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Impact of high solar and wind penetrations and different reliability targets on dynamic operating reserves in electricity generation expansion planning

Yusak Tanoto [a,b,*], Iain MacGill [a], Anna Bruce [c], Navid Haghdadi [c]

[a] School of Electrical Engineering and Telecommunications and Collaboration on Energy and Environmental Markets, University of New South Wales, High Street Kensington NSW 2033, Sydney, Australia
[b] Electrical Engineering Department, Petra Christian University, Surabaya, Indonesia
[c] School of Photovoltaic and Renewable Energy Engineering and Collaboration on Energy and Environmental Markets, University of New South Wales, High Street Kensington NSW 2033, Sydney, Australia

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ABSTRACT

Wind and solar are increasingly cost-competitive as well as environmentally less harmful alternatives to the fossil-fuel generation that dominates most electricity industries. However, their highly variable and somewhat unpredictable output still requires high levels of dispatchable plants to ensure demand can be met at times of low renewables availability. While this capacity overhead has associated costs, it does offer potentially useful outcomes for dynamic operating reserves. We present a method for assessing these potential outcomes in electricity industry planning. We use an evolutionary programming-based capacity expansion model, NEMO, that solves least-cost generation mixes through full operational dispatch of candidate solutions, using high-temporal resolution demand and wind and solar profiles, over a year or more. We apply our method through a case study of the Java-Bali grid, considering future scenarios both with and without variable renewables, and under different carbon pricing scenarios, reliability targets, and minimum operating reserves requirements. Our study suggests that not only might high renewable penetrations reduce industry costs and emissions, their inclusion provides significantly higher operating reserves over most of the year, hence the ability to cover unexpected plant failures and other disruptions. Lower reliability targets reduce this capacity overhang but still see improved operating reserves.

1. Introduction

Solar photovoltaic (PV) and wind generation technologies are playing a key role in the low-carbon electricity industry transition around the world. They are increasingly cost-competitive alternatives to the conventional, carbon emission-intensive, fossil-fuel coal and gas generation technologies that currently dominate the generation mix of most jurisdictions. However, growing penetrations of these highly variable renewable energy (VRE) technologies also raise security and reliability questions for electricity industry planners and policymakers (Kroposki, 2017; IEA, 2017), and form the motivation for the study presented here.

Early deployment of utility-scale PV and wind largely occurred in the electricity industries of OECD countries, and they now offer examples of successful integration at relatively high penetrations. However, VRE also shows great promise for the electricity sectors of emerging economies to address their affordability and environmental challenges. Solar and wind penetrations are climbing rapidly in many jurisdictions and are now being widely incorporated into electricity planning studies across the developing world (Senatla et al., 2018; Luz et al., 2018; Barasa et al., 2018).

While solar PV and wind costs continue to fall, their highly variable and some unpredictable output does raise several challenges for secure and reliable power system operation. In particular, the need for sufficient generation capacity to meet demand at all times and locations, and periods of low PV and wind availability, means that even major VRE deployment still requires significant levels of highly dispatchable generation (Monyei et al., 2019), which is conventionally provided by coal, gas, or hydro plant. Of course, these conventional generation options are also subject to occasional plant failures, and there are other possible risks to availability including fuel supply interruptions, droughts,

* Corresponding author at: School of Electrical Engineering and Telecommunications and Collaboration on Energy and Environmental Markets, University of New South Wales, High Street Kensington NSW 2033, Sydney, Australia.
E-mail address: y.tanoto@student.unsw.edu.au (Y. Tanoto).

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extreme weather events, and natural disasters (Gülen and Bellman, 2015). Power systems therefore typically maintain some level of generation operating reserves to cover periods where even generally highly dispatchable plants might prove unavailable.

Wind and solar generation pose some difficulties for establishing appropriate levels of operating reserves given the highly complex and somewhat uncertain availability of the wind and solar resource looking forward in time (Dorsey-Palmateer, 2019), particularly if and as their penetrations climb. However, they also offer some advantages as they are typically deployed in a highly modular fashion – parallel strings of PV modules and inverters for solar farms and tens to hundreds of MW scale turbines for wind farms. As such, they do not tend to have the single points of failure that are present with large thermal plant units. Furthermore, periods of high wind and/or solar may represent times where the unexpected failure of some generation, renewable or conventional, can be more easily managed due to excess online generating capacity. Understanding operational uncertainty of the power system with high solar and wind penetrations is therefore one of the key factors for planners and utilities in ensuring the system meets reliability criteria (Go et al., 2020), including the level of reserves.

An additional complexity is what level of reliability might be reasonably expected given the costs associated with higher reliability targets, regardless of the generation mix. This question is particularly vexed for the electricity industries of emerging economies where achieved reliability is often considerably lower than for developed economies, for a range of reasons that extend beyond insufficient operating reserves, and where increased industry costs must be carefully balanced against affordability concerns.

An early key study established that wind variability and uncertainty need not be treated as a potential contingency, yet also highlighted the challenges of securing sufficient operating reserves at times of high demand and low wind (Holttinen et al., 2012). (Vos and Driesen, 2014) suggested that reserves should be dynamically calculated with ongoing economic/market dispatch, depending on the level of variable generation, rather than statically fixing reserve capacity for extended periods, with the risk of over-estimating these needs. Possible reductions to conventional operating reserve requirements and hence generation cost savings were assessed using a probabilistic approach to forecasting wind power. (Krad et al., 2017) also argued for dynamic rather than static operating reserve requirements, including ramping reserves, to improve reliability and economic outcomes as renewable penetrations grow. Meanwhile, the value of geographical dispersion of utility renewables to smooth reserve requirements is highlighted in (Choukri et al., 2018). However, in this study wind generation estimates were produced by scaling up linearly from 12 % to 100 %, which does not account for spatial smoothing (Choukri et al., 2018). An international comparison of how different jurisdictions incorporate wind generation into their process for setting operating reserves is presented in (Milligan et al., 2010), which found that most jurisdictions apply a statistical approach such as Monte Carlo simulations, to handle wind variability when establishing regulating reserves, while some use methods like scenario analyses, and less than half of jurisdictions surveyed considered ramping reserve type in their integration studies. Of relevance to this paper, (Vos and Driesen, 2015) used a unit commitment model to show the potential of wind as a downward operating reserve provider, and the impact on system scheduling and generation costs. (Vos et al., 2019) presented dynamic sizing methods, including machine learning methods, for determining the required sizing of frequency restoration reserve during risk periods due to increasing renewable generation.

Our study seeks to address some key gaps in work around operating reserves and high VRE penetrations to date. To the authors' best knowledge, these key gaps include: (i) detailed assessment of the opportunity and impact of possible future high solar and wind penetrations on dynamic operating reserves, (ii) the implications of high PV rather than wind penetrations of these reserves, and (iii) the use of real-world high temporal resolution (hourly) wind, PV and demand data over the year time frame commonly used for assessing operating reserves within electricity generation planning.

Our study considers very high VRE penetrations, particularly solar PV, in future generation scenarios and quantifies the opportunities that these penetrations might offer to improve the reliability and security of the grid, due to the extra dispatchable generation capacity required for those few periods of very low wind and solar availability.

We introduce a novel approach for presenting operating reserves, based on plotting dynamic operating reserves against Load Duration Curves (LDC) over a typical year of operation. Our study also assesses the impact of different reliability standards on the magnitude of dynamic operating reserves. This question is particularly relevant to the electricity sector in emerging economies where achieved levels of reliability are far lower than for developed economies for a range of reasons, and hence where very exacting reliability standards in generation capacity planning might not always be appropriate.

We apply an open-source generation capacity expansion model, National Electricity Market Optimiser (NEMO) (Elliston et al., 2013), which solves this techno-economic optimization using an evolutionary programming-algorithm that solves a full year of operational dispatch for all candidate solutions. We demonstrate its application for the case study of the Java-Bali grid in Indonesia. Future least-cost generation mixes are solved for a range of scenarios including ones that exclude as well as permit VRE, apply different levels of carbon pricing, and set different minimum operating reserve requirements. For each scenario, we assess the impact of different least-cost generation mixes on dynamic operating reserve levels, total industry generation costs, and CO_2 emissions. The Java-Bali grid presents a useful case study as the region has an excellent solar resource as well as abundant coal-fired generation potential, while facing growing environmental, affordability and reliability challenges as electricity demand continues to grow.

This paper extends the analysis conducted in our previous study (Tanoto et al., 2019), as we now consider wider implications of different reliability requirements, as measured by Unserved Energy (USE) targets, on dynamic reserves, rather than just applying a single, reasonably stringent target.

Our study is the first to explicitly model possible futures for the Java-Bali grid that include high wind and PV penetrations and assess operating reserves, total industry costs, and emissions, over a yearly time horizon at a range of reliability standard levels. However, more broadly, the methods presented here apply to sustainable electricity industry planning in the growing number of jurisdictions considering possible future electricity sector development pathways with high solar and wind penetrations.

The rest of this paper is organised as follows. Section 2 presents a brief overview of the capacity expansion tool, NEMO, used for our study. Section 3 introduces the Java-Bali grid case study and then details its implementation in NEMO. Results obtained from the analysis of a range of possible future scenarios for the Java-Bali grid are presented and their broader implications are discussed in Section 4. Finally, Section 5 provides some concluding discussion of the findings and potential future work.

2. Method

2.1. NEMO modelling, simulation and optimization overview

NEMO (Elliston, 2018) is an economic dispatch and evolutionary optimization model, which is implemented in Python 3 and has been used by a range of researchers to conduct optimization studies around future electricity industry capacity planning.

The tool has been applied to assess the technical and economic viability of different possible 100 % renewable electricity futures in the Australian National Electricity Market (NEM), as well as possible low-emission generation mixes including renewables as well as conventional fossil fuel options, carbon capture and storage (CCS) and nuclear

(Elliston et al., 2014). NEMO allows the user to set very high-reliability requirements and will solve least-cost generation mixes that ensure there is sufficient generation to meet even peak demand periods that coincide with low wind and PV availability (Elliston et al., 2012). These studies with NEMO have not only shown that high VRE penetrations are a key opportunity for delivering future highly reliable low-emissions electricity systems, but they can also reduce the risks associated with future fuel costs and emission reductions policies by comparison with future generation mixes that continue to rely primarily on fossil fuel options (Riesz and Elliston, 2016).

NEMO's evolutionary programming optimizer uses the Distributed Evolutionary Algorithms in Python (DEAP) platform, based on a robust-randomized search Covariance Matrix Adaptation Evolution Strategy (CMA-ES) (Auger and Hansen, 2012). The CMA-ES parameters and working principles within the evolutionary programming process are described in previous work (Tanoto et al., 2019).

2.2. NEMO inputs, settings and outputs

NEMO inputs are as follows: 1) A high resolution chronological demand profile over the period of study (typically 30 min to hourly over a year). NEMO builds the generation mix to meet this demand profile; 2) Fixed capital and O&M, variable costs, and emissions intensities for all available generation technologies, as well as any constraints in terms of their total possible installed capacity. NEMO solves the least cost mix of available generation to meet this demand; 3) For wind and solar, chronological normalised generation profiles over the same time period as demand. Multiple locations for these options, each with their own traces, can be specified, and NEMO will find the least cost mix across these potential sites.

Key NEMO settings beyond the evolutionary optimization parameters noted in the previous section are the minimum reliability required in the solution (defined as the allowed % unserved energy) and minimum reserve levels. Other constraints (not considered in this study) can include minimum renewable penetrations, minimum synchronous generation penetrations and industry emissions limits. Rather than using hard constraints, NEMO can also incorporate reliability, security, and environmental objectives through the cost function – e.g. carbon pricing emissions from fossil fuel generation.

NEMO outputs an ordered list of possible generation mixes to meet demand within constraints, ranked from least cost. Emissions and reliability outcomes for each generation mix are also calculated. Importantly for this work, NEMO outputs include the least cost dispatch of the solution generation mix over the study period, allowing investigation of system operation including ramping rates, plant starts and stops and, key to this study, available generation capacity in excess of demand per time period.

2.3. Assessment of dynamic operating reserves

There are some complexities and choices in classifying different types of generation capacity reserves for power system planning (Dubitsky and Rykova, 2015) as well as different sizing methods for estimating operating reserves (Vos et al., 2019). While approaches for estimating operating reserves are often differentiated according to the nature and timing of reserves availability, we do not attempt to categorise hot and cold reserves or any demand-side opportunities in our modelling. Instead, we focus on the impact of least-cost generation mixes with high VRE penetrations on the dynamic system operating reserves at an hourly resolution over a future simulated year of power system operation.

These system dynamic operating reserves are calculated according to the level of undispatched-dispatchable fossil-fuel plants and any curtailed 'surplus' energy generated by VRE each hour. Given its very low operating costs, available VRE generation is dispatched by the model before any-fossil fuel generation is called upon. That displaced dispatchable generation is then available as reserves if and as required. When there is sufficient VRE to entirely meet demand and it is being curtailed, then this provides even greater reserves. Hence, hourly system operating reserves are calculated as (Tanoto et al., 2019):

$$Sys\_res_h = Undispatched\_disp\_res_h + VRE\_spill_h \quad (1)$$

where Sys_res_h is the system operating reserves in hour h, $Undispatched\_disp\_res_h$ is those reserves obtained from undispatched conventional plants in hour h, and VRE_spill_h is any surplus VRE during hour h.

A plot of dynamic reserves can be created by sorting a year of power system operation into an LDC from highest to lowest hourly demand and then plotting the actual operating reserves for each of those hours. Given the potentially considerable hour to hour variability in such operating reserves, we use a moving average (2 day) windows to better show the trend in dynamic reserves.

3. Case study - the Indonesia's Java-Bali grid

3.1. Current Indonesian electricity industry context

The Indonesian electricity sector is currently largely vertically integrated and government owned, with generation, transmission, and distribution largely undertaken by a single state-owned monopoly, Perusahaan Listrik Negara (PLN). Private sector participation is currently limited to Independent Power Producers (IPPs) who generate electricity and sell it to PLN as the industry's single buyer.

Total national installed capacity was 58 GW in 2018, with some 72 % of capacity owned and operated by PLN, around 27 % held by IPPs contracted with PLN, and the remainder of generation capacity rented (PLN, 2019). In the larger and more populated islands, including Java and Sumatra, electricity is delivered via large, interconnected grids. Smaller grids in Sulawesi and Kalimantan (Borneo) are planned to be fully connected within each island in 2021 and 2023, respectively.

Indonesia's largest interconnected electricity network, the Java-Bali grid, served around 167.5 TWh of electricity consumption in 2018 – equivalent to around 71 % of total national consumption, and a 4.7 % increase from 2017, with a peak demand of 27 GW (PLN, 2019). The current generation mix for this grid is dominated by coal (68.8 % of energy), followed by gas (24.7 %), hydro (3.9 %), geothermal (2%), and insignificant diesel (0.7 %) (PLN, 2019). Until very recently, no utility-scale solar PV and wind generation had been integrated onto the grid despite major cost reductions over recent years for these technologies, and the significant resource potential, particularly solar, of the region.

The Indonesian government does have an ambitious target of 23 % renewable energy share, equivalent to around 45 GW of renewable generation in 2025, increasing to a 31 % share in 2050 (MEMR, 2014). While the share of coal-fired generation in the national mix is expected to fall to 55 % in 2025, the new renewable generation is expected to be mostly hydro and geothermal, while the contribution of utility-scale solar and wind would remain insignificant until 2027 (PLN, 2018). Continuing cost reductions in wind and solar, however, suggest that more ambitious renewable targets might be achievable.

Improving system reliability is one of the Indonesian electricity sector's major challenges, including in the Java-Bali grid. PLN's grid planning studies generally set the required operating reserves at 30 % of the system's peak load (PLN, 2018). However, in practice, actual system reserves have been observed mostly less than this, particularly during high demand periods, with consequent reliability and security risks. The Java-Bali outage in August 2019 was triggered by multiple gas turbines failures and impacted Indonesia's capital and its neighbouring cities (Adamczyk, 2019). It has heightened PLN and energy policymaker's concerns regarding the potential limitations of relying on fossil-fuel-based generation and seasonally affected hydropower plants

to provide sufficient system reserves to cover unexpected generating unit failures and other possible disturbances. More generally, many regions of Indonesia still face relatively poor standards of electricity service reliability, often due to network-related issues.

Therefore, it is important to examine reasonable levels of reliability to target at a system-level given this reality and given the costs of having higher reserves. This challenging context motivates our study into how future high wind and solar penetrations might impact on operating reserves under a range of reliability targets.

3.2. Future Java-Bali grid scenarios

NEMO optimizations for this study were carried out to solve the least-cost 'greenfield' (i.e. all new build) generation mixes for reliably meeting projected 2030 Java-Bali grid demand. NEMO provides a 'least-cost' capacity and generation mix of the available technologies, overall annualised total industry generation costs (including both operating and investment costs) and expected total annual industry CO_2 emissions.

The scenarios considered include the case where solar and wind are, or are not available, where three possible future carbon prices (CPs) are applied - \$0/tCO_2 (CP0), \$30/tCO_2 (CP30) and \$60/tCO_2 (CP60) - and where minimum operating reserve levels are set at zero or 30 % of peak demand. As in (Elliston et al., 2012), NEMO's two most important parameters for the evolutionary optimization, the number of generations (g) and σ, are set at 100 and 2, respectively.

A key feature of the NEMO optimization is the ability to set a reliability target for this 'least cost' generation mix. This reflects the planning reality that the costs of ensuring all demand is always met can be considerable, and some small level of USE is generally acceptable. In previous work, we used a fixed 0.005 % upper USE limit reflecting a very high-reliability requirement.

In this work, we now also explore the implications of 0.5 % and 1 % up to 5 % USE limits in all simulations without reserves constraints. Thus, we assess the implications of different reliability standards on least-cost generation capacity mixes, overall industry costs and CO_2 emissions, and more importantly dynamic operating reserves.

We apply actual 2015 hourly demand – to capture daily and seasonal demand variability and uncertainty – of the PLN's Java-Bali electricity grid as a baseline for modelling the 2030 demand profile. This baseline demand profile is scaled up assuming an annual (PLN would argue conservative) growth of 5 %, which results in almost 350 TWh demand and peak demand of 50 GW in 2030 (Tanoto et al., 2017).

3.3. Renewable energy generation potential

This study models Java-Bali wind and solar potential using Renewables Ninja, an online open-source renewable energy simulation tool, which can estimate an hourly PV and wind generation traces for an historical year at any global location. The PV output traces are provided based on the NASA MERRA2 weather dataset (Pfenninger and Staffell, 2016), while the wind traces are obtained from a global Numerical Weather Prediction (NWP) model. For our study, we provided NEMO with a normalised PV generation profile over the year 2015 for six different sites across the Java-Bali region, one in each province, following a methodology used in earlier studies (Tanoto et al., 2017; Simaremare et al., 2017).

We chose several potential wind generation placements across the Java-Bali grid based on the Indonesia wind prospecting map (A/S, 2017) and provided normalised hourly traces for these locations for 2015 to NEMO. We should note that there is considerable uncertainty regarding the total potential scale of wind and PV deployment in Indonesia. Some studies have made fairly conservative estimates of the potential total installed capacity for each technology (Veldhuis and Reinders, 2013; NREEC, 2017; IRENA, 2017). However, we chose not to limit the maximum capacity of either wind or solar in the NEMO optimization, given the still very high uncertainty regarding the underlying wind and solar resources across the Java-Bali region.

For geothermal and hydro generations, however, we constrained the total potential capacity of each to a maximum of 10 GW and 8 GW, respectively based on (IRENA, 2017). The resource potential of these technologies is arguably easier to assess provided their more restricted underlying resources, and the extensive existing work assessing their potential availability.

3.4. Fuel and technology capital and operating costs

We assess least-cost generation capacity mixes drawn from a broad range of fossil fuel and renewable generation technology candidates - geothermal, hydropower, coal-fired steam cycle, Open Cycle Gas Turbine (OCGT), Combined Cycle Gas Turbine (CCGT), biomass combustion, as well as of course, solar PV fixed axis plant and onshore wind farms. Technology capital costs are annualised assuming a discount rate of 5 % and standard economic plants lives, while Indonesian coal and gas prices in 2030 are taken to be \$3.50/GJ and \$10.90/GJ, respectively based on (IRENA, 2017). Our study applies mid-level 2030 technology cost estimates compiled from recently available reports (DEN, 2017; DEN, 2016), and are as shown in Table 1 (Tanoto et al., 2019).

4. Results and discussion

The simulation results in terms of 2030 electricity generation mix in the Java-Bali grid, with or without a reserves constraint, are categorised in two groups, (i) with large-scale VRE integration, and (ii) without VRE. The simulation results for the least cost mix without VRE consist of coal, OCGT, hydro and geothermal, and are similar to that planned by PLN in the latest 10-year plan of 2019–2028, which contains neither wind nor solar PV, whereas the least-cost mix with VRE comprises coal, CCGT, hydro, geothermal, solar PV and wind. These results allow us to compare the total generation cost and CO_2 emissions due to the presence or absence of large-scale VRE in the system.

4.1. Simulations without reserves constraint and with 0.005 % upper USE limit

In the case of no reserves constraints and a minimum 0.005 % USE requirement, wind and solar both reduces total industry costs as well as CO_2 emissions, even in the absence of a CP. Setting a CP delivers even greater industry cost and emission reductions, as shown in Fig. 1. The generation technology capacity mixes for these least-cost mixes both with and without VRE are shown in Fig. 2.

It is perhaps surprising that the CP has a remarkably limited impact on the least cost capacity mixes, or on total industry CO2 emissions, when VRE is unavailable. This is a result of the high assumed cost of gas in 2030 compared with coal which means there is a little substitution of coal with lower emission gas-fired generation, even at CP60.

The higher costs in this scenario represent the impact of a carbon 'tax' on generation, and we note also that this 'tax' represents revenue which could be used to compensate energy users for higher costs. Hence, caution is required when presenting total industry costs in the presence

Table 1
2030 mid-level technology cost components.

Technology	Capital ($/kW)	Fixed O&M($/kW-year)	Variable O&M ($/MWh)
Geothermal	3,200	16.7	0.7
Hydro	2,000	35.8	3.8
Coal	1,360	35.8	3.8
OCGT	400	22.5	3.8
CCGT	700	22.5	3.8
Biomass	1,600	43.8	6.5
Wind onshore	1,310	52	0.8
Solar PV fixed	610	12.5	0.4

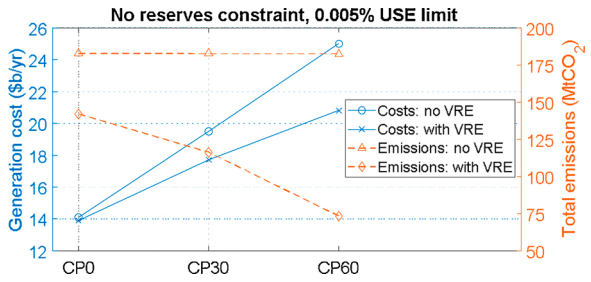

Fig. 1. Total industry costs and CO_2 emissions of the least-cost generation mixes with 0.005 % upper USE limit and no reserves constraint.

of a CP.

In the least cost generation mixes with VRE available, the key reason for lower industry generation costs in the CP0 scenario is reduced coal operation due to the presence of PV, and higher efficiency CCGT replacing some coal and OCGT capacity. For the CP30 and CP60 scenarios, the increasing total costs of the generation mixes is an outcome of both the capital costs of more PV plants capacity (and for CP60 also wind capacity), with far less reduction in coal capacity, as well as the carbon tax imposed on industry CO_2 emissions.

Fig. 3 shows cases of operating reserve duration curves resulting from NEMO optimizations with and without VRE, ordered according to the corresponding estimated 2030 Java-Bali LDC.

For the least cost generation mixes without VRE available, the operating reserves curves are almost equal for all CP scenarios. Given that in our study, NEMO is not configured to model stochastic generating plant availability, the least cost mix with only dispatchable generation - coal, OCGT, CCGT, hydro, and geothermal - will typically have total generation capacity just below or equal to peak hourly demand over the year. Hence, there will be some periods of no or low reserves, particularly during the higher demand periods in most of the first 2,000 h of the LDC, as highlighted in the lower part of Fig. 3.

Meanwhile, the least cost generation mixes with VRE available, including different levels of Coal, CCGT, hydro, geothermal as well as now also PV and wind depending on CP, all deliver significantly higher levels of operating reserves for most of the year. Even without any carbon tax (CP0), the Java-Bali grid gains significant additional reserves during most of the first 4,000 h of the LDC compared to the case of least-cost generation mixes without VRE. With a carbon tax (CP30, CP60), dynamic operating reserves are pushed even higher during those periods, and over the year, given the greater penetrations of wind and solar in the least cost generation mixes.

Based on the 2 day operating reserves moving average, the minimum system reserves corresponding to the periods of highest system demand are now 0.57 GW, 1.12 GW and 3.58 GW for the carbon tax scenarios CP0, CP30, and CP60, respectively, while the maximum system reserves are now 34.89 GW, 43.30 GW and 44.16 GW respectively. It is clear that the least cost generation mixes when VRE is available always provide some improvement in minimum available operating reserves and far higher levels of reserves for much of the year than when VRE is not present.

Fig. 4 shows how the VRE spill (curtailment) rises as VRE penetrations increase with higher CP under the 0.005 % upper USE limit and without a reserve constraint. Without a carbon tax (CP0), energy spilled by a total capacity of 24.7 GW PV is insignificant and only occurs during a few periods (around 30 h) of the lowest demand. Thus, we can conclude that the CP0 operating reserves curve is effectively formed by undispatched fossil-fuel plants displaced by high PV generation during

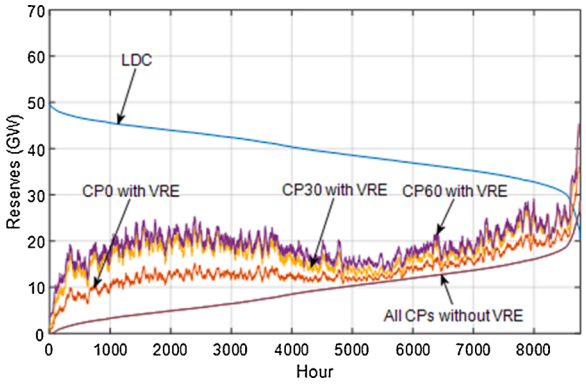

Fig. 3. Operating reserves curves of least-cost mix with and without VRE vs LDC with 0.005 % upper USE limit and no reserves requirement for all CPs.

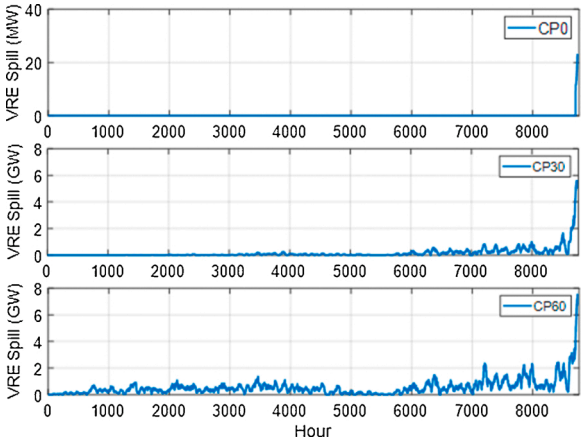

Fig. 4. Energy spills from least-cost mix solutions with VRE for each CP at 0.005 % upper USE limit and without any reserve requirement.

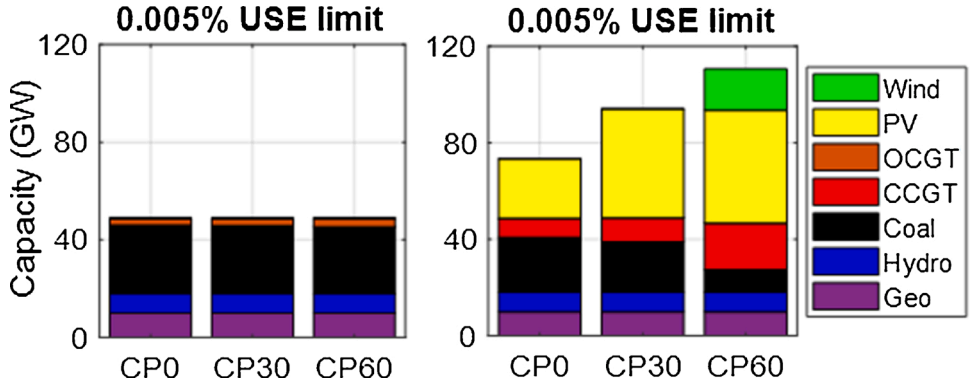

Fig. 2. Least-cost capacity mixes for all CPs at 0.005 % USE limit without reserves constraint and (left) without VRE, (right) with VRE.

daylight hours.

In simulations with CP30 and CP60, the least cost mix solutions result in almost double the PV capacity (in CP30) than without carbon tax, and eventually with the significant wind (in CP60), generate greater spill over more hours of the year. Increased spill in CP60 even during high demand periods (most of the first 4,000 h) is mainly contributed by wind and pushes the corresponding operating reserves curves slightly higher.

4.2. Simulations with VRE, no system reserves and with 0.5 % – 5 % upper USE Limit

Relaxation of the system reliability requirement in the NEMO optimization by increasing the USE limit constraint up to 5 %, reduces both total industry generation costs and CO_2 emissions of the least-cost capacity mixes with VRE available and no reserve constraint, for all CPs as shown in Fig. 5.

Total generation cost reductions of around 11–15 % are achievable at the expense of accepting a 5 % USE limit by comparison with a much stricter reliability requirement. The cost reductions arise from reduced generation capacity requirements and operating costs to meet those infrequent periods of high demand and low VRE availability.

CO_2 emissions of all least-cost capacity mixes decrease as the carbon tax increases. Nevertheless, some variation of CO_2 emissions exists within the same CP as the reliability requirement changes due to capacity trade-off between coal and gas in some of the least-cost mix solutions.

Fig. 6 highlights some of the complex interactions of different CPs and reliability requirements on the least cost capacity mix. Total capacity generally falls with a higher USE limit. The share of fossil-fuel plant capacity in the least cost mix solutions decreases as USE and CP increases whereas the share of solar PV increases as carbon tax imposed.

The composition of coal and gas plants also changes although there are some complexities in gas generation capacity as a CP is introduced, reflecting the trade-off between the higher capital costs and emissions, yet lower operating (fuel) costs of coal versus gas generation. VRE capacity share in the least cost mix solutions increases as CP increases in all USE limits, with a substantial addition of PV built in CP30.

Similar shares of solar PV between CP30 and CP60 are seen across all USE limits presented in Fig. 6, and eventually wind contributes to the VRE capacity in CP60. Considering a range of different USE limits, the average capacity share of VRE is around 41 %, 54 %, and 66 % of the total capacity in the least cost mix solutions with CP0, CP30, and CP60, respectively. It is notable that this increase is entirely due to wind and solar PV given the maximum capacity constraint of hydro and geothermal renewables on the Java-Bali grid.

Figs. 7–9 show dynamic reserves curves – which correspond to the projected 2030 Java-Bali LDC – of the least cost capacity mixes without a reserves requirement and with VRE over upper USE limits varied from a 0.5 % up to 5 % USE limit, for all CPs, respectively.

The operating reserves for the case of USE 5 % and no VRE are also plotted for comparison and, along with Fig. 3, highlights that while lower reliability requirements still see VRE adding to operating reserves, there may now be some periods when operating reserves are actually greater for least-cost mixes without VRE (evident from the 5 % USE curve with VRE falling below that without VRE for some periods during lower periods of demand over the year).

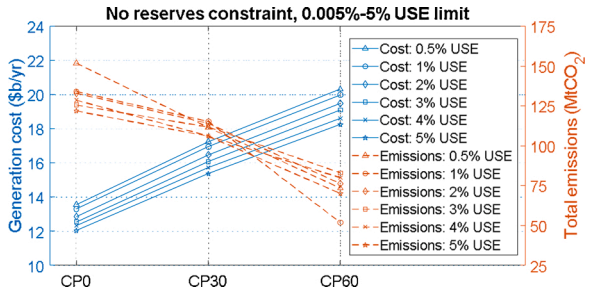

Fig. 5. Generation costs and CO_2 emissions of least-cost generation mixes as the upper USE limit is varied from 0.5 %-5 %, and without reserves constraint.

Without a carbon tax, the maximum availability of the dynamic reserves is up to around 10 GW during most of the first 4,000 h of the LDC, as shown in Fig. 7. With a carbon tax of CP30, however, the availability of dynamic reserves is considerably higher as a result of the higher VRE penetration, as shown in Fig. 8.

There is less additional impact as carbon pricing increases to CP60, as shown in Fig. 9. Still, CP30 and CP60 provide higher reserves up to almost 20 GW during some periods of the first 4,000 h (higher demand periods) of the LDC. Higher USE does, unsurprisingly, reduce the levels of these operating reserves but it is notable that for CP60, it is very rare for reserves even at 5 % USE to fall below the level available if no VRE is in the least cost mix.

Table 2 (Tanoto et al., 2019) presents a comparison between hours with system reserves less than 30 % of that hour's demand, and hours with zero reserves, for the least-cost generation mixes both with and without VRE available and given no reserves constraint.

Hours with low system reserves decrease as CP increases, and hence the VRE penetration increases. Both the number of hours with operating reserves less than 30 % of hourly demand, as well as hours with zero reserves increase with higher CP. At CP60, only around 27 % of the year sees reserves less than 15 GW or 30 % of peak demand – 30 % being the system reserve requirement stipulated by PLN for its planning studies. Meanwhile, less than 10 % of hours across the year have less than 5 GW operating reserves across all CPs in the case with VRE. As you might expect, those hours with operating reserves less than 10 % of the demand are typically periods of higher demand.

4.3. Simulations with 15 GW system reserves

Next, we consider least-cost generation mixes with a minimum of 15 GW dynamic reserves requirement (representing 30 % of expected 2030 peak demand). As with the results obtained in the simulations with 0.005 % upper USE limit, total generation costs and CO_2 emissions of the least cost mixes with VRE are lower than those without VRE. As expected, however, costs are now higher with the reserve constraint, due to the additional capacity that must be built. Generation costs and CO_2 emissions of the least cost mixes for all CP scenarios with this minimum 15 GW reserve constraint are presented in Fig. 10.

The installed capacities of each technology for these least-cost capacity mixes are presented in Fig. 11. For both the VRE and non-VRE least-cost mixes, we now see the addition of considerable OCGT plant as the lowest cost option for assured additional dispatchable capacity. When VRE is not available, there is relatively little change to the capacity of this OCGT even for the higher CP scenarios. By contrast, the proportion of OCGT/CCGT increases significantly with the higher CP scenarios when VRE is in the mix.

Fig. 12 depicts the 2-day moving average of dynamic operating reserves for the 2030 Java-Bali grid for all scenarios with the 30 % (15 GW) minimum reserves constraint. When VRE is not present, these reserve curves are almost equal for all CPs, as highlighted in the lower part of Fig. 12. Minimum and maximum operating reserves are around 15 GW and 44.6 GW, respectively. With VRE in the mix higher system operating reserves are present due to the higher VRE penetrations, and these reserves increase with the higher CP scenarios (CP30 and CP60). The 2-day moving average curve indicates that an average of more than 30 GW of dynamic operating reserves are available across the highest 2,000 h of demand, in marked contrast to the case with no VRE. Again, these dynamic operating reserves are higher for the CP30 and CP60 scenarios.

The VRE curtailment component of the dynamic operating reserves curves of the least cost mixes with VRE, with a minimum 15 GW reserves

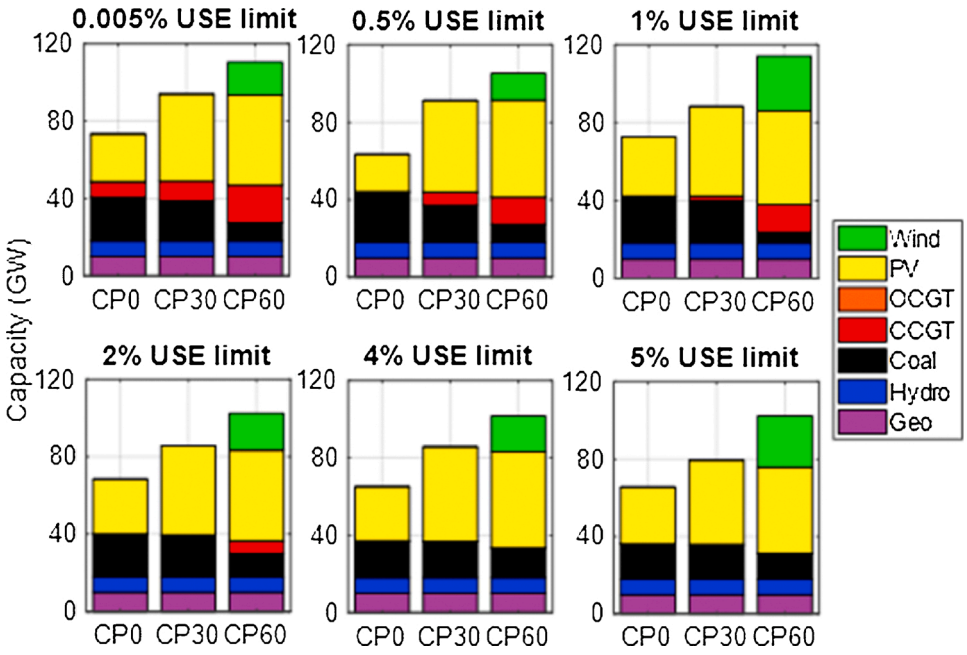

Fig. 6. Comparison of the least cost capacity mix solutions of all CPs without reserves constraint and with 0.005 % - 5 % upper USE limit and VRE.

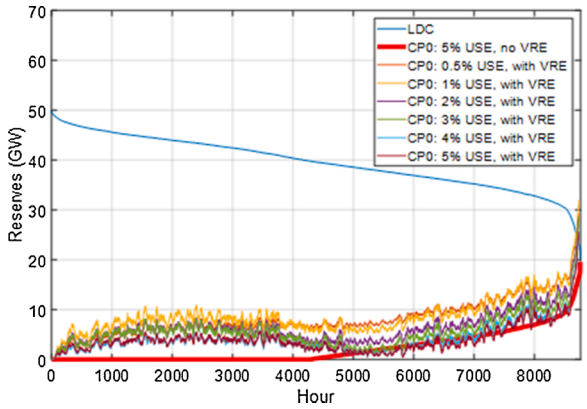

Fig. 7. Operating reserves curves of least-cost mix with VRE vs LDC at 0.5 % - 5 % upper USE limit and without reserves requirement for CP0 and their comparison with reserves curve without VRE at 5 % upper USE limit.

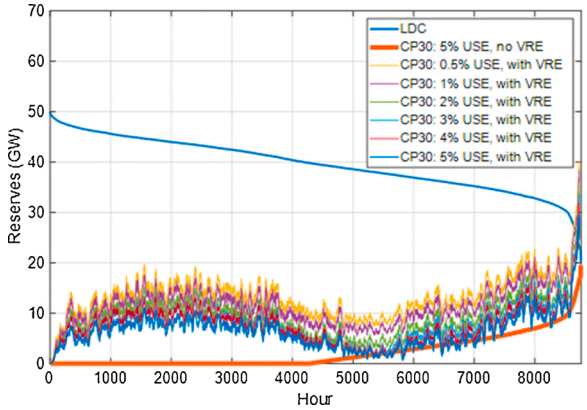

Fig. 8. System operating reserves curves of least-cost mix with VRE vs LDC at 0.5 %-5% upper USE limit and without reserves requirement for CP30, and their comparison with reserves curve without VRE at 5 % upper USE limit.

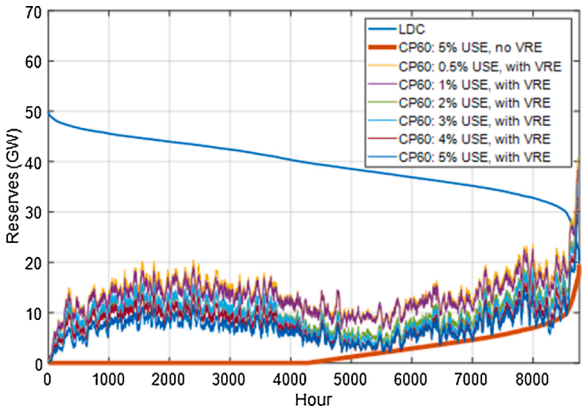

Fig. 9. System operating reserves curves of least-cost mix with VRE vs LDC at 0.5 % - 5 % upper USE limit and without reserves requirement for CP60, and their comparison with reserves curve without VRE at 5 % upper USE limit.

Table 2
Generation costs and CO_2 emissions of all least-cost generation mixes with no reserve constraint.

CP	Least cost mix with VRE		Least cost mix without VRE	
	Hours with reserves < 30 % hourly demand	Hours with zero reserves	Hours with reserves < 30 % hourly demand	Hours with zero reserves
0	3,640	48	5,580	50
30	2,854	23	5,580	50
60	2,386	15	5,580	50

constraint, and at 0.005 % upper USE limit is presented in Fig. 13. In the case without a carbon tax (CP0), energy spilled by a total capacity of 25.5 GW PV (a slightly higher-capacity build than without reserves constraint) during the few lowest demand periods of LDC rises to more than three times that seen without a reserve constraint. In simulations with a CP (i.e. CP30 and CP60), higher VRE curtailment results during most of the lower 50 % of the LDC by the least-cost mix solutions due to the substantial addition of PV capacity seen in CP30, and even further

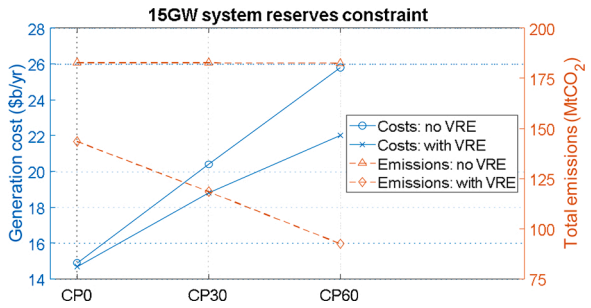

Fig. 10. Total industry costs and CO_2 emissions of all least-cost mixes with minimum 30 % (15 GW) reserves constraint for all CPs.

with the wind capacity added in CP60.

5. Conclusion

This paper presents a study extending previous work using the NEMO capacity expansion optimization tool to assessing dynamic reserves for different least-cost generation capacity mixes. The assessment approach was demonstrated for the case study of Indonesia's Java-Bali grid We solved least-cost generation capacity mixes for an assumed 2030 Java-Bali power system demand, based on actual 2015 Java-Bali electricity grid hourly demand scaled at a 5 % annual growth rate, and with simulated hourly solar and wind output traces for that same year.

We constructed reserves curves by plotting a 2-day moving average of hourly dynamic operating reserves against the total grid demand LDC, over a simulated year of power system operation for a range of scenarios, including the availability or otherwise of wind and solar and three CP scenarios, a set minimum of 30 % planning reserves requirement, and a range of reliability targets ranging from 0.005 % to 5 % upper USE limits, reflecting the complex tradeoffs present in the electricity sectors of emerging economies where improved reliability must be traded off against the higher industry costs involved. VRE energy spills curves were also plotted for the least-cost mix solutions at 0.005 % USE and with and without reserves constraints, for all CPs.

Our case study results found that the least-cost mixes with VRE available exhibited lower total industry generation costs and CO_2 emissions compared to those mixes without VRE, for all CPs. With higher VRE penetrations, with or without a minimum reserve constraint, higher levels of dynamic operating reserves are available at all time periods, including at times of high demand, than are present without VRE in the mix. This is due, of course, to the increased build of the dispatchable plant to cover times of low VRE. The amount of additional operating reserves does, however, vary considerably over the year given the variability of VRE.

In the scenarios with different upper USE reliability requirements, increasing from 0.5 %–5 % upper USE limit, the share of fossil-fuel plant capacity in the least cost mix solutions decreases across all USE limits, and as CP increases. Higher reliability targets for the same CP provide the system with higher dynamic operating reserves curves for most of the year, including during the periods of high demand.

While these findings are specific to the Java-Bali grid, the insights have broader relevance for electricity industry planners and policy-makers in other jurisdictions, particularly in encouraging emerging economies to increase their share of solar and wind penetrations towards a more sustainable electricity industry.

As always, there are limitations to the modelling that suggests

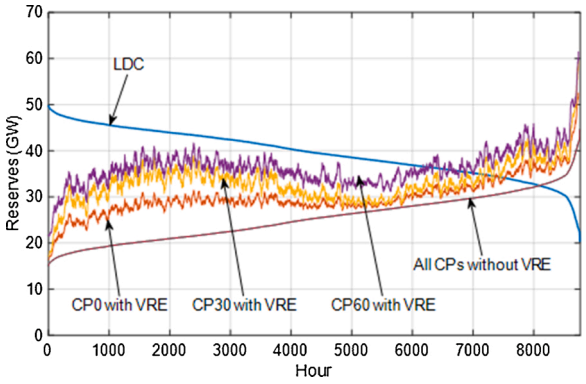

Fig. 12. System operating reserves curves of least-cost mixes both with and without VRE vs LDC and with minimum 30 % reserves constraint for all CPs at 0.005 % upper USE limit.

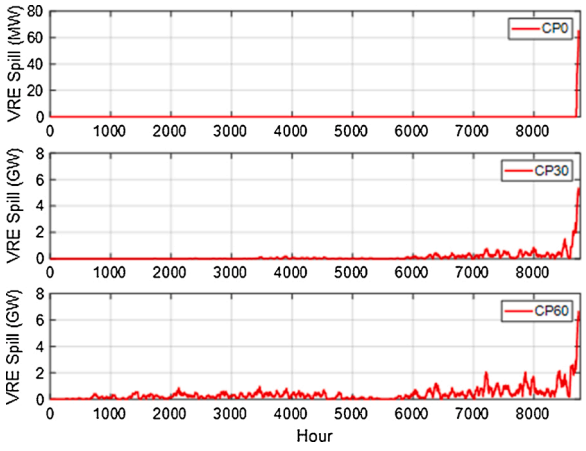

Fig. 13. Energy spills from least-cost mix with VRE for each CP in the system with 30 % reserves constraint and 0.005 % upper USE limit.

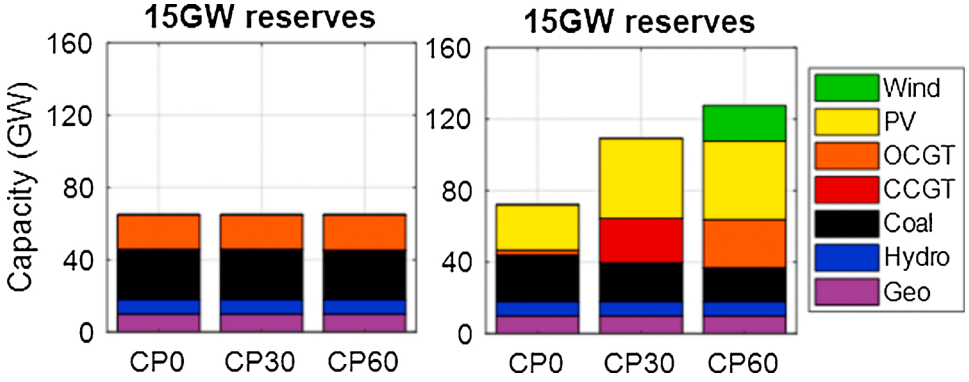

Fig. 11. Least-cost capacity mixes for all CPs with 15 GW reserves constraint and (left) without VRE, (right) with VRE.

caution in a direct interpretation of the results. Better categorising these reserves in terms of 'hot' and 'cold' availability is one area for future work. Another would be more careful consideration of operation without any conventional dispatchable plant running – a situation that does occur in our results for the higher CP scenarios. Still, the general finding would still seem to hold; higher VRE penetrations can offer future electricity industries higher dynamic reserve margins.

Declaration of Competing Interest

The authors report no declarations of interest.

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References

A/S, E.I., 2017. Wind Energy Resources in Indonesia [Online]. Available: http://indonesia.windprospecting.com/ [Accessed 20 March 2018].
Adamczyk, E., 2019. Power Outage Hits Jakarta and Indonesia's Java and Bali Islands [Online]. Jakarta: UPI. Available: https://www.upi.com/Top_News/World-News/2019/08/04/Power-outage-hits-Jakarta-and-Indonesias-Java-and-Bali-islands/3681564933647/ [Accessed August 15 2019].
Auger, A., Hansen, N., 2012. Tutorial CMA-ES: evolution strategies and covariance matrix adaptation. GECCO (Companion) 827–848.
Barasa, M., Bogdanov, D., Oyewo, A.S., Breyer, C., 2018. A cost optimal resolution for Sub-Saharan Africa powered by 100% renewables in 2030. Renew. Sustain. Energy Rev. 92, 440–457.
Choukri, K., Naddami, A., Hayani, S., 2018. Evaluation of the reserve capacity in a grid supplied by intermittent energy sources. IET Renew. Power Gener. 12, 399–406.
DEN, 2016. Indonesia Energy Outlook 2016 [Online]. Available: https://www.den.go.id/index.php/publikasi/download/34 [Accessed 3 August 2017].
DEN, 2017. Technology Data for Indonesian Power Sector: Catalogue for Generation and Storage of Electricity [Online]. Available: https://www.den.go.id/index.php/publikasi/download/55 [Accessed 2 March 2018].
Dorsey-Palmateer, R., 2019. Effects of wind power intermittency on generation and emissions. Electr. J. 32, 25–30.
Dubitsky, M.A., Rykova, A.A., 2015. Classification of Power Reserves of Electric Power Systems Reliability: Theory & Applications, 10, pp. 60–69.
Elliston, B., 2018. National Electrical Market Optimiser (NEMO). Sydney, Australia.
Elliston, B., Diesendorf, M., Macgill, I., 2012. Simulations of scenarios with 100% renewable electricity in the Australian National Electricity Market. Energy Policy 45, 606–613.
Elliston, B., Macgill, I., Diesendorf, M., 2013. Least cost 100% renewable electricity scenarios in the Australian National Electricity Market. Energy Policy 59, 270–282.
Elliston, B., Macgill, I., Diesendorf, M., 2014. Comparing least cost scenarios for 100% renewable electricity with low emission fossil fuel scenarios in the Australian National Electricity Market. Renew. Energy 66, 196–204.
Go, R., Kahrl, F., Kolster, C., 2020. Planning for low-cost renewable energy. Electr. J. 33, 106698.
Gülen, G., Bellman, D.K., 2015. Scenarios of resource adequacy in ERCOT: mandated reserve margin, impact of environmental regulations and integration of renewables. Electr. J. 28, 89–100.
Holttinen, H., Milligan, M., Ela, E., Menemenlis, N., Dobschinski, J., Rawn, B., Bessa, R. J., Flynn, D., Gomez-Lazaro, E., Detlefsen, N.K., 2012. Methodologies to determine operating reserves due to increased wind power. IEEE Trans. Sustain. Energy 3, 713–723.
IEA, 2017. Getting Wind and Sun onto the Grid: a Manual for Policy Makers. International Energy Agency., Paris.
IRENA, 2017. Renewable Energy Prospects: Indonesia, a REmap Analysis. International Renewable Energy Agency, Abu Dhabi.
Krad, I., Gao, D.W., Ela, E., Ibanez, E., Wu, H., 2017. Analysis of operating reserve demand curves in power system operations in the presence of variable generation. IET Renew. Power Gener. 11, 959–965.
Kroposki, B., 2017. Integrating high levels of variable renewable energy into electric power systems. J. Mod. Power. Syst. Clean Energy 5, 831–837.
Luz, T., Moura, P., Almeida, A.D., 2018. Multi-objective power generation expansion planning with high penetration of renewables. Renew. Sustain. Energy Rev. 81, 2637–2643.
MEMR, 2014. Government Regulation No. 79/2014 on National Energy Policy. Ministry of Energy and Mineral Resources of the Republic of Indonesia, Jakarta, Indonesia.
Milligan, M., Donohoo, P., Lew, D., Ela, E., Kirby, B., Holttinen, H., Lannoye, E., Flynn, D., O'malley, M., Miller, N., Eriksen, P.B., Gøttig, A., Rawn, B., Gibescu, M., Lázaro, E.G., Robitaille, A., Kamwa, I., 2010. Operating reserves and wind power integration: an international comparison. In: The 9th Annual International Workshop on Large-Scale Integration of Wind Power into Power Systems as Well as on Transmission Networks for Offshore Wind Power Plants Conference. October 18-19 2010 Quebec, Canada, pp. 1–16.
Monyei, C.G., Sovacool, B.K., Browne, M.A., Jenkins, K.E.H., Viriri, S., Li, Y., 2019. Justice, poverty, and electricity decarbonization. Electr. J. 32, 47–51.
Nreec, D., 2017. Statistics Book of New, Renewable Energy and Energy Conservation 2016 (in Bahasa Indonesia). Jakarta, Indonesia.
Pfenninger, S., Staffell, I., 2016. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy 114, 1251–1265.
PLN, 2018. Electricity Supply Business Plan (RUPTL) PLN 2018-2027 (in Bahasa Indonesia). PT. PLN (Persero), Jakarta, Indonesia.
PLN, 2019. PLN Statistics 2018. P.T. Perusahaan Listrik Negara (Persero), Jakarta.
Riesz, J., Elliston, B., 2016. Research and deployment priorities for renewable technologies: quantifying the importance of various renewable technologies for low cost, high renewable electricity systems in an Australian case study. Energy Policy 98, 298–308.
Senatla, M., Nchake, M., Taele, B.M., Hapazari, I., 2018. Electricity capacity expansion plan for Lesotho – implications on energy policy. Energy Policy 120, 622–634.
Simaremare, A.A., Bruce, A., Macgill, I., 2017. Least cost high renewable energy penetration scenarios in the Java Bali grid system. In: Asia Pacific Solar Research Conference. Melbourne, Australia.
Tanoto, Y., Haghdadi, N., Bruce, A., Macgill, I., 2017. Photovoltaic deployment experience and technical potential in Indonesia's Java-Madura-Bali electricity grid. In: Asia Pacific Solar Research Conference. Melbourne, pp. 1–13.
Tanoto, Y., Bruce, A., Macgill, I., Haghdadi, N., 2019. Impact of high variable renewable penetrations on dynamic operating reserves in future Indonesian electricity industry scenarios. In: The 19th IEEE International Conference on Environment and Electrical Engineering and 3rd IEEE Industrial and Commercial Power Systems Europe. June, 11-14 2019 Genoa, Italy, pp. 1–6.
Veldhuis, A., Reinders, A.H., 2013. Reviewing the potential and cost-effectiveness of grid-connected solar PV in Indonesia on a provincial level. Renew. Sustain. Energy Rev. 27, 315–324.
Vos, K.D., Driesen, J., 2014. Dynamic operating reserve strategies for wind power integration. IET Renew. Power Gener. 8, 598–610.
Vos, K.D., Driesen, J., 2015. Active participation of wind power in operating reserves. IET Renew. Power Gener. 9, 566–575.
Vos, K.D., Stevens, N., Devolder, O., Papavasiliou, A., Hebb, B., Matthys-Donnadieu, J., 2019. Dynamic dimensioning approach for operating reserves: proof of concept in Belgium. Energy Policy 124, 272–285.

Yusak Tanoto is a PhD student at the School of Electrical Engineering and Telecommunications, University of New South Wales (UNSW), Sydney, Australia. His research focuses on the framework for sustainable electricity industry and energy trilemma tradeoffs for sustainable electricity generation planning, including the impact of high variable renewables penetrations in the context of emerging economies. Yusak has his M.Eng. in Energy-Electric Power System Management from the Asian Institute of Technology (AIT), Thailand and holds a B.Eng. in Electrical Engineering from the Petra Christian University (PCU), Indonesia.

Iain MacGill is an Associate Professor in the School of Electrical Engineering and Telecommunications at UNSW Sydney, and Joint Director (Engineering) for the University's Collaboration on Energy and Environmental Markets (CEEM). He leads CEEM's research theme in Sustainable Energy Transformation including energy technology assessment, electricity market design and renewable energy integration. He also has research interests in energy and climate policy. Iain has a PhD (Electrical Engineering) from UNSW Sydney, and a M.Eng.Sc. (Biomedical) and B.E. from the University of Melbourne.

Anna Bruce is a Senior Lecturer in the School of Photovoltaic and Renewable Energy Engineering (SPREE) and Research Coordinator (Engineering) at the Collaboration on Energy and Environmental Markets (CEEM) at UNSW Sydney, Australia. She leads CEEM's research theme in Distributed energy systems including 'smart grids' and 'smart' homes, distributed generation and demand-side participation. Her research focuses on modelling, analysis and integration of renewable energy and distributed energy resources into electricity industries; energy access in developing countries; and energy policy and regulation. Anna has her Ph.D. (Photovoltaics and Renewable Energy Engineering) from UNSW Sydney.

Navid Haghdadi is a postdoctoral research fellow at the School of Photovoltaic and Renewable Energy Engineering (SPREE), and Collaboration on Energy and Environmental Markets (CEEM) at UNSW Sydney, Australia. He obtained his Ph.D. from UNSW, SPREE in 2017 and holds B.Sc. and M.Sc. in Electrical Engineering from the University of Tehran, Iran. His main research interests include data-driven performance analysis and grid integration of distributed PV systems in electricity networks, electricity tariffs, and power system planning.