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282 Harnessing the economic potential of ocean thermal energy conversion in Indonesia with upscaling scenarios

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Abstract

Ocean Thermal Energy Conversion (OTEC) produces electricity using the temperature difference between warm surface and cold deep seawater. Despite a gigantic theoretical potential of up to 44 PWh worldwide, OTEC is still at an early development stage and many countries cannot benefit from OTEC's clean and predictable baseload power yet. In a series of papers, the economic potential of OTEC was studied at an unprecedented depth. First, practically suitable sites for OTEC are mapped with a novel *Geographic Information Systems (GIS)* methodology. Then, the economic potential of OTEC at these sites was simulated with an upscaling scenario model that scales up OTEC from small pilot plants to full-scale commercial plants until 2050, considering the cost-reducing effects of technological learning and economies of scale. Indonesia is used as a case, the country with arguably the best prerequisites for OTEC in terms of ocean thermal resources and electricity demand. Including criteria like seawater depth and temperature as well as conservation zones, more than 1,700 practically suitable sites for OTEC are detected in Indonesia. Under the consideration of upscaling and economies of scale, the economic potential ranges between 6–41 GW_{net}. Among the studied upscaling scenarios, the highest aggregated *Net Present Value (NPV)* from OTEC is US$(2018) 24 billion in 2050. In that scenario, OTEC would have a significant impact on Indonesia's energy transition, with more than 8% of national electricity demand being covered in 2050. OTEC could be cost-competitive against any other energy technology in Indonesia. Notwithstanding these promising outlooks, this work also shows OTEC's challenges. Cost optimisation is essential from day one and learning effects must be strong and continuous over multiple decades. To which extent this is possible in practice is still unclear, but this paper shows that further development of OTEC is worthwhile, not only for Indonesia, but for many other countries worldwide.

Keywords

Ocean Thermal Energy Conversion, Economic Potential, Upscaling, Technological Learning, Indonesia

Introduction

Ocean Thermal Energy Conversion (OTEC) produces clean electricity with the temperature difference between warm surface and cold deep-sea water (Fujita et al., 2012; Vega, 2012). Despite a massive global resource potential of up to 44 PWh per year (IRENA, 2020), OTEC is still at an early development stage with small-scale pilots. Much is still uncertain about OTEC economics and a critical literature review (Langer et al., 2020) revealed seven knowledge gaps in contemporary literature, namely (i) absence of spatial economic analyses, (ii) omission of natural external influences on real power output, (iii) uncertainty of system and component cost, (iv) operational uncertainty, (v) impact of various risks on interest and discount rate, (vi) omission of technological learning, and (vii) omission of further economic assessment tools. Hence, it is unknown how much of the global resource potential can be tapped practically and economically, especially once OTEC has been scaled up from small-scale pilots to commercial large-scale systems. Tackling these knowledge gaps could be worthwhile, as OTEC could provide stable and affordable baseload to tropical regions and thus boost the energy transition there. This is especially relevant for Indonesia, the arguably most interesting country for OTEC in terms of ocean thermal resources (Asian Development Bank, 2014; Langer et al., 2021a), oceanography (GEBCO Compilation Group, 2020), and electricity demand. The world's largest archipelago is still dependent on domestic fossil fuel resources to meet the strongly growing national electricity demand (ESDM, 2020) and could thus benefit from OTEC as a renewable alternative.

This paper presents the methods and results of a series of studies (Langer et al., 2021a, 2021b, 2020) that shed light on six of the seven knowledge gaps above with the following research question:

Where are practically suitable sites for OTEC in Indonesia and what is OTEC's economic potential there considering upscaling and technological learning?

Knowledge gaps (i) and (ii) are addressed by mapping practically suitable sites for floating closed-cycle OTEC plants using a novel *Geographic Information System (GIS)* methodology. Knowledge gaps (iii) and (v–vii) are treated with upscaling scenarios until 2050 using a range of possible *Capital Expenses (CAPEX)* and *Operational Expenses (OPEX)*, cost-reducing technological learning rates, and economic assessment tools like *Levelized Cost of Electricity (LCOE)*, *Net Present Value (NPV)*, experience curves, and cash flow diagrams. This work contributes to the OTEC research field by shedding more light on OTEC's economic feasibility beyond today's state of the art. Recent discussions focus too much on current costs without taking into account that these costs will decline once the technology moves towards maturity. But since this process does not happen overnight, this paper also elaborates on the technical and economic prerequisites that have to be met for the upscaling scenarios shown here. The broader social relevance of this work comes from raising awareness about OTEC as an interesting option for the global energy transition for policymakers, renewable energy developers, and relevant institutions.

Methods

Mapping of practically suitable OTEC sites

This study follows the methods proposed by Langer et al. (2021a). Five years of daily seawater temperature data in Indonesia and its *Exclusive Economic Zone (EEZ)* are downloaded as point data from the *HYbrid Coordinate Ocean Model (HYCOM)* in a horizontal resolution of 27.8 km at depths of 0 m and 1,000 m. At these depths, the warm surface seawater and cold deep-sea water are extracted to drive an *Organic Rankine Cycle (ORC)* with ammonia as the working fluid. The horizontal resolution was chosen to limit local thermal degradation at the seawater exhaust pipes and the potentially negative ecological implications arising from it (Lockheed Martin, 2012; Nihous, 2010). Each data point is assumed to represent one OTEC plant. Then, the mesh of data points is projected over a map of Indonesia in the QGIS interface together with restrictive layers where OTEC cannot be implemented. These restrictions include water depth, average seawater temperature, and marine protected areas. Regarding water depth, areas with depths smaller than 1,000 m are excluded, as OTEC plants must extract sufficiently cold water from this depth to maintain the ORC. Moreover, sites with depths larger than 3,000 m are excluded to account for current technical limits of mooring lines (Ahmed Ali et al., 2019; Xu and Guedes Soares, 2020). At each point, the five-year temperature data is averaged and points with a temperature difference between surface and deep seawater of less than 20 °C are excluded. Lastly, points within marine protected areas (Direktorat Konservasi Kawasan dan Jenis Ikan, 2013) are removed as well. The output of this filtering process is a point layer that contains all practically suitable sites for OTEC. These practically suitable sites are then connected to adequately populated onshore connection points via marine power cables. In this study, the onshore connection points are regency capitals in Indonesia. Besides the distance from plant to connection point, the applicable electricity tariff at the connection point is assigned to the data points. In Indonesia, renewables are currently remunerated based on a *Power Purchase Agreement (PPA)* scheme, for which the maximally receivable tariffs for OTEC varied regionally between 5.87–18.18

US¢(2018)/kWh in 2018 (ESDM, 2019). These tariffs are assumed to stay constant throughout the upscaling scenarios.

Upscaling scenarios with technological learning

After obtaining the set of practically suitable sites, a model scales up OTEC from small pilots to large-scale systems over 30 years until 2050 (Langer et al., 2021b). At each year, an installation target is declared based on a growth rate chosen by the user, in the following called *OTEC growth rate*. The model tries to achieve the target by selecting favourable sites for OTEC deployment based on a (1) close distance to shore, a (2) high local electricity tariff, and a (3) sufficient electricity demand at the connected province. The electricity demand at the province is updated annually with a user-defined *demand growth rate,* which is assumed to be 6.4 % per year based on past records (ESDM, 2020, 2010) and official future projections (Presiden Republik Indonesia, 2017). If a province temporarily does not have demand for a new OTEC plant, it is not considered by the model until there is enough demand again in later years. In the upscaling scenarios, no other generation technologies are considered to meet the demand. In the beginning, the implementation targets are small and at OTEC's early development stage, only small-scale plants in the range of 10 MW_{net} are initially available to meet them. But with each year, the available plant sizes grow as it is assumed that plants can be built gradually bigger with growing experience. In this study, the maximum reachable system size is 100 MW_{net}, which is often used as a representative size for commercial, full-scale systems (Banerjee and Blanchard, n.d.; Martel et al., 2012; Oko and Obeneme, 2017; Vega, 2012).

For the techno-economic analysis of the scenarios, the LCOE is calculated for each plant that is deployed by the model using equation (1). To account for the high uncertainty of costs in contemporary literature, this study uses *Low-Cost (LC)* and *High-Cost (HC)* assumptions drawn from literature (Langer et al., 2020). The cost approximation functions for location-independent and location-dependent components are listed in Table 1. Additional techno-economic assumptions are listed in Table 2. Technological learning during the upscaling scenario is included by adjusting the CAPEX, OPEX, and discount rate of each implemented plant with a learning rate of 7% (Avery, 2003; Martel et al., 2012) with equations (2–5). Applying the learning rate to the discount rate is a novelty of this work. This assumes that technological learning will not only reduce investment and operational costs over time, but also financing costs as can already be observed for solar PV (GrantThornton, 2018). In this study, a learning rate of 7% lead to a decline of discount rate from initially 10% (Langer et al., 2021a) to 5% in 2050, a rate which harmonises with the ones of today's mature technologies (Rubin et al., 2015). However, comparing discount rates only by technology would exclude myriad other financial and socio-political influences (Bloomberg, 2015). Hence, the concept suggested here needs further validation.

$$LCOE_h = \frac{CRF_h * CAPEX_h + OPEX_h}{E_h} \quad (1)$$

$$with\ CRF_h = \frac{DR_0 * \left(\frac{P_{inst,h}}{P_{inst,0}}\right)^{-b} * \left(1 + DR_0 * \left(\frac{P_{inst,h}}{P_{inst,0}}\right)^{-b}\right)^N}{\left(1 + DR_0 * \left(\frac{P_{inst,h}}{P_{inst,0}}\right)^{-b}\right)^N - 1} \quad (2)$$

$$CAPEX_h = CAPEX_0 * \left(\frac{P_{inst,h}}{P_{inst,0}}\right)^{-b} \quad (3)$$

$$PR = 2^{-b} \quad (4)$$

$$LR = 1 - PR \quad (5)$$

Inputs

b: Learning Coefficient
PR: Progress Rate
LR: Learning Rate
N: Project Lifetime
CAPEX: Capital Expenses
OPEX: Operational Expenses
P: Installed Capacity
CRF: Capital Recovery Factor
DR: Discount Rate
LCOE: Levelized Cost of Electricity

Indices

0: Starting Year
*h: h^th^* Implemented Plant
inst: Installed
H: Total Number of Implemented Plants

Table 1 Cost Functions in US$ (2018) Million. ΔT: seawater temperature difference [°C], *d:* distance from plant to connection point [km], P_{net}: nominal plant size [MW_e]. Adapted from (Langer et al., 2021a).

Cost Component	Location-dependent?	Scale Curves/ Approximation functions	
		LC-OTEC (Vega, 2010)	HC-OTEC (Martel et al., 2012)
Platform & Mooring	No	$(39.6 * P_{net}^{-0.418}) * P_{net}$	$(51.8 * P_{net}^{-0.315}) * P_{net}$
Power Generation			
Water Ducting			
Deployment & Installation			
Others			
Heat Exchangers	Yes, seawater temperature difference (Martel et al., 2012)	$(1.97 - (\Delta T - 20\ °C) * 0.19) * P_{net}$	$(5.82 - (\Delta T - 20\ °C) * 0.56) * P_{net}$
Power Transfer	Yes, distance to connection point (Martel et al., 2012; Vega, 2010)	$(0.0497 * d + 0.304) * P_{net}$	

Table 2 Techno-economic assumptions regarding OTEC plants. Adapted from (Langer et al., 2021a).

Parameter	Value [Unit]		Reference
	LC-OTEC	HC-OTEC	
OPEX	5% of CAPEX per year	3% of CAPEX per year	(Martel et al., 2012; Vega, 2010)
Nominal Size	10 – 100 MW_e		
Lifetime	30 Years		(Bluerise, 2014; Martel et al., 2012)
Capacity Factor	91.2%		(Jung et al., 2016; Martel et al., 2012; Vega, 2012, 2010)
Discount Rate	10%		(Harrison, 2010; Zhuang et al., 2007)
Transmission Efficiency	$(100 – 2*10^{-4} * d^2 – 1.99*10^{-2} * d)$ %		(Langer et al., 2020; Martel et al., 2012)

After calculating the LCOE for each deployed OTEC plant, the aggregated NPV is determined with equation (6).

$$NPV = \sum_{h}^{H} \sum_{i}^{i+N} \frac{E_h * (PPA - LCOE_h)}{\left(1 + DR_0 * \left(\frac{P_{inst,h}}{P_{inst,0}}\right)^{-b}\right)^i} \tag{6}$$

Inputs

i: Year of Plant Implementation

NPV: Net Present Value

PPA: Tariff from Power Purchase Agreement

The NPV is used in this study to estimate the economic potential of OTEC. If an upscaling scenario returns a positive aggregated NPV, then the economic potential encompasses the installed capacity of all deployed plants in that scenario, even the ones with a negative NPV. With this, it is assumed that the experience gained from these unprofitable plants contribute to reduce the costs of follow-up plants, which then are profitable.

In this study, it is first assessed which OTEC growth rate yields the highest aggregated NPV while leaving all other scenario parameters unchanged. For the optimal OTEC growth rate, a techno-economic analysis is conducted with outputs like a cash flow diagram, plant distribution across Indonesia, and experience curves that show how the LCOE develops throughout the scenario timeframe. However, the goal of this study is not to find *the* optimal scenario, but to indicate the impact of individual variables on the upscaling scenarios and the key outputs like NPV and LCOE. This is done with a sensitivity analysis for the discount rate, learning rate, and demand growth rate.

Results and Discussion

Mapping of practically suitable OTEC sites

Based on the filtering process in the previous section and Figure 1, a total of 1,704 suitable OTEC sites are identified within Indonesia and its EEZ. If all sites were occupied with a 100 MW_{net} plant each, the total practical potential would be 170.4 GW_{net}. Note that these numbers differ from an earlier work (Langer et al., 2021a), because not only the marine provincial borders but also the EEZ outside provincial borders were included. As seen later in Figure 4, most practically suitable sites are situated in East Indonesia, which is not as economically developed as the economic centres of Java and Bali. Therefore, OTEC could be an interesting technology to boost socio-economic development and to provide clean, stable baseload power to hitherto disadvantaged communities. Regarding the exclusion criteria, the water depth of less than 1,000 m is the most effective one with 3,840 removed sites. Moreover, 3,006 sites are removed with a depth of more than 3,000 m. This is a valuable insight as the local water depth is not always included in spatial OTEC resource assessments (Asian Development Bank, 2014; Lewis et al., 2011; Nihous, 2010). The impact of a maximum water depth is especially noticeable for the Banda Sea in the East, where the water can be as deep as 7,000 m. The minimum seawater temperature difference of 20 °C only removed 25 sites, which can be explained by Indonesia's highly favourable climatic conditions for OTEC. Nonetheless, this exclusion criterion is still essential, especially in other regions suitable for OTEC with less favourable thermal resources.

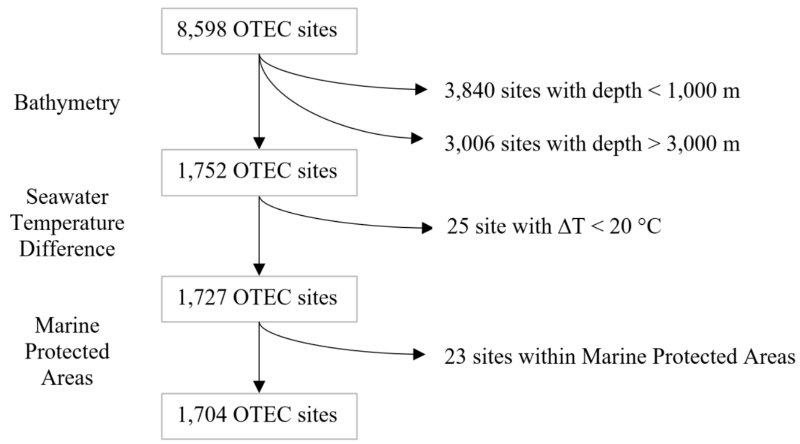

Figure 1 Filtering process for OTEC site selection. The 1,704 sites form a practical potential of 170,4 GW_{net} in Indonesia. Adapted from (Langer et al., 2021a).

Upscaling scenarios with technological learning

Whether a practically suitable site is actually used for OTEC deployment strongly depends on how the upscaling process takes place as presented in this section. Figure 2 shows how the impact of OTEC growth rate on (a) final installed capacity, (b) final aggregated NPV, and (c) average LCOE.

In Figure 2(a), the aggregated installed capacity rises with the OTEC growth rate until reaching a plateau at 45 GW_{net}. The initial exponential increase of aggregated installed capacity is not maintained, because supply growth is eventually higher than demand growth. Consequently, the regions that are suitable for OTEC become maximally saturated with OTEC. Then, an even higher growth rate only leads to a faster saturation without increased aggregated capacities.

Figure 2(b) shows that OTEC could be profitable in the long run even if initial CAPEX are high. The aggregated NPV peaks at 26% for low-cost assumptions and at 28% under high-cost assumptions. The total installed capacities at such OTEC growth rates are 9 GW_{net} with US$ 3 billion with aggregated NPV and 16.5 GW_{net} with US$ 23 billion, respectively. The NPV reaches zero at growth rates between 24% and 32% and lead to an economic potential of 6–41 GW_{net}.

The LCOE reaches a minimum of 8.5–12.8 US¢/kWh at an OTEC growth rate of 30% in Figure 2(c). At higher growth rates, the LCOE rises again, as fewer large plants can be implemented without oversupplying the respective provinces. Consequently, more small- to mid-sized plants are implemented with weaker economies of scale and thus higher LCOE.

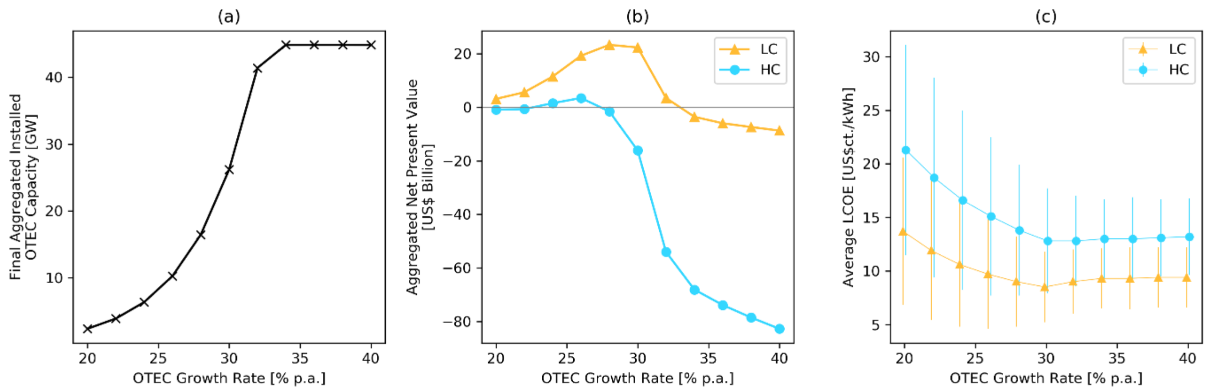

Figure 2 The influence of the OTEC growth rate on (a) aggregated installed capacity, (b) aggregated net present value after 60 years, and (c) average LCOE (error bars show standard deviation). Adapted from (Langer et al., 2021b).

For a NPV-optimal OTEC growth rate of 28% per year, the results of the upscaling scenario are presented in more detail with Figure 3. In Figure 3(a) shows that OTEC could be as important to Indonesia's future power system as already established renewables like geothermal (Presiden Republik Indonesia, 2017). OTEC implementation occurs without limitations by electricity demand, reaching a final aggregated capacity of roughly 16.5 GW_{net}.

The first 100 MW_{net} OTEC plant is implemented after 16 years. This is reasonable as the main priorities in the first decade could be the collection of operational data and the monitoring of pilot plants. With the experience gained from these initial projects, larger systems could follow at lower costs. This is a new perspective to the upscaling period to full-scale 100 MW_{net} plants of 5–6 years in literature (Martel et al., 2012; Vega, 2012). Of course, full-scale OTEC could be achieved faster than projected here, but at the technology's current stage no final conclusion can be drawn.

The decline of LCOE with time and cumulated capacity can be seen in the two experience curves in Figure 3(b). Initially, the LCOE ranges between 33.5–49.9 US¢/kWh for the first pioneer plant and decreases to 9.0–13.8 US¢/kWh in 2050 at full scale. However, the LCOE does not drop indefinitely. After an initial decline to a minimum of 6.2 US¢/kWh, the LCOE rises again. High-quality sites close to shore and with high PPA tariffs become more scarce and instead gradually economically less attractive sites are selected. 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 (Rodrigues et al., 2015).

Figure 3(c) depicts the aggregated NPV, where LC-OTEC breaks even after 19 years and reaches US$ 24 billion after 60 years. Before the breakeven point, negative cash flows of pre-maturity plants accumulate to a total of US$ 378 million. This sum could be understood as the total financial support required for OTEC contractors to reach profitability. In contrast to LC-OTEC, HC-OTEC does not break even, as many full-scale projects remain unprofitable late into the scenario as seen in Figure 3(d). For HC-OTEC to reach a positive final aggregated NPV, the OTEC growth rates indicated in Figure 2(b) are necessary.

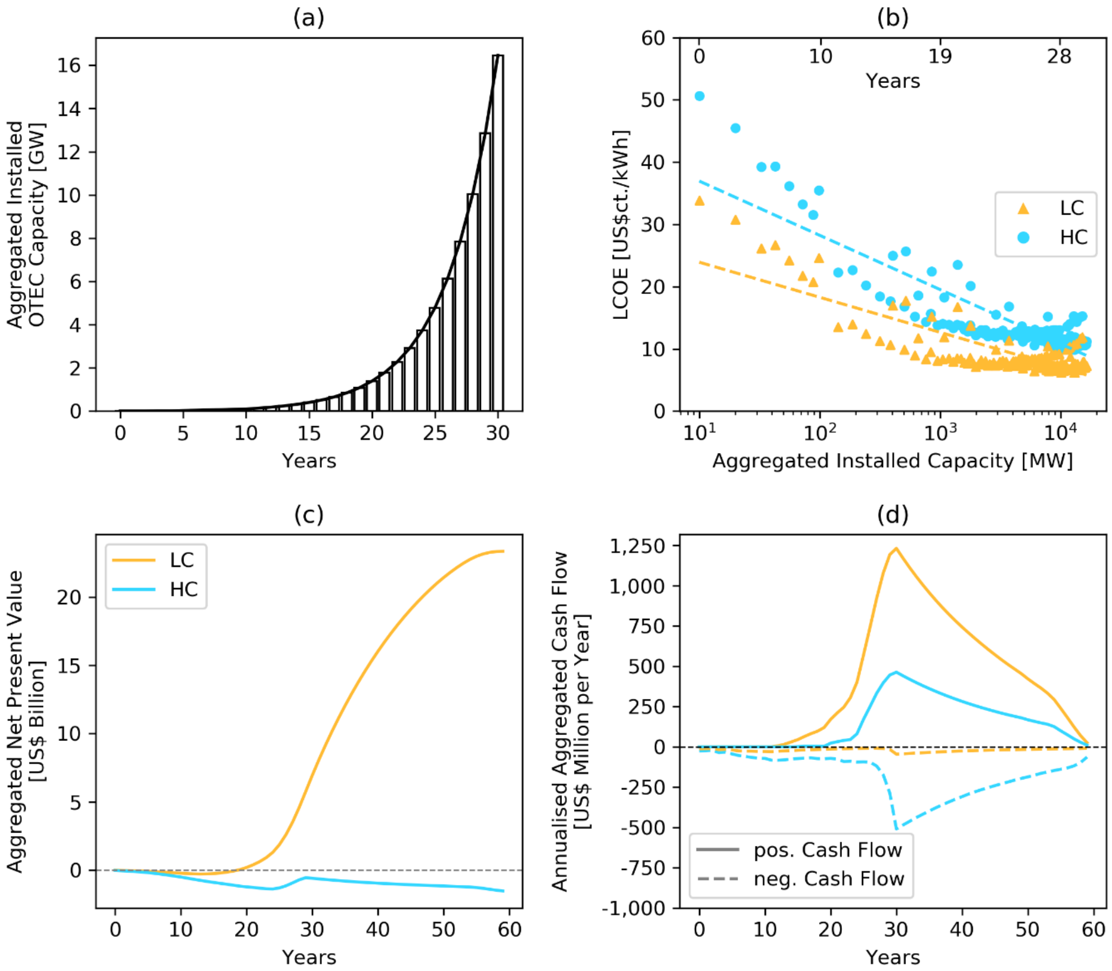

Figure 3 Results of the economically optimal scenario. (a) Aggregated installed capacity. (b) Experience curves. (c) Aggregated NPV. (d) Annualised aggregated cash flows. Adapted from (Langer et al., 2021b).

With a OTEC growth rate of 28% per year, OTEC could cover 44.3% of all supplied provinces and 8.4% of national electricity demand, respectively. Table 3 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. In this scenario, 184 sites or 11% of the practically suitable sites are occupied with OTEC plants. Especially the sites far from shore and at provinces with very low electricity tariffs like Java are only occupied at higher OTEC growth rates. Figure 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 provinces like Maluku and Maluku Utara, while large-scale OTEC is deployed nationwide, including economic centres like Sumatera and Bali. This is because the upscaling model focusses primarily on the economics of the plant, which could be perceived as a limitation. In practice, the upscaling strategy might be different and pioneer OTEC plants are implemented in the economic centres of Indonesia where the necessary infrastructure like roads and harbours are already given. At an early stage, profitability might not be the highest priority and an easy access to the site for installation, operation, monitoring, and maintenance might be more important. Once enough experience is gained, the OTEC industry could diffuse from the West to the East with a stronger focus on profitability. Therefore, the model presented here could benefit from a multi-criterion decision-making logic that incorporates the aspects above and more.

Table 3 Key results of the economically optimal scenario per province. The PPA tariff is weighted based on installed capacity. Adapted from (Langer et al., 2021b).

Province	Aggregated Installed Capacity [MW_{net}]	Weighted Average PPA Tariff [US¢/kWh]	LCOE [US¢/kWh] $\bar{x} \pm \sigma$		Supply of Electricity Demand [%]
			LC	HC	
Sumatera Barat	2,300	13.5	8.1 ± 1.4	12.1 ± 1.3	79.3
Aceh	2,092	11.7	7.4 ± 0.1	11.7 ± 0.3	98.8
Sulawesi Selatan	1,500	8.3	6.9 ± 0.3	10.6 ± 0.3	33.4
Nusa Tenggara Barat	1,400	18.1	7.8 ± 0.4	12.2 ± 0.6	96.1
Sulawesi Utara	1,354	13.9	9.1 ± 5.2	14.6 ± 7.4	99.5
Sumatera Utara	1,300	19.6	9.0 ± 1.3	13.0 ± 1.1	14.9
Sulawesi Tengah	900	19.2	7.8 ± 0.3	12.2 ± 0.7	94.0
Sulawesi Tenggara	700	16.6	8.0 ± 0.7	12.9 ± 1.3	94.0
Papua	689	17.2	8.8 ± 3.4	12.9 ± 4,7	92.3
Nusa Tenggara Timur	667	20.4	9.6 ± 1.8	15.4 ± 2.8	88.3
Bali	600	6.9	6.7 ± 0.2	10.6 ± 0.1	14.0
Bengkulu	600	7.5	6.8 ± 0.2	10.7 ± 0.1	80.8
Maluku	481	21.0	17.1 ± 8.1	25.5 ± 11.8	99.1
Kalimantan Timur	400	10.6	7.6 ± 0.2	11.1 ± 0.1	13.3
Papua Barat	400	16.8	7.5 ± 0.6	11.7 ± 0.7	85.9
Gorontalo	300	13.5	7.3 ± 0.0	11.3 ± 0.2	72.7
Maluku Utara	273	20.2	12.5 ± 5.8	19.5 ± 8.7	83.0
Lampung	200	7.3	6.9 ± 0.2	10.6 ± 0.1	5.7
Sulawesi Barat	200	8.3	6.8 ± 0.5	11.4 ± 1.1	71.6
Kalimantan Utara	100	10.6	8.0 ± 0	11.4 ± 0	65.4
Total	**16,456**	**14.5**	**9.0 ± 8**	**13.8 ± 12**	**44.3**

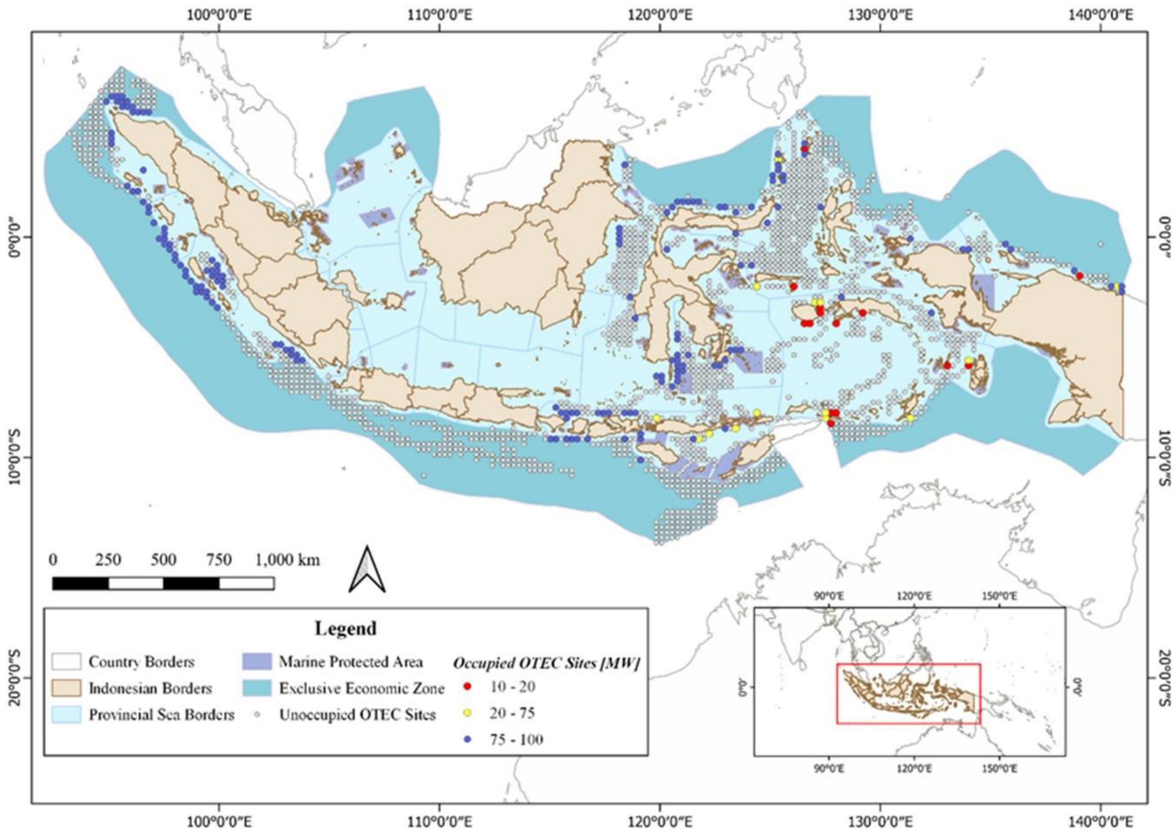

Figure 4 Map of practically suitable and occupied OTEC sites including system size for the economically optimal scenario. Adapted from (Langer et al., 2021b).

Another key result is OTEC's economic viability within Indonesia's electricity mix. As seen in Figure 5, large-scale OTEC could be cost-competitive against all other currently deployed energy technologies in Indonesia. This harmonises with Vega (Vega, 2012), who estimated cost-competitiveness of OTEC for a range of 50–100 MW_{net}. Note that Figure 5 implicitly implies that the LCOE of all competing technologies will not change during OTEC's upscaling. But unlike OTEC, these competitors have been on the market for several decades and have benefitted from cost reductions. Furthermore, fossil fuels like coal are currently heavily subsidised by the Indonesian government (Maulidia et al., 2019). With these aspects in mind, Figure 5 is still useful to project OTEC's competitiveness in terms of LCOE.

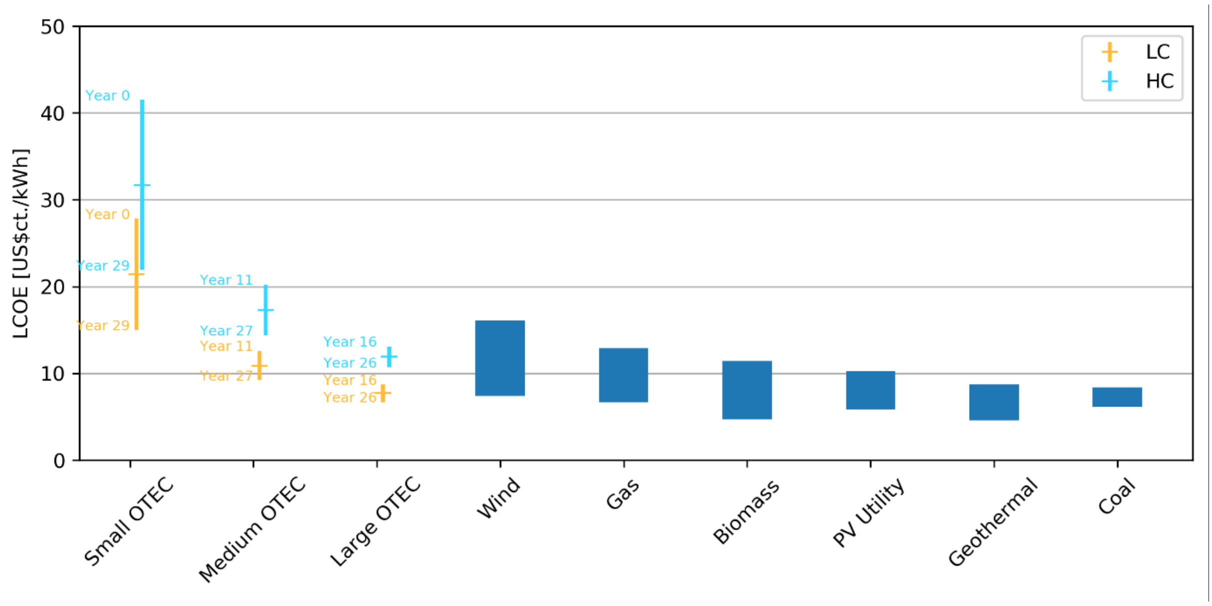

Figure 5 OTEC's competitiveness against other energy technologies (IESR, 2019) **in Indonesia. Error bars show standard deviation. Adapted from (Langer et al., 2021b).**

As explained earlier, a novel feature of the upscaling model is the use of a dynamic discount rate. Not only CAPEX and *Operating Expenses (OPEX)* will decrease with experience, but also the cost of finance, represented by the discount rate, as risks associated with the technology will gradually decline.

With this assumption, Figure 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. Figure 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.

Figure 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% increases 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%, which supports the observation in Figure 3(c), where HC-OTEC was just shy from breaking even at a learning rate of 7%.

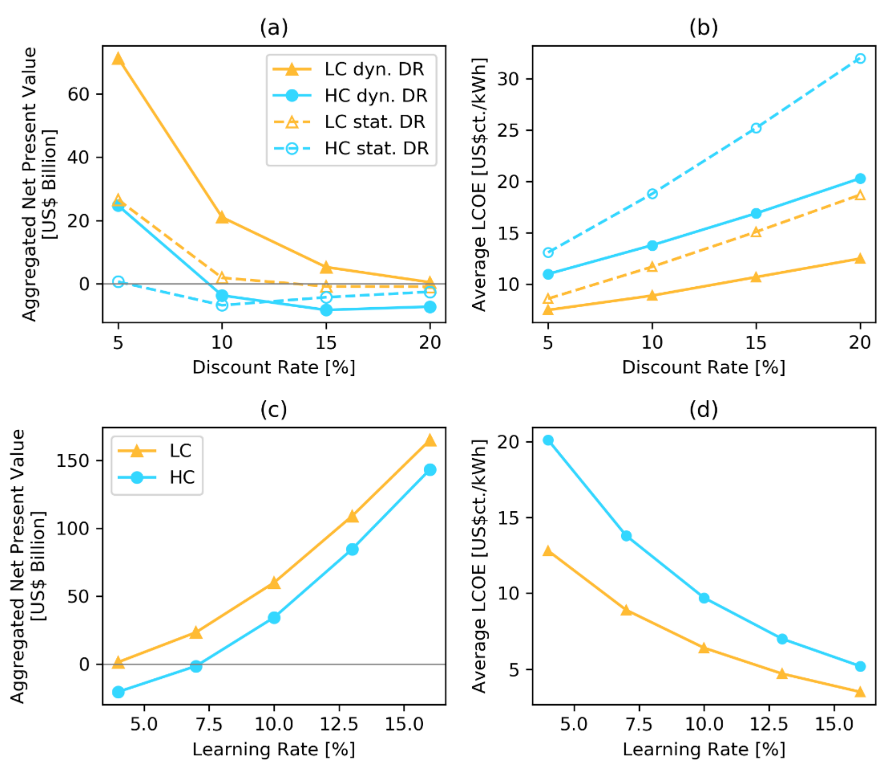

Figure 6 Impact of discount rate on (a) aggregated NPV and (b) average LCOE and impact of learning rate on (c) aggregated NPV and (d) average LCOE. Adapted from (Langer et al., 2021b).

The relationship between electricity supply and demand is depicted in Figure 7. At too high OTEC growth rates, supply eventually outpaces demand and implementation slows down. Then, an increase in electricity demand growth provides more room for OTEC implementation and at a certain point allows unhampered upscaling, as depicted in Figure 7(a) for a 32% p.a. OTEC growth rate.

Figure 7(b) shows once more the detrimental economic effects of a too high OTEC growth rate. At low to moderate demand growth rates, the aggregated NPV is lowest at a 32% p.a. OTEC growth rate, 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. For the 32% p.a. case, breakeven is achieved at a sustained annual demand growth of 6–9%.

Then again, if demand growth is higher than OTEC growth, NPV as well as LCOE stabilise as shown in Figure 7(c). At a sufficiently high demand growth, 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.

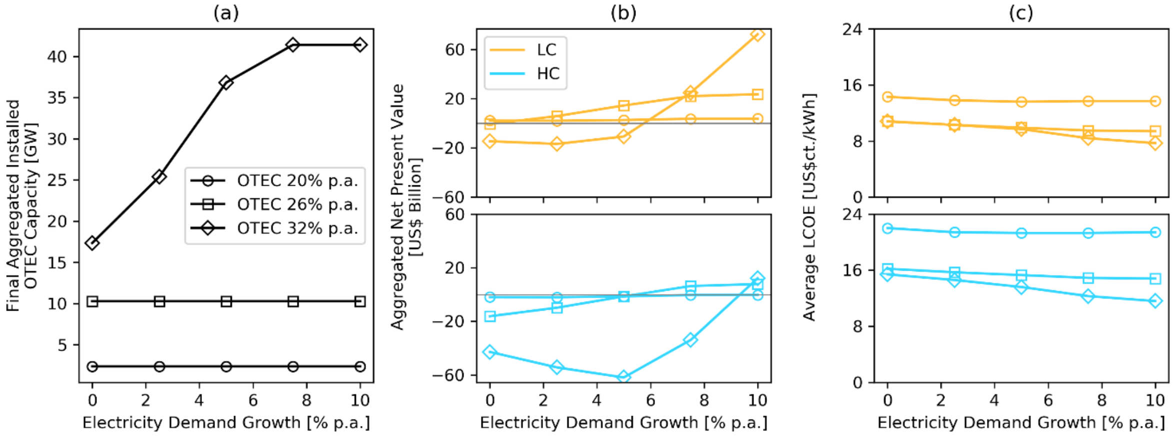

Figure 7 Impact of electricity demand growth on (a) installed capacity, (b) aggregated NPV, and (c) average LCOE. Adapted from (Langer et al., 2021b).

Conclusion

This paper provides an overview of a series of studies that shed light on where practically suitable sites for *Ocean Thermal Energy Conversion (OTEC)* are located in Indonesia and what the economic potential of OTEC is considering upscaling and technological learning. By using a novel *Geographic Information System (GIS)* methodology, more than 1,700 practically suitable sites could be mapped within Indonesia's marine provincial area and *Exclusive Economic Zone (EEZ)*. Most of these sites are located in the economically less developed East of the country, which underlines OTEC's potential of fostering socio-economic development by providing clean, reliable, and continuous baseload. However, OTEC must be scaled up from current small-scale pilot plants to large-scale commercial systems. This study shows that technological learning and economies of scale significantly boost OTEC's economic feasibility, with an economic potential ranging between 6–41 GW_{net}. Until 2050, OTEC could provide clean, affordable electricity and serve more than 8% of Indonesia's electricity demand at *Levelized Cost of Electricity (LCOE)* as low as 6.2 US¢./kWh. Full-sized OTEC plants could be cost-competitive in less than 20 years against all currently deployed energy technologies in the country. Therefore, this paper presents OTEC as an interesting alternative for Indonesia's energy transition. However, our studies also show the challenges OTEC might face on its way to maturity. Cost optimisations are essential from day one and the conservative cost assumptions found in literature must be avoided. OTEC will also require strong, continuous learning over several decades to drive down costs at a sufficiently high rate. To which extent this is feasible in practice is still unclear, given that some components like turbine and generator are already mature. Then again, OTEC's costs mainly consist of components with lots of room for innovation, for example the cold water pipe and the heat exchangers. Another challenge will be to match the abundantly available OTEC resources in many countries with the local electricity demand. For Indonesia, the upscaling scenarios showed that the regions with the highest economic potential for OTEC are often in regions with low electrification rates and limited socio-economic development. This insight can easily be translated to a global perspective, as OTEC is often seen as an interesting technology for small island developing states. Then again, there are also countries suitable for OTEC with sufficient electricity demand like Japan, South Korea, and the USA, so OTEC could still be developed profitably on a global scale. With these aspects in mind, this paper provides reasons why the further development of OTEC is worthwhile despite the challenges ahead. After all, not only Indonesia, but many other countries worldwide could benefit from OTEC.

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