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Renewable Energy Zones: Real-Time Line Ratings and Generator Cost Allocation

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Abstract
Renewable Energy Zones (REZ) and associated transmission network infrastructure are an important policy development in Australia's transitioning electricity market. Stylised on the Texas model, REZs form the basis upon which to expand renewable hosting capacity of Australia's National Electricity Market at scale, while simultaneously minimising the footprint of infrastructure – noting community, cultural heritage and environmental (i.e. biodiversity) sensitivities. In the Queensland region of the market, REZs have been developed outside the regulatory framework as 'merchant' assets, where connecting generators pay user charges rather than the rate base. However, as a geographically dispersed coalition of generators seek to connect over longer distances, cost allocation and the financial tractability of merchant REZs rises in complexity. In this article, we show how real-time line ratings and algorithmic cost allocation extends their financial viability.

Keywords: Renewable Energy Zones, Real-Time Line Ratings, Renewables, Battery Storage, Cost Allocation.

JEL Codes: D52, D53, G12, L94 and Q40.

1. Introduction

Renewable Energy Zones (REZs) are a key policy initiative in Australia's National Electricity Market (NEM), designed to coordinate multiple renewable projects and minimise marginal transmission costs. If transmission costs were trivial and community attitudes consistently favourable, coordination may be unnecessary. However, renewable projects and transmission infrastructure encroaches on private land, competes with environmental (i.e. biodiversity) and agricultural objectives, and risks disturbing cultural sites (Simshauser and Newbery, 2024). Above all, transmission is costly. Consequently, REZs are essential even in a country as vast as Australia.

While REZs in Australia have largely followed the Texas / ERCOT model, each of the NEM's three largest regions (New South Wales, Queensland and Victoria) have taken subtly different approaches. New South Wales opted for a contestable model in 2020, planning large-scale, capital-intensive augmentations capable of hosting ~4-8GW in each REZ. Time, complexity and costs were vastly understated with only one reaching financial close after six years of activity[1]. Victoria created VicGrid in 2021, with no progress to date. Queensland pursued smaller, non-regulated (merchant) REZ augmentations extending from the transmission backbone and underwritten by generator

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[1] The Central West Orana REZ in NSW reached financial close albeit at multiples of the initial cost estimate.

user charges rather than as regulated assets paid by end-use consumers. This model enabled rapid deployment with three REZs planned, developed and energized in just four years – adding a cumulative 4.5GW hosting capacity. The next REZ (~4GW) is under development at the time of writing.

While the Queensland model has the advantage of speed, it must deal with the primal challenge of reaching financial viability. This only occurs after multiple renewable projects have reached financial close and committed to connection. Yet, wind and solar projects take years to develop and secure approvals and financing, meaning simultaneous generator commitments connecting in a common zone could only occur by chance. More importantly, as with all scarce resources, REZs form an upward sloping supply curve. As REZs extend further away from the transmission backbone, costs rise, and so too will generator user charges. Under such conditions, user charges may exceed generators 'capacity to pay'.

Prior research on merchant REZs examined how various parameters alter hosting capacity including (i) the complementarity of renewable resources (Simshauser, Billimoria and Rogers, 2022; McDonald, 2023, 2024), (ii) access regimes (Newbery and Biggar, 2024; Simshauser and Newbery, 2024), (iii) line ratings (Simshauser, 2024) and (iv) battery storage (Simshauser, 2025). However, prior research assessed each parameter independently, and more crucially, REZ user charges to connecting generators were greatly simplified and allocated by expected output and by asset class. Such an approach ignores important locational differences and potentially binding *capacity to pay* constraints.

In this article, we extend prior research by combining all parameters to identify the optimal mix of renewable plant in a REZ, and define a set of efficient, fair and defendable user charges to be allocated to connecting generators. Using an applied example involving a 275kV REZ, we also navigate through a binding 'capacity to pay' problem by examining maximal combinations of connecting generators by contrasting static, seasonal, and real-time transmission line ratings.

Model results show real-time ratings dramatically increase renewable hosting capacity and consequently, the collective capacity to pay by connecting generators. While the scenario we construct is applied to an example of a merchant REZ in the NEM's Queensland region, the framework is capable of being generalised and applied to any transitioning power system seeking to develop scale-efficient REZs under either a merchant or regulated model.

This article is structured as follows: Section 2 reviews relevant literature. Section 3 introduces models and data. Section 4 presents results. Policy implications and conclusions follow.

2. Review of Literature

REZs can be defined as an area comprising high quality renewable resources capable of being developed at scale (Pack *et al.*, 2021). The origins of renewable zones can be traced back to the Texas // ERCOT market, with the Public Utilities Commission of Texas approving the first 'Competitive REZ' or 'cREZ' in 2008 (Dorsey-Palmateer, 2020). By 2009, investment in wind capacity had stalled with curtailment rates rising to ~17% (Gowdy, 2022; Du, 2023). This had been anticipated in 2005, and consequently 2400

miles of 345kV transmission was approved at a final investment cost of ~$6.8 billion – specifically to connect remote wind resources with urban load centres (Jang, 2020). Wind transfer capacity in West Texas and the Panhandle was increased from ~6900 to 18,500MW (Du and Rubin, 2018). Following the cREZ, wind investments surged, and curtailment rates were cut to ~0.5% (Dorsey-Palmateer, 2020).
The main advantage of REZs is their ability to coordinate the connection of disparate VRE proponents that would otherwise act independently (Simshauser, 2021; McDonald, 2023; Newbery and Biggar, 2024). In this sense, REZs are designed to eliminate otherwise duplicate network investments (Simshauser, Billimoria and Rogers, 2022; McDonald, 2024). In Australia, REZs have become an important initiative to facilitate additional renewable hosting capacity (McDonald, 2024). In the NEM's Victorian and NSW regions, REZs are state-led regulated asset developments. As noted in Section 1 in the NEM's Queensland region, planned REZs are comparatively smaller in scale, larger in number, and merchant investments led by a benevolent, state-owned transmission planner (Newbery and Biggar, 2024; Simshauser and Newbery, 2024). However, all prior research greatly simplified user charges under conditions of perfect entry (Simshauser, Billimoria and Rogers, 2022; Simshauser, 2024, 2025; Simshauser and Newbery, 2024)

The literature on cost sharing in transmission networks is extensive and has a long-standing history. The use of Game Theory to address multiple aspects of cost sharing in power systems is well known (Contreras, 1997). A thorough review of approaches to cost sharing in transmission networks in these circumstances is presented in Khan and Agnihotri (2013). Much of this literature focuses on the classic 6-bus system introduced by Garver (1970). This is a system involving a DC load flow model subject to a series of constraints (e.g. Kirchhoff's laws).

Other related research on transmission cost allocation includes Kristiansen et al., (2018), which reviews flexibility providers such as fast ramping gas turbines, hydropower and demand-side management using a generation and transmission capacity expansion planning model. The focus was on the different ways a technology can add value to a combination of technologies. Fuentes González et al., (2022) use a similar framework focusing on community energy projects.

Our situation is different to the classic bus literature and the related transmission cost allocation research.[2] Our problem, given a merchant REZ model, is the efficient allocation of shared infrastructure costs to large-scale renewable generators without regulator involvement. The closest research to the work presented in this article is that found in Nylund (2014), where multiple entities in different countries collaborate to regionally expand power networks. We apply the concepts of cost sharing based on cooperative game theory (Hougaard, 2009). Other approaches from the cost allocation literature are also possible. However, these approaches don't consider coalition structures and combined cost profiles of multiple players – which are relevant for the present context. In addition, given the costs of projects considered in this article are transferable between parties, a TU-game (or transferable utility game) is an appropriate approach to model the current situation (see Shellshear and Sudhölter, 2009). For these

[2] Our equivalence to the traditional bus approach would be to take the volume weighted production price as the synthetic version of a bus system (price being a proxy for demand with intermittent resources). However, this is still not a good match because there are definite economies of scale with shared REZ assets, hence our approach in this article.

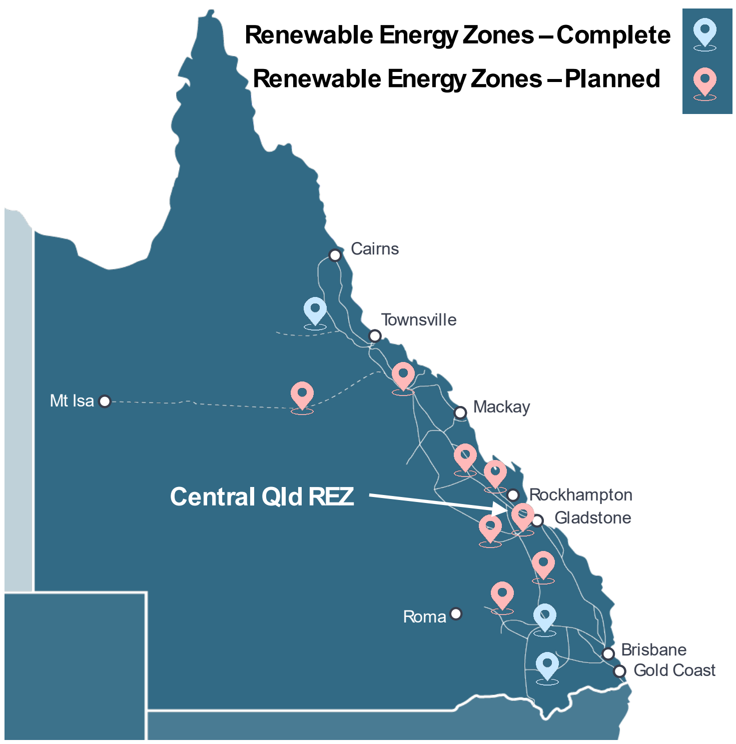
reasons, we solve the current cost allocation problem using the Shapley Value (Shapley, 1957) given its properties are desirable characteristics sought in the current context.

3. REZ data and models

Our task is to identify the optimal mix of renewable generation in a merchant REZ and examine cost allocation to a coalition of participating generators given capacity to pay constraints. We examine an applied case study from the NEM's Queensland region, noting the principles and modelling framework can be generalised to any power system.

By way of brief background, the topography of the Queensland power system comprises a 275kV transmission backbone extending over a 1500km range, from the north near Cairns to the southern border with New South Wales (Fig.1). Renewable resources can be found along the length and breadth of the network with ideal locations identified in Fig.1. The present analysis will focus on the Central Queensland REZ.

Figure 1: Renewable Energy Zones in Queensland



3.1 REZ layout

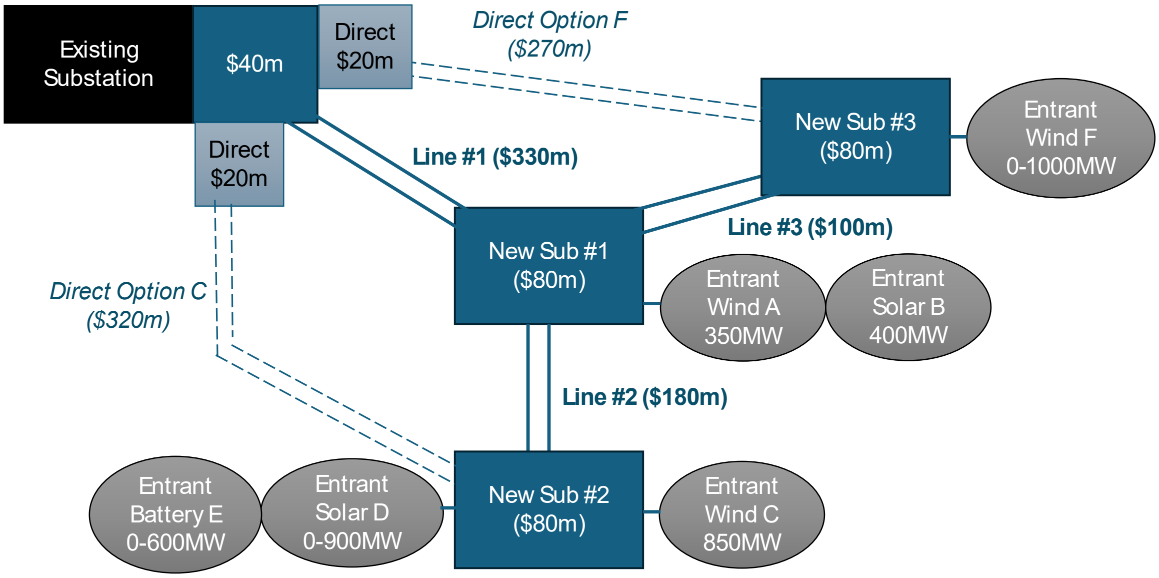
The Central Queensland REZ layout is presented in Fig.2. To summarise, there are six potential tenants (Wind A, Solar B, Wind C, Solar D and Battery E) which trigger investment in Lines #1 and #2, and Substations #1 and #2, while 'Wind F' triggers Line #3 and Substation #3.

It can be seen that an optimised REZ comprising all generation projects A..F involves an investment of $890m – the simple sum of Lines 1-3, Substation 1-3 and the $40m expansion of the Existing Substation. For a benevolent transmission planner, breakeven 'user charges' equate to 8.2% per annum (i.e. ~1.7% O&M and ~6.5% Return on

Capital). Given $890m capital invested, breakeven user charges therefore equal $73m pa (i.e. $890m x 8.2% = $73m).

The task of the transmission planner is to identify the optimal mix of wind, solar and storage for the REZ and to identify a fair, efficient and defendable allocation of user charges across connecting generators within a capacity-to-pay constraint (see Section 3.4). Two generators (C and F) have 'Direct Options' to connect. However, as can be seen from Fig.2, if each generator pursued direct connections (i.e. Options C and F), total investment costs would rise from $890m to $1,200m with breakeven user charges rising from $73m to $98m. This exemplifies the notion of REZs – minimising costs and avoiding otherwise duplicative transmission infrastructure.

Figure 2: Renewable Energy Zone Layout



3.2 REZ line ratings

For modelling purposes, REZ transmission line capacity is assumed to comprise a double circuit (twin sulphur) 275kV radial connection extending from the main transmission backbone, connecting the six renewable and storage generators. REZ network transfer limits are driven by conductor type and allowable operating temperatures (~200km from Australia's coastline). To maintain continuity with prior REZ research (Simshauser, 2021; Simshauser and Newbery, 2024), static and seasonal line transfer limits are outlined in Tab.1.

Table 1: Static vs Seasonal REZ Line Transfer Limits (Double Circuit 275kV)

	Normal Rating **(Amps Double Circuit)**	Emergency Rating **(Amps Single Circuit)**
Static	1734	1281
Seasonal		
- Summer	1734	1281
- Mild Seasons	1981	1387
- Winter	2162	1461
	(MW Double Circuit)	**(MW Single Circuit)**
Static	1536	1145
Seasonal		
- Summer	1536	1145
- Mild Seasons	1756	1229
- Winer	1916	1295
$FCAS$ raise		+750
Interconnect Limit $(\theta_{t=Sum}^{Seas})$	2863	

The derivation of results in Tab.1 for seasonal line ratings, using summer $\left(REZ_{t=Sum}^{Seasonal}\right)$ as the example, is as follows:

$$REZ_{t=Sum}^{Seasonal} = Min\left[\left(2 \cdot \sqrt{3} \cdot 0.275 \cdot NR_{t=Sum}^{Seasonal} \cdot 0.93\right), \left(\sqrt{3} \cdot 0.275 \cdot ER_{t=Sum}^{Seasonal} \cdot 0.93 + FCAS\right), \theta^{Static}\right] \rightarrow REZ_{t=Sum}^{Seasonal} = Min(1536, \langle 1145 + FCAS\ 750 \rangle = 1895, 2863MW) \quad (1)$$

The first term in Eq.1 identifies seasonal thermal transfer capacity for each conductor for each of two circuits (2 x √3 x 0.275 x Current) operating at Normal Rating during summer $\left(NR_{t=Sum}^{Seasonal}\right)$ and converted to MW assuming a power factor of 0.93. The second term in Eq.(1) repeats this process for a single circuit operating at its Emergency Rating during summer $\left(ER_{t=Sum}^{Seasonal}\right)$ with a 'runback scheme' enabled inside the REZ, and Frequency Control Ancillary Services ($FCAS$) relied on outside the REZ under normal operating conditions (the limits of which are based on the loss of a single circuit due to, for example, lightning strikes). The third term θ^{Static} is an exogenously determined downstream constraint (i.e. maximum transfer capacity of the connecting substation in Fig.2).

In this research, we also examine real-time line ratings. The array of variables driving real-time line ratings includes Conductor Type CT, emergency temperature rating T_{max}, number of conductors C_n, wind speed W_s, wind angle to the conductor W_{ang}, ambient temperature T_{am}, solar angle S_{ang}, solar absorption coefficient A and the emissivity of the conductor surface over time E as set out on the RHS of Eq.2.

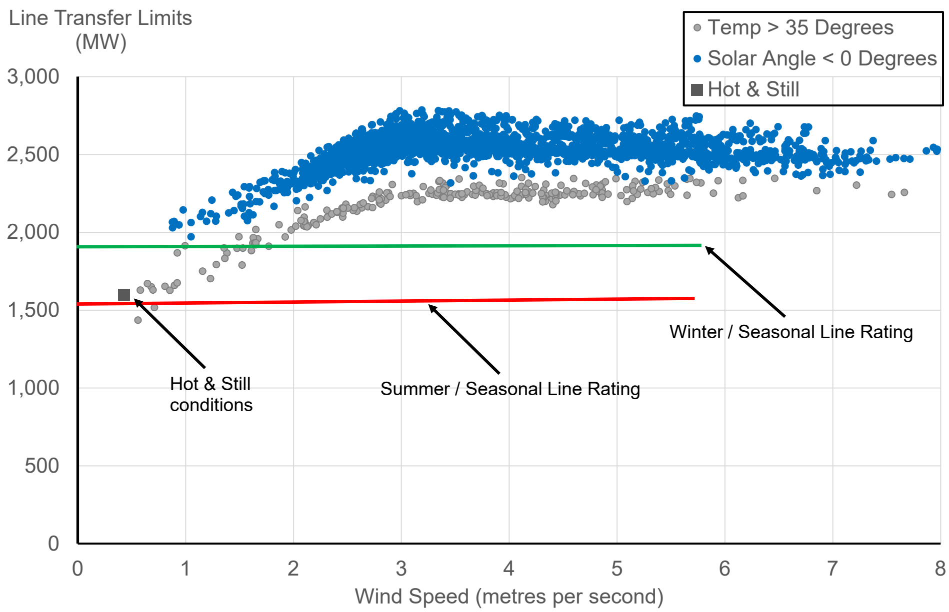
$$\begin{gathered} REZ_{t=Sum}^{RTR} = Min\begin{bmatrix} \left(2 \cdot \sqrt{3} \cdot 0.275 \cdot NR_t^{RTR}\right) \cdot 0.93, \\ \left\{\left(\sqrt{3} \cdot 0.275 \cdot ER_t^{RTR}\right) \cdot 0.93 + FCAS\right\} \\ \theta^{Static}, \end{bmatrix} \rightarrow \\ NR_t^{RTR}, ER_t^{RTR} = F\left(CT, T_{max}, C_n, W_s, W_{ang}, T_{am}, S_{ang}, A, E\right), \\ \forall\, t \in T \end{gathered} \quad (2)$$

By comparison to static or seasonal limits, real-time ratings can lead to material increases in transfer capacity. This is illustrated in Fig.3, where the y-axis measures line transfer limits and the x-axis measures wind speed.

Historically, maximum line transfer limits would, by necessity, be based on conservative engineering assumptions and weather conditions. A lack of real-time locational weather data, and the need to ensure the power system could meet critical event maximum demand periods required such an approach. In the case of Queensland, these conditions correlated with very hot, still conditions during the middle of the day (i.e. 12:30pm) when household, commercial and industrial cooling loads would reach their peaks, and when the power system was reliant on coal and gas-fired generators to meet the prevailing maximum demand. In Fig.3, such conditions are highlighted by the square-shaped black marker, and by the horizontal red line which represents the static (and summer seasonal) rating for a double circuit 275kV line.

Real-time line ratings (hourly resolution) in Fig.3 are represented by the grey and blue markers. These markers rise steadily as the windspeed rises from 0 to 3m/s (at which point the thermal cooling properties of wind for line ratings plateaus). The grey markers represent hourly periods where ambient temperatures exceed 35^{0}C while the blue markers represent hourly periods where the solar angle was negative (i.e. non-solar periods) which implies cooler conditions – and notice that these periods also dominate high-wind conditions – consistent with the diurnal patterns of Queensland's wind resources (as Fig.5 subsequently reveals).

Figure 3: Real-Time Ratings vs Seasonal & Static Ratings



Why real-time line ratings are important is because in a high-renewables grid, power system demand and supply conditions are distinctly different from the historic thermal system:

1. In regions such as Queensland – which has the highest take-up rate of rooftop solar PV in the world – grid-supplied maximum demand has visibly shifted (blue-shaded area, Fig.4). While aggregate final demand still occurs at ~12:30pm, the 'grid-supplied' maximum demand has shifted to ~5:30pm due to self-supply from rooftop solar (yellow-shaded area, Fig.4). This time-of-day constraint no long matches maximum demand. Specifically, while aggregate final demand in Fig.4 is 12,800MW, grid-supplied load during the middle of the day is only 8800MW due to ~4000MW of behind-the-meter rooftop solar PV production. Real-time line ratings better match transfer capacity with evening periods (i.e. for planning purposes).

2. Technology has advanced. It is now possible to deploy low cost transmission line mounted' weather stations, capable of streaming real-time weather data back to control rooms, meaning real-time ratings are now viable.

3. REZs *primarily exist* to connect wind projects and as the scatter plot in Fig.3 illustrates, higher wind speeds are associated with higher line transfer capacity. And as Fig.5 notes, Queensland wind resources reach their peak output during evening periods. The combination of the solar angle (< 0 Degrees) and elevated wind speeds provides for ideal conditions vis-à-vis real-time line ratings.

Figure 4: Maximum demand event in Queensland (2025)

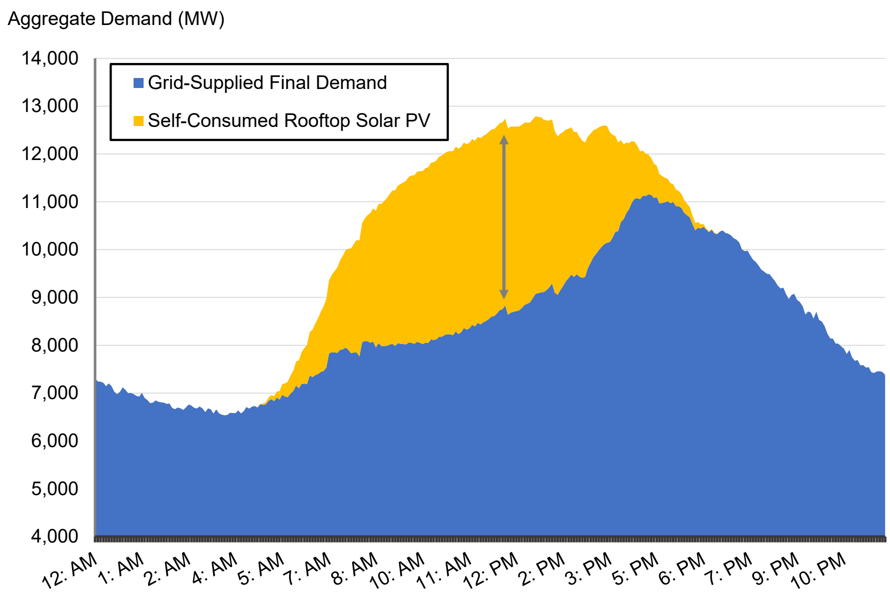
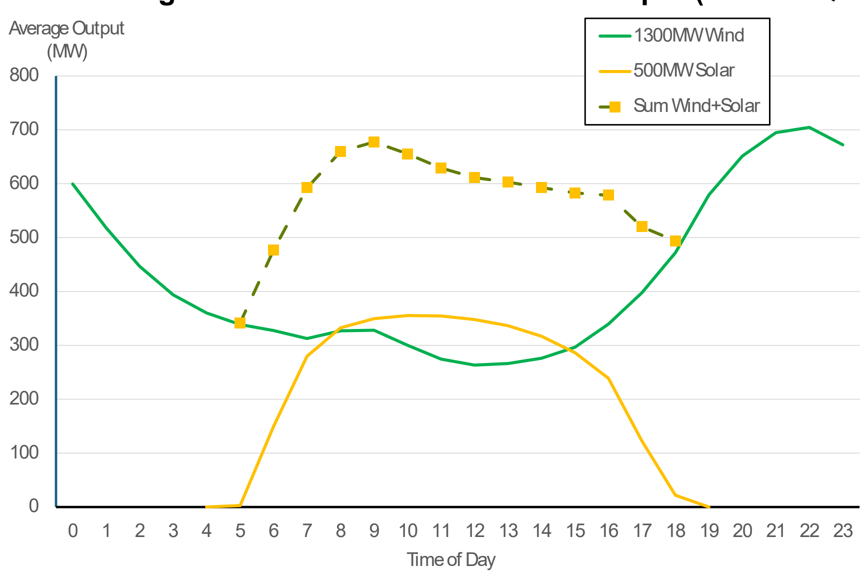


Figure 5: Average Summer Wind and Solar PV output (Central Queensland)



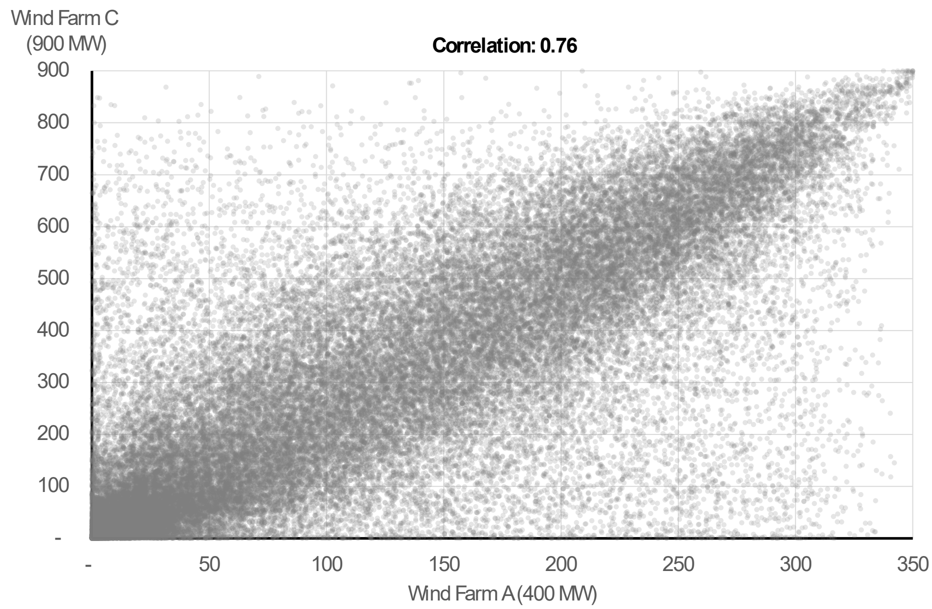
In our REZ Optimisation Model simulations, we will contrast the impact of static, seasonal and real-time line ratings on renewable generation hosting capacity, REZ cost allocation, and associated user charges.

3.3 Wind and solar data

Fig.5 illustrated the diurnal pattern of wind and solar in Central Queensland, which exhibits a level of complementarity. Average wind output rises either side of solar PV output. The hourly correlation between wind and solar is -0.42 during summer, -0.29 in winter and -0.43 during spring. Even for the same technology (Wind A and Wind C in

Fig.2, located ~50kms apart), output exhibits strong but imperfect correlation, as Fig.6 illustrates.

Figure 6: 7½ years of matched wind output, adjacent locations (Central REZ)



Given the complementarity of wind and solar, the optimal installed renewable plant capacity (MW) will exceed REZ transmission line transfer limits. However, only time-sequential modelling can identify the extent of diversity (see Guerra et al., 2020; Merrick et al., 2024), which is the main task of our REZ Optimisation Model.

In doing so, we rely on 7½ years of historic hourly weather reanalysis from 2018-2025 (drawn from Gilmore et al., 2025). A summary of the appropriately time-matched spot price statistics over the same period appears in Tab.2.

Table 2: Statistical summary of spot prices and dispatch-weighted prices (2025$)

	Spot Prices		2018	2019	2020	2021	2022	2023	2024	2025	AVG
1	Time Weighted Average	($/MWh)	92.7	87.4	49.1	101.7	135.0	93.5	112.2	103.7	96.4
2	Wind Dispatch Weighted	($/MWh)	92.5	90.8	53.3	110.8	153.0	113.7	139.1	134.2	108.3
3	Wind % of Average Spot	(%)	100%	104%	109%	109%	113%	122%	124%	129%	112%
4	Solar Dispatch Weighted	($/MWh)	92.1	82.9	48.3	80.6	98.3	70.5	87.8	73.2	79.8
5	Solar % of Average Spot	(%)	99%	95%	98%	79%	73%	75%	78%	71%	83%
6	Negative Price Events	(Hrs)	14	152	378	546	391	1156	1208	581	4426
7	90th Precentile Spot Price	($/MWh)	62.5	48.0	19.2	18.7	24.4	-19.8	-23.1	-18.7	18.9
8	10th Precentile Spot Price	($/MWh)	133.5	132.6	75.4	146.1	232.5	176.6	209.3	166.3	167.6
9	Coefficient of Variation*	($/MWh)	0.5	0.6	1.3	4.0	2.3	2.2	3.3	3.7	2.7
10	Kurtosis	($/MWh)	354.4	511.7	302.7	744.7	421.2	657.6	816.9	745.7	1,329.6
11	Skewness	($/MWh)	13.5	9.5	13.9	23.1	18.0	21.0	25.5	25.5	30.8
12	Mininum Spot Price	($/MWh)	-183.0	-836.0	-688.8	-1,000.0	-62.8	-95.6	-136.6	-44.8	-1,000.0
13	Maximum Spot Price	($/MWh)	1,615.4	2,652.1	1,551.0	17,983.3	9,903.8	9,050.0	15,747.9	13,289.7	17,983.3

* Coefficient of Variation based on hourly data (Std Dev / Time Weighted Average)

Source: Australian Energy Market Operator.

Renewable plant capacity additions impact hourly prices differentially. During daylight hours, adding solar PV has a depressing effect (i.e. merit order effect) on spot prices. But as Bushnell and Novan (2021) and Gonçalves and Menezes (2022) identify, spot prices rise in non-solar periods. Wind output has equivalent effects. Consistent with the modelling approach in Simshauser and Newbery (2024), our REZ Optimisation Model re-models spot prices using the hourly regression coefficients from Gonçalves and Menezes (2022) on a dynamic basis as wind and solar capacity levels are altered. Coefficients are outlined in Appendix I.

3.4 Renewable and Storage Plant costs

We use a commercial-grade *Project & Corporate Finance Model* (PCF Model) to produce entry cost estimates of wind, solar and utility-scale batteries. As the title suggests, the model is capable of producing either on-balance sheet or project financed plant. The generalised post-tax, post-financing Levelized Cost of Electricity estimates calculated by the model incorporate co-optimised structured finance and taxation variables. Model logic, engineering and capital markets input parameters appear in Appendix II. Estimated entry costs from the PCF model (excluding REZ user charges) are set out in Tab.3 (see Column 'a', Lines 1-4). These entry cost estimates, which are assumed to be divisible, form a critical cost input into our REZ Optimisation Model.

An important variable in the subsequent analysis is generators *'capacity to pay'* connection charges. Since the REZ under examination is a merchant asset with user charges paid for by connecting generators, some estimate of their reasonable capacity to pay is required. For obvious reasons, a generator's capacity to pay is not endless. For this purpose, we rely on the specific work undertaken by Aurecon (2025), who collated costs from their 'due diligence' reports for banking purposes across 60,000MW of wind, solar and battery projects in Australia's NEM. To summarise the results of that work, a generators capacity to pay connection investment costs (and the annual user charges that follow) trends towards 10% (-2%/+5%) of the overnight capital cost of wind and solar plant. As project capacity factors rise, capacity to pay rises, and vice versa. Capacity to pay no doubt varies by jurisdiction, but for our purposes we will rely on 10% as the capacity to pay given our wind and solar capacity factors broadly align with market medians. How we translate a 10% capacity to pay 'limit' for a wind farm is as follows:

- The overnight capital cost of wind (per Appendix II) is $3373/kW;
- Capacity to pay is 10% of the overnight capital cost, or $337/kW;
- Consequently, a 1000MW wind farm has the 'capacity to pay' (or underwrite) $337m (1000MW x 337/kW) of REZ transmission infrastructure.
- Noting user charges flow at 8.2% per annum (as specified in Section 3.1[3]), this translates $337m x 8.2% ≈ $27,500 per MW per annum ($/MW/a) as illustrated in Tab.3, line 1, column b.
- Given an annual capacity factor of ~34.5%, wind capacity to pay of $27,500/MW/a converts to a unit cost of $9.3/MWh (see line 1, column c).

We repeat this process for solar PV and battery storage (Lines 2-3, column b), with charges converted to a unit cost ($/MWh) in column c, with the final generalised entry cost estimate for the three technologies appearing in column d.

[3] Recall this comprised of a 1.7% charge for O&M and 6.5% for Capital Charges at the weighted average cost of capital.

Table 3: Plant entry costs[4] and REZ 'capacity to pay'

	Entry Costs	Unit Cost (Excl. REZ)	Capacity-to-Pay		Unit Cost (Incl. REZ)
		($/MWh)	($/MW/a)	($/MWh)	($/MWh)
		a	b	c	d = (a + c)
1	Wind	93.9	27,500	9.3	103.2
2	Solar PV	47.9	10,500	4.4	52.3
3	Battery Capacity (1hr)	9.0	12,500	*1.4	20.0**
4	Each +1hr Storage	3.6			
	* Based on 4hr battery ** Battery cost expressed as an hourly capacity charge in $/MW/h				

Final REZ user charges will be the subject of modelled outcomes. However, the capacity-to-pay parameters in Tab.3 provide a binding constraint or 'upper bound' to REZ transmission user charges. These upper bounds naturally raise the prospect of an affordability gap, which we explore in Section 4.

3.5 Overview of REZ Optimisation Model

The REZ Optimisation Model ostensibly follows a form of Stackelberg setup. A welfare maximising benevolent transmission planner is the leader, and renewable firms are followers. The first stage involves the planner identifying the optimal mix of generation plant for the REZ, and sizing its infrastructure accordingly. The second stage involves Nash-Cournot games amongst renewable firms in two timeframes, (i) ex-ante profit-maximising investment in planning timeframes, and (ii) dynamic ex-post profit-maximising dispatch in operational (hourly resolution) timeframes.

REZ Optimisation model logic is grounded firmly in welfare economics. All changes in producer and consumer surplus are tracked for each scenario. Onshore renewables form the lowest cost producers, and transmission network hosting capacity for renewables is a scarce resource.[5] Consequently in the model, entry occurs continuously until economic rents are competed away, or entry parameters of each asset class reach binding limits of project finance covenants, which in turn are applied by risk averse banks. Incorporating this into our REZ model logic occurs as follows:

Let $r \in R$ be the set of generators, each with installed capacity K_r. The REZ has network transfer capacity which varies according to rating regime, $\left(REZ^{static,Seas,RTR}\right)$. Let $t \in T$ be the set of hourly dispatch intervals over our 7½ year simulation. In the model, $C_{r,t}$ is the divisible unit cost of each generation technology regardless of scale ($/MWh) and represents an output from our PCF Model. Let plant availability $\beta_{r,t}$ be a binary variable equal to an element of the set $\{0,1\}$. Let the ex-post or actual output of generator r in trading interval t be $q_{r,t}$ while the ex-ante 'expected' output be $e\left(q_{r,t}\right)$, noting that expected output can be adversely impacted by uncertain events, viz. REZ transmission line congestion and negative price events which are ultimately constrained by a bankable curtailment rate (δ_r). The relevant spot price for each trading interval is given by $p_{r,t}$. The objective function from this point becomes a relatively straightforward one:

[4] These represent the "carrying cost" of the battery. To determining the annual fixed and sunk costs of a 200MW, 800MWh battery before REZ costs is therefore as follows: ($9.0 + 3 x $3.6) x 200 x 8760hrs = $34.7 million pa.
[5] As noted in the introduction, transmission is costly and there are limits to augmentation applied by community opposition, cultural and heritage considerations, and environmental (i.e. biodiversity) constraints. Consequently, transmission capacity developed for the purposes of renewable generation is a scarce resource.

$$OBJ_W = Max\left(\sum_{t\in T}\sum_{r\in R} q_{r,t}\right), \tag{3}$$

S.T.

$$\sum_{r\in R} q_{r,t} \leq K_r \cdot \beta_{r,t} \;\forall\, r \in R, t \in T, \tag{4}$$

$$\sum_{r\in R} q_{r,t} \leq REZ_t^{RTR} \;\forall\, t \in T \;\middle|\; \left(q_{r,t} = 0 \; if \; p_{r,t} < 0\right) \tag{5}$$

$$\left(\sum_{t\in T}\sum_{r\in R} q_{r,t}\right) \geq \left[\sum_{t\in T}\sum_{r\in R}(1-\delta_r)\cdot e\left(q_{r,t}\right)\right], \tag{6}$$

$$\left(\sum_{t\in T}\sum_{r\in R} q_{r,t}\cdot p_{r,t}\right) - \left(\sum_{t\in T}\sum_{r\in R} K_r \cdot C_{r,t}\right) \geq 0. \tag{7}$$

The Objective Function in Eq.(3) seeks to maximise production subject to a set of constraints. Wind and solar projects bid their output into the spot market at the relevant marginal running cost (i.e. \$0/MWh). Eq.(4) ensures generation dispatch is constrained by total plant capacity and plant availability $K_r \cdot \beta_{r,t}$. Aggregate output for trading interval $t \in T$ is constrained by transmission line transfer limits in Eq.(5), in this case REZ_t^{RTR} (noting REZ_t^{Seas} and REZ_t^{Static} are also examined). Crucially, in Eq.(6) wind and solar curtailment rates (δ_r) drive the difference between expected $e\left(q_{r,t}\right)$ and actual output $\left(q_{r,t}\right)$ and must not exceed exogenously determined *bankability limits* associated with contemporary project financings outlined in Appendix II as specified in Simshauser & Newbery (2024). Finally, any production maximising solution is constrained by normal returns via Eq.(7). Renewable fleet revenues are derived by production output $q_{r,t}$ and spot prices $p_{r,t}$ with normal profit being determined by the point at which unit revenues meet entry costs $C_{r,t}$ set out in Tab.3 (as derived by the PCF Model).

In the model, batteries h form part of the potential coalition of REZ generators such that $h, r \in R$. Batteries are assumed to maximise arbitrage profit each day $\left(Arb_{h,d}\right)$ for any given level of storage, j, via generating $\left(q_{h,t}\right)$ at round trip efficiency (γ_h) during maximum daily spot market price events $(pmax_t)$, and re-charging $\left(-q_{h,t}\right)$ during minimum spot price events $(pmin_t)$, such that $q_{h,t} \in [-K_h, +K_h]$. We assume batteries constrain their activity to one cycle per day with the optimisation ensuring the diurnal storage balance is met $\left(\sum_{t=1}^{n} q_{h,t} = 0\right)$. This is formally implemented with perfect foresight of day ahead spot prices. Consequently, bids and offers are dynamically solved each day to meet the objective function. Any battery is assumed to sit within a renewable portfolio and thus in any trading interval where aggregate wind and solar output $q_{r,t}$ exceeds transmission line ratings REZ_t^{RTR}, the spot price for the battery during that interval $\left(p_{h,t}\right)$ is deemed $\left(\hat{p}_{h,t} = 0\right)$, meaning the signal to generate disappears, and conversely, may provide an opportunity to re-charge at a zero price unless there are higher value (i.e. negative prices) on the day such that:

$$Arb_{h,d} = \left(\left(\sum_{t=1}^{n} \hat{p}max_{h,t}\cdot q_{h,t}\cdot \gamma_h\right) + \left(\sum_{t=1}^{n} \hat{p}min_{h,t}\cdot -q_{h,t}\right)\middle| if \begin{cases} \sum_{r=1}^{R} q_{r,t} \geq REZ_t^{s}, \hat{p}_{h,t} = 0 \\ \sum_{r=1}^{R} q_{r,t} < REZ_t^{s}, \hat{p}_{h,t} = p_{h,t} \end{cases}\right). \tag{8}$$

3.6 Overview of Cost Sharing Model

Our approach to efficient and fair cost allocation amongst the final coalition of connecting generators, $h, r \in R$, leverages Game Theory techniques to provide a set of market-inducing characteristics of a cost sharing solution. Game Theory is a rich theoretical edifice providing a versatile set of techniques which have been applied to everything, from apportionment methods (Shellshear, 2010) to electricity markets (Contreras, 1997).

Our cost allocation approach is based on a set of desirable principles, viz. a cost sharing approach for the coalition of generators should fulfill and build upon principles that are known to produce closed-form cost sharing solutions that can be applied directly.

Before we explain the desirable characteristics of a cost sharing solution, we provide four *core principles* that guide our cost sharing solution, which in turn provide the right incentives for generators to participate in REZs:

1. REZ cost sharing should incentivize generators to co-operate as a coalition, that is, provide each *expected generator* with a better solution than if they attempt to act independently and should do so “fairly” in the eyes of participants, e.g. higher cost-incurring generators should pay more.

2. Any cost sharing solution for the coalition of expected generators must always exist irrespective of the cost profiles of each generator, because infrastructure costs associated with connecting each generator are not obliged to adhere to any specific mathematical structure (meaning our solution cannot guarantee, e.g., a non-empty core, excluding this solution).

3. Any cost sharing solution must identify a single unique value to ensure each expected generator faces a binary option to join the coalition (i.e. no ex-post negotiations are required); and finally,

4. The cost sharing solution must observe a broader *capacity to pay* constraint, meaning there is an affordability cap which may leave some of the costs recommended by the cost sharing protocol to be recovered from other sources.

Based on the above considerations, a cooperative game theory approach makes sense as our problem structure is a standard cost sharing problem with a group of players, or rival generators, that ultimately need to be coordinated by the benevolent transmission network planner in a transparent manner (noting direct cooperation amongst rivals violates competition law).

We now introduce the needed game theoretical notation. Let $N = \{1, 2, 3, \dots, n\}, n \in \mathbb{N}$, represent the set of players in the game. A coalition S is defined as a subset of N, i.e. $S \subseteq N$. The null set is called the empty coalition and the set N is called the *grand coalition*. A *game* is a pair, (N, v), where v is a real-valued function, called the characteristic function, defined on the subsets of N, i.e., $v: 2^N \to \mathbb{R}$, that satisfies $v(\emptyset) = 0$. The value $v(S)$ represents the value of a coalition S, which in our case is the minimal capital cost the coalition S can guarantee by acting on its own and coordinating with its own members, irrespective of what other players and coalitions do. Another useful concept is that of monotonicity. A game is *monotonic* if for all coalitions $S, T \subseteq N$, with $S \subseteq T$, implying that:

$$v(S) \le v(T)$$

The cost allocation function in our game is defined by the cost of the minimum transmission infrastructure required to serve the coalition of generators, noting such a definition means the game is monotonic. Specifically, we have a set of players, $h, r \in R$, and we number them, $N = \{1, \dots, n\}$ where $n = |R|$. For a coalition S, let $C(S)$ be defined as the minimum cost infrastructure required to connect the generators in S to the REZ including the REZ costs. The coalition function v is then defined as $v(S) \coloneqq C(S)$. This defines a game (N, v). The minimum infrastructure costs are provided below in the Model Results section.

A cost allocation rule is a function, $\phi(N, v) \rightarrow \mathbb{R}^n$, defined on a game (N, v) which assigns to each player a cost share, $\phi_i(N, v) \in \mathbb{R}$ to each player $i \in N$ such that,

$$\sum_{i \in N} \phi_i(N, v) = v(N). \qquad (9)$$

In the following we supress the (N, v) in our solution notation as the specific game will always be clear. In addition, we will write $\phi(S) \coloneqq \sum_{i \in S} \phi_i$. Based on the two principles above, our solution concepts must be defined for all games and satisfy the following constraint:

$$\phi_i \leq v(i), i \in N. \qquad (10)$$

Any vector satisfying the previous constraint and $\phi(N) = v(N)$ from Eq.(9) is called an imputation.

When allocating REZ costs, we have a number of desirable or 'optimal' criteria that any solution should fulfill. These desirable properties are as follows (note there are other criteria such as *anonymity* which may or may not be required, hence are not included below):

1. *Individual Rationality*: Each generator should pay less than what it would cost them were they to act in isolation per Eq.(9).

2. *Linear*: For each REZ, the cost allocation should be additive across other zones, i.e. for each REZ sub-game, the combined cost solutions should be linear.

3. *Dummy generator*: if a generator causes no cost, it should not be charged anything.

4. *Efficiency*: The sum of costs allocated to generators should equal the total cost, i.e. no cost should not be covered, and the sum of allocated costs should not exceed total costs per Eq.(10).

5. *Symmetry*: Generators with identical cost profiles should have the same solution value, i.e. for $i, j \in N, i \neq j$, if $v(S \cup i) = v(S \cup j) \, \forall \, S \subseteq N, i, j \notin S$, then $\phi_i = \phi_j$.

6. *Monotonicity*: Generators with higher transmission network requirements should pay more, i.e. if $i, j \in N, i \neq j$, if $v(S \cup i) \leq v(S \cup j) \, \forall \, S \subseteq N, i, j \notin S$, then $\phi_i \leq \phi_j$.

These six criteria are considered highly desirable, to which one could add further criteria such as $\phi(S) \leq v(S)$. However, by adding this additional criterion we violate our second core principle above, that a solution always exists (an imputation that satisfies this additional condition belongs to the core, which is empty for some games). By keeping the above six criteria, we are able to guarantee a suitable solution concept that always exists and has a simple expression and intuitive interpretation, the Shapley value, and it also fulfills our four core principles.

The Shapley value is defined for a game (N, v) as follows:

$$\phi_i = \sum_{S \subseteq N \setminus i} \frac{|S|!(|N|-|S|-1)!}{|N|!} \big(v(S \cup i) - v(S)\big), \quad (11)$$

where $|S|$ stands for the cardinality of S. It is known that the Shapley value fulfills the six criteria above (Hougaard, 2009) and can be interpreted as a type of average across a particular contribution by a connecting generator to a coalition of connecting generators, independent of the way that the generator joins the REZ coalition.

Other solutions such as the core, von Neumann-Morgenstern set, nucleolus, kernel, tau value (Hoougard, 2009) and others may also be relevant. However, each of these options was rejected for the following reasons:

- *The core*: it is not guaranteed to be non-empty as mentioned above.
- *The von Neumann-Morgenstern set*: it is not guaranteed to be non-empty.
- *The nucleolus*: we are not interested in the excesses of each coalition and trying to maximise them as this is not a realistic aspect of our model given geographical limitations – that is, generators either join the REZ or not, and cannot form another sub-coalition given community and environmental limits (i.e. of developing transmission assets).
- *The kernel*: although it always exists, it does not provide a unique payoff outcome, however, a set of outcomes, hence violating one of our principles.
- *The tau value* is defined on the set of quasi-balanced games and so is not defined for all games. In addition, it does not satisfy another possible desirable property called aggregate monotonicity (i.e. if the value of the grand coalition increases while all other coalitions remain the same, then no generator should get less than before) as well as not necessarily satisfying individual rationality (Hoougard, 2009).

We apply the Shapley value in our Model Results section given its desirable properties and ease of calculation for games with a small number of generators, as is invariably the case with REZs.

4. Model Results

Recall from Fig.5 that a defining characteristic of Queensland renewables is the complementarity of wind and solar resources. This makes for an interesting case study because the efficient level of connecting generation capacity (MW) will always exceed

REZ line transfer capacity given the NEM's open access, multi-zonal market setup. We model three REZ scenarios (1) static, (2) seasonal, and (3) real-time line ratings.

4.1 Scenario 1: optimal renewables with static line ratings

In our REZ, entry is assumed to occur under conditions of the NEMs 'Open Access' regime, meaning renewable plant curtailment in any trading interval is shared amongst the coalition members on a volume-weighted basis, with the zonal spot price prevailing. There are no side-payments when plant is constrained-off. This places a considerable burden on renewable investors to predict market congestion conditions because the risk of curtailment cannot be re-allocated to consumers.

Using data outlined in Section 3, we run our REZ Optimisation Model through 100 iterations to identify the optimal mix of wind and solar PV. We opt for 100 iterations due to the nonlinearity of the problem given the rich blend of resources, line ratings, merit order effects, curtailment and storage options. And due to the non-smooth nature of certain constraints and properties, we rely on an evolutionary algorithm to find optimal solutions. As results illustrate in Fig.7, there are multiple credible equilibria across the five entrant projects vis-à-vis size and scale.

A logical line of inquiry is whether the existence of multiple equilibria might create too much uncertainty for renewable investors to commit within the REZ. Yet a close inspection of Fig.2, and of Fig.7, reveals that:

1. In practice, the number of potential projects, and potential project sites, is known by the transmission planner – see Fig.2. What is uncertain is the final capacity of wind and solar projects in aggregate;

2. In Fig.7 (y-axis), *all iterations* involved a minimum level of wind (~1800MW) and tend to cluster around 1950MW;

3. Similarly, in Fig.7 (x-axis), all iterations involved a minimum level of solar (~650MW) and cluster around 850-875MW; and

4. at a 10% Probability of Exceedance (PoE10), which in a sense reflects an upper limit optimal results, iterations typically comprise ~1950MW of wind, and ~875MW of solar.

Consequently, while there may be some level of plant mix uncertainty at the very margins, the number of sites is fixed, and iterations trended towards *at least* 1800MW of wind, and 850MW of solar. And in practice, any wind and solar plant capacity above these levels face no more risk than any other project in the NEM's open access regime.

The binding constraint in this set of iterations is renewable plant curtailment (i.e. 'spill) due to line congestion. Some level of curtailment inside a REZ is efficient. But in practice, there are *'tolerable limits'* to curtailment applied by risk-averse project banks and risk-neutral equity investors. Recall the REZ Optimisation model incorporates a variable for this purpose, viz. the curtailment constraint (δ_r) in Eq.(6). For our purposes, as outlined in Appendix II we have set (δ_r) to $\leq 5.25\%$ for wind entrants and $\leq 8\%$ for solar PV entrants, consistent with the assumptions in Simshauser and Newbery (2024). In Fig.7, Eq.(6) is binding for wind and solar entrants, which in turn regulates entry to 1950MW of wind, and 875MW of solar (at PoE10).

Figure 7: REZ static line ratings – optimal wind capacity vs. solar PV capacity

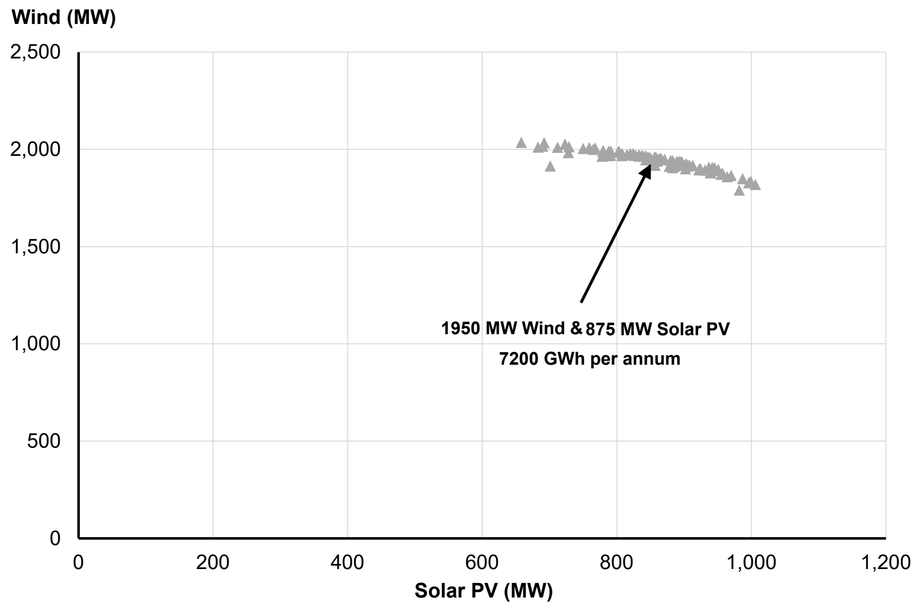
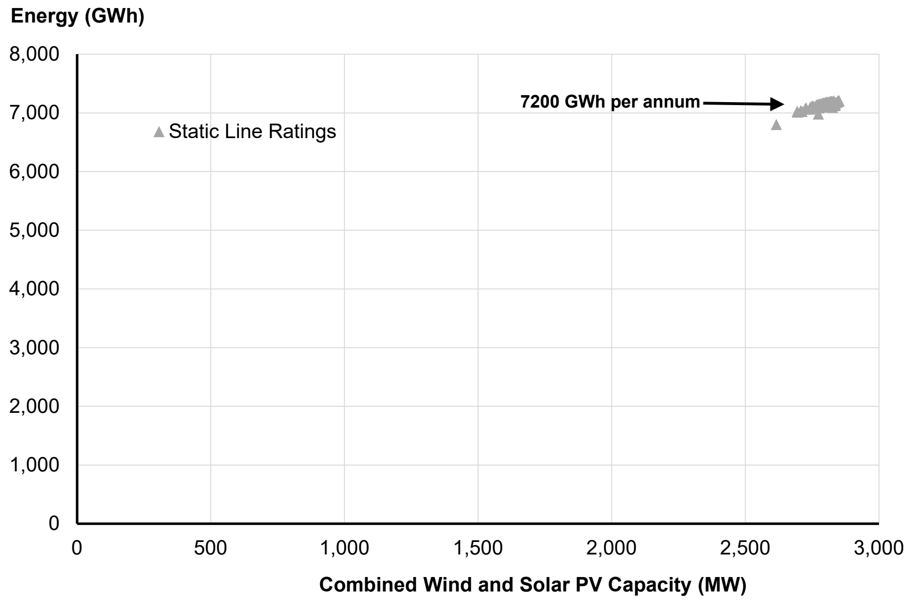


Fig.7 contrasted 100 iteration results from the REZ model by examining wind capacity (y-axis) and solar capacity (x-axis). In Fig.8, we take the same set of results and illustrate 100 iterations of production output (GWh) on the y-axis, and on the x-axis, we combine wind and solar capacity (MW). What this shows is that, although there appears to be some variation in the plausible mix of wind and solar (per Fig.7), the annual production from those combinations lies within a tight range, viz. 7160GWh +/-1%.

Figure 8: REZ static line ratings – energy (GWh) vs renewable capacity (MW)



Our allocation of REZ user charges underpinning Figs.7-8 are presented in Tab.4. The various power projects are listed from Lines 1-6 (note Entrant E 'Battery' = 0). Capacity (MW) appears in column 'a', while *'capacity to pay'* user charges are listed in columns 'b' and 'c'. Column 'd' is included only by way of historic reference to prior research i.e. user charges levied by way of simple output allocation (i.e. MWh output). The contrast with Shapley Values (column 'e') is striking. Column 'f' notes there is a *capacity to pay* shortfall of $9.9m pa, and when applied on a project-by-project basis using the minimum of the Shapley Value and capacity to pay, user charges amount to only 78% (column g) of the breakeven cost of $73m (column e, line 7).

Table 4: REZ Shapley Values (Static Line Ratings)

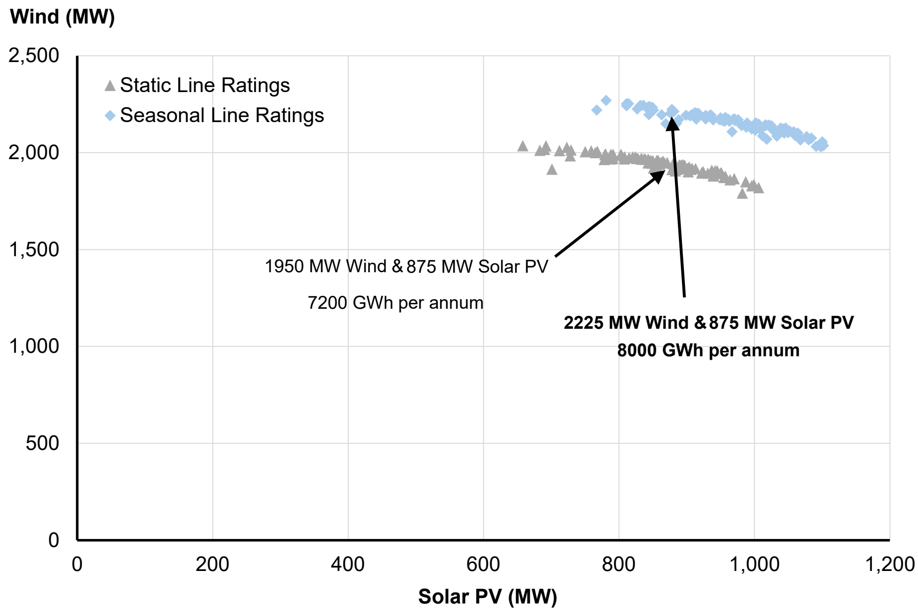
	Static Line Ratings		Capacity (MW)	Capacity to Pay ($/MW)	Capacity to Pay ($M)	Output ($M)	Shapley Value ($M)	Surplus ($M)	Recovery (%)
	Capex = $890m		a	b	c = (a x b)	d	e	f = (c - e)	g=∑min(e,c) ÷ ∑e
1	Project A	Wind	400 MW	$27,500	11.0	10.6	6.7	4.3	$6.0
2	Project B	Solar	400 MW	$10,500	4.2	8.7	2.5	1.7	
3	Project C	Wind	900 MW	$27,500	24.8	25.2	32.8	-8.1	
4	Project D	Solar	500 MW	$10,500	5.3	10.9	7.0	-1.7	-$9.8
5	Project E	Battery	0 MW	$12,500	0.0	0.0	0.0	0.0	
6	Project F	Wind	650 MW	$27,500	17.9	17.6	24.0	-6.1	
7	TOTAL				$63.1	$73.0	$73.0	-$9.9	78%

Prima facie, results in Tab.4 suggest the merchant REZ is financially intractable. If there were no investment alternatives, and the REZ was nonetheless considered welfare enhancing, there are policy levers available to overcome such shortfalls and these will be discussed in Section 5. For now, variations to transmission line ratings are feasible, which may bridge the apparent gap that exists in Tab.4. This leads us to Scenario 2, and the impact of moving from static to seasonal line ratings.

4.2 Scenario 2: optimal renewables with seasonal line ratings

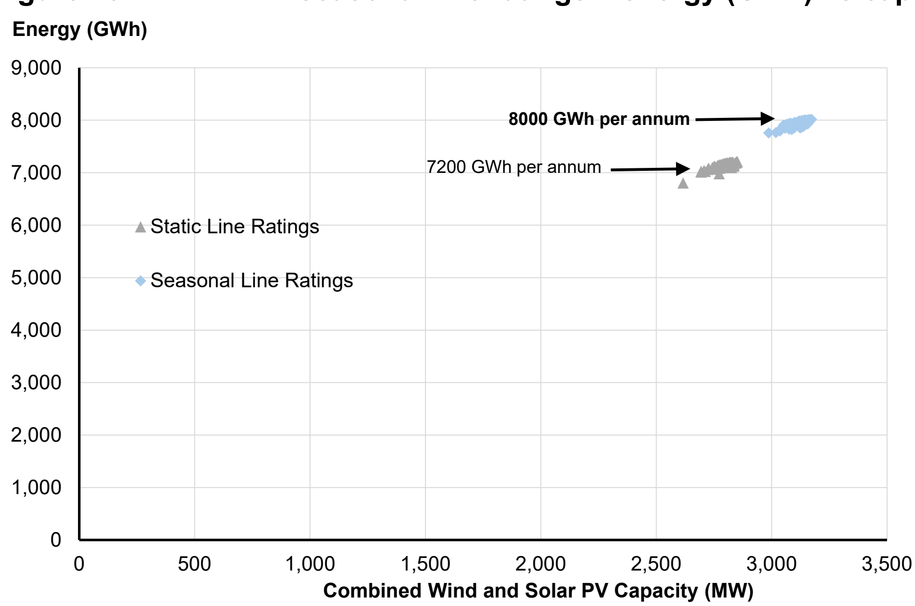
In Scenario 2, we alter our line ratings in the mild and winter seasons as outlined in Tab.1. This means in winter, line transfer capacity increases to 1916MW and in the mild seasons, to 1756MW. Our summer rating remains at the static rating of 1536MW. Fig.9, presents the optimal combinations of wind solar, and at PoE10 equates to 2225MW of wind (+275MW more than static line ratings, with no change to solar). Such results reflect the fact that the additional line transfer capacity coincides with windy conditions (Fig.3).

Figure 9: REZ seasonal line ratings – optimal wind vs. solar PV



The productivity of the REZ has increased commensurately, with no change to infrastructure costs. Fig.10 illustrates that energy output has increased by 11%, from 7200 to 8000GWh.

Figure 10: REZ seasonal line ratings – energy (GWh) vs capacity



The change from static to seasonal line ratings is welfare enhancing, as depicted in Tab.5 (+$149.3m pa). Consumer welfare increases by $72.4m. Consumers prefer the more productive REZ because the fixed costs of transmission investment are spread across more units of output. Additionally, recall onshore wind and solar PV are lowest cost entrants in the NEM, and exhibit marginally lower entry costs with a more productive REZ. Producer surplus also rises, albeit with mixed results as a class. Wind producers may develop projects that would otherwise be stranded ($86.1m). Solar producers ($-1.2m) face marginally more congestion with additional wind entering the REZ, albeit this remains within acceptable or 'tolerable' banking limits. And finally, differential merit order effects arise from the entry of wind and solar which, in aggregate, result in wealth transfers from producers to consumers ($8.1m).

Table 5: Welfare analysis (static vs seasonal line ratings)

		Static Ratings vs Seasonal Line Ratings ($ Million pa)
1	Chg in Consumer Surplus	72.4
2	Chg in Producer Surplus (Wind)	86.1
3	Chg in Producer Surplus (Solar)	-1.2
4	Wealth Transfers	-8.1
5	Gross Chg in Producer Surplus	76.9
6	Change in Total Welfare (1+5)	149.3

REZ user charges underpinning Figs.9-10 are presented in Tab.6. As with static line ratings, capacity to pay is binding for generators C, D and F, but are moving closer to our Shapley Values. The cost recovery ratio has increased from 78 to 88%.

Table 6: REZ Shapley Values (Seasonal Line Ratings)

	Seasonal Line Ratings		Capacity (MW)	Capacity to Pay ($/MW)	Capacity to Pay ($M)	Output ($M)	Shapley Value ($M)	Surplus ($M)	Recovery (%)
	Capex = $890m		a	b	c = (a x b)	d	e	f = (c - e)	g=∑min(e,c) ÷ ∑e
8	Project A	Wind	400 MW	$27,500	11.0	9.5	6.2	4.8	$7.0
9	Project B	Solar	500 MW	$10,500	5.3	9.8	3.0	2.3	
10	Project C	Wind	1,000 MW	$27,500	27.5	25.2	34.5	-7.0	
11	Project D	Solar	400 MW	$10,500	4.2	7.8	5.3	-1.1	-$8.1
12	Project E	Battery	0 MW	$12,500	0.0	0.0	0.0	0.0	
13	Project F	Wind	850 MW	$27,500	23.4	20.6	24.0	-0.6	
14	TOTAL				$71.3	$73.0	$73.0	-$1.7	88%

Our next Scenario examines the impact of moving from seasonal to real-time line ratings.

4.3 Scenario 3: optimal renewables with real-time line ratings

Scenario 3 simulates real-time line ratings. This has profound effects on the renewable hosting capacity, the energy output and REZ productivity generally. Fig.11 illustrates the change in the optimal capacity mix, with wind rising to 3275MW, and solar PV rising to 1425MW.

Figure 11: REZ real-time line ratings – optimal wind vs. solar PV

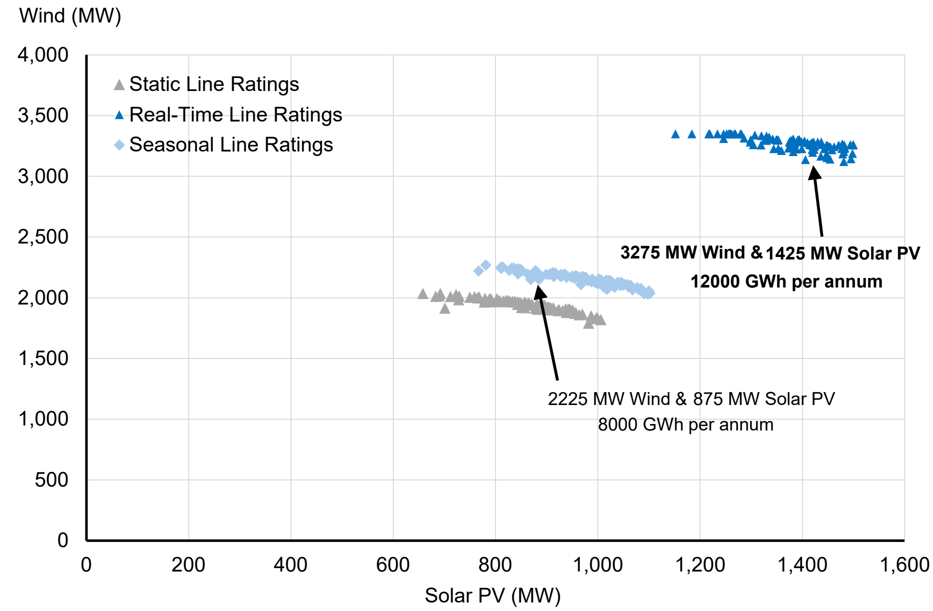
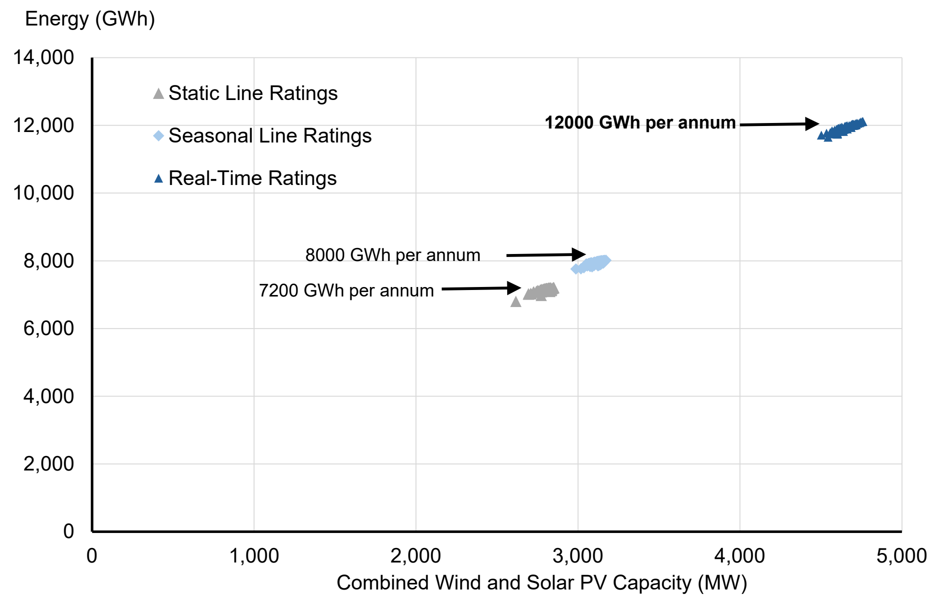


Fig.12 highlights the change in REZ productivity, with output rising by 50% to 12,000GWh.

Figure 12: REZ real-time line ratings – energy (GWh) vs capacity



Welfare analysis similarly reveals material changes, with consumer surplus up $323.7m. Both wind and solar producer surplus increases, although to be clear, there are mixed results for solar producers with (1) initial incumbents slightly worse off, but (2) otherwise stranded resources able to be monetised with the net gain being +$62.2m. Wealth transfers from producers to consumers arising from merit order effects amounts to -$18.6m.

Table 7: Welfare analysis (static vs real-time line ratings)

		Static Ratings vs Real-Time Ratings ($ Million pa)
1	Chg in Consumer Surplus	323.7
2	Chg in Producer Surplus (Wind)	385.2
3	Chg in Producer Surplus (Solar)	62.2
4	Wealth Transfers	-18.6
5	Gross Chg in Producer Surplus	428.8
6	Change in Total Welfare (1+5)	752.4

Perhaps the main result from this scenario is that generator capacity to pay now exceeds the REZ annual charges and the Shapley Value of each entrant, as illustrated in Tab.8.

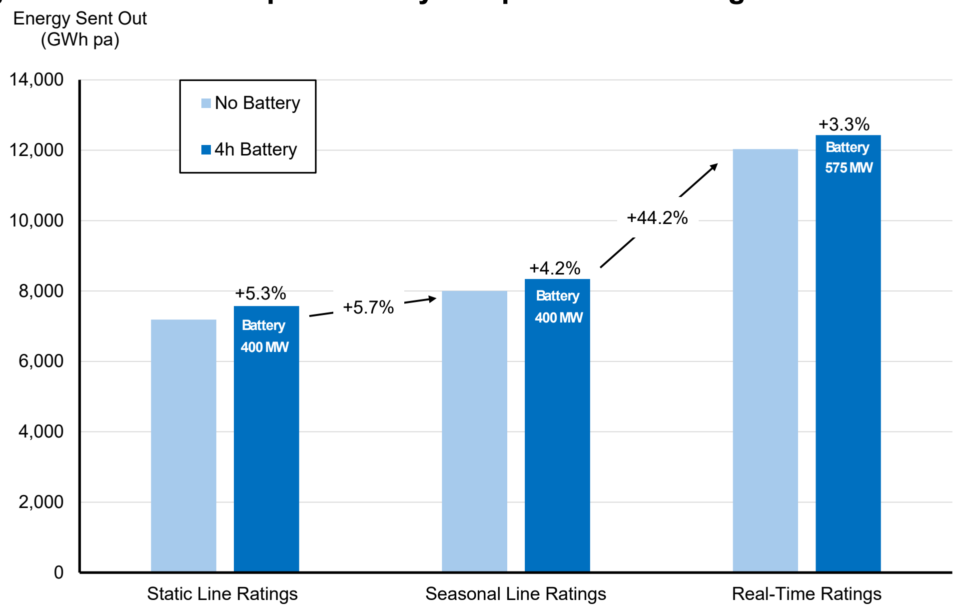
Table 8: REZ Shapley Values (real-time line ratings)

	Real-Time Line Ratings		Capacity (MW)	Capacity to Pay ($/MW)	Capacity to Pay ($M)	Output ($M)	Shapley Value ($M)	Surplus ($M)		Recovery (%)
	Capex = $890m		a	b	c = (a x b)	d	e	f = (c - e)		g=∑min(e,c) ÷ ∑e
22	Project A	Wind	750 MW	$27,500	20.6	12.1	6.7	13.9	$19.3	
23	Project B	Solar	750 MW	$10,500	7.9	9.9	2.5	5.3		
24	Project C	Wind	1,200 MW	$27,500	33.0	20.4	33.0	0.0	$0.1	
25	Project D	Solar	650 MW	$10,500	6.8	8.6	6.8	0.0		
26	Project E	Battery	0 MW	$12,500	0.0	0.0	0.0	0.0		
27	Project F	Wind	1,350 MW	$27,500	37.1	22.1	24.0	13.1		
28	TOTAL				$105.5	$73.0	$73.0	$32.5		100%

4.4 Does battery storage matter?

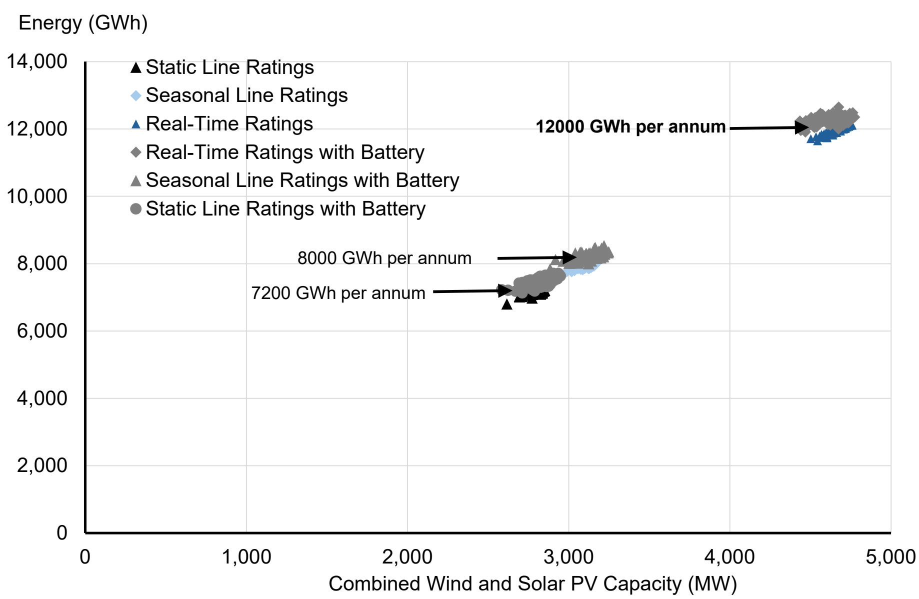
In each of Scenarios 1-3, batteries were excluded. Given intermittency, the addition of battery storage should facilitate additional entry, increase REZ productivity, and enhance REZ cost recovery. However, while optimisation results show gains across all REZ transmission line rating scenarios are positive, they are marginal and decrease with line rating capacity. This is illustrated in Fig.13.

Figure 13: REZ productivity – impact of line ratings and batteries



Note in Fig.13 that within the REZ optimisation model, 4h batteries dominated iterations, with optimal battery capacity trending towards 400-575MW. Batteries had the effect of increasing REZ productivity by ~3.3-5.3%. Larger gains were extracted through pursuing real-time line ratings, with the shift from static to seasonal line ratings (+5.7%), and from seasonal to real-time line ratings (+44.2%). Fig.14 overlays the iteration results for the battery cases relevant to the non-battery cases.

Figure 14: REZ energy (GWh) with battery storage



It is to be noted that oversized batteries would reverse these results (see in particular Simshauser, 2025). Specifically, oversized batteries compete with wind and solar for REZ access, and this would have the effect of reducing the generation fleet's capacity to pay.

5. Policy implications

Our analysis demonstrated the gains from altering REZ line transfer capacity, from static, to seasonal and finally, to real-time ratings. Batteries enhanced REZ productivity, but by comparison to line ratings, gains were marginal and diminishing in nature. Historically, establishing real-time line ratings was costly. This is no longer the case. An emerging set of low-cost technologies now exists, including transmission line-mounted weather stations, making real-time ratings viable. Evidently, for existing power systems with thermally constrained transmission lines and credible renewable resources, this should form a priority for investment. It is to be noted that not all transmission lines are thermally constrained – often other constraints emerge (e.g. voltage stability, transient stability limits etc). However, where lines are thermally constrained, real-time ratings offer great potential at a very low marginal cost.

In prior REZ research in the Australian context, user charges (i.e. REZ cost allocation) was simplified and based on output. The focus of analysis was on deriving the optimal mix of plant. A quick review of Table results (Tabs.4, 6, 8) in Section 4 reveals there was no scenario in which an output-based cost allocation method was tractable for solar PV projects. Yet we know its role in the energy transition to be crucial. To that end, we combined a mix of renewable and battery resources, and different line rating methodologies with the Shapley Value method to identify an efficient, fair and defendable set of user charges for generators connecting to a merchant REZ. And importantly, we did so by introducing capacity to pay limits reflective of conditions in the Australian market.

For low cost transmission augmentations, capacity to pay limits are unlikely to be a problem. This was the experience with early REZs in the NEM's Queensland region. However, as with all scarce resources, there is an upward sloping supply curve for Renewable Energy Zones. As distances rise, and as costs increase, user charges rise making financial tractability of REZs more difficult to navigate on a purely merchant basis.

In the present exercise with static and seasonal line ratings, our Shapley Values (and by definition, an output allocation method) faced binding capacity-to-pay constraints. In the static line rating scenario, cost recovery was ~78%. This rose to 88% with seasonal line ratings. Adding storage, while not specifically identified, added ~2 percentage points to these cost recovery ratios. It was not until we introduced real-time ratings, which materially increased renewable hosting capacity, were we able to navigate the capacity to pay problem.

This raises a tangential policy issue. What if some other network limitation (e.g. transient stability limit) constrained line ratings such the full capacity of real-time ratings was not viable? Would this be fatal for a merchant REZ? The short answer is, on a purely merchant basis, more than likely. However, other policy options exist that migrate the REZ to a semi-merchant model if, and only if, the overall portfolio of projects is welfare enhancing at the whole-of-system level. These policy options include:

1. Concessional finance, which can be deployed to lower the aggregate annual user charges. Concessional agencies are quite common, and Australia has the 'Clean Energy Finance Corporation' which exists for this purpose. Concessional

finance would have the effect of lowering the cost of capital, and in turn, user charges holding all else equal.

2. Allocating some component of project capital costs to the Regulatory Asset Base. Specifically, where a residual transmission investment cost may exist within a REZ program, and the overall program of transmission, wind, solar and storage investments are otherwise thought to be beneficial, allocation to the Regulatory Asset Base provides a suitable pathway. This allocation may be transient to deal with uncertainty of the timing of renewable project entry, or permanent where a residual exists. After all, this policy represents the default policy for 100% cost recovery in most jurisdictions.

6. Conclusion

Development of REZ in Australia's NEM represents a critical policy initiative aimed at facilitating the energy transition in an efficient manner. REZ are designed to coordinate multiple renewable projects that would otherwise act independently, thereby minimizing marginal transmission costs, and the various community, environmental, and cultural sensitivities associated with large-scale infrastructure development. Queensland's approach to REZ development, characterized by a merchant model, has enabled rapid deployment of renewable projects. Its distinctive feature is that connecting generators, not consumers, underwrite the capital cost through annual user charges.

When renewable entry is perfect and REZ distances are small, investment commitment by a risk neutral benevolent transmission planner is clear cut. As REZ distances are extended from the transmission backbone, capital costs rise, and user charges may exceed generators reasonable capacity to pay. Maximising the renewable hosting capacity of a REZ is therefore an important means by which to navigate such constraints. And, other policy options exist to deal with any residual shortfall.

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Appendix I: Goncalves & Menezes (2022) NEM spot price coefficients

Hour	Wind			Solar		
	Min95	Est.	Max95	Min95	Est.	Max95
0	-0.00021	-0.00028	-0.00033	0.00350	-0.00067	-0.00095
1	-0.00020	-0.00030	-0.00033	0.00325	-0.00056	-0.00073
2	-0.00019	-0.00033	-0.00036	0.00555	-0.00051	-0.00076
3	-0.00024	-0.00035	-0.00039	0.00421	-0.00041	-0.00061
4	-0.00027	-0.00038	-0.00042	0.00252	-0.00041	-0.00057
5	-0.00028	-0.00038	-0.00044	0.00412	-0.00032	-0.00050
6	-0.00019	-0.00031	-0.00040	0.00534	-0.00015	-0.00070
7	-0.00015	-0.00039	-0.00049	0.00861	-0.00113	-0.00161
8	-0.00023	-0.00029	-0.00034	0.00507	-0.00104	-0.00130
9	-0.00015	-0.00022	-0.00032	0.00456	-0.00082	-0.00116
10	-0.00010	-0.00029	-0.00035	0.00673	-0.00093	-0.00129
11	-0.00009	-0.00033	-0.00040	0.00696	-0.00079	-0.00119
12	-0.00015	-0.00033	-0.00039	0.00903	-0.00086	-0.00119
13	-0.00009	-0.00032	-0.00038	0.00610	-0.00067	-0.00104
14	0.00004	-0.00022	-0.00031	0.00679	-0.00056	-0.00124
15	0.00029	-0.00005	-0.00019	0.01042	0.00013	-0.00105
16	0.00048	0.00003	-0.00018	0.01389	-0.00015	-0.00150
17	0.00066	-0.00001	-0.00026	0.01916	0.00049	-0.00101
18	0.00021	-0.00044	-0.00061	0.01114	0.00074	-0.00045
19	0.00030	-0.00038	-0.00053	0.00941	0.00040	-0.00094
20	0.00005	-0.00028	-0.00033	0.00527	-0.00060	-0.00094
21	-0.00008	-0.00024	-0.00028	0.00348	-0.00068	-0.00092
22	-0.00021	-0.00026	-0.00029	0.00480	-0.00074	-0.00092
23	-0.00017	-0.00024	-0.00028	0.00495	-0.00071	-0.00090

Appendix II – PCF Model Logic

In the PCF Model, prices and costs increase annually by a forecast general inflation rate (CPI).

$$\pi_j^{R,C} = \left[1 + \left(\frac{CPI}{100}\right)\right]^j , \tag{1}$$

Energy output q_j^i from each plant (*i*) in each period (*j*) is a key variable in driving revenue streams, unit fuel costs, fixed and variable Operations & Maintenance costs. Energy output is calculated by reference to installed capacity k^i, capacity utilisation rate CF_j^i for each period *j*. Plant auxiliary losses Aux^i arising from on-site electrical loads are deducted. Plant output is measured at the Node and thus a Marginal Loss Factor MLF^i coefficient is applied.

$$q_j^i = CF_j^i . k^i . \left(1 - Aux^i\right) . MLF^i, \tag{2}$$

A convergent electricity price for the *i*[th] plant $\left(p^{i\varepsilon}\right)$ is calculated in year one and escalated per Eq. (1). Thus, revenue for the *i*[th] plant in each period *j* is defined as follows:

$$R_j^i = \left(q_j^i . p^{i\varepsilon} . \pi_j^R\right), \tag{3}$$

If thermal plants are to be modelled, marginal running costs need to be defined per Eq. (4). The thermal efficiency for each generation technology ζ^i is defined. The constant term '3600'[6] is divided by ζ^i to convert the efficiency result from % to kJ/kWh. This is then multiplied by raw fuel commodity cost f^i. Variable Operations & Maintenance costs v^i, where relevant, are added which produces a pre-carbon short run marginal cost.

Under conditions of externality pricing CP_j, the CO_2 intensity of output needs to be defined. Plant carbon intensity g^i is derived by multiplying the plant heat rate by combustion emissions $\dot{g}^i$ and fugitive CO_2 emissions $\hat{g}^i$. Marginal running costs in the *j*[th] period is then calculated by the product of short run marginal production costs by generation output q_j^i and escalated at the rate of π_j^C.

$$\vartheta_j^i = \left\{ \left[\left(\frac{\left(3600/\zeta^i\right)}{1000} . f^i + v^i \right) + \left(g^i . CP_j\right) \right] . q_j^i . \pi_j^C \middle| g^i = \left(\dot{g}^i + \hat{g}^i\right) . \frac{\left(3600/\zeta^i\right)}{1000} \right\}, \tag{4}$$

Fixed Operations & Maintenance costs FOM_j^i of the plant are measured in \$/MW/year of installed capacity FC^i and are multiplied by plant capacity k^i and escalated.

$$FOM_j^i = FC^i . k^i . \pi_j^C, \tag{5}$$

[6] The derivation of the constant term 3,600 is: 1 Watt = 1 Joule per second and hence 1 Watt Hour = 3,600 Joules.

Earnings Before Interest Tax Depreciation and Amortisation (EBITDA) in the j^{th} period can therefore be defined as follows:

$$EBITDA_j^i = \left(R_j^i - \vartheta_j^i - FOM_j^i\right), \tag{6}$$

Capital Costs $\left(X_0^i\right)$ for each plant *i* are Overnight Capital Costs and incurred in year 0. Ongoing capital spending $\left(x_j^i\right)$ for each period *j* is determined as the inflated annual assumed capital works program.

$$x_j^i = c_j^i . \pi_j^C, \tag{7}$$

Plant capital costs X_0^i give rise to tax depreciation (d_j^i) such that if the current period was greater than the plant life under taxation law (*L*), then the value is 0. In addition, x_j^i also gives rise to tax depreciation such that:

$$d_j^i = \left(\frac{X_0^i}{L}\right) + \left(\frac{x_j^i}{L-(j-1)}\right), \tag{8}$$

From here, taxation payable $\left(\tau_j^i\right)$ at the corporate taxation rate $\left(\tau_c\right)$ is applied to $EBITDA_j^i$ less Interest on Loans $\left(I_j^i\right)$ later defined in (16), less d_j^i. To the extent $\left(\tau_j^i\right)$ results in non-positive outcome, tax losses $\left(L_j^i\right)$ are carried forward and offset against future periods.

$$\tau_j^i = Max\left(0, \left(EBITDA_j^i - I_j^i - d_j^i - L_{j-1}^i\right) . \tau_c\right), \tag{9}$$

$$L_j^i = Min\left(0, \left(EBITDA_j^i - I_j^i - d_j^i - L_{j-1}^i\right) . \tau_c\right), \tag{10}$$

Relevant inputs are as follows:

Table A1: Plant Technical & Cost Assumptions (pre-REZ costs)

Table 1A - Renewable Fleet		Wind	Solar	Battery
Project Capacity	(MW)	1,000	400	400
- Storage Capacity	(Hrs)	-	-	4
Overnight Capital Cost	($/kW)	3,373	1,133	525
- Storage	($/kWh)	-	-	380
- Contingency		10%	-	-
Plant Capital Cost	($ M)	3,710	453	409
Operating Life	(Yrs)	35	30	20
Annual Capacity Factor	(%)	33-43%	21-27%	14.7%
Transmission Loss Factor	(MLF)	0.970	0.950	1.000
Transmission REZ Costs	($/MW/a)		*Modelled*	
Fixed O&M	($/MW/a)	25,000	20,000	10,000
Variable O&M	($/MWh)	0.0	0.0	0.0
FCAS	(% Rev)	-1.0%	-1.0%	4.0%

Source: Gohdes (2022, 2023).

The debt financing model computes interest and principal repayments on different debt facilities depending on the type, structure and tenor of tranches. There are two types of debt facilities – (a) corporate facilities (i.e. balance-sheet financings) and (2) project financings. Debt structures available in the model include bullet facilities and semi-permanent amortising facilities (Term Loan B and Term Loan A, respectively).

Corporate Finance typically involves 5- and 7-year bond issues with an implied 'BBB' credit rating. Project Finance include a 5-year Bullet facility requiring interest-only payments after which it is refinanced with consecutive amortising facilities and fully amortised over an 18-25 year period (depending on the technology) and a second facility commencing with tenors of 5-12 years as an Amortising facility set within a semi-permanent structure with a nominal repayment term of 18-25 years. The decision tree for the two Term Loans was the same, so for the Debt where DT = 1 or 2, the calculation is as follows:

$$if\ j \begin{cases} > 1, DT_j^i = DT_{j-1}^i - P_{j-1}^i \\ = 1, DT_1^i = D_0^i.S \end{cases} \tag{11}$$

D_0^i refers to the total amount of debt used in the project. The split (S) of the debt between each facility refers to the manner in which debt is apportioned to each Term Loan facility or Corporate Bond. In most model cases, 35% of debt is assigned to Term Loan B and the remainder to Term Loan A. Principal P_{j-1}^i refers to the amount of principal repayment for tranche *T* in period *j* and is calculated as an annuity:

$$P_j^i = \left(\frac{DT_j^i}{\left[\frac{1-\left(1+\left(R_{Tj}^z+C_{Tj}^z\right)\right)^{-n}}{R_{Tj}^z+C_{Tj}^z} \right]} \middle| z \begin{cases} = VI \\ = PF \end{cases} \right) \tag{12}$$

In (12), R_{Tj} is the relevant interest rate swap (5yr, 7yr or 12yr) and C_{Tj} is the credit spread or margin relevant to the issued Term Loan or Corporate Bond. The relevant interest payment in the j^{th} period $\left(I_j^i\right)$ is calculated as the product of the (fixed) interest rate on the loan or Bond by the amount of loan outstanding:

$$I_j^i = DT_j^i \times \left(R_{Tj}^z + C_{Tj}^z\right) \tag{13}$$

Total Debt outstanding D_j^i, total Interest I_j^i and total Principle P_j^i for the i^{th} plant is calculated as the sum of the above components for the two debt facilities in time *j*. For clarity, Loan Drawings are equal to D_0^i in year 1 as part of the initial financing and are otherwise 0.

One of the key calculations is the initial derivation of D_0^i (as per eq.11). This is determined by the product of the gearing level and the Overnight Capital Cost $\left(X_0^i\right)$. Gearing levels are formed by applying a cash flow constraint based on credit metrics applied by project banks and capital markets. The variable γ in our PF Model relates specifically to the legal structure of the business and the credible capital structure achievable. The two relevant legal structures are Vertically Integrated (VI) merchant utilities (issuing ‘BBB’ rated bonds) and Independent Power Producers using Project Finance (PF).

$$iif\ \gamma \begin{cases} = VI,\ \frac{FFO_j^i}{I_j^i} \geq \delta_j^{VI} \forall\ j \left| \frac{D_j^i}{EBITDA_j^i} \geq \omega_j^{VI} \forall\ j \right| FFO_j^i = \left(EBITDA_j^i - x_j^i\right) \\ = PF, Min\left(DSCR_j^i, LLCR_j^i\right) \geq \delta_j^{PF}, \forall\ j \left| DSCR_j = \frac{\left(EBITDA_j^i - x_j^i - \tau_j^i\right)}{P_j^i + I_j^i} \right| LLCR_j = \frac{\sum_{j=1}^{N}\left[\left(EBITDA_j^i - x_j^i - \tau_j^i\right).(1+K_d)^{-j}\right]}{D_j^i} \end{cases} \tag{14}$$

Credit metrics[7] $\left(\delta_j^{VI}\right)$ and $\left(\omega_j^{VI}\right)$ are exogenously determined by credit rating agencies and are outlined in Table 2. Values for δ_j^{PF} are exogenously determined by project banks and depend on technology (i.e. thermal vs. renewable) and the extent of energy market exposure, that is whether a Power Purchase Agreement exists or not. For clarity, FFO_j^i is ‘Funds From Operations’ while $DSCR_j^i$ and $LLCR_j^i$ are the Debt Service Cover Ratio and Loan Life Cover Ratios. Debt drawn is:

$$D_0^i = X_0^i - \sum_{j=1}^{N}\left[EBITDA_j^i - I_j^i - P_j^i - \tau_j^i\right].(1+K_e)^{-(j)} - \sum_{j=1}^{N} x_j^i.(1+K_e)^{-(j)} \tag{15}$$

Relevant inputs are as follows:

Table A2: Project Finance Parameters

Project Finance		
Debt Sizing Constraints		
- DSCR	(times)	1.8
- Gearing Limit	(%)	0.4
- Default	(times)	1.05
Project Finance Facilities - Tenor		
- Term Loan B (Bullet)	(Yrs)	5
- Term Loan A (Amortising)	(Yrs)	10
- Notional amortisation	(Yrs)	15
Project Finance Facilities - Pricing		
- Term Loan B Swap	(%)	4.09%
- Term Loan B Spread	(bps)	180
- Term Loan A Swap	(%)	4.19%
- Term Loan A Spread	(bps)	209
- Refinancing Rate	(%)	6.1%
Expected Equity Returns	(%)	8.0%

[7] For Balance Sheet Financings, Funds From Operations over Interest, and Net Debt to EBITDA respectively. For Project Financings, Debt Service Cover Ratio and Loan Life Cover Ratio.

Balance Sheet Finacing			
Credit Metrics (BBB Corporate)		Merch	Reg.
- FFO / I	(times)	4.2	2.4
- Gearing Limit	(%)	40.0	65.0
- FFO / Debt	(%)	20%	9%
Bond Issues			
- 5 Year	(%)	5.45%	
- 7 Year	(%)	5.59%	
- 10 Year	(%)	5.65%	
Commonwealth Bonds			
- 10 Year	(%)	4.14%	
Expected Equity Returns	(%)	10.0%	

Source: Gohdes (2022, 2023), Bloomberg.

At this point, all of the necessary conditions exist to produce estimates of the long run marginal cost of power generation technologies along with relevant equations to solve for the price $(p^{i\varepsilon})$ given expected equity returns (K_e) whilst simultaneously meeting the constraints of δ_j^{VI} and ω_j^{VI} or δ_j^{PF}given the relevant business combinations. The primary objective is to expand every term which contains $p^{i\varepsilon}$. Expansion of the EBITDA and Tax terms is as follows:

$$0 = -X_0^i + \sum_{j=1}^{N}\left[\left(p^{i\varepsilon}.q_j^i.\pi_j^R\right) - \vartheta_j^i - FOM_j^i - I_j^i - P_j^i - \left(\left(p^{i\varepsilon}.q_j^i.\pi_j^R\right) - \vartheta_j^i - FOM_j^i - I_j^i - d_j^i - L_{j-1}^i\right).\tau_c\right].(1 + K_e)^{-(j)} - \sum_{j=1}^{N} x_j^i.(1 + K_e)^{-(j)} - D_0^i \quad (16)$$

The terms are then rearranged such that only the $p^{i\varepsilon}$ term is on the left-hand side of the equation:

Let $IRR \equiv K_e$

$$\sum_{j=1}^{N}(1-\tau_c).p^{i\varepsilon}.q_j^i.\pi_j^R.(1+K_e)^{-(j)} = X_0^i - \sum_{j=1}^{N}\left[-(1-\tau_c).\vartheta_j^i - (1-\tau_c).FOM_j^i - (1-\tau_c).\left(I_j^i\right) - P_j^i + \tau_c.d_j^i + \tau_c L_{j-1}^i).(1+K_e)^{-(j)}\right] + \sum_{j=1}^{N} x_j^i.(1+K_e)^{-(j)} + D_0^i \quad (17)$$

The model then solves for $p^{i\varepsilon}$ such that:

$$p^{i\varepsilon} = \frac{X_0^i}{\sum_{j=1}^{N}(1-\tau_c).P^{\varepsilon}.\pi_j^R.(1+K_e)^{-(j)}} + \frac{\sum_{j=1}^{N}\left((1-\tau_c).\vartheta_j^i + (1-\tau_c).FOM_j^i + (1-\tau_c).\left(I_j^i\right) + P_j^i - \tau_c.d_j^i - \tau_c L_{j-1}^i).(1+K_e)^{-(j)}\right)}{\sum_{j=1}^{N}(1-\tau_c).q_j^i.\pi_j^R.(1+K_e)^{-(j)}} + \frac{\sum_{j=1}^{N} x_j^i.(1+K_e)^{-(j)} + D_0^i}{\sum_{j=1}^{N}(1-\tau_c).q_j^i.\pi_j^R.(1+K_e)^{-(j)}} \quad (18)$$

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Appendix III – Model Outputs

Static Line Ratings

	Wind	1,950 MW	2018	2019	2020	2021	2022	2023	2024	2025	TOT/AVG
1	Potential Wind Output	(GWh)	6,116	6,008	5,702	5,776	5,927	5,590	5,679	3,010	43,808
2	Practical Wind Output	(GWh)	5,960	5,875	5,618	5,671	5,820	5,499	5,590	2,952	42,985
3	REZ Congestion	(GWh)	156	133	85	104	107	91	89	58	823
4	Energy Curtailed	(% of Prod)	2.5%	2.2%	1.5%	1.8%	1.8%	1.6%	1.6%	1.9%	1.9%
5	Economic Wind Output	(GWh)	5,957	5,807	5,439	5,429	5,634	5,046	5,024	2,788	41,125
6	Spill -ve spot prices	(GWh)	3	68	179	242	185	453	566	164	1,860
7	Energy Spilled	(%)	0.1%	1.2%	3.3%	4.5%	3.3%	9.0%	11.3%	5.9%	4.5%
8	Total Curtail & Spill	(GWh)	159	201	264	346	293	543	654	222	2,683
9	Total Curtail & Spill	(% of Prod)	2.6%	3.4%	4.6%	6.0%	4.9%	9.7%	11.5%	7.4%	6.1%
10	Potential ACF	(% - ACF)	35.8%	35.2%	33.3%	33.8%	34.7%	32.7%	33.2%	35.5%	34.3%
11	Economic ACF	(% - ACF)	34.9%	34.0%	31.8%	31.8%	33.0%	29.5%	29.3%	32.9%	32.2%
12	ACF Loss	(% - ACF)	0.9%	1.2%	1.5%	2.0%	1.7%	3.2%	3.8%	2.6%	2.1%
13	Revenue	$m	570.5	551.8	298.1	595.1	971.4	612.7	588.5	395.9	4,584.1
14	Costs (incl. REZ)	$m	605.2	605.9	607.5	605.9	605.9	605.9	607.5	300.4	4,544.1
15	Economic Profit	$m	-34.7	-54.1	-309.4	-10.7	365.5	6.9	-19.0	95.5	40.0
16	Unit Revenue	($/MWh)	95.8	95.0	54.8	109.6	172.4	121.4	117.1	142.0	111.5
17	Unit Cost	($/MWh)	101.6	104.3	111.7	111.6	107.5	120.1	120.9	107.8	110.5
18	Economic Profit	($/MWh)	-5.8	-9.3	-56.9	-2.0	64.9	1.4	-3.8	34.3	1.0
	Solar PV	**880 MW**	2018	2019	2020	2021	2022	2023	2024	2025	TOT/AVG
19	Potential Solar Output	(GWh)	2,184	2,261	2,149	2,098	2,009	2,156	2,053	976	15,887
20	Practical Solar Output	(GWh)	2,125	2,210	2,114	2,060	1,967	2,120	2,016	950	15,563
21	REZ Congestion	(GWh)	59	51	35	38	42	36	37	26	324
22	Energy Curtailed	(% of Prod)	2.7%	2.3%	1.6%	1.8%	2.1%	1.7%	1.8%	2.7%	2.0%
23	Economic Solar Output	(GWh)	2,119	2,116	1,889	1,721	1,706	1,370	1,253	754	12,929
24	Spill -ve spot prices	(GWh)	5	95	225	339	261	750	764	195	2,634
25	Energy Spilled	(%)	0.3%	4.5%	11.9%	19.7%	15.3%	54.7%	60.9%	25.9%	20.4%
26	Total Curtail & Spill	(GWh)	64	146	260	377	303	786	800	222	2,958
27	Total Curtail & Spill	(% of Prod)	3.0%	6.4%	12.1%	18.0%	15.1%	36.4%	39.0%	22.7%	18.6%
28	Potential ACF	(% - ACF)	27.6%	28.7%	27.3%	26.7%	25.5%	27.5%	26.1%	24.8%	26.8%
29	Economic ACF	(% - ACF)	27.5%	27.4%	24.4%	22.3%	22.1%	17.8%	16.2%	19.7%	22.2%
30	ACF Loss	(% - ACF)	0.1%	1.2%	2.9%	4.4%	3.4%	9.7%	9.9%	5.1%	4.6%
31	Revenue	$m	198.7	177.5	89.0	125.7	165.3	95.5	81.3	58.1	991.1
32	Costs	$m	110.5	110.6	110.9	110.6	110.6	110.6	110.9	54.8	829.5
33	Economic Profit	$m	88.3	66.9	-21.9	15.1	54.7	-15.1	-29.6	3.2	161.5
34	Unit Revenue	($/MWh)	93.8	83.9	47.1	73.0	96.9	69.7	64.9	77.0	76.7
35	Unit Cost	($/MWh)	52.1	52.3	58.7	64.3	64.8	80.7	88.5	72.7	64.2
36	Economic Profit	($/MWh)	41.6	31.6	-11.6	8.8	32.1	-11.1	-23.6	4.3	12.5
37	Portfolio Output (Line 5+23)	(GWh)	8,076	7,923	7,328	7,150	7,340	6,417	6,277	3,542	54,054
37	Portfolio Profit (Lines 15+33)	$m	35.8	22.3	-68.5	6.8	96.9	-9.7	-27.4	38.5	13.5

Seasonal Line Ratings

	Wind	2,225 MW	2018	2019	2020	2021	2022	2023	2024	2025	TOT/AVG
1	Potential Wind Output	(GWh)	6,973	6,852	6,502	6,588	6,758	6,376	6,470	3,428	49,948
2	Practical Wind Output	(GWh)	6,792	6,696	6,406	6,486	6,626	6,280	6,377	3,346	49,010
3	REZ Congestion	(GWh)	181	156	96	102	132	96	93	82	938
4	Energy Curtailed	(% of Prod)	2.6%	2.3%	1.5%	1.6%	2.0%	1.5%	1.4%	2.4%	1.9%
5	Economic Wind Output	(GWh)	6,788	6,615	6,195	6,203	6,411	5,755	5,723	3,157	46,847
6	Spill -ve spot prices	(GWh)	4	81	211	283	215	526	655	189	2,164
7	Energy Spilled	(%)	0.1%	1.2%	3.4%	4.6%	3.4%	9.1%	11.4%	6.0%	4.6%
8	Total Curtail & Spill	(GWh)	184	237	307	385	347	622	748	271	3,101
9	Total Curtail & Spill	(% of Prod)	2.6%	3.5%	4.7%	5.9%	5.1%	9.7%	11.6%	7.9%	6.2%
10	Potential ACF	(% - ACF)	35.8%	35.2%	33.3%	33.8%	34.7%	32.7%	33.1%	35.5%	34.3%
11	Economic ACF	(% - ACF)	34.9%	33.9%	31.7%	31.8%	32.9%	29.5%	29.3%	32.7%	32.1%
12	ACF Loss	(% - ACF)	0.9%	1.2%	1.6%	2.0%	1.8%	3.2%	3.8%	2.8%	2.2%
13	Revenue	$m	649.9	627.8	339.0	681.5	1,111.1	700.1	671.4	450.0	5,230.8
14	Costs (incl. REZ)	$m	691.2	692.0	693.9	692.0	692.0	692.0	693.9	343.2	5,190.1
15	Economic Profit	$m	-41.3	-64.2	-354.9	-10.5	419.2	8.1	-22.5	106.8	40.7
16	Unit Revenue	($/MWh)	95.7	94.9	54.7	109.9	173.3	121.7	117.3	142.5	111.7
17	Unit Cost	($/MWh)	101.8	104.6	112.0	111.6	107.9	120.2	121.3	108.7	110.8
18	Economic Profit	($/MWh)	-6.1	-9.7	-57.3	-1.7	65.4	1.4	-3.9	33.8	0.9
	Solar PV	**880 MW**	2018	2019	2020	2021	2022	2023	2024	2025	TOT/AVG
19	Potential Solar Output	(GWh)	2,182	2,260	2,147	2,097	2,010	2,154	2,052	975	15,877
20	Practical Solar Output	(GWh)	2,129	2,215	2,119	2,068	1,970	2,123	2,020	944	15,588
21	REZ Congestion	(GWh)	52	45	28	29	40	32	32	31	289
22	Energy Curtailed	(% of Prod)	2.4%	2.0%	1.3%	1.4%	2.0%	1.5%	1.6%	3.1%	1.8%
23	Economic Solar Output	(GWh)	2,124	2,119	1,890	1,725	1,706	1,368	1,250	748	12,931
24	Spill -ve spot prices	(GWh)	5	96	228	343	263	755	770	196	2,657
25	Energy Spilled	(%)	0.2%	4.5%	12.1%	19.9%	15.4%	55.2%	61.6%	26.2%	20.6%
26	Total Curtail & Spill	(GWh)	58	141	256	372	304	786	802	227	2,947
27	Total Curtail & Spill	(% of Prod)	2.6%	6.3%	11.9%	17.7%	15.1%	36.5%	39.1%	23.3%	18.6%
28	Potential ACF	(% - ACF)	27.7%	28.7%	27.4%	26.8%	25.6%	27.5%	26.1%	24.7%	26.8%
29	Economic ACF	(% - ACF)	27.6%	27.5%	24.5%	22.4%	22.1%	17.7%	16.2%	19.6%	22.2%
30	ACF Loss	(% - ACF)	0.1%	1.2%	3.0%	4.5%	3.4%	9.8%	10.0%	5.1%	4.6%
31	Revenue	$m	198.9	177.3	88.8	126.0	166.3	95.3	81.2	57.4	991.3
32	Costs	$m	109.3	109.4	109.7	109.4	109.4	109.4	109.7	54.3	820.6
33	Economic Profit	$m	89.6	67.9	-20.9	16.6	56.9	-14.1	-28.5	3.2	170.8
34	Unit Revenue	($/MWh)	93.6	83.7	47.0	73.1	97.5	69.6	65.0	76.8	76.7
35	Unit Cost	($/MWh)	51.4	51.6	58.0	63.4	64.1	80.0	87.8	72.5	63.5
36	Economic Profit	($/MWh)	42.2	32.1	-11.0	9.6	33.4	-10.3	-22.8	4.2	13.2
37	Portfolio Output (Line 5+23)	(GWh)	8,912	8,734	8,085	7,928	8,117	7,123	6,973	3,905	59,777
37	Portfolio Profit (Lines 15+33)	$m	36.1	22.4	-68.3	7.9	98.7	-8.9	-26.7	38.1	14.1

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Real-Time Ratings

	Wind	3,275 MW	2018	2019	2020	2021	2022	2023	2024	2025	TOT/AVG
1	Potential Wind Output	(GWh)	10,294	10,115	9,610	9,728	9,977	9,417	9,548	5,059	73,749
2	Practical Wind Output	(GWh)	10,031	9,936	9,474	9,569	9,781	9,280	9,383	4,952	72,407
3	REZ Congestion	(GWh)	263	179	136	158	197	137	165	107	1,343
4	Energy Curtailed	(% of Prod)	2.6%	1.8%	1.4%	1.6%	2.0%	1.5%	1.7%	2.1%	1.8%
5	Economic Wind Output	(GWh)	10,026	9,812	9,159	9,145	9,457	8,499	8,414	4,670	69,182
6	Spill -ve spot prices	(GWh)	6	124	315	425	324	780	969	282	3,224
7	Energy Spilled	(%)	0.1%	1.3%	3.4%	4.6%	3.4%	9.2%	11.5%	6.0%	4.7%
8	Total Curtail & Spill	(GWh)	269	304	451	583	520	918	1,134	388	4,567
9	Total Curtail & Spill	(% of Prod)	2.6%	3.0%	4.7%	6.0%	5.2%	9.7%	11.9%	7.7%	6.2%
10	Potential ACF	(% - ACF)	35.9%	35.3%	33.4%	33.9%	34.8%	32.8%	33.2%	35.6%	34.4%
11	Economic ACF	(% - ACF)	35.0%	34.2%	31.8%	31.9%	33.0%	29.6%	29.2%	32.8%	32.2%
12	ACF Loss	(% - ACF)	0.9%	1.1%	1.6%	2.0%	1.8%	3.2%	3.9%	2.7%	2.2%
13	Revenue	$m	955.7	928.6	498.4	1,003.8	1,633.7	1,032.8	985.8	663.0	7,701.9
14	Costs (incl. REZ)	$m	989.9	991.1	993.8	991.1	991.1	991.1	993.8	491.5	7,433.1
15	Economic Profit	$m	-34.2	-62.4	-495.4	12.8	642.7	41.8	-7.9	171.6	268.8
16	Unit Revenue	($/MWh)	95.3	94.6	54.4	109.8	172.8	121.5	117.2	142.0	111.3
17	Unit Cost	($/MWh)	98.7	101.0	108.5	108.4	104.8	116.6	118.1	105.2	107.4
18	Economic Profit	($/MWh)	-3.4	-6.4	-54.1	1.4	68.0	4.9	-0.9	36.7	3.9
	Solar PV	**1,420 MW**	2018	2019	2020	2021	2022	2023	2024	2025	TOT/AVG
19	Potential Solar Output	(GWh)	3,522	3,648	3,465	3,385	3,243	3,477	3,312	1,573	25,625
20	Practical Solar Output	(GWh)	3,455	3,597	3,431	3,345	3,192	3,436	3,269	1,536	25,261
21	REZ Congestion	(GWh)	67	51	35	40	51	41	43	37	365
22	Energy Curtailed	(% of Prod)	1.9%	1.4%	1.0%	1.2%	1.6%	1.2%	1.3%	2.4%	1.4%
23	Economic Solar Output	(GWh)	3,446	3,435	3,055	2,778	2,757	2,208	2,018	1,217	20,913
24	Spill -ve spot prices	(GWh)	9	162	376	568	435	1,228	1,251	319	4,347
25	Energy Spilled	(%)	0.3%	4.7%	12.3%	20.4%	15.8%	55.6%	62.0%	26.2%	20.8%
26	Total Curtail & Spill	(GWh)	75	213	410	608	486	1,269	1,294	356	4,712
27	Total Curtail & Spill	(% of Prod)	2.1%	5.8%	11.8%	17.9%	15.0%	36.5%	39.1%	22.6%	18.4%
28	Potential ACF	(% - ACF)	27.8%	28.9%	27.5%	26.9%	25.7%	27.6%	26.2%	24.9%	26.9%
29	Economic ACF	(% - ACF)	27.7%	27.6%	24.5%	22.3%	22.2%	17.8%	16.2%	19.7%	22.2%
30	ACF Loss	(% - ACF)	0.1%	1.3%	3.0%	4.6%	3.5%	9.9%	10.0%	5.2%	4.7%
31	Revenue	$m	320.4	286.0	142.0	202.0	267.0	152.9	130.1	92.4	1,592.9
32	Costs	$m	172.4	172.6	173.1	172.6	172.6	172.6	173.1	85.6	1,294.5
33	Economic Profit	$m	148.0	113.4	-31.0	29.4	94.4	-19.7	-43.0	6.9	298.4
34	Unit Revenue	($/MWh)	93.0	83.3	46.5	72.7	96.9	69.2	64.5	75.9	76.2
35	Unit Cost	($/MWh)	50.0	50.2	56.7	62.1	62.6	78.2	85.8	70.3	61.9
36	Economic Profit	($/MWh)	43.0	33.0	-10.2	10.6	34.3	-8.9	-21.3	5.6	14.3
37	Portfolio Output (Line 5+23)	(GWh)	13,472	13,247	12,214	11,922	12,214	10,707	10,432	5,888	90,096
37	Portfolio Profit (Lines 15+33)	$m	39.5	26.7	-64.2	12.0	102.2	-4.0	-22.2	42.4	18.2