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The electricity system benefits of improved, short-term wind generation forecasts

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Executive summary

This analysis quantified the complex interactions between short-term renewable generation forecasts, demand forecasts, generator unit commitment and economic dispatch. Studies with current short-term wind forecasting errors (Reference) were complemented by studies with High (×2), Low (×0.5) and Perfect (zero) forecasting error.

Less accurate short-term wind forecasts of course results in greater operational uncertainty. This analysis showed that this:

- **increased** the scheduling of thermal plant and energy storage to maintain system reliability and security; and
- **increased** renewable curtailment since thermal plant and storage are then more available.

Market performance then deteriorated, with:

- **increased** hours of unserved energy and time spent at the market price cap;
- **increased** total system costs and prices;
- **significantly increased** returns to thermal generators and energy storage;
- **reduced** returns to wind generators;
- slightly increased emissions; and
- **significantly increased** risks of system insecurity (i.e. loss of frequency control) since renewables displace synchronous generation and increase operational uncertainty.

These impacts start to become significant once the operational uncertainty caused by renewable generation becomes larger than that of demand. For wind in the NEM:

- this is once wind generates more than roughly 30% by annual energy; and
- below this threshold, demand forecasting is the primary source of operational uncertainty.

For the NEM, the value of improved short-term wind generation forecasts therefore becomes significant for systems with >30% renewables by annual energy. In such cases:

- reductions in average market prices of 5 $/MWh or more appear plausible; and
- this represents ~$200M or more of savings for consumers, which should far exceed the costs of implementing improved forecasting.

This value of improved forecasts is primarily realised by **energy consumers** through a lower average energy price. Because this value is not primarily realised by the renewable generator, there is a good case for:

- improved forecasting to be implemented by the System Operator on behalf of consumers; and/or
- mandating greater control of dispatch by renewable generators, for example via some combination of improved forecasting, dispatch control systems, or (likely limited) on-site firming.

Acknowledgement and disclaimer

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Context

As the proportion of variable renewable generation (VRG) capacity rises, so too will the associated absolute (MW) forecast errors in their generation. That is, for a given generation forecast accuracy as a percentage of capacity, the total energy generation discrepancy due to the forecast error increases with the installed capacity of renewable generators.

Increased capacity (MW) × renewable forecast error (% capacity):

- increased renewable forecast errors (MW)
- increased operational demand forecast errors (MW)

Studies suggest that once wind and solar exceed 30-40% of annual generation, short-term renewable forecast errors will start to exceed short-term demand forecast errors. These penetrations of VRG should be achieved in the NEM and other systems in the next few years.

Key characteristics of wind and solar PV
Variability and uncertainty
Correlation
Low operating costs
Lack of ancillary services
Potential implications
Downward pressure on electricity prices for all participants.
Lowest prices when renewables sell most of their energy → lower revenues for highly correlated plants.
Requirement of thermal (or battery) plant for ancillary services, even when prices below their SRMC.
Increasing need for ancillary services with increasing absolute forecast error.

Table 1. Characteristics and implications of the renewable energy system

Table of Acronyms

Acronym	Meaning
VRG	Variable Renewable Generation
WACC	Weighted average cost of capital
AEMO	Australian Energy Market Operator
ARMA	Auto-regressive Moving Average
UC&ED	Unit Commitment & Economic Dispatch
IRR	Internal Rate of Return
CCGT	Combined Cycle Gas Turbine
OCGT	Open Cycle Gas Turbine
PHES	Pumped Hydro Energy Storage

Table 2. Table of Acronyms

Objective of this work

Objective: to quantify the electricity market impacts of short-term wind forecasts as wind generation increases.

To do this, we:

- first determine optimal fleets for increasing abatement using our **capacity investment (generation expansion planning) model**;
- then use our **stochastic unit commitment market model** to simulate the decisions made by each dispatchable generator in a market, subject to operational constraints, e.g. minimum output, minimum on time, minimum off time, start-up costs, etc.;
- have examined systems with increasing penetrations of VRG and a range of forecast errors for wind generation output, i.e. generator scheduling decisions are made under uncertainty with forecast errors in demand, wind and solar generation;
- quantify the results using common metrics of market performance, including:
    - wholesale market prices and costs,
    - rates of return of each class of generator,
    - system greenhouse gas emissions, and
    - certain system reliability and security-related metrics.

Modelling methodology and input assumptions

Capacity investment model:

- determines generating plant investments (MW-installed) needed to meet electricity demand, subject to an emissions constraint;
- minimises the sum of the, annualised capital costs (5.9% WACC), fixed and variable operating and maintenance costs, fuel costs, and penalty costs associated with insufficient reserves or unserved demand (i.e. load shedding);
- incorporates capital cost projections with technology learning for renewables, and an emissions constraint (linear reduction to zero in 2050).

Unit commitment and economic dispatch model:

- determines when to turn generators on and off in order to serve electricity demand, given constraints for inflexible generators;
- minimises start-up costs, fuel and variable operating costs, penalties associated with unserved demand or insufficient reserves; then
- economic dispatch model takes commitment schedule as fixed and optimises final dispatch schedule and prices for energy and reserves; so
- energy/reserve price in each hour is set by the short-run marginal costs of the marginal generator in that hour.

Input data used in the modelling primarily sourced from AEMO's 2020 ISP database [AEMO 2020], including:

- hourly Victorian demand for electricity (42 TWh annual, 9.6 GW peak);
- technical & cost data for a range of candidate generation technologies (e.g. wind, solar PV, batteries, pumped hydro, brown coal, gas turbines);
- hourly wind and solar PV availability profiles.

Input forecasts

Uncertainty in demand, wind and solar generation is incorporated using an **auto-regressive moving-average (ARMA) model.** Unit commitment schedule minimises costs over **10 uncertainty scenarios**, **where inflexible generators have constant schedules** across all scenarios.

The ARMA model simulates day-ahead forecasts:

$$\text{Forecast} = \text{Actual demand/availability} + \text{Forecast error}$$

Forecast error $= \boldsymbol{w_h} = \boldsymbol{\alpha w_{h-1}} + \boldsymbol{Z_h} + \boldsymbol{\beta Z_{h-1}}$, where $\boldsymbol{Z_h}$ is a random Gaussian variable with 0 mean and $\boldsymbol{\sigma_Z}$ standard deviation, representing the probability distribution of forecast stochasticity.

Reference forecasts are calibrated against current demand, wind and solar PV generation forecasts. To assess wind generation forecast accuracy, standard deviation of ARMA model is adjusted.

	α	β	σ_Z	1-hour MAE	1-hour RMSE
Demand	0.391	0.761	0.0299	180 MW	231 MW
Wind	0.936	-0.168	0.0376	2.41%	3.70%
Solar PV	0.810	-0.042	0.0460	3.32%	4.60%

Table 3. *ARMA parameters for reference input forecasts.*

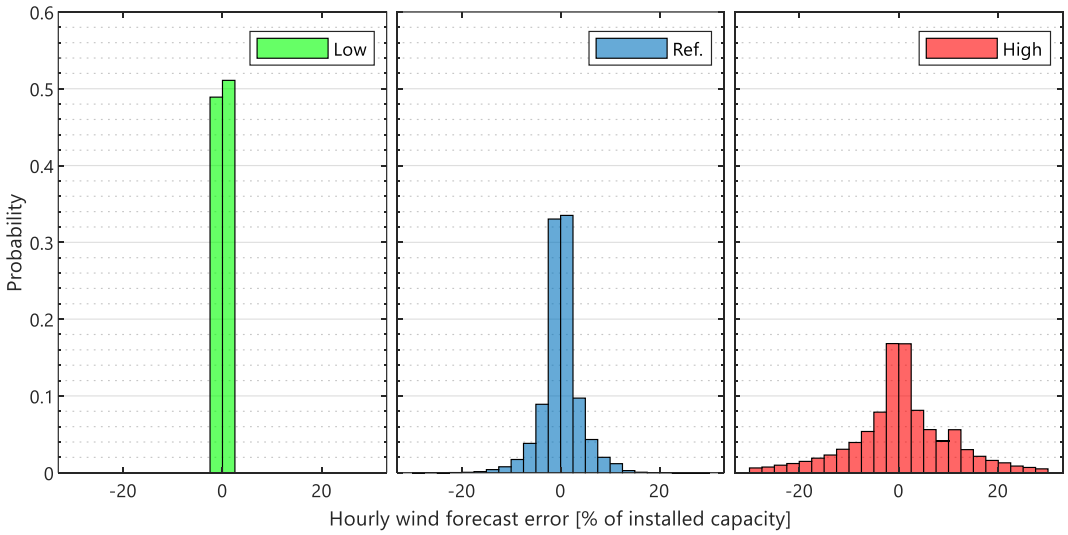

Figure 1. *Forecast error distributions for the wind forecasts assessed.*

Generator fleets – investment model results

With the tightening constraint on total system emissions, the optimal fleet becomes dominated by wind/solar PV generation, backed by forms of energy storage.

- Emissions constraint is not binding in 2020/2030.
- Shadow price on emissions relatively low for 2040/2045 emissions constraint, suggests technology learning (reduced capital costs) has significant role to play.
- These final fleets are the output of the investment model optimisation, adjusted for all generators to have reasonable rates of return (in the absence of forecast uncertainty). Adjusted through iteration of the UC&ED model.

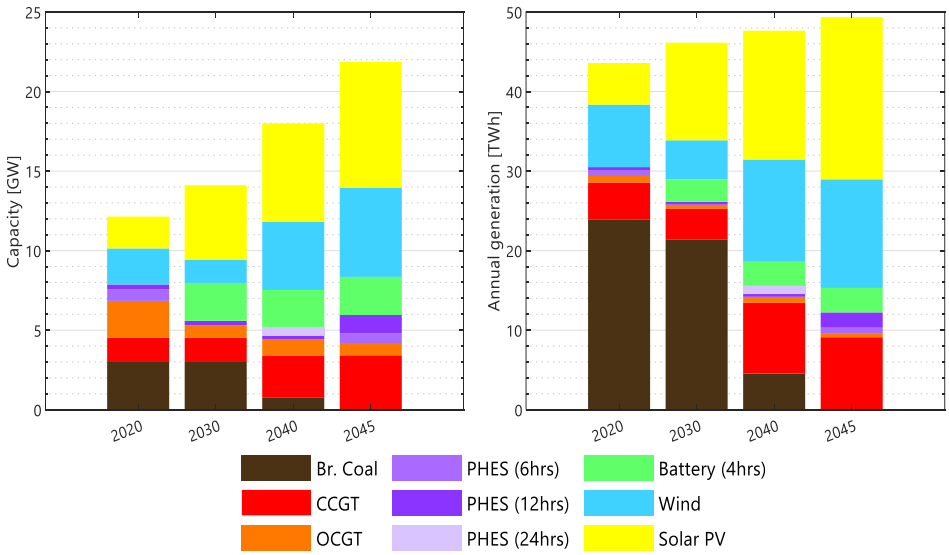

Figure 2. *Installed capacity and annual generation of the fleets assessed in this work, by technology type.*

	2020	2030	2040	2045
Emissions constraint [t-CO_2e / MWh]	0.91	0.61	0.30	0.15
VRG penetration [% of total generation]	30	37	61	69
CO_2 price [$/t-$CO_2$e]	0	0	40.5	47.1

Table 4. *Modelled emissions constraint for the four fleets of generators assessed, and resulting penetration of VRG and shadow emissions price.*

Unit commitment and economic dispatch results

The **week of maximum wind generation** below shows that wind (and solar PV) depress energy prices at times when they generate most.

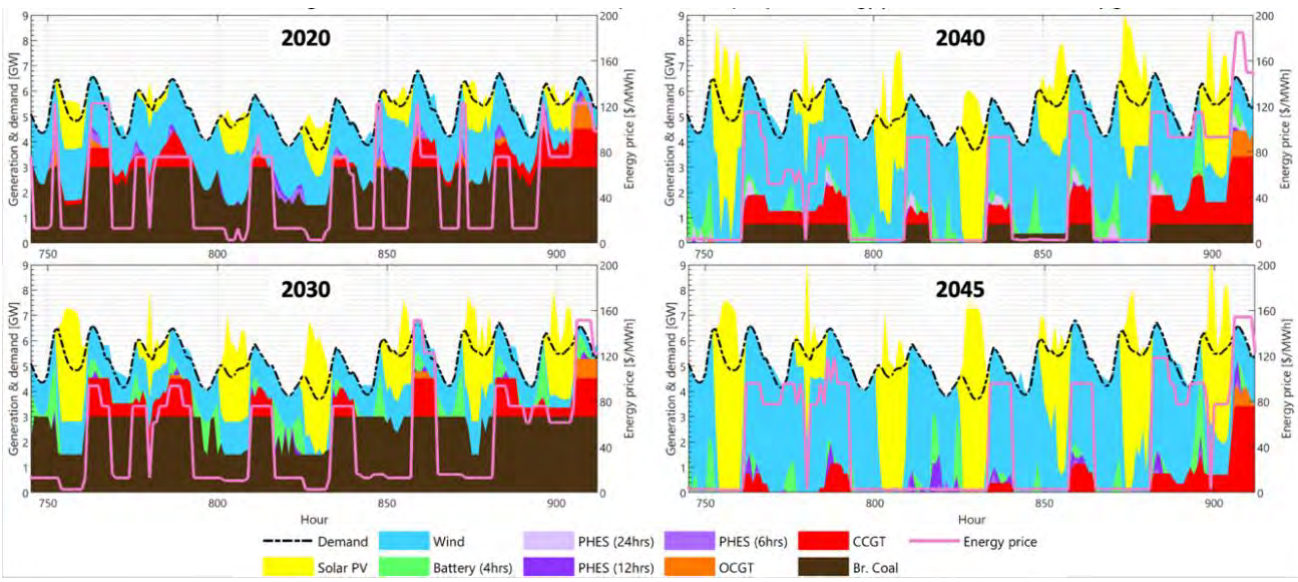

Figure 3. *Week of maximum wind generation in the simulated years 2020, 2030, 2040 and 2045.*

The effect of fleet composition – no uncertainty

Compare generator internal rate of return (IRR) with discount rate used to annualise capital costs in investment sub-model.

IRR and discount rate should match for all generators if non-convex effects are reasonably small and investment and operational decisions are least-cost optimal [Caramanis et al. 1982; Marshman et al. 2020; Perez Arriaga & Meseguer 1997; Schweppe et al. 2013].

With greater VRG, non-convex effects could increase, resulting in instances where certain plants make losses in both the short and long-run. Fleets have been adjusted so that generators receive reasonable rates of return and system IRR > discount rate (in absence of forecast uncertainty).

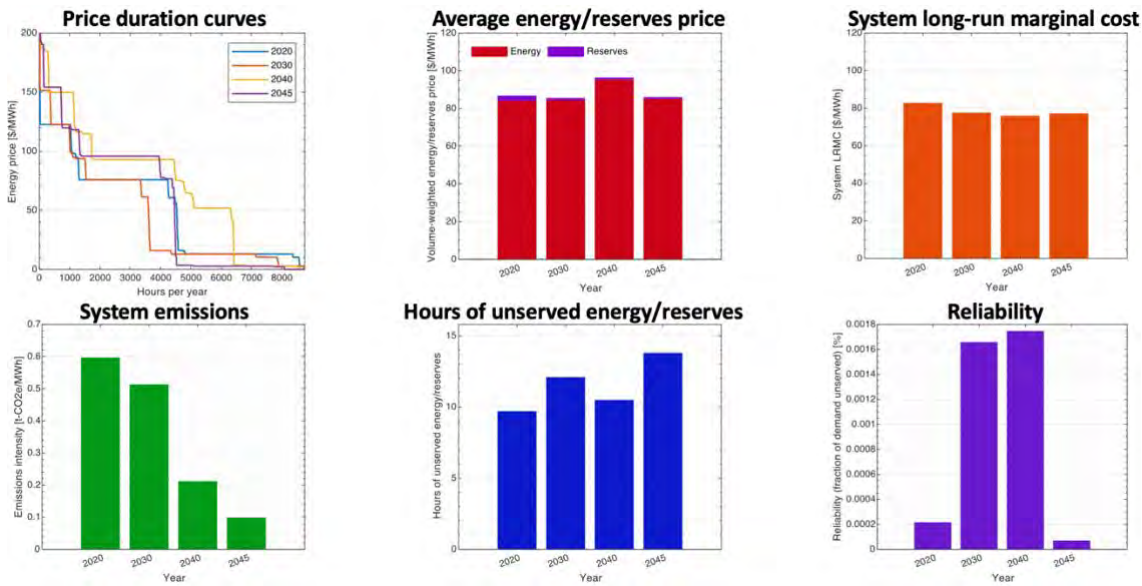

Figure 4. *Price duration curves and simulated electricity market metrics for the generator fleets simulated for 2020-2045.*

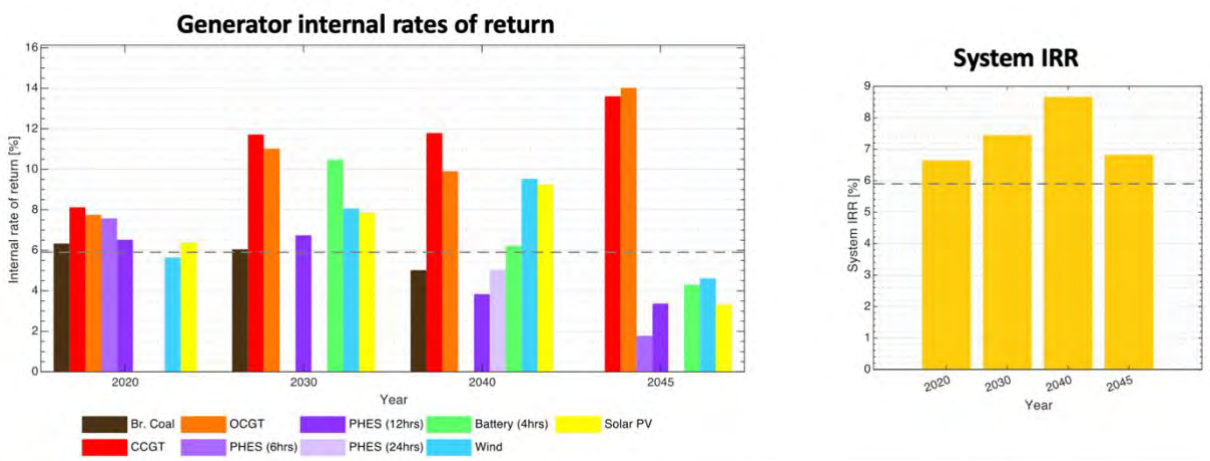

Figure 5. *Projected generator and electricity system internal rates of return for 2020-2045: No uncertainty*

The effect of wind forecast accuracy – 30% VRG

Assess the impact of three wind generation forecasts with **low**, **reference**, and **high** forecast error.

- Reference case forecasts for demand and solar PV generation used.
- Perfect: No forecast uncertainty in wind / solar PV generation or demand.

Higher forecast errors lead to:

- Prices set by gas turbines less often, despite being required on.
- Increase in unserved demand
- Increase in average energy/reserves prices.
- Higher IRRs, due to higher average prices.
- Wind IRRs decrease with increased forecast error.
- Plants deliver a greater proportion of their energy at lower price, and rely to greater extent on high price scarcity events.

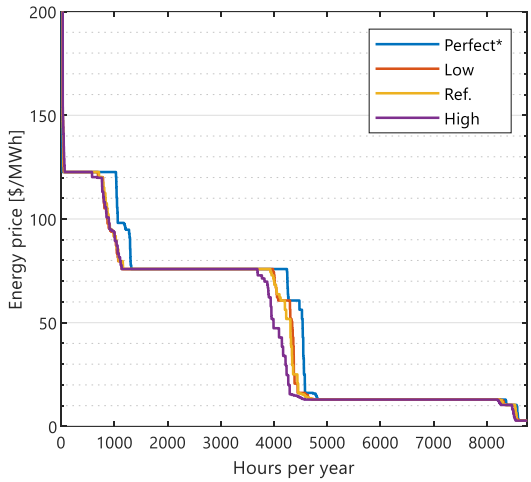

Figure 6. *Price duration curves for the 2020 system with 30% VRG and for the perfect to high uncertainty forecasts cases.*

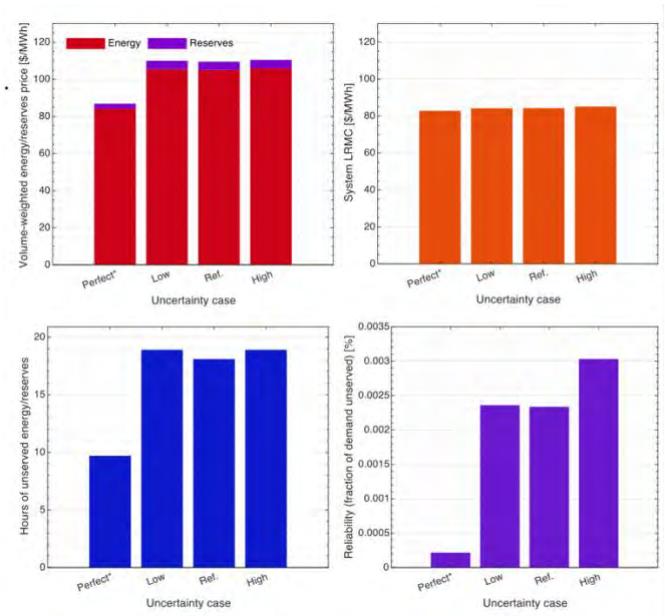

Figure 7. *Electricity market performance metrics for the 2020 system with 30% VRG and for the perfect to high uncertainty forecasts cases.*

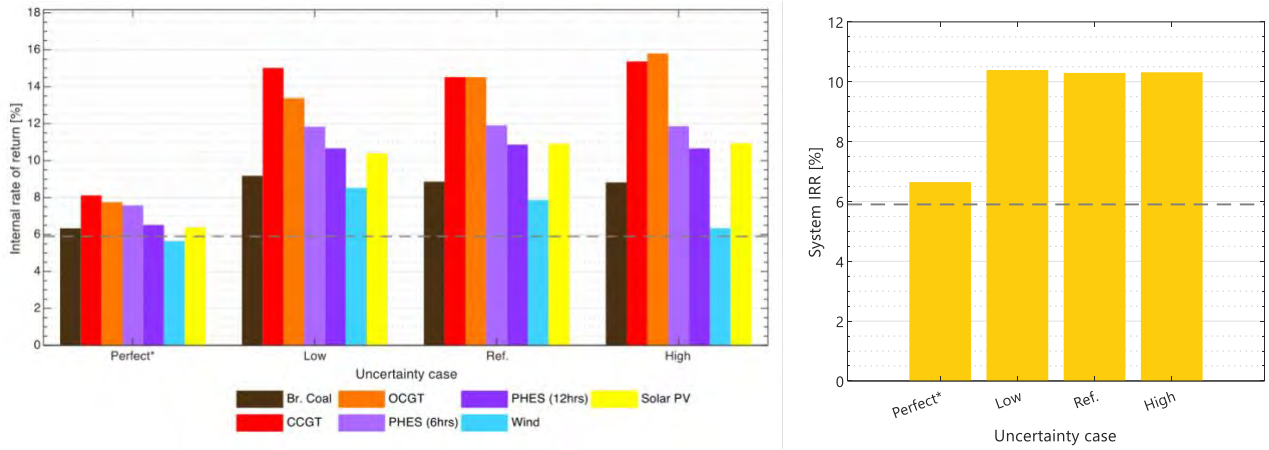

Figure 8. *Generator and electricity system internal rates of return for the 2020 system with 30% VRG and for the perfect to high uncertainty forecasts cases.*

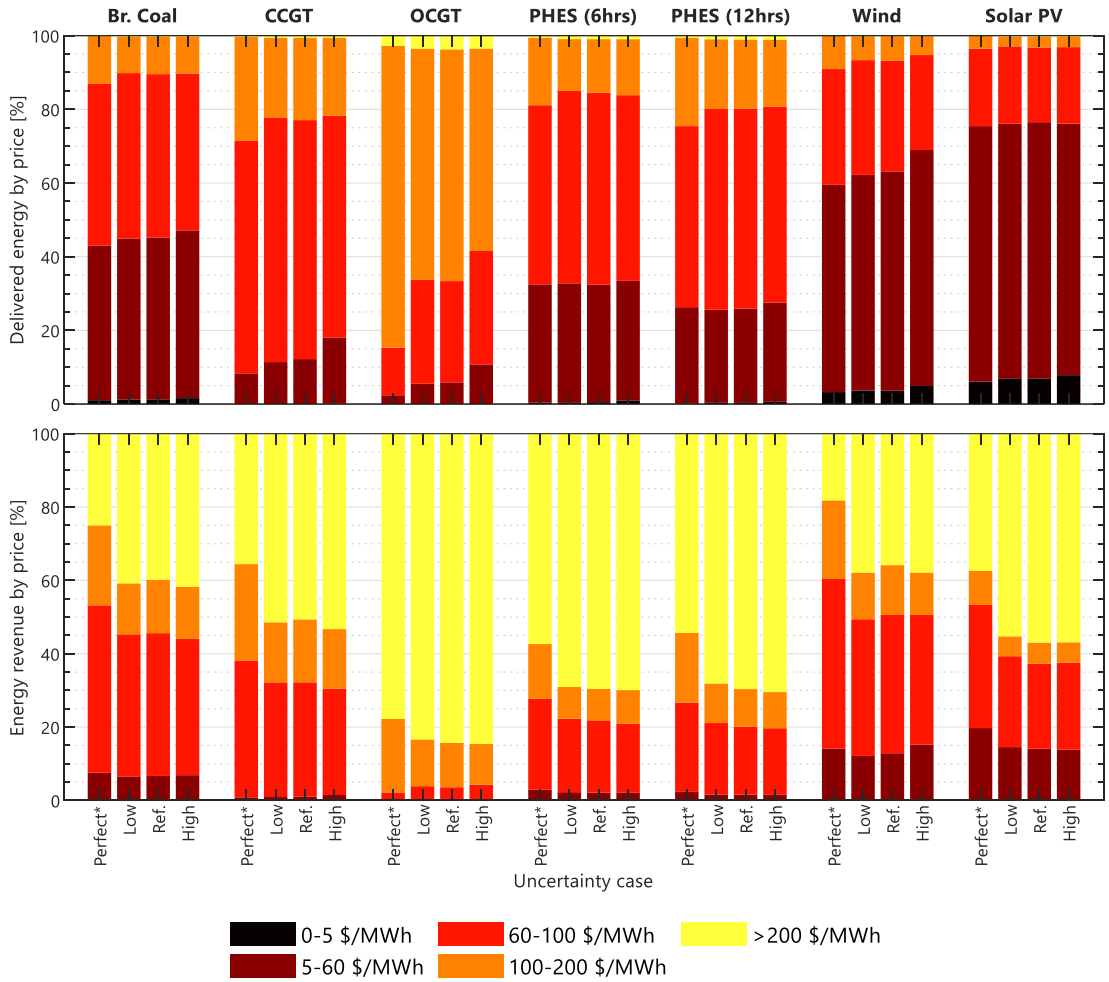

Figure 9. *Delivered Energy and Energy revenue, by different price bands of different technologies, for the 2020 system with 30% VRG and for the perfect to high uncertainty forecasts cases.*

The effect of wind forecast accuracy – 61% VRG

With higher levels of VRG, the previous effects are amplified.

- Both the amount and number of hours of unserved energy/reserves increase with greater forecast error.
- The higher number of hours at market price cap inflates the average energy/reserves prices.
- IRRs are also inflated by higher average prices, particularly thermal and storage plant.
- Wind IRRs decrease by >2% with forecast errors increasing from low to high.
- Wind/solar now deliver ~50%/80% of energy at <60$/MWh, but still rely on scarcity events for majority of revenue.
- Relying on few price spike events for majority of energy revenue is a risky prospect (especially when generation is weather dependent!)
- Improved wind forecasts can improve this reliance.

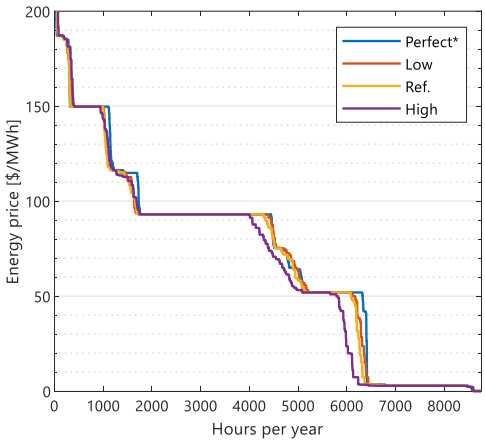

Figure 10. *Price duration curves for the 2040 system with 61% VRG and for the perfect to high uncertainty forecasts cases*

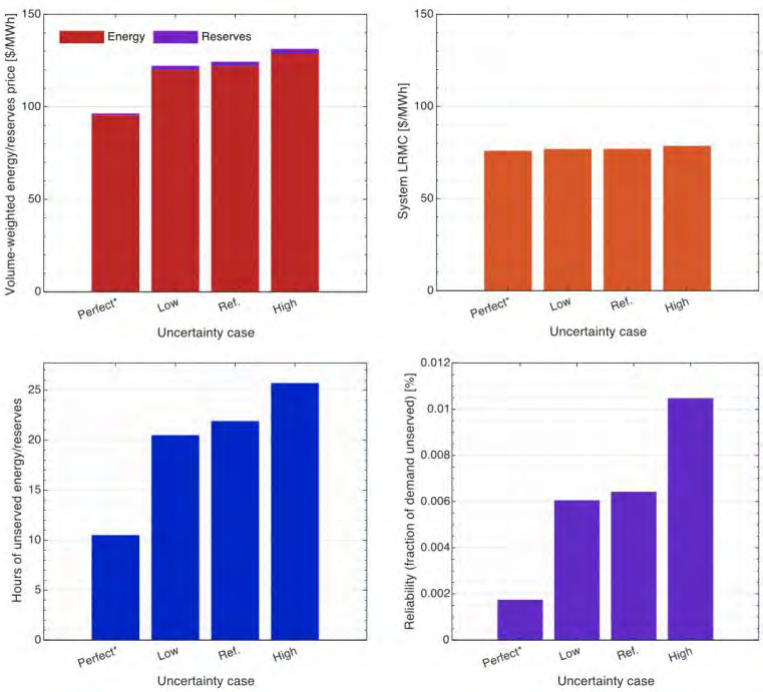

Figure 11. *Electricity market performance metrics for the 2040 system with 61% VRG and for the perfect to high uncertainty forecasts cases.*

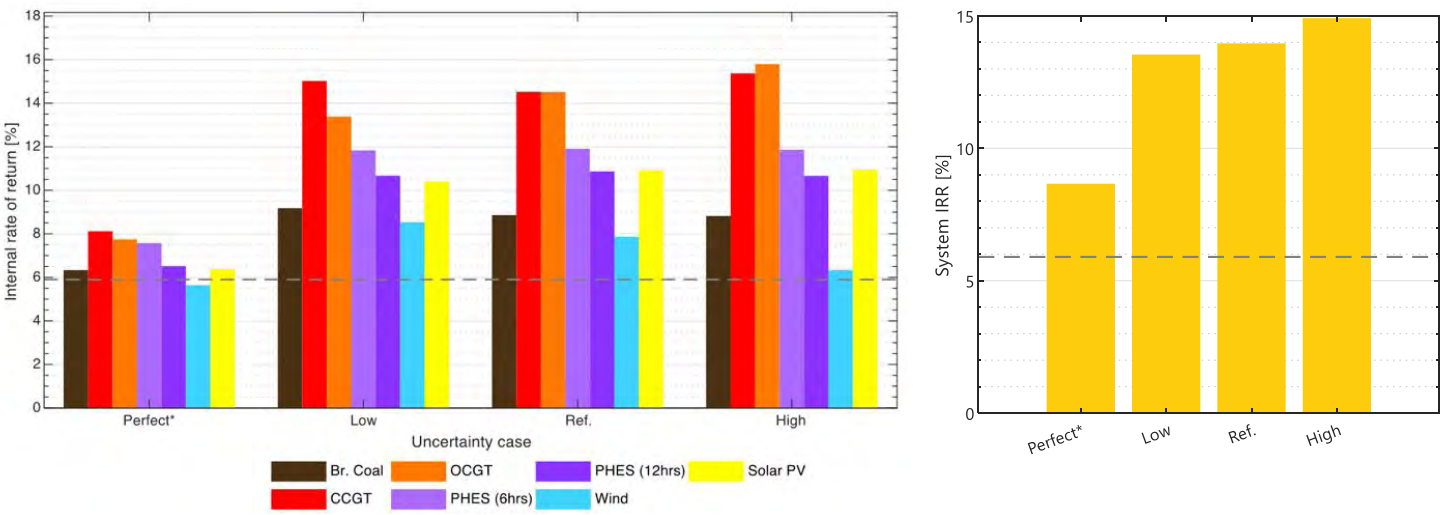

Figure 12. *Projected generator and electricity system internal rates of return for the 2040 system with 61% VRG and for the perfect to high uncertainty forecasts cases.*

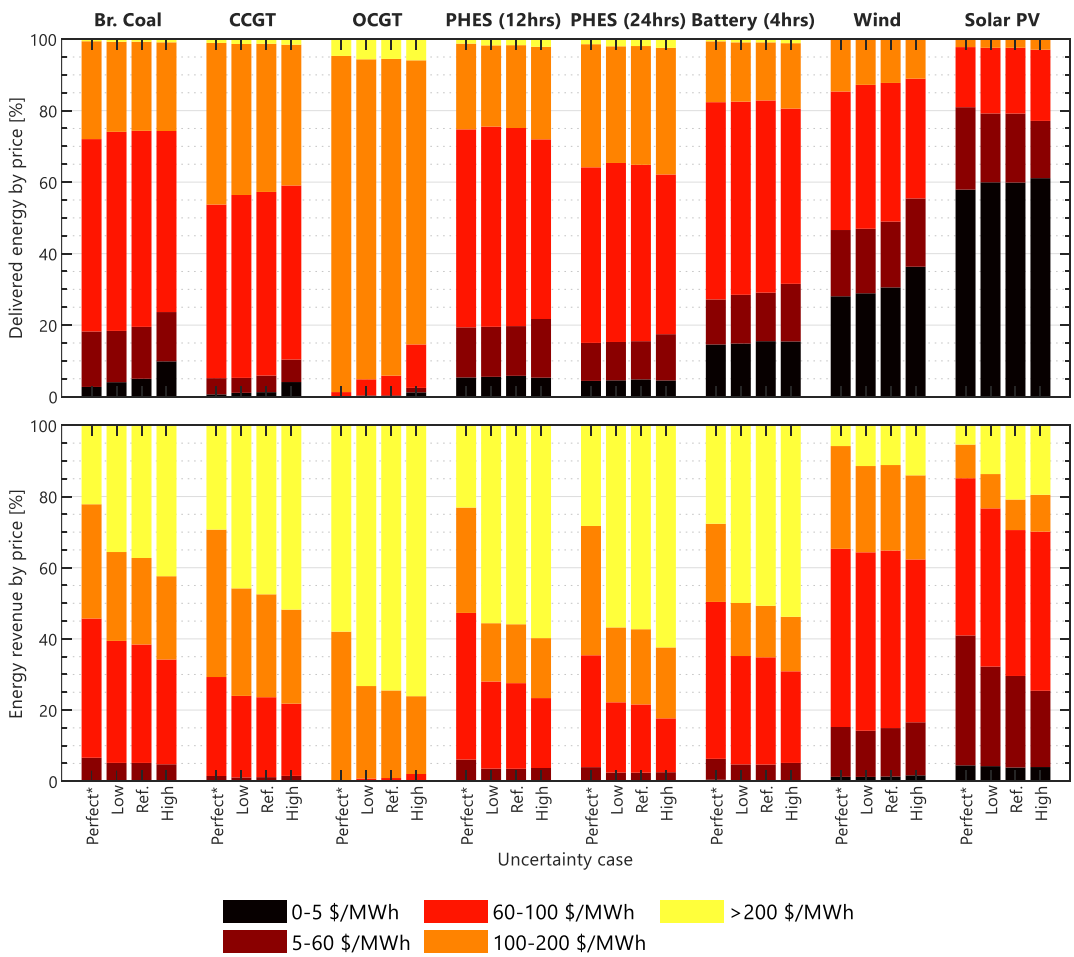

Figure 13. *Delivered Energy and Energy revenue, by different price bands of different technologies, for the 2040 system with 61% VRG and for the perfect to high uncertainty forecasts cases.*

Forecast accuracy effect on other metrics

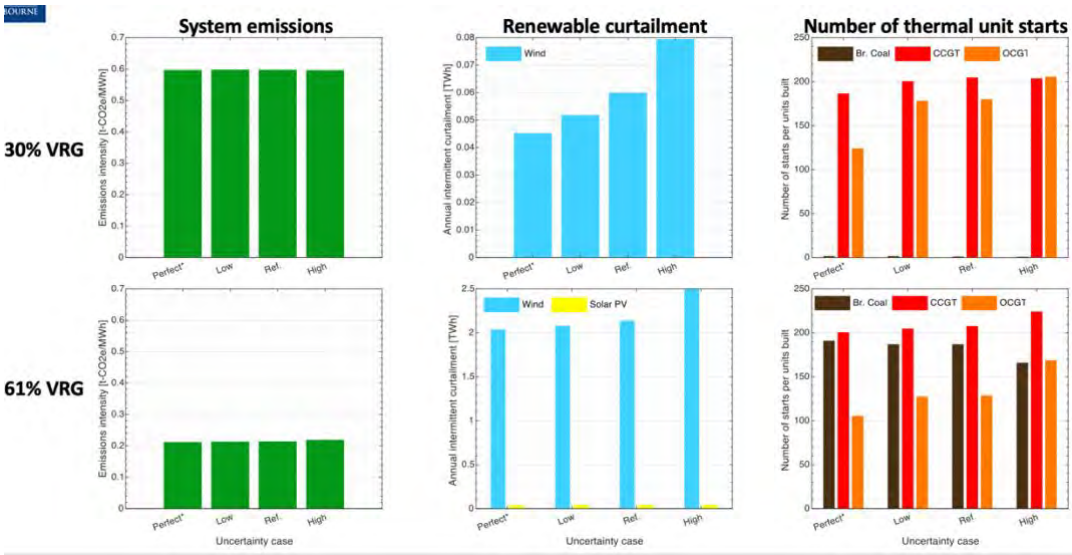

Figure 14. *System emissions, renewable curtailment and thermal unit starts for different levels of VRG penetration and for the perfect to high uncertainty forecasts cases.*

We assess levels of online inertia, assuming inertia is solely provided by thermal/synchronous plant.

We also calculate the potential system RoCoF due to a wind forecast error imbalance, and present as probability distributions.

$$|\text{RoCoF}| = \left|\frac{df}{dt}\right| = \frac{|\Delta P|}{2H_{\text{sys}}} f_0$$

Probability of RoCoF > 1 Hz/s small with 30% VRG, regardless of forecast accuracy.

With 61% VRG, wind forecast accuracy has significant influence on potential RoCoF.

Note: whilst we assess system inertia, this is not a detailed assessment of system security and reliability. Such an assessment is a large and separate undertaking.

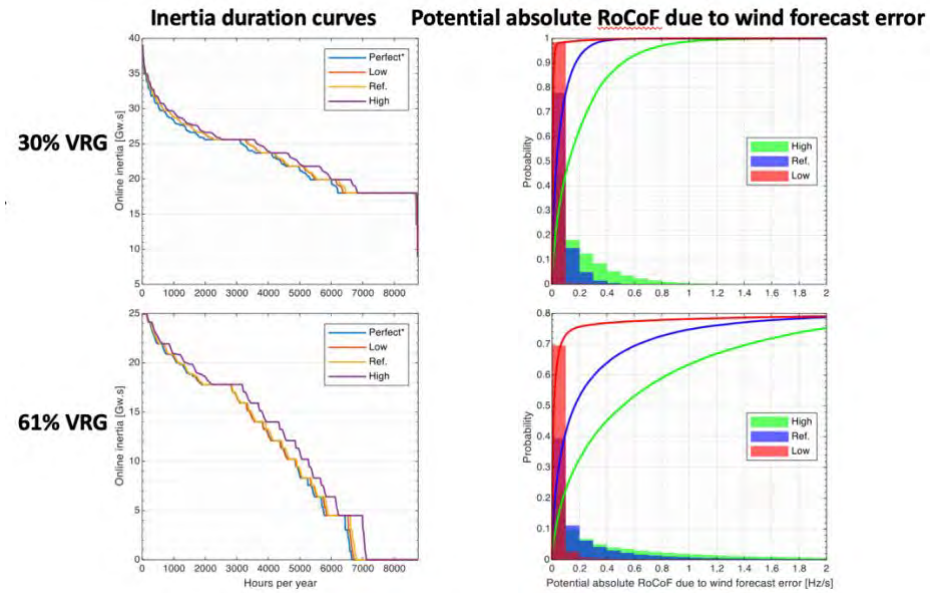

Figure 15. *Simplified assessment of system Inertia and probability distribution of a potential absolute RoCoF due to wind forecast error, for different levels of VRG penetration and for the perfect to high uncertainty forecasts cases.*

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Appendix 1: Capacity investment model

- Determines generating plant investments needed to meet electricity demand, subject to an emissions constraint.
- Four representative years modelled – 2020, 2030, 2040, 2045 – with capacity investment decisions made in isolation for each representative year, i.e. without considering currently existing plants, or consistency between the years modelled. Fleets in each year can therefore be considered as 'greenfield' fleets.
- Considers an entire year of electricity demand in Victoria, wind and solar profiles, and uses projected (2020 – 2045) annualised capital costs of each technology at a weighted average cost of capital of 5.9%. This rate was also used in the ISP.
    - Investment decisions are made to minimise the sum of the:
    - annualised capital costs;
    - fixed operating and maintenance costs;
    - fuel costs and variable operating and maintenance costs; and
    - penalty costs associated with insufficient reserves or unserved demand (i.e. load shedding).
- Increasing penetrations of VRG incorporated by:
    - Modelling representative years out to 2045 with corresponding cost projections that feature significant capital cost reductions of wind and solar PV technologies (wind and solar PV have increasing share of the least-cost technology mix)
    - Applying an emissions constraint in each representative year modelled, consistent with a linear trajectory to an emissions-free system in 2050 (a linear decrease to zero from 0.91 t-CO2e/MWh in 2020).
- Emissions constraint in investment model provides shadow carbon price that is applied in the UC&ED model to ensure consistency between sub-models.

- Simplifications of investment model:
    - Investment decision modelling is optimized over one year horizon and optimizes capacities, some detail of plants dispatch limits to ensure computational tractability.
    - Commitment decisions are not included in this model.
    - Plants can provide reserves even if they are not online.

Appendix 2: Unit commitment & economic dispatch model

- The **unit commitment** process determines when to turn generators on and off in order to serve electricity demand. The unit commitment model used in this study makes commitment decisions to minimise:
    - start-up costs;
    - fuel and variable operating costs;
    - penalties associated with unserved demand or insufficient reserves.
- Constraints on the commitment schedule of inflexible generators include:
    - always running at or above their minimum stable generation;
    - remaining on for at least their minimum on time;
    - remaining off for at least their minimum off time; and
    - when providing reserves, having sufficient margin between their current dispatch and their minimum generation level (for lower reserves) or capacity (for raise reserves).
- Inflexible generators are: Brown coal, CCGT, OCGT.
- The output of the unit commitment model is a 48-hour (24-hour look ahead) schedule of commitment decisions to meet demand and reserves requirements.
- **An economic dispatch model** is then run, which is very similar to the commitment optimisation, but takes this commitment schedule as **now fixed**. This allows the determination of a final dispatch schedule and prices for energy and reserves.
- Prices for energy and reserves are determined from the shadow price of the constraints requiring generation to equal load and for the reserve requirement to be met, respectively. That is, the **energy/reserve price** in each hour is set by the **short-run marginal costs** of the **marginal generator** in that hour.
- In periods in which there is a shortage of energy or reserves, the price will rise to the market price cap. This is expected to occur for a small number of hours per year on average.

Appendix 3: Generator fleets assessed in this work

- Thermal plant modelled as having an integer number of units, with fixed unit capacity.
- Renewable / storage plant not modelled as individual units.
- These final fleets are the output of the investment model optimisation, adjusted for all generators to have reasonable rates of return (in the absence of forecast uncertainty). Adjusted through iteration of the UC&ED model.

	Number of units				Total capacity [MW]			
	2020	2030	2040	2045	2020	2030	2040	2045
Br. Coal	4	4	1	0	3000	3000	750	0
CCGT	4	4	7	9	1520	1520	2660	3420
OCGT	9	3	4	3	2322	774	1032	774
Wind	-	-	-	-	2266	1456	4271	5607
Solar PV	-	-	-	-	2000	4686	6200	7900
Battery (4 hours)	-	-	-	-	0	2378	2325	2393
PHES (6 hours)	-	-	-	-	720	0	0	600
PHES (12 hours)	-	-	-	-	310	297	210	1160
PHES (24 hours)	-	-	-	-	0	0	550	0

Table 5. *Generator Fleets used in this work.*

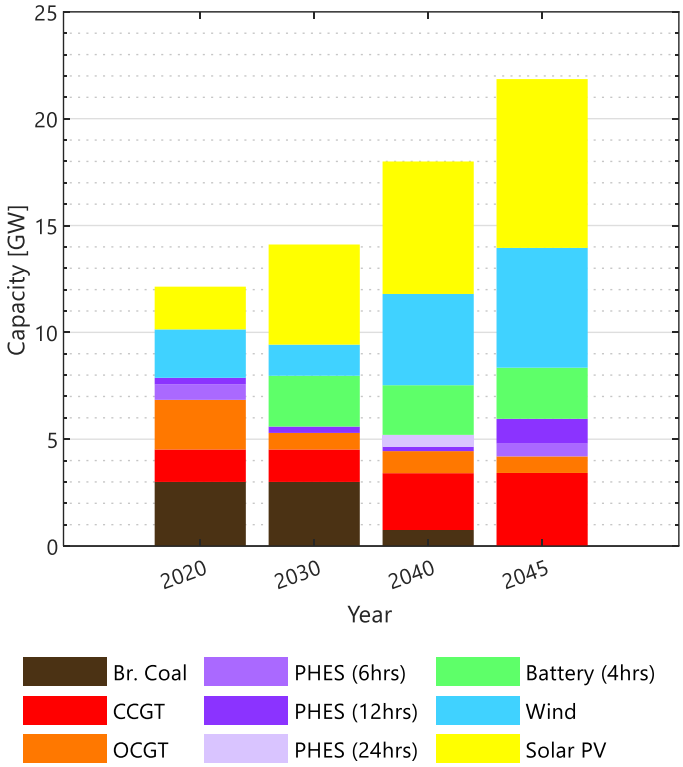

Figure 16. *Installed capacity of generator fleets used in this work.*

Appendix 4: Input data

Generator type	Financial life	Capital cost				Annualised capital cost				Fixed O&M cost	Variable O&M cost	Fuel cost	SRMC
		2020	2030	2040	2050	2020	2030	2040	2050				
	[years]	[$/kW]				[$/kW/year]				[$/kW/year]	[$/MWh]	[$/GJ]	[$/MWh]
Brown coal	25	5097	5092	5086	5082	394.9	394.5	394.1	393.8	69.9	5.33	0.67	12.93
CCGT	25	1690	1688	1687	1685	130.9	130.8	130.7	130.6	10.6	7.46	9.03	75.87
OCGT	25	1411	1410	1408	1407	109.3	109.2	109.1	109.0	4.3	10.66	9.53	122.63
Wind	25	1745	1603	1489	1403	135.2	124.2	115.4	108.7	37.6	2.78	-	2.78
Solar PV	25	1280	827	663	557	99.2	64.0	51.4	43.2	15.4	0	-	0
Battery (2 hours)	10	1152	540	527	523	155.8	73.0	71.2	70.7	8.1	0	-	0
Battery (4 hours)	10	1799	693	669	662	243.3	93.7	90.5	89.5	8.1	0	-	0
PHES (6 hours)	30	2314	2283	2252	2221	166.3	164.1	161.8	159.6	16.2	0	-	0
PHES (12 hours)	30	2648	2612	2576	2541	190.3	187.7	185.2	182.7	16.2	0	-	0
PHES (24 hours)	30	3403	3357	3311	3266	244.6	241.3	238.0	234.8	16.2	0	-	0
PHES (48 hours)	30	5114	5044	4975	4908	367.5	362.5	357.6	352.8	16.2	0	-	0

Table 6. *Generator technical input data*

Generator type	Unit capacity	Emissions intensity	Thermal efficiency	Min. generation level	Start-up fuel	Shut down fuel	Min. up/down time	Max. ramp up/down rate	Primary reserve capability	Round-trip storage efficiency	Inertia
	[MW]	[kg-CO_2e/MWh]	[%]	[MW/MW-capacity]	[GJ/MW]	[GJ/MW]	[hours]	[MW/MW-capacity]	[MW/MW-capacity]	[%]	[MW.s/MW-capacity]
Brown coal	750	964	31.8%	0.4	61.5385	6.1538	8	0.72	0.065	-	6
CCGT	380	424	47.5%	0.3	13	1.3	4	1.263158	0.0325	-	5
OCGT	258	670	30.6%	0.1	0.16	0.016	1 (0*)	1	0.1	-	4
Wind	210	0	-	0	-	-	-	-	0	-	0
Solar PV	100	0	-	0	-	-	-	-	0	-	0
Battery (2 hours)	25	0	-	0	-	-	-	-	2	81%	0
Battery (4 hours)	25	0	-	0	-	-	-	-	2	81%	0
PHES (6 hours)	100	0	-	0.5	-	-	-	-	0.5	80%	4
PHES (12 hours)	100	0	-	0.5	-	-	-	-	0.5	80%	4
PHES (24 hours)	100	0	-	0.5	-	-	-	-	0.5	80%	4
PHES (48 hours)	100	0	-	0.5	-	-	-	-	0.5	80%	4

Table 7. *Generator financial input data*

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