Impact of High Variable Renewable Penetrations on Dynamic Operating Reserves in Future Indonesian Electricity Industry Scenarios

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***Abstract*— This paper investigates the impact of high variable renewable energy (VRE) penetrations on dynamic operating reserves, focusing on the future of Indonesia's Java-Bali grid. We use an open source evolutionary programming-based techno-economic optimization model, National Electricity Market Optimizer (NEMO), to first assesses possible least cost generation mixes both with and without VRE, and under different carbon pricing scenarios and reserves requirements. While low cost generation, major deployment of wind and solar still requires high levels of conventional dispatchable plant, typically thermal and hydro, and while there are costs associated with this overhead, it does have interesting implications for operating reserves. Our study explores this issue and shows that not only might wind and solar reduce overall industry costs for Java-Bali in 2030, the resulting generation mix would have significantly higher reserves, and hence ability to cover unexpected plant failures and other interruptions, over most of the periods with considerably high demand.**

Keywords*— *variable renewable energy, least cost generation mix, system operating reserves, Java-Bali electricity grid

I. INTRODUCTION

Variable renewable energy (VRE) seems certain to have a key role in shifting electricity industries around the world from their present high fossil-fuel and emissions intensive era to a low or even zero carbon emissions future. The opportunities, challenges and potential solutions for integrating of large-scale wind and solar VRE capacity into power systems has been widely discussed in recent years [1]-[4]. While early deployment of these technologies was driven largely by OECD countries, VREs also present major opportunities for the electricity sectors of emerging economies and have been incorporated in recent electricity planning studies in a growing number of such jurisdictions, using various methods and tools [5]-[7].

While wind and solar are an increasingly low-cost generation option, their high variability does raise challenges for power system reliability. Major deployment of these technologies still requires high levels of dispatchable conventional, typically thermal and hydro plant to cover periods of low or no wind and solar. Of course, this is not just an issue with renewables, and electricity sectors generally have some level of generation reserves to cover periods where even normally dispatchable generation might prove unavailable due to reasons such as plant failure, or events interrupting fuel supply. However, VRE pose some particular challenges for establishing reserves as while they are highly modular and hence don't tend to experience major failures, the availability of wind and solar is a complex and uncertain question. This in turn raises the question of what power system reserves may look like in high VRE penetration electricity industries given the dynamics of demand as well as wind and solar generation.

Our study seeks to contribute to discussions about possible future development paths for the electricity sector in terms of large scale-grid connected VRE in developing countries and their potential implications for reliability as well as costs and emissions, with a focus on the Java-Bali grid of Indonesia. We particularly focus on the issue of how solar and wind can impact on dynamic reserve levels. Our study is, the first that we are aware of that explicitly models possible futures for the Java-Bali grid, and dynamic reserves, in this manner.

In this study, we apply an open source evolutionary programming-based techno-economic optimization model, National Electricity Market Optimizer (NEMO) [8], to first assesses possible least cost future generation mixes for Indonesia's Java-Bali grid both with and without VRE, and under different carbon pricing scenarios and reserves requirements, and to analyse the hourly generation resulting from the different capacity mix in our analyses.

The rest of this paper is organized as follows. Section 2 provides an overview of the existing Java-Bali grid in Indonesia, and its key future generation options. The study methodology is presented in Section 3. Result obtained from the simulations are presented and discussed in Section 4, and followed by some initial conclusions, and thoughts for future work, in Section 5.

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II. OVERVIEW OF ELECTRICITY INDUSTRY IN INDONESIA

Electricity services in Indonesia are entrusted to Perusahaan Listrik Negara (PLN), a state-owned, vertically integrated, and largely monopoly electricity company. On the large islands, electricity is distributed to consumers through interconnected grids. The Java-Bali grid is the largest electricity network in Indonesia. In 2017, it served around 60% of the total national population with 165TWh or around 74% of the total national consumption and 25.6GW peak load [9].

The generation mix for the Java-Bali grid is heavily dependent on coal (55% of energy), followed by gas (34%), hydro (8.5%), geothermal (1.2%) and diesel (1%) [9]. Despite excellent solar resources and untapped wind potential in the Java-Bali area, and decreasing price of VRE technologies, present electricity industry development plans suggest that coal's share in future mix will increase significantly along with geothermal and hydro power, while wind and solar play only a very minor role [10] in current planning processes for Indonesia's future electricity generation mix.

In Indonesia's interconnected electricity network including the Java-Bali grid, the operating reserves margin is set at 30% of the peak load for planning purposes [10]. However, actual daily available reserves are often less than what was planned and largely depend on the availability of limited fossil fuel-based, geothermal and hydropower generating units. Given concerns around system reserves, it is useful to analyse the impact of potential high VRE future generation mixes on reserves.

III. METHODOLOGY

A. *Simulation Overview*

Working as a chronological dispatch model, NEMO [8], which is developed using Python 2.7, has been used as a tool to conduct studies around optimization of the future electricity industry capacity and generation mix and to perform sensitivity analysis of the future electricity industry planning incorporating high penetrations of variable renewables.

In previous studies, NEMO has been used to compare technical and economic outcomes under 100% renewable electricity scenarios in the Australian National Electricity Market with low emissions fossil fuel scenarios [11], and to assess the ability of 100% renewable electricity to meet evening peak demand during winter months [12]. These studies showed that high penetration VRE is a feasible option for a zero-emissions electricity system, resulting in lower risks around fuel and carbon costs than fossil fuel options.

This study applies NEMO to solve least cost generation mixes for Indonesia's future electricity sector under different scenarios of carbon pricing and reserves requirements and assesses the impact of high VRE penetrations on dynamic system reserve levels.

The evolutionary programming part in NEMO is developed under the Distributed Evolutionary Algorithms in Python (DEAP) platform and applies a robust Covariance Matrix Adaptation Evolution Strategy (CMA-ES) [14] which is stochastic and suitable for non-convex continuous optimization problems. Thus, the CMA-ES can be considered as a randomized black box search algorithm. The CMA-ES has four key operators involved in the evolution process, i.e. number of offspring to produce at each generation, selection and recombination, covariance matrix adaptation and step size adaptation control.

In the CMA-ES, evolution process generates initial population by sampling a normal distribution value according to user-specified mean value and initial standard deviation of the distribution (sigma). Several key parameters used in the CMA-ES include population size or number of children to produce in each generation (λ), individual's size (n), number of parents (μ), the initial covariance matrix of the distribution that will be sampled (c-matrix) and recombination weight (w_i). The parameter λ, μ, and w_i are defined according to the following equations [15]:

$$\lambda = 4 + [3 \ln n]; \ \mu = \left[\frac{\lambda}{2}\right] \tag{1}$$

$$w_i = \frac{\ln(\mu+1) - \ln i}{\mu \ln(\mu+1) - \sum_{j=1}^{\mu} \ln j} \text{ for } i = 1, \dots, \mu \tag{2}$$

The simplified CMA-ES evolutionary algorithm flowchart is presented in Fig. 1.

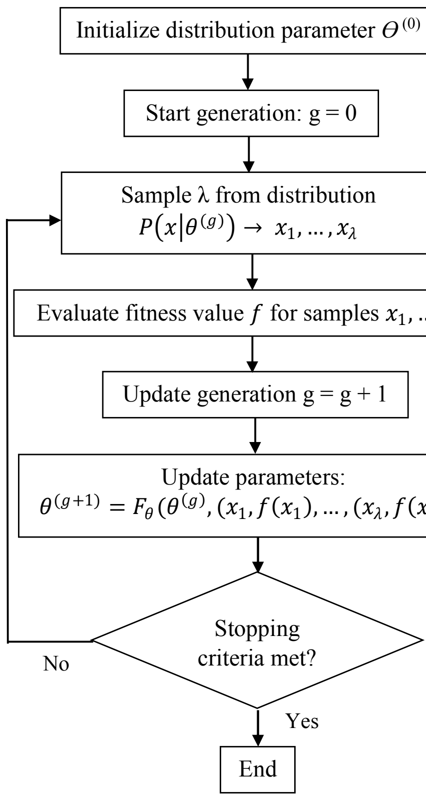

Figure 1. Simplified CMA-ES flowchart algorithm. Adapted from [15].

Simulations were initially carried out to obtain least cost 'greenfield' generation solutions for estimated 2030 Java-Bali grid demand, in terms of capacity and generation mix, overall annualized industry generation cost (both operating and investment) and expected annual CO_2 emissions. The scenarios investigated included the exclusion or availability of solar and wind, three CPs - \$0/tCO_2 (CP0), \$30/tCO_2 (CP30) and \$60/tCO_2 (CP60), and reserve levels of zero and minimum 30%. In this study, as in [8], two important parameters for NEMO's evolutionary optimization, the number of generations (g) and sigma are set at 100 and 2, respectively.

In all simulations without reserves, a 0.005% unserved energy (USE) limit is imposed to ensure a high reliability generation mix solution that can reasonably be compared with those scenarios with reserves and hence no unserved energy. The 2015 Java-Bali electricity grid hourly demand [16] is used as a baseline to model 2030 demand. The 2015 demand is assumed to have a conservative growth of 5% annually, resulting in a 346.5TWh demand and 50GW peak load in 2030.

B. Renewable Energy Potential Data

Gridded hourly PV output data for 2015 covering the Java-Bali area is used in this study. The data is obtained from Renewables Ninja (RN), an online renewable energy simulation tool, from which an hourly PV output trace can be obtained, based on the NASA MERRA2 weather dataset [17]. A PV trace is then provided to NEMO for six selected locations across the Java-Bali grid, one in each province, following a methodology used in earlier studies [18, 19].

Hourly wind power output traces for 2015 are also obtained from RN. Locations assigned for wind farm candidates were selected from the Indonesia wind prospecting map [20]. Considering the high uncertainty of underlying resource potential for PV and wind across the Java-Bali grid, neither technology has its capacity capped in this study, despite some relatively conservative estimates of their potential capacity in some studies [21]-[23]. On the other hand, geothermal and hydro capacity are limited to a maximum 10 GW and 8 GW, respectively [23], considering that those technologies are easier to assess given their more restricted resources than PV and wind.

C. Fuel and Technology Costs Data

We assess least cost generation mixes from a range of fossil fuel and renewable generation technologies comprising geothermal, hydropower, coal fired, Open Cycle Gas Turbine (OCGT), Closed Cycle Gas Turbine (CCGT), biomass, solar PV fixed axis and onshore wind turbine. Technology capital costs are annualised using a discount rate of 5% while coal and gas prices in 2030 are assumed to be \$3.5/GJ and \$10.9/GJ, respectively [23]. This study uses mid-level 2030 technology costs which are compiled from recently available official sources [24, 25] and are as shown in TABLE I.

TABLE I. 2030 MID-LEVEL TECHNOLOGY COST COMPONENTS

No.	Technology	Capital (\$/kW)	Fixed O&M (\$/kW-year)	Variable O&M (\$/MWh)
1.	Geothermal	3,200	16.7	0.7
2.	Hydro	2,000	35.8	3.8
3.	Coal	1,360	35.8	3.8
4.	OCGT	400	22.5	3.8
5.	CCGT	710	22.5	3.8
6.	Biomass	1,600	43.8	6.5
7.	Solar PV fixed	610	12.5	0.4
8.	Wind onshore	1,310	52	0.8

D. Dynamic Reserves Assessment

Classification of generating capacity reserves for power system planning is discussed in [26]. While the approaches for estimating planning reserves are differentiated according to the nature and timing of reserves availability, this study does not attempt to categorise hot and cold reserves, or any demand-side opportunities. Instead, our focus in this study is on the impact of least cost generation mixes with VRE on the dynamic system operating reserves over a future year of power system operation.

In this study, we calculate system dynamic operating reserves on an hourly basis according to the level of undispatched-dispatchable fossil-fuel plants and any curtailed ‘surplus’ energy generated by VRE. When VRE generation is available, it should be first dispatched and therefore will offset dispatchable fossil-fuel generation due it’s lower operation cost. That displaced generation is then available as reserves should there be a major loss of generating plant or unexpected increase in demand. When there is sufficient VRE to displace all fossil fuel plant and VRE is being curtailed, then this provides even greater reserves. The hourly system operating reserves can be simply calculated as:

$$Sys\_res_h = Undispatched\_disp\_res_h + VRE\_spill_h \quad (3)$$

where Sys_res_h is the hourly system operating reserves; $Undispatched\_disp\_res_h$ is hourly reserves obtained from undispatched-dispatchable plants including additional amount due to VRE penetrations; VRE_spill_h is any unused surplus generated by VRE during their operation hours.

A plot of dynamic reserves can be created by sorting a year of power system operation into a load duration curve (LDC), and then plotting the actual operating reserves for each hour of demand. In order to observe the trend in the reserves data, a curve is created through a moving average (2-day).

IV. RESULTS AND DISCUSSION

A. Simulations without Reserves Constraint

In the least cost generation mix solutions without a reserve constraint and with a 0.005% USE limit, the availability of VRE reduces both generation costs and CO_2 emissions even without a carbon price and offers even greater cost and emission reductions when there is a carbon price, as presented in TABLE II. Meanwhile, the least cost capacity mixes with and without VRE are presented in TABLE III and TABLE IV, respectively.

TABLE II. GENERATION COSTS AND CO_2 EMISSIONS OF ALL LEAST COST MIX WITH 0.005% USE LIMIT AND WITHOUT RESERVES CONSTRAINT

CP (\$/tCO_2)	Least Cost Mix without VRE		Least Cost Mix with VRE	
	Generation cost (b\$/year)	*CO_2 emissions (MtCO_2)*	*Generation cost (b\$/year)*	*CO_2 emissions (MtCO_2)*
0	14.1	182.8	13.9	142.1
30	19.5	182.7	17.7	116.3
60	25.0	182.5	20.8	73.3

TABLE III. LEAST COST MIX WITHOUT RESERVES CONSTRAINT AND VRE AND WITH 0.005% USE LIMIT

CP (\$/tCO_2)	Geo (GW)	Hydro (GW)	Coal (GW)	OCGT (GW)	PV (GW)	Wind (GW)	Total (GW)
0	10	8	27.94	2.93	n/a	n/a	48.87
30	10	8	27.76	3.11	n/a	n/a	48.87
60	10	8	27.29	3.58	n/a	n/a	48.87

TABLE IV. LEAST COST MIX WITHOUT RESERVES CONSTRAINT AND WITH VRE AND 0.005% USE LIMIT

CP ($/t$CO_2$)	Geo (GW)	Hydro (GW)	Coal (GW)	CCGT (GW)	PV (GW)	Wind (GW)	Total (GW)
0	10	8	22.76	7.86	24.7	0	73.32
30	10	8	20.87	10.06	45.1	0	94.03
60	10	8	9.48	19.28	46.8	17	110.56

It is notable that the carbon price has very little impact on the generation mix without VRE, or on emissions – an outcome of the high cost of gas compared with coal that sees little substitution even at CP60. The higher costs in this scenario represent the impact of a carbon 'tax' on generation.

In the least cost mix with VRE, the main reason for lower generation cost in the CP0 scenario is reduction in coal operation due to the presence of PV, and CCGT replacing some coal and OCGT capacity. For CP30 and CP60, the increasing costs of the least cost generation mix is an outcome of both the capital costs of building more PV plants (and for CP60 Wind), with far less reduction in coal build, as well as the carbon tax on remaining greenhouse emissions.

Fig. 2 shows reserves curves corresponding to the projected 2030 Java-Bali LDC for the least cost mix without VRE, with no reserve requirement, for all CPs. Given that NEMO does not model stochastic plant availability, the least cost mix with only dispatchable generation will generally have capacity just below or equal to peak demand. As a result, there will be some period of no or low reserves, as highlighted in Fig. 2.

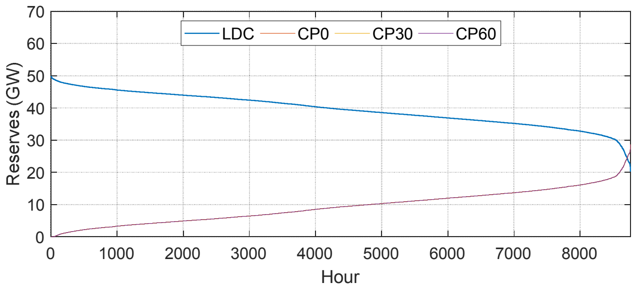

Figure 2. System operating reserves vs LDC, obtained from the least cost mixes without VRE and reserves constraint, and with 0.005% USE limit.

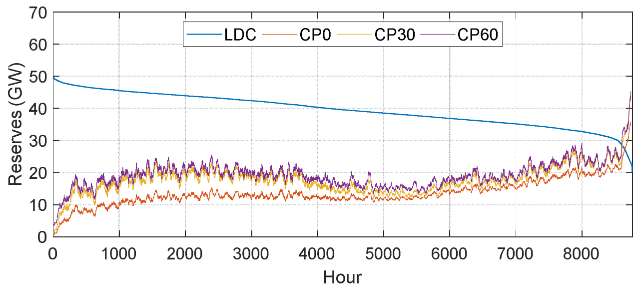

Figure 3. System operating reserves curves vs LDC, obtained from the least cost mixes with VRE and 0.005% USE limit and without reserves constraint.

As depicted in Fig. 3, the least cost generation mix with VRE provides much higher levels of operating reserves for almost the entire year. Without a carbon tax, the system gains significant additional reserves during most of the first 4,000 hours of the system load duration compared to the reserves shown in Fig. 2. With a carbon tax, system reserves are pushed even higher during those periods, and over the year as a whole, given more contributions of VRE in the least cost generation mixes.

Based on the moving average over 48hrs (Fig. 3), the minimum system reserves corresponding to the highest system demand are obtained at 0.57GW, 1.12GW and 3.58GW for CP0, CP30 and CP60, respectively, while the maximum system reserves are 34.89GW, 43.30GW and 44.16GW. Clearly, the least cost mix with VRE offers far higher levels of reserves for most of the year.

TABLE V presents a comparison in terms of hours with system reserves less than 10% and 30% hourly demand and hours with zero reserves, both for the least cost mixes with and without VRE, given no reserves constraint.

TABLE V. HOURS WITH SYSTEM OPERATING RESERVES LESS THAN 10% AND 30% HOURLY DEMAND AND HOURS WITH ZERO OPERATING RESERVES

CP ($/t$CO_2$)	Least Cost Mix with VRE			Least Cost Mix without VRE		
	Hours with Reserves < 10% Hourly Demand	*Hours with Reserves < 30% Hourly Demand*	*Hours with Zero Reserves*	*Hours with Reserves < 10% Hourly Demand*	*Hours with Reserves < 30% Hourly Demand*	*Hours with Zero Reserves*
0	782	3,640	48	1,704	5,580	50
30	691	2,854	23	1,704	5,580	50
60	458	2,386	15	1,704	5,580	50

Hours with low system reserves decrease as CP increases and VRE in the mix increases. A decrease can be seen in hours with operating reserves less than 10% and 30% of hourly demand, as well as hours with zero reserves. At CP60, around 27% of the total hours in a year have reserves less than 15GW or 30% of peak demand (the system reserve requirement stipulated by PLN for planning purposes).

Less than 10% of the total hours in a year have less than 5GW operating reserves across all CPs (8.9% at CP0 to only 5.2% at CP60). It is notable that those hours with operating reserves less than 10% hourly demand are typically hours with high demand. A higher CP does not impact hourly reserves when no VRE is built.

B. Simulations with Reserves Constraint

Least cost generation mix solutions with a 15GW (30% of peak demand) reserves constraint applied must meet all hourly demand with no unserved energy. Generation costs and CO_2 emissions of the least cost mixes with the constraint, with and without VRE are presented in TABLE VI.

TABLE VI. GENERATION COST AND CO_2 EMISSIONS OF ALL LEAST COST MIX WITH 30% RESERVES CONSTRAINT

CP ($/t$CO_2$)	Least Cost Mix without VRE		Least Cost Mix with VRE	
	Generation cost (b$/year)	*CO_2 emissions ($MtCO_2$)*	*Generation cost (b$/year)*	*CO_2 emissions ($MtCO_2$)*
0	14.9	182.8	14.7	143.5
30	20.4	182.7	18.8	118.5
60	25.8	182.5	22.0	92.6

As with the results obtained in the previous section, generation costs and CO_2 emissions of the least cost mixes with VRE are lower compared to those without VRE. However, costs are higher with the reserves constraint, compared to without, due to additional capacity built to achieve a minimum 30% hourly reserve level. The least cost capacity mixes with and without VRE are presented in TABLE VII and TABLE VIII, respectively.

TABLE VII. LEAST COST MIX WITHOUT VRE AND WITH RESERVES CONSTRAINT

CP ($/t$CO_2$)	Geo (GW)	Hydro (GW)	Coal (GW)	OCGT (GW)	PV (GW)	Wind (GW)	Total (GW)
0	10	8	27.93	18.98	n/a	n/a	64.91
30	10	8	27.76	19.15	n/a	n/a	64.91
60	10	8	27.4	19.51	n/a	n/a	64.91

TABLE VIII. LEAST COST MIX WITH VRE AND RESERVES CONSTRAINT

CP ($/t$CO_2$)	Geo (GW)	Hydro (GW)	Coal (GW)	CCGT (GW)	OCGT (GW)	PV (GW)	Wind (GW)	Total (GW)
0	10	8	26.14	0	20.64	25.5	0	90.28
30	10	8	21.86	24.75	0	44.6	0	109.21
60	10	8	18.97	0	27	43.6	20.1	127.67

Both the non-VRE and VRE least cost generation mixes see the addition of considerable OCGT plant as the lowest cost option for assured additional dispatchable capacity. For cases with the 30% reserves constraint and no VRE, Fig. 4 shows operating reserves (2-day moving average) corresponding to the hourly LDC (capacity mix presented in TABLE VII).

Reserve curves are almost equal for all CPs. Minimum operating reserves obtained from the 2-day moving average are around 15GW and maximum reserves are around 44.6GW. Meanwhile, system operating reserves for the least cost generation mixes with VRE and three levels of CP are depicted in Fig. 5.

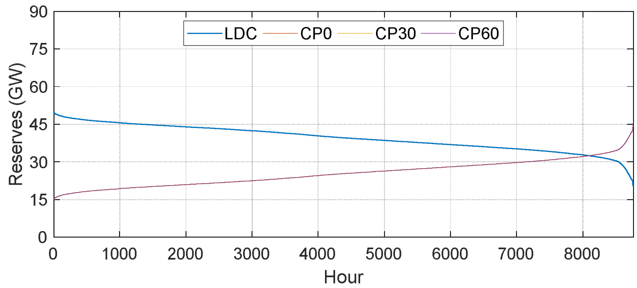

Figure 4. System operating reserves vs LDC, obtained from the least cost mixes without VRE and with reserves constraint.

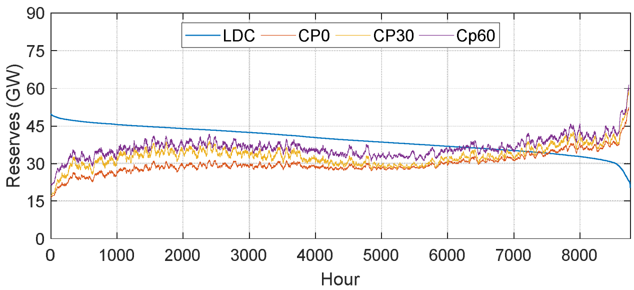

Figure 5. System operating reserves curves vs LDC, obtained from the least cost mixes with VRE and reserves constraint.

Fig. 5 shows that higher VRE mixes (i.e. CP30 and CP60) have higher system operating reserves. The 2-day moving average curve as shown in this figure indicates that on average more than 30GW of operating reserves is achieved across the top 2,000 hours of demand, or from around first 500 to 3,000 hours of the peak demand. Although the operating reserves for CP0 are obtained less than for CP30 and CP60, they are higher than without VRE during the top 2,000 hours of demand (shown in Fig. 4).

V. CONCLUSIONS

This paper presents an extension to previous optimization studies where least cost generation mixes have been simulated using the evolutionary techno-economic optimization model, NEMO. In this study, generation mix optimizations have been conducted for the 2030 Java-Bali electricity system, and, given concerns around sufficiency of system reserves, dynamic hourly operating reserves have been analyzed, with different carbon prices, at 0.005% USE, and with a minimum 15GW (30% of peak demand) reserves constraint. For all carbon prices considered in the simulations, the least cost mixes with VRE penetrations exhibit lower generation costs and CO_2 emissions compared to those mix without considering VRE. Operating reserves curves were constructed by plotting a moving average of operating reserves against corresponding demand in an LDC.

The results show that with higher VRE penetrations, with or without the reserves costraint, higher operating reserves are available, including at times of high demand, due to increased build of dispatchable plant to cover times of low VRE and additional VRE available for dispatch at times when there is splilled VRE. High VRE mixes were obtained for cases with a higher carbon price, and, without a reserves constraint, reduced the number of hours with zero operating reserves and operating reserves less thean 10% or 30% of hourly demand.

While the results obtained from this study can provide valuable insights for policy makers regarding the potential roles of VRE in future electricity industry planning, issues around hot and cold operating reserves, among others, are identified as an area for further work.

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