby replacement intervals) as an input to the financial model, we further distinguish between two aging mechanisms[38]: cycle aging, which occurs because of the use of the battery to perform a duty cycle as defined by dispatch optimization; and calendric aging, which in this model is purely time-dependent, representing the fact that even if a battery is not used, its capacity fades and eventually needs to be retired from operation. One cycle (referred to as equivalent full cycle, EFC) is defined as a full charge and discharge of the battery within the depth-of-discharge bounds that are to be respected to achieve the stated cycle life. EFCs can then be recalculated to derive the battery throughput. The throughput is obtained from the optimized battery dispatch profile and serves as basis to calculate a battery's cycle life for a given simulation run.

Although throughput has been shown to be a reliable indicator of battery aging in stationary applications, the literature shows further influential factors, such as the battery's average state-of-charge, c-rate, and temperature [38–45]. However, these influences are not addressed in the present study. Detailed, semi-empirical degradation models are difficult to calibrate, requiring many experiments with the newest cells to collect sufficient amounts of data [46]. Their implementation into NPV-maximizing battery dispatch algorithms is non-trivial (please refer to He and colleagues (2018) [47] and Beuse (2018) [48] for details). Finally, the PV-STOR model runs on a 15-minute resolution. Thus, any dispatch strategy aiming to moderate the strain on the system (c-rate) could not be reflected properly in coarse charging profiles.

3.2.1.4. Battery system specification. Battery capacity, rated power, and roundtrip efficiency, must be adjusted for degradation (Eqs. (3.2.1a–3.2.1c)). As previously described, nominal values are used in the financial model to calculate CAPEX and OPEX, while degradation-adjusted parameters are passed on to the optimization problem as follows.

$$S_{batt} = \frac{(S_{batt,nom} + S_{batt,nom} \times EoL_{cap}) \times DoD}{2} - S_{backup} \times DoD \tag{3.2.1a}$$

$$P_{batt} = \frac{P_{batt,nom} + P_{batt,nom} \times EoL_{pow}}{2} - P_{backup} \tag{3.2.1b}$$

$$\eta = \frac{\eta_{nom} + \eta_{nom} \times EoL_{\eta}}{2} \tag{3.2.1c}$$

where S_{batt} is the battery system's capacity (in kWh) used as input for the battery dispatch optimization; $S_{batt,nom}$ reflects the installed battery capacity (in kWh) used to calculate CAPEX and OPEX of the battery system; EoL_{cap} is the share (in %) of the battery's installed capacity that is still useable after degradation at its expected end of life; DoD is the Depth-of-Discharge (in %) which constrains the useable battery capacity to avoid extreme degradation and is related to the assumed cycle-life values of the battery system; and S_{backup} represents the amount of battery capacity (in kWh) that is reserved to provide backup services. Equivalent to the battery capacity, P_{batt} reflects the battery's installed power (in kW) used as input for the battery dispatch optimization; $P_{batt,nom}$ is the installed battery power (in kW) used to calculate battery system CAPEX; EoL_{pow} is the share (in %) of the battery power at its expected end-of-life; P_{backup} (in kW) is the amount of battery power reserved for backup service provision. Finally, η represents the battery system's roundtrip efficiency (in %) used as input for the battery dispatch optimization; η_{nom} is the roundtrip efficiency of the installed system; and EoL_{η} is the expected roundtrip efficiency at the end-of-life.

3.2.1.5. PV system specification. Similar to the battery system, degradation of PV modules needs to be accounted for. Accordingly, the PV system is specified as follows:

$$P_{PV,nom} = A_{roof} \times (1 - SF) \times P_{mod,max} \times A_{mod} \tag{3.2.1d}$$

$$P_{PV} = \frac{[P_{PV,nom} + P_{PV,nom} \times (1 - T_{PV} \times DR)]}{2} \tag{3.2.1e}$$

where $P_{PV,nom}$ is the installed PV system size (in kWp) used for CAPEX and OPEX calculations; A_{roof} is the area (in m^2) of the C&I consumers roof that is useable for the installation of PV panels; SF is the average share (in %) of the useable rooftop area that shaded; $P_{mod,max}$ is the power output (in kWp) of a single installed PV panel; A_{mod} reflects the size of such a panel (in m^2); P_{PV} represents the PV systems power (in kWp) used as input for the battery dispatch optimization; T_{PV} is the expected lifetime of the installed panels (in years); and DR is the annual performance degradation (in %).

3.2.2. Storage operation

The optimal battery schedule, which is a prerequisite to calculate the revenue streams of PV and battery projects, is calculated based on an optimization problem that minimizes the electricity bill of the consumer subject to battery capacity constraints and energy balance requirements [32]. This problem is explained in detail below. The required parameters as well as information about their sources fare provided in Section 3.3.3 and Tables A1–A3*;* time series (such as load profiles and solar irradiation profiles) are provided in a digital appendix. The defined routines and respective supporting methods are formulated using Pyomo 5.6.1, a Python-based software package [49]. For the computation, the problem is numerically solved through the commercial optimization solver CPLEX V12.8 using the Solver Studio add-in to Microsoft Excel [50,51]. This solver has been universally adopted in different fields of research, and it is able to solve a variety of mathematical programming problems using primal or dual variants of the simplex method [52]. The optimization routine yields a linear programming problem (LP), which is defined as follows. Microsoft Excel is used for the financial model to make the model more accessible to practitioners.

3.2.2.1. Objective function. As described in Section 3.1, the optimization is aimed at co-optimizing the battery dispatch across various revenue sources. Monthly costs are defined as the sum of energy and capacity charges net of revenues from feed-in to the grid by either the PV system or the battery. Electricity prices are exogenously given and depend on the consumer's load profile, grid connection voltage level and country. The electricity flows between the system's various components designate the decision variables and specify how storage is dispatched.

Thus, the objective function for the minimization of costs C_{total} (in US$) on the monthly electricity bill is given by:

$$\begin{aligned} minC_{total} &= \sum_{t=1}^{m} [(E_{grid\_batt,t} + E_{grid\_load,t}) \times C_{E,t}] + (P_{grid,max} \times C_{P,t}) - \\ &\sum_{t=1}^{m} [(E_{PV\_grid,t} \times \eta_{tran} \times C_{PV,t}) + (E_{batt\_grid,t} \times \eta_{tran} \times \sqrt{\eta_{batt.}} \times C_{batt,t})] \end{aligned} \tag{3.2.2a}$$

where at each quarter hour t, $with t = 1, \cdots, m$, total energy charges are given as the product of received electricity (in kWh) by the battery $E_{grid\_batt,t}$ or by the load $E_{grid\_load,t}$ and the energy charges (US$ per kWh) $C_{E,t}$; revenues from feeding back to the grid are defined as the product of injected electricity (in kWh) ($E_{PV\_grid,t}$ or $E_{batt\_grid,t}$) and feed-in prices (US$ per kWh) ($C_{PV,t}$ or $C_{batt,t}$) adjusted for system losses; that is, considering transformer efficiency (η_{tran} in %) and battery efficiency ($\eta_{batt.}$ in %) losses. In all the studied cases, capacity charges are invoiced on a monthly basis as the product of a customer's maximum demand in that month ($P_{grid,max}$ in kW) multiplied by the demand charge C_P (US$ per kW). For this reason, the program was run separately for 12 successive months to generate the optimal battery schedule for one year.

3.2.2.2. Energy balance constraints. The system topology, as previously described, is passed to the optimization in the form of energy balance constraints. These constraints are defined as follows:

$$\begin{aligned} \forall\ t,\ S_{batt,t} &= S_{batt,t-1} + E_{PV\_batt,t} \times \sqrt{\eta_{batt.}} + E_{grid\_batt,t} \times \eta_{tran} \\ &\times \sqrt{\eta_{batt.}} - E_{batt\_load,t} - E_{batt\_grid,t} \end{aligned} \tag{3.2.2b}$$

$$with\quad S_{batt,0} = S_{batt,m} = \frac{1}{2} S_{batt} \tag{3.2.2c}$$

$$\forall\ t,\ E_{load,t} = E_{PV\_load,t} + E_{batt\_load,t} \times \sqrt{\eta_{batt.}} + E_{grid\_load,t} \times \eta_{tran} \tag{3.2.2d}$$

$$\forall\ t,\ E_{PV,t} = E_{PV\_grid,t} + E_{PV\_batt,t} + E_{PV\_load,t} + E_{PV\_curtail,t} \tag{3.2.2e}$$

where the battery's state of charge (SOC) is at all times defined as the difference in energy inflow (in kWh) from the PV modules ($E_{PV\_batt,t}$) or the grid ($E_{grid\_batt,t}$) and the energy outflow to the load ($E_{batt\_load,t}$) or the grid ($E_{batt\_grid,t}$) added to the battery's SOC at the previous time stamp. The SOC at the beginning of each month ($S_{batt,0}$ in kWh) is initialized at half of the battery's capacity (S_{batt} in kWh). Moreover, to enable monthly instead of annual optimization, the SOC at the end of each month ($S_{batt,m}$ in kWh) is equal to the battery's state at the beginning of the next month.

The load at t is given as the sum of electricity provided to the consumer from the PV modules ($E_{PV\_load,t}$ in kWh), from the battery ($E_{batt\_load,t}$ in kWh), or from the grid ($E_{grid\_load,t}$ in kWh). The electricity generated by the PV modules can either be fed into the grid ($E_{PV\_grid,t}$ in kWh), to the battery ($E_{PV\_batt,t}$ in kWh), and to the load ($E_{PV\_load,t}$ in kWh), or – at worst – it must be curtailed ($E_{PV\_curtail,t}$ in kWh). As in the objective function, all balances are adjusted for losses throughout the system.

3.2.2.3. Battery capacity constraints. The technical constraints imposed by the battery's capacity and power limitations are as follows:

$$\forall\ t,\ 0 \le S_{batt,t} \le S_{batt} \tag{3.2.2f}$$

$$\forall\ t,\ 0 \le P_{PV\_batt,t} + P_{grid\_batt,t} \times \eta_{tran} \le P_{batt} \tag{3.2.2g}$$

$$\forall\ t,\ 0 \le P_{batt\_grid,t} + P_{batt\_load,t} \le P_{batt} \tag{3.2.2h}$$

where S_{batt}, as defined in Eq. (3.2.1a), is the degradation-adjusted energy capacity of a battery (in kWh). Consequently, its dispatch is bounded by Eq. (3.2.2f). Furthermore, optimization is constrained by storage's degradation-adjusted power P_{batt} in units of kW. Naturally, while charging or discharging, it can neither exceed this value nor drop below zero (Eqs. (3.2.2g) and (3.2.2h)).

3.2.2.4. Application constraints. Lastly, in order to simulate distinct policy scenarios, the programming problem must allow for application-specific adaptions to the topology of the system:

$$\forall\ t,\ E_{PV_{grid},t} = 0,\ if\quad PVF = 0 \tag{3.2.2i}$$

$$\forall\ t,\ E_{batt\_grid,t} = 0,\ if\quad BF = 0 \tag{3.2.2j}$$

$$\forall\ t,\ E_{grid\_batt,t} = 0,\ if\quad BC = 0 \tag{3.2.2k}$$

$$\forall\ t,\ P_{grid,max} \le P_{grid\_load,t} + P_{grid\_batt,t} \tag{3.2.2l}$$

Eqs. (3.2.2i)–(3.2.2k) allow the prohibition if energy flows between certain components of the system, which means that if PV feed-in to the grid (PVF = 0), battery feed-in to the grid (BF = 0), or charging the battery from the grid (BC = 0) are either prohibited or unfeasible in the studied energy system, and then their respective decision variables are set to zero. Lastly, (3.2.2l) defines the maximum amount of power a customer used in any interval t during the billing period m. This constraint applies only to cases in which the battery is designed to serve in peak shaving applications.

3.3. Financial model

The financial model enables the evaluation of a project's economic viability by applying the discounted cash flow method. Hence, the profitability of an investment is expressed by its net present value (NPV), which is calculated as the sum of each year's net cash flow discounted back to its present value (Eq. (3.3a)) [53]. Hence, the financial model relies on the optimized battery dispatch as an input to calculate revenues. NPV is calculated as follows:

$$NPV = \sum_{t=0}^{N=25} \frac{R_t}{(1+i)^t} = \sum_{t=0}^{N=25} \frac{CAPEX_t - OPEX_t + Y_{EC,t} + Y_{CC,t} + Y_{PV,t} + Y_{batt,t} + Y_{Backup,t}}{(1+i)^t} \tag{3.3a}$$

where R_t is the net cash flow in year t (in US\$) obtained by subtracting capital and operating expenditures from the revenues ($Y_{EC,t}$, $Y_{CC,t}$, $Y_{PV,t}$, $Y_{batt,t}$, $Y_{Backup,t}$) for each period (see Section 3.3.1 for calculation of different revenue streams). This sum includes R_0 that contains the investment costs of both the PV and the battery system in year 0, and R_N at the end of the project's lifetime of $N = 25$ years. Future cash flows are discounted based on the discount rate i, which reflects the risk that investors associate with the project (the discount rate used in private investment appraisals reflects the risks associated with a given investment project, including from risk factors such as macroeconomic risk, political risk in a country, specific regulatory risk in a sector, and technology risk [54]). The evolution of cash-flows of the project's lifetime is exemplified in Fig. A3 in the appendix.

Based on this calculation, the NPV-maximizing configuration is obtained by applying a grid search algorithm over the domain Ω_x, which contains discrete values of nominal PV and battery capacity and rated battery power ($\boldsymbol{x} = [\boldsymbol{P}_{PV,nom}, \boldsymbol{S}_{batt,nom}, \boldsymbol{P}_{batt,nom}]$).

$$\max NPV = \max_{\boldsymbol{x}} \left\{ \sum_{t=0}^{N=25} \frac{R_t}{(1+i)^t} \right\}, \; with \, \boldsymbol{x} \in \Omega_x \tag{3.3b}$$

The grid search approach is a strength of the model, as it allows for the computation of the results in finite time. However, it also presents a limitation because it limits the solution space to discrete values in a predefined grid. Thereby, there is a risk of potentially disregarding better solutions either within or beyond the spanned grid. As a countermeasure, it is recommended to the user of PV-STOR to start with a broad grid that contains an optimal solution and then improve the found result by increasing the grid's granularity.

A further limitation of the approach in this study – drawing on time-varying but deterministic solar radiation and electricity price curves is that potential intrinsic value of batteries in exploiting uncertainty of electricity prices is neglected. However, for C&I PV plus battery installations such situations have no practical relevance, with the exception of batteries delivering backup services for uninterrupted power supply (which we include explicitly).

Another limitation of the presented approach is its presumption that several project-related parameters remain constant throughout the project's lifetime of 25 years. While the model accounts for escalation factors in the adopted cost and remuneration data as well as learning curves for technology replacement costs, it does not incorporate systemic changes. Thus, the reader should note that in analyzing the results presented in Section 4, the risk of substantial changes to the electricity demand and changing regulatory regimes should be considered.

3.3.1. Revenue streams

Despite the approach of value stacking used in this study, the model allows for the separation of generated revenue streams. These are calculated based on the resulting energy flows between PV modules, the battery, the consumer load, and the electricity grid, which result from the optimization and respective cost and remuneration vectors. Thus, the financial model differentiates revenue streams from savings on the energy charge (per kWh consumed), capacity charge (per kW peak demand), direct PV and battery feed-ins into the grid, and opportunity costs of conventional diesel backup generators.

Generally, savings on energy charges (Y_{EC} in US\$) are calculated as the difference between the total cost without and with the PV and battery systems. Savings are first calculated at all points in time t in a month m and then summed up over the entire year ($M = 12$). While these savings are set to zero in the year of project construction (Eq. (3.3.1a)), a constant energy cost projection rate i_{EC} is considered for all following years except the first year (Eqs. (3.3.1b) and (3.3.1c)).

$$Y_{EC,0} = 0$$

$$Y_{EC,1} = \sum\nolimits_{m=1}^{M} \sum\nolimits_{t=1}^{T} [(E^{old}_{grid\_batt,t} + E^{old}_{grid\_load,t} - E_{grid_{batt},t} - E_{grid\_load,t}) \times C_{E,t}] \tag{3.3.1b}$$

$$Y_{EC,n} = Y_{EC,n-1} \times (1 + i_{EC}) \tag{3.3.1c}$$

Savings on capacity charges (Y_{PC} inUS\$) are calculated analogously. Although demand charges are billed on a monthly basis, the power cost vector can include varying costs per kW depending on the day and time that the maximum power demand in a month occurred (Eqs. (3.3.1d) and (3.3.1f)).

$$Y_{CC,0} = 0 \tag{3.3.1d}$$

$$Y_{CC,1} = \sum_{m=1}^{M} [(P^{old}_{grid,max,m} - P_{grid,max,m}) \times C_{P,t}] \tag{3.3.1e}$$

$$Y_{CC,n} = Y_{PC,n-1} \times (1 + i_{PC}) \tag{3.3.1f}$$

Revenues from the PV feed-in remuneration (Y_{PV} in US\$) are calculated based on the injected amount of energy and the associated feed-in tariffs at t. Eqs. (3.3.1g)–(3.3.1i) account for the losses due to inefficiencies in the transformer (η_{tran}).

$$Y_{PV,0} = 0 \tag{3.3.1g}$$

$$Y_{PV,1} = \sum_{m=1}^{M} \sum\nolimits_{t=1}^{T} [E_{PV\_grid,t} \times \eta_{tran} \times C_{PV,t}] \tag{3.3.1h}$$

$$Y_{PV,n} = Y_{PV,n-1} \times (1 + i_{PV}) \tag{3.3.1i}$$

Similarly, the revenue generated by direct feed-ins from the battery to the grid (Y_{batt} in US\$) is calculated using the prices available in the wholesale electricity markets and as in Eqs. (3.3.1j)–(3.3.1l), including the losses that occurred through discharging inefficiencies.

$$Y_{batt,0} = 0 \tag{3.3.1j}$$

$$Y_{batt,1} = \sum_{m=1}^{M} \sum\nolimits_{t=1}^{T} [E_{batt\_grid,t} \times \eta_{tran} \times \sqrt{\eta_{batt.}} \times C_{batt,t}] \tag{3.3.1k}$$

$$Y_{batt,n} = Y_{batt,n-1} \times (1 + i_{batt}) \tag{3.3.1l}$$

Finally, the savings incurred by avoiding diesel consumption (Y_{Backup} in US\$) need to be calculated when parts of the installed battery are used instead of a diesel generator as a backup power system. Because such conventional systems are widely used by C&I customers in the selected countries, the backup systems comprise a significant share of the costs. For the battery to be able to perform this service, it must at all times be fully operational to provide the required backup power over the average duration of interruption. Thus, for the purpose of the analysis, it is assumed that the required energy capacity and power are exclusively reserved for this application and cannot be used for other applications, such as peak shaving or increases in self-consumption. To consider all savings in opportunity costs related to the substitution of diesel power generators, Eq. (3.3.1m) defines the investment costs for this aggregate. Eq. (3.3.1n) is used to calculate the on-going savings per year as the costs of diesel fuel plus the expected operation and maintenance costs minus the costs of charging the battery from the grid. The time series is amended with a constant inflation rate, as in previous equations (Eq. (3.3.1o)).

$$Y_{Backup,0} = P_{Backup} \times C_{Backup} \tag{3.3.1m}$$

$$Y_{Backup,1} = \frac{1}{M}\frac{1}{T}\sum_{m=1}^{M}\sum\nolimits_{t=1}^{T} E_{load,t} \times D_{Backup} \times (C_{Backup,fuel} - \min_{T}\{C_{E,t}\}) + P_{Backup} \times C_{Backup,O\,\&\,M} \tag{3.3.1n}$$

$$Y_{Backup,n} = Y_{Backup,n-1} \times (1 + i) \tag{3.3.1o}$$

3.3.2. Capital and operating expenditures

The costs of the PV and battery system are grouped into CAPEX and OPEX (in US$). CAPEX include the total cost of both the PV and the battery system, which depend on their sizes, i.e., the system design. Moreover, the components of the two systems are restricted by individual lifetime constraints. While the PV panels and the two inverters are assumed to age only with time, battery cells age both over time and according to their use. Thus, both are monitored to identify, which criterion is reached first (*lifetime* = min*(cycle life; calendar life)*). For simplification, interactions between calendar and cycle aging are disregarded in this study. To account for these constraints and their effects on investment costs, the financial model applies replacement costs. In doing so, each component may be subject to multiple replacements at the reduced costs derived from learning curve estimates and adjusted for inflation [55]. At the end of the project's lifetime, the model accounts for the dismantling costs and the reimbursement of residual values based on residual terms.

Operating expenditures are comprised of operation, maintenance, and insurance costs. Like capital expenditures, operating costs are dependent on the size of the installed system. To incorporate the effects of inflation, a constant energy cost projection rate is applied to all but the first year of the time series. In some countries, license fees are required for PV system installations to regulate injections into the grid, which are included in the operation costs. These fees may be a lump sum that is paid at the start of construction or a recurring fee that is often a function of the installed power (in kWp) or the electricity produced (in kWh).

3.3.3. Input data

The PV-STOR model presented above can be applied to any given project set-up. It should be noted that the two sub-models can be viewed as genuinely independent. While the dispatch model is fed with degradation-adjusted parameters, nominal values are used to calculate the revenues, CAPEX, and OPEX in the financial model. In the problem at hand, the cases introduced in Section 2 pre-define the data selection process. The input parameter values for the simulations are presented in the *Appendix* in Tables A1–A3. All inputs have been aligned with project developers and investors currently active in the respective regions.

3.3.3.1. Customer specification. Table A2 shows a summary of the customer-specific parameters and selected data sources. As a condition of precise optimization, all vectors were provided in a resolution of 15 min. While some data were available in granular form (e.g., load profiles), the PV vector was interpolated linearly from an hourly to a quarter-hourly resolution. This is a typical simplification that should not influence the accuracy of our results in a meaningful way [56]. The backup capacity requirement was calculated as the backup power requirement multiplied by the system average interruption duration index (SAIDI) divided by the system average interruption frequency index (SAIFI).

3.3.3.2. Electricity costs and remuneration. Table A2 provides a summary of all electricity and remuneration vectors. Their values depend on the country-specific policies presented in Section 2. Because some data are not given in a 15-minute resolution, the cost and remuneration data points were extended to their sub-hourly constituents.

4. Results

In this section, we provide an overview of the results. We ran a total of 1080 optimizations to account for the regulatory regimes of three countries (Vietnam, Thailand, and Malaysia), three load profile archetypes of three C&I industries (i.e., textiles, consumer goods, and electronics), two investment years (2018 and 2030) to account for reductions in the investment costs of the rapidly improving technologies used, and different discount rates (9%, 12%, 6%) to reflect investors' varying return expectations. For each combination of the above, we ran 30 simulations to account for different potential system designs (i.e., different sizes of PV, in kWp, and battery system, in kWh and kW). These differed according to the installed PVs and battery system sizes. The resulting NPVs are represented in Fig. 5 in the form of heat maps.

Fig. 5 shows that under 2018 investment conditions, profitable investment opportunities exist in all three South-East Asian countries and in all three industries. This is true for both PV systems and projects that combined PV and battery installations. However, in all 270 simulations for 2018, we find that every PV-only project is more profitable than projects that include a battery. Furthermore, no profitable set-up was found for the consumer goods industry in Thailand, the reasons for which are discussed below.

To further understand the reasons for these results and to clarify the interdependencies between countries, their respective regulatory regimes, and their load profile archetypes, Fig. 6 show the details of two specific technological set-ups in the three geographies and industries.

In comparing the regulatory regimes across countries, we can identify the influence of specific policies and regulations. In Vietnam, the FiT contributes most revenues, achieved by feeding electricity generated from the PV system directly into the grid. This finding is similar in all three simulated load profile archetypes. We expected similar outcomes in Malaysia, which has a net metering scheme. However, only in the case of the consumer goods industry we observe the direct PV feed-in to the grid. The reason is that solar irradiation and load seldom coincide in this archetype. The textile industry and electronics industry archetypes have high electricity demands compared with PV generation. In these cases, it is more profitable to directly consume the produced electricity and avoid efficiency losses. Unlike a FiT, which can be higher than the retail electricity rate (as it is the case in Vietnam), net metering returns the exact retail rate. For a conceptual consideration of various paradigms depending on retail electricity rates, remuneration for PV, and levelized costs of PV electricity, compare to the work of Ossenbrink (2017) [14].

The addition of a battery, even though it is not profitable in the calculations for 2018, shows how the systems operate under various

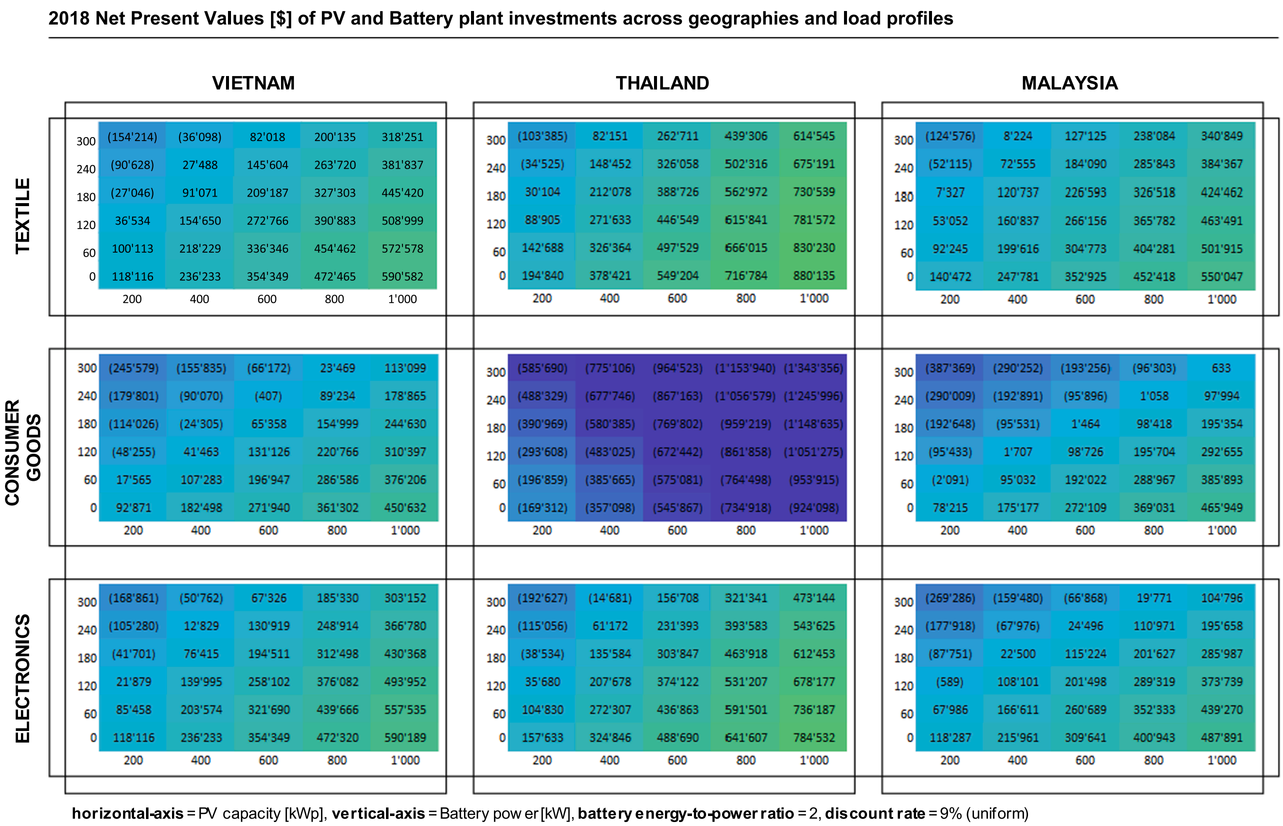

Fig. 5. 2018 net present value (NPV) of PV and battery plant installations across three different geographies (Vietnam, Thailand, and Malaysia) and three different industry archetypes with differing load profiles (textiles, consumer goods, and electronics). Each heat map consists of 30 NPV data points for which the installed PV capacity is shown on the horizontal axis, and the respective battery power is shown on the vertical axis. The energy-to-power ratio of the battery system is set to 2, which means 2 kWh of capacity per 1 kW of rated power capability. The discount rate for the NPV calculation is set to a constant (in time and across simulations) value of 9%. The NPV figures in parentheses refer to negative values.

regulatory and tariff regimes (see Fig. 4). In the textile and electronics industries in Vietnam, the addition of a battery does not influence the PV feed-in. The utilization of the existing time-dependent electricity rates, however, allows for arbitrage that reduces the energy-related costs on the electricity bill. In the consumer goods industry, these arbitrage opportunities are even more pronounced. The optimal battery dispatch even increases the energy-related electricity cost, but then generates revenue by feeding electricity from the battery into the grid. This energy flow is possible only because of the wholesale market in Vietnam, which is not available in the other two countries investigated in this study. In Thailand and Malaysia, the battery system increases the self-supply ratio by charging the battery from PV electricity that is generated on site and discharged into the site's load. Moreover, the existing demand charges are utilized, thereby reducing capacity-related electricity costs. In addition, the battery creates value by providing a backup power supply in the case of grid outages in all cases.

In the following, we focus on the textile industry and show the results of two key sensitivities: the applied discount rates and the investment expenditures for capital equipment.

Fig. 7 shows the sensitivity of the discount rate. While the higher discount rates generally reduces project profitability, the lower rates improve it – the typical pattern for projects with a high upfront investment and later revenues that are discounted. Even at the higher discount rate of 12%, however, many profitable PV and battery project set-ups can be identified. At the lower discount rate of 6%, only one of the simulated system set-ups in Vietnam, which use a large battery (300 kW, 600kWh) and a small PV system (200 kWp), is not profitable. All other combinations deliver a positive NPV. A key finding in lower discount rates is that the relatively high investment cost of battery systems become less relevant, so adding a battery to the PV plant is less detrimental to a project's profitability. In Vietnam, in several instances, the addition of a small battery system increases profitability. Therefore, depending on the investors' perception of risk, combining PV and battery systems can be the most profitable option.

The findings on sensitivity provide insights for policymakers and financial institutions such as the World Bank Group that aim to foster battery technology. If they are able to significantly reduce the investment risks in PV and battery projects (and by extension justify using a lower discount rate), the profitability of battery storage could be improved. Two important options are financial and policy de-risking. The former transfers risks to third parties (e.g., through guarantees), whereas the latter improves the investment environment through improved policy and regulation [57]. The results of the discount rate sensitivity in the two remaining load profile archetypes are provided in the *Appendix* (Figs. A1 and A2). Although the findings are similar, no profitable battery investment opportunities are indicated in these scenarios.

To investigate the effects of potential future investment cost reductions on PV and battery systems, we use learning curves to estimate the values in 2030. To facilitate the comparison and isolate the effects

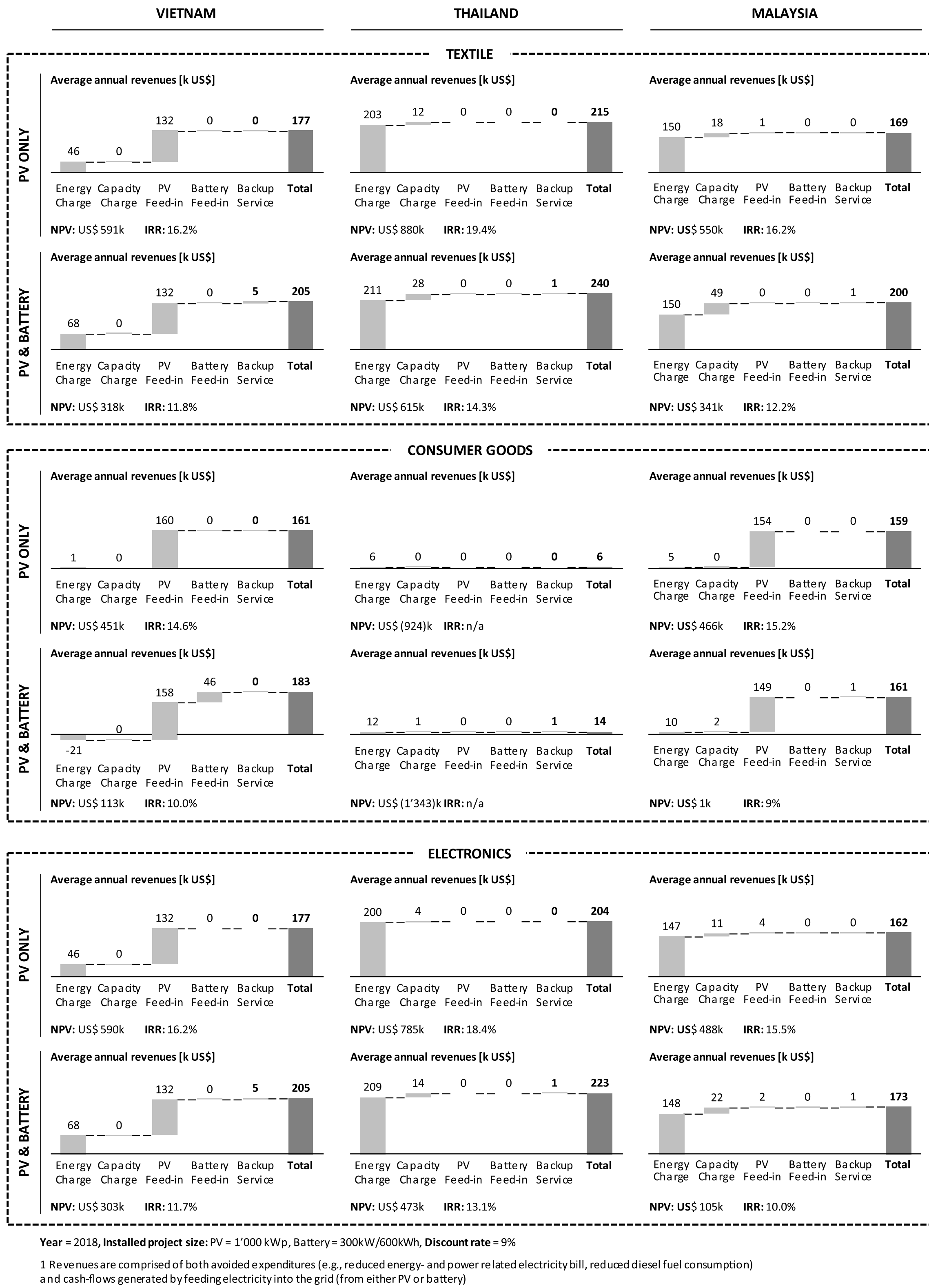

Fig. 6. Key performance indicators for PV as well as PV and battery projects in Vietnam, Thailand, and Malaysia in 2018 in the textile, consumer goods and electronics industries.

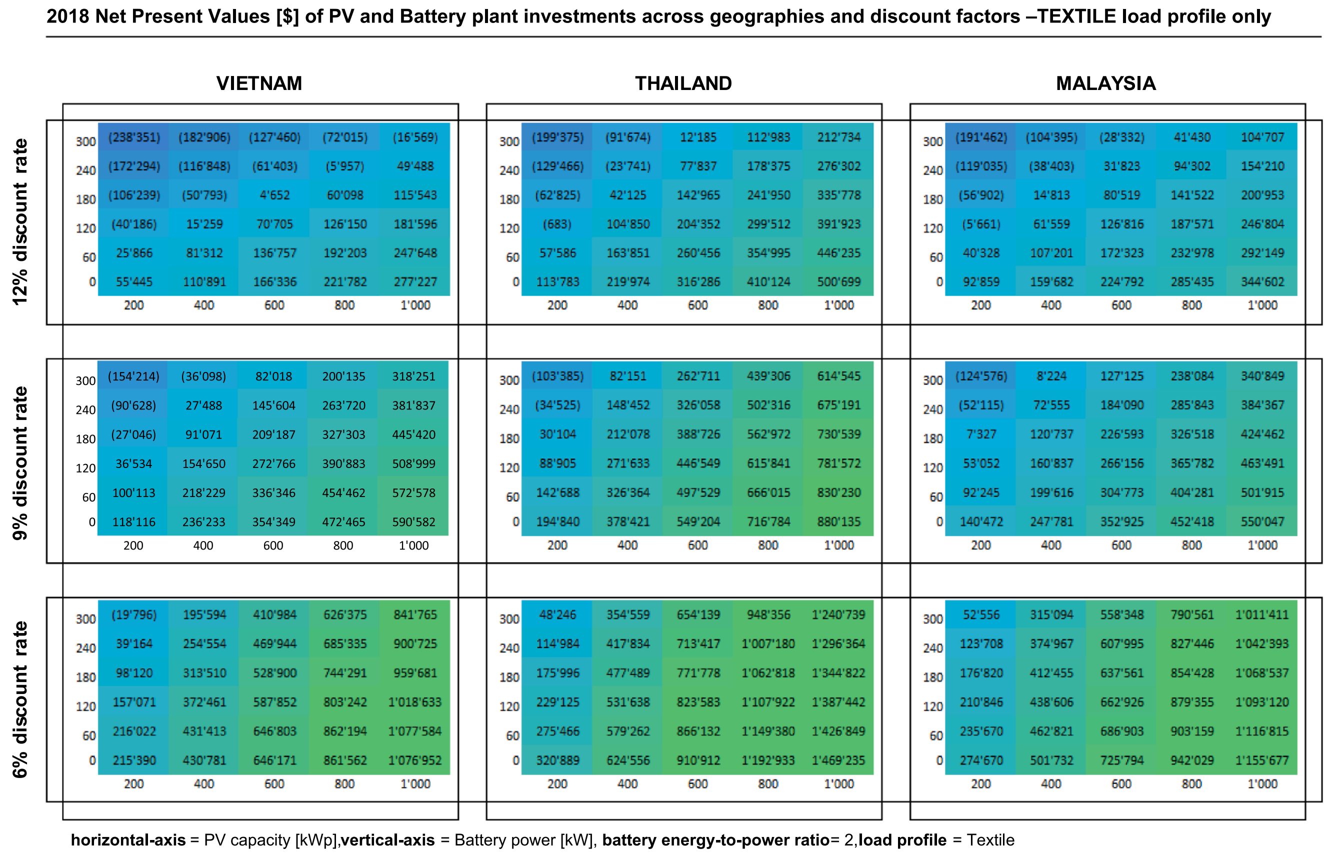

Fig. 7. 2018 net present value (NPV) of PV and battery plant installations across three different geographies (Vietnam, Thailand, and Malaysia) and three different discount rates (6%, 9%, and 12%). Each heat map consists of 30 NPV data points for which the installed PV capacity is shown on the horizontal axis, and the respective battery power is shown on the vertical axis. The energy-to-power ratio of the battery system is set to 2, which means 2 kWh of capacity per 1 kW of rated power capability. The load profile archetype used is the textile industry. Please note: the NPV figures in parentheses reflect negative values.

of these cost reductions, we leave all other factors the same as in the 2018 projects (ceteris paribus approach). The resulting NPV heat maps are presented in Fig. 8.

We find that among all profitable projects, the addition of a battery generally improves the project's profitability in the textile and electronics industries, whereas it reduces profitability in the consumer goods industry. In cases where the battery system improves the project's profitability, it was possible to determine the optimal battery size using a grid search. For example, with the applied load profile for the electronics industry in Vietnam, the overall highest profitability is achieved by installing a 1000 kWp PV system with a 60 kW/120 kWh battery system. However, in the textile industry in Thailand, the highest profitability is achieved by installing a 1000 kWp PV system with a large battery system of 180 kW/360 kWh.

For decision makers, these findings indicate that we can expect increasing battery deployments as the technologies improve. Policymakers can accelerate the advent of the expected technology cost reductions. While the costs for PV modules and battery packs are typically considered to follow a global learning curve [58–60], benefitting from deployment across countries and sectors, the balance-of-system costs are typically dependent on local conditions [58,61]. For example, governments in Vietnam, Thailand, and Malaysia can ensure speedy permitting processes, foster local capability building. In addition, import duties for PV panels, inverters and battery packs should be avoided.

In summary, the results indicate that it is not a question of if batteries will be deployed to accelerate the energy transition in South-East Asia, but rather when batteries will be deployed in the coming years and how rapid the technology diffusion is going to be. This fact is critical to understand for investors that have to get ready to assess the more complex PV and battery projects, but also for policymakers that have the opportunity to accelerate this development. We will discuss the available options in the following section.

5. Discussion and policy implications

The objective of this work was to assess the profitability of investments in C&I PV and battery projects in South-East Asian countries and to identify levers for policy makers to accelerate the deployment of such projects. Two key findings from our modeling results are: (1) profitable investment opportunities are already widely available across countries and industries, with PV-only projects achieving higher profitability than projects including a battery; and (2) project-specific results highly depend on the interactions between countries' regulatory regimes and industries' load profile characteristics. Further important factors are technology- and project-specific parameters, such as investment costs

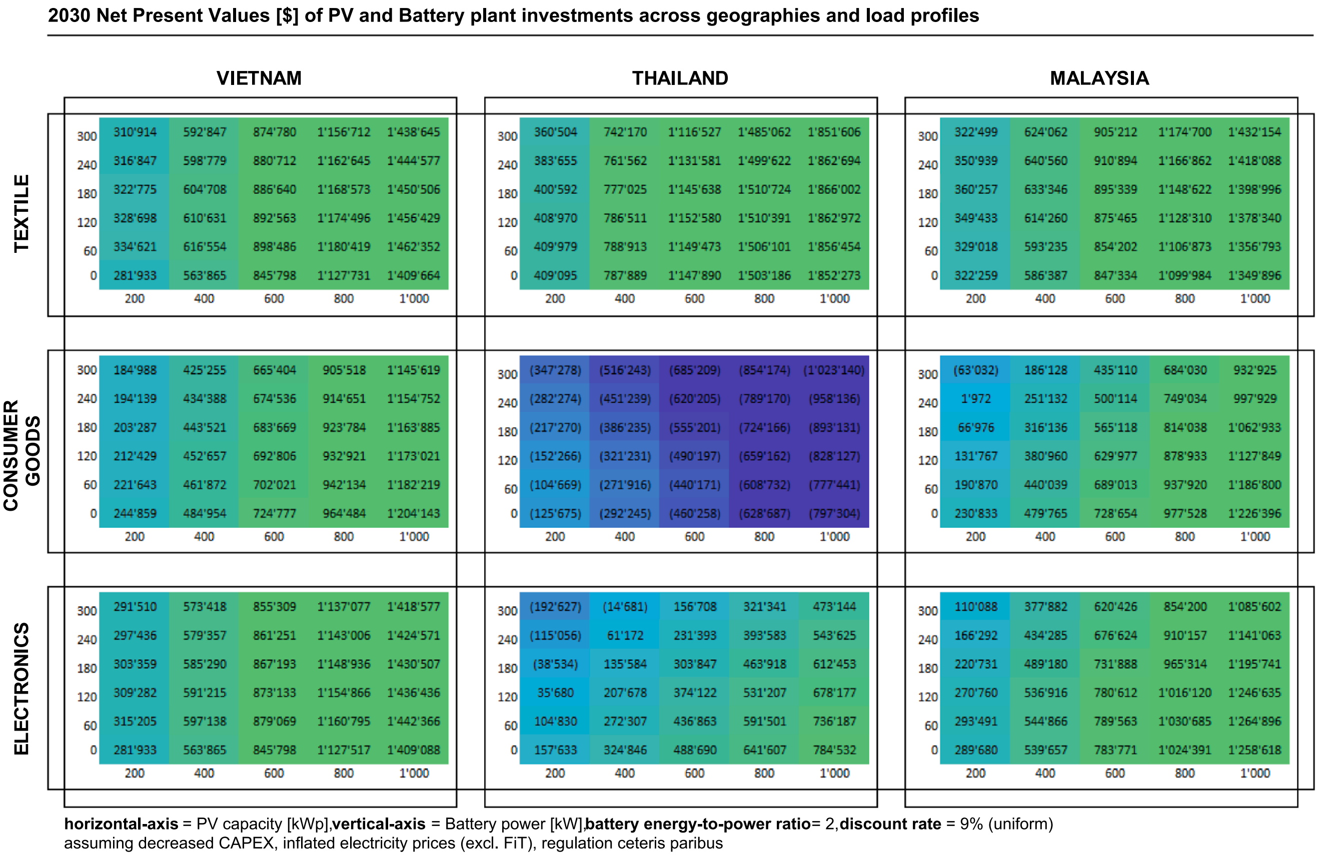

Fig. 8. Future (with capital cost reductions projected by 2030) net present value (NPV) of PV and battery plant installations in three different geographies (Vietnam, Thailand, and Malaysia) and three different industry archetypes with differing load profiles (textiles, consumer goods, and electronics). Each heat map consists of 30 NPV data points for which the installed PV capacity is shown on the horizontal axis, and the respective battery power is shown on the vertical axis. The energy-to-power ratio of the battery system is set to 2, meaning 2 kWh of capacity per 1 kW of rated power capability. The discount rate in the NPV calculation is set to a constant (in time and across simulations) value of 9%. Please note: the NPV figures in parentheses reflect negative values.

and discount rates. Because of these complex interactions of input parameters, it is crucial to employ optimization-based techno-economic models, such as PV-STOR. While simple spreadsheet-based models might have been sufficient for assessing PV-only projects, adding a battery means adding complexity, and thereby necessitates the use of more sophisticated assessment methods.

From a public policy perspective, it is important to highlight that investment attractiveness does not depend on the enacted policy instrument alone, such as the FiT in Vietnam or the net metering scheme in Malaysia. Instead, project profitability depends on the complete regulatory regime and its detailed design parameters, such as the level of the FiT (in relation to levelized cost of combined PV and battery systems), and the level and structure of electricity tariffs [14]. The results of the present study show that batteries enable revenue generation from the utilization of price differentials in time-of-use tariffs as well as from reducing peak demand charges. The absolute amount and thereby the relevance of the revenue generated depends on the tariff design. In addition, policymakers can significantly influence the degrees of freedom by which a combined PV and battery system operates by allowing or forbidding various energy flows to and from the electricity grid.

More specifically, for the case of the investigated South-East Asian countries, the developed optimization model allows us to discuss specific policy design options to improve the profitability of projects with batteries and thereby increase their deployment.

A key barrier to further deployment of PV is its system integration. Even though Vietnam and Malaysia support further deployment with a FiT and a Net Metering scheme, respectively, both Malaysia and Thailand levy license fees for the installation of PV systems. These fees are intended to raise funds aiding PV integration. As highlighted in the motivation, installing battery systems is an alternative way to aid PV system integration. Chaianong and colleagues (2020) use the case of residential batteries in Thailand to show that batteries can reduce PV integration cost [62]. Therefore, in a separate step we analyzed the impact of eliminating fees for projects that combine PV and battery systems in Malaysia and Thailand. While the NPV increases, the increase does not suffice to make PV and battery projects' (without fees) more profitable than PV-only projects (with fees) in any of the analyzed scenarios (scenarios as in Fig. 5). Nevertheless, eliminating license fees could potentially speed up the deployment of battery storage systems if combined with other policy support options.

A second option for policymakers in Vietnam and Malaysia is to reroute their support schemes for PV electricity to combined PV and battery projects. Since profitable projects are available for both

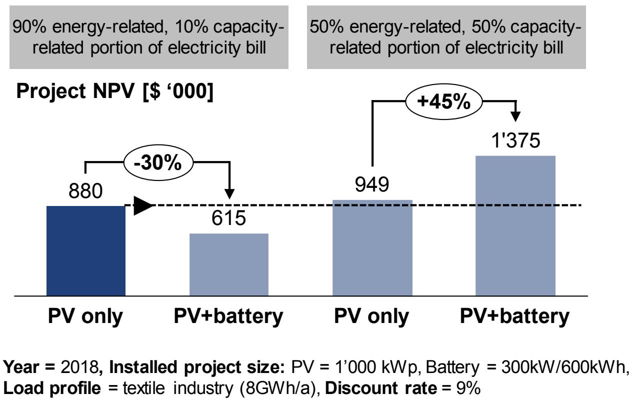

Fig. 9. Influence of changing electricity tariff design on PV and battery project economics.

countries and all industries, such a policy change could reduce risk of over subsidizing investors while at the same time delivering flexibility for the electricity system through batteries. However if such a strategy were to be pursued, a potential influence on technology diffusion should be considered. Our modelling shows that while profitable investment opportunities would still be available, the NPV would be lower in all cases, which might lead to an unintended slowdown in RE deployment [63].

Furthermore, another option available in all three investigated countries is to enable further value creation in electricity markets and by providing balancing services to the electricity system [19]. So far, only Vietnam allows PV and battery system operators to participate in electricity markets. Provision of services to the electricity grid could be enabled by introducing flexibility markets, bespoke programs, or bilateral contracts based on local flexibility needs. To this end, however, flexibility needs must be transparent to grid operators first. The heat maps provided by this study can then serve as an indication for how high remuneration of these services would need to be in order for investors to favor combined PV and battery projects over standalone PV systems. Decision makers can use the PV-STOR model for detailed analysis of their design decisions by incorporating price vectors for such services.

A remaining, although arguably more complex, option to influence further battery deployment is to change the electricity tariff design. While keeping the overall electricity bill constant in the baseline case (without PV or battery), the shares of the energy- and capacity-related portions of the electricity bills could be adapted. Implementing peak demand charges to recover fixed and capacity-related cost of the electricity grid, especially in times of load defection due to PV installations, is already applied in the United States [64,65] and discussed in studies assessing future tariff design options for low-carbon electricity systems [66,67]. As we show in Fig. 6, in both Thailand and Malaysia battery installations are able to generate value by shaving-off demand peaks. Without PV or battery installation the energy-related portion of the electricity bill makes up for about 90% of the bill, the capacity-related portion for the remaining 10% (load profile archetype of the textile industry in Thailand). To which extent the NPVs change when shifting this to an exemplary 50%/50% split (but same total electricity cost without PV and battery installation) is shown in Fig. 9.

In the base case with 90% energy-related cost on the electricity bill, adding a battery to a PV project reduces the NPV by 30%, making this investment unlikely. Changing the electricity tariff design such that the energy- and capacity related cost are evenly distributed leads to PV as well as PV and battery investments to be more profitable. More importantly, the combined PV and battery projects now show a 45% higher NPV compared to the PV-only projects, making this measure particularly powerful for fostering battery deployment. The reason behind this shift is the battery's ability to shave demand peaks by intelligently charging and discharging. While in the base case, revenues from peak shaving are only of minor relevance to the project profitability (as can be seen in Fig. 6), with the adapted electricity tariff design, peak shaving makes up for more than 50% of the project's revenues. When choosing this option of influencing PV and battery project profitability it is key to assess how batteries would be operated (e.g., using PV-STOR) and how this influences the grid stability. Also note that the overall electricity tariff collected by the utility is lower in this case, and other customers might be affected positively or negatively (which makes electricity tariff design changes a complex endeavor).

It is important to keep in mind that the benefits of battery deployment enabling integration of renewable energies are not given by default, as it is possible to operate batteries that create value to consumers but create costs for the electricity grid. Time-variant electricity tariffs and peak demand charges are typically used to shift demand away from undersupplied periods. Tariffs are however typically not constantly updated to reflect actual supply and demand balances. Any intervention with the existing regulatory regime should therefore consider not only a battery's profitability, but also the expected optimal battery dispatch (e.g., derived from PV-STOR) and its effect on (local) grid stability. In cases where batteries are used to increase the on-site consumption of PV generated electricity, they have shown to reduce the strain on the grid by shifting electricity from times of oversupply to times of local demand [34].

6. Conclusion

To conclude, for future electricity systems based on large shares of wind and solar electricity, flexible options, such as battery systems, are crucial. For the case of commercial & industrial customers, we investigate the viability of projects in Vietnam, Thailand, and Malaysia, considering three different industries (textile, consumer goods, and electronics). Our model identifies several profitable investment opportunities in photovoltaics and battery projects, even though adding a battery typically reduces profitability vis-à-vis standalone photovoltaics. Our results could provide guidance for policymakers interested in "kick-starting" the development of clean energy technologies in South-East Asia. Firstly, de-risking investment projects (reducing the discount rate) will improve profitability of battery deployments vis-à-vis photovoltaics standalone projects. Secondly, expected technology cost reductions will make battery investment the most profitable choice for investors. Governments can accelerate this development, for example by fostering local learning for system cost components that do not benefit from global learning curves, such as the installation and commissioning. Thirdly, eliminating license fees for projects including batteries and/or re-orienting support policies to projects including batteries could further accelerate battery deployment. Beyond these measures, re-designing electricity tariffs can be a powerful lever. To ensure batteries actually operate in a way to is beneficial to the electricity grid this needs to be done with great care. In addition, to reap the full benefits that batteries can deliver, provision of grid services should be enabled. To this end, grid operators need to understand their flexibility needs with increasing electrification and deployment of decentral energy resources.

In this study, we add to the existing literature by providing a techno-economic optimization model for commercial & industrial photovoltaics and battery projects and applying this model to different countries and industries in South-East-Asia. The investigated cases differ strongly in their regulatory regimes and thereby deliver deep insights for decision makers. These insights are valuable also for other regions and regulatory regimes and can inform policy design for such systems.

However, before decision makers act on the presented results and discussion, we want to highlight several further considerations. While our study benefitted from the use of actual load profiles from the region, the analysis should be carried-out again based on a broader set of measured load profiles to estimate technology diffusion in the respective regions. Furthermore, impacts of increased deployment of photovoltaics and battery projects on the electricity grid as well as cost recovery of utilities needs to be investigated to understand the full implications.

CRediT authorship contribution statement

Martin Beuse: Conceptualization, Formal analysis, Writing - original draft, Writing - review & editing. **Mathias Dirksmeier:** Data curation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. **Bjarne Steffen:** Conceptualization, Funding acquisition, Project administration, Writing - review & editing. **Tobias S. Schmidt:** Conceptualization, Funding acquisition, Project administration, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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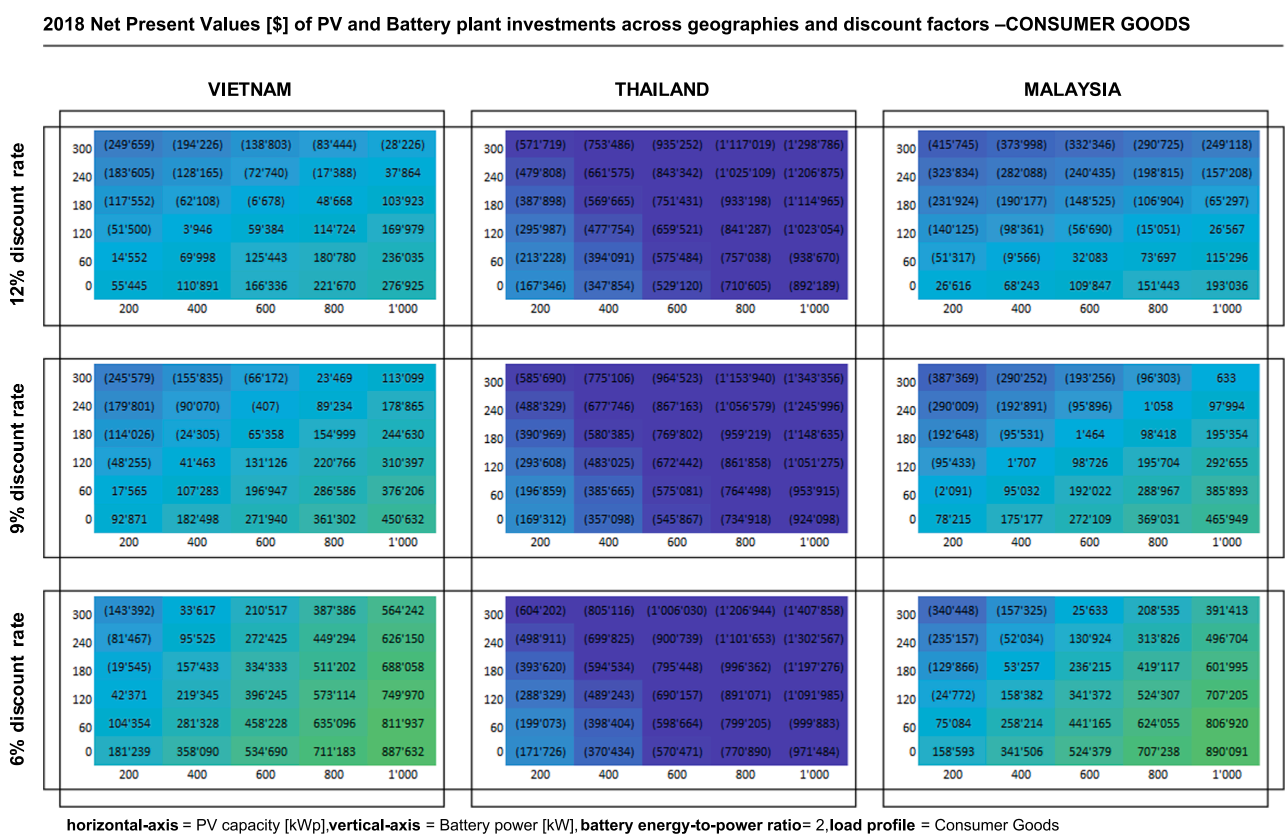

Fig. A1. 2018 net present value (NPV) of PV and battery plant installations across three different geographies (Vietnam, Thailand, and Malaysia) and three different discount rates (6%, 9%, and 12%). Each heat maps consists of 30 NPV data points for which the installed PV capacity is shown on the horizontal axis and the respective battery power is shown on the vertical axis. The energy-to-power ratio of the battery system is set to 2, which means 2 kWh of capacity per 1 kW of rated power capability. The load profile archetype is the consumer goods industry. Please note: the NPV figures in parentheses reflect negative values.

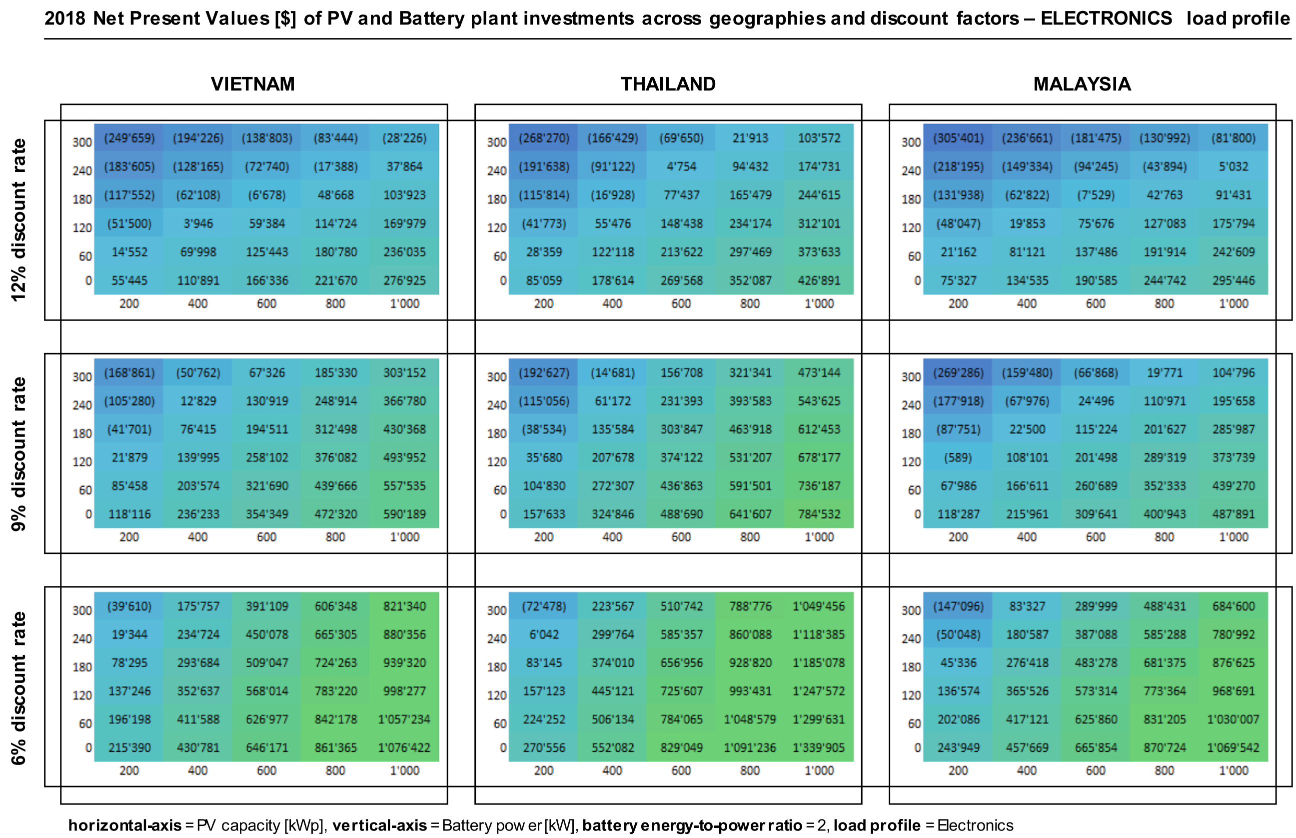

Fig. A2. Current (2018) net present value (NPV) of PV and battery plant installations across three different geographies (Vietnam, Thailand, and Malaysia) and three different discount rates (6%, 9%, and 12%). Each heat map consists of 30 NPV data points for which the installed PV capacity is shown on the horizontal axis and the respective battery power is shown on the vertical axis. The energy-to-power ratio of the battery system is set to 2, which means 2 kWh of capacity per 1 kW of rated power capability. The load profile archetype is the electronics industry. Please note: the NPV figures in parentheses reflect negative values.

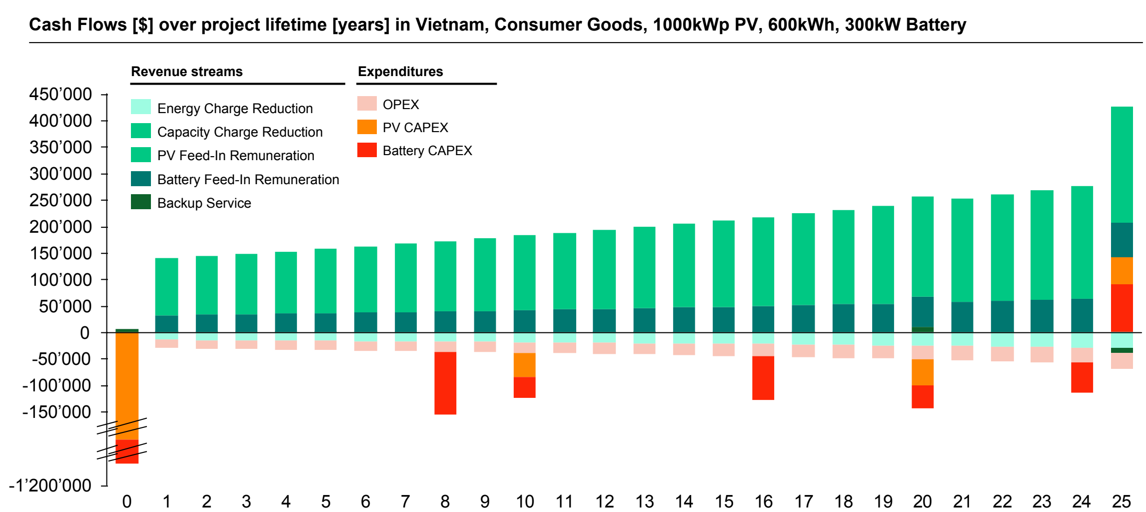

Fig. A3. Cash Flows over lifetime of PV and battery plant installation in Vietnam, using Consumer Goods load profile archetype, 1000 kWp PV, 600 kWh, 300 kW Battery. The recurring capital expenditures in years 8, 10, 16, 20, and 24 are accounting for the necessary replacements of the PV and battery inverters, and the battery packs. The positive value for capital expenditures in year 25 is due to their scrap values, reduced by dismantling costs (1% of CAPEX). Electricity prices are escalating with time, which is why revenue streams for their reduction are increasing as well.

Appendix A

Table A1
PV-STOR model input parameter values by country.

Variable	Unit	Vietnam	Thailand	Malaysia	Sources
PV system technical specification					
Panel Size	m^2	1.71	1.71	1.71	[68]
Power Output per Panel	kWp	0.33	0.33	0.33	[68]
Tracking?	Yes/no	No	No	No	[69]
Annual Performance Degradation	%	0.8	0.8	0.8	[69]
Panel Lifetime	years	25	25	25	[69]
Inverter Lifetime	years	10	10	10	[69]
Inverter Efficiency	%	97.5	97.5	97.5	[69]
Other Losses	%	6.5	6.5	6.5	[70]
Transformer Losses	%	1.5	1.5	1.5	[70]
PV CAPEX (incl. import duties and VAT)					
Panels	US$/kWp	270	270	295	[69]
Inverter	US$/kWp	55	60	60	[69]
Hardware Balance-of-System	US$/kWp	400	390	315	[69]
Soft Cost Balance-of-System	US$/kWp	60	60	60	[69]
End-of-life Cost	% of CAPEX	0	0	0	[69]
PV OPEX					
Operations & Maintenance (O&M)	US$/kWp p.a.	7.5	7.5	7.5	[69]
O&M Cost Escalation	% p.a.	3	3	3	[69]
Insurance	% of CAPEX	0.4	0.4	0.4	[69]
One-off license fees	US$	0	max(1.6*kWp;1600)	24.8	[69]
Annual license fees	US$ p.a.	0	0.36*m^2_roof	1488.83	[69]
Annual license fees	US$/kWp		0.17*0.16*kWp	557.9	[69]
Annual license fees	US$/kWh		0.00032*annual_kWh	0	[69]
Battery system technical specification					
Depth-of-Discharge	% of capacity	90	90	90	[34,71]
Calendar Life	years	12	12	12	[58]
Cycle Life	# cycles	4996	4996	4996	[58]
Inverter Lifetime	years	10	10	10	[71]
Roundtrip Efficiency	%	90.5	90.5	90.5	[72]
End-of-Life Capacity	% of capacity	80	80	80	[73]
End-of-Life Power	% of power	80	80	80	[73]
End-of-Life Efficiency	% of efficiency	96	96	96	[73]
Initial State of Charge	% of capacity	50	50	50	
Battery CAPEX (incl. import duties and VAT)					
Battery Pack	US$/kWh	315	315	315	[58]
Inverter	US$/kW	155	155	155	[71]
Balance-of-System Cost	US$/kWh	185	185	185	[72,58]
Balance-of-System Cost	US$/kW	95	95	95	[72,71]
End-of-life Cost	% of CAPEX	1	1	1	[74]
Battery OPEX					
Operations & Maintenance (O&M)	US$/kW p.a.	6	6	6	[69]
O&M Cost Escalation	% p.a.	3	3	3	[69]
Insurance	% of CAPEX	0.75	0.75	0.75	[69]
Costs for Alternative Backup System (Diesel)					
System Cost	US$/kW	300	300	300	[75]
System Lifetime	years	20	20	20	[75]
Fuel Cost	US$/kWh	0.26	0.26	0.26	[76,77]
O&M Cost	US$/kW	0.02	0.02	0.02	[75]

Time series data for electricity tariffs, load profiles, irradiation profiles and support schemes are provided in a digital appendix.

Table A2
Notation and Sources of Customer-specific Data.

Variable/Parameter	Unit	Sources
Load profile	kWh	[69]
PV profile	kWh	[78]
Average interruption duration	h/year	[79]
Average interruption frequency	times/year	[79]
Backup power requirement	kW	[69]
Backup capacity requirement	kWh	Subj. to calc.
Discount rate, nominal	%	[69,80]
Inflation rate	%	[69,80]

Table A3
Notations and Sources of Electricity Costs and Remuneration Data.

Variable/Parameter	Unit	Sources
Energy charge vector	US$/kWh	[69]
Capacity charge vector	US$/kW	[69]
Feed-in tariff/PPA	US$/kWh	[69]
Wholesale prices	US$/kWh	[69]
Energy charge projection	%/year	[69]
Capacity charge projection	%/year	[69]
Feed-in tariff projection	%/year	[69]
Wholesale prices projection	%/year	[69]

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2020.115218.

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