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Upscaling scenarios for ocean thermal energy conversion with technological learning in Indonesia and their global relevance

Jannis Langer *, Jaco Quist, Kornelis Blok

Delft University of Technology, Faculty of Technology, Policy and Management, Department of Engineering Systems and Services, Jaffalaan 5, 2628, BX, Delft, the Netherlands

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ABSTRACT

Ocean Thermal Energy Conversion (OTEC) is a promising renewable energy technology that is the most economical at large scale. But contemporary literature does not address how OTEC could reach such scale with current technology, and what the techno-economic impact of location-dependent factors and technological learning are. This paper tackles these issues by simulating OTEC's upscaling with a model that implements OTEC to meet local electricity demand and extrapolates to the global relevance of OTEC. The model uses a learning rate for investment costs and cost of finance. This study shows that up to 45 GW of OTEC capacity can be installed in Indonesia with national demand coverage of 22% in 2050. Even with small cost reduction rates, OTEC could be profitable and cost-competitive against other power generation technologies with an aggregated *Net Present Value (NPV)* of up to US$ 23 billion. OTEC's upscaling could be funded via state budget reallocation or international financial institutions, e.g. via the feed-in tariff suggested in the paper. However, large-scale OTEC is only feasible in regions with high electricity demand and until that size is reached, upscaling must be coordinated globally, e.g. with the proposed upscaling strategy. To contribute to the global energy transition, OTEC needs to grow by 28% per year, a rate similar to wind power and solar PV. This paper provides good reasons to fight for the attention of global decision makers and future research could focus on refining the concepts of this study.

1. Introduction

In the last two decades, Indonesia's electricity demand has grown by more than 6% annually [1,2] and is expected to rise at a similar rate until 2050 [3]. Despite abundant domestic reserves of coal and natural gas [4], the recent depletion of Indonesia's oil reserves shows that these reserves may not be enough to satisfy the country's hunger for electricity on the long term [5]. Currently, Indonesia aims to increase the share of renewables in the energy mix and policymakers explicitly call for the refinement of ocean energy potentials, including *Ocean Thermal Energy Conversion (OTEC)* [3].

OTEC produces electricity by utilising the temperature difference between warm surface and cold deep-sea water. Despite a theoretical potential of up to 30 TW [6] globally, OTEC is still in early development with no commercial plants, so countries like Indonesia cannot yet benefit from clean baseload power from OTEC and additional applications like cooling and freshwater production [7,8]. This is unfortunate, as an earlier work [9] showed the practical potential of large-scale OTEC is 103.2 GW in Indonesia, with up to 2.0 GW that could be implemented profitably today under certain techno-economic conditions. However, that study omitted the cost-reducing effects of technological learning during the upscaling process from small to large OTEC plants.

In response to the points raised above, this paper aims to shed light on the following research question:

What are possible upscaling scenarios of OTEC in Indonesia using technological learning, and what global techno-economic insights can be drawn from them?

The combination of growing electricity demand and the region's steeply declining seabeds enabling floating OTEC installations nearshore make Indonesia an excellent subject to study the upscaling of OTEC to reach its high economic potential [9,10]. But given the myriad of countries suitable for OTEC [11], its upscaling is a global challenge and should be treated as such. As Indonesia consists of over 16,000 islands [12] with significant differences in electricity demand, electricity tariff, oceanography, and ocean thermal resources, the country can be viewed as a host of multiple cases. For instance the isle of Java, the economic centre of Indonesia, could serve as a proxy for Hawai'i, USA, with its high electricity demand. Meanwhile, the rural, dispersed communities in Maluku and Kepulauan Nusa Tenggara could represent Small Island

* Corresponding author.
E-mail address: j.k.a.langer@tudelft.nl (J. Langer).

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Abbreviations, Symbols, and Indices

ΔT	Seawater Temperature Difference °C
ADB	Asian Development Bank
b	Learning Coefficient
BPP	Basic Cost of Electricity Production (*Biaya Pokok Penyediaan)* US¢/kWh
c	Capacity Factor %
CAPEX	Capital Expenses US$ million
CRF	Capital Recovery Factor %
d	Distance from Plant to Populated Connection Point at Shore km
DR	Discount Rate %
E	Annual Electricity Production MWh/year
EEZ	Exclusive Economic Zone
FIT	Feed-In Tariff US¢/kWh
GIS	Geographic Information System
HC	High Cost
LCOE	Levelized Cost of Electricity US¢/kWh
LR	Learning Rate %
LC	Low Cost
N	Plant Lifetime Years
NPV	Net Present Value US$ billion
OPEX	Operational Expenses US$ million per year
OTEC	Ocean Thermal Energy Conversion
P	Power MW, GW
PPA	Power Purchase Agreement (Tariff) US¢/kWh
PR	Progress Rate %
r	Growth Rate % per year
SIDS	Small Island Developing States
η	Transmission Efficiency %

Index	*Meaning*
0	First Ever Implemented Plant
agg	Aggregated
dem	Demand
diff	Difference
f	Factor
goal	Implementation Goal
h	h^{th} Implemented Plant in Year i
H	Total Number of Implemented Plants in Year i
HX	Heat Exchanger
i	Year of Implementation Scenario
ind	Independent
inst	Installed
max	Maximum
min	Minimum
net	Nominal Net Power Output
prov	Provincial
sup	Supply
trans	Transmission

Developing States (SIDS). Therefore, the results presented are not only relevant for Indonesia, but also for several other regions of the world.

This study aims to shed light on how OTEC's commercialisation could be promoted, when OTEC could make meaningful contributions to Indonesia's and the global energy transition, how the upscaling could be financed, and what hurdles lie ahead. It is assessed how OTEC could be scaled up from its current pilot stage to full commercial size. The upscaling process considers local conditions such as electricity demand and its growth, electricity tariffs, and the location of the plants. To the authors' knowledge, such detailed upscaling scenarios are innovative in OTEC literature. Another novelty of this work is the application of a learning rate not only to *Capital Expenses (CAPEX)*, but also to the discount rate. With this, the gradual reduction of financing costs as seen in practice for other renewables is simulated. Moreover, this study proposes a support scheme to finance OTEC's upscaling via a *Feed-In Tariff (FIT)*. This addresses an important knowledge gap in literature, as the costs of OTEC are frequently assessed but not its financing. Lastly, the results are gathered to propose a global OTEC upscaling concept. These insights are not only valuable for OTEC researchers, but also global policymakers who search for ways to decarbonise their energy systems and decrease their dependency on imported fossil fuels.

This paper is organised as follows. Section 2 presents current work on technological learning in the fields of energy technologies and OTEC specifically. Section 3 elaborates the methods, data and assumptions deployed in this study. Section 4 encompasses the results and discussion of the scenarios as well as the global upscaling concept. The paper ends with conclusions in Section 5.

2. Literature overview and knowledge gaps

2.1. Technological learning and upscaling scenarios in OTEC literature

Technological learning is commonly visualised via *experience curves* showing the development of a technology's costs against its economic output, e.g. the installed capacity or produced electricity. An important metric is the *learning rate*, by which the costs of a technology change per doubling of economic output of that technology [13,14]. Currently, there are no empirical OTEC experience curves due to the absence of commercial plants and long-term operational data [15,16]. Current work mainly estimates the cost reduction potential based on experience in related industries, such as shipbuilding, petroleum, and utility engineering. In OTEC literature, a learning rate of 7% is frequently assumed based on the maturity of several system components like turbines and generators [17,18]. The total cost reduction potential is estimated to be 30% of initial CAPEX [16], reached after the 4^{th} or 5^{th} doubling of installed capacity [18]. Cost reductions are expected to be achieved by standardisation and technical improvements of components like heat exchangers and seawater pumps [18,19].

In current OTEC literature, only two studies report on upscaling scenarios. Vega [20] outlined the development from pre-commercial plants below 5 MW to commercial 100 MW plants in Hawai'i, USA. In the same region, Martel et al. [18] analysed scaling up of OTEC via 100, 200 and 400 MW plants. Both studies implied the technical viability of large-scale OTEC within 5–6 years due to OTEC's modularity [18].

2.2. Knowledge gaps and how they are addressed

Section 2.1 indicates three knowledge gaps in OTEC literature regarding upscaling and technological learning. First, no studies were found that simulate the upscaling of OTEC from today's pilot stage to large commercial systems. Instead, current literature implies that the latter is within reach in the next years. However, such outlooks disregard the current state of the art of some OTEC components. For example, some studies suggest cold seawater pipes with diameters of at least 10 m for a 100 MW_{net} system [16,18], while current pipes only reach diameters of up to 4 m [21]. This is an indication that not only the OTEC plants must be developed to reach commercial scale, but also the industries associated with OTEC, like pipe manufacturers and offshore contractors who need vessels suitable to lay such large pipes. Second, existing scenarios do not take into account the local conditions on shore that affect the plants' economic viability, such as local electricity demand and tariffs. Thus, it is unclear whether the suggested upscaling scenarios are economically feasible and what funding would be necessary to finance the plants' operation. Third, technological learning plays a limited role in OTEC literature. Only one study created hypothetical experience curves for OTEC's deployment [18], which differ greatly from curves found in learning literature. In an earlier study these differences and the validity of the experience curves were discussed [15]. Consequently, most current studies only look at OTEC's economics through the lens of today without considering what the future might be.

This study tackles all three knowledge gaps above by envisioning the natural progression of OTEC from small to large scale. The upscaling scenarios presented here consider the pace of OTEC implementation, local bottlenecks imposed by provincial electricity demand and regional electricity tariffs, and location-dependent costs and electricity production of OTEC plants. It is shown when and how OTEC could reach full scale as well as the associated techno-economic implications. OTEC's cost decline through time is visualised with experience curves. By comparing the required tariff to breakeven with the existing local electricity tariffs, it is possible to deduce the annual funding requirements of the upscaling scenarios, e.g. via a FIT scheme. Technological learning is a key element in this study to not only show by how much costs could decline in the future, but vice versa to indicate what cost reduction rates are necessary to make OTEC profitable in the mid to long term. Using and combining the pace of OTEC implementation, location-specific costs and regional market factors are novel and innovative in the view of the authors and can potentially add significant value to the existing body of OTEC literature.

3. Methodology

The methodology in this paper builds on earlier work [9] and has been further developed to allow the modelling of upscaling scenarios. First, suitable OTEC sites are mapped across the Indonesian sea at a resolution of 0.25° or 27.8 km using a *Geographic Information System (GIS)* approach. With this resolution, the goal is to limit local thermal degradation at the seawater outlets of the OTEC plants. This is important as thermal degradation not only has negative impacts on the local ecosystem, but also on the technical performance of the plant due to the decrease of seawater temperature difference [6]. Suitable sites are determined via the criteria of (1) water depth, (2) seawater temperature difference, and (3) marine protected areas. Regarding (1), sites are excluded with a depth of less than 1000 m and more than 3000 m to ensure the extraction of sufficiently cold water while considering the current state of the art of mooring lines. Regarding (2), the 5-year average seawater temperature difference must be at least 20 °C. Regarding (3), the sites within marine protected areas are excluded, which is a common practice when mapping offshore wind resources [22,23]. Then, a model was created that scales up OTEC from small to large scale over 30 years until 2050. For each year, an installation target is declared based on a predetermined OTEC growth rate r_{OTEC}. The model tries to achieve this target by selecting favourable sites for OTEC implementation based on distance to shore and local electricity generation cost in provinces with sufficient electricity demand. The upscaling scenarios are evaluated based on the aggregated *Net Present Value (NPV)* of all implemented plants. The NPV considers the devaluation of future cash flows and represents the cash balance at the end of the scenario in today's currency. Next, the results of the scenario with the highest NPV are presented in more detail, including the collective economic potential and hypothetical experience curves displaying the *Levelised Cost of Electricity (LCOE)*. The collective economic potential refers to all plants of a net profitable scenario. Thus, even if individual plants are unprofitable, they contribute to the accumulation of experience and drive down the costs of future plants. Next, the impact of variables outside the control of OTEC stakeholders on the results are studied. The analysis is concluded by presenting a nationally uniform FIT to finance OTEC. All costs are denoted in US$(2018).

3.1. Data and assumptions

3.1.1. Suitable OTEC sites

This study adopts the methodology of Langer et al. [9] to obtain a dataset of suitable sites for moored OTEC, including Indonesia's *Exclusive Economic Zone (EEZ)*. Especially at later stages of the implementation scenarios, when costs have decreased, sites outside provincial sea borders and within the EEZ become economically interesting.

The dataset of potential OTEC locations used for the model contains the following information:

- Longitude and latitude of the OTEC site and its connection point
- Province of connection point
- Distance between plant and connection point d in kilometres [km]
- Seawater temperature difference ΔT in degrees Celsius [°C]
- Water depth in metres [m]
- Electricity tariff at connection point in US¢/kWh

3.1.2. Techno-economic assumptions regarding OTEC

Based on a previous literature review [15], estimations on CAPEX found in OTEC literature form a total of three scale curves. These curves show how the specific CAPEX decline with increased system size due to economies of scale. However, the lowest of the three cost curves is based on system designs and cost assumptions that are yet to be validated within the OTEC field. This curve is therefore omitted in this study and the two remaining cost curves are referred to as *Low-* and *High-Cost Curves (LC* and *HC)*. Besides this terminology, all technical and economic assumptions of the OTEC plants are adopted from an earlier study [9], as summarised in Table 1. Regarding the location-independent cost, the functions in Ref. [9] return the costs in US$(2018)/kW. Therefore, functions shown in Table 1 were slightly changed to return costs in US $(2018) million. Moreover, in contrast to Ref. [9], the *Operational Expenses (OPEX)* of LC-OTEC are assumed to be 3% of LC-CAPEX and 5% of HC-CAPEX, respectively.

3.1.3. Technological learning and LCOE

This study assumes a constant learning rate of 7% [17,18], which includes learning-by-doing, research & development, standardisation, automation and knowledge spill-overs from other industries [13,14]. The relationship between costs and learning rate are described with equations (1)–(3). Learning is assumed to be continuous for the entire timespan, which goes beyond current practice reported in OTEC literature.

Table 1
Techno-economic assumptions for OTEC plants.

Technical assumptions		
Lifetime N	30 years	
Capacity Factor c_f	91.2%	
Transmission Efficiency η_{trans} (function of distance from plant to shore d)	$(100 - 2 * 10^{-4} * d^2 - 1.99 * 10^{-2} * d)$ %	
Economic assumptions	**LC-OTEC**	**HC-OTEC**
Location-independent components $CAPEX_{ind}$ [US $(2018) million] (function of net power output P_{net})	$(39.6 * P_{net}^{-0.418}) * P_{net}$	$(51.8 * P_{net}^{-0.315}) * P_{net}$
Heat Exchangers $CAPEX_{HX}$ [US $(2018) million] (function of seawater temperature difference ΔT and net power output P_{net}	$(1.97 - (\Delta T - 20°C) * 0.19) * P_{net}$	$(5.82 - (\Delta T - 20°C) * 0.56) * P_{net}$
Power Transmission $CAPEX_{trans}$ [US$(2018) million] (function of distance from plant to shore d and net power output P_{net})	$(0.0497 * d + 0.304) * P_{net}$	
Operational Expenses $OPEX$	3% of CAPEX per year	5% of CAPEX per year

The discount rate is used to determine the present value of future cash flows [24]. This study assumes an initial discount rate *DR* of 10% [9] which harmonises with previous studies on OTEC [19,25,26] and other ocean technologies like tidal current and wave current power [27, 28]. Then again, it is relatively high compared to more mature renewable technologies implemented in more developed countries. With rising experience, the risks of implementing a technology can decline and with them the discount rate [29,30]. For instance, the average discount rate for solar PV was as low as 4% in 2018 in Japan [31]. Therefore, this study suggests a discount rate that decreases with accumulated experience. The LCOE and NPV are calculated using equations (4)–(7), respectively.

$$CAPEX_h = \left(CAPEX_{ind,h} + CAPEX_{HX,h} + CAPEX_{trans,h}\right)*\left(\frac{P_{inst,h}}{P_{inst,0}}\right)^b \tag{1}$$

$$PR = 2^b \tag{2}$$

$$LR = 1 - PR \tag{3}$$

$$E_h = P_{net,h}*c_f*8,760*\eta_{trans} \tag{4}$$

$$LCOE_h = \frac{CRF_h*CAPEX_h + OPEX_h}{E_h} \tag{5}$$

$$with\ CRF_h = \frac{DR_0*\left(\frac{P_{inst,h}}{P_{inst,0}}\right)^b*\left(1+DR_0*\left(\frac{P_{inst,h}}{P_{inst,0}}\right)^b\right)^N}{\left(1+DR_0*\left(\frac{P_{inst,h}}{P_{inst,0}}\right)^b\right)^N - 1} \tag{6}$$

$$NPV = \sum_{h=1}^{H}\sum_{i=1}^{i+N}\frac{E_h*(PPA - LCOE_h)}{\left(1+\ DR_0*\left(\frac{P_{inst,h}}{P_{inst,0}}\right)^b\right)^i} \tag{7}$$

Inputs		Indices
η: Efficiency	LR: Learning Rate	0: Starting Year
b: Learning Coefficient	N: Project Lifetime	h: hth Implemented Plant
CAPEX: Capital Expenses	NPV: Net Present Value	inst: Installed
CRF: Capital Recovery Factor	OPEX: Operational Expenses	H: Total Number of Implemented Plants
DR: Discount Rate	P: Installed Capacity	net: Nominal Net Power Output
E: Annual Electricity Production	PPA: Tariff from Power Purchase Agreement	trans: Transmission
i: Year of Plant Implementation	PR: Progress Rate	
LCOE: Levelized Cost of Electricity		

3.1.4. *Provincial electricity demand and electricity tariff*

The dataset of provincial electricity demand was extracted from BPS Statistics Indonesia [32]. Based on the growth since 2000 [1,2] and the projected development until 2050 [3], this paper assumes a uniform constant electricity demand growth rate r_{dem} of 6.4% p. a. for all provinces. The model does not take into account load variations, but only the total demand within a year. In practice, OTEC would occasionally be shut down in times of low demand and a continuous operation at full capacity might not be possible.

Under the current renewable energy regulation, the remuneration for renewables is based on the basic cost of electricity production in Indonesia, also referred to as *Biaya Pokok Penyediaan (BPP)*. Next to a national BPP of 7.85 US¢/kWh in 2018, there are also regional BPP, which varied in 2018 between 6.91 and 21.34 US¢/kWh [33]. Depending on technology and region, different fractions of the BPP are used as a benchmark for *Power Purchase Agreements (PPA)* between the state-owned utility company and the plant operator. For OTEC, the PPA tariff can be up to 85% of the regional BPP if it is higher than the national BPP. If the regional BPP is equal or lower than the national BPP, the PPA tariff is based on negotiations with the state-owned utility company [34,35]. For simplicity, all PPA tariffs are assumed to be equal to 85% of the local BPP, resulting in a PPA tariff range of 5.87–18.14 US ¢/kWh [33]. It is further assumed that these PPA tariffs stay constant for the entire useful lifetime of the plant.

These assumptions bear some limitations that are discussed here. In practice, many PPA tariffs would probably be lower, as the 85% rule merely functions as a cap, but not as a guaranteed tariff. Therefore, the profitability of OTEC plants might be overestimated in regions where the local BPP is higher than the national BPP. On the other hand, the profitability might be underestimated in high-demand regions like Java, Sumatera, and Bali, where the regional BPP is lower than the national BPP. Furthermore, the BPP will most likely not stay constant throughout the perceived timespan. Renewable energy policies in Indonesia were frequently subject to fundamental changes in the last years with varying effects on the technologies' implementation [36]. The stimulation scheme on which this study foots is relatively new itself and thus does not allow the extrapolation of PPA tariffs. Practically, the PPA tariffs assumed in this study would probably not persist over the perceived timespan, and upcoming reforms might affect the upscaling potential of OTEC in an unpredictable way. Despite these limitations, the results presented here provide a useful projection of the long-term profitability of OTEC.

3.2. *Upscaling model*

The logic of the model is summarised in the flowchart depicted in Fig. 1. The implementation of OTEC starts at year $i = 1$ in the year 2021 and ends at year $i = 30$ in the year 2050. At the start of each year *i*, the annually growing variables are updated, namely the maximum OTEC system size P_{max}, the implementation goal P_{goal} and the provincial electricity demand $E_{dem,prov}$. It is assumed that the maximum available system size grows at the same rate as the implementation goal, namely by the OTEC growth rate r_{OTEC}. While the implementation goal can grow unlimitedly, the maximum system size P_{max} is capped at 100 MW, as it is a large-scale size commonly analysed in OTEC literature [16,18] and assumed to be adequate for most provinces in Indonesia.

Next, the model enters an implementation loop, in which the difference P_{diff} is calculated between implementation goal P_{goal} and currently installed capacity P_{inst}. If P_{diff} is smaller than the smallest available system size P_{min}, the implementation goal is considered fulfilled and the next year is initiated. In this paper, a P_{min} of 10 MW was chosen based on the recent efforts to build such a system in Hawai'i, China and Martinique [37]. If P_{diff} is higher than P_{min}, the implementation goal is not fulfilled yet and the model tries to implement more systems.

Regarding the selection of a suitable site, the model differentiates between a supply- and demand-driven logic. If there is enough demand across provinces for the electricity supply of the maximum available system size $E_{sup,max,i}$ from $P_{max,i}$, the model acts supply-oriented and picks the most favourable site based on a weighted index. The index by which the available sites are ranked consists of the distance from the plant to a populated connection point and the local PPA tariff as shown in equation (8). These two site criteria were found to have the highest influence on OTEC's profitability [9]. The smallest distance and the highest PPA tariff within the dataset of available OTEC sites are used as references for the index to ensure that the model selects sites close to shore with high enough tariff.

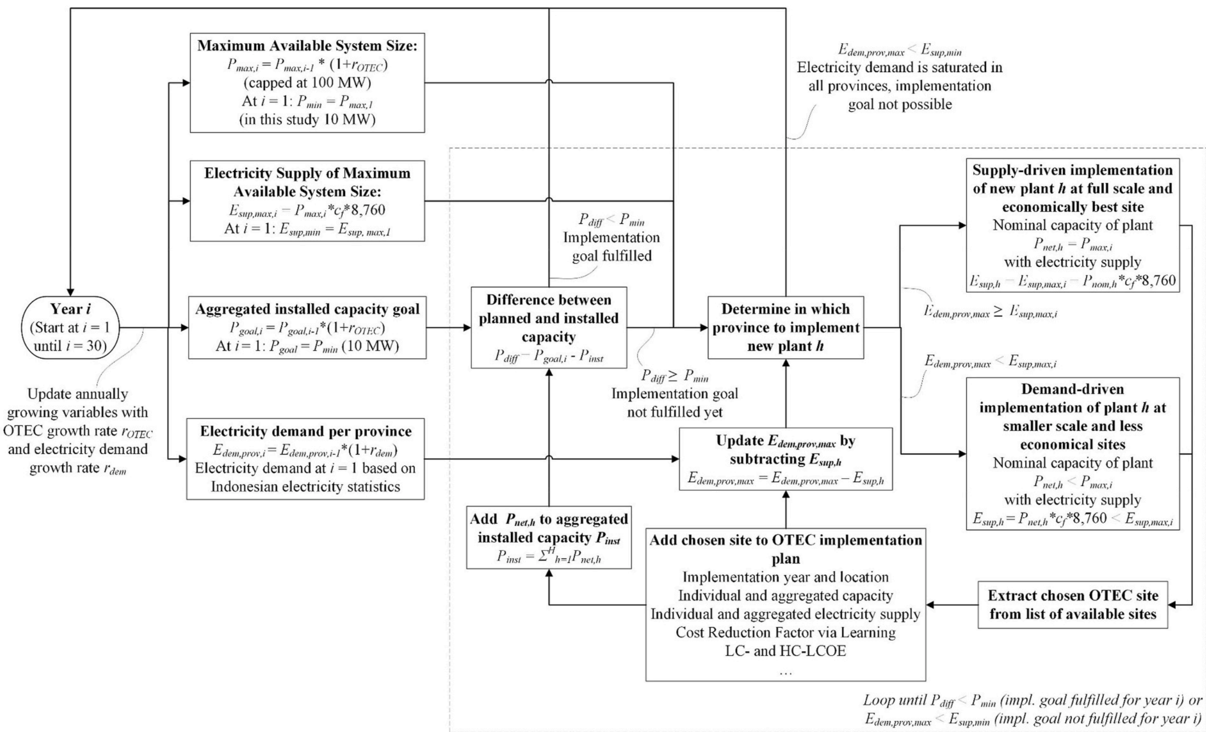

Fig. 1. Flowchart of the upscaling model used in this study.

$$Index_h = \frac{d_{min}}{d_h} * \frac{PPA_h}{PPA_{max}} \tag{8}$$

Inputs	Indices
d: Distance between OTEC Plant and Connection Point	h: hth Implemented Plant
PPA: Tariff from Power Purchase Agreement	min: minimum max: maximum

If the remaining demand in every provinces is lower than $E_{sup,max,i}$, the model switches to a demand-driven logic. In that case, the model picks the province with the highest remaining electricity demand $E_{dem,prov,max}$ and chooses an appropriate plant size below P_{max} to cover as much of that demand as possible. The sites at the province available for selection are again ranked by the above-mentioned index.

After a site has been selected, it is removed from the set of available sites and added to an implementation plan with details like implementation year and location as well as individual and aggregated capacity and electricity production. Once a site is occupied, it is not available throughout the plant's lifetime N of 30 years. The capacity of the newly selected plant is added to P_{inst}. P_{diff} is recalculated and the implementation loop starts anew.

If $E_{dem,\ prov,max}$ is lower than the electricity production of the smallest available OTEC plant $E_{sup,min}$, the model breaks the implementation loop and continues with the next year, as no more OTEC plant can be implemented without oversupplying the province. In such case, the implementation goal cannot be fulfilled.

3.3. Sensitivity analysis and nationally uniform feed-in tariff

The goal of this study is not to specify one favourable scenario under rigid boundary conditions, but to indicate the impact of individual variables on the upscaling scenarios and key metrics like aggregated installed capacity, aggregated NPV and LCOE. For this, the discount rate DR, learning rate LR, and demand growth rate r_{dem} are varied and their impact on the outputs is assessed. Moreover, a nationally uniform FIT is presented as an alternative to the regionally varying PPA scheme which is currently used. For this, the regionally varying BPP benchmarks in the dataset are swapped for a uniform FIT. As in the other scenarios, the uniform FIT does not change throughout time and is perceived as an average FIT. However, such an average FIT would not offer insights on the subsidy requirements of pioneer plants with costs above average, which is why the concept is expanded with an annually updated FIT scheme based on the average values.

4. Results and discussion

4.1. Impact of the OTEC growth rate on costs and capacity

Fig. 2 shows how the OTEC growth rate r_{OTEC} affects (a) the final installed capacity, (b) the aggregated NPV at the end-state of the scenario, and (c) the average LCOE of the implementation scenarios.

In Fig. 2(a), the aggregated installed capacity rises with r_{OTEC} until reaching a plateau at 45 GW at a growth rate of 34% per year. The exponential growth cannot be maintained, because supply growth eventually outpaces demand growth. Consequently, the regions that are suitable for OTEC become maximally saturated with OTEC and a higher growth rate merely leads to a faster saturation, but not to higher aggregated capacities. With an annual electricity production of 339 TWh, 45 GW of OTEC could cover 22% of Indonesia's electricity demand in 2050. These results show both OTEC's potential and hurdles, not only in Indonesia but worldwide. Large-scale OTEC could become a centrepiece in global energy systems, but only where there is sufficient demand. Even in a country of the size of Indonesia, local electricity demand proves to be a major bottleneck and the technical, economic, and ecological benefits of full-size OTEC cannot be fully harnessed in some areas. This indicates that only tiny fractions of the global theoretical and technical OTEC potential can be tapped economically. For example, in island states in the Pacific, where ocean thermal resources are especially high [6,11], a few small-scale plants would already be

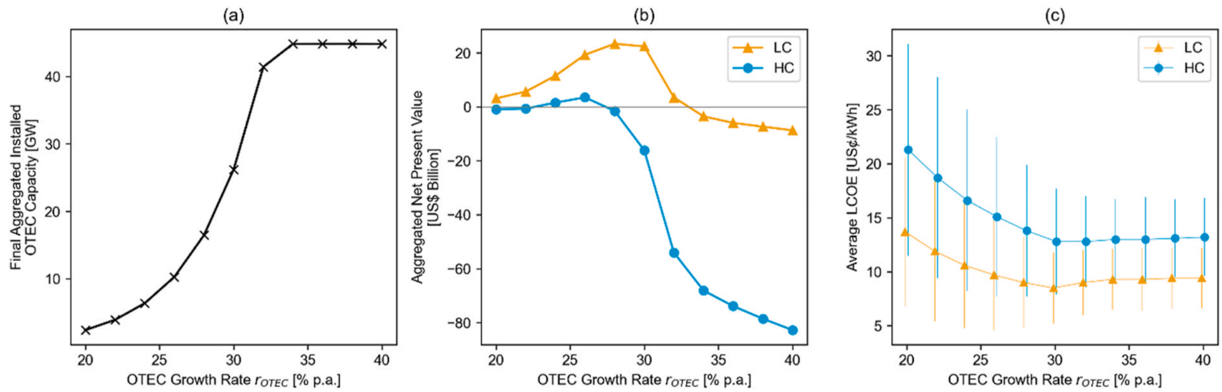

Fig. 2. The influence of the OTEC growth rate r_{OTEC} on the (a) aggregated installed capacity, (b) aggregated net present value after 60 years, and (c) average LCOE (error bars show standard deviation).

sufficient to cover demand.

The scenarios are evaluated based on the aggregated NPV, which reflects the cash balance at the end-state of the scenario. For scenarios with an aggregated NPV $\geq$0, the economic potential encompasses the capacities of all installed plants. This includes plants with a negative NPV, as the experience gained from these plants reduces the costs of follow-up plants, which then are profitable. As seen in Fig. 2(b), the aggregated NPV is highest at annual growth rates of 26–28% with a total installed capacity of 9–16.5 GW and a NPV of US$ 3–23 billion, respectively. The NPV reaches zero at growth rates between 24% and 32% and lead to an economic potential of 6–41 GW. To illustrate what these OTEC growth rates mean, it might help to compare them to the global growth rates of solar PV and wind power. Between 2009 and 2019, solar PV and wind power capacity grew on average by 39% and 15% per year, respectively [38]. Hence, OTEC would have to grow at a rate higher than wind power and lower than solar PV. Given how much policy support these two maturing technologies received in the last decades, this paper shows that strong global policy support will also be necessary for OTEC to make a meaningful contribution to the global energy transition in the near future. Illustrations like Fig. 2(b) might help to show that public investments in OTEC could eventually pay off not only ecologically but also economically. To the authors' knowledge, this study is the first to discuss OTEC's required growth, the way to enable such growth, and its possible economic merit. With these contributions, this study has the potential to encourage the field to shift from a solely engineering-oriented perspective to a more multidisciplinary one that draws the attention of global decision makers.

A minimum average LCOE between 8.5 and 12.8 US¢/kWh can be reached at an annual growth rate of 30% as shown in Fig. 2(c). At lower growth rates, OTEC is scaled up slower and full scale is reached later. Due to the weaker economies of scale of small-scale and medium-scale plants, the average LCOE is higher. At growth rates higher than 30% per year, the LCOE also rises, as fewer large plants can be implemented without oversupplying the respective provinces. Instead, more small-to mid-sized plants are implemented with weaker economies of scale. Furthermore, to maintain such high growth rates, more and more OTEC plants must be implemented. First, these systems are deployed in high-quality sites close to shore with high local PPA tariffs. But eventually, the model is forced to use economically less attractive sites further away from shore. The consequent increase in power transmission costs and losses increase the average LCOE. Shown as error bars in Fig. 2(c), it can be seen that the standard deviation of the sample of LCOE decreases with r_{OTEC}. At low growth rates, the standard deviation is calculated with a rather small sample size, as only few plants are implemented with even fewer full-size systems. At higher growth rates, more and more larger systems are implemented, which increases the sample size. Since the model tries to deploy as many full-size systems as possible with lower and less sensitive LCOE, the standard deviation decreases at these OTEC growth rates. The global significance of the LCOE and their ranges is discussed in more detail in the following section.

4.2. Results of the scenario with highest NPV

This section presents the key results of the scenario that yielded the highest aggregated NPV at r_{OTEC} of 28% p. a. Fig. 3(a) shows that OTEC implementation proceeds exponentially without restrictions by electricity demand with a final aggregated capacity of roughly 16.5 GW. Within the context of Indonesia's national energy plan, OTEC could be as important to Indonesia's future power system as already established renewables like geothermal [3]. However, OTEC would not be able to fully replace Indonesia's coal power capacity, which was 31.6 GW in 2018 [39].

In this scenario, the first 100 MW OTEC plant is implemented after 16 years. This is reasonable as the main priorities in the first decade would probably be the collection of operational data and monitoring of pilot plants. Due to technological learning from these initial projects, larger systems would follow at lower costs. This interpretation adds a practical touch to the otherwise hypothetical scenario and offers a novel perspective to the upscaling period of 5–6 years in literature [16,18]. With more and more countries suitable for OTEC pledging to carbon neutrality by 2050 or 2060, like USA [40], Brazil [41], and Indonesia [42], this finding is important as it shows that OTEC could be scaled up fast enough to make a meaningful contribution to fulfilling these pledges.

The LCOE of all implemented plants form two experience curves as presented in Fig. 3(b). They illustrate the development of LCOE throughout time and cumulative capacity, from an initial range of 33.9–50.7 US¢/kWh for the first pioneer plant to 6.2–9.9 US¢/kWh in 2050 after reaching maturity. However, the LCOE does not drop indefinitely. After a decline to a minimum of 6.2 US¢/kWh, the LCOE tends to rise again. Attractive sites close to shore and with high PPA tariffs become more scarce, resulting in the selection of gradually economically less attractive sites. This is in line with practical observations made in the offshore wind industry. There, the trend of going further offshore also led to increased CAPEX, although this probably stems more from the motivation of utilising the higher wind speeds further offshore for higher electricity yield than from the depletion of implementation sites [43].

Throughout the scenario, the system costs of 100 MW plants were driven down by 43%, which exceeds the estimations in literature [16,18,19]. This is due to the assumption of continuous learning, which is not restricted by fixed cost reduction rates [16,19] or doublings of output [18] as described in Section 2. Despite the usefulness of the learning rate for this study and the research field as a whole, a constant single-factor learning rate as used here has limitations, which are briefly addressed. First, the cost reductions in Fig. 3(b) cannot be pinpointed to specific learning mechanisms, which would have been possible with a

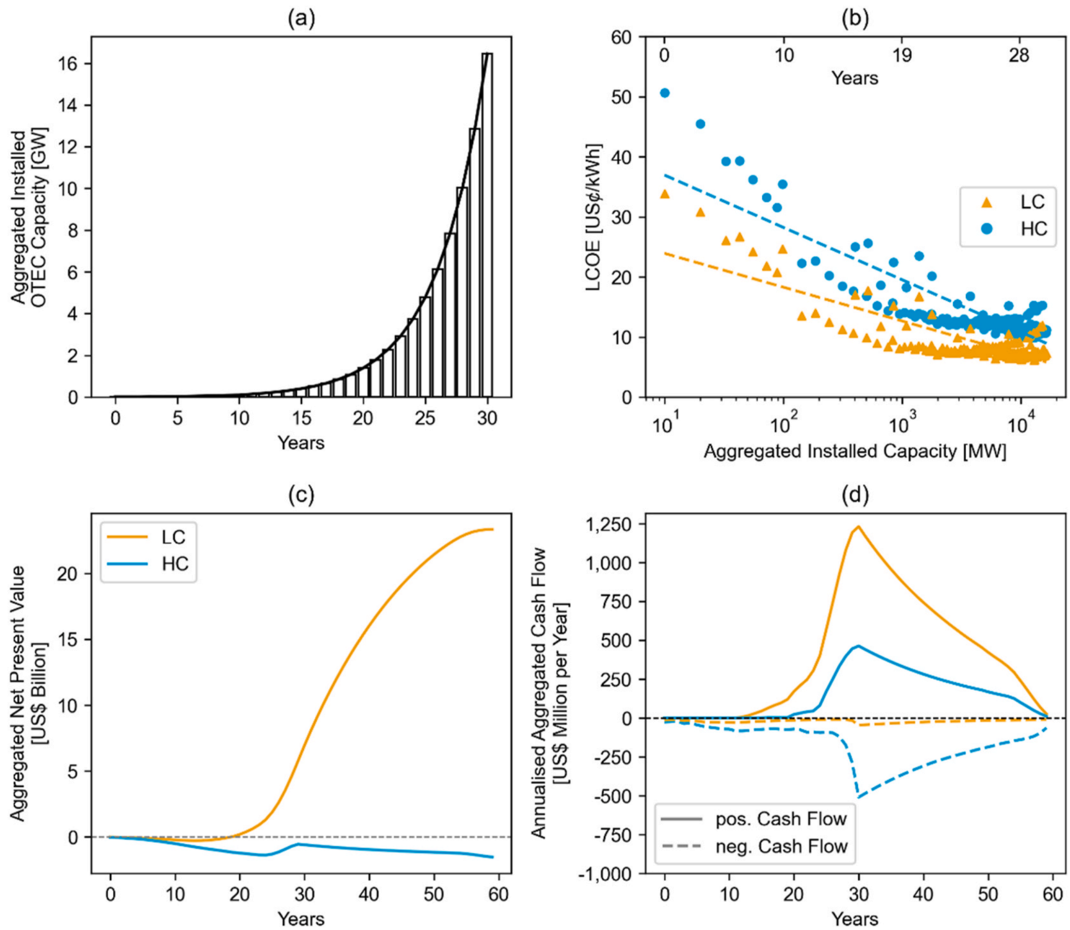

Fig. 3. Results of the highest-NPV scenario. (a) Aggregated installed capacity. (b) LCOE over aggregated installed capacity and time. Interpolating through these LCOE yields the experience curves shown as dotted lines. (c) Aggregated NPV. (d) Annualised aggregated cash flows.

multi-factor rate. Second, the learning rate is not constant in practice and can vary over time [44,45]. But since it is not yet possible to predict the impact of individual learning factors on OTEC's costs, the simplified approach in this paper is adequate until more practical data is available.

Fig. 3(c) depicts the aggregated NPV, where HC-OTEC does not break even, as many full-scale projects remain unprofitable late into the scenario as seen in Fig. 3(d). LC-OTEC collectively breaks even after 20 years and yields US$ 23 billion after 60 years. Before the breakeven point, negative net cash flows of pre-maturity plants accumulate to a total of US$ 378 million, which could be understood as the total financial support required for OTEC contractors to break even with all costs at the end of the lifetime of these pioneer plants. This sum is only a fraction of what the Indonesian government spent on electricity subsidies in 2018 with roughly US$ 3.4 billion [46], so a reallocation of public subsidies could be a way to finance OTEC's upscaling. Globally, international banks could take the lead especially for SIDS where public spending might be more restricted. Also in terms of mere investment costs, OTEC's funding is feasible. Until breakeven after 20 years, OTEC would require US$ 2.5–4.6 billion of investment, which is considerably less than the US$ 10.5 billion that the World Bank invested in fossil fuels in the five years since the Paris Agreement [47]. This paper shows that OTEC's upscaling, despite its capital intensity, could be easily funded, either via public support or private engagement.

OTEC could cover 43.6% of all supplied provinces and 8.4% of national electricity demand, respectively. Table 2 shows how both average LC- and HC-LCOE are below the average local PPA tariff, thus implying the cost-competitive supply of up to 99% of local electricity demand. Fig. 4(a) shows the distribution of OTEC plants and their sizes across Indonesia in the NPV-optimised scenario. Small-scale OTEC is primarily implemented in rural provinces like Maluku and Maluku Utara, while large-scale OTEC is deployed on larger and more urbanised islands like Sumatera and Bali. These insights are used for the global OTEC upscaling concept in Section 4.5.

The island of Java has by far the highest electricity demand in Indonesia, as well as many suitable sites for OTEC plants. However, no plant was implemented in Java in the highest-NPV scenario. This is because OTEC sites and connection points in Java tend to be further away from shore compared to other high-demand islands like Sumatera and Bali, thus increasing costs. But at annual OTEC growth rates above 30%, implementation shifts noticeably towards Java. Fig. 4(b) shows the implementation of OTEC across Indonesia at an annual growth rate of 40%. In that scenario, 45 GW of OTEC could cover 22% of national electricity demand.

Another key result is OTEC's economic viability within Indonesia's electricity mix. As seen in Fig. 5, large-scale OTEC could be cost-competitive against all other energy technologies currently deployed in Indonesia. This is in good agreement with Vega [16], who estimated cost-competitiveness for a range of 50–100 MW. Embodied in Fig. 5 is the implicit assumption that the LCOE of all competing technologies will not change in the next thirty years. But unlike OTEC, these competitors have been on the market for several decades and already benefitted from cost reductions.

The competitiveness of OTEC in Indonesia could also be explained by the challenges renewables generally face there [5]. If the USA is used as the reference, OTEC is not competitive against solar PV and wind power even at full scale and after 30 years of learning. But against other baseloads like geothermal and coal, medium-scale and large-scale OTEC remain competitive. This indicates that OTEC could be an economically

Table 2
Key results of the highest-NPV scenario per province. The PPA tariff is weighted based on installed capacity.

Province	Aggregated Installed Capacity [MW]	Weighted Average PPA Tariff [US¢/kWh]	LCOE [US¢/kWh] $\bar{x} \pm \sigma$		Supply of Electricity Demand [%]
			LC	HC	
Sumatera Barat	2300	11.5	8.1 ± 1.4	12.1 ± 1.3	79.3
Aceh	2092	10.0	7.4 ± 0.1	11.7 ± 0.3	98.8
Sulawesi Selatan	1500	7.0	6.9 ± 0.3	10.6 ± 0.3	33.4
Nusa Tenggara Barat	1400	15.4	7.8 ± 0.4	12.2 ± 0.6	96.1
Sulawesi Utara	1354	11.8	9.1 ± 5.2	14.6 ± 7.4	99.5
Sumatera Utara	1300	16.7	9.0 ± 1.3	13.0 ± 1.1	14.9
Sulawesi Tengah	900	16.3	7.8 ± 0.3	12.2 ± 0.7	94.0
Sulawesi Tenggara	700	14.1	8.0 ± 0.7	12.9 ± 1.3	94.0
Papua	689	14.6	8.8 ± 3.4	12.9 ± 4,7	92.3
Nusa Tenggara Timur	667	17.4	9.6 ± 1.8	15.4 ± 2.8	88.3
Bali	600	5.9	6.7 ± 0.2	10.6 ± 0.1	14.0
Bengkulu	600	6.3	6.8 ± 0.2	10.7 ± 0.1	80.8
Maluku	481	17.8	17.1 ± 8.1	25.5 ± 11.8	99.1
Kalimantan Timur	400	9.0	7.6 ± 0.2	11.1 ± 0.1	13.3
Papua Barat	400	14.3	7.5 ± 0.6	11.7 ± 0.7	85.9
Gorontalo	300	11.4	7.3 ± 0.0	11.3 ± 0.2	72.7
Maluku Utara	273	17.2	12.5 ± 5.8	19.5 ± 8.7	83.0
Lampung	200	7.0	6.9 ± 0.2	10.6 ± 0.1	5.7
Sulawesi Barat	200	6.2	6.8 ± 0.5	11.4 ± 1.1	71.6
Kalimantan Utara	100	9.0	8.0 ± 0	11.4 ± 0	65.4
Total	**16,455**	**12.7**	**8.9 ± 8.4**	**13.8 ± 12.2**	**43.6**

attractive baseload not only in Indonesia, but also other countries and the economic potential of OTEC there should be addressed in future research.

4.3. Sensitivity of scenario with highest NPV

As explained in more detail in the methodology section, a novel feature of the upscaling model is the use of a dynamic discount rate. Not only do CAPEX and OPEX decrease with experience, but also the cost of finance, represented by the discount rate, as the risk associated with the technology will gradually decline.

With this assumption, Fig. 6(a) shows that OTEC could be profitable even at high initial financing costs, as long as these costs decline at later stages. If the financing costs remain static, a discount rate of 5–13% is required to break even with costs in 2050, while the range changes to 10–20% with a dynamic rate. Considering that the interest rate on a concessionary loan from the *Asian Development Bank (ADB)* can be as low as 2% [50], the above-mentioned discount rates could be feasible for many developing countries. Fig. 6(a) also illustrates how the effects of discount rate dynamisation become less prominent with the increase of the initial discount rate. In the case of HC-OTEC, a high dynamic discount rate even leads to a worse NPV compared to a static one. This can be explained by the nature of the discount rate. The present value of future cash flows declines with an increasing discount rate. As shown in Fig. 3(d), most HC-OTEC plants remain unprofitable even after reaching full scale. Hence, a high discount rate devalues financial losses and instead puts a stronger value on the cash flows of early pioneer plants. This phenomenon is far more prominent for HC-OTEC than for LC-OTEC, since the latter is profitable after reaching full scale. Thus, a devaluation of future positive cash flows does not improve the aggregated NPV in the LC-case. In the scenario with the highest aggregated NPV, the discount rate drops to 5% after 30 years, which harmonises with the rates for more mature technologies [51]. However, the discount foots not only on technology, but many other, non-technical influences [24]. Therefore, the reduction of discount rate shown here should be validated in more detail in future research.

Fig. 6(c) and (d) illustrate the strong impact of the learning rate on OTEC's profitability. A doubling of learning rate from 7 to 14% would increase NPV by almost a fourfold. While LC-OTEC could collectively break even at a learning rate of 4%, HC-OTEC requires a rate slightly above 7%. These learning rates are smaller than the average learning rates observed for other power generation technologies, which were 8% for coal, 14–15% for gas, 12% for wind power, 23% for solar PV, and 11–32% for biomass [51]. This indicates that the cost reductions presented here could be feasible and might even be higher if OTEC's learning rate follows the ones of other power generation technologies.

The relationship between electricity supply and demand can be seen in Fig. 7. If the OTEC growth rate r_{OTEC} is too high, supply eventually outpaces demand and the growth slows down. In such a case, an increase in electricity demand growth r_{dem} provides more room for OTEC implementation and at a certain point allows unhampered upscaling, as depicted in Fig. 7(a) at a r_{OTEC} of 32% per year. This and Fig. 7(b) support the results from Section 4.1 regarding the bottleneck imposed by electricity demand and its growth. The aggregated NPV is lowest at a r_{OTEC} of 32% p. a., because the model resorts to small- and medium-scale plants at low-PPA-tariff locations to meet the implementation targets. This growth rate only becomes economically viable if it is matched with a high demand growth r_{dem}. For a r_{OTEC} of 32% p. a., breakeven is achieved at a sustained annual demand growth r_{dem} of 6–9%. Then again, if r_{dem} is higher than r_{OTEC}, NPV as well as LCOE stabilise as shown in Fig. 7(c). At a sufficiently high r_{dem}, the model locks in on few provinces with high availability of close-to-shore sites and high PPA tariffs. Eventually, an optimum implementation configuration is reached and a further increase of demand growth has no effect on OTEC implementation.

Until now, it was assumed that OTEC may cover as much of Indonesia's electricity demand as possible. In practice however, most of that demand is already covered by other power generation technologies, today by fossil-fuelled generators, in the future by renewables. So, how does electricity demand affect OTEC's upscaling in a competitive environment? In large countries like Indonesia, electricity demand will probably be even more restrictive than assumed in this study due to the broad set of renewables that are and will be deployed there over the next years [3,52]. In SIDS, where most electricity is produced via expensive, imported Diesel [53,54] and where there might not be enough area for solar PV and onshore wind power [55], OTEC might face less competition. Then again, electricity demand in SIDS is not particularly high and can already be met with small OTEC plants. Thus, to materialise the economic potentials shown in this study, OTEC must prevail against strong global competition from fossil and renewable energy technologies and will probably rely on sustained public and private support to do so.

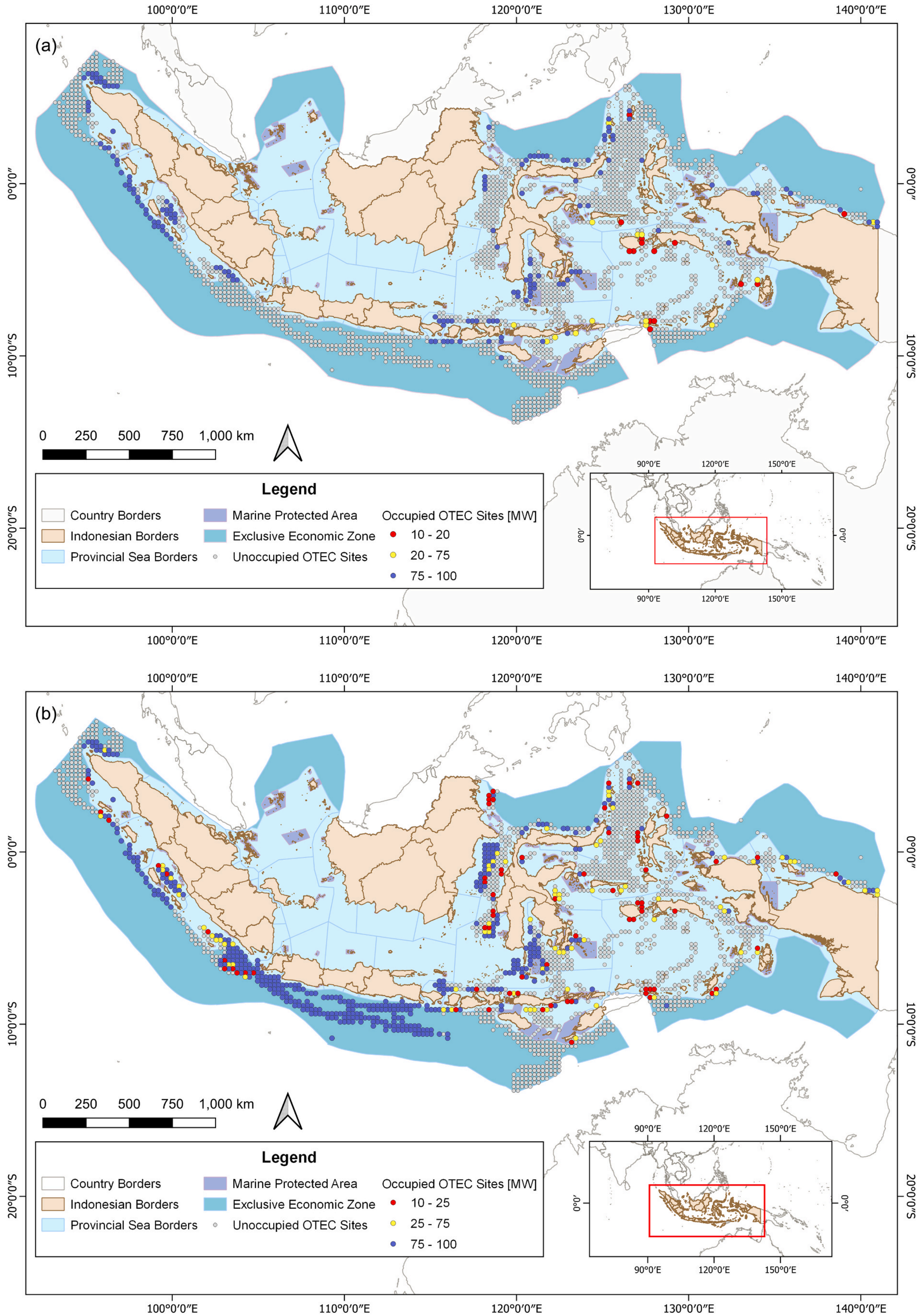

Fig. 4. Map of available and occupied OTEC sites including system size for the (a) highest-NPV and (b) maximum possible capacity scenario.

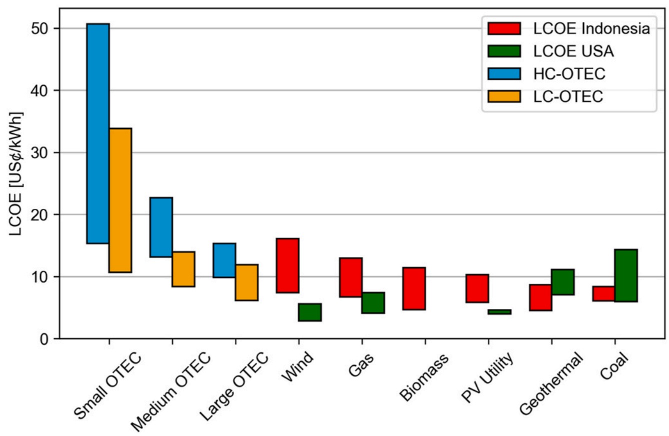

Fig. 5. OTEC's competitiveness against other energy technologies in Indonesia in 2019. Small OTEC < 20 MW, medium OTEC 20 MW < P_{net} < 75 MW, large OTEC 75 MW < P_{net} < 100 MW. Gas includes open-cycle, closed-cycle, and combined-cycle. Coal refers to subcritical plants. LCOE of competing technologies based on [48] in Indonesia and based on [49] in USA.

4.4. Impact of a nationally uniform FIT

All results above adhere to the existing PPA-based support scheme in Indonesia. This section briefly presents a novel FIT-based scheme and its impact on the NPV. Fig. 8(a) only shows a linear increase of NPV, as only the profit margin changes while the installed capacity and LCOE remain unaffected. To break even in 2050, an average FIT of roughly 8–12 US ¢/kWh is needed. This could be reflected by a FIT scheme as depicted in Fig. 8(b), in which the FIT starts at 34–50 US¢/kWh and eventually decreases to around 7–11 US¢/kWh. To gain the same NPV for LC- and HC-OTEC as shown in Section 4.2, an average nationally uniform FIT of roughly 12–14 US¢/kWh would be required.

In recent years, subsidies on fuels and electricity have strained Indonesia's state budget considerably [5]. At first glimpse, this FIT scheme might be seen as an additional burden. However, the initial high rates would only apply to a few pilot plants. For example, the first implemented OTEC plant requires a FIT of maximally 50 US¢/kWh to compensate US$ 40 million of annualised lifecycle cost. This is only 1.2% of total electricity subsidies paid out by the Indonesian government in 2018. Moreover, at a range of 7–12 US¢/kWh starting from year 22 in Fig. 8(b), one might wonder whether the FIT would have to be financed by subsidies at all, given Indonesia's electricity tariff of 5.7–10.1 US¢/kWh in 2018 and its recent upwards trend despite subsidies [56]. Nevertheless, the concept presented here needs further refinement, e.g. on the impact on stakeholders within and outside the electricity sector.

4.5. Towards a global OTEC upscaling strategy

The OTEC upscaling scenario presented in Section 4.2 can be expanded to a global OTEC upscaling strategy as shown in Fig. 9. Initial small-scale plants would be implemented in SIDS and small islands of larger countries. This makes sense, because these islands need an alternative to fossil fuels as fast as possible. Moreover, although the LCOE of small-scale OTEC is rather high, it might still be lower than the current costs for imported diesel [57] and thus near-term implementation of OTEC is economically reasonable. These initial plants could be funded by international institutions like the World Bank or ADB with

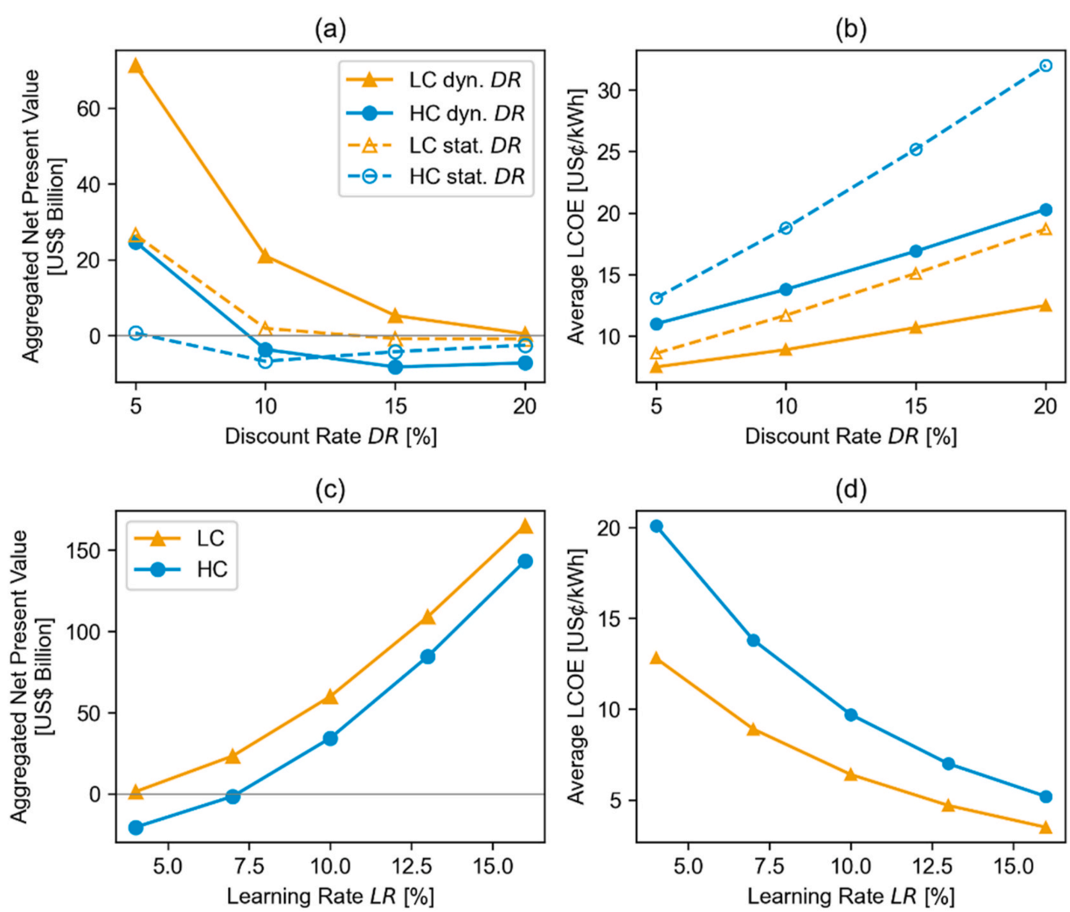

Fig. 6. Impact of discount rate *DR* on (a) aggregated NPV and (b) average LCOE and impact of learning rate *LR* on (c) aggregated NPV and (d) average LCOE.

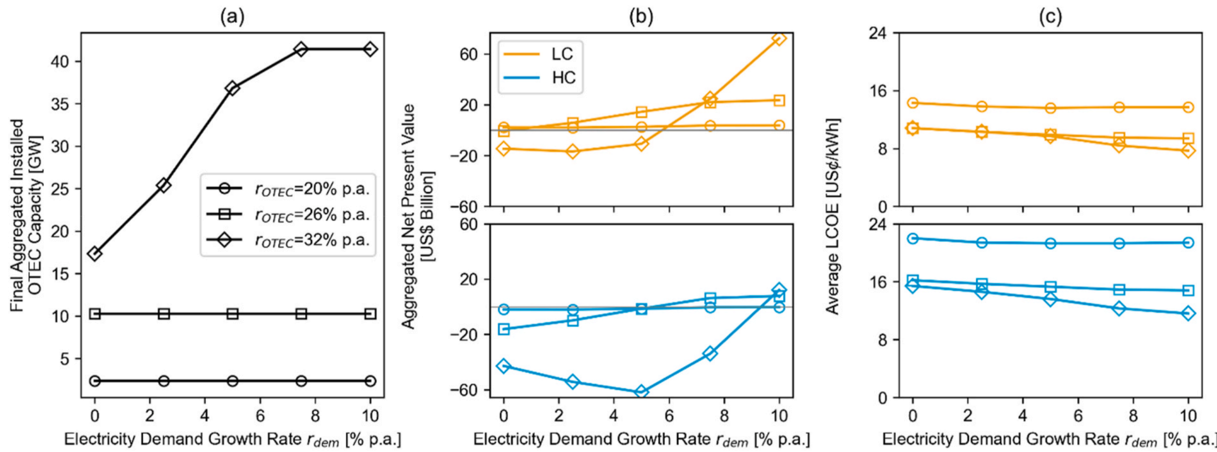

Fig. 7. Impact of electricity demand growth r_{dem} for LC-OTEC and HC-OTEC and different r_{OTEC} on (a) aggregated capacity, (b) aggregated NPV, and (c) average LCOE. To avoid repetition, the legends for LC-OTEC, HC-OTEC, and r_{OTEC} are only shown once, but they apply for all three figures where relevant.

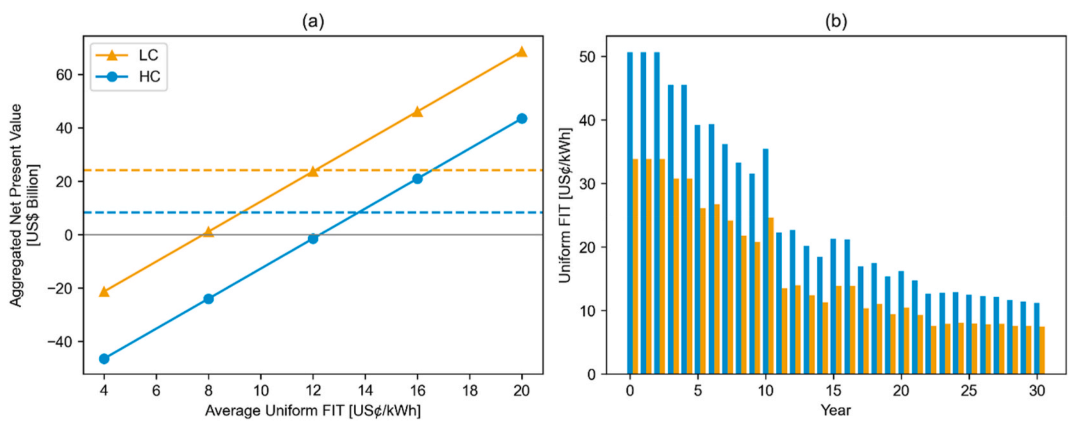

Fig. 8. (a) Impact of a nationally uniform FIT (Solid Lines) compared to the current PPA scheme (Dashed Line) on aggregated NPV. (b) Annually updated FIT scheme to break even in 2050.

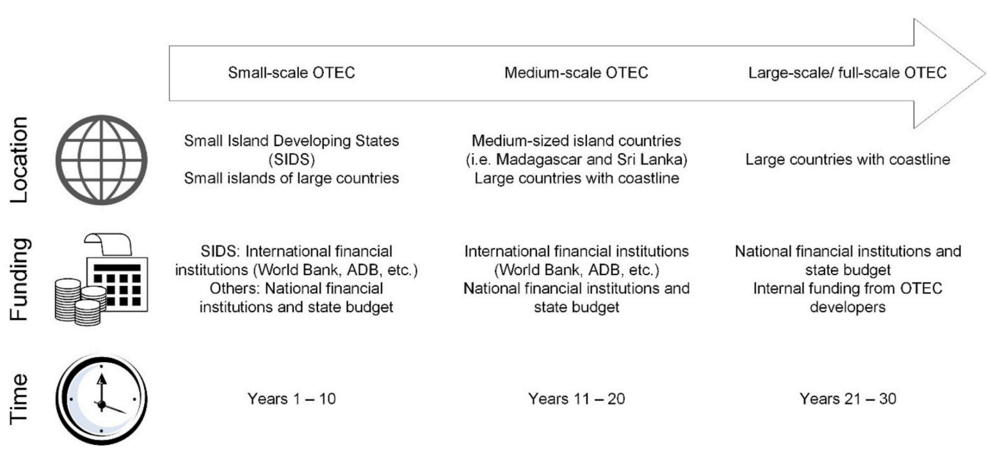

Fig. 9. Proposed global upscaling strategy for OTEC.

low-interest finance or the financing scheme proposed in Section 4.4. While these first plants are operating, policymakers could prepare the regulatory framework to streamline the permitting processes associated with OTEC, which today can take several years [16]. The experience gained from the pioneer plants paired with easier permitting would allow OTEC to diffuse at a faster pace to larger island states, where population and electricity demand are higher, e.g. Sri Lanka and Madagascar. As shown in Fig. 5, medium-scale OTEC could also make sense economically in large developed countries, so some plants could be implemented there as well. Depending on the state budget of these islands, these 2nd generation plants could be financed by national financial institutions, the state budget, or again by the international institutions above. Once OTEC reaches full scale, it can be implemented in large developed countries like Indonesia, USA, Japan, and many others. If the cost reductions shown in Fig. 3(b) materialise, OTEC might be profitable enough so that developers are able to finance their projects internally, at least partially.

5. Conclusion

This paper reports scenarios for the upscaling of *Ocean Thermal Energy Conversion* (*OTEC*) from small pilots to large-scale plants using a simulation model, which implements OTEC plants based on annual growth targets. Novel elements of the model include the (1) use of location-specific data like electricity demand, electricity tariff, and investment costs as a function of distance to shore and seawater temperature difference, as well as (2) the inclusion of technological learning as a cost-reducing mechanism on both investment cost and cost of finance. Upscaling is simulated in Indonesia, but discussed globally as this diverse country can serve as a proxy for many other regions worldwide. This study shows OTEC's promises as well as its barriers. On the one hand, OTEC could make a significant contribution to the decarbonisation of global energy systems, with up to 45 GW in Indonesia. OTEC's commercialisation could be financed easily either via reallocation of electricity subsidies or with loans from international banks. These investments could pay off, as 16.5 GW in Indonesia could yield more than US$ 23 billion by 2050. The rate by which OTEC's costs would have to decline is relatively small compared to other power generation technologies. Based on the *Levelized Cost of Electricity (LCOE)*, medium-scale to large-scale OTEC could be competitive against other baseload generators. On the other hand, this study shows that most likely only a tiny fraction of the massive global theoretical OTEC potentials in literature can actually be tapped economically. In regions where resources are the highest, e.g. in the Pacific, population and electricity demand are too low and can already be met with small, less economic OTEC plants. Therefore, large-scale OTEC will probably only be relevant for an exclusive group of sufficiently large countries in the tropics and subtropics. If OTEC should play a role in reaching carbon neutrality as pledged by several countries, it would require capacity growth rates in the dimensions between wind power and solar PV, both of which enjoyed sustained global policy support for decades. However, OTEC's upscaling will require global efforts and collaboration beyond country borders. To initiate this, OTEC must reach the desks of public and private decision makers as soon as possible. The capital to fund OTEC is there, the technology to build OTEC, at least on small scale, is also there. The only thing that is missing is commitment from people outside the field. Since most global decision makers probably have never heard of OTEC, proponents must convey the technology's unique benefits and address the concerns of opponents. This might generate enough confidence to boost its development. For this, the *Feed-In Tariff (FIT)* scheme and the global upscaling strategy presented in this paper might get more relevant and provide a roadmap to guide OTEC's expansion. All of these things might sound daunting. However, as shown in this paper's model, upscaling OTEC would benefit millions of people by providing reliable, clean electricity. Therefore, the endeavour, albeit challenging, is worthwhile.

Data availability

The dataset related to this article can be found under the DOI 10.4121/16,634,908, hosted at the repository 4TU.ResearchData.

Author contributions

JL: Conceptualization; Data curation; Formal analysis; Investigation; Extension of Methodology; original draft. JQ: Contributions to methodology; Supervision; Validation; Writing - review & editing. KB: Contributions to methodology; Supervision; Validation; Writing - review & editing.

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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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