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Assessing the impact of solar PV and Li-ion battery learning rate on power sector decarbonization in Indonesia

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Abstract:
Renewable energy, such as Solar PV, is expected to play a significant role due to their enormous potential, maturity, and declining costs. However, literature reveals considerable variability in projected solar PV cost reductions and a limited assessment of how this uncertainty affects Solar PV adoption and power system planning. Moreover, the adoption of Solar PV is significantly shaped by grid flexibility providers such as batteries, and subsequent reductions in the technology's cost further drive increased Solar PV adoption. Therefore, by using a learning curve approach within the TIMES optimization power system model, this study evaluates the impact of wide dispersion of Solar PV and Li-ion Battery learning rates on Indonesia's power sector planning, particularly the effect on emissions, investment, and the electricity generation cost. This study examined three scenarios (A: pessimistic, B: moderate, C: optimistic) of Solar PV and Li-ion Battery cost reductions on Indonesia's power system through 2060 under the least-cost basis (BAU) and coal phase-out planning (BAU PO). The results show while faster learning rates for Solar PV and Li-ion batteries significantly accelerate deployment by 5-10 years in BAU, their impact on adoption timing is negligible in BAU-PO. Although BAU-PO achieves a lower emission trajectory, this reduction is primarily attributable to coal phase-out policies. In contrast, in BAU, emission reduction of 8-25% by 2060 is driven mainly by technology learning effects. BAU requires a lower total investment, 535-541 billion USD versus 553-584 billion USD in BAU-PO, with more back-loaded investments, whereas BAU-PO spreads investment over time.
***Keywords**: learning rate, Solar PV, Li-ion battery, power system, Indonesia.*

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INTRODUCTION

The power generation sector contributed 33.3% to total emissions in the energy sector in 2022 (CilmateWatchData, 2022). Compared to the industrial sector, the power generation sector is considered less complex for decarbonization, owing to its greater readiness and maturity of mitigation efforts. Key strategies for decarbonizing the power sector include improving efficiency and integrating renewable energy. Although efficiency improvement is a rapid and low-cost solution, its absolute impact on emission reduction is modest; consequently, integrating renewable energy on a massive scale is essential. Currently, the global renewable energy mix is limited to only 34.5%, with hydropower and biomass as the main contributors (IEA, 2024a). According to (IEA, 2024b; IRENA, 2024; UNEP-CCC & CTCN, 2024), renewable energy technologies such as Solar PV and wind turbines are expected to contribute significantly in the future, given their significant potential, mature technology, and considerable cost reductions. According to Grafström and Poudineh (2021) and Chang et al. (2022), the primary contributor to the decline in Solar PV costs is the drastic decline in cell and module prices.

The cost reduction of a technology or product can be considered using various methods, such as expert judgment, engineering assessment, and learning curve (Bolinger et al., 2022).

However, the latter method is widely used in academic literature (Grafström & Poudineh, 2021), which was first introduced by Wright (1936). This method shows that technology cost reduction occurs along with the cumulative doubling of installed technological capacity (Louwen & Lacerda, 2020).

However, the estimation of learning rates, particularly for Solar PV, remains highly variable across studies. This may be due to differences in data collection methods and variations in characteristics between the early and more mature phases (Kim et al., 2019). UNEP-CCC and CTCN (2024) tabulate learning rates for various technologies from various previous studies. Solar PV ranges from 4% to 32%. A narrower range was shown by Chang et al. (2022) and Grubb et al. (2021). Chang et al. (2022) indicates that PV module efficiency declines by an average of 18–22% per doubling of capacity, and rooftop PV is lower at approximately 19% due to factors related to installation and customization, while according to Grubb et al. (2021), for every doubling of cumulative installed solar PV capacity, solar PV prices have decreased by 20% ± 6% over the past 40 years. Meanwhile, Samadi (2018) presented a more pessimistic learning rate. This study revealed a learning rate of 15-23% for the short term and 8-17% for the long term, based on the historical curve of global PV solar module installations (1975–2015) in the United States. In contrast, the most optimistic learning rate is reported by IRENA (2025). They estimate the reduction in utility-scale Solar PV reached 33.8%, globally. Rubin's study shows that the learning rate for solar PV varies quite widely, between 12% and 40% (Rubin et al., 2015). The IESR report estimates the learning rate for Solar PV in Indonesia at only 19% for the period 2019–2022 (IESR, 2025), which is lower than the global trend.

Indeed, the learning curve, or learning rate, concept is valuable for planning the transformation of energy systems towards a more sustainable future, as it identifies the most cost-effective technology mix, and provides critical insights to support policy design and development (Louwen & Lacerda, 2020). However, the wide range of reported learning rates produces divergent forecasts of electricity-generation cost reductions, amplifying uncertainty about future Solar PV adoption and leading to either over- or underestimation of deployment—ultimately risking the formulation of inappropriate policy measures. Limited studies have evaluated the impact of this uncertainty on the generation expansion planning. Dai et al. (2024) examined the impact of the learning curve on power generation competition in China, using an optimization model through 2050. However, this study is limited to considering the learning curve of power generation technologies, Solar PV and wind, similar to the approach taken in prior research by Kosugi (2023). However, integrating a massive scale of variable renewable energy requires sufficient grid flexibility, which can be provided by energy storage, such as batteries. Therefore, projected energy storage prices will impact on the future competitiveness of solar PV.

In addition, several studies have already examined battery learning rates. Vatankhah Ghadim et al. (2025) estimated a ~15% cost reduction for utility-scale storage, while Schmidt et al. (2017) place the battery learning rate at 10–20% per doubling of capacity. Ziegler and Trancik (2021) estimated the learning rate for all types of cells is 20%. MEMR (2024) sets the learning rate at 15%, which serves as a reference in national power system planning, particularly for utility-scale storage.

Therefore, to address the considerable variation in Solar PV and Battery learning rates as well as limited assessment of how this uncertainty affects cost reduction and power system planning, this study evaluates the impact of wide dispersion of reported Solar PV learning rates, capturing the resultant uncertainty and explicitly incorporates the operation constraints and battery cost reduction that critically shape the Solar PV integration and adoption in Indonesia's power sector planning. Specifically, this study aims to investigate the economic competitiveness of solar PV with other technologies in various price reduction scenarios and its impact on emissions, investment, and the cost of electricity production using a power system optimization model, TIMES-Indonesia. The Indonesian case study was chosen considering the aspects of a developing country that still values affordability and still has enormous coal subsidies. The power system model was developed from 2020 to 2060. Ultimately, in addition to filling the existing research gap, this study provides policymakers with a clear picture of how uncertainty in solar-PV price reductions will affect the future decarbonization of Indonesia's electricity system, thereby helping them devise appropriate policies.

METHODOLOGY

This study examined the effect of varying learning rates for solar PV and battery technologies on the power system, using the TIMES-Indonesia optimization framework, as illustrated in Figure . The TIMES-Indonesia model was designed based on a generator model (TIMES) developed through the IEA's Energy Technology Systems Analysis Programme. This model was used to find the least-cost pathway of the power system until 2060 for the Indonesia case study, as shown in Eq. 1 and Eq. 2.

$$Total\ Discounted\ System\ Cost = \sum_{y \in YEARS} (1+d)^{REFYR-y} \times ANNCOST_y \quad (1)$$

$$ANNCOST\ (y) = INV(y) + FOM(y) + VOM(y) \quad (2)$$

which, y is modeled year, d is discount rate, REFYR is reference year, and $ANNCOST_y$ is the annual cost of year y, $INV(y)$ is investment cost in year y in USD, $FOM(y)$ is fixed operational and maintenance cost in year y in USD, and $VOM(y)$ is variable operational and maintenance cost in year y in USD. TIMES-Indonesia has been developed since 2018 and has produced multiple publications (Herawati & Purwanto, 2025; Reyseliani et al., 2022; Reyseliani et al., 2024; Reyseliani & Purwanto, 2021).

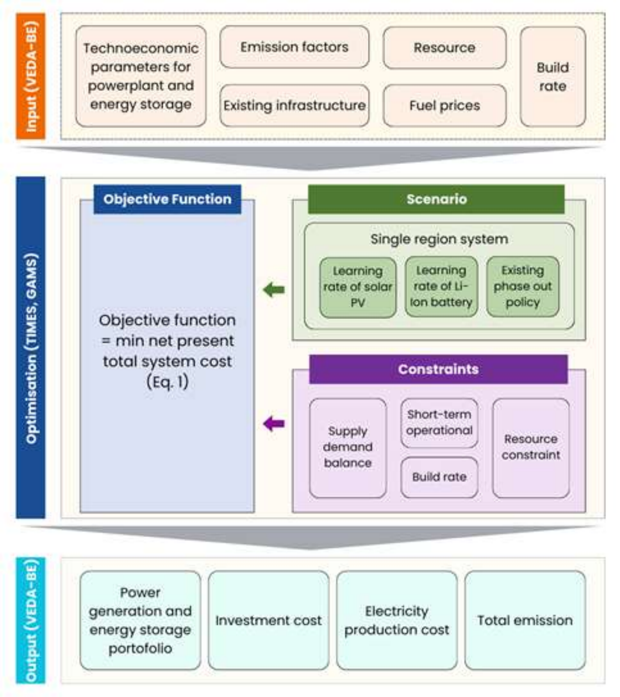


Figure 1. Model Framework

The input parameters for this model include techno-economic parameters of power plants and energy storage technologies, emission factors, resource potential, build rate, fuel prices, and existing infrastructure are based on data from previous publications (Reyseliani et al., 2022; Reyseliani et al., 2024; Reyseliani & Purwanto, 2021). Several equations incorporated in TIMES-Indonesia, including supply-demand balance, short-term operational, build rate, and resource supply, constrained the optimization performed.

Supply-demand balance

The supply-demand balance is shown in the Eq. 3.

$$DEM_{c,s,t} + EXP_{c,s,t} \leq \sum_{p=1}^{P} PRD_{p,c,s,t} + IMR_{c,s,t} \quad (3)$$

Where, $DEM_{c,s,t}$ is the total demand of commodity c in *time slice s* and period t (PJ), $EXP_{c,s,t}$ is the export of commodity c in every *time slice s* and period t (PJ), $PRD_{c,s,t}$ is the production of commodity c in every *time slice s* and period t (PJ), $IMR_{c,s,t}$ is the import of commodity c in every *time slice s* and period t (PJ)

<u>Short-term operational constraint (Unit Commitment)</u>

Existing capacity of process p in period t is shown in Eq. 4.

$$CAP_{r,t,p} = CAPN_{r,p} + CAPO_{r,p} - CAPR_{r,t,p} \quad (4)$$

Where, $CAPN_{r,p}$ is the capacity of new technology p in regional r, $CAPO_{r,p}$ is the capacity of the existing technology p in regional r, $CAPR_{r,t,p}$ is the capacity of retired technology p in period t and regional r. Online process capacity p in period t is shown in Eq. 5.

$$CAPon_{r,t,p} = CAP_{r,t,p} - \sum_{s=1}^{S} CAPoff_{r,t,p,s} \quad (5)$$

Where, $CAPon_{r,t,p}$ is the online capacity of technology p in period t and regional r, $CAPoff_{r,t,p,s}$ is the offline capacity of technology p in period t and regional r. Minimum stabilization operation is shown in Eq. 6.

$$PRD_{r,t,p,s} \geq MINLD_{r,p} \times CAPon_{r,t,p} \times CA_{r,p} \times X_{r,s} \tag{6}$$

Where, $MINLD_{r,p}$ is the minimum load of technology p in region r, $CA_{r,p}$ is the capacity to activity conversion of technology p in region r, $X_{r,s}$ is time slice s fraction in every year. Start-up dan shut-down process is shown in Eq. 7 to Eq. 9.

$$CAPups_{r,t,p,s} - CAPlos_{r,t,p,s} = CAPoff_{r,t,p,s-1} - CAPoff_{r,t,p,s} \tag{7}$$

$$MCAPoff_{r,t,p,s} \geq CAPoff_{r,t,p,s} \tag{8}$$

$$\sum_{s}^{S} CAPups_{r,t,p,s} \geq MCAPoff_{r,t,p,s} \tag{9}$$

Where, $CAPups_{r,t,p,s}$ is the start-up capacity of technology pin region r, period t, and time slice s, $CAPlos_{r,t,p,s}$ is the shut-down capacity of technology pin region r, period t, and time slice s, and $MCAPoff_{r,t,p,s}$ is the maximum offline capacity of technology pin region r, period t, and time slice s. Production should be higher than *losses* as the effect of *part-load efficiency* is shown in Eq. 10.

$$PRD_{r,t,p,s} \geq PRDpll_{r,t,p,s} \tag{10}$$

Where, $PRDpll_{r,t,p,s}$ is losses due to part-load efficiency on technology p in period t, region r, and time slice s.

<u>Resource Supply</u>

For commodities whose quantity is limited depending on reserves, the limit is shown in Eq. 11.

$$\sum_{p=1}^{P} \sum_{n=1}^{N=lifetime} PRD_{c,p,t,r} = RSV_{c,r} \tag{11}$$

Where, $PRD_{c,p,r,y}$ is the production of commodity c in technology p which is installed at period t and regional r (PJ), N is the lifetime technology p, $RSV_{c,r}$ is the total reserve of commodity c in region r.

This study reviewed two main scenarios: the least-cost power system, business as usual (BAU), and the least-cost power system with the implementation of coal phase-out planning (BAU PO), as outlined in Presidential Regulation 112/2022 (GOI, 2022). These two scenarios were evaluated on a least-cost basis, without any environmental policy interventions, such as emission targets or carbon budgets, to assess competitiveness based solely on economic factors. Meanwhile, BAU was considered to see the level of competitiveness of solar PV if the coal phase-out policy does not proceed as planned. Furthermore, this study reviewed three learning rates for solar PV and Li-ion battery sub-scenarios. A represents the sub-scenario with a pessimistic learning rate, B represents the moderate sub-scenario, and C represents the optimistic sub-scenario, based on the literature described, as shown in Table 1.

Table 1. Scenarios

Scenarios		Description
BAU	A	Least-cost power system optimization with pessimistic learning rate of 12% for Li-ion battery and 19% for Solar PV

	B	Least-cost power system optimization with realistic learning rate of 16% for Li-ion battery and 27% for Solar PV
	C	Least-cost power system optimization with optimistic learning rate of 20% for Li-ion battery and 36% for Solar PV
BAU-PO	A	Least-cost power system optimization with phase-out strategy and pessimistic learning rate of 12% for Li-ion battery and 19% for Solar PV
	B	Least-cost power system optimization with phase-out strategy and realistic learning rate of 16% for Li-ion battery and 27% for Solar PV
	C	Least-cost power system optimization with phase-out strategy and optimistic learning rate of 20% for Li-ion battery and 36% for Solar PV

The learning curve formula used in this study uses a single-factor learning curve, as shown in Eq. 12 to Eq. 14.

$$C_t = C_1 {X_t}^{-b} \tag{12}$$

$$PR = 2^{-b} \tag{13}$$

$$LR = 1 - PR \tag{14}$$

Which C_t is the unit cost of production at time t, C_1 is the first unit's production cost, X_t is cumulative production at time t, b is the learning parameter, PR is the progress ratio, and LR is the learning rate.

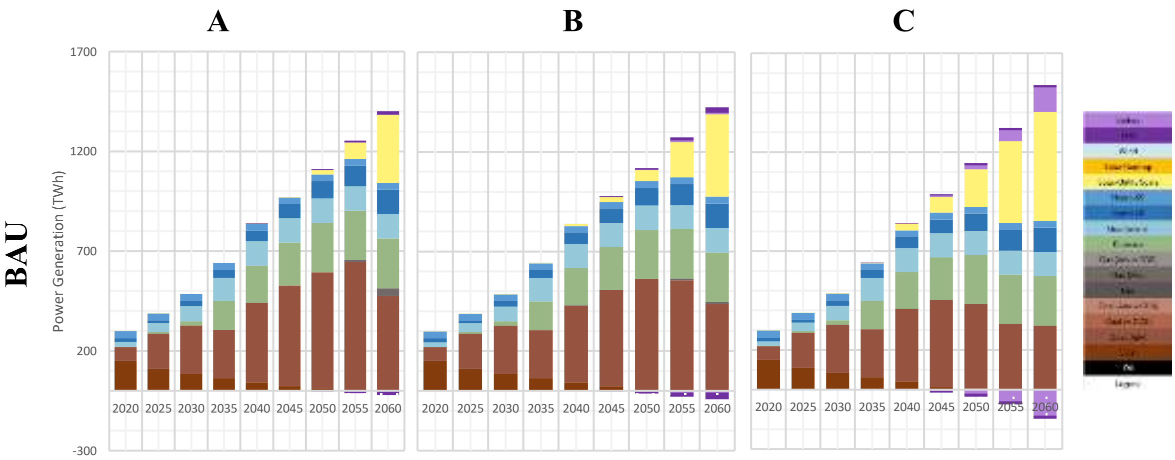
RESULTS AND DISCUSSION

Generation Expansion Planning Portfolio

A comparison of the power generation production for all the scenarios is shown in figure 2. In the BAU, coal power plants are expected to play a critical role in electricity generation throughout the projection period. In BAU-A and BAU-B, electricity production from coal power plants will increase until 2055, from 220 TWh in 2020 to 644 TWh and 554 TWh in 2055. In 2060, the electricity production from coal power plants will decline by 26% and 21% for BAU-A and BAU-B, respectively. Renewable energy penetration begins to occur significantly in 2035, with 18% and 22% of electricity supplied by geothermal and biomass power plants with a total capacity of 14.9 GW and 19.8 GW, respectively. Subsequently, the annual increase in electricity production from biomass power plants is only 2.4% until 2060, and coal power plants meet the majority of the rise in electricity demand. In BAU-A, solar PV installations begin to occur significantly in 2055, and their electricity production increased by 320% by 2060, with a capacity of 58.9 GW to 247.8 GW. The moderate learning rate in BAU-B causes significant solar PV penetration to begin to occur 5 years earlier, namely in 2050, which results in 21.5% greater electricity production compared to BAU-A in 2060. A different trend is evident in the optimistic learning rate, BAU-C, which begins in 2040. A total of 24.6 GW of Solar PV started to be installed, contributing 4% to the electricity supply. Solar PV will continue to increase drastically from 2050 to 2060. In 2060, the solar PV mix in the electricity system reached 39% or equivalent to 551 TWh. The significant increase in solar PV installations over the last decade has led to substantial growth in Li-ion battery capacity, reaching 82 GW.

The implementation of the coal phase-out policy generally causes the peak electricity production from coal-fired power plants to occur in 2025. After that, in accordance with the provisions of Presidential Regulation 112/2022, no coal-fired power plants will be operational again. In 2030, biomass power plants' capacity is expected to expand, after which Solar PV will make a significant contribution in all three BAU PO sub-scenarios, accounting for 7.9-12.6% of total electricity production by 2035. An increase in the electricity production mix occurs for all three sub-scenarios until 2060, accompanied by additional contributions from biomass, geothermal, and a small amount of hydropower. This results in a significant increase in solar PV capacity across all three sub-scenarios, specifically 287.6 GW, 294.9 GW, and 450.1 GW, respectively. Additionally, the construction of gas power plants with combined cycle gas turbine technology occurs in all scenarios, serving as a baseload.

The difference in learning rates for solar PV and Li-ion batteries has a different impact on the two main scenarios, as shown in Figure 3.2. In BAU, without any coal phase-out planning, a more optimistic learning rate will cause solar PV penetration to be significantly faster, 5 years earlier compared to the moderate scenario, and 10 years earlier than the pessimistic scenario. Therefore, at a learning rate of 36% for Solar PV and 20% for Li-ion batteries, and assuming Indonesia's power system evolves based purely on cost efficiency - without any emission-related policies- Solar PV will only become economically competitive starting in 2045, and its share in the power mix will grow significantly from 2050 onward. Meanwhile, in the BAU PO, the implementation of the coal phase-out policy does not affect the penetration year of solar PV and Li-ion batteries. All three sub-scenarios indicate that Solar PV will begin to penetrate significantly in the same year, in 2035. The difference in learning rates affects the annual amount of Solar PV penetration, resulting in varying penetration levels compared to gas plants for the two scenarios. This suggests that if the advancement of Solar PV technology with Li-ion batteries does not proceed according to optimistic assumptions—leading to less significant technology cost reductions—then the readiness of midstream gas infrastructure, which currently faces significant limitations, must be carefully considered. This is further compounded by Indonesia's limited gas reserves, which could lead to massive gas imports (Reyseliani et al., 2024). This impact can be mitigated by implementing emission-related policies that further reduce the role of gas in the electricity mix, potentially at a higher electricity production cost.



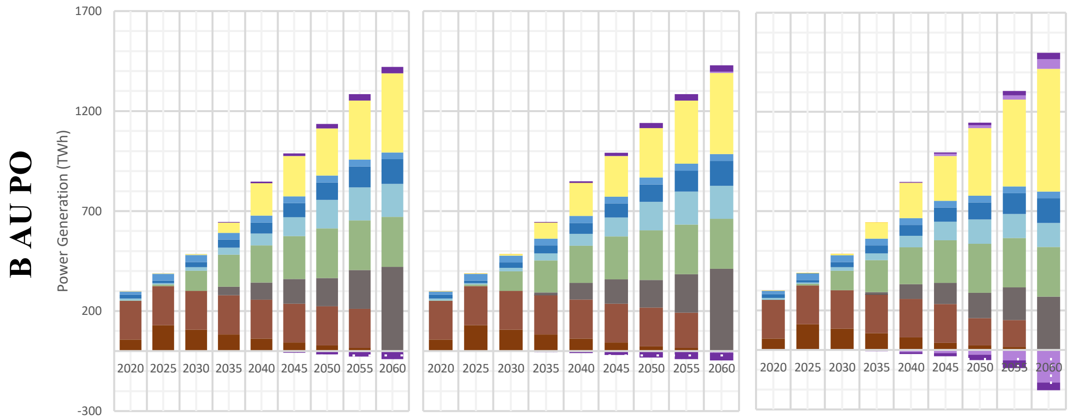


Figure 2. Comparison of power generation

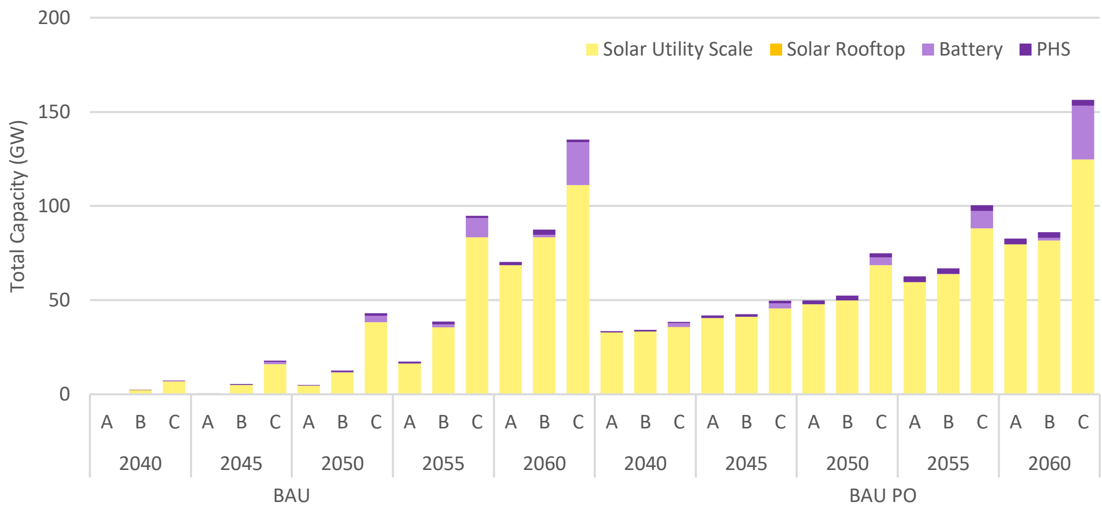


Figure 3. Solar PV and Li-ion Battery Capacity

Emission Trajectory

The emission trajectory produced in each scenario is illustrated in Figure 3. Emissions in both main scenarios are relatively similar until 2035. A 4.6% difference in emissions occurs between 2030 and 2035 due to variations in the electricity production share from biomass and geothermal power plants. In the following period, there is a significant spike in emissions in BAU caused by an increase in the electricity production from coal power plants. Peak emissions in BAU-A and BAU-B occur in 2055, while the peak emissions in BAU-C occur earlier, in 2050, which is in line with the trend of coal electricity production. After 2055, there is an annual decrease in emissions by 3.6% and 3.0%, respectively, in BAU-A and BAU-B due to a significant increase in electricity production from Solar PV. Meanwhile, a more gradual and distributed decrease in emissions occurs in BAU-C with an average annual decline of 1.12%. In general, as seen in Figure 4. increasing the learning rate in the moderate scenario does not have a substantial impact on reducing emissions compared to the pessimistic scenario, cumulatively only 4.3%, however, an optimistic learning rate can shift the peak emissions 5 years earlier and cumulatively reduce emissions by up to 15.7%, compared to BAU-A.

Meanwhile, BAU PO maintains a relatively stagnant future emissions trajectory compared to 2020, with an average annual increase of 0.5% to 1.2%. Peak emissions in all three scenarios occur in the same year, 2055, indicating the final year coal can supply electricity in accordance with Presidential Regulation 112/2022. The minimal difference in the solar PV mix between BAU PO-A and BAU PO-B results in insignificant emissions reduction. Meanwhile, in BAU PO-C, there is a larger annual emission reduction from 2050 to 2060, with an average annual emission reduction of 3.1% between sub-scenarios, due to a larger solar PV mix and lower electricity production from gas plants. In addition, the contribution of emission reduction due to the coal phase-out policy is more dominant, namely 39.4-43.6% in 2060, compared to the contribution of the increase in the learning rate of Solar PV and Li-ion batteries of 18.9-24.5% in 2060.

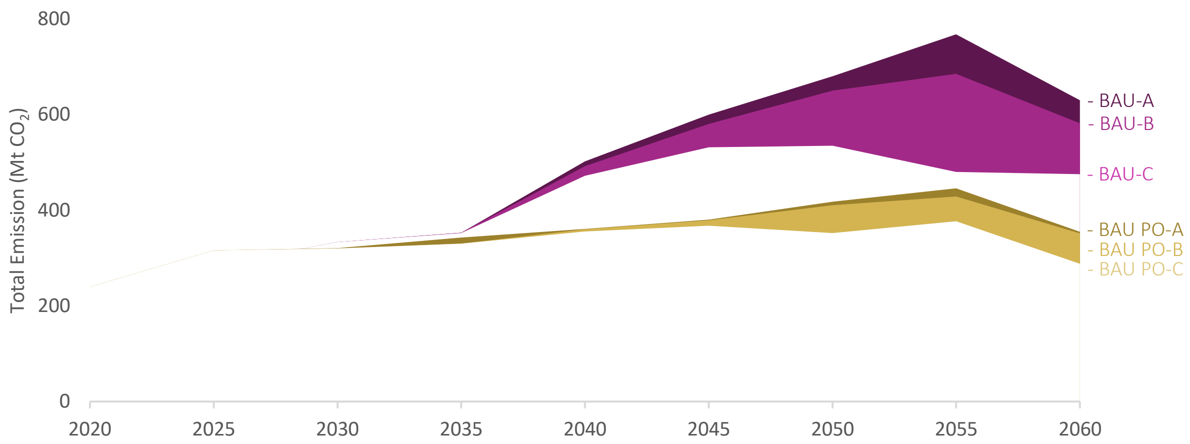


Figure 4. Emission trajectory

Investment Cost

Based on the investment costs illustrated in Figure 5. BAU requires a lower cumulative investment compared to BAU PO, reaching around 535.4-541.2 billion USD, while BAU-PO is in the range of 552.8-584.3 billion USD. In the BAU, investment shows a significant surge, particularly in the last decade of the projection period, from 40-53 billion USD in 2050 to nearly 92-162 billion USD in 2060. This is caused by an increase in solar PV capacity by 54.8-62.6% compared to 2050, as in Figure 3.2. A notable peak also occurs in 2035, reaching 75 billion USD, mainly driven by significant additions of biomass power plants. In the following period, investment in fossil fuels will be balanced with renewable energy, although the share will eventually decline to nearly 8-15% by 2060, with renewable energy dominating. In contrast, the BAU PO follows a more gradual and stable trajectory, with investment distributed more evenly over the decades, with an average annual increase of 0.8%. The total investment for BAU PO in 2060 is in the range of 103-138 billion USD, below that of BAU. The increase in the fossil fuel mix in 2040 and 2060 in all BAU PO scenarios occurs due to additional gas power plant capacity.

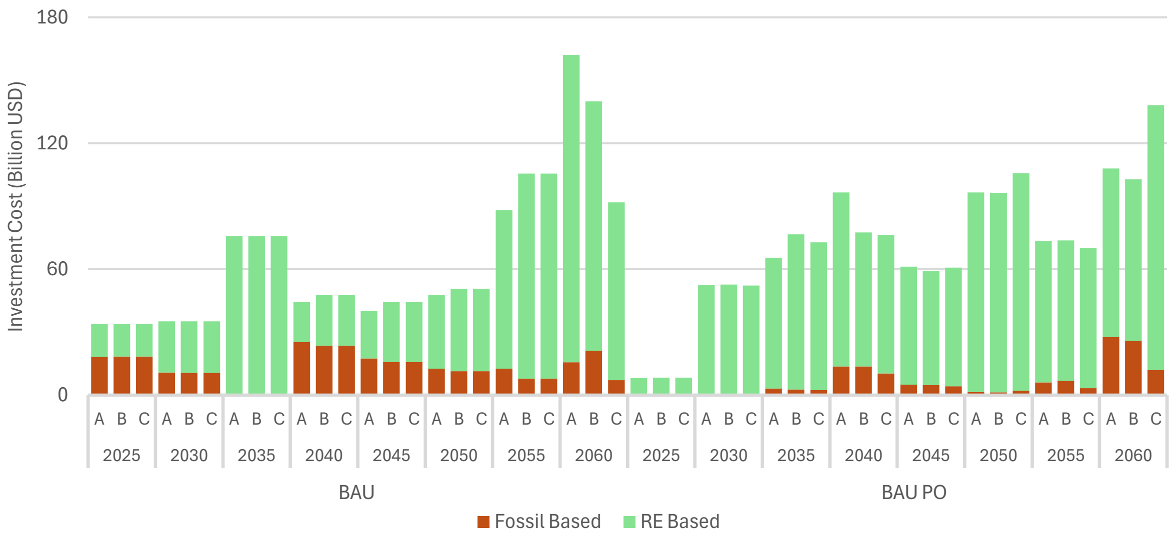


Figure 5. Investment cost

Table 2. Cumulative Investment

Technology	**BAU**			**BAU PO**		
	A	B	C	A	B	C
Fossil based	120.7	116.6	84.7	57.4	55.2	34.4
RE based	414.7	424.7	455.4	504.8	497.6	549.9
Total	535.4	541.2	540.1	562.1	552.8	584.3

Electricity Generation Cost

The electricity generation cost for all scenarios is shown in Figure 3.4. The cost considered in this analysis encompasses only the power plant technology and electricity storage, and excludes the transmission, distribution, and other ancillary costs. Overall, the cost of electricity generation for both scenarios will increase from 2030. After 2030, a more significant increase occurs in BAU PO until 2060, while BAU will tend to remain constant throughout the projection years. The contribution of solar PV to total electricity production, which is not much different in the BAU, causes generation costs to range within a small range for each year, generally. A slightly larger range occurs from 2045 to 2050, namely 6.50-6.67 cents/kWh and 6.57-6.78 cents/kWh, due to the difference in the start years of solar PV significant adoption within three scenarios. Meanwhile, in BAU PO, the same adoption year of solar PV within three sub-scenarios yields projected electricity generation cost within a narrow range until 2050. After that, the generation costs range from 6.93 to 7.10 cents/kWh and from 6.78 to 7.35 cents/kWh in 2055 and 2060, respectively. The average annual increase in electricity generation cost is 1.06–1.11% for BAU, while it ranges from 1.30% to 1.51% for BAU-PO due to the more significant contribution of Solar PV, Li-ion Batteries, and Gas Power Plant in the power system.

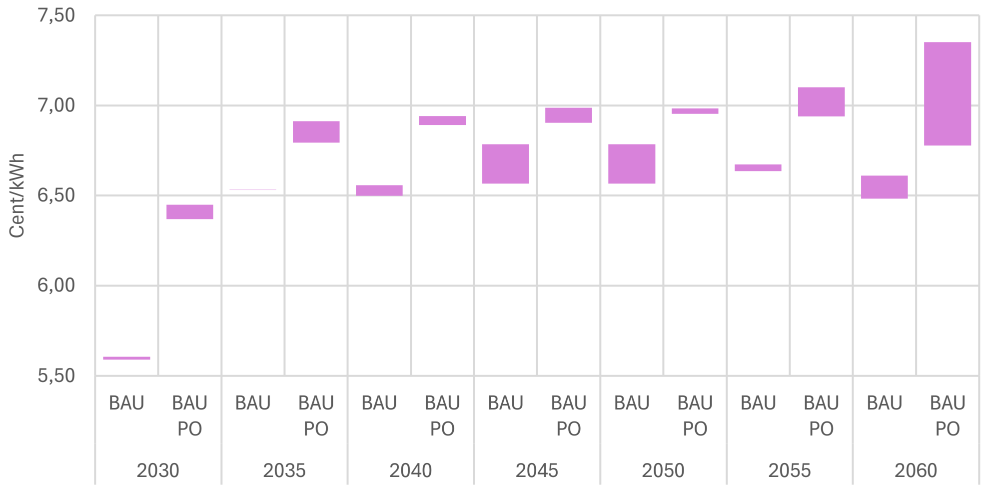


Figure 6. Electricity Generation Cost

CONCLUSION

This study examines the impact of variation in learning rates for solar PV, along with Li-ion batteries as a balancing system, on Indonesia's power system planning using a learning curve approach within the TIMES-Indonesia optimization model from 2020 to 2060. There are two main scenarios reviewed, BAU (least-cost power system) and BAU PO (least-cost power system with coal phase out planning), and three sub-scenarios; A is pessimistic, B is moderate, and C is optimistic learning rate of Solar PV and Li-ion Battery. The results indicate that the difference in learning rate of Solar PV and Li-ion batteries has a different impact on BAU and BAU PO. A more optimistic learning rate will accelerate the competitiveness of solar PV 5 and 10 years earlier than the moderate and pessimistic scenarios in BAU. Meanwhile, the difference in learning rates between Solar PV and Li-ion batteries does not affect the start year of adoption, which is 2035, for the two technologies in the BAU PO, but rather the magnitude of penetration each year. BAU requires a lower cumulative investment, approximately 535.4-541.2 billion USD, compared to 552.8-584.3 billion USD under BAU-PO, with investments in BAU being more concentrated in the final decade, whereas BAU-PO shows a more evenly distributed investment pattern over time. BAU-PO indicates lower emissions trajectory compared to BAU; however, the impact of learning rates is more pronounced in BAU, where emission reduction by 2060 ranges from 8% to 25% compared to the pessimistic scenario. In contrast, emission reduction BAU-PO is primarily driven by coal phase-out policies rather than by the effect of learning rates. The average annual increase in electricity generation cost is 1.06–1.11% for BAU, while it ranges from 1.30% to 1.51% for BAU-PO due to the more significant contribution of Solar PV and Li-ion batteries in the power system. This study highlights the advancements in Solar PV and Li-ion batteries, driving faster declines in investment costs, significantly accelerating technology adoption and reducing emissions. Furthermore, when combined with the coal phase-out policy, the cost reduction effectively curbs emission growth through 2060. However, if Solar PV and Li-ion batteries fail to achieve substantial cost reductions despite coal phase-out policies, a massive gas infrastructure becomes inevitable. As this study is limited to the consideration of learning rates exogenously in power system model, future research should adopt endogenous learning models that link cost reduction to optimized cumulative installed capacity, enabling a more dynamic representation of technology evolution. This research received no external funding. The author thanks all individuals and institutions that provided informal support and access to data, without which this work would not have been possible.

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