Renewable Energy Zones: generator cost allocation under uncertainty

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

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

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On Renewable Energy Zones and the impact of real-time transmission line ratings

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November 2025

Abstract
Renewable Energy Zones (REZs) are increasingly used to coordinate large-scale renewable investments while minimising the cost and footprint of transmission infrastructure in transitioning power systems. In the Queensland region of Australia's National Electricity Market, REZs have been developed as merchant assets, with transmission costs recovered from connecting generators rather than consumers. While this model enables rapid deployment, its financial viability becomes challenging as REZs extend further from the transmission backbone, and user charges approach generators' capacity-to-pay limits. Prior research examined individual drivers of REZ performance, including resource complementarity, access regimes, transmission line ratings and battery storage. However, these factors have been treated in isolation and under simplified cost allocation assumptions, leaving uncertainty about the bankability of merchant REZs once rising capital costs and realistic financing constraints are jointly considered. This article develops an integrated optimisation framework that determines the efficient mix of wind, solar, and storage within a merchant REZ with cooperative game-theoretic cost allocation and a generator capacity-to-pay constraint. Central to the analysis is a comparison of static, seasonal, and real-time transmission line ratings. Using an applied case study from Queensland, we show real-time line ratings substantially increase renewable hosting capacity, energy output and the aggregate capacity to pay. This transforms a merchant REZ from financially constrained to bankable. Seasonal ratings deliver intermediate gains, while static ratings leave a persistent revenue shortfall. Although based on Australia, the framework and insights are generalisable to other power systems pursuing scale-efficient renewable integration.

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1. Introduction

Renewable Energy Zones (REZs) are a key policy initiative in Australia's National Electricity Market (NEM). REZs are 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

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risks disturbing cultural sites (Simshauser and Newbery, 2024). Above all, transmission is costly and so REZs are essential even for a country as vast as Australia.
While REZs reduce duplication and social impacts, their effectiveness ultimately depends on whether transmission investments are financeable under prevailing market and regulatory arrangements, particularly where costs are recovered from generators rather than consumers. Internationally, REZ-style coordination originated in Texas under a regulated cost-recovery framework. In Australia's NEM, the New South Wales and Victorian regions have pursued large-scale, state-led or public–private models with costs borne by consumers. By contrast, Queensland originated a merchant REZ model in which transmission investments are jointly underwritten by the transmission utility and generator user charges, rather than forming part of the Regulatory Asset Base underwritten by consumers. This distinction makes Queensland's experience uniquely informative for assessing the financial limits of *market-led* transmission expansions.

While the Queensland model has the advantage of speed, it must deal with the primal challenge of financial viability, which is the focus of this article. As with all scarce resources, each REZ forms part of an upward sloping supply curve of REZ options. 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'* – prima facie making the entire program of merchant investments (REZ transmission infrastructure, wind and solar projects) *un-bankable*.

Prior research on merchant REZs examined how various parameters alter hosting capacity including (i) the complementarity of renewable resources (McDonald, 2023, 2024), (ii) access regimes (Newbery and Biggar, 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 in all prior research was small and simplified (i.e. allocated by output). As capital costs rise, the accuracy of user charges becomes critical, as are incorporating important locational differences and the *capacity to pay*. These variables are likely to become a binding constraint in the project finance of new renewables.

In this article, we extend prior research by combining all parameters simultaneously to identify the optimal mix of renewable plant in a REZ and define a set of efficient, fair and defendable user charges to connecting generators given a 'capacity to pay' constraint. We apply cooperative game theory to derive efficient and defensible transmission cost allocations, moving beyond output-based charging rules used in prior REZ research. Maximising combinations of complementary renewable generators may help alleviate prevailing capacity to pay constraints. To this end, a comparison of static, seasonal and real-time transmission line ratings on the quantity of connecting renewable generators forms a central focus of the analysis. These explicit capacity-to-pay constraints are consistent with contemporary renewable power project financings, enabling a direct assessment of REZ bankability rather than efficiency alone.

Model results show real-time transmission line ratings dramatically increases renewable hosting capacity, and consequently, may lead to a great aggregate 'capacity to pay' pool, thus enhancing the bankability of merchant REZ infrastructure and connecting renewable generators (cf. static line ratings). While the merchant REZ scenario we construct is an applied example in NEM's Queensland region, the modelling framework we develop 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. Above all, by increasing effective network hosting capacity of renewables without material capital expenditure, real-time line ratings and efficient cost sharing rules have the potential to relax binding capacity-to-pay constraints and restore the financial viability of merchant REZs.

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

By definition, REZs comprise an area of 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 (McDonald, 2023). In this sense, REZs are designed to eliminate otherwise duplicate network investments (Simshauser et al., 2022). 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 fundamentally state-led regulated asset developments. In the NEM's Queensland region, REZs are smaller in scale, larger in number, and merchant investments led by a benevolent, state-owned transmission planner (Newbery and Biggar, 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).[1]

Our situation is different to the classic bus literature and the related transmission cost allocation research[2] as well as other cost sharing models such as distribution and peer-to-peer trading, as investigated in (Noorfatima *et al.*, 2022) (albeit being a different application, this work further underscores the conceptual and mathematical relevance of cooperative game theory for allocating shared infrastructure costs). Our problem, given a merchant REZ model, is the efficient allocation of shared infrastructure costs to large-scale renewable generators without regulatory 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

[1] 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.
[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.

concepts of cost sharing based on cooperative game theory (Hougaard, 2009) but within a capacity to pay or *bankability* constraint and focused on REZ cost allocation rather than other models

Other approaches from the cost allocation literature are also possible. However, these approaches don't always consider coalition structures and combined cost profiles of multiple players – which are relevant for the present context. For example, flow-based cost allocation methods (which provide alternative frameworks to Shapley-value approaches, see below), are useful in highly renewable and meshed networks where usage of transmission assets varies dynamically with generator injections and for which such coalition profiles are not the defining factor (Tranberg *et al.*, 2018). 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 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.

A recent article related to the work here is that of (Go *et al.*, 2025) that models the transmission expansion costs to renewable energy resource owners via a stochastic cooperative game. In that paper they choose to model the cost allocation via the nucleolus which does not work in our scenario as trying to maximise the excesses of each coalition is not a realistic aspect of our model given geographical limitations. In addition, we capture stochasticity outside of the cooperative game, allowing for a simpler cost sharing analysis.

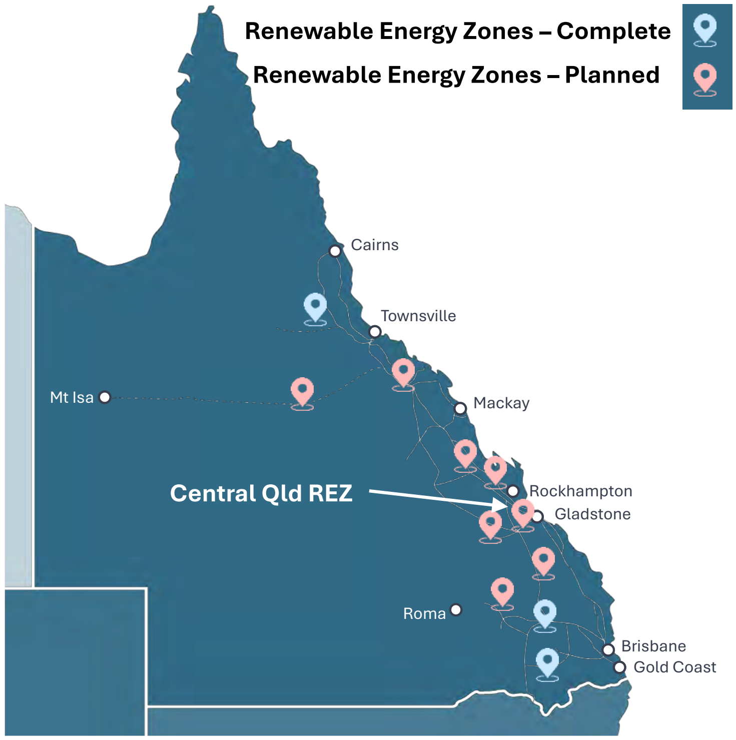
Overall, cooperative game approaches have been applied beyond simple cost sharing to broader resource and flexibility allocation problems, illustrating the versatility of game-theoretic solutions in energy systems and reinforcing their applicability to REZ cost allocation and future innovative research (Sanjab, Le Cadre and Mou, 2022).

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 framework can be generalised to any system.

By way of brief background, the Queensland power system comprises a 275kV transmission backbone extending over a 1500km range, from Cairns (north) to New South Wales (south) as Fig.1 notes. Renewable resources can be found along the length and breadth of the network. The present analysis will focus on a Central Queensland REZ per Fig.1.

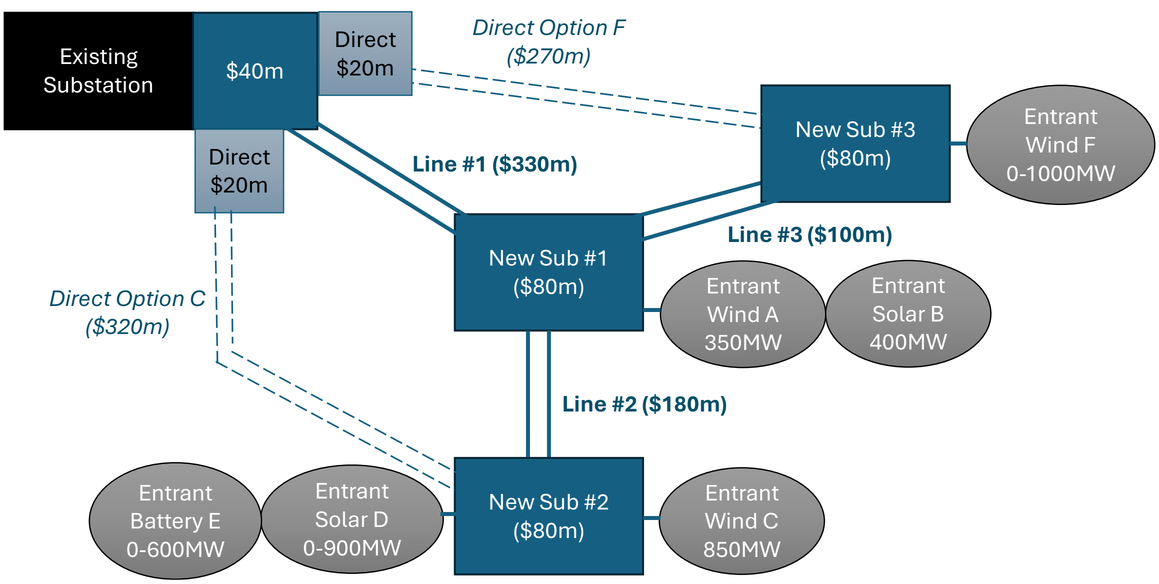
Figure 1: Renewable Energy Zones in Queensland



3.1 REZ layout

A representative Central Queensland REZ layout is presented in Fig.2. To summarise, there are six potential tenants (Wind A, Solar B, Wind C, Solar D, Battery E, Wind F). Entrants A-E trigger investment in Lines 1-2, and Substations 1-2, whereas entrant F triggers Line 3 and Substation 3.

Figure 2: Renewable Energy Zone Layout



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' are assumed to equate to 8.2% per annum (i.e. ~1.7% O&M and ~6.5%

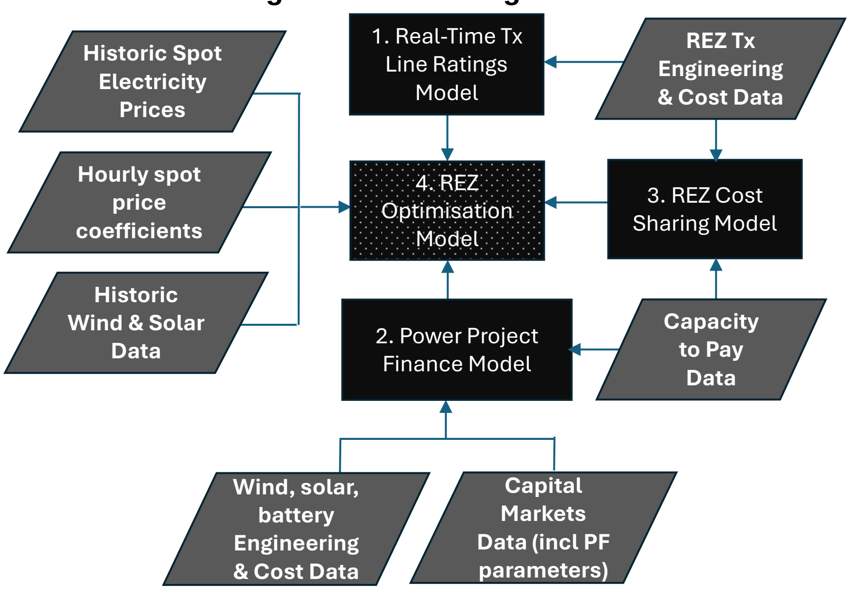
Return on Capital). Given $890m capital invested, breakeven user charges therefore equal $73m pa (i.e. $890m x 8.2% = $73m).

The task of the transmission planner is to identify the optimal mix of wind, solar and storage for the REZ along with fair, efficient and defendable 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, from Fig.2 it can be seen that direct connections (i.e. Options C and F) raise total investment costs from $890m to $1,200m (and user charges from $73m to $98m). This exemplifies the notion of REZs – minimising costs and avoiding duplicative infrastructure.

3.2 Overview of Data and Models

The task of analysing the financial tractability of a merchant REZ requires an array of interlinked models and datasets, as outlined in Fig.3. There are four models including (1) Real-Time Tx Line Ratings Model, (2) Power Project Finance Model, (3) the REZ Cost Sharing Model and finally, the (4) REZ Optimisation Model. Data required for each model is clearly identified in Fig.3. Details of models and data are outlined in Sections 3.3 – 3.8.

Figure 3: Modelling Structure



3.3 Real-Time Transmission Line Ratings Model

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 to connect the 6 potential entrants. 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 $\left(\theta_{t=Sum}^{Seas}\right)$	2863	

The derivation of results in Tab.1 for seasonal line ratings for summer $\left(REZ_{t=Sum}^{Seasonal}\right)$ 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.

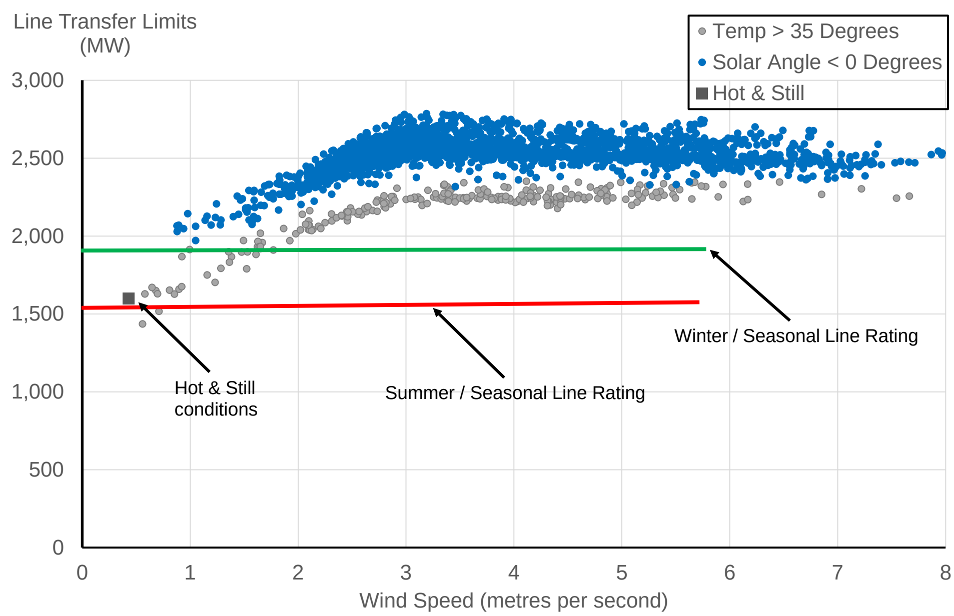
$$REZ_{t=Sum}^{RTR} = Min\begin{bmatrix} \left(2 \cdot \sqrt{3} \cdot 0.275 \cdot NR_t^{RTR}\right) \cdot 0.93, \\ \left\{\left(\sqrt{3} \cdot 0.275 \cdot ER_t^{RTR}\right) \cdot 0.93 + FCAS\right\} \\ \theta^{Static}, \end{bmatrix} \rightarrow$$
$$NR_t^{RTR}, ER_t^{RTR} = F\left(CT, T_{max}, C_n, W_s,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

By comparison to static or seasonal limits, real-time ratings can lead to material increases in transfer capacity. This is illustrated in Fig.4, where the y-axis measures line transfer limits and the x-axis measures wind speed.

Historically, maximum 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.4, 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.4 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.4 subsequently reveals).

Figure 4: Real-Time Ratings vs Seasonal & Static Ratings



Why real-time line ratings matter 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.5). 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.5). This time-of-day line constraint no long matches maximum demand. Specifically, while aggregate final demand in Fig.5 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 very low capital cost transmission 'line mounted' weather stations, capable of streaming real-time weather data back to control rooms (i.e. real-time ratings are viable).

3. REZs *primarily exist* to connect wind projects and as the scatter plot in Fig.4 illustrates, higher wind speeds are associated with higher line transfer capacity. And as Fig.6 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 5: Maximum demand event in Queensland (2025)

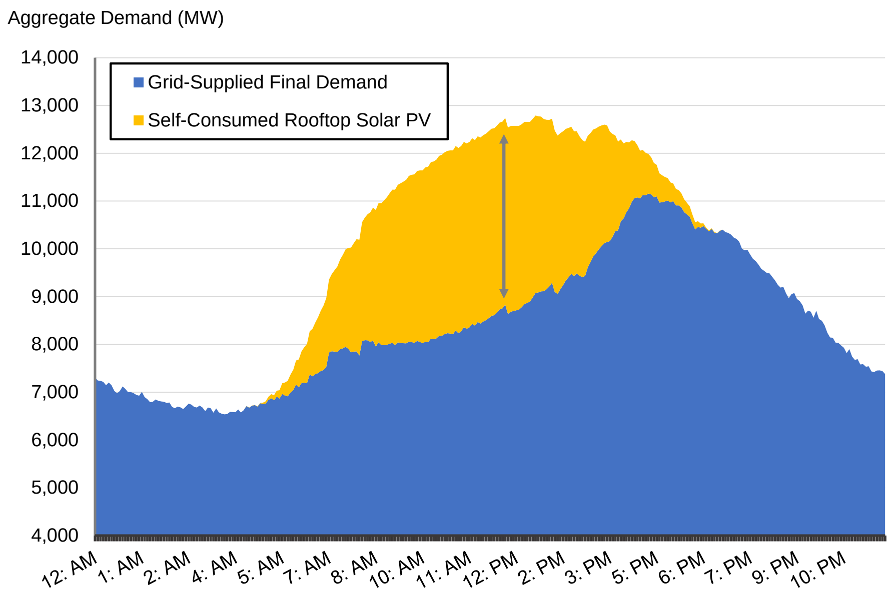
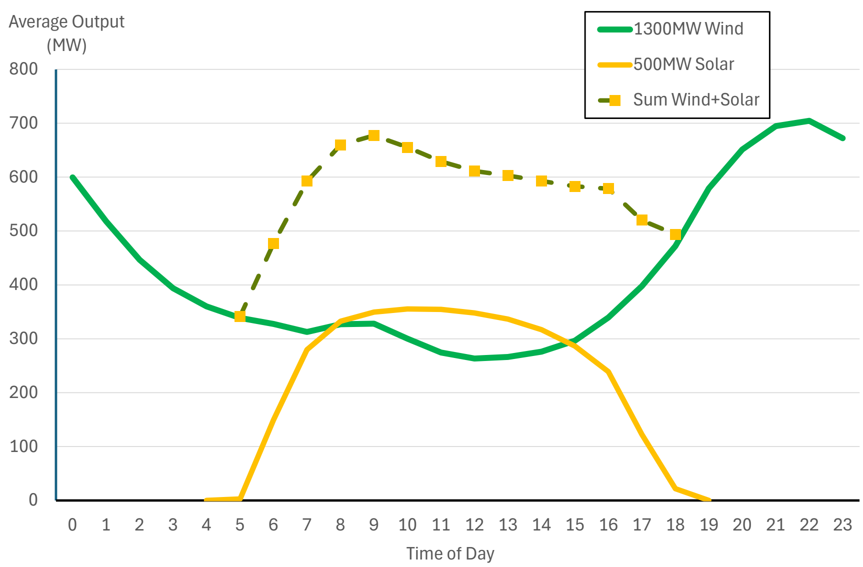


Figure 6: Average Summer Wind and Solar PV output (Central Queensland)

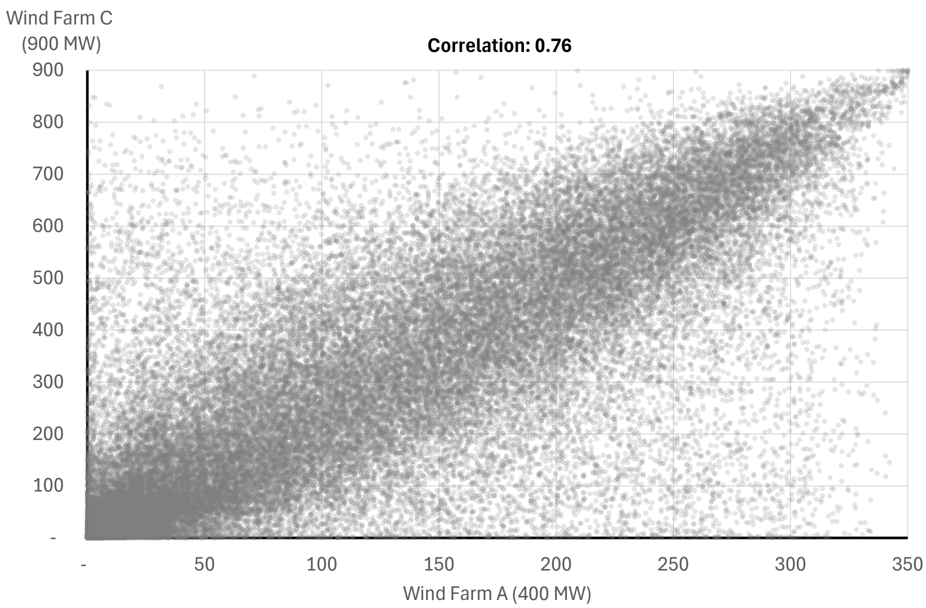


In our REZ Optimisation Model simulations, we will contrast the impact of static, seasonal and real-time line ratings on renewable generation hosting capacity, REZ costs and charges.

3.4 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 (Fig.7).

Figure 7: 7½ years of matched wind output, adjacent locations (Central REZ)



Time-sequential modelling is required to 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 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 appear in Appendix I).

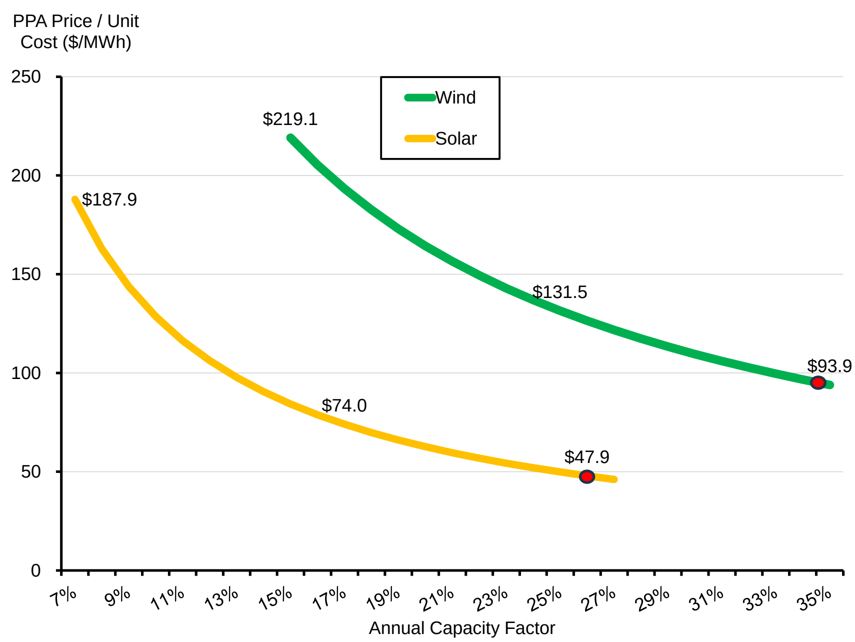
3.5 Wind, Solar and Battery plant costs

We use a commercial-grade *Power Project Finance Model* (PPF Model) to produce entry cost estimates of project financed 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. Full model logic, engineering and capital markets input parameters appear in Appendix II. Estimated entry costs from the PPF model (excluding REZ user charges) are set out in Tab.3 (see Column 'a', Lines 1-4). Fig.8 shows how sensitive these project financed entry cost estimates are to 'curtailment' – and in turn why REZ Optimisation (line ratings, optimal renewable plant mix) is so critical.

Table 3: Plant entry costs[3] 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				

Figure 8: Project Finance Wind and Solar – entry cost



[3] 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.

3.6 The ‘capacity to pay’ REZ charges

An important variable in Tab.3, and the subsequent analysis, is generators *‘capacity to pay’* REZ 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. A generator’s capacity to pay is not endless. For this purpose, we rely on specific work undertaken by engineering firm Aurecon (2025), who collated costs from ‘due diligence’ reports for project banking purposes across 60,000MW of wind, solar and battery projects in Australia and New Zealand.[4] To summarise that work, a generators *capacity to pay* connection investment costs trends towards 10% (-2%/+5%) of the investment cost of wind and solar plants. 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% given wind and solar capacity factors used here align with market medians. How we translate a 10% *‘capacity to pay limit’* for a wind farm is as follows:

- The capital cost of wind (Appendix II) is $3373/kW;
- Capacity to pay is 10% of the 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 (per Section 3.1[5]), this translates to $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.

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 a REZ bankability gap, which we examine in Section 4.

3.7 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 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 profit-maximising dispatch in operational timeframes (hourly resolution).

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.[6] Consequently in the model, project financed wind and solar entry occurs continuously until economic rents are competed away – or – the entry

[4] The authors are indebted to Mr Paul Gleeson and his team at Aurecon for allowing the authors to use this unique dataset.

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

[6] 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.

parameters of an asset class reaches the binding limits of established project finance covenants applied by risk averse banks. Incorporating this into 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 PPF 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:

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

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 PPF 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 $(p_{h,t})$ is deemed $(\hat{p}_{h,t} = 0)$, 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:

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

3.8 REZ 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 relies on principles that are known to produce closed-form solutions that can be applied directly. The 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 an affordability cap may leave some costs recommended by cost sharing protocols 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). The model logic that produces user charges appears in Appendix III.

4. Model Results

Our modelling efforts seek to identify the welfare maximising mix of wind, solar and battery storage capacity within a REZ, where generator entrants face a profitability constraint, and with respect to REZ user charges, a capacity-to-pay constraint. This involves an extensive and granular simulation modelling exercise spanning 7½ years of hourly spot price dispatch intervals (i.e. ~65,000 trading intervals), and 7½ years of chronologically matched hourly wind and solar data across three geographical locations (i.e. ~395,000 weather readings). The basis of simulation scenarios has been selected to achieve an inherent level of sensitivity analysis to assist with the robustness of final results. While the array of plausible sensitivities is endless, four simulation scenarios, comprising ~100 iterations each (i.e. 4 x 100 simulation iterations), has the effect of 'bookending' sensitivities in a logical and sequential manner. The four scenarios are:

1. Wind and solar only, with static line ratings for the REZ (i.e. conservative transmission line transfer capacity, high-cost scenario);

2. Wind and solar only with seasonal line ratings for the REZ (enhanced line transfer capacity);

3. Wind and solar only with real-time line ratings for the REZ (maximum plausible line transfer capacity, low-cost scenario); and

4. Wind, solar and the introduction of battery storage within the REZ with real-time line ratings, maximising line transfer capacity and generation capacity, while simultaneously isolating any beneficial effects of localised storage.

Recall from Fig.6 that a defining characteristic of Queensland renewables is the complementarity of wind and solar resources. This complementarity means the efficient level of connecting generation capacity (MW) will always exceed REZ line transfer capacity (MW), however only high-resolution modelling is capable of identifying the extent of this complementarity.

4.1 Scenario 1: optimal renewables with static line ratings

In our REZ, entry is assumed to occur in a perfectly competitive market (i.e. until profits are competed away), or, marginal entrants face binding constraints imposed by project banks (e.g. curtailment limits). Furthermore, entry occurs 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. This has important implications for project financing, viz. there are no side-payments to investors when plant is constrained-off. This places a considerable burden on both renewable investors and project banks to predict market congestion conditions, because the risk of curtailment cannot be directly re-allocated to consumers. This is a primary function of the REZ Optimisation Model in that it tracks curtailment rates in detail.

Using data outlined in Section 3, the REZ Optimisation Model runs through 100 iterations to identify the optimal mix of wind and solar PV (and battery storage when initiated). We opt for 100 iterations due to the non-linearity of the problem given the rich blend of wind and solar resources, line ratings, merit order effects, curtailment rate constraints 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.9, 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 and banks to commit within a REZ. Yet a close inspection of Fig.2, and of Fig.9, reveals that:

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

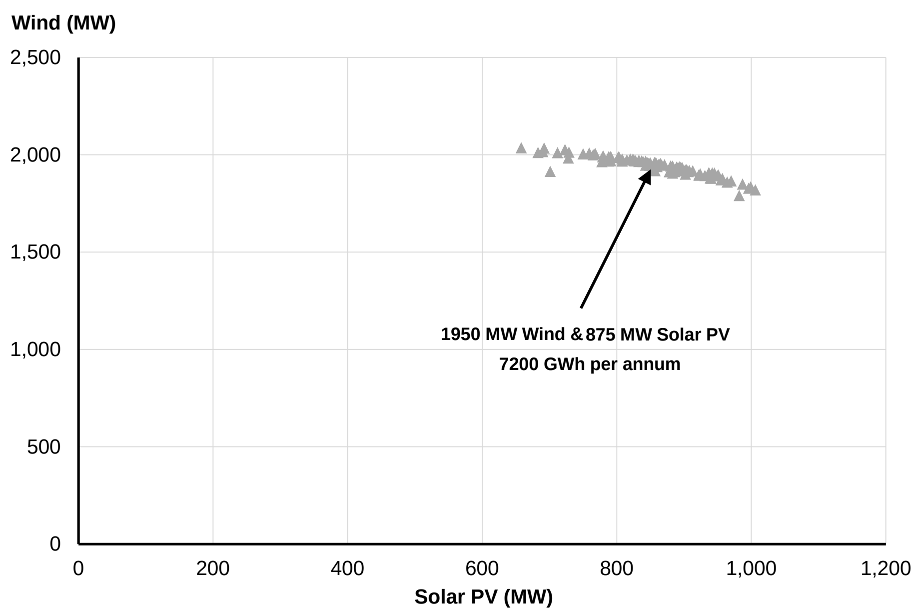
2. In Fig.9 (y-axis), *all iterations* involve a minimum level of wind (~1800MW) and cluster at ~1950MW;

3. Similarly, in Fig.9 (x-axis), all iterations involved a minimum level of solar (~650MW) and cluster at ~850MW; and

4. at a 10% Probability of Exceedance (PoE10), which in a sense reflects a risk-adjusted *upper limit* optimal result, iterations comprise ~1950MW of wind, and ~875MW of solar.

Consequently, while there may be some level of plant mix uncertainty at the margins, the number of sites is fixed, and iterations trended towards *at least* 1800MW of wind, and *at least* 700MW 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.

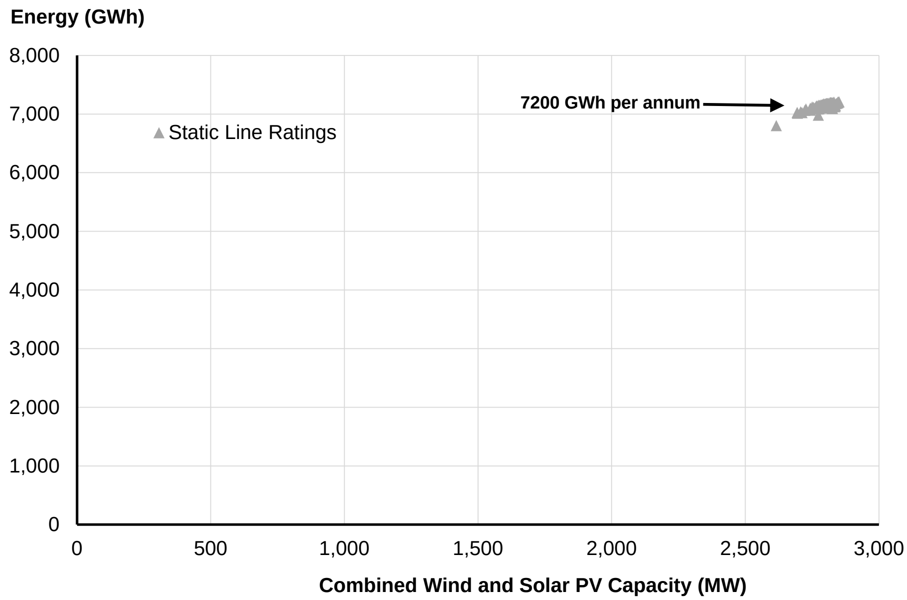
Figure 9: REZ static line ratings – optimal wind capacity vs. solar PV capacity



The binding constraint in this set of iterations is renewable plant curtailment (i.e. 'spilled energy') due to transmission line congestion. Some level of curtailment inside a REZ is efficient. But in practice, there are *'bankable 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, largely consistent with the assumptions in Simshauser and Newbery (2024). In Fig.9, Eq.(6) is binding for wind and solar entrants, which in turn regulates entry to 1950MW of wind, and 875MW of solar (at PoE10).

Fig.9 contrasted 100 iteration results from the REZ model by examining wind capacity (y-axis) and solar capacity (x-axis). In Fig.10, the same set of results is displayed with production output (GWh) on the y-axis and combined wind and solar capacity (MW) on the y-axis. What this shows is that, although there appears to be some variation in the plausible mix of wind and solar (per Fig.9), the annual production from those combinations lies within a *very tight range*, viz. 7160GWh +/-1%.

Figure 10: REZ static line ratings – energy (GWh) vs renewable capacity (MW)



Our allocation of REZ user charges underpinning Figs.9-10 appears in Tab.4. The various project financed power projects are listed from Lines 1-6 (note potential "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 the calculated 'Shapley Values' in column e – that is, the results of our cost allocation model outlined in Appendix III – is striking. Column 'f' notes 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 REZ's minimum bankable revenues of $73m (column e, line 7).

Table 4: REZ Shapley Values (Static Line Ratings)

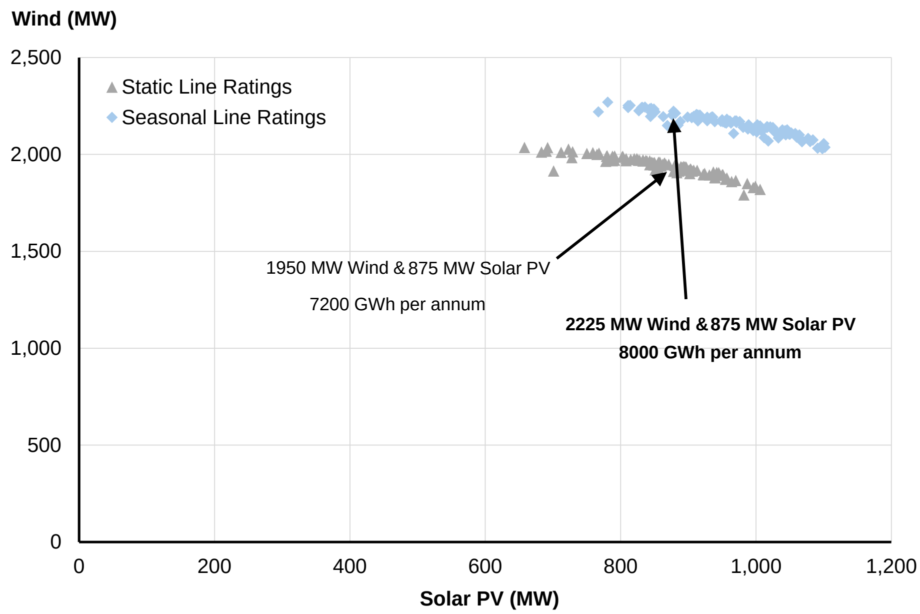
	Static Line Ratings		Capacity (MW)	Capacity to Pay ($/MW)	Capacity to Pay ($M)	Output ($M)	Shapley Value ($M)	Surplus ($M)		Recovery (%)
	Capex = $890m		a	b	c = (a x b)	d	e	f = (c - e)		g =∑min(e,c) ÷ ∑e
1	Project A	Wind	400 MW	$27,500	11.0	10.6	6.7	4.3	$6.0	
2	Project B	Solar	400 MW	$10,500	4.2	8.7	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, transmission line ratings for the REZ.

4.2 Scenario 2: optimal renewables with seasonal line ratings

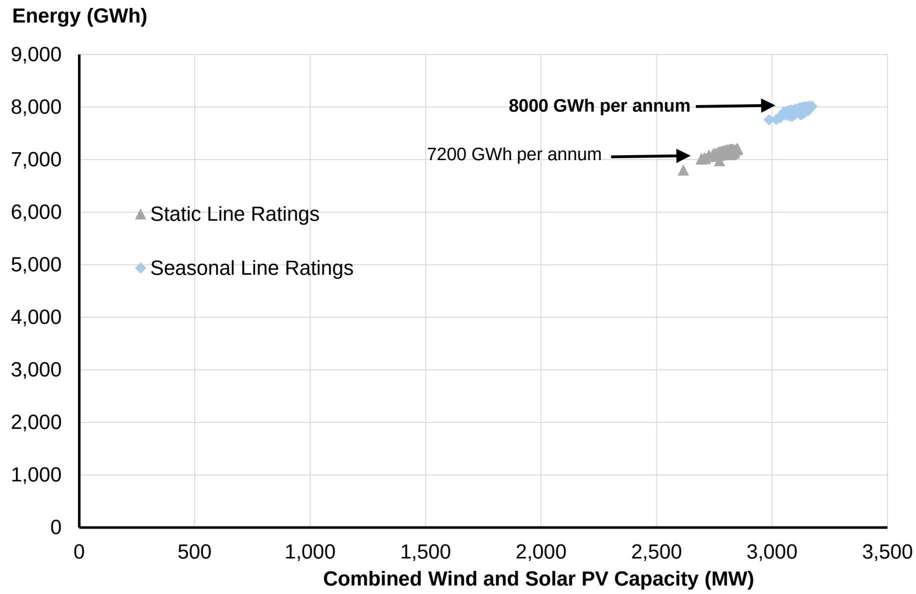
In Scenario 2, we alter our line ratings in the mild and winter seasons as outlined in Tab.1. This means in winter, line transfer capacity increases to 1916MW and in the mild seasons, to 1756MW. Our summer rating remains at the static rating of 1536MW. Fig.11 presents the optimal combinations of wind solar. At PoE10, optimality equates to 2225MW of wind (+275MW more than static line ratings) and no change to solar. Such results reflect the fact that the additional line transfer capacity largely coincides with windy conditions (Fig.3).

Figure 11: REZ seasonal line ratings – optimal wind vs. solar PV



The productivity of the REZ has increased commensurately, with no change to infrastructure costs. Fig.12 illustrates that energy output has increased by 11%, from 7200 to 8000GWh.

Figure 12: 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). These gains also dwarf the REZ user charges shortfall – suggesting that if commercial solutions cannot be found, a regulated overlay should be pursued (see Section 5) noting consumer welfare alone increases by $72.4m (cf. REZ user charges shortfall of $1.7m pa per Tab.6). Consumers prefer the more productive REZ because the fixed costs of transmission investments are spread across more units of output. Additionally, recall that project financed onshore wind and solar PV are lowest cost entrants in the NEM. Consequently, wind and solar exhibit marginally lower entry costs with a more productive REZ. Producer surplus also rises, albeit with mixed results as a class. Wind investors develop projects that would otherwise be stranded ($86.1m). Solar investors ($-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.11-12 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 optimal (Shapley Value) user charges. The revenue-cost recovery ratio for the REZ 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	-$8.1	
11	Project D	Solar	400 MW	$10,500	4.2	7.8	5.3	-1.1		
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.13 illustrates the change in the optimal capacity mix, with wind rising to 3275MW, and solar PV rising to 1425MW.

Figure 13: REZ real-time line ratings – optimal wind vs. solar PV

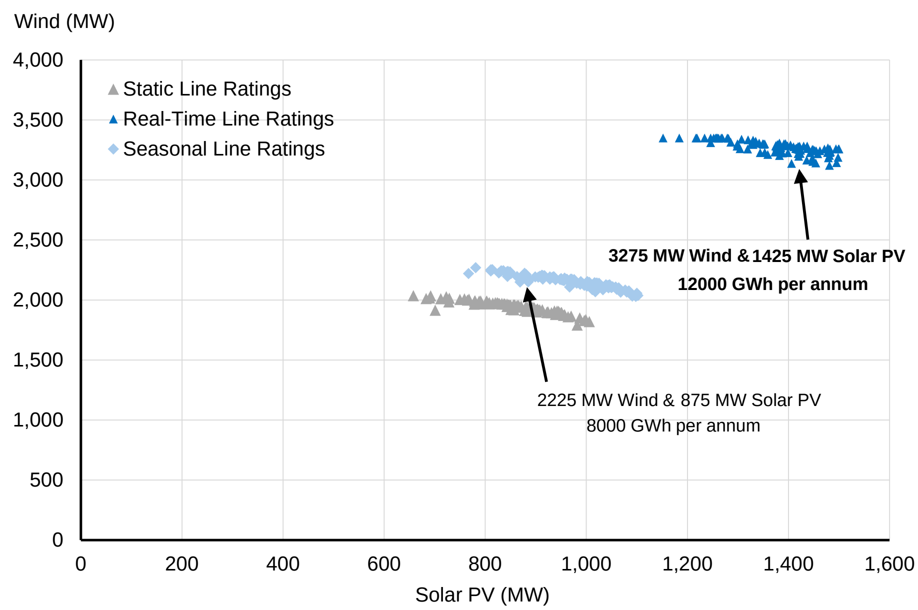
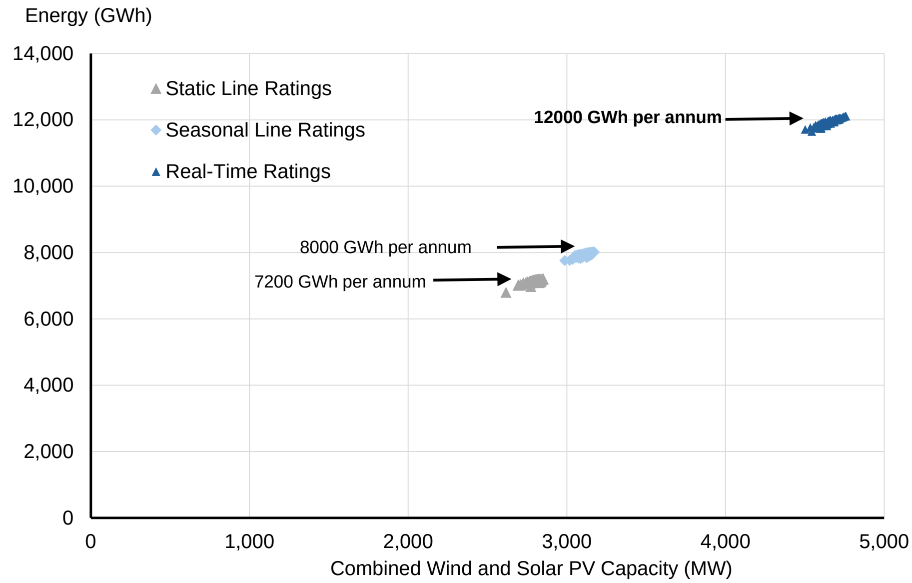


Fig.14 highlights the change in REZ productivity, with output rising by 50% to 12,000GWh.

Figure 14: 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 investors 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 ideal REZ annual charges and Shapley Value of each entrant, as illustrated in Tab.8.

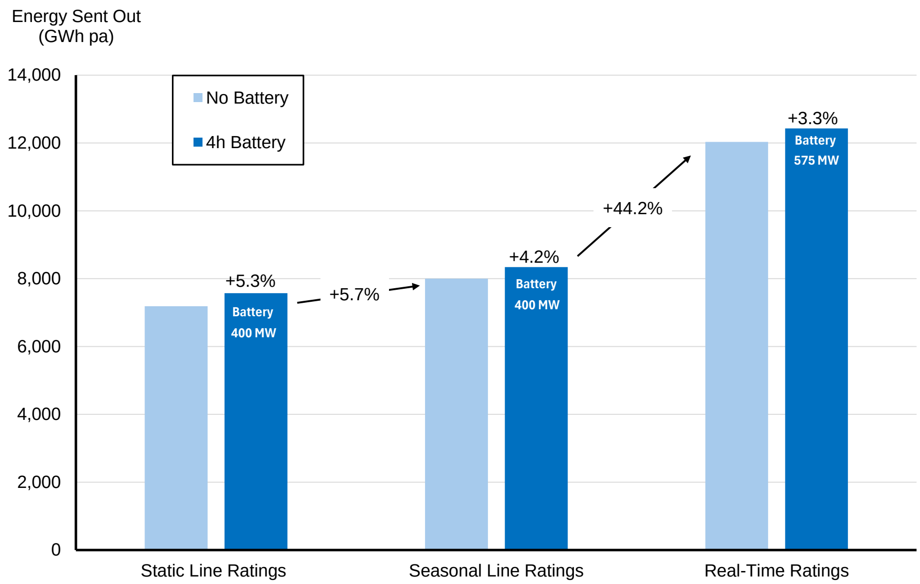
Table 8: REZ Shapley Values (real-time line ratings)

	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	
25	Project D	Solar	650 MW	$10,500	6.8	8.6	6.8	0.0	$0.1
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?

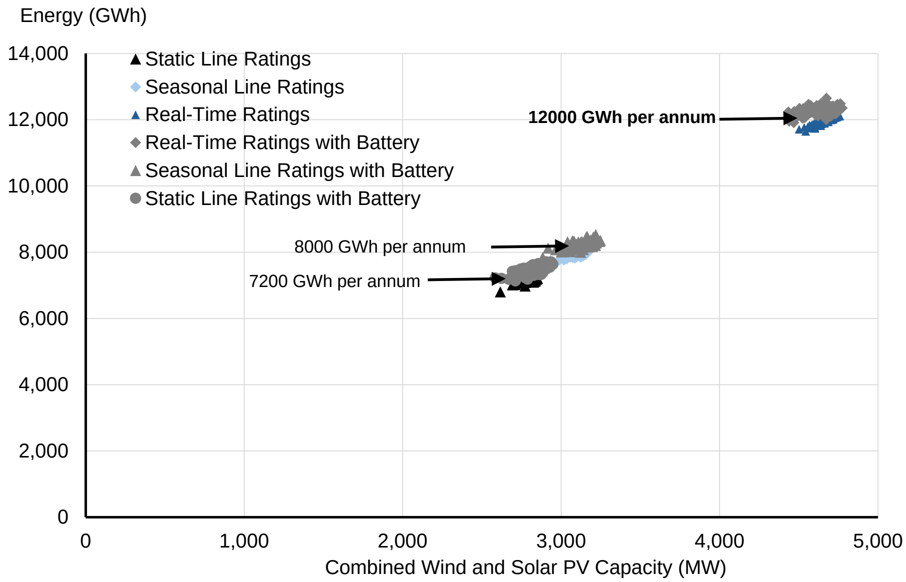
In each of Scenarios 1-3, battery storage was deliberately excluded. Given intermittency, the addition of battery storage *should* facilitate additional entry, increase REZ productivity, and enhance REZ cost recovery. However, while optimisation results show gains across all REZ transmission line rating scenarios are positive, they are marginal and decreasing with line rating capacity. This is illustrated in Fig.15.

Figure 15: REZ productivity – impact of line ratings and batteries



Within the REZ Optimisation Model, 4h batteries dominated iterations, with optimal battery capacity trending towards 400-575MW as Fig.15 highlights. Batteries had the effect of increasing REZ productivity by ~3.3-5.3%. Larger gains were extracted through pursuing real-time line ratings rather than storage per se, with the shift from static to seasonal line ratings (+5.7%), and from seasonal to real-time line ratings (+44.2%). Of course, line ratings and storage are not mutually exclusive and therefore both are beneficial. Fig.16 overlays the iteration results for the battery cases relevant to the non-battery cases.

Figure 16: REZ energy (GWh) with battery storage



It is to be noted that oversized batteries inside a REZ reverse these results (see Simshauser, 2025). Specifically, oversized batteries compete with wind and solar output for REZ transmission line access, and increase curtailment rates, which in turn limits their bankability and reduces the generation fleet capacity to pay.

4.5 Sensitivities

Results presented thus far were reliant on the assumed entry costs of wind, solar and batteries, the transmission infrastructure, and market prices. What happens when costs and prices vary? Altering these results within the REZ Model reveals the following:

1. As the cost of transmission infrastructure rises, REZ user charges rise which in turn adversely impacts the ‘capacity to pay’ constraint. Comparison of Scenario 3 (Section 4.3) against Scenario 1 (Section 4.1) shows the impact of rising transmission costs. Recall from Scenario 1 (Table 4) that binding capacity to pay constraints meant that REZ user charges produced a $9.9m per annum shortfall. This shortfall was eliminated through real-time line ratings by introducing a greater pool of connecting generators. If transmission costs rose even faster, a shortfall may re-emerge. Potential policy solutions for welfare maximising scenarios are examined in Section 5.

2. The cost and profitability of wind and solar in our Model were reliant on the quality of the weather resource in which they were located, and of the prevailing market prices. Using single year data to drive optimisation results would invariably lead to biased outcomes. Consequently, our modelling was purposefully solved over multiple (i.e. 7½) years to capture variations inherent in weather and market prices, chronologically matched at hourly resolution. Indeed, with respect to wind and solar generation, weather patterns exhibited a combination of high resource, low resource and mixed resource years. And our period of analysis spanned an entire energy market business cycle which included high price years, low price years, and years resembling long run equilibrium. These variations have been captured in the full result set for each transmission line rating scenario (i.e. static, seasonal, real time line ratings) and have been presented in Appendix IV. Close examination of Appendix IV reveals significant variation in prices, production and profits across calendar years.

3. Finally, we re-ran the REZ Model to examine the impact of material variations to generator costs. To generalise, if prices are held constant and generator costs fall, their profitability rises (and capacity to pay REZ user charges rises). Conversely, if market-wide generator costs fall, then prices would also fall and the capacity to pay constraint remains constant.

   The crucial sensitivity for the purposes of robustness testing is to examine *differential changes* in technology costs under real-time line ratings (i.e. a sensitivity to Scenario 4 in Section 4.4). Furthermore, of the array of variables that could be tested, the most critical is a rise in wind costs, and sharply falling costs of solar and battery storage. What would this mean for the REZ?

   To examine this scenario, we increased the entry cost of wind (+5%) which approaches the limits of wind profitability given prevailing prices, and lowered the entry cost of solar (-20%) and the marginal cost of incremental storage (-50%). Intuitively, this would suggest the optimal mix of wind, solar and battery storage would change in related directions.

   However, there was virtually no change in the optimal plant mix. Prima facie, this seems counterintuitive. But a closer inspection of results reveals that: (1). REZ user charges are dominated by wind generators as a class – representing over 85% of the capacity to pay, and of Shapley Values, (2). As a result, in all simulation scenarios wind tends to be prioritised with solar 'filling in the gaps' to the limits of its bankable curtailment rates, and (3) consistent with the results in Simshauser (2025), adding more battery storage tends to cannibalise marginal wind generation, thus reducing the aggregate capacity to pay.

   Since solar is already at its limits vis-à-vis bankable curtailment rates, adding more solar due to falling costs violates Eq.(6). Consequently, the model holds solar PV largely constant, and profits rise (holding market prices constant).

4. Finally, at what point does the REZ break-even on a merchant basis? For the Shapley Values to be met (i.e. leaving no residual REZ user charge shortfall), ~2800MW of wind represented is required to be connected – meaning at this point the REZ becomes a commercial proposition.

5. Policy implications

The analysis presented in this article demonstrated the gains from altering REZ line transfer capacity, from static, to seasonal and finally, to real-time ratings. Adding battery storage enhanced REZ productivity. But by comparison to line ratings, gains from batteries were marginal and diminishing in nature. Historically, establishing real-time transmission 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 investment. It is to be noted that not all transmission lines are thermally constrained – often other constraints emerge (e.g. voltage stability limits, transient stability limits etc). However, where lines are thermally constrained, real-time ratings offer great potential at a very low marginal cost of investment.

In prior research in the Australian context, REZ user charges was based on a simplified output metric. 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 the role of solar in the energy transition is crucial. To that end, when a mix of renewables, battery storage, line rating methodologies and the Shapley Value method was deployed to identify an efficient, fair and defendable set of user charges for connecting project financed plant, the merchant REZ appeared bankable. Importantly, a capacity to pay limit, reflective of conditions in the Australian market, constrained REZ user charges to reasonable levels.

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 will be upward sloping supply curve for REZs in all markets. As distances rise and as costs increase, user charges rise making financial tractability of REZs more difficult to navigate on a merchant basis.

In the present exercise, static line rating 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 real-time ratings were introduced that the capacity to pay problem could be navigated. And, one of the critical insights from Section 4 was the central role of wind in underwriting REZs – with both the capacity to pay and the Shapley Values for this asset class accounting for >85% of the total. Sensitivity testing revealed at least 2800MW of wind was an important threshold from a capacity-to-pay perspective.

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, and wind was constrained below 2800MW? Would this be fatal for a merchant REZ? The short answer is, on a purely merchant (i.e. commercial) basis, yes – it would prove fatal.

However, other policy options exist that may migrate the merchant REZ to a semi-merchant model if, and only if, the overall portfolio of projects is welfare enhancing at the whole-of-system level (hence the inclusion of the welfare analyses, in Tables 5 and 7). These policy options include:

1. Concessional finance can be deployed against the REZ 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. This was in fact the method of debt finance used in the first REZ in Queensland (for details, see Simshauser, 2021)

2. Allocating some component of the REZ's initial capital cost to the Transmission Regulatory Asset Base (thus recovered from end-use consumers) similarly has the effect of reducing subsequent user charges to the connecting renewable generators. Specifically, where a residual transmission cost may exist (e.g. as was the case in Scenario 2, see Table 6, line 14), and the overall program of transmission and renewable investments are otherwise thought to be beneficial (e.g. Scenario 2, Table 5), partial asset allocation to the Regulatory Asset Base provides a suitable pathway.

Finally, is the matter of renewable project entry timing. In each of the scenarios outlined in Section 4, renewable projects were assumed to enter 'simultaneously'. In practice, 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. How then is the REZ itself bankable?

If early entrants are sufficiently large, and subsequent entrants sufficiently advanced, a risk-neutral benevolent transmission planner may find a corporate financing tractable (as was the case with the first three REZs in Queensland). If not, transient allocation of the REZ asset to the Transmission Regulatory Asset Base provides a suitable pathway to deal with uncertainty over renewable project entry timing. It is to be noted that 100% allocation to the Regulatory Asset Base forms the default policy for cost recovery in most other jurisdictions.

6. Conclusion

REZs 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. A merchant REZ 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 small, investment commitment is comparatively straight forward with user charges being trivial and not disrupting the flow of primary investment into project financed wind and solar entrants. However, as REZ distances extend further from a transmission backbone and capital costs rise, user charges may start to impinge on the capacity of renewable generators to pay. Maximising the renewable hosting capacity of a REZ is therefore an important means by which to navigate crucial bankability constraints. Other policy options exist to deal with any residual cost.

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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: PPF Model Logic

In the PPF 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'[7] 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.

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

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

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

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

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 (τ_c) 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:

$$I_j^i = DT_j^i \times \left(R_{Tj}^z + C_{Tj}^z \right)$$
(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[8] (δ_j^{VI}) and (ω_j^{VI}) 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:

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

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%

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:

[8] 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.

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

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:

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

Appendix III: Cost Sharing Model (Shapley Value)

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., $v: 2^N\ \rightarrow\ \mathbb{R}$, 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,

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

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:

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

Appendix IV: 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

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