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EPRG Working Paper 2022

Cambridge Working Paper in Economics 2077

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Keywords electricity planning, transmission capacity, geographic and technological diversification, mean-variance portfolio theory (MPT)

JEL Classification Q48; L98; G11; Q42; C60

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Publication August 2020
Financial Support TransGrid

www.eprg.group.cam.ac.uk

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Keywords: Australia, electricity planning, geographic diversification, technological diversification, competition and complementarities, wind, solar, transmission capacity, mean-variance portfolio theory (MPT)

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* Financial support from TransGrid is fully acknowledged.

Disclaimer: *This paper represents the opinions of the authors and is the product of academic research. It is not intended to represent the position or opinions of TransGrid, nor of any of its staff members.*

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1. Introduction

In responding to the enormity of the challenge of climate change, there are numerous approaches to decarbonisation that might be adopted. Making decisions on the combination and timing of deploying these options is a daunting prospect for many decision-makers. Even if there is agreement that a combination of approaches will be required, there is a need to establish the basis on which such a portfolio approach might be pursued.

The power sector can act as a linchpin in decarbonisation since, aside from existing end uses, a low-carbon electricity sector is an essential first step in decarbonising passenger transport and even domestic and industrial heat. In order to achieve the 1.5 °C aim established in the Paris Agreement, annual CO_2 emission from the energy sector needs to be reduced by over 70% from 34 Gt CO_2 today to 9.8 Gt CO_2 in 2050, of which three-quarters of the reduction can be achieved via the electrification of heating and transport as well as switching to renewable energy sources, RES, (IRENA 2019). Moreover, electrification continues to outpace growth in energy overall. In 2018, global electricity demand rose by 4% (900 TWh), almost twice as fast as overall energy demand. While low-carbon sources (RES and nuclear) met over half (54%) of this growth, the remaining 46% of the gap was filled by coal and gas, resulting in a 2.5% *increase* in power sector emissions. Although RES has been growing steadily since 2003 by around 7% annually (Ritchie and Roser, 2020), only 26% of the 26.7 PWh of total electricity generated globally in 2018 came from RES, of which 7% came from the variable renewable energy (VRE) sources wind and solar, and 19% from hydro and other controllable renewables, 64% of the electricity still came from burning fossil fuels and the remaining 10% from nuclear energy (IEA 2019).

The challenge for the power sector is not simply adding some renewables to the system to raise the share from, say, 10% to 30%, but to fundamentally shift towards one dominated by VRE. There are many ultra-low carbon systems that are almost completely reliant on traditional renewable sources such as hydroelectric power (e.g., Norway, Iceland, Quebec, Tasmania) or nuclear power (e.g., France), but expansion of hydropower is location-specific and nuclear power is not viable on social or economic grounds in many locations. So, for many countries, the main prospect for establishing a low-carbon power grid will require dramatically increasing the share of VRE onto a system that has traditionally relied on fossil fuels.

One country that has seen rapid growth in VRE in recent years has been Australia, where RES hit a record high of 21.3% of the total electricity generation in 2018, up from 14.9% in 2013 (Clean Energy Council 2019). While hydro remains the largest single RES in Australia, accounting for 35.2% of renewable generation in 2018, it made up over half (55%) of renewable generation as recently as 2013. The main new entrants are *variable* renewables, onshore wind and in particular solar (of all scales), which saw their shares increasing from 27% and 11% respectively in 2013 to 33.5% and 24.2% in 2018. Nevertheless, this transition towards VRE is not uniform across the country and the picture differs massively from state to state, due to the vastly different geography and climate across Australia as well as financial and regulatory support at the state level. For instance, South Australia is the national leader in VRE with 50.5% of total electricity generation coming from wind and solar in 2018, but in Queensland this figure is merely 5.6%.

Although Australia is set to surpass its large-scale federal Renewable Energy Target of 33 TWh (ca. 23.5% of total generation) by 2020, electricity generation remains the biggest source of greenhouse gas emissions in Australia, responsible for 178.5MtCO_{2-e} or 33.1% of total emissions, although this was down from 182.4MtCO_{2-e} the year before (DEE 2019). Under the Paris Agreement, the federal government in Australia committed to reducing GHG emissions by 26-28% relative to 2005 levels by 2030 (441MtCO_2-e) (UNFCCC, 2015). The states and territories have moved even more aggressively – all have assumed net zero greenhouse gas emissions targets by 2050 and all have also set aggressive renewable targets (e.g., net 100% renewable generation in South Australia by the 2030s and 50% renewables by 2030 in Victoria and Queensland, although the latter is not binding) (Climate Council, 2019).

As Australia shifts increasingly towards clean energy, finding an optimal generation mix consisting of non-dispatchable and highly volatile VRE is not the only challenge. The transmission network also needs to be able to keep pace with the changing patterns of electricity flow induced by VRE. For example, South Australia has a high penetration of variable renewables with 50.5% of electricity already coming from wind and solar; in the third quarter of 2018, total curtailment of non-synchronous generation in South Australia, which (comprises of large-scale wind and solar farms) reached a record high of 150 GWh, which is equivalent to 10% of the state's total non-synchronous generation in that period when curtailment occurred 26% of the time (AEMO 2018). The cause of this massive curtailment was primarily that there were insufficient synchronous generators available to meet the system strength requirements. In order to make the most of growing VRE penetration, such transmission bottlenecks must be avoided. Thus, our primary objective here is to understand the role of electricity transmission in integrating a high share of VRE in Australia's National Electricity Market[1] (NEM) using a Mean-Variance Portfolio Theory (MPT) approach. The rest of this paper is organised as follows: the next section tries to put the MPT approach in the context of the wider literature on long-term energy investment planning; in §3, we present the mathematical formulations of the different objectives and §4 presents scenarios and sensitivity analyses we plan to conduct. The results and optimal solutions for each case are then presented in §5, where their implications are also analysed. We finally conclude in §6 and summarise the value of the current transmission constraints for each case.

2. Mean-Variance Portfolio Theory and Energy Investment Planning

Electric utility resource planning is a complex optimisation problem which requires economic, engineering and environmental insights. Since such decisions involve significant investments with far-reaching impacts, a range of optimisation methods have been developed over the years to address different attributes of the problem, from generation cost to system reliability and environmental externalities. Following the liberalisation of many electricity markets and the expansion of VRE, optimisation models are becoming increasingly complex and sophisticated in response to the growing *uncertainty*.

Hobbs (1995) reviewed some of the early endeavours to solve the optimal scheduling of additional generation capacity combined with demand side management in a decentralised electricity market using mixed integer linear programming (MILP), or dynamic programming (DP) when uncertainty was incorporated into the model. More recently, various approaches have been proposed to tackle specifically the uncertainty brought by the deployment of wind power, an intermittent and non-

1 The NEM, the largest power system in Australia, covers the eastern states of Queensland, New South Wales, and Victoria, as well as South Australia, the island state of Tasmania and the Australian Capital Territory (ACT). The NEM has a total generation capacity of over 54 GW and supplies approximately 200 TWh of electricity every year to 9 million business and residential household customers through 40,000 km of transmission and distribution lines (AEMO, 2018).

dispatchable energy source. For a comprehensive review of recent studies of generation capacity expansion problems see e.g., Koltsaklis et al. (2018) and with a particular focus on high VRE penetration, see Dagoumas et al. (2019).

As VRE output fluctuates greatly, most existing networks will have insufficient transmission capacity to utilise VRE in large quantities and hence transmission and interconnections across large distances could be valuable in accommodating more VRE. For example, van der Weijde and Hobbs (2012) emphasised the importance of uncertainty in transmission planning with high share of VRE and introduced a two-stage stochastic optimisation model formulated as a MILP to capture the multi-stage nature of transmission planning under uncertainty, which could yield more robust and adaptive expansion solutions than conventional, one-period deterministic planning methods. Following a similar research framework, Munoz et al. (2013) developed this two-stage stochastic optimisation framework further by explicitly including Kirchhoff's voltage law in their problem formulation. The resulting model was applied to a 240-bus system representing the Western Electricity Coordinating Council in the United States. They concluded that heuristic- and deterministic-based transmission scenario planning could be suboptimal compared to a stochastic two-stage optimisation model. Other relevant studies on transmission planning under uncertainty include Park and Baldick (2013) and Konstantelos and Strbac (2014) as well as work on co-optimisation of transmission and generation capacity expansion by O'Neill et al. (2013), Grimm et al., (2016), Spyrou et al. (2017), Chao and Wilson (2020). For a comprehensive literature review on the topic of transmission and generation expansion see e.g., work by Lumbreras and Ramos (2016), and by Krishnan et al. (2016).

Despite many advantages of these frameworks, such as detailed representation of the electricity sector, these frameworks treat *uncertainty* as another dependent variable or parameter in the model rather than an *objective*. Mean-variance portfolio theory (MPT) is a well-established analytical approach that can treat both risk and cost of the VRE deployment simultaneously on equal footing in the optimisation. Pioneered by Markowitz (1952), MPT was originally designed to solve the optimal investment portfolio problem for risk-averse investors. It provides a mathematical framework to construct optimal portfolios of assets which offer the highest expected return at given levels of risk; together these optimal portfolios make up the "efficient frontier". The theory also establishes a rigorous formalisation of investment diversification and risk hedging, and it shows that higher risk is an intrinsic aspect of higher return. Since its publication in 1952, the powerful framework has found many applications outside finance, including in the energy sector, where it was first adopted by Bar-Lev and Katz (1976) to carry out a cost-risk analysis for different mixes of fossil fuels.

MPT is now a widely adopted method to solve energy planning investment problems, covering many different scenarios and generation technologies under a range of different objectives. An extensive review of the literature on energy planning using MPT can be found in (deLlano-Paz et al. 2017); past studies fall broadly into two main categories depending on whether the objectives are based on economic or electricity production criteria.

Within the wider context of economic criteria, one may still tackle the problem either from a cost minimisation or return maximisation perspective. Doherty et al. (2005; 2006), applied the cost-risk approach to analyse the optimal future generation portfolios in Ireland, considering the capital, operation and maintenance costs as well as fuel costs. In addition, Doherty et al. (2005) argued that, following Stirling (1994), since long-term fuel price dynamics follow no clear pattern, diversification is really a response to ignorance rather than to any quantifiable risk. Thus, the authors considered also the maximisation of the diversity as measured by the Shannon-Wiener index, alongside the conventional risk minimisation objective where the risk is represented by the standard deviation of the cost of electricity produced.

Awerbuch and Yang (2007) carried out a cost-risk analysis of electricity generating portfolios in the EU with the focus on uncertain CO_2 prices. Krey and Zweifel (2008) applied seemingly unrelated regression estimation (SURE) to filter out any common shocks in the costs before conducting cost-risk analysis for the US and Switzerland.

There are also multiple methods to evaluate the returns; one way is to treat the returns as the inverse of generation cost, which was the view taken in Humphreys and McClain (1998), and later in Awerbuch and Berger (2003) where RES was first included. As for the corresponding risk, Awerbuch and Berger (2003) characterised RES (except biomass) as risk-free assets in the portfolio since they incur no fuel cost or emission levy and are therefore free from any commodity price volatility. Arnesano et al. (2012), however, associated the economic risk of RES with the availability of wind or solar radiation "fuel'. Alternatively, returns could be evaluated based on the net present value (NPV) of each generation asset as in Roques et al. (2008) and Westner and Madlener (2010), or the internal rate of return (IRR) as in Muñoz et al. (2009). Liu and Wu (2007) opted to define the rate of return to be simply the difference between the spot price and generation cost divided by the generation cost itself, which was adopted by Gökgöz and Atmaca (2012; 2017) in their studies of the Turkish market.

The application of MPT to energy planning from the perspective of generation output was first introduced in Roques et al. (2010), where the optimal wind power deployment in five European countries was analysed and the effect of geographical diversification on smoothing out the fluctuations in the overall output was investigated by taking advantage of the weak or negative correlation in the weather pattern between different locations spread across large distances. Their objectives were to maximise the wind generation output per unit of installed capacity (capacity factor) and to minimise the associated uncertainty from the variation in the output. Subsequently, Rombauts et al. (2011) adopted the same idea but refined the calculation for the risk so that the effect of cross-border transmission capacity constraints could be considered more explicitly as an objective and not merely treated as constraints.

Thus, we can see that the application of the MPT approach to long-term energy planning has proliferated. Moreover, we should note that, in fact, the MPT approach is closely associated with multicriteria optimisation framework and that competing objectives in transmission and generation investment planning could be treated explicitly in the multicriteria analysis (see e.g., review by Lumbreras and Ramos (2016)). In this regard, the application of the MPT approach to long-term energy investment planning and the resulting "efficient frontiers" sits well within the general modelling literature on multicriteria energy investment planning.

In this paper, we apply the MPT framework to investigate the optimal wind and solar deployment in the NEM. We contribute to the MPT energy planning literature in several ways. First, we incorporate solar into the optimal portfolios on top of wind; thus, we will be examining technological diversification as well as geographical diversification. The potential benefit of technological diversification can already be seen from the heatmap in Figure *1*. For example, we can see from the heatmap that building wind generation in three regions (SWQ, NNS and CQ) seems to be a no-regrets decision to hedge against uncertainties of potential massive rollout of solar generation in all 16 NEM zones, provided there is transmission capacity available. Including solar in the MPT approach has interesting methodological challenges including how best to model the trade-off between technological diversification, the relatively low average capacity factor (zero output at night), and the mismatch between peak load and peak solar generation hours, which we discuss in the next section. Our second contribution is on the empirical side: as far as we are aware, there have been limited applications of the MPT approach to the Australian context for both wind and solar generation. Thirdly, it is a timely intervention that could potentially contribute to the energy policy debate in Australia, in particular, shedding light on the value of geographical and technological diversification in the context of Australia's coordinated generation and transmission planning market re-design policy process (see e.g., Australia's Energy Security Board review of Post 2025 Market Design for the National Electricity Market (COAG Energy Council, 2019).

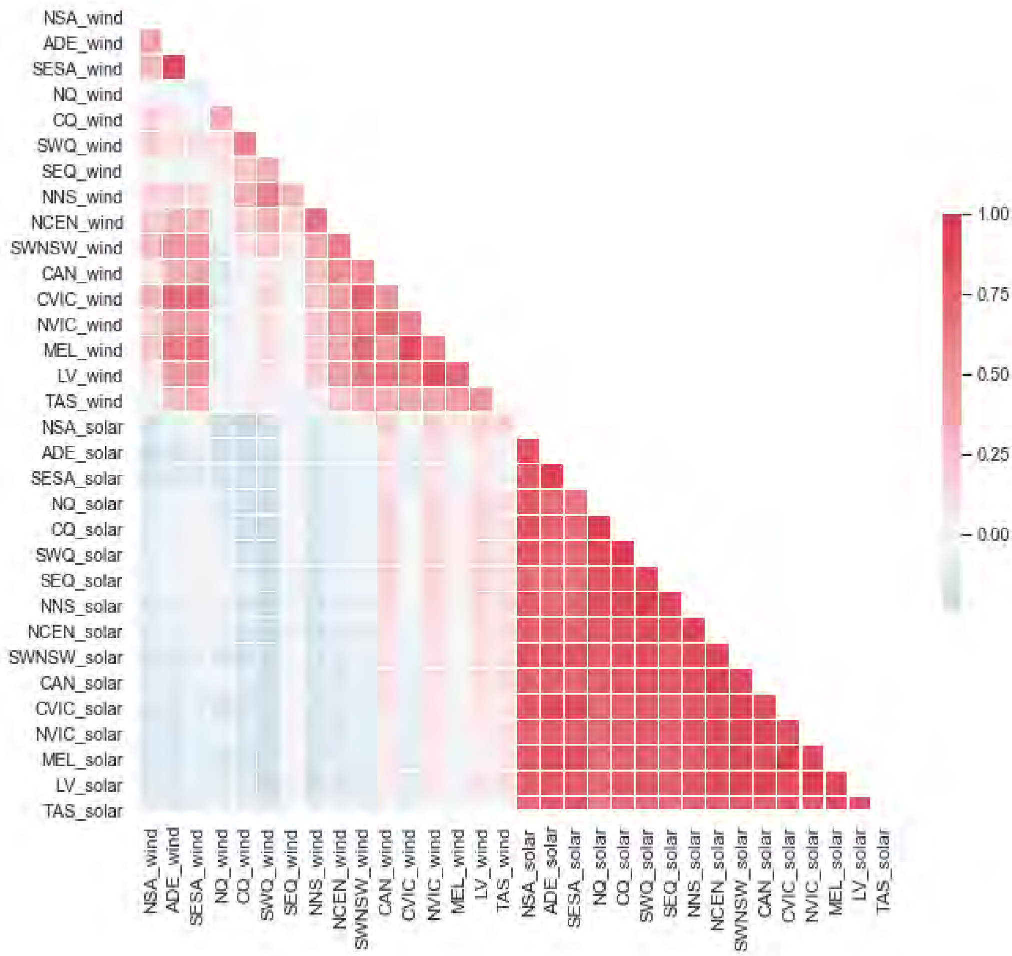

Figure 1: Heatmap summarising the correlations between different zone-tech pairs during daytime.
Notes: The blue coloured zone-tech pairs are negatively correlated and are therefore preferable in reducing the overall risk (variability) of the portfolio.

3. Mathematical formulation

In this section we first present a formulation that maximises energy output from wind and solar as our starting point and then we move to describe our proposed approach that models solar generation in the MPT approach robustly.

As the NEM is made up of 16 zones across five market regions (Figure *2*), labelled by z= 1, …, 16, there are 32 *zone-techs* in our portfolios, labelled by i. Unless otherwise stated, the indices 1-16 are assigned to wind (w) and 17-32 to solar (s) for each zone-tech i. The time series data we need to carry out our analysis are the generation output for each zone-tech $p_{i,t}$ and the demand for each zone $d_{z,t}$, where t labels time in hourly step. In addition, we need the export limit for each zone to calculate the upper bounds for the constrained scenario (see §4 for more details). Limited by data availability, we use 19 years of estimated wind and solar generation data as well as 9.5 years of demand data in this paper. The sources of raw data as well as the methodology for processing them are discussed in detail in Appendix A. All our analysis is carried out with *dimensionless* quantities. For instance, the output from each generation source is expressed in terms of its capacity factor rather than the absolute power as measured in Watts or megawatts. This allows us to scale up to any total (or partial) installed capacity required in NEM. Therefore, for the output maximisation approach (see this and the next section, §3.1), all our results are reported in terms of average capacity factors (averaged both over time and between wind and solar) that could be optimally achieved for every level of portfolio risk we consider. For the residual demand minimisation approach, all results are reported in terms of the minimum cost of meeting NEM demand that could be achieved for every level of portfolio risk we consider (for more details see §3.2).

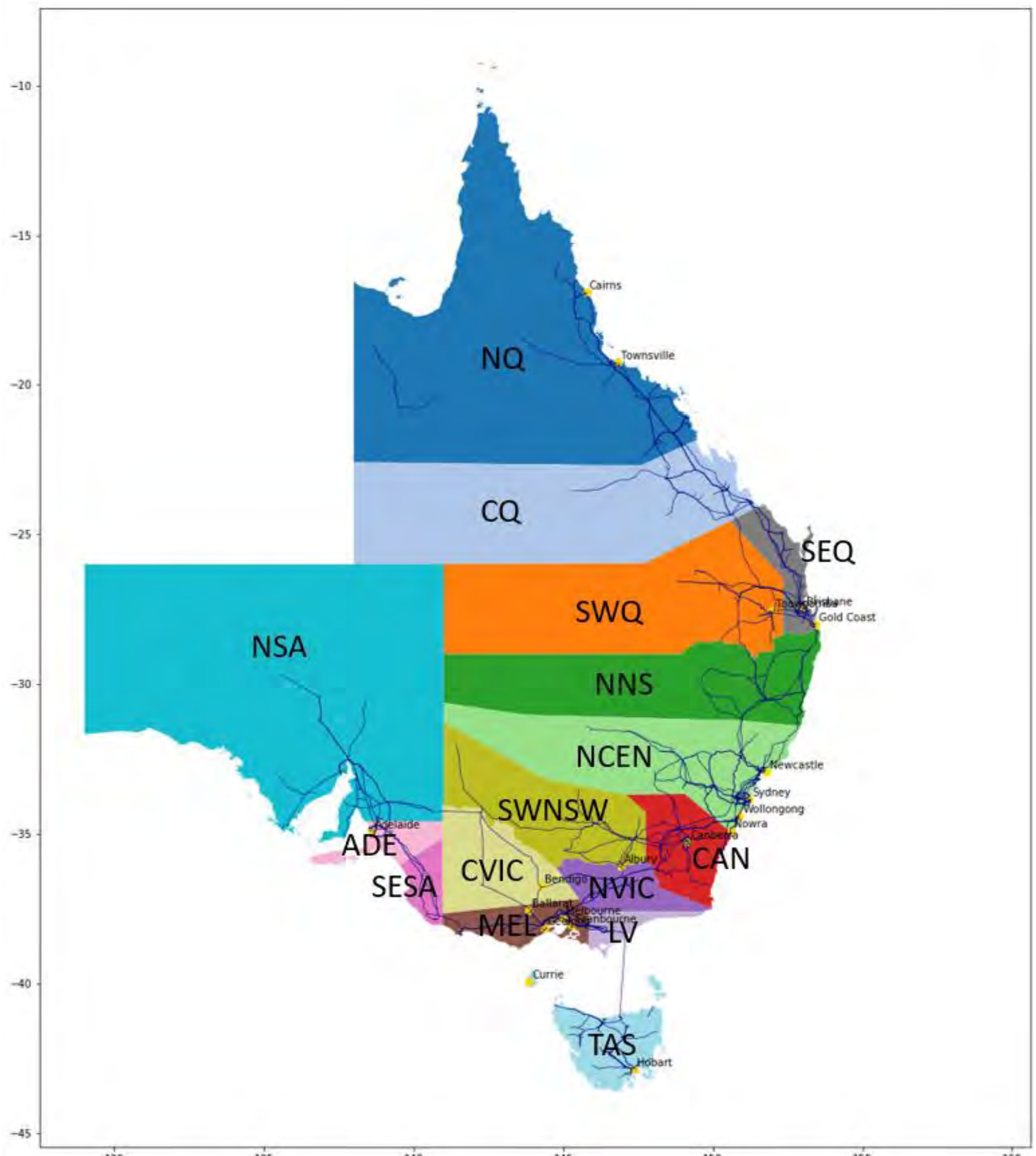

Figure 2: NEM zones and transmission network

Before we move on, let us reflect on the definition of *risk*. Risk in energy planning arises from *uncertainty*. For intermittent wind and solar power output, there are two sources of uncertainty: variability and unpredictability. For example, Roques et al. (2010) presented two different objectives: the first was to maximise the *average* wind power output for the entire year, and the second was to maximise the contribution of wind power to system reliability by considering the average for only the top 10% of *peak demand hours*. The measure of risk also differed for the two objectives. For the average output, it was taken to be the standard deviation of the first difference in the output time series, whereas for the top 10% peak hours output, it was the standard deviation of the output samples. Clearly, the latter is a measure of the average *variability* of the output, and the former can be interpreted as the average *unpredictability* of the output if we treat wind generation as a stationary autoregressive process of order 1 (AR(1)). For long-term renewable generation investment, we believe that it is the *variability* that matters most; whereas for other tasks such as day-ahead scheduling and unit commitment decisions, *unpredictability* is more relevant. Hence, we will be focussing on the *variability* risk in this paper, but we provide sensitivity analysis for the case when risk is treated as *unpredictability*.

Following the Roques et al. (2010) framework for output maximisation, the objectives of output maximisation and minimisation of the associated risk can be written as:

$$\max_{X_P^i} Ep(p) := \sum_{i=1}^{N} X_p^i E(p_i) \tag{1}$$

$$\min_{X_P^i} \sigma_P^2\,(p) := \sum_{i,j=1}^{N} X_P^i X_p^j p_{ij} \sigma_i\, \sigma_j = \sum_{i,j=1}^{N} X_P^i X_p^j Cov(p_i\,, p_j) \tag{2}$$

Subject to (3)

$$\sum_{i=1}^{N} X_p^i = 1, \qquad 0 \leq X_P^i \leq 1$$

where $N = 16$ here, the subscript $_P$ denotes the portfolio P, $E(p_i)$ is the expected wind power output of zone i which is the time average of the time series $\{p_{i,t}\}$, σ_i is the corresponding risk, and X_P^i is the decision variable which is the optimal share of wind installed capacity of zone i in portfolio P. Since X_P^i is a weight, X_P^i must be between 0 and 1 and the X_P^i's must sum to unity. One may think of a portfolio P as defined by the set $\{X_P^i\}$. As we are taking the variability as the risk, we simply have $\sigma_i = \sigma(p_i) = std\big(\{p_{i,t}\}\big)$.

Since solar only generates electricity during the day, in general, it has a lower *average* output per unit of installed capacity, making it less favourable in the output maximisation objective compared to wind. However, solar generation could potentially contribute by supplementing wind when wind is not generating (technological diversification). To better reflect these trade-offs, we propose two separate refinements to the MPT framework.

The first modification is to split the problem into day and night and treat them independently, with both wind and solar available during the day and wind only at night. This leads to the absence of cross terms involving solar and night-wind in the risk objective, analogous to the zero cross-border transmission case in Rombauts et al. (2011) where there are no cross terms between different countries. The second proposal is to look at the minimisation of the *residual demand* rather than maximising the output. Minimising the residual demand will better reflect the potential interplay between VRE output and electricity load; for example, due to the potential coincidence of solar generation with system peak hour demand (on a hot day electricity demand might be high because of cooling load but so is solar generation). We discuss those two refinements in turn below.

3.1. Incorporating solar

A row indexed by time step t in the time series data table is classified as "night" if the solar output in all 16 zones are zero, and "day" otherwise. However, as the number of solar PV panels and wind turbines cannot change from day to night, the decision variables X_i must be same regardless of the time of the day, so both problems must share the common X_i. The average output in this case is therefore the weighted mean of the day and night outputs

$$E_p(p) = \alpha^d E_P^d(p) + \alpha^n E_P^n(p) \tag{4}$$

$$E_p(p) = \alpha^d \sum_{i \in w,s} X_P^i \, E(p_i^d) + \alpha^n \sum_{i \in w} X_P^i E(p_i^n) \tag{5}$$

where the superscripts d and n denote day and night respectively, α^d and α^n are the proportions of day and night observations which sum to one, and the expectation values $E_P^d(p)$ and $E_P^n(p)$ are defined by eq. (1) accordingly, with $E_P^d(p)$ summing over all wind and solar generations and $E_P^n(p)$ summing over wind generations only. It is easy to see that eq. (5) reduces exactly to the same expression in eq. (1) except now $N = 32$, hence there is no need for computational purposes to separate day and night, and the output maximisation objective is just the same as in eq. (1) before. Note that due to the common X_P^i's, we have the linear $max(E_P(p)) = \alpha^d max\left(E_P^d(p)\right) + \alpha^n max(E_P^n(p))$, thus in practice there is no difference between maximising $E_P(p)$ and maximising $E_P^d(p)$ and $E_P^n(p)$ separately under the constraint ${X_P^i}^d = {X_P^i}^n = X_P^i$ and then taking the weighted sum, therefore the day and night problems can still be seen as separate problems.

By treating the expected output as the *weighted mean* of day and night outputs eq. (4), the portfolio risk is then the weighted covariance of the day and night samples, namely

$$\sigma_P^2 = \alpha^d \sigma_P^{d2} + \alpha^n \sigma_P^{n2} \tag{6}$$

$$\sigma_P^2 = \alpha^d \sum_{i,j \in w,s} X_P^i \, X_P^j p_{ij}^d \sigma_i^d \sigma_j^d + \alpha^n \sum_{k,l \in w} X_P^k \, X_P^l p_{kl}^n \sigma_k^n \sigma_l^n \tag{7}$$

$$\sigma_P^2 = \sum_{i,j \in w,s} X_P^i X_P^j (\alpha^d p_{ij}^d \sigma_i^d \sigma_j^d + \alpha^n (p^n \oplus 0)_{ij} \sigma_i^n \sigma_j^n \tag{8}$$

where σ_i^d and σ_i^n are the standard deviations of the day and night outputs for zone-tech i. The factorisation in the last equality is just for computational convenience, with $\oplus$ denoting algebraic direct sum and **0** denoting the 16×16 0-matrix and $\sigma_i^n = 0 \forall i \in s$ by construction. There is no cross term between solar and wind at night. Note that this is *not* the same as regarding the day and night output as independent random variables, in which case α^d and α^n should also be squared in the risk objective eq. (8). Taking the linear weight ensures that, when the portfolio consists of only one wind zone-tech, we estimate the portfolio risk as the standard deviation of the output of that zone-tech. Taking the squared weight on the other hand would result in a smaller portfolio risk in such case.

3.2. Minimising residual demand

Since we are working dimensionlessly for the ease of up-scaling, in order to compute the residual demand, we need to first convert the total NEM demand into a dimensionless quantity analogous to the capacity factor. This can be done by dividing the hourly demand by the highest value it assumes, which we shall call "demand factor" d_t (without the z label, this refers to the total NEM demand summed over all 16 zones). The *residual demand* for zone-tech i at any time t is then defined to be

$$r_{i,t} = d_t - p_{i,t} \tag{9}$$

By taking the difference directly between the demand factor and the capacity factor, we are implicitly making the assumption that they share the same *base*. In other words, we are assuming that the installed capacity is equal to the absolute peak demand (in MW). This is not a bad assumption as the residual demand $r_{i,t}$ would then tell us exactly how closely the output of zone-tech i matches with the demand in the time series, as if *all* of the NEM demand could be supplied *solely* by i. Thus, if there were a magic technology I whose output matches the demand exactly i.e. $r_{I,t} = 0\forall t$, then the optimal solution would just be 100% investment in I. $r_{i,t}$ is negative when the output of i is greater than the demand. Since storage is not included in our model, we interpret negative residual demand as curtailment. Although not as costly as backup generation to fill residual demand, curtailment still incurs a cost as lost investment and should therefore be suppressed in the objective too. In order to penalise positive and negative deviations from the demand with different weights, we define a *mismatch cost* or *deviation cost* $\tilde{r}_{i,t}$ as a function of the residual $r_{i,t}$ by

$$\tilde{r}_{i,t} \coloneqq \theta\left(r_{i,t}\right) + \alpha \cdot \theta\left(-r_{i,t}\right) \tag{10}$$

where θ is the Heaviside step function and $\alpha < 1$ is the cost of curtailment relative to the cost of peak generation. In Australia, open cycle gas turbines (OCGT) are the most commonly used flexible generation technology to support the increasing penetration of VRE. According to Graham et al. (2018), the levelised cost of electricity (LCOE) for OCGT is estimated to be A$175/MWh, versus A$55/MWh for wind and solar; this means $\alpha = 55/175$. As $\tilde{r}_{i,t}$ is again unitless and strictly between 0 and 1 by definition, it really represents a normalised cost. The linear objective is then the minimisation of the expected cost of not matching the demand, i.e.,

$$\min_{X_P^i} E_P(\tilde{r}) \coloneqq \sum_{i=1}^{N} X_P^i E(\tilde{r}_i) \tag{11}$$

where $E(\tilde{r}_i) := (1/T)\sum_{t=1}^{T} \tilde{r}_{i,t}$ is just the time average of the deviation cost.

On the other hand, generation pairs with negatively correlated residuals should be favoured as they can complement each other to bring down the overall residual. This is rewarded in the quadratic objective

$$\min_{X_P^i} \sigma_p^2(r) \coloneqq \sum_{i,j=1}^{N} X_P^i X_P^j Cov(r_i, r_j) \tag{12}$$

$$= \sum_{i,j=1}^{N} X_P^i X_P^j p_{ij} \sigma_i \sigma_j \tag{13}$$

Note that this is computed from the residual r rather than the mismatch cost $\tilde{r}$. Both objectives eq. (11) and eq. (13) are subject to the usual unity constraint as described in eq. (3). In order to see that $\sigma_i = std(r_i)$ can be interpreted as risk, recall that here we are essentially using wind and solar as non-dispatchable generation and OCGT for the remaining load. Thus, the variation in the residual demand from wind and solar poses an uncertainty on determining how much OCGT capacity is needed.

3.3. Solution algorithm

We can find the efficient frontier for each case by following the same procedure: first we find the extremal points on the efficient frontier corresponding to the solutions of the linear and quadratic objectives separately, and then we solve for the sample points in between by solving the quadratic objective while holding the values of the linear objective fixed. More explicitly, using the output maximisation objective as an example, the efficient frontier is plotted by performing algorithm 1.

Algorithm 1: Finding the efficient frontier

Step 1: Find the minimum attainable risk portfolio $\underline{\boldsymbol{P}}$

$$\min_{X_{\underline{P}}^i} \sigma_{\underline{P}}^2 = \sum_{i,j=1}^{N} X_{\underline{P}}^i X_{\underline{P}}^j p_{ij} \sigma_i \sigma_j$$

subject to $\sum_i^N X_{\underline{P}}^i = 1$

return $X_{\underline{P}}^i, E_{\underline{P}}(p), \sigma_{\underline{P}}$

Step 2: Find the maximum attainable output portfolio $\overline{\boldsymbol{P}}$

$$\max_{X_{\overline{P}}^i} E_{\overline{P}}(p) \coloneqq \sum_{i=1}^{N} X_{\overline{P}}^i E(p_i)$$

subject to $\sum_i^N X_{\overline{P}}^i = 1$

return $X_{\overline{P}}^i, E_{\overline{P}}(p), \sigma_{\overline{P}}$

Step 3: Plot the efficient frontier with M samples

for $E_{\underline{P}}(p) < E_m(p) < E_{\overline{P}}(p), m \in \{1, \dots, M\}$ ***do***

$\min_{X_m^i} \sigma_m^2 \coloneqq \sum_{i,j=1}^{N} X_m^i X_m^j p_{ij} \sigma_i \sigma_j$

subject to $\sum_i^N X_m^i = 1$

$\sum_{i=1}^{N} X_m^i E(p_i) = E_m\,(p)$

return X_m^i, E_m, σ_m

end for

Step 2 is just a straightforward linear maximisation problem. Steps 1 and 3 on the other hand are quadratic programming problems; since only equality constraints are involved, they may also be expressed as a Lagrangian. For example, step 3 can be written as minimising the Lagrangian

$$\begin{aligned}\mathcal{L}(\mathrm{X_m^i}, \lambda_\mathrm{I}, \lambda_\mathrm{P}, \lambda_\mathrm{i}) \\ &= \sum_{\mathrm{i,j}=1}^{\mathrm{N}} \mathrm{X_m^i X_m^j Cov_{i,j}} + \lambda_\mathrm{I}\left(\sum_{\mathrm{i}}^{\mathrm{N}} \mathrm{X_m^i} - 1\right) + \lambda_\mathrm{P}\left(\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{X_m^i}\ \mathrm{E(p_i)} - \mathrm{E_m(p)}\right) \\ &+ \sum_{\mathrm{i}}^{\mathrm{N}} \lambda_\mathrm{i}\ \mathrm{X_m^i}\end{aligned} \tag{14}$$

and solved using the Euler-Lagrange method. However, since the matrix ρ need not be positive definite, they are not convex optimisations in general.

4. Sensitivity analysis

This section provides a summary of our sensitivity analysis. We first look at the impact of putting transmission constraints on efficient frontiers of wind and solar generation portfolios in the NEM regions. The inherent problem with MPT approach applied to the electricity capacity planning is the peak hour representation – MPT averages the whole time series of analysis thus smoothing out all peaks and troughs. To see the importance of peak hour dynamics we look at only top 10% of peak hours load. Lastly, we test sensitivity of results with respect to the definition of risk.

In §3.2, we considered a hypothetical situation where an ideal energy source would receive all investment to serve all demand in the market. In fact, it is easy to see that the solution to eq. (1) is just $X_P^I = 1$ and $X_P^{i \neq I} = 0$ for the single (assuming there is no degeneracy) zone-tech I whose average output $E(p_I)$ is the highest. This solution is just one of the endpoints of the efficient frontier. However, even if putting all the eggs in one basket can be mathematically justified, technically it is impossible to realise, because the transmission network has limited capacity. Therefore, to be realistic, we impose upper bounds on the X_P^i's so that the total wind and solar share of each zone in the portfolio cannot exceed the maximum level at which it can consume and export, which can be expressed by

$$X_P^{z_w} + X_P^{z_s} \leq \overline{X}_z := \frac{max\ demand\ in\ z\ (MW)\ +\ export\ limit\ in\ z\ (MW)}{max\ demand\ in\ NEM\ (MW)} \tag{15}$$

$\forall z \in$ {zones}. Using this definition, the maximum portfolio share for each of the 16 zones is summarised in Table A. *1*, Appendix A.

While the peak demand can be found straightforwardly from the data, we are not aware of any sources for the export limits. We therefore estimate them from the network edge and electrical property data in Xenophon and Hill (2018). Details of the calculation are given in Appendix A.

As noted above, to test the sensitivity of results with respect to potential smoothing out of time series, we follow the same procedure as described in Roques et al. (2010) and take the top 10% of NEM demand samples from the time series. We repeat the approach adopted in §3.1 and §3.2 with these top 10% samples and compare the results.

Lastly, although we argued that the risk should be measured by the variability of the linear objective in the context of the optimal VRE generation mix, for completeness we also compare the results of §3.1 and §3.2 with when the risk is taken to represent the unpredictability. This definition of risk, i.e. $\sigma_i = \sigma(\Delta p_i) = std(\{p_{i,t} - p_{i,t-1}\})$, was also studied in Holttinen (2005) and Holttinen et al. (2008), where its effect on system operation and the planning for operational reserve was investigated. Only wind power has been considered along this line in the literature; however whereas wind power can be treated as a *stationary* AR(1) process, solar output is highly periodic due to the rotation of the earth, hence the non-stationary modularity must be subtracted away first and the hourly difference is then taken from the stationary residuals.

Table *1* summarises the five different cases we investigate in this study, for the three different objectives. Both the transmission capacity constrained (applying eq. 15) and unconstrained scenarios (neglecting eq. 15) are analysed in all cases. 19 years (2000-2018) of wind and solar output data are used for the first two objectives/scenarios; however, the analysis on the residual demand uses only 9.5 years of data because demand data was only available for that period (Jul 2009-Dec 2018).

Table 1:Scenarios considered in this paper

	objective	base case	top 10% peak load	unpredictability
1.	wind output	1	-	-
2.	wind + solar output	2	-	-
3.	residual demand	3	4	5

For our analysis, we are interested in:

1. Comparing results from cases 1 and 2 to quantify the impact of including solar in our portfolio analysis.
2. Comparing cases 2 and 3 to test how sensitive our results are with respect to the formulation of objectives functions; in particular, how minimising the residual demand might impact optimal share of solar compared to when we looked at purely output maximisation.
3. Comparing cases 3 and 4 to test how sensitive our results are if we analyse only peak hours.
4. Comparing cases 3 and 5 to test how sensitive our results are to different definition of risks.

In the next section we report our main results and discuss them.

5. Analysis and results

5.1. Quantifying the value of technological diversification of solar

One of the key objectives of this research was to quantify the impacts of adding solar to the portfolio of wind and how this might further increase the share of wind for the same level of risk, for example; that is, what are technological synergies between solar and wind resources across large distances of the NEM? This section discusses findings in relation to this question.

Figure 3 shows the effect of incorporating solar in the absence of transmission constraints. It clearly shows that technological diversification helps further reduce the risk by lowering the average variability in the aggregate output.

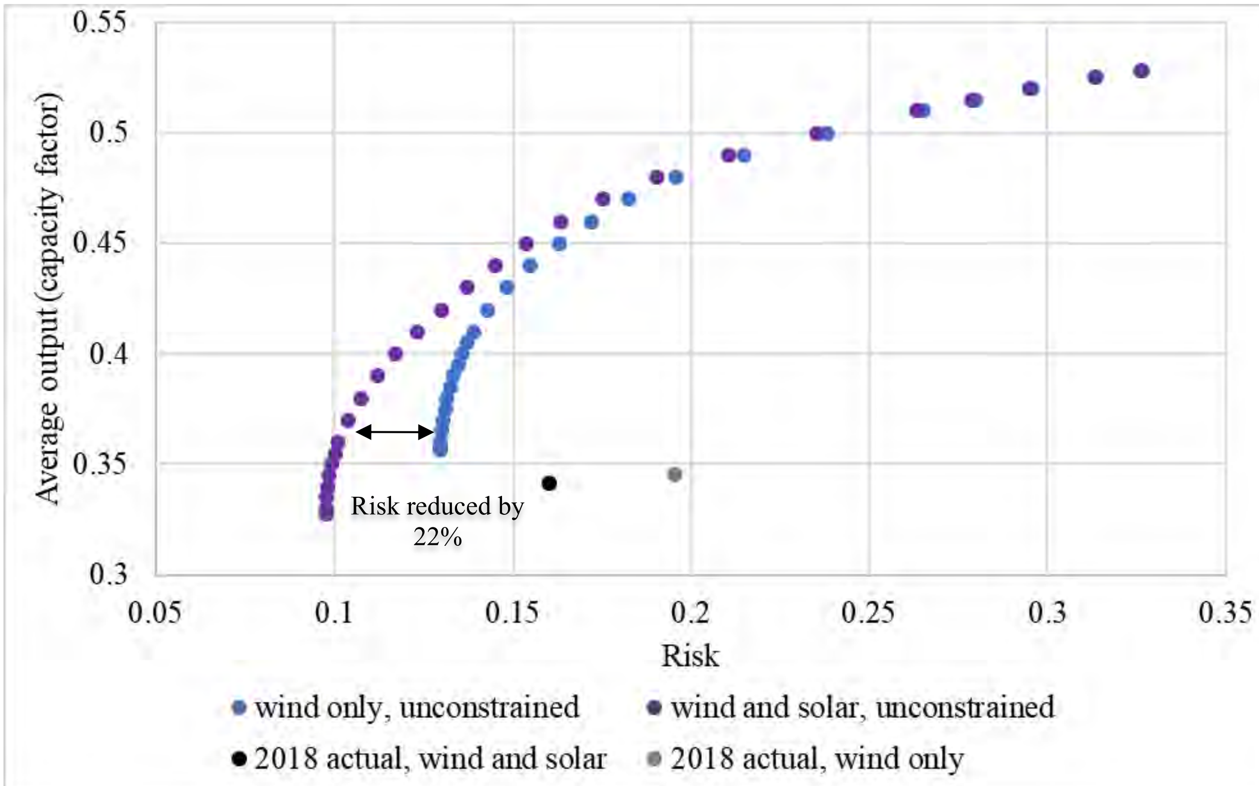

Figure 3: Comparison of the efficient frontiers for wind plus solar generation versus wind generation only

The minimum risk can be reduced by a further 22% by incorporating solar generation into the portfolio. Alternatively, for the same level of risk (e.g., at 13%) including solar could increase combined average capacity factor by 7 p.p.. We should note that as SESA wind remains the zone-tech with the highest average output, both efficient frontiers also converge towards 100% SESA wind. Figure 4 shows the optimal composition of wind and solar for portfolios along the efficient frontier. Because, on average, solar outputs only about half of what wind does, solar generation is not favoured in the output maximisation objective. This explains the low shares of solar in Figure 4. In fact, solar generation is not present in the optimal solutions beyond a risk level of around 0.15 (portfolios with capacity factors higher than 0.440). Despite their importance in further risk hedging, solar generation retains a low share in all the efficient portfolios, and they are not even included in the high output and risk solutions, because the low average output is not favourable in the output maximisation objective. Thus, by including solar the average capacity factor across all 27 portfolios[2] is reduced by 1 p.p. while the average risks of those 27 portfolios is reduced by 1.7 p.p.

2 We have chosen 27 portfolios for the purposes of obtaining relatively smooth efficient frontier curves. We could have chosen even more portfolios, which would result in even smoother efficient frontier curves than reported here or fewer portfolios, which would result in the efficient frontier curves being less granular and more like step functions.

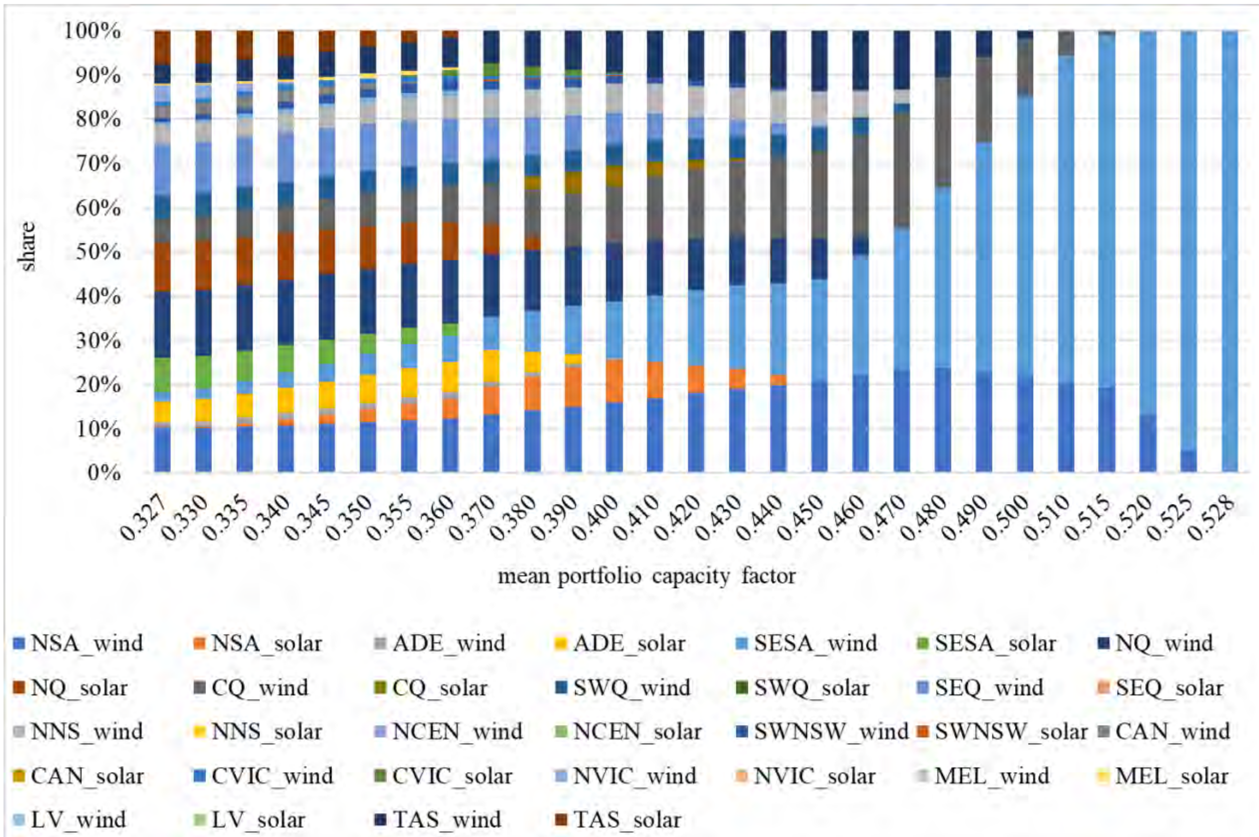

Figure 4: Efficient portfolios for wind and solar (transmission capacity is unlimited)

So far, we have assumed no transmission constraints between the Australia's NEM regions, rather, the value of geographical diversification depends on existing transmission capacity. For example, Tasmania's solar resources are negatively correlated with North Queensland's wind resources and so to monetise this geographical diversity we need transmission capacity. One way to quantify the benefits of having "unlimited" transmission capacity is to compare the above results with the one where we impose existing transmission constraints. The resulting efficient frontier is shown in blue in Figure 5 and the optimal portfolios are shown in Figure 6.

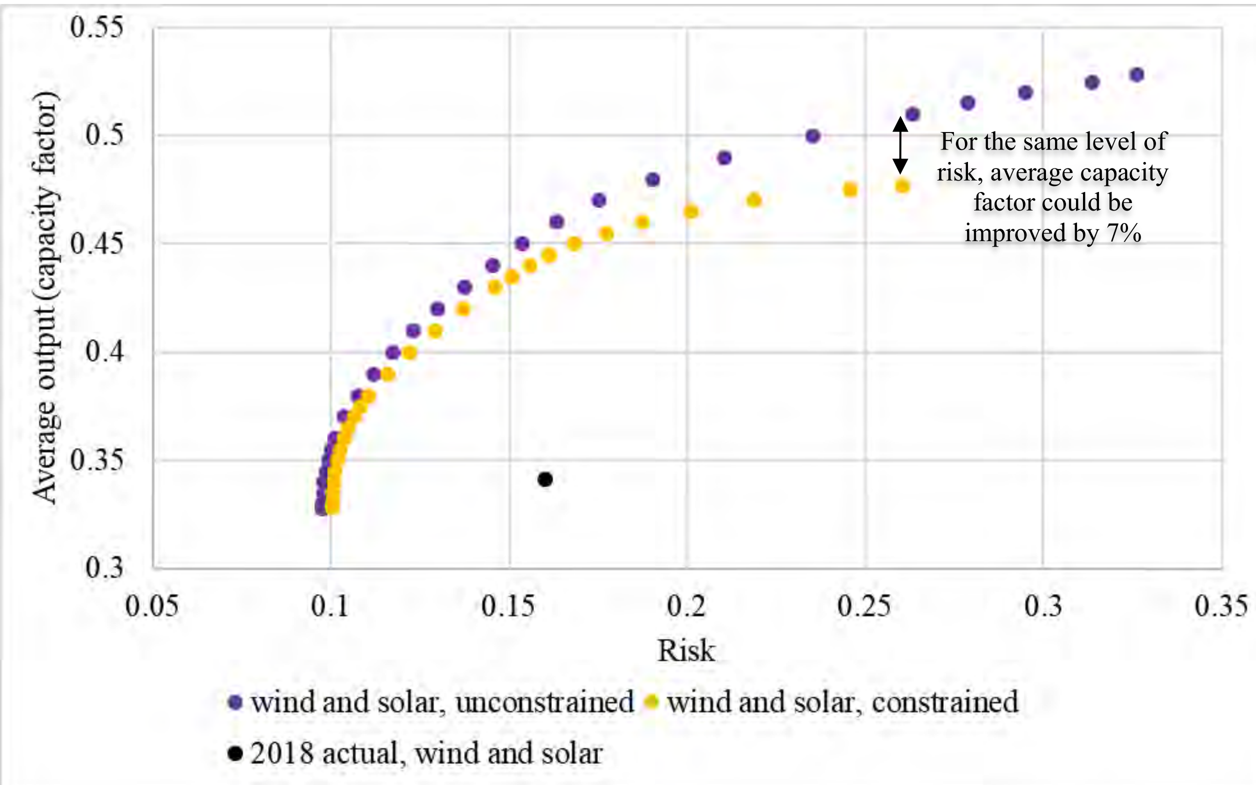

Figure 5: The efficient frontiers (wind and solar) for constrained and unconstrained transmission capacity cases

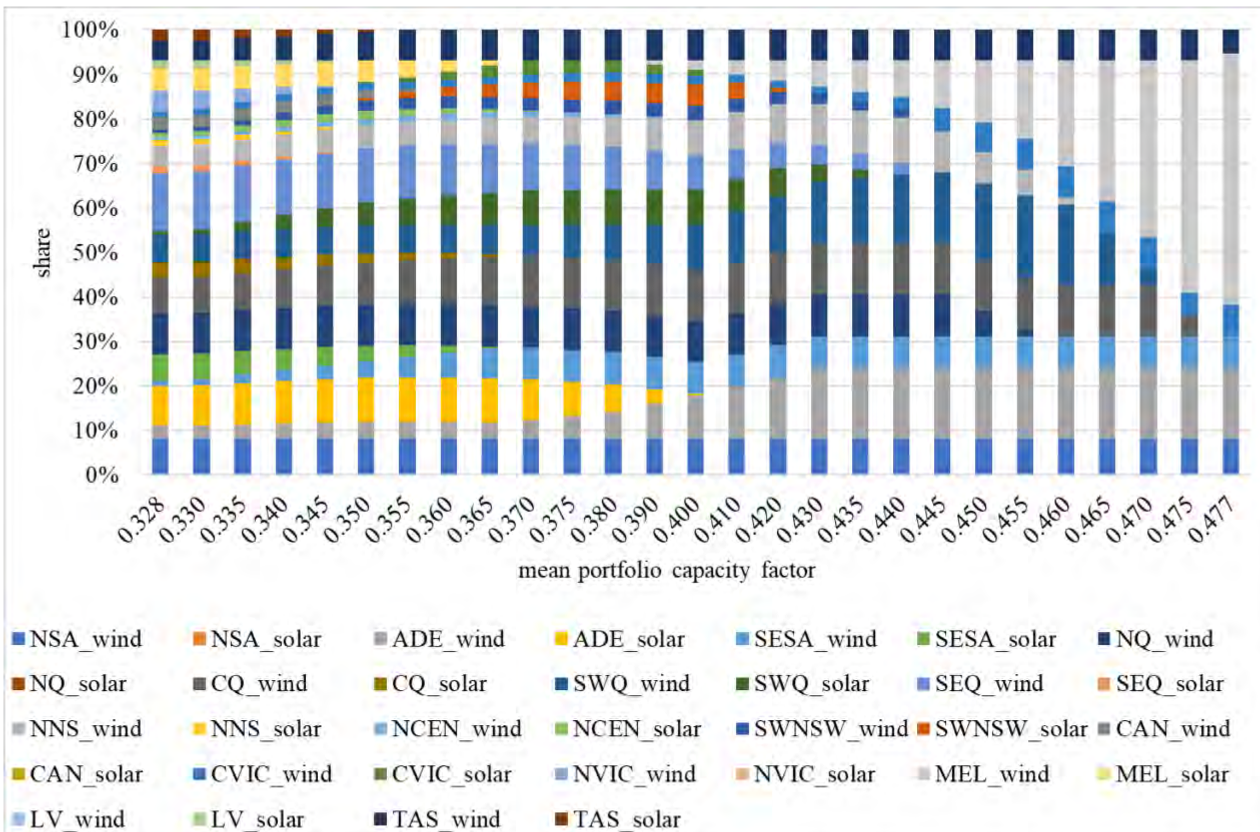

Figure 6: Efficient portfolios for wind and solar (with existing transmission capacity)

First, transmission constraints affect mostly the solutions towards the riskier end of the frontier curve. For example, we can see that for the same level of risk (at the higher end of the efficient frontier curves), average capacity factor could be improved by 3.3 p.p., or 7% higher if there was unlimited access to transmission capacity for the 16 NEM zones. The principal reason for this is that technological diversification between solar and wind is first achieved within each region (see Figure 1) before any transmission constraints become binding and then only between regions where transmission constraints limits the potential for further diversification. Secondly, it seems that existing transmission limits do limit the potential for aggressive wind and solar penetration in NEM – on average (for all 27 portfolios), transmission constraints reduce capacity factor of wind and solar by 2.1 p.p. and risks by 2 p.p. while the maximum achievable capacity factor reduces to 47% compared to an average of 50% across 7 highest portfolios[3] under unconstrained case. Lastly, comparing Figure 4 with Figure 6 we can see that, without transmission limits, investments in wind and solar are more concentrated in fewer regions while, with transmission constraints, investments are much more geographically spread out across NEM's regions. For example, under the lowest risk portfolio, investments in wind and solar are made in 28 zone-techs for the constrained case compared to 20 zone-techs under the unconstrained case.

All in all, we can see that solar and wind resources in Australia's NEM complement each other and that to facilitate their further integration we might need more transmission capacity between NEM's regions. For example, Figure 7 shows the marginal impact of transmission boundaries on the portfolio risk under the transmission constrained case. This is derived by looking at "shadow price" of each of 16 transmission constraints (eq. 15). First, one can see that not all boundaries are binding and only 7 boundaries seem to contribute to limiting risk diversification. For example, relieving the constraint in SESA (by marginally increasing its capacity relative to NEM peak hour demand) could reduce the average risk by 0.15 p.p. or by up to 0.47 p.p. for a very risky portfolio (Figure 7: "high risk portfolio").

[3] Ignoring the last portfolio (N27), which consists of 100% wind investment in SESA alone

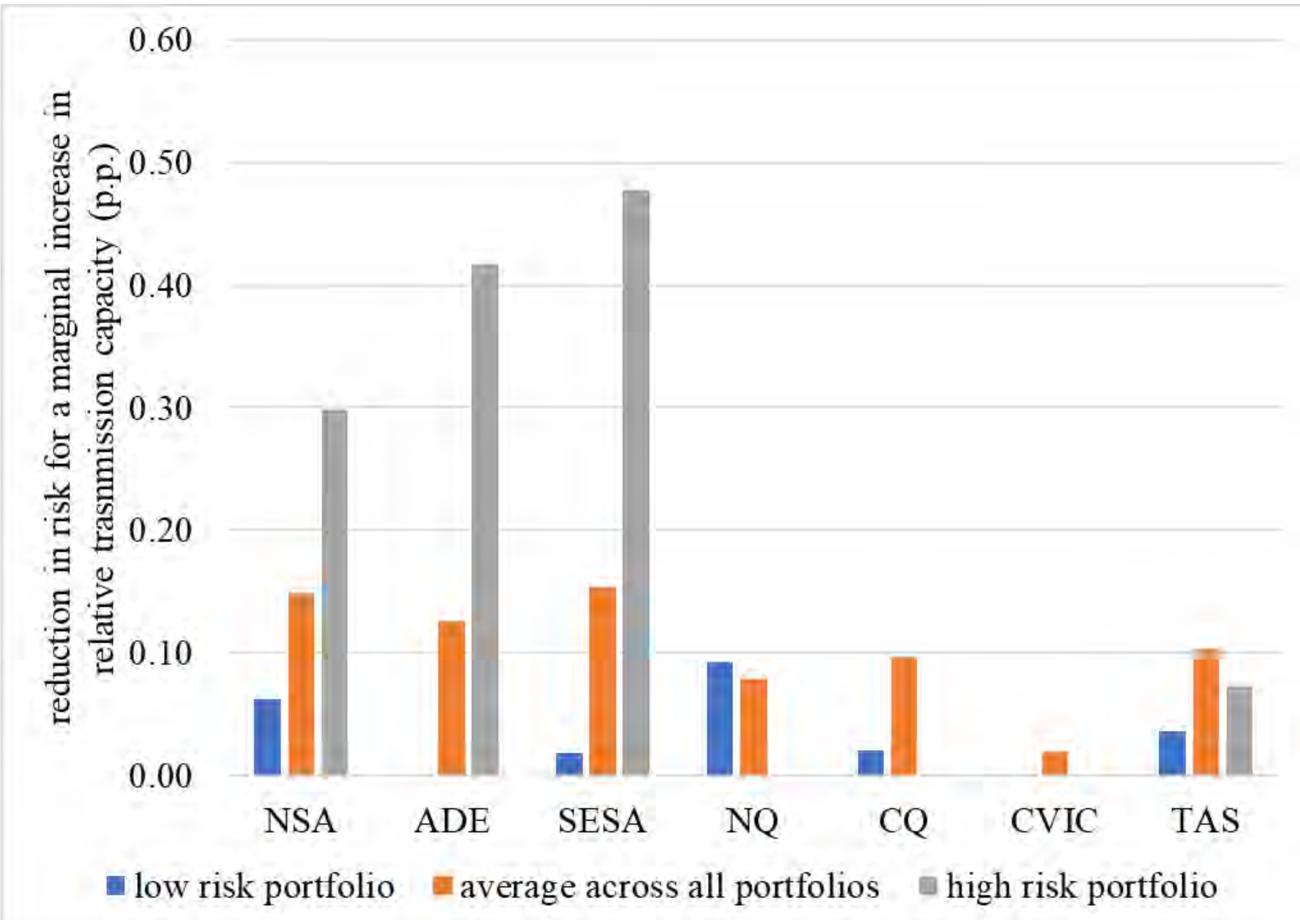

Figure 7: Marginal impact of transmission constraints on the risk of 26 portfolios[4]

Secondly, the reason that the transmission capacity of these 7 regions binds is:

(a) wind generation in these 7 zones are all negatively correlated with solar generation in all 16 NEM solar zones (as can be seen the heatmap in Figure *1*);

(b) the relative peak hour load (i.e., relative to the average NEM peak hour) in these 7 regions is relatively small (roughly 2% or less of NEM's peak hour load) except for the ADE region where the peak hour load amounts to 8% of the NEM peak hour load. This means that although there is high negative correlation between the wind resource base in these 7 zones with solar generation across the entire NEM, transmission capacity is very important for these 7 zones. If we were to invest more in wind in these 7 zones it would have two benefits – wind capacity factors are higher than those for solar but importantly it hedges against potentially aggressive solar penetration in the rest of NEM. That is, if the rest of NEM had a high share of solar in the energy mix then the wind resource base in these 7 regions would become even more important to reduce the average risk of NEM's VRE portfolios, provided transmission capacity is sufficient in those 7 zones.

If we look again at the heatmap in Figure 1 we can see that the SWQ wind resource exhibits the highest negative correlation with all 16 solar NEM zones (on average) but the capacity constraint is not binding

[4] Ignoring the last portfolio (N27), which consists of 100% wind investment in SESA alone

for SWQ simply because the zone (according to our calculations – see Appendix B) has a large transmission export capacity – ca. 6.3 GW or 17.5% of NEM's peak hour load.

Another interesting observation is that NNS wind also exhibits relatively high negative correlation with all solar generation zones in NEM (in fact, it has the third highest negative correlation after SWQ wind and CQ wind). However, the transmission constraint for NNS is also not binding – the total export capacity out of NNS is around 13% of NEM peak demand but half of that export capacity goes to SWQ and being close neighbours means that wind to wind correlation is highly positive (no hedging value). By contrast, while there is some hedging value between SWQ solar and NNS wind once again because solar has on average lower capacity factor, the MPT output maximisation approach does not favour significant solar investment.

There are other three regions where wind resource is negatively correlated with solar – SEQ, NCEN and SWNSW. Transmission capacity is not binding for SEQ and NCEN simply because these two regions have very high demand: SEQ peak demand is 20% of NEM and NCEN – 33%. This means that any wind and solar being invested in these two regions will be consumed in those regions first and only then exported outside for hedging purposes. In all our optimal portfolios both SEQ and NCEN obtain a very low share of investment in wind and solar (even for the unconstrained transmission capacity case) simply because these two regions have a very low wind resource base (they are both amongst the lowest 6 regions out 16); the average wind capacity factor is only 31% in SEQ and 39% in NCEN, which can be compared to the much higher capacity factors for wind in SESA (52%), ADE (50%), and MEL (47%). Lastly, the SWNSW transmission capacity is not binding because its rather modest wind resource base (not in the top 5 regions) means that optimal portfolios involving SWNSW wind and solar are just high enough to cover its demand and will use existing transmission capacity to export surplus of energy (if any).

So far, we used output maximisation objective and therefore the interaction between solar generation and demand might not be well represented in this objective. The next Section present results using an alternative objective function formulation – minimisation of residual demand.

5.2. Minimising residual demand

For the residual demand minimisation approach, solar plays an increased role in the optimal mixes compared to the output-maximising portfolios (compare results in columns A and B in Table A1, Appendix A). One can see that there is no difference in the results from the two different formulations for the first nine portfolios (with lower risks). As we look at portfolios with higher risks minimisation of residual demand rewards solar more compared to the output maximisation framework. Also, it is worth noting that the solar share is positive in 16 portfolios under the output maximisation framework whereas under the residual demand minimisation approach the solar share is positive in 21 portfolios. This is because the $\sigma(r_{i_s})$ are lower than the $\sigma(r_{i_w})$ and the solar generation values are negatively correlated with most wind generation, making solar energy more favourable in the risk minimisation objective. Thus, on average (across all 27 portfolios) solar share reaches 15.4% under the residual demand minimisation approach versus 12.5% under output maximisation.

The efficient frontier for the two transmission capacity cases are plotted in Figure 8. In this case, the two efficient frontiers are much closer to each other and transmission constraints seem to have rather marginal impact – on average (across all 27 portfolios) transmission constraints increase average residual demand by 1 p.p. – in other words, OCGTs are operated more when we have transmission constraints than when we do not have transmission constraints.

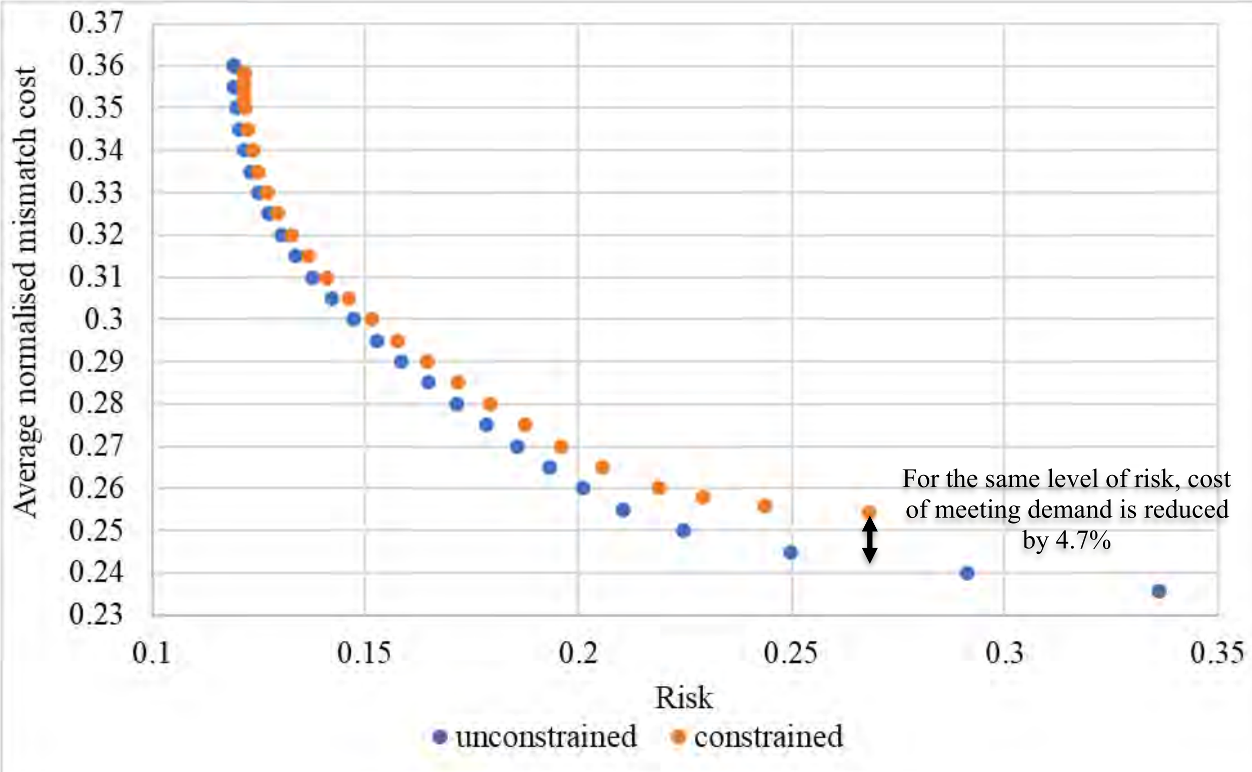

Figure 8: Efficient frontiers for constrained and unconstrained transmission capacity cases

In terms of share of wind and solar in NEM, transmission constraints have marginal impact except for the middle risk portfolio cases (portfolios 7-14, columns B in Table A1, Appendix A). It is interesting to note that when transmission constraints are imposed in the optimisation, we see a slight increase in the share of solar at the expense of wind. Again, as we noted before, this is because solar and wind are negatively correlated within each region and hence when we have transmission constraints for each region the model chooses relatively more solar to spread the risks.

We should also note that generation pairs which deviate from the demand in opposing directions are good complements to each other for an optimal generation mix because they help to minimise the cost of meeting the overall residual demand. However, this diversification potential is not fully reflected in objective (eq. 11); in fact, since we only take *time-averaged* statistics in our objectives, it is not possible to obtain an accurate measure on how well certain combinations of generations match with the demand as all temporal information is lost in taking the time average before the optimisation. Hence, we undertake a sensitivity analysis in the next section which addresses this issue (§5.3.1).

5.3. Sensitivity analysis

This section discusses the main insights from our sensitivity analysis. We have already discussed the role of transmission constraints, so this section will focus on the top 10% peak load (average over the entire time series vs averages only for the top 10% of peak load hours) and the definition of risk (variability vs unpredictability).

5.3.1. Top 10% peak load hours

The main rationale for examining this sensitivity is to understand the role of wind and solar resources in contributing to system demand peak hours in NEM, in particular, the relative role of wind and solar in meeting system peaks. Our results suggest that, unlike the output maximisation case, the peak load scenario does not increase the share of solar in the efficient portfolios (compare columns B and D in Table A1, Appendix A). This is because solar generation potentially only contributes to the morning demand peak while the evening peak (which is on average larger than the morning peak) needs to be covered by wind as there is no or little solar generation in the evening (Figure 9). Thus, solar does not contribute much to the peak hours demand and hence by just looking at those peak hours our residual demand minimisation framework favours solar less than in case where we look at the entire time series.

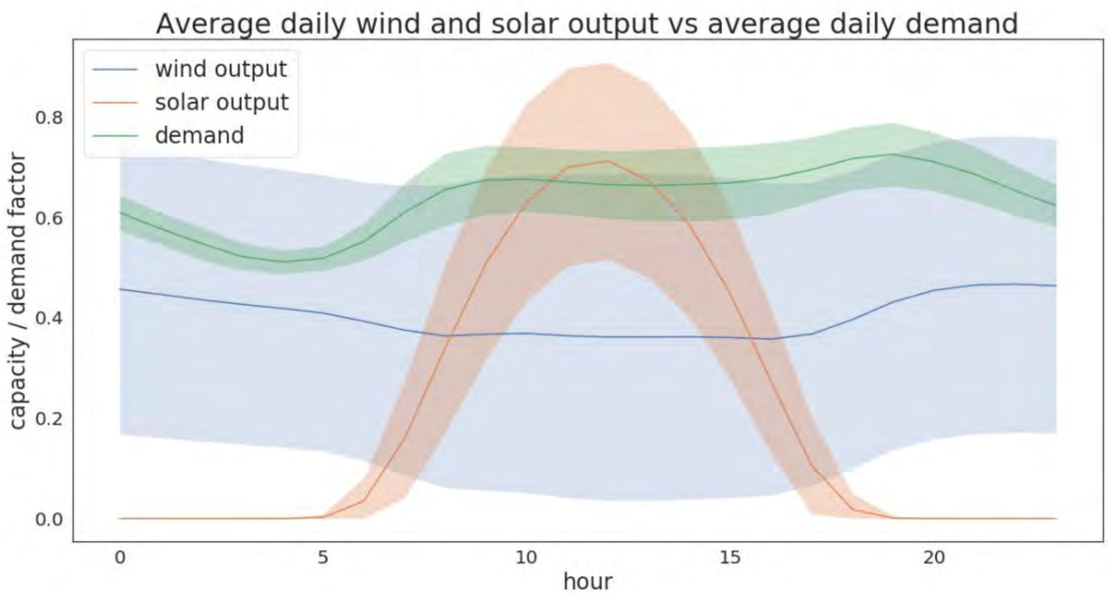

Figure 9: wind, solar and demand profile in NEM.
Note: the shaded areas represent +/- one std. dev.

The resulting efficient frontiers for both the unconstrained and constrained cases are presented in Figure 10. Here, the results do not change dramatically from those presented in Figure 8 where we used whole time series – we see that transmission constraints affect portfolios which are riskier, similar to what see in Figure 8.

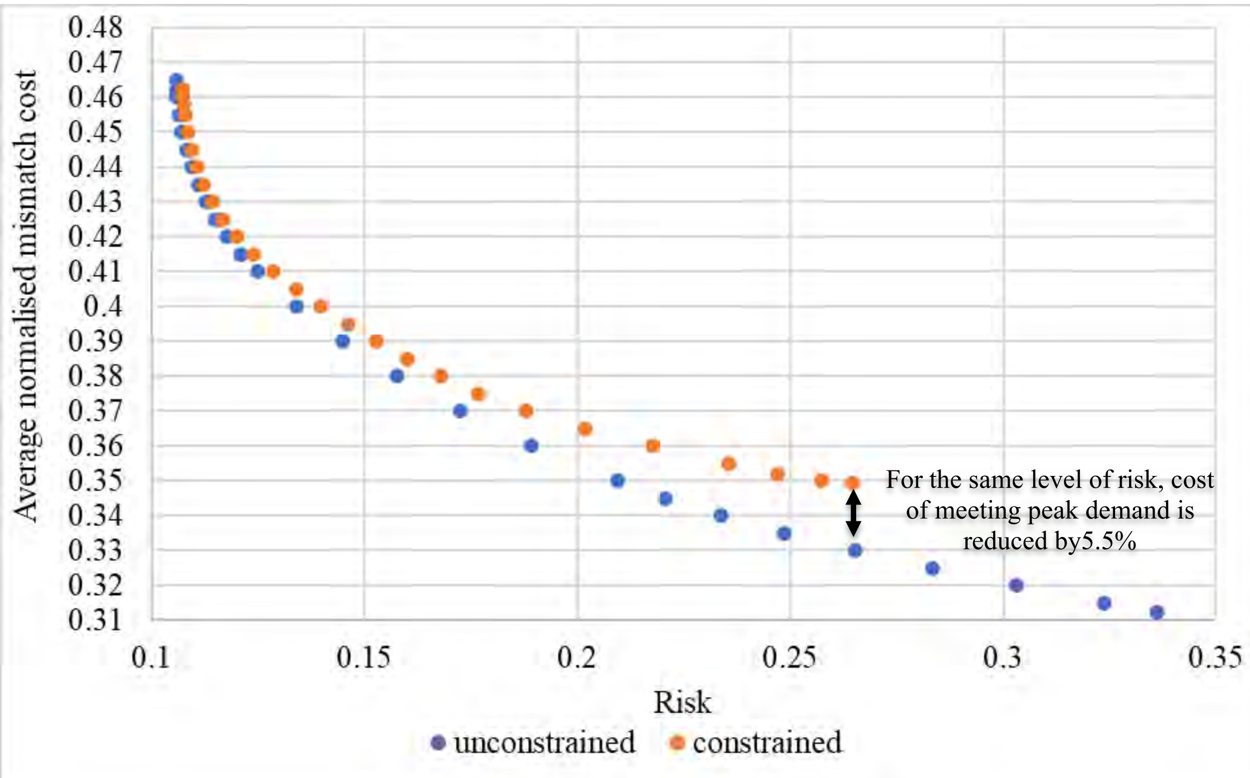

Figure 10: Constrained and unconstrained deviation cost and risk minimising efficient frontiers for the top 10% of peak load hours.

Thus, focusing on peak load instead of whole time series changed our results with respect to solar share in optimal portfolios but the impact of transmission constraints appears quite similar. In the next section, we discuss how sensitive our results are with respect to risk definition.

5.3.2. Unpredictability

For this sensitivity analysis, we simply replace the risk definition that we have used (i.e., replace the standard deviation of time series with the standard deviation of their first differences) and repeat our analysis as presented in §5.2. The optimal solutions on the efficient frontier for both the unconstrained and constrained cases are shown in Figure 11. Unlike in §5.2 where the noise around the solar output fluctuates much less than the wind output, which was modelled as pure noise, here with the demand also taken into account, solar loses this advantage over wind and so it does not get a boost in its share in the optimal portfolios (compare columns B and E in Table A1, Appendix A). On average, the share of solar reduces by a factor of two from ca. 15% down to 7.5%. Thus, it seems that the solar generation share in optimal portfolios is much more sensitive to the definition of risk than to a particular time series used to calculate mean and risks (§5.3.1).

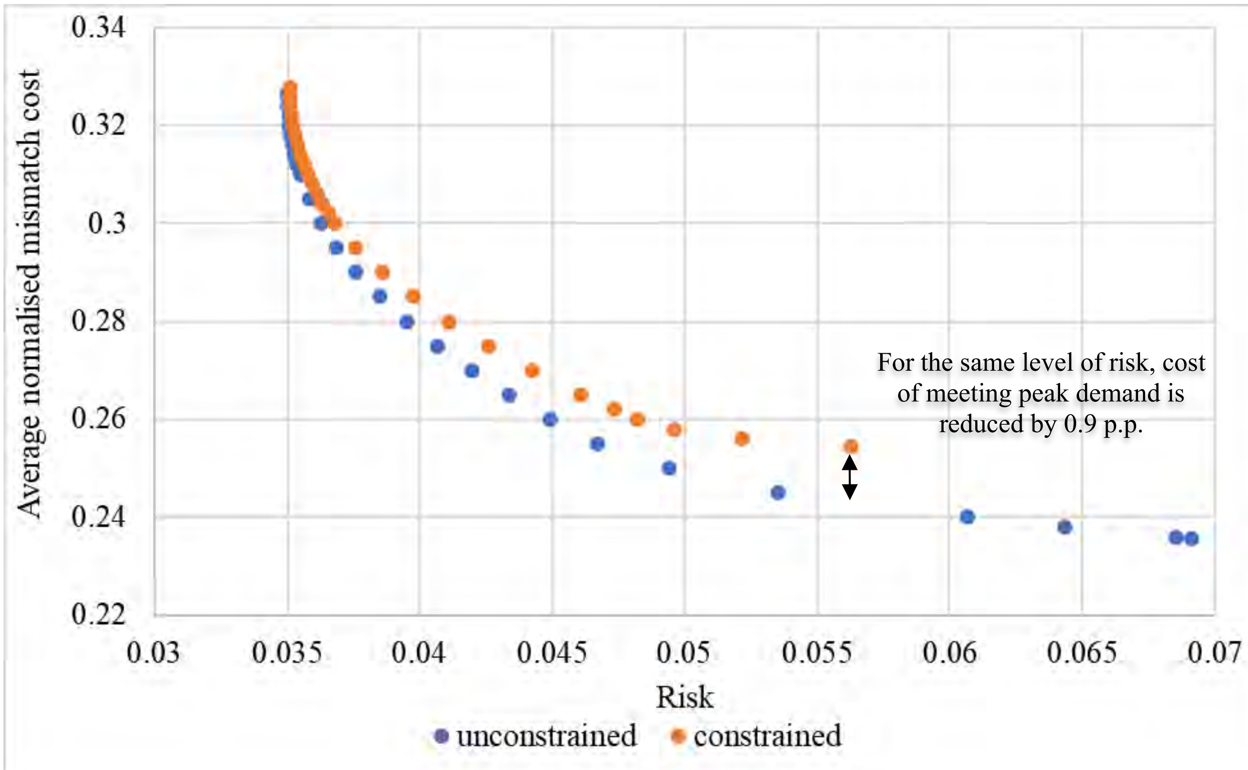

Figure 11: Efficient frontiers for constrained and unconstrained cases (risk treated as unpredictability)

5.3.3. Transmission constraints

Finally, we can calculate the value of the transmission constraints by looking at how much the unconstrained efficient frontier deviates from the constrained one in each case (as we have discussed some of findings already above). Table 2 summarises the value of transmission for different cases as a percentage increase in the expected output or decrease in the expected mismatch cost (residual demand minimisation) with the removal of transmission constraints at low, medium and high levels of risk. The first thing to note is that moving from a low-risk to a high-risk portfolio the value of transmission constraints rises. Definitions of risk and peak hour sensitivities do not seem to change the value of transmission much in the low- and medium-risk portfolios whereas in the high-risk portfolio, the value of transmission capacity is marginally reduced using the output maximisation framework but significantly increased in the residual demand minimisation framework. The main reason for this divergence seems to be that output maximisation framework penalises solar generation in the peak hour and unpredictability sensitivities (see above sections) and so wind is favoured, which enhances the value of geographical diversification but only when transmission capacity is large enough. As we noted, the value of technological diversification of solar mainly arises from hedging wind risks in the same region (hence there is less of a need for transmission capacity) and less so across regions. In this regard, solar generation's technological diversification reduces the need for more transmission capacity while transmission capacity complements wind generation.

Table 2: The value of transmission constraints*

	Objective	base case	top 10% peak load	unpredictability
Low Risk	wind output	+0.7	-	-
	wind + solar output	+0.3	+0.9	+0.9
	residual demand	-0.5	-0.5	-0.4
Medium Risk	wind output	+ 2.3	-	-
	wind + solar output	+2.5	+2.5	+2.7
	residual demand	-1.7	-1.2	-1.8
High Risk	wind output	+4.8	-	-
	wind + solar output	+6.9	+5.3	+6.4
	residual demand	-1.9	-4.3	-3.2

Note: * Value is measured by the percentage change in the expectation value of the (linear) objective when transmission constraints are removed

6. Conclusion and policy implications

This paper introduced a new method (residual demand minimisation) that can be used to analyse interactions between solar and wind generation in the MPT framework. We used this framework to investigate the optimal generation mix consisting of wind and solar at different levels of risk for Australia's National Electricity Market. We focused on the risk (uncertainty) arising from the variability rather than the unpredictability because for long term energy planning it is the overall variation around the expectation value of the linear objective that is relevant.

We first looked at the optimal generation mix that maximised the generation output with wind energy only and confirmed the risk hedging benefit of geographical diversification. We then included solar into the portfolio and showed that technological diversification further reduces the risk. Since the output maximisation framework might lose some dynamic interactions between wind and solar generation and demand, we then shifted our attention to the alternative objective of minimising the deviation of the generation output from the demand (i.e., residual demand minimisation). We defined a mismatch cost to account for the fact that the cost of backup generation (e.g., OCGT) is higher than the investment loss from the curtailment of wind or solar. Under the new objective, solar became much more favourable in the optimisation than when the objective was output maximisation, and therefore the share of solar in the optimal portfolios in NEM increased significantly. Nevertheless, the disadvantage of solar only being able to generate during the day remained and wind still dominated in the solutions. Furthermore, our sensitivity analyses suggest that the way we treat risks and the way we choose our sample of our time series (top 10% of peak load hours vs whole time series) could dramatically alter the optimal share of solar in optimal generation portfolios.

From a policy point of view, our findings suggest a number of recommendations for different stakeholder groups. To incentivise investors to integrate their generation portfolio across NEM a finer wholesale electricity price signal might be required that would then be used to link with renewable support schemes. For example, instead of the five reference price points currently in the NEM, there could be a move to a more granular locational (e.g., nodal) pricing system, at least for generators. Thus, linking revenue streams of a wind (or solar) farm to nodal wholesale electricity market prices would incentivise merchant investors to hedge locational risks and take advantage of geographical diversification. A move to finer-grained wholesale electricity prices is in line with the current discussion by Australia's Energy Security Board (COAG Energy Council, 2019), which has put forward a series of market reforms including nodal pricing, marginal loss factors applied to individual generators. Other proposed reforms include differentiating between different renewable zones and access regimes to networks[5] giving a finer-grained approach to coordinated investments in renewables and transmission assets. In this regard, even though our 16 regions only provide a crude estimation, our findings about the locational value of existing transmission boundaries, wind and solar resources base and their correlations for hedging purposes can contribute to the policy discussion around potential market redesign to minimise total system cost for the NEM as it moves towards very high shares of wind and solar.

Secondly, adopting an integrated investment planning approach where generation and transmission planning is viewed holistically could minimise system cost in the NEM – this would take advantage of our finding that wind generation and transmission capacity expansion are complements (higher wind penetration always requires more transmission so that to minimise the balancing cost of wind, or in the MPT framework, minimises risk at a chosen level of wind output) while solar generation complements

[5] For example, greenfield with shared access to transmission via a dedicated asset or access via shared transmission network vs brownfield with shared access to transmission via a dedicated asset or access via shared transmission network

wind generation at closer proximity (within the same zone). This also means that solar generation competes with transmission capacity expansion at low levels of solar penetration. But overall, with a very high wind and solar penetration in NEM, transmission capacity will be needed to minimise system risks associated with wind and solar uncertainties. Thus, while generation investment in the NEM is largely on a merchant basis and transmission investment is regulated, a careful integrated planning process that would minimise risks for generation investment is required – in this regard, our results show that in order to minimise risks of a VRE dominant generation portfolio, transmission capacity and efficient access will become very important. The lack of transmission capacity therefore implies higher risks and hence higher returns and thus potentially higher energy prices at high levels of VRE penetration.

That said, our proposed research framework does not value exactly how much transmission capacity would be optimal at every level of risk associated with each generation portfolio. Secondly, while our proposed approach looks at wind and solar (and implicitly at backup generation like OCGT and curtailment of VRE), including other emerging technologies like battery storage or even traditional generation technologies like hydro run-of-river, hydro pumped storage or combined-cycle gas turbines (CCGTs) would add value to both policy discussion around optimal transition pathways for Australia's NEM to more renewables. Modelling those technologies explicitly in the MPT approach would alter the efficient frontier and might reward solar generation more than what we currently show in our results (i.e., solar coupled with storage would make the technology almost dispatchable and hence lower its uncertainties). Adding storage might also alter our findings with regard to the extent to which existing transmission capacity is influenced by the wind resource base and its negative correlation with solar. Furthermore, our proposed approach could be applied to other jurisdictions with potentially large VRE potential but also where benefits of geographical diversity could be high (e.g,, Europe, North America, China).

Finally, our results appear quite sensitive to the choice of time series (e.g, whole time series vs sample of peak-hours only). This finding comes simply from the fact that only time-averaged statistical parameters are considered under the current conventional MPT approach; therefore, all temporal information was lost and it failed to identify generation mixes which could complement each other to reduce the deviation from the demand on an hour by hour basis. In other words, it collapses two rather distinctive stages – investment in capacity and chronological hourly dispatch – into a single framework. And so, although the MPT approach in this traditional form is versatile, it has limitations when we apply it to a large-scale power system with high VRE penetration. Thus, an integrated approach which can handle both power [MW] and energy [MWh] is required for a full analysis (see e.g., Delarue et al., 2011). Another improvement that relates to this integrated approach that would shed further light on the potential market re-design in the NEM would be to develop a DC-Optimal Power Flow network and unit commitment model of the NEM that co-optimises both dispatch and investment decisions. Using such an integrated model, it would be possible to develop efficient frontiers and explore the value of co-optimisation of renewables investment with investment in transmission assets (whether on a merchant or socialised basis). We leave all these questions and suggestions for future research.

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Appendix A: Detailed sensitivity results

	A		B		C		D		E	
Portfolio N	**wind share**	**solar share**	**wind share**	**solar share**	**wind share**	**solar share**	**wind share**	**solar share**	**wind share**	**solar share**
1	0.68	0.32	0.68	0.32	0.69	0.31	0.73	0.27	0.85	0.15
2	0.69	0.31	0.68	0.32	0.69	0.31	0.73	0.27	0.85	0.15
3	0.69	0.31	0.69	0.31	0.69	0.31	0.73	0.27	0.85	0.15
4	0.70	0.30	0.69	0.31	0.69	0.31	0.74	0.26	0.85	0.15
5	0.71	0.29	0.70	0.30	0.70	0.30	0.74	0.26	0.86	0.14
6	0.72	0.28	0.71	0.29	0.70	0.30	0.75	0.25	0.86	0.14
7	0.73	0.27	0.72	0.28	0.70	0.30	0.75	0.25	0.86	0.14
8	0.74	0.26	0.73	0.27	0.71	0.29	0.76	0.24	0.86	0.14
9	0.77	0.23	0.75	0.25	0.73	0.27	0.77	0.23	0.86	0.14
10	0.80	0.20	0.77	0.23	0.74	0.26	0.78	0.22	0.87	0.13
11	0.83	0.17	0.79	0.21	0.76	0.24	0.80	0.20	0.87	0.13
12	0.86	0.14	0.81	0.19	0.79	0.21	0.81	0.19	0.88	0.12
13	0.89	0.11	0.82	0.18	0.81	0.19	0.83	0.17	0.89	0.11
14	0.92	0.08	0.84	0.16	0.83	0.17	0.86	0.14	0.91	0.09
15	0.95	0.05	0.86	0.14	0.85	0.15	0.90	0.10	0.93	0.07
16	0.98	0.02	0.88	0.12	0.87	0.13	0.94	0.06	0.94	0.06
17	1.00	-	0.90	0.10	0.90	0.10	0.99	0.01	0.96	0.04
18	1.00	-	0.92	0.08	0.92	0.08	1.00	-	0.98	0.02
19	1.00	-	0.94	0.06	0.94	0.06	1.00	-	0.99	0.01
20	1.00	-	0.96	0.04	0.96	0.04	1.00	-	1.00	-
21	1.00	-	0.98	0.02	0.99	0.01	1.00	-	1.00	-
22	1.00	-	1.00	-	1.00	-	1.00	-	1.00	-
23	1.00	-	1.00	-	1.00	-	1.00	-	1.00	-
24	1.00	-	1.00	-	1.00	-	1.00	-	1.00	-
25	1.00	-	1.00	-	1.00	-	1.00	-	1.00	-
26	1.00	-	1.00	-	1.00	-	1.00	-	1.00	-
27	1.00	-	1.00	-	1.00	-	1.00	-	1.00	-
average	**0.87**	**0.13**	**0.85**	**0.15**	**0.84**	**0.16**	**0.88**	**0.12**	**0.92**	**0.08**

Notes: A – output maximisation methodology (see §3.1); B – residual demand minimisation methodology (see §3.2); C – residual demand minimisation with existing transmission constraints (see §4); D – residual demand minimisation with the top 10% of peak load hours and unlimited transmission capacity (see §4); E – residual demand minimisation with risk as unpredictability and unlimited transmission capacity (see §4).

Appendix B: Data sources and calculations

The mean and variance of the wind and solar capacity factors for the 16 NEM zones are calculated using 19 years (2000-2018) of processed data obtained from Pfenninger and Staffell (2016) and Staffell and Pfenninger (2016), which converts weather data from the NASA MERRA reanalysis (Rienecker et. al 2011) into wind and solar power output. It uses the *Virtual Wind Farm* model (Staffell and Pfenninger 2016) to compute the wind output from the wind speeds and the *Global Solar Energy Estimator* (Pfenninger and Staffell 2016) to compute the solar output from the solar irradiance data. In obtaining the output data, the (approximate) geographical centre of each zone is taken to be the representative point of the zone, the coordinates of the representative points can be found in Table A. *1*. We also assume that all wind turbines are the Siemens Gamesa SG 4.5 145 model with hub height 100m, and all solar PV are installed at 30 degrees tilt and 180 degree azimuth, with zero system loss and without tracking. In practice however, there will, of course, be different wind turbine technologies and vintages and solar PV with different efficiencies and some might have tracking systems thereby enabling higher capacity factors. We leave these potential improvements for future research.

Table A. 1: Coordinates of the representative points (geographical centroids) of the NEM zones.

NEM zone	Latitude	Longitude	NEM zone	Latitude	Longitude
NSA	-30	135	NCEN	-33	147.5
ADE	-36	139	SWNSW	-35	144.5
SESA	-37.5	140	CAN	-35.5	149
NQ	-18	143	CVIC	-36.5	142.5
CQ	-24	144	NVIC	-37	147.5
SWQ	-27	146	MEL	-37.5	144
SEQ	-27	152	LV	-37.5	147
NNS	-30	148	TAS	-42.5	147

The demand data from July 2009 to the end of 2018 are taken from the P5MIN_REGIONSOLUTION dataset published on the AEMO Market Data site (AEMO, 2019). We take the 'DEMAND_AND_NONSCHEDGEN' column in the data set as the gross demand and 'TOTALDEMAND' as the operational demand. The raw data captured from AEMO are recorded state by state; to disaggregate the state demand into zone demand we use the population proportion method illustrated in (Xenophon and Hill 2018). The current transmission limits between zones are also estimated using the data from (Xenophon and Hill 2018)).

From Xenophon and Hill (2018) we can obtain the following information: the end points (nodes) of the transmission lines, the line length l [km], line voltage V [kV], resistance R [Ω/km], inductance reactance X_L [Ω/km], and the line-neutral capacitance C [nF/km]. The AC frequency in Australia is 50 Hz. In the absence of other information, we use the surge impedance loading (SIL) [MW] to estimate the transmission limit in MW, where

$$SIL = \frac{V^2}{Z_c \vee}$$

with the characteristic impedance [Ω]

$$Z_c = \sqrt{\frac{R + jX_L}{j2\pi fC}},$$

and the transmission limit [MW] is obtained by multiplying the SIL with the loadability, which is empirically found to be (as calculated graphically from the empirical curve given in Gutman, Marchenko, and Dunlop (1979)

$$loadability = \begin{cases} 3 & l < 80 \\ 58.091 l^{-0.661} & 80 \leq l \leq 1000. \\ 0.5 & l > 1000 \end{cases}$$

Hence, according to this methodology to model the transmission constraint, the shorter the line, the higher the limit according to the empirical loadability curve. We have not included other equipment such as transformers in the model because we do not have enough information.

Using the definition in eq. (14) in Section 3.3, the transmission limits between the 16 operational zones in NEM were calculated (Table A.2) and the maximum portfolio share for each of the 16 zones is summarised in Table A.4.

Table A.3:Derived transmission limits between NEM's operational transmission zones

FROM	**TO**	**TRANSFER LIMIT, MW**	**TYPE**	**FROM**	**TO**	**TRANSFER LIMIT, MW**	**TYPE**
NNS	SWQ	1,700.86	['EDGE', 'AC INTERCONNECTOR']	CAN	NCEN	5,217.25	['EDGE']
NNS	SEQ	315.67	['EDGE', 'AC INTERCONNECTOR']	CAN	SWNSW	1,139.83	['EDGE']
NNS	NCEN	1,560.15	['EDGE']	ADE	SESA	757.19	['EDGE']
CQ	SWQ	508.86	['EDGE']	ADE	NSA	2,202.13	['EDGE']
CQ	SEQ	1,289.24	['EDGE']	NCEN	NNS	1,560.15	['EDGE']
CQ	NQ	1,798.93	['EDGE']	NCEN	CAN	5,217.25	['EDGE']
NVIC	SWNSW	1,273.06	['EDGE', 'AC INTERCONNECTOR']	SEQ	SWQ	3,537.06	['EDGE']
NVIC	CVIC	375.92	['EDGE']	SEQ	NNS	418.67	['EDGE', 'AC INTERCONNECTOR']
NVIC	MEL	1,253.82	['EDGE']	SEQ	CQ	1,289.24	['EDGE']
NVIC	CAN	1,407.09	['EDGE']	SWQ	NNS	2,178.86	['EDGE', 'AC INTERCONNECTOR']
CVIC	NVIC	375.92	['EDGE']	SWQ	CQ	508.86	['EDGE']
CVIC	MEL	756.13	['EDGE']	SWQ	SEQ	3,537.06	['EDGE']
CVIC	SWNSW	585.73	['EDGE', 'AC INTERCONNECTOR']	SWNSW	NVIC	1,203.70	['EDGE', 'AC INTERCONNECTOR']
CVIC	NSA	220.00	['HVDC']	SWNSW	CVIC	554.90	['EDGE', 'AC INTERCONNECTOR']

LV	MEL	7,396.29	['EDGE']	SWNSW	CAN	1,139.83	['EDGE']
LV	TAS	478.00	['HVDC']	SESA	MEL	1,658.46	['EDGE', 'AC INTERCONNECTOR']
MEL	NVIC	1,253.82	['EDGE']	SESA	ADE	757.19	['EDGE']
MEL	SESA	1,758.46	['EDGE', 'AC INTERCONNECTOR']	NQ	CQ	1,798.93	['EDGE']
MEL	CVIC	756.13	['EDGE']	NSA	ADE	2,202.13	['EDGE']
MEL	LV	7,396.29	['EDGE']	NSA	CVIC	200.00	['HVDC']
CAN	NVIC	1,407.09	['EDGE']	TAS	LV	594.00	['HVDC']

Table A.4: Maximum portfolio weight for each zone

Zone	$\overline{X}_z$
NSA	0.082
ADE	0.159
SESA	0.072
NQ	0.093
CQ	0.115
SWQ	0.194
SEQ	0.348
NNS	0.132
NCEN	0.512
SWNSW	0.098
CAN	0.253
CVIC	0.070
NVIC	0.132
MEL	0.565
LV	0.229
TAS	0.067