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From fossil fuels to renewables: An analysis of long-term scenarios considering technological learning

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ABSTRACT

This study analyses a diffusion of renewable energy in an electricity system accounting for technological learning. We explore long-term scenarios for capacity expansion of the Java-Bali electricity system in Indonesia, considering the country's renewable energy targets. We apply the Long-range Energy Alternative Planning (LEAP) model with an integration of technological learning. Our results reveal that, at the medium and high pace of technological learning, the total costs of electricity production to achieve the long-term renewable energy target are 4–10% lower than the scenario without considering technological learning. With respect to technology, solar PV and wind become competitive with other types of renewables and nuclear. Moreover, the fulfilment of the renewable energy targets decreases CO_2 emissions by 25% compared to the reference scenario. Implications of our results indicate that energy policies should focus on the early deployment of renewables, upgrading the grid capacity to accommodate variable renewable energy, and enabling faster local learning.

1. Introduction

Renewable energy is a critical component for combating climate change. In fact, most of Nationally Determined Contributions (NDCs) submitted by countries under the Paris Agreement include renewable energy as their measure to address climate change (IRENA, 2017). The implementation of NDCs will add at least 1.3 terawatts to the global renewable installed capacity. This ambitious target would need a considerable investment cost—1700 billion USD by 2030, according to the IRENA estimate.

The high upfront expense for installation of renewable technologies is one of the factors that hinder the deployment of renewable energy. However, the capital costs of energy technologies are known to decline over time due to cost-reducing technological changes, usually referred to as learning (IEA, 2000; Lafond et al., 2017; McDonald and Schrattenholzer, 2001; Rubin et al., 2015; Watanabe, 1995). The concept of the learning effect has been widely used and analysed empirically in many applications (Grübler et al., 1999). The earliest example is Wright (1936), who reported that unit labour costs in airframe manufacturing declined with accumulative experience measured by cumulative output.

Cost savings brought up by technological learning are especially attractive for developing countries, which are still facing rapid growths of electricity demand while also pledging their NDCs. This case applies to Indonesia, the fourth most populous country in the world. Electricity demand in the country is projected to grow at an average of 8.3% per year in the next decade (PLN, 2017a). Meanwhile, it pledges to reduce 29% of its greenhouse gas emissions against its business-as-usual scenario by 2030 (Government of The Republic of Indonesia, 2016). While, in 2015, renewable energy accounted only for 4% of the national energy mix[1] (DEN, 2016b), the most recent national energy policy (NEP) requires it to increase by 23% in 2025 and 31% in 2050 (Government of The Republic of Indonesia, 2014). In the context of the electricity sector, renewable energy currently accounts for 10% of the national electricity generation mix[2] (PLN, 2016b). The Electricity Supply Business Plan 2016–2025 (RUPTL) estimates an increase in unit costs of electricity production by 22% to realize the NEP target in the electricity sector by 2025. Such increases, if they occur, will cause a burden on the electricity sector and, in turn, on the national economy. Yet, these projections neglect the learning process of electric power technologies.

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[1] Energy mix is a set of various primary energy sources used to meet energy needs in a region (ton oil equivalent and % contributions).

[2] Electricity generation mix is a set of primary energy sources that constitute the total electrical energy production in a region (Megawatt hour and % contributions).

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As discussed above, technological learning may reduce the unit costs of electricity production, making investments in renewable energy technologies more economically attractive.

Considering the essential role of technological learning, it is necessary to take it into account when projecting a long-term electricity supply. In this study, we integrate technological learning into the Long-range Energy Alternative Planning System (LEAP) model to explore a number of electricity expansion scenarios. Prior to commencing this study, the LEAP model was validated using historical data of the Indonesian electricity system in Handayani et al. (2017). LEAP has been actively used for assessing renewable energy expansion in many countries, such as Pakistan (Ishaque, 2017), Bulgaria (Nikolaev and Konidari, 2017), Ghana (Awopone et al., 2017), Thailand (Wongsapai et al., 2016), Iran (Eshraghi and Maleki, 2016), Indonesia (Kumar, 2016), India (Kumar and Madlener, 2016), Malaysia (Samsudin, 2016), Brazil (Andrade Guerra et al., 2015), Korea (Park et al., 2013), and Lebanon (Dagher and Ruble, 2011). Despite its extensive use, little attention has been paid to incorporating technological learning in the LEAP model, which is likely to underestimate future deployment of renewable energy. This study focuses on the Java-Bali electricity system, which represents more than 70% of the Indonesian electricity production (PLN, 2016b). We first develop scenarios for capacity expansion from 2016 through to 2050. Then, we apply a learning model for each power generation technology into the LEAP cost function. The simulation results are analysed in terms of energy, costs, and CO_2 emissions.

The innovative contribution of this study is twofold. First, methodologically, it moves beyond the current practice of LEAP usage by incorporating a learning model with respect to energy technologies into the LEAP cost function. Although there are some energy system models that have included technology cost learning, such as MESSAGE-MACRO, MARKAL-TIMES, NEMS, POLES, ERIS, GALLM, and EXO-XEL (Heuberger et al., 2017), to the best of our knowledge, our study is the first to include technological learning endogenously in LEAP. Secondly, this article adds an understanding regarding the role of technological learning in driving the transition from fossil fuel-based power generation to a lower carbon electricity system in the context of developing countries.

The remainder of this paper is organized as follows: Section 2 presents the literature review; Section 3 explains the methodology, scenarios, and the model input parameters for the future Java-Bali electricity system; Section 4 discusses the results of model simulations; and Section 5 presents the main conclusions and policy implications of this study.

2. Literature review

2.1. Technological learning

The development of technology is not an autonomous, independent process. Instead, it evolves from a number of interactions within social systems as well as from experience in using the technology itself (Barreto, 2001). The processes of technological change require considerable time from innovation to widespread diffusions, such as what has occurred in the past concerning the global technology transitions from traditional biomass to coal-based technology and from coal-based technology to electricity and petroleum-based technologies (Wilson and Grubler, 2011).

The development and introduction of new technologies involve a learning process that results in the improvement of the production process and product, which, in turn, often makes the costs lower (GEA, 2012). The learning process starts from the first practical use of a new technology until its maturation stage (Sagar and van der Zwaan, 2006). Learning is a crucial element of early adoption of technologies, and it indicates the experiences gained through the practical use of technology and contributes to cost reduction over time (Sagar and van der Zwaan, 2006). Since learning is a self-enforcing process, more accumulated experiences in technology lead to lower cost, and more increase in technology competitiveness leads to even more accumulated experience (Gillingham et al., 2008). As such, it is not always the case that a new technology is used because it becomes cheap but also a technology becomes cheap because of its increased use and learning process (Berglund and Söderholm, 2006). In addition to cost reduction, learning can also lead to greater proficiency in technology operation as well as institutional transformation necessary to allow the widespread use of new technologies (Sagar and van der Zwaan, 2006).

The learning process triggering cost reduction is expressed as a function of the accumulation of knowledge and experience related to R&D expenditures, the production, and the use of technology (Kahouli-Brahmi, 2008). Quantification of these learning patterns is presented in the literature using so-called one-factor and multi-factor learning curves (Kahouli-Brahmi, 2008; Rubin et al., 2015). The former is the most widely used method for endogenously forecasting changes in technology costs. Its experience performance is indicated by the cumulative installed capacity or the cumulative production. The multi-factor approach includes factors beyond the cumulative installed capacity or production that contribute to technology cost reduction, such as R&D spending, knowledge spill-overs, and economies of scale (Rubin et al., 2015). However, due to data requirements and theoretical limitations, this approach is less prevalent in the literature compared to the one-factor model (Farmer and Lafond, 2016; Rubin et al., 2015).

The term that is used to express experience gained from a technology is referred to as “learning rate.” The latter is measured as the percentage, by which the unit cost declines with each doubling of cumulative production or, alternatively, as the fraction by which the unit price of energy service, such as electricity, declines with each doubling of installed capacity (Sagar and van der Zwaan, 2006). The corresponding change in price compared to its previous price with each doubling of capacity is referred to as “progress ratio” (Berglund and Söderholm, 2006). A progress ratio of 75% indicates that the costs of technology have declined to 75% of its previous level after a doubling of its cumulative capacity. In this case, the corresponding learning rate is 25%.

2.2. Overview of the Indonesian electricity sector

Indonesia is an archipelagic country with more than 17,000 islands (Prasetya, 2017) and 238 million in population (BPS, 2010). The demand for electricity in this country has been growing at a fast rate—a 7.8% rise, on average, during 2010–2014 (PLN, 2015). PLN, the national electricity company, supplies most of the country’s electricity needs and solely owns the power transmission and distribution networks. By 2015, 76% of the national power generation capacity belonged to PLN, while the rest are owned by independent power producers (IPPs) (PLN, 2016c). Due to its archipelagic state, Indonesia has many electricity systems distributed throughout the archipelago. The largest one is the Java-Bali electricity system, which supplies electricity within the Java, Madura, and Bali islands. These islands are the most populated islands, as they are inhabited by 140.5 million or 59% of the national population (BPS, 2010). In 2015, the Java-Bali islands covered 74% of the national electricity demand (PLN, 2016b).

Fig. 1 illustrates the electricity generation mix in 2015 (PLN, 2016b), 90% of which are fossil fuels. The primary fossil fuels here are coal (56%), natural gas (25%), and oil (9%). Meanwhile, renewable energy constitutes 10%, which is shared between geothermal (4%) and hydro and other renewables (6%). With respect to dispatch order, coal and geothermal operate as base load power plants, while hydro, natural gas, and oil act as intermediate and peak load power plants (PLN, 2016b). As Fig. 1 demonstrates, the Java-Bali’s electricity generation mix is equivalent to the national situation, in which 91% of electricity supply is sourced from fossil fuels—mainly coal. In fact, the Java-Bali system mirrors the national electricity sector in terms of the energy mix

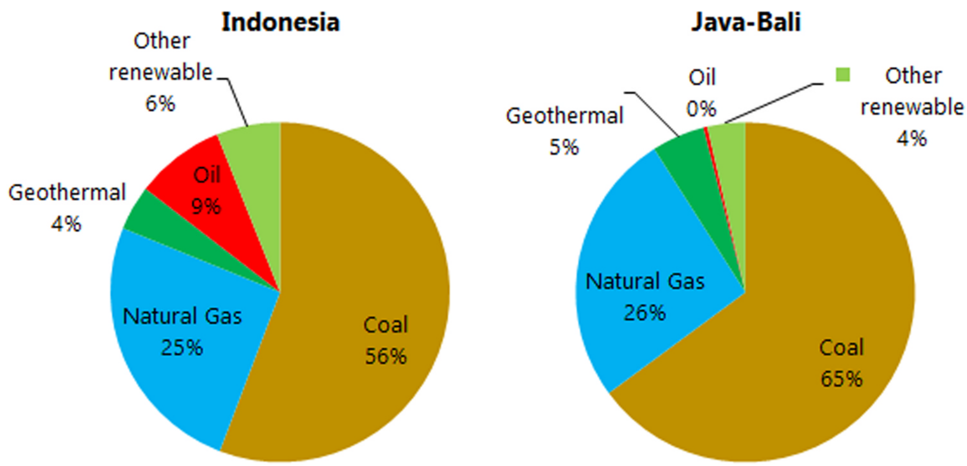

Fig. 1. Electricity production by sources in 2015 (PLN, 2016b). [These data include both PLN and IPP productions].

Table 1
Renewable energy potential and current practice in Indonesia.

Renewable	Potential in Gigawatt		Renewable deployment by 2015, total Indonesia		Sources
	Total Indonesia	Java- Bali islands	Installed capacity (Gigawatt)	Renewable utilization (%)	
Hydro	75	4.2	5.1	6.8%	DEN (2016a), DJK ESDM (2016)
Hydro pumped storage	4.3	3.9	0	0%	PLN (2017a), DJK ESDM (2016)
Mini hydro	19.4	2.9	0.2	0.9%	DEN (2016a), DJK ESDM (2016)
Geothermal	17.5[a]	6.8[a]	1.4	8%	DEN (2016a), DJK ESDM (2016)
Biomass	30	7.4	0.1	0.3%	DEN (2016a), DJK ESDM (2016)
Solar	5374[b]	2747[b]	8.9	0.2%	Kunaifi and Reinders (2016), DJK ESDM (2016)
Wind	60.6	24.1	0.0004	0%	DEN (2016a), DJK ESDM (2016)

[a] Excluding the speculative and hypothetical potential.
[b] In Gigawatt peak.

and electricity supply and demand. Given our access to the unique, high-quality data of the Java-Bali system, we focus the rest of this study on this system, assuming that similar trends are likely to apply for the country as a whole.

Indonesia's historical reliance on fossil fuels stems from its abundant fossil fuels resources, primarily coal. The country's coal reserve is estimated to be as much as 88.6 billion ton oil equivalent (toe), the national natural gas and oil reserves account for 3.9 and 0.5 billion toe, respectively (MEMR, 2016). While Indonesia also possesses abundant renewable energy resources, such as geothermal, hydro, solar, and wind, they are currently underutilized. Table 1 illustrates the potential of renewable energy sources in Indonesia and the amount that has been harnessed until present. The geothermal and hydro potentials have been utilized up to 8% and 7%, respectively, while, for each of the rest, less than 1% has been utilized.

The NEP 2014 proposes ambitious new[3] and renewable energy (NRE) targets for increasing the role of renewable energy. The NRE targets relate to two stages. In Stage 1, by 2025, the share of NRE should be at least 23% of the national energy mix. In Stage 2, by 2050, the share of NRE should be at least 31% of the national energy mix. NEP also mentions that the economic aspects of renewables are taken into consideration in achieving its targets (Government of The Republic of Indonesia, 2014). Furthermore, NEP also considers nuclear as an alternative energy to achieve its NRE targets, although it is the last option after maximizing the use of renewable energy sources.

[3] The term "new energy" is defined as energy that is stemmed from new technologies such as nuclear and hydrogen (Government of The Republic of Indonesia, 2014).

3. Methodology and data

3.1. The LEAP model

LEAP is a software tool for modelling energy systems and was developed at the Stockholm Environment Institute. The "scenario manager" in LEAP allows simulations of various paths of the electricity system expansion to achieve the NRE targets. LEAP includes a range of accounting, simulation, and optimization methodologies for modelling electric sector generation and capacity expansion planning (Heaps, 2017). The accounting setting enables an analysis of power capacity expansion based on various assumptions. We use this setup when simulating the reference scenario, which assumes the continuation of the fossil fuel-based power generation. Meanwhile, the optimization setting allows the construction of least-cost models of an electricity system's capacity expansion and dispatch under various constraints. We use this setting for alternative scenarios (renewable energy scenarios), putting the NRE targets as constraints in the simulation.

3.1.1. Electricity demand projection

In this study, demand for electricity is calculated based on the demand growth projection stipulated in the Electricity Supply Business Plan 2016–2025 (RUPTL) and the Indonesia Energy Outlook 2014 (IEO). Hence, the electricity demand in a specific year is the sum of electricity demanded in the previous year and its anticipated growth:

$$ED_t = (ED_{t-1} * EDG_t) + ED_{t-1}, \quad (1)$$

where ED_t is the electricity demand in year t, and EDG_t is the percentage of growth in the electricity demand in year t. Total electricity demand in the electricity system for a specific year (TED_t) is calculated as the sum of electricity demanded and electricity losses (EL_t) during transmission and distribution (T&D) process in that year:

$$TED_t = ED_t + EL_t \tag{2}$$

and

$$EL_t = ED_t * TL_t, \tag{3}$$

where TL_t is the percentage of T&D losses in year t.

3.1.2. Capacity expansion in LEAP

The capacity of a set of technologies can be added both exogenously and endogenously in LEAP. We specify exogenously the previously existing capacities as well as committed additional capacities, such as the power plants that are currently under construction. We also add the capacity of hydro-pumped storage exogenously, in accordance with the RUPTL assumptions (PLN, 2016a)

For the endogenous capacity addition, LEAP calculates the amount of capacity to be added using the Eqs. (4)–(6) below (Awopone et al., 2017; Heaps, 2017). In the reference scenario, which uses the accounting setting, we specify the types of the power plant to add, but LEAP decides when they will be added based on the system's requirement. In the renewable energy scenarios, which make use of LEAP's optimization capability, LEAP decides what types of technology should be added and when it will be added based on the least-cost principal and the set constraints. In these scenarios, we set the minimum capacity of natural gas power plants to be added each year as intermediate and peak plants as well as for balancing the variability of intermittent renewable energies.

$$C_{En} = D_p(PRM - RM), \tag{4}$$

$$D_p = \frac{ED}{LF*8760}, \tag{5}$$

and

$$RM = \frac{C_p - D_p}{D_p}, \tag{6}$$

where C_{En} is the endogenous capacity addition, D_p is the peak electricity demand, PRM is planning reserve margin, RM is the reserve margin before addition, ED is electricity demand, LF is the load factor (calculated as the ratio of the average load and the peak load), and C_p is the capacity before addition.

3.1.3. Total costs calculation

The total cost of the electricity system is the total net present value of the system costs over the entire period of calculation:

$$TC = \sum_{t}^{N_t} \sum_p \frac{1}{(1+d)^t}\left(Cc*Ca_t + foc_t*Ca_t + Voc_t*P_t + Fc_t\right), \tag{7}$$

where TC is total cost, N_t denotes the total years from 2016 through to 2050, p is the process (technology), d is the discount rate, Cc is the initial capital cost, Ca_t is the capacity in year t, foc_t is the fixed operation and maintenance costs in year t, Voc_t is the variable operation and maintenance costs in year t, P_t is the output power in year t, and Fc_t is the fuel cost in year t.

3.1.4. CO_2 emissions calculation

CO_2 emissions from electricity production are calculated as follows (Feng and Zhang, 2012):

$$CE = \sum_p \sum_f EF_{f,p} * \frac{1}{E_p} * P_p, \tag{8}$$

where CE is the CO_2 emissions, $EF_{p,f}$ is the CO_2 emission factor from one unit of primary fuel type f consumed for producing electricity through technology p, E_p is efficiency of technology p, and P_p is the output power from technology p.

3.2. Integration of the learning model

LEAP does not provide a built-in expression for capturing technological learning. In this study, we integrate the one-factor learning model into LEAP by adding an additional expression in LEAP representing the learning curve of electric power technologies. We build the syntaxes in LEAP that enable the calculation of changes in capital costs for each technology type along with changes in cumulative capacity and in learning rate value of the technology for each learning phase.

The capital cost of energy technology in a specific year is calculated using the following formulas (Kim et al., 2012):

$$K_t = K_0\left(\frac{C_t}{C_0}\right)^{\beta} \tag{9}$$

and

$$\text{Learning rate(LR)} = 1{-}2^{\beta}, \tag{10}$$

where K_t denotes the capital cost in year t, K_0 is the initial capital cost, C_t is the cumulative capacity until year t, C_0 is the capacity in the base year, and β is the positive learning parameter (learning by doing index) which characterizes the inclination of the curve.

The shapes of learning curves for different energy technologies depend on two factors: initial learning rates and the speed of their change. To initialize the learning curve model, we retrieve the learning rate values for electric power technologies from Rubin et al. (2015) and Heuberger et al. (2017), see Appendix B. Further, with respect to the speed of learning, we assume four learning phases throughout the time horizon of this study. We assume the learning rate of each electric power technology decreases with every phase, as shown in Table 2. Our assumption refers to the World Energy Outlook (WEO) Model 2016, which assumes reductions in the capital costs of renewable energy over time. WEO distinguishes the capital costs in four time steps: 2015, 2020, 2030, and 2040 (OECD/IEA, 2017). The learning curve of solar PV, as the results of its substantial deployment along the time horizon of our study, is depicted in Appendix C (Fig. C.1).

3.3. Future scenarios

In this study, we design five scenarios for the future development of the Java–Bali electricity system. The first one is the reference scenario, which assumes the continuation of the present technology mix in the Java-Bali electricity system. The other four are scenarios for meeting the NEP's NRE targets. The NRE targets aim at increasing the share of new and renewable energy in the national energy mix, which refers to the total national energy use coming from various sources. In this study, we assume the same target is applied to the electricity sector. Accordingly, we analyse four scenarios for maximizing the use of renewable energy—as mandated by NEP—in the context of the Java-Bali electricity system and assess their impacts on costs and CO_2 emissions. We employ the LEAP optimization method to analyse the least-cost options of meeting the NRE targets with and without technological learning. The assumptions for each scenario are as follows:

a. *Reference scenario (REF)*: The reference scenario assumes a continuity of fossil fuel-based power generation in the Java-Bali electricity system. Hence, the technology mix in the future is expected to be equivalent to the present situation. The main characteristics of this scenario are as follows:

– Deployment of technology is limited to conventional technologies that have been deployed up to 2015, mainly coal-fired power plants
– Renewable capacity expansion only limited to geothermal and hydro, as they are the only renewable technologies existed in the base year

Table 2
Assumptions of learning rates of electric power technologies 2016–2050.

Technology	REN-Low LR scenario[a]: Low value of the initial learning rate				REN-Medium LR scenario[b]: Medium value of the initial learning rate				REN-High LR scenario[c]: High value of the initial learning rate			
	Phase I 2016–2020	Phase II 2021–2030	Phase III 2031–2040	Phase IV 2040–2050	Phase I 2016–2020	Phase II 2021–2030	Phase III 2031–2040	Phase IV 2040–2050	Phase I 2016–2020	Phase II 2021–2030	Phase III 2031–2040	Phase IV 2040–2050
Solar PV	10.0%	7.1%	4.0%	1.6%	23.0%	16.3%	9.1%	3.7%	47.0%	33.4%	18.7%	7.7%
Wind Turbine	− 11.0%	− 7.8%	− 4.4%	− 1.8%	12.0%	8.5%	4.8%	2.0%	32.0%	22.7%	12.7%	5.2%
Biomass	0.0%	0.0%	0.0%	0.0%	11.0%	7.8%	4.4%	1.8%	24.0%	17.0%	9.5%	3.9%
USC Coal	5.6%	4.0%	2.2%	0.9%	8.3%	5.9%	3.3%	1.4%	12.0%	8.5%	4.8%	2.0%
NGOC	10.0%	7.1%	4.0%	1.6%	15.0%	10.7%	6.0%	2.4%	22.0%	15.6%	8.7%	3.6%
NGCC	− 11.0%	− 7.8%	− 4.4%	− 1.8%	14.0%	9.9%	5.6%	2.3%	34.0%	24.1%	13.5%	5.5%
Hydro	1.4%	1.0%	0.6%	0.2%	1.4%	1.0%	0.6%	0.2%	1.4%	1.0%	0.6%	0.2%
Nuclear	− 6.0%	− 4.3%	− 2.4%	− 1.0%	− 1.0%	− 0.7%	− 0.4%	− 0.2%	6.0%	4.3%	2.4%	1.0%

Note: The learning rates for the first phase is based on Rubin et al. (2015). For the other phases, we estimate learning rates ourselves based on data from OECD/IEA (2017).

[a] The initial learning rates (LR), i.e., the LR values in Phase I refer to the lowest values in Rubin et al. (2015) and assumption on the low LR value for nuclear in Heuberger et al. (2017).

[b] The initial learning rates (LR), i.e., the LR values in Phase I refer to the mean values in Rubin et al. (2015) and assumption on the medium LR value for nuclear in Heuberger et al. (2017).

[c] The initial learning rates (LR), i.e., the LR values in Phase I refer to the highest values in Rubin et al. (2015).

– No limitation on the domestic fossil fuels uses
– Geothermal and hydro expansions are dependent on their availability (potentials) in the Java and Bali islands
– No specific target is set for renewable energy deployment
– No technological learning is considered

a. *Renewable energy scenario (REN)*: The renewable energy scenario takes into consideration the NRE targets when projecting the electricity system expansion. Besides hydro and geothermal that already operate in Indonesia, three types of renewable energy are added over the time horizon of this study: solar, wind, and biomass. Moreover, in line with NEP, nuclear is considered as a new technology to be added after maximizing renewable energy uses. This scenario includes the following characteristics:

– The capacity expansion aims at achieving the NRE targets. Thus, the NRE targets are set as constraints in the model
– The types of technology that are considered for future capacity expansion include ultra-supercritical (USC) coal, natural gas combined cycle (NGCC), natural gas open cycle (NGOC), hydropower, geothermal, wind power, biomass, solar photovoltaic (PV), and nuclear
– The renewables' capacity expansions are dependent on their availability (potentials) in the Java and Bali islands
– LEAP will choose the types of technology to be employed based on costs and the set objectives
– No technological learning is considered

In addition, we suggest three variations of this scenario, which vary in the initialization of technological learning for electric power technologies. We consider the learning rate of not only renewable energy technologies but also of non-renewables. Following the setup of endogenous technology cost learning (ETL) in Section 3.2, we assume that the technological learning for all energy technologies occurs in four phases. We run LEAP with ETL assuming three different initial values for the learning rate: low (REN-low LR in Table 2), medium (REN-medium LR in Table 2), and high (REN-high LR in Table 2).

(i) *Renewable energy scenario with low learning rate (REN-low LR):* the initial learning rate values refer to the minimum learning rate values (REN-low LR in Table 2).
(ii) *Renewable energy scenario with medium learning rate (REN-medium LR):* the initial learning rate values refer to the mean learning rate values (REN-medium LR in Table 2).
(iii) *Renewable energy scenario with high learning rate (REN-high LR)*: the initial learning rate values refer to the maximum learning rate values (REN-high LR in Table 2).

3.4. Data

We have collected most of the model input data from PLN and governmental reports, rather than relying on default data provided by LEAP. Therefore, this study represents the actual characteristics of the Indonesian electricity system, making policy projections more reliable. Table 3 presents the model input parameters and their sources. The electricity demand projection for 2016 through to 2025 is based on RUPTL with an annual average of 7.3% (PLN, 2016a). Meanwhile, the demand growth projections for 2026 onwards refer to the Indonesia Energy Outlook (IEO) with an annual average of 5.6% from 2026 through to 2040 and 4.3% from 2041 through to 2050 (DEN, 2014). The transmission and distribution losses data come from the Electricity Supply General Plan (RUKN), which estimates a reduction from 8.5% in 2015 to 7.9% in 2030 onwards. The planning reserve margin is set at 35%, in accordance with the RUKN criteria (KESDM, 2015). The energy load shape in LEAP is drawn based on the hourly load data of the Java-

Table 3
Summary of model input parameter.

Input Data	Value	Source
Annual demand growth 2016–2030	4.3–7.3%	Refers to the RUPTL and IEO estimates (DEN, 2014; PLN, 2017a)
Transmission & distribution losses	7.9–8.5%	Refers to the draft RUKN estimates (KESDM, 2015)
System load shape	Fig. B.1	Based on hourly demand data recorded by P2B (P2B, 2016)
Reserve margin[a]	35%	Refers to the RUKN criteria (KESDM, 2015)
Environmental parameter	Per technology	The IPCC Tier 1 default emission factors, embedded in the LEAP's technology database (Heaps, 2017)
Discount rate	12%	The discount rate used by PLN (JICA, 2010)

[a] Reserve margin is the percentage of reserve capacity relative to the capacity needed to meet the standard peak demand.

Bali electricity system that were collected from the Java-Bali grid operator (see Appendix B, Fig. B.1). In our model, we take the Java-Bali's load characteristics into consideration by dividing the demand in a year into 48 time-slices, which represent four variations for each month. This approach is based on historical load characteristics where there are four main variations in electricity demand, which occur during the day, night, weekend, and weekday. Meanwhile, owing to a reasonably constant temperature in Indonesia throughout the year, there are no significant variations in demand between seasons.

The technological data of existing power plants is collected from PLN. It includes capacity, planned retirement, heat rate, historical production, and capacity factor. The accuracy of these data is essential to ensure a reliable base year representation, as it is used as the starting point for the future capacity expansion. There are currently 64 power plants with 7 different technologies, namely coal steam turbine (CST), NGCC, NGOC, diesel generator, hydroelectric (small and large-scale), and geothermal. The existing coal power plants in the Java-Bali electricity system employed a conventional boiler, which has a lower efficiency than the supercritical (SC) and ultra-supercritical (USC) technologies. However, the RUPTL states that only the USC boiler will be employed for the future coal power plants (PLN, 2016a). Accordingly, we only consider the USC boiler for the newly added coal capacity.

The characteristics of newly added technologies, including ultra-supercritical CST, biomass, wind turbine, solar PV, and nuclear power, were retrieved from various studies (see Table 4). Most of the technology costs assumptions were taken from the RUPTL cost data (PLN, 2017b), complemented with DEN (2016a), ACE (2016), OECD/IEA (2017), and the IEA and NEA (2015). The fuel costs data for coal and natural gas were retrieved from the PLN Statistics 2015 (PLN, 2016c), while nuclear and biomass fuel costs data were taken from EIA and ASEAN Energy Centre studies (ACE, 2016; IEA and NEA, 2015), respectively. For renewable, we assume that the publicly available data of the Indonesian renewable energy potential (Table 1) is accurate, and they can be exploited over the time horizon of this study without any constraints. Furthermore, since NEP listed nuclear as the least preferred option for meeting the NRE targets, we assume that nuclear will be deployed for the first time in 2035 when all renewable energy potentials have been largely exploited. Coal, nuclear, and biomass power plants are expected to cover the baseload, while natural gas and hydro power plants are expected to cover the peak load. With regard to the supply characteristics of intermittent renewable power plants (wind and solar), we specify exogenously capacity addition for hydro-pumped storages as well as set a minimum amount of natural gas power plant to be added each year to balance the intermittent renewable energies.

Since LEAP does not provide for simulation of the expansion of transmission and distribution lines, this study assumes that electricity supply can be transmitted at any time to any load station without additional constraints in the electricity networks.

4. Results and discussions

Following the model calculation of the demand growth (Eq. (1)), demand for electricity in 2025 reaches 332 TWh, doubling values recorded in 2015. Furthermore, in 2050, it increases up to 1159 TWh—over three-fold of those in 2025. In the following sections, we discuss the results of our five scenarios for the Java-Bali electricity system's expansion to satisfy the projected future demand.

4.1. Reference scenario (REF)

In the *REF* scenario, with the business as usual technology composition, the coal capacity is added expansively over the time horizon of the study, followed by natural gas (see Fig. 2). Consequently, the electricity generation mix in the Java-Bali electricity system is dominated by coal. In total, fossil fuels (coal and natural gas) account for 92% and 94% of electricity supply in 2025 and 2050, respectively. Interestingly, renewable energy share reduces from 8% in 2025 to 6% in 2050 despite the full utilization of geothermal and hydro potentials of the Java-Bali islands. Therefore, the electricity generation mix in the REF scenario is far from what is expected by NEP. These results indicate

Table 4
Characteristics of technologies in the Java-Bali LEAP model.

Technology	Lifetime of power plant (years)[a]	Efficiency (%)[a]	Maximum availability* (%)[b]	Capacity credit (%)**	Capital cost (2015 US $/kW)[a]	Fixed OM*** cost (2015 US $/kW)[a]	Variable OM cost (2015 US$/MWh)[a]	Fuel cost[c] (2015 US$)
Ultra-supercritical coal	30	40	80	100	1400	31.3	2	51.8 US$/ton
Natural gas combined cycle	25	55	80	100	800	19.2	1	7.6 US $/MMBTU
Natural gas open cycle	20	36	80	100	700	18	1	7.6 US $/MMBTU
Hydro	50	100	41	51	2000	6.6	1	–
Mini hydro	25	100	46	58	2400	6.6	1	–
Hydro-pumped storage	50	95[b]	20	25	800	6.6	1	–
Geothermal	25	10[d]	80	100	3500	30	1	–
Solar PV	20	100	17	22	2069[e]	24.8[e]	0.4[b]	–
Wind power	20	100	28	35	2200	44[d]	0.8[b]	–
Nuclear	40[f]	34	85[g]	100	6000	164[d]	8.6[g]	9.33 US$/MWh[f]
Biomass	20[h]	35[d]	80	100	2228[d]	78[d]	6.5[b]	11.67 US$/ton[e]

* Maximum availability in LEAP is defined as the ratio of the maximum energy produced to what would have been produced if the process ran at full capacity for a given period (expressed as a percentage) (Heaps, 2017).

** Capacity credit in LEAP is defined as the fraction of the rated capacity considered firm for calculating the reserve margin. The values are calculated based on the ratio of availability of the intermittent plant to the availability of a standard thermal plant (Heaps, 2017).

*** OM: Operation and Maintenance.

[a] PLN (2017b).
[b] DEN (2016a).
[c] PLN (2016c).
[d] OECD/IEA (2017).
[e] ACE (2016).
[f] Rothwell and Rust (1997).
[g] IEA and NEA (2015).
[h] IRENA (2012).

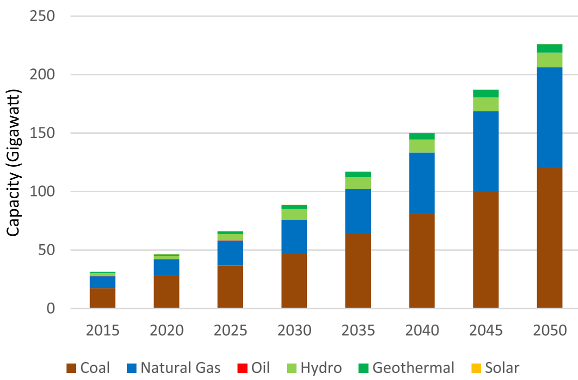

Fig. 2. Installed capacity, *REF* scenario.

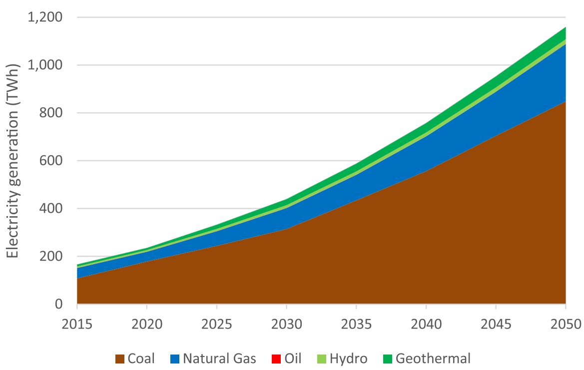

Fig. 3. Electricity generation mix, *REF* scenario.

that it is not possible to increase renewable energy share if the sector is to rely on geothermal and hydro alone without exploiting other types of renewable energy (Fig. 3).

4.2. Renewable energy scenario (REN)

The total power generation capacity of the Java-Bali electricity system reaches 69.6 Gigawatt (GW) at the end of NEP's Stage 1 (2025) under the *REN* scenario without technological learning (Fig. 4). In this scenario, the renewable capacity expands up to 15.2 GW—a nearly two-fold increase compared to *REF*. Accordingly, there is a 22% decrease in coal capacity. During the NEP Stage 2 period in the REN scenario, the system's capacity expands further, reaching 244.4 GW in 2050. Interestingly, nuclear capacity is added significantly during this time. It is first installed in 2035 and adds up to 22 GW by 2050. In the same year, renewable capacity reaches 41 GW—three-fold of that in *REF*.

Looking more closely into the electricity generation mix, the total electricity generation in 2025 and 2050 are 332 TWh and 1159 TWh, respectively (Fig. 5). We observe that renewable energy accounts for 23% of the Java-Bali electricity generation mix in 2025, compared to 8% in *REF*. Hence, the NRE target Stage 1 is achieved solely by exploiting renewable energy. However, in 2050, renewable energy share constitutes only 17.3% despite full utilization of hydro, geothermal, and biomass potentials (Fig. 5b), which is below the NRE target Stage 2. This gap is filled by nuclear, which accounts for 14.2% of the Java-Bali electricity generation mix. These results imply that the least-cost option to achieve the NRE target Stage 2, assuming no changes in relative costs of energy technologies, is to combine renewables and nuclear. However, this scenario neglects technological learning, whereas most of these technologies become more cost-effective over time.

In the following sections, we discuss the results of the *REN* scenarios, which take into account the learning curves of both renewable and non-renewable technologies. In these scenarios, the capital costs of electric power technologies change along with their increased capacity depending on their learning rates.

4.2.1. Renewable energy scenario with low learning rate values (REN-low LR)

REN-low LR scenario assumes the minimum value of learning rate of each technology in Phase I, which evolves throughout the other phases. The results indicate that there is a significant change in the 2025's electricity generation mix when compared to *REN* (Figs. 6a vs. 5a). Solar now accounts for 6% of the electricity generation mix, partially replacing biomass and geothermal, in contrast to 1% in *REN*. It implies that in the early phase of technological learning, even in its minimum learning rate value, solar becomes competitive with other renewables. Furthermore, the natural gas share slightly increases as compared to *REN*, compensating a slight reduction in coal.

These changes are seen substantially by 2050. The share of nuclear and wind power present in *REN* is replaced by solar (compare Figs. 6b and 5b). The solar share is now 18%, which also slightly replaces the coal share. Hence, this result suggests that when the minimum learning rate values for all technologies are considered, solar becomes more economically attractive compared to other technologies. Remarkably, even under the most modest assumptions regarding technological progress, solar proliferates from less than 1% to become the third most used energy source after coal and natural gas. A reasonable explanation could be that, in this scenario, the initial learning rate of solar PV (10%) is the highest, compared to those of nuclear (-6%), wind power (-11%), and coal (5.6%). This also explains why nuclear and wind hardly appear in the 2050's electricity generation mix.

4.2.2. Renewable energy scenario with medium learning rate values (REN-medium LR)

When the medium learning rate value for each technology is applied, a significant change is also seen in the 2025's electricity generation mix (Fig. 7a) as compared to *REN*. Renewable energy is now shared between biomass (7%), solar (6%), geothermal (5%), hydro (4%), and wind (1%). This result suggests that, in the early phase of technological learning when a medium learning rate for each technology is assumed, solar and biomass compete with each other. Coal and natural gas still support 77% of the Java-Bali electricity production while the renewables share accounts for 23% of the electricity generation mix, as targeted.

Turning now to the electricity generation mix in 2050, Fig. 7b shows that renewables account for 30% of the electricity generation, supplying nearly 350 TWh of electricity to the Java-Bali system. With an additional 10 TWh electricity supply from nuclear, NRE now constitutes 31% of the electricity generation mix, as targeted. An interesting finding is revealed when comparing these results with those in *REN-low LR*. It can be seen that the solar share in this scenario is 4% lower than that in *REN low-LR* despite the fact that its learning rate in this scenario is higher than that in *REN-low LR*. The 4% portion is

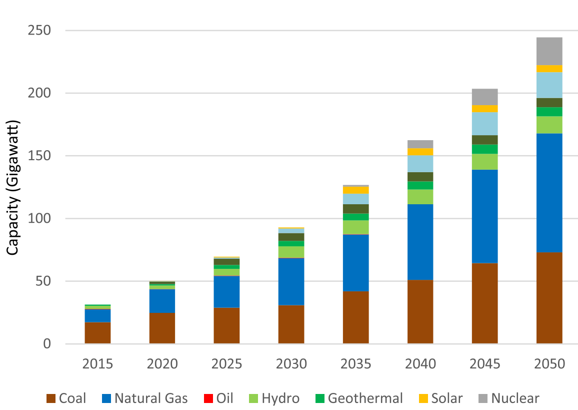

Fig. 4. Installed capacity in the renewable energy scenario (*REN*), no technological learning.

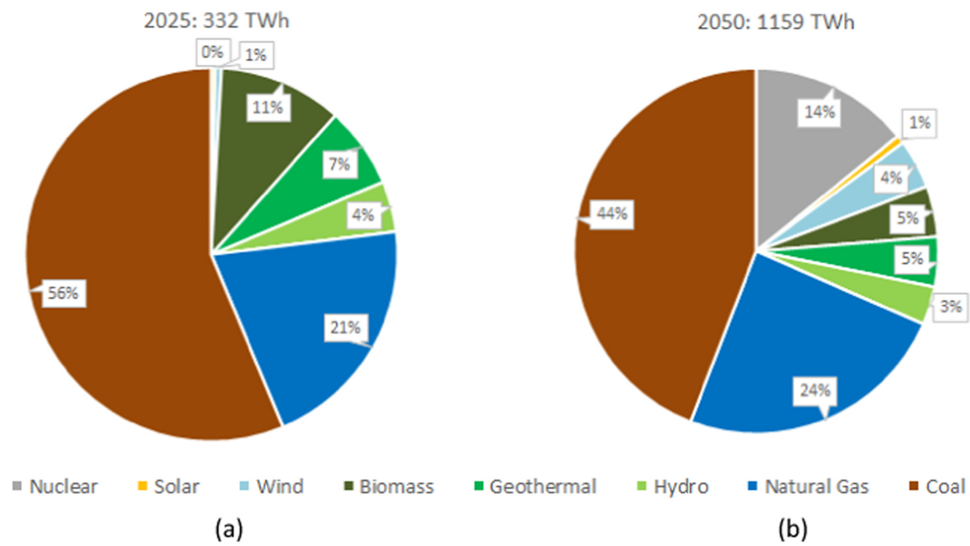

Fig. 5. Electricity generation mix in the renewable energy scenario (*REN*), no technological learning.

replaced by wind, which hardly appears before (Fig. 7.a). This result indicates that, in the later phases of technological learning when the learning rate values of each technology diminish, the wind power is more competitive than it is in the earlier phases.

4.2.3. Renewable energy scenario with high learning rate values (REN-high LR)

In the scenario with the high learning rate value for each technology, it can be seen that the 2025 electricity generation mix is comparable with those in the *REN-low LR* and *REN-medium LR* scenarios (Fig. 8a vs. 6a and 7a). This finding suggests that, regardless of the initial learning rate values, solar is competitive against other renewables when it is deployed in the early phases.

Our results for 2050 under the intensive technological learning show that hydro, geothermal, and biomass expand up to 28.1 GW, reaching their maximum plausible capacities. Meanwhile, wind capacity adds up to 20.5 GW, almost reaching its maximum potential of 24 GW. In total, these renewables account for a 16% share of the electricity generation mix (Fig. 8b). After these renewables reach their maximum plausible capacities, solar and nuclear are the only options for meeting the NRE targets. Together with 14% of solar and 1% of nuclear shares, NRE constitutes 31% of the Java-Bali electricity generation mix, satisfying the NRE target Stage 2. This is comparable with *REN-medium LR*, indicating that, at the medium and high initial learning rate values, all types of renewable compete with each other to achieve the NRE target Stage 2.

Comparing results from the three renewable energy scenarios, several significant findings emerge. Firstly, the integration of endogenous technological learning in LEAP reveals comparable results for the early phase of technological learning (2016–2025). In this phase, hydro, geothermal, biomass, and solar PV compete with each other to meet the NRE target Stage 1. Meanwhile, in the later phases, when the learning rate value of all technologies decrease, the results are slightly different between the *REN-low RE* scenario and the two other technological learning scenarios. While, in the former scenario, the wind power share is negligible, in the latter scenarios, wind is competitive with other renewables. Secondly, as far as technological learning scenario is concerned, they meet the NRE targets mostly through renewables without depending on nuclear.

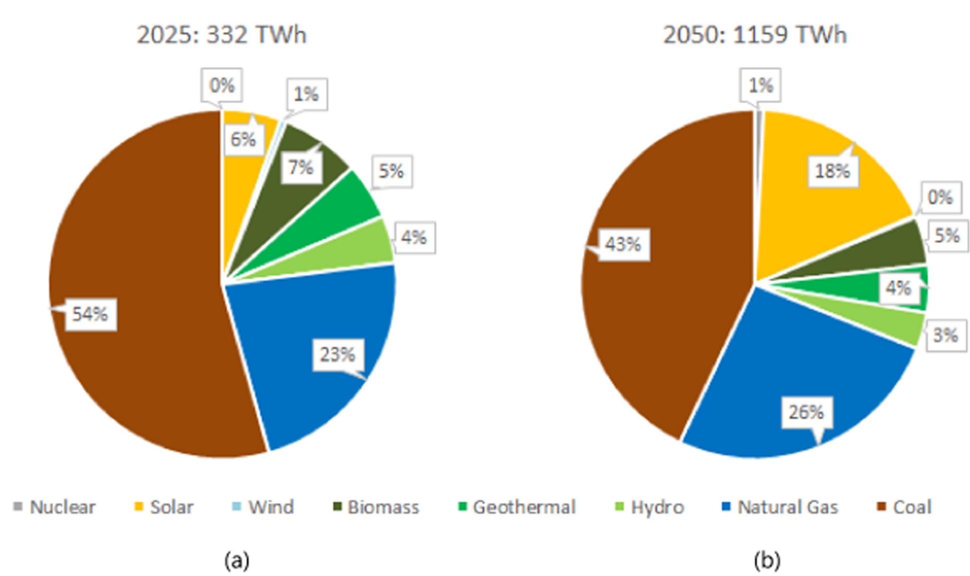

Fig. 6. Electricity generation mix in the *REN-low LR* scenario, technological learning occurs at the minimum pace.

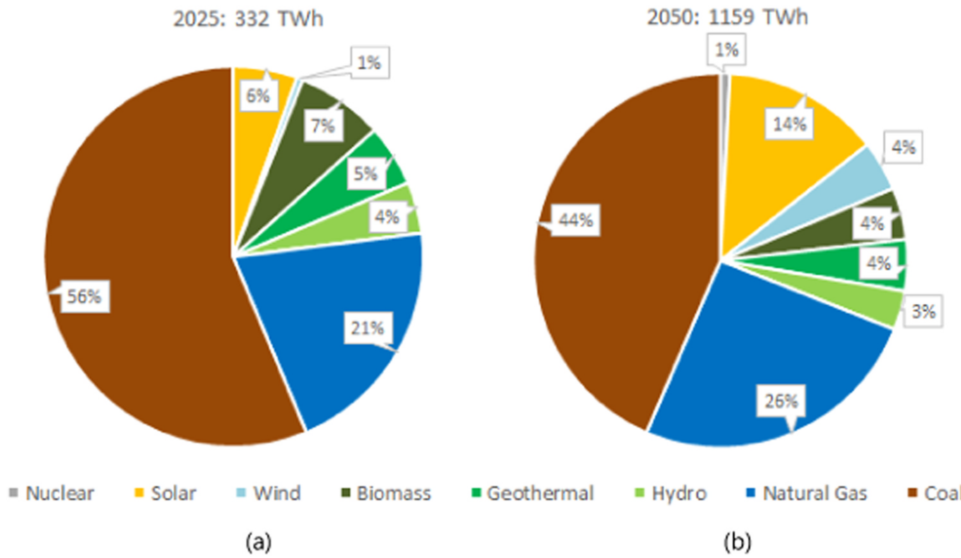

Fig. 7. Electricity generation mix in the REN-medium LR scenario, average pace of technological learning.

4.3. Costs

Given the pressure from the competing socio-economic priorities, including poverty eradication and other sustainable development goals (SDGs), any effort in achieving the NRE targets relies on making NRE technologies economically feasible. Hence, assessing the costs of meeting these targets is essential. Here, we compare the results of simulations from the five scenarios with respect to their capacity expansion and dispatch costs (Fig. 9). The total costs to achieve the NRE target by 2050 are 103.1 billion USD in *REN* in the absence of technology learning, 15.9% higher when compared to 88.9 billion USD in *REF*.

The technological learning has an impact on the costs projections, which vary non-linearly with the change in the learning pace. Our results show that the total costs of *REN-medium LR* and *REN-high LR* become 4% and 10% lower, respectively, when compared to *REN* in 2050 (see Fig. 9). Meanwhile, the total costs of *REN-low LR* are 2% higher than *REN*, which is due to the assumptions of negative learning rates of NGCC, wind, and nuclear in this scenario (see Table 2). Interestingly,

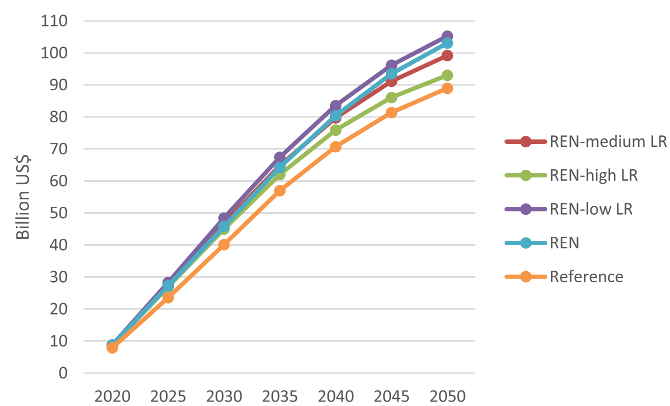

Fig. 9. Total costs of electricity production under the reference and four renewable energy scenarios.

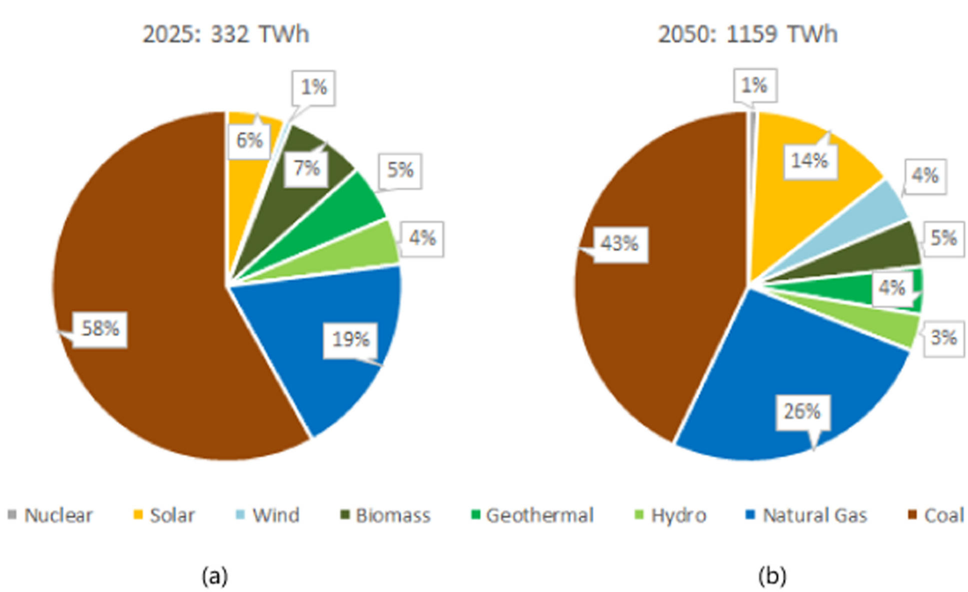

Fig. 8. Electricity generation mix in the *REN-high LR* scenario, high pace of technological learning.

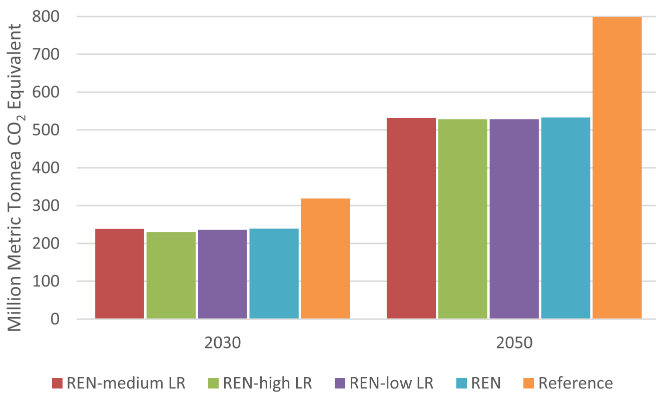

Fig. 10. CO_2 emissions under the reference scenario and the renewable energy scenario.

when the high learning rates are applied (*REN-high LR*), the total costs become lower than REN even by 2025. This indicates that if progress in energy technologies and their adoption intensifies, the cost reduction starts earlier and the total costs of the expanding electricity sector increase at a slower rate already before 2025, making it attractive to invest in renewable energy.

4.4. CO_2 emissions

Aligned with the Paris Agreement on mitigation of climate change, the Government of Indonesia has announced its targets to reduce greenhouse gas emissions by 29% in 2030 against the business-as-usual scenario. Eleven-percent of the 29% target is allocated to the energy sector. Our results indicate how much the NRE targets will contribute to the achievement of the Indonesian CO_2 reduction target (Fig. 10). As expected, all renewable scenarios, regardless of technological learning, result in lower emissions compared to *REF*. In 2030, CO_2 emissions from *REN* reaches 239 million-ton CO_2e, as compared to 318 million-ton CO_2e in *REF*. This is equal to 25% of CO_2 reduction, more than two-fold of what is targeted for the energy sector.

From 2030 onwards, the CO_2 emissions gap between the reference and the renewable energy scenarios becomes higher. In 2050, CO_2 emissions under *REN* reaches 533 million ton, compared to 798 million-ton CO_2e under *REF*, promising 33% emission reduction. Since the contribution from achieving the NRE targets goes beyond the country's Paris climate target, it can contribute to the roadmap for rapid decarbonization, which aims at achieving zero net emissions by mid-century or soon thereafter (Rockström et al., 2016).

5. Conclusions and policy implications

5.1. Conclusions

The aim of the present study is to analyse the long-term capacity expansion in the Java-Bali electricity system in Indonesia, taking the national NRE targets into consideration. To the best of our knowledge, this is the first study to assess the impacts of this national policy quantitatively considering technological learning. On the methodological side, this article makes an innovative contribution to the literature by accounting for endogenous technological learning in the future electricity supply analysis using LEAP. We employ a unique detailed dataset to simulate five scenarios for the capacity expansion of the Java-Bali system. The reference scenario assumes a business-as-usual electricity generation mix and no technological change. Renewable energy scenarios assess the electricity system expansion under the national energy policy in Indonesia, using the new and renewable energy targets as constraints. Furthermore, we differentiate between the standard renewable energy scenario with fixed technological costs and three renewable energy scenarios that include technological learning of electric power technologies. We discuss the simulation results in terms of the electricity generation mix, costs, and CO_2 emissions. Our analysis suggests the following conclusions:

1. In the reference scenario, the future capacity mix reflects the situation in 2015. This results in fossil fuels continuing to dominate in the future Java-Bali's electricity generation mix. In 2025 and 2050, fossil fuels account for 92% and 94% share of the electricity generation mix, respectively.
2. The renewable energy scenario fulfils the NRE target Stage 1. In the absence of technological change, it is driven mainly by expanding geothermal and hydro capacity and by adding biomass. Meanwhile, the NRE Stage 2 target is achieved by expanding renewables (17%) and deploying nuclear (14%).
3. The inclusion of technological learning rates significantly alters the electricity generation mix in 2025. In this phase of technological learning, solar PV is competitive with other renewables. Furthermore, by 2050, regardless of technological learning pace, solar PV is competitive against other renewables and nuclear. Meanwhile, in the long-run, wind power is competitive in the scenarios with medium and high learning rate values.
4. Without considering technological learning, the fulfilment of the NRE targets increases the total costs of electricity production by 15%. The incremental costs become 4% and 10% lower, respectively, when the medium and high paces of technological learning are considered, but the effect changes non-linearly with the learning rate.
5. The fulfilment of NRE targets provides co-benefits in term of reducing CO_2 emissions. By 2030, CO_2 emissions decrease by 25% as compared to the reference scenario, thereby assuring the achievement of the energy sector's CO_2 emission reduction target.

This study provides a framework to explore the cost-reducing effect of technological learning in the electricity sector using the LEAP model. Furthermore, it also indicates the least-cost option for the Java-Bali electricity system to meet the NRE targets. Looking further ahead, more detailed research is needed to cover transmission capacity and spatial analysis of each power plant including data on the supply characteristics of intermittent energy sources, such as wind speed and solar radiation in each region.

5.2. Policy implications

Our analysis has a number of policy implications, which relate to the timing of renewable energy deployment, local learning processes and improvement in the grid capacity.

Early deployment of renewable energy: With regard to timing, the deployment of renewable energy should start as early as possible to gain the benefits of technological learning. Moreover, the early deployment of renewable energy helps avoiding excessive investments in coal-based power plants and their related infrastructures, which have decades to serve after they are built.

Local learning: Conditions for future investments in renewable energy technologies in developing countries depend on a combination of global and local learning processes. Since local learning has a significant impact on the costs of renewable energy (Huenteler et al., 2016), the conditions that enable faster local learning should be made available. These include an increased number of skilled workforce, a stable regulatory framework, and the establishment of sustainable business models. Furthermore, improvement in infrastructure, such as accessibility of remote areas, is required to enable faster distribution of renewable energy technologies. Moreover, the involvement of all parties, including users, suppliers, competitors, universities, and regulators, is critical as interactions between them is the key for the learning and innovation processes to occur (Lundvall, 2016).

Improvements in the grid capacity: Integration of the vast renewable energy capacity presents new challenges to any electricity system operations and planning. Variable energy resources, such as wind and solar, have intermittent characteristics, which will likely change the way electricity is dispatched and transmitted by the grid operator. Therefore, the acceleration of renewable energy deployment should go hand-in-hand with the improvement of grid capacity in terms of technical and human capital capacity. Furthermore, other disruptive technologies, such as the internet of energy, energy storage, and electric vehicles, require the global utility sector for transforming to a smarter grid.

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Appendix A. Descriptions of LEAP

LEAP is a popular software tool for analysing energy policy and climate change and has been used by thousands of organizations in 190 countries (Heaps, 2017). With respect to electricity capacity expansion, LEAP consists of three modules. First, the demand module projects yearly electricity demand during the study period. Second, the transformation module adds new capacity of power generation technologies that are required to satisfy the future demand and assigns them to dispatch electricity. Third, the resource module calculates the primary energy required to generate electricity based on the fuel efficiency of each technology. Additionally, LEAP calculates an electricity system's total costs based on costs input data. Moreover, LEAP includes a Technology and Environmental Database (TED) that allows the calculation of CO_2 emissions from the electricity production based on the IPCC Tier 1 emission factor (Heaps, 2017).

In LEAP, the optimal solution is defined as the electricity system with the lowest total net present value of the total costs over the entire period of calculation (from the base year through to the end year) (Heaps, 2017). The optimization setting works through integration with the Open Source Energy Modelling System (OSeMOSYS). LEAP automatically writes the data files required by OSeMOSYS making use of the same data that were input into LEAP. The results of the optimization are also read back into LEAP so that all relevant results can be viewed in LEAP. The OseMOSYS, in turn, depends on a solver software tool for developing decision optimization models. Due to the complexity of our study, instead of using the LEAP built-in GNU Linear Programming Kit (GLPK), we use a more powerful solver namely CPLEX optimizer, a software toolkit developed by IBM.

Appendix B. Input data for the LEAP simulations

B.1. Assumptions of learning rates

Our assumptions for the initial learning rates are based on Rubin et al. (2015), as presented in Table B.1. They provide a review of learning rates from various studies. Due to the wide range of learning rate values presented in that study, we use the minimum, mean, and maximum values of learning rate of each technology in our analysis (*REN-low LR*, *REN-medium LR*, and *REN-high LR*). In the case of hydropower, only one study is present in Rubin et al. (2015). Therefore, we use only one value for hydro in all three *REN LR* scenarios. Moreover, this secondary data specified a negative minimum learning rate value for nuclear, while its mean value is not provided. In our study, we assume the minimum learning rate value for nuclear is −6%, while the mean learning value for nuclear is assumed to be −1%, following the assumptions in Heuberger et al. (2017). Since learning rate for geothermal is not available, we assume it as 0% in all three scenarios.

Table B.1
Learning rate values of power generation technologies (Rubin et al., 2015).

Technologies	Learning Rates[b]			Years covered across the studies
	Minimum	Mean	Maximum	
Solar PV	10%	23%	47%	1959–2011
Wind Turbine	− 11%	12%	32%	1979–2010
Biomass	0%	11%	24%	1976–2005
Pulverized coal	5.6%	8.30%	12%	1902–2006
Gas turbine	10%	15%	22%	1958–1990
NGCC[a]	− 11%	14%	34%	1980–1998
NGOC	10%	15%	22%	1958–1990
Hydro	1.4%	1.4%	1.4%	1980–2001
Nuclear	Negative	–	6%	1972–1996

[a] NGCC: Natural gas combined cycle.
[b] The learning rate values are based on empirical data reported in the literature that were collected and reviewed by Rubin et al. (2015).

B.2. Load shape of the Java-Bali electricity system

See Fig. B.1

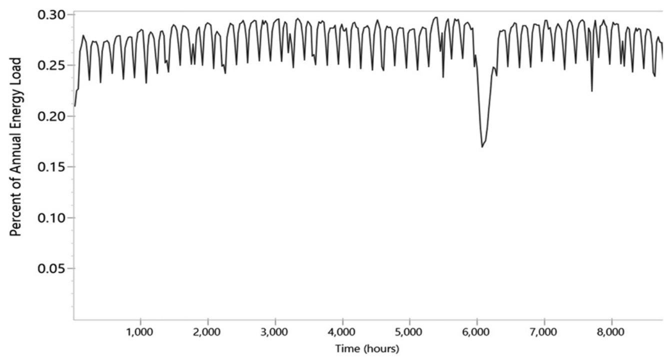

Fig. B.1. Load shape of the Java Bali electricity system (P2B, 2016).[4]

Appendix C. Learning curves of solar PV

The optimization simulations in LEAP result in a massive deployment of solar PV in all three technological learning scenarios. Hence, the capital cost of solar PV reduced over time, as depicted in Fig. C.1 (for the *REN-medium LR* scenario). Fig. C.1 (a) shows a continues reduction in the capital cost of solar PV along with the increase in its cumulative capacity. As Fig. C.1 (b) illustrates, in Phases I and II, the cost reduction occurs faster. Meanwhile, in the later phases, the costs reduce slower partly because of the reduction in the learning rate value as well as the cumulative capacity already being high. In Phase II, the cumulative capacity reaches nearly 20 GW; thus, in Phase III, it requires another 20 GW of additional capacity to gain 9% cost reduction, as assumed for the *REN-Medium LR* scenario (see Table 2). Furthermore, in Phase IV, it requires another nearly 40 GW additional capacity to gain 4% of cost reduction.

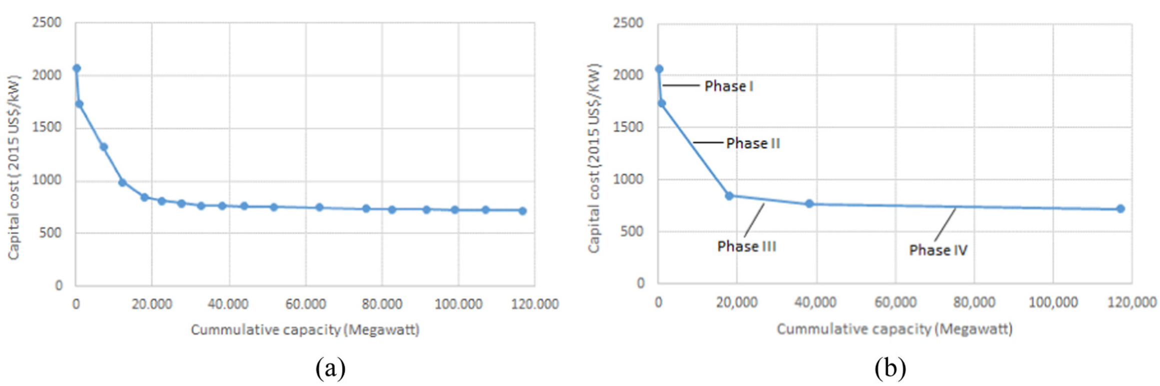

Fig. C.1. Learning curves of solar PV assuming the medium value of the initial learning rate: (a) depicts a continues cost reduction based on Eq. (9), while (b) depicts a linear approximation of the cost reduction in (a) that divides in four phases.

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