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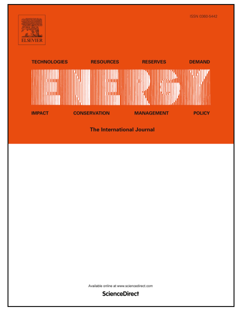

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Techno-Economic Analysis of Energy Storage Systems for Application in Wind Farms

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Abstract

The objective of this paper is to analyse reduction in wind power variability through aggregation and use of energy storage systems. A key focus is to evaluate the impact of regulatory framework in addition to the capital expenditure to ascertain techno-economic feasibility of energy storage systems in wind farm applications. A generic techno-economic is developed which takes into account the effects of regulatory framework in addition to the technical and economic features of storage options. Existing wind farms from South Australia are used as test cases. First, a detailed quantitative analysis is performed to establish the variability associated with individual wind farms and the aggregations of their power outputs. Then, the appropriateness of a number of existing energy storage types are evaluated using the developed techno-economic model. Relationships between wind farm sizes, wind farm variability levels, storage capacity requirements, storage costs and storage payback times are determined and discussed for both current and potential future economic and regulatory scenarios. It is found that regulatory framework can be of paramount importance in ascertaining the economic feasibility of energy storage. For example, if the ramp-rate violation penalty (determined to be \$8.89/MW/min) is doubled, then the payback time of energy storage capital investment is found to reduce from 5.32 years to 2.52 years. It is also found that larger wind farms require smaller energy storage capacity and smaller wind farms generally results in a shorter energy storage system payback times.

Keywords: Wind power smoothing, aggregation, storage

1 Introduction

The need for concerted global efforts for decarbonising electricity generation is well recognised. These efforts include setting up of mandatory renewable energy targets and providing incentives for investment in renewable generation. Among various renewable generation options, the wind and solar generation are widely recognised as the key components of future power systems [1]. Wind power generation is estimated to be 40% of all new renewable generation installations from 2013 to 2038 [2]. In China, the wind is predicted to become the third largest energy resource by 2050 after thermal and hydro [3]. Similar trends are supported in growth forecasts for Europe, the US and India [4], [5]. In Australia, a number of studies on the feasibility of high renewable penetration have been performed which emphasise the wind and solar as the main components of growth in renewable generators (see for example [6, 7, 8, 9]).

Many existing predictions and feasibility studies are based only on the generation capacity meeting peak demand without comprehensively accounting for the core operational requirements of power systems (such as frequency and voltage stability) and, therefore, are not directly transferable to real future power networks. The growth in renewables is hindered due to two main factors, namely, high capital expenditure and output variability. With technological advancements, the cost of wind generation has been steadily declining to be on par with conventional generators. According to [2],[10], the levelised cost of electricity (LCOE) for coal is \$91/MWh whereas that of onshore wind is \$120/MWh. Although wind turbines have gradually become affordable, the variability associated with wind power production continues to be a challenge and is a major limiting factor in the wind energy penetration levels [11].

The overall operational stability of power networks is reliant on matching instantaneous generation and demand. Deviations in an instantaneous generation and demand translate to frequency excursions which, if not addressed promptly, may result in system outages and blackouts. An example is a blackout in South Australia in 2016. South Australia, which has nearly 30% wind penetration by generation capacity, frequently relies on the inter-connectors with the neighbouring Australian state of Victoria for any generation shortfalls. Consequently, growth in wind penetration entails growth in reserve requirements [12], [13]. The National Electricity Market (NEM) in Australia is the longest AC power network in the world and is weakly meshed (network impedances are significant relative to the demand). Weakly meshed networks are particularly susceptible to voltage and frequency excursion, which further limit the wind power penetration. In Australia, the reserve is provided in the form of Frequency Control Ancillary Services (FCAS). Although a number of approaches and advanced electricity market clearing methods have been reported to optimise the reserve requirement associated with increasing wind penetration (e.g. [14, 15, 16, 17]), FCAS associated cost remains the main limiting factor in the proliferation of wind farms [18]. In fact, it is demonstrated in [19] that in wind-thermal power systems (similar to the Australian power network), the rise in uncertainty associated with increased wind penetration levels leads to increased cost and reserve requirements.

While growth in wind generation necessitates devising methods for smoothening rapid power output fluctuations, much of the smoothing may be achieved through the aggregation of wind farms with substantial geographical separation [20, 21]. Understanding the characteristics of aggregate wind farm output over large areas and their correlations are critical to understand potential impacts of large quantities of wind generation ([22],[23],[24]). Nevertheless, aggregation alone is unlikely to be sufficient to completely address the technical challenges arising due to uncontrollable and intermittent wind power generation. Consequently, additional technical mechanisms are necessary. One solution is through the provision of synthetic inertia (also referred to as virtual inertia), which involves appropriate control of wind turbine power ramp-rates to emulate the inertial response of conventional generators [25],[26]. However, this approach involves wind power curtailment. A potential alternative is to utilise energy storage systems (ESS) [27, 28, 29].

The biggest challenge with the use of ESSs is their high capital expenditure requirements. While the optimal scheduling of energy storage in thermal-wind power systems is considered in literature (e.g. [30]), there are a large number of ESS options currently available with different technical characteristics, financial characteristics and levels of technological development. Which energy option is most suited for application with wind farms is not immediately obvious, and must be determined by considering regulatory frameworks (in addition to technical and financial considerations).

The objective of this paper is to present a techno-economic evaluation of the appropriateness of different ESS options for wind power smoothing. A detailed analysis of wind farm variability and its mitigation through the use of ESSs is performed. The main feature of this analysis is that it takes into account the effects of regulatory framework (in addition to technical and financial characteristics) on ascertaining the suitability of an ESS option. Although regulatory framework has a significant effect on the viability of an ESS as an option, as this paper demonstrates, this effect is often ignored in existing studies. First, a techno-economic modelling and analysis approach is developed. Then, using the existing major Australian wind farms as the test cases, a comprehensive intermittency analysis is performed and a number of energy storage options are considered to evaluate their economic viability in the application of wind farm power output smoothing. A comprehensive sensitivity analysis is performed to evaluate the effect of variations in future uncertain factors such as storage price and changes in the regulatory frameworks. Such an analysis, though urgently needed to facilitate de-carbonisation of future power networks, is not yet performed or reported in literature for Australia.

The paper is organised as follows: Section 2 presents the background information for the chosen wind farms, storage types and regulatory framework. Section 3 contains the results and discussion of the intermittency analysis. In section 4, a techno-economic modelling approach is presented. Sections 5 and 6 present the results and discussion followed by sensitivity analyses in section 7.

2 Background

2.1 Chosen wind farms

Two clusters wind farms are selected (shown in Figure 1). Each cluster comprises of three wind farms. All the six wind farms are located in the state of South Australia which has the highest wind generation penetration in Australia with nearly 30% penetration by generation capacity [31]. The criteria for the selection of wind farms includes size, contribution to wind generation penetration and distance from one another within each cluster.

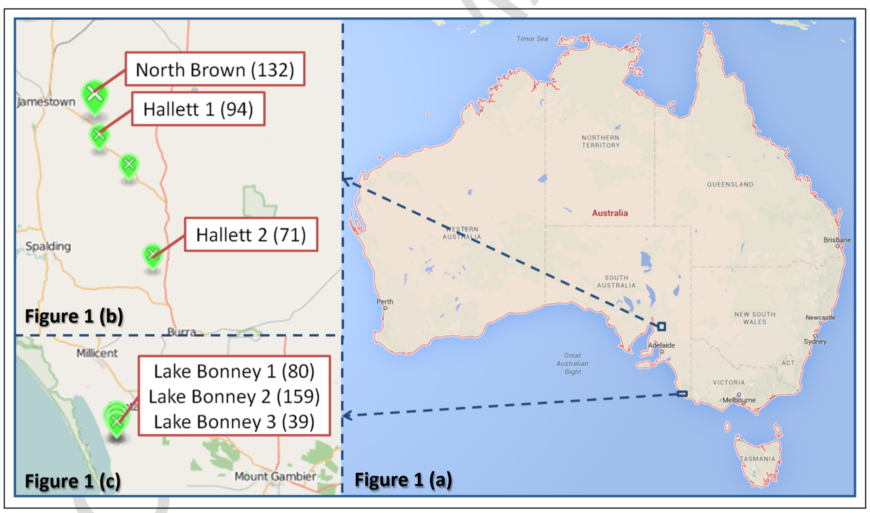

Figure 1: Wind farm locations and sizes (MW) [32, 33]

The first of the chosen clusters consists of the three Lake Bonney Area (LBA) wind farms: Lake Bonney 1 (80 MW), Lake Bonney 2 (159 MW) and Lake Bonney 3 (39 MW). All three of these farms are adjacent to one another. The second cluster consists of the three Hallett and North Brown Area (HNB) farms: Hallett 1 (94 MW), Hallett 2 (71 MW) and North Brown (132 MW). Table 1 shows the distance between the wind farms comprised in the HNB cluster. The aggregated capacities of the two cluster LBA and HNB are 278 MW and 297 MW respectively. Furthermore, the distances between the cluster HNB and the cluster LBA is 509.4 km. The distances along with the wind data were recorded using [32]. The wind farm data has a 5-minute resolution.

In order to gain insight into the relationship between the geographical distance and reduction in intermittency through aggregation of wind farms, three aggregations of wind farms within each cluster

Table 1: Distance between HNB farms [32]

Wind Farms	Hallett 1 - Hallett 2	Hallett 1 - North Brown	Hallett 2 - North Brown
Distance (km)	29.5	8	37.2

are considered. The aggregations include (i) a single wind farm, (ii) aggregation of two wind farms within the same cluster and (iii) aggregation of all three wind farms within the same cluster. Table 2 summarises the details of the various wind farm aggregations considered within each cluster.

Table 2: List of wind farm aggregations used

Aggregation name	*Wind farms*	*Aggregated capacity (MW)*
Lake Bonney Area Aggregation 1 (LBA1)	Lake Bonney 2	159
Lake Bonney Area Aggregation 2 (LBA2)	Lake Bonney 2, Lake Bonney 1	239
Lake Bonney Area Aggregation 3 (LBA3)	Lake Bonney 3, Lake Bonney 2, Lake Bonney 1	278
Hallett & North Brown Area Aggregation 1 (HNB1)	Hallett 1	94
Hallett & North Brown Area Aggregation 2 (HNB2)	Hallett 1, Hallett 2	165
Hallett & North Brown Area Aggregation 3 (HNB3)	Hallett 1, Hallett 2, North Brown	297

2.2 Choice of ESS types

Storage requirements can be divided into three categories: energy management, power quality and bridging power. Energy management includes the ability to shift large amounts of energy over an extended period of time, (hours), including load levelling, transmission deferral and firm capacity [34]. Power quality refers to applications such as frequency regulation and transient stability while bridging refers to the capability of a storage system to 'bridge' the transition between energy sources, referring to applications such as ramping power and contingency reserves [35]. Power quality and bridging power correspond to Ancillary Services (AS) and usually do not require constant discharge for long periods [36].

On the other hand, existing storage technologies can be broadly classified into four categories: mechanical, electrical, chemical and electrochemical [37]. Of these, various ESS types have reached different levels of technological and commercial maturity. The key technical considerations that govern the choice of storage type include round-trip efficiency, power, energy density, cost, lifespan and maturity. For applications in wind farms, existing storage types are largely dominated by large-scale storage options such as compressed air storage and pumped hydro [38]. The widespread adoption of both these storage options is limited due to their geographical requirements.

These limitations are overcome through the use of battery-based ESSs whose portability, scalability, response time and ability to absorb and deliver power spikes make them well suited for managing the intermittency related to wind farm outputs. This paper considers the key ESS technologies that are in their advanced stages of trail/ commercialisation. In particular, ESS technologies that are considered in this paper include (i) Flywheels, (ii) Lithium-Ion batteries, (iii) Sodium-Sulphur batteries, (iv) Vanadium Redox Flow batteries and (v) Supercapacitors. The technical and financial details of these ESS types are summarised in section 3.

2.3 Ramp rate regulatory framework

The intermittency of wind farm power output, if not managed adequately, directly affects the power system frequency by disturbing the balance between electricity demand and supply. To compensate for this mismatch, other dispatchable generators must be ramped up and down through the provision of so-called FCAS. Since the growth in wind generation will inevitably affect the power system stability and FCAS requirements, many countries around the world have modified their regulatory framework for wind farm connections to grids in the form of National Grid Codes. Grid codes specify a ramp rate limitation and corresponding financial penalties in the event of a ramp rate violation of a given size [39]. A review of the ramp rate limits specified in different grid codes comprising of high wind penetration levels reveals that generally two methods are used in specifying ramp rate limits - one in the form of ramp rate limitation brackets and the other based on the total installed capacity. Overall, the general trend is that higher wind power penetration in an electrical grid is linked to a more restrictive ramp rate. The permissible ramp rate also becomes more restrictive as the wind farm size increases. This paper assumes a ramp rate of 4%, as a lower ramp rate is required at higher wind penetration. With wind power making up 30% of the South Australia's energy generation, a ramp rate of 4% is consistent with the level of wind penetration [31].

In Australia, the cost of intermittency is calculated by Australian Energy Market Operator (AEMO) in the form of FCAS. The penalty system to recover FCAS costs in Australia is referred to as causer pays whereby the overall monthly cost of FCAS is shared among various electricity market participants responsible for the frequency excursions. In particular, every month AEMO calculates 'FCAS contribution factors' for various market participants, which in conjunction with the total monthly FCAS costs are used to determine monthly penalties for ramp-rate violations. AEMOs publicly available 'causer pays' data has been used to estimate the approximate ramp-rate penalties in Australia. The details of the estimation of the penalty factor for Australia are given later in this paper in Section 4.2.

3 Intermittency Analysis

This section presents an analysis to gain insight into the level of intermittency reduction that can be achieved through aggregation of Australian wind farms. Using the aggregations of each of the two wind farm clusters presented in Table 2, the effects of factors such as wind farm size and the distance between aggregated wind farms are explicitly considered and analysed. Variance and the correlation coefficients of power output ramp rate violations of different farm aggregations are calculated.

3.1 Variance analysis

Variance in power output ramp-rates for each of the two clusters is calculated separately. For each cluster, the wind farms are considered individually as well as their aggregations (as per Table 2). Along with calculating these figures annually, due to changing weather patterns in the different seasons quarterly, iterations of these figures are also calculated for summer, autumn, winter and spring.

Figure 2 and 3 summarise the results for the two wind farm clusters. Ramp-rates are expressed as a percentage of maximum capacity. It can be seen from Figure 2 that ordering both the individual farms and aggregations by capacity, all variances conform to one consistent trend that is clearly noticeable. As the capacity increases, the variance becomes smaller. This trend remains consistent at annual and seasonal levels. Furthermore, as the benefit from size and aggregation is the result of varying wind conditions averaging out each other's spikes, the lower the correlation between wind farms, the greater the benefit of this effect. As the weather is a local phenomenon, geographically separated areas are more likely to take advantage of this effect. This is confirmed in Figure 3 which shows the trend that aggregation results in reductions in variance.

Given the greater distance between Hallett and North Brown wind farms compared to the adjacent Lake Bonney wind farms it is also expected that aggregation would result in a greater reduction in variance of HNB wind farms. Lake Bonney experiences far more ramp rate violations throughout the year, so comparing statistical trends provides a better context for analysis than net statistical quantities. Calculating the drop in Hallett and North Brown variance between the individual and aggregated wind farms and comparing this difference to the corresponding differences between the values in Figure 2 for Lake Bonney it is found that variance reduction in Figure 3 is greater.

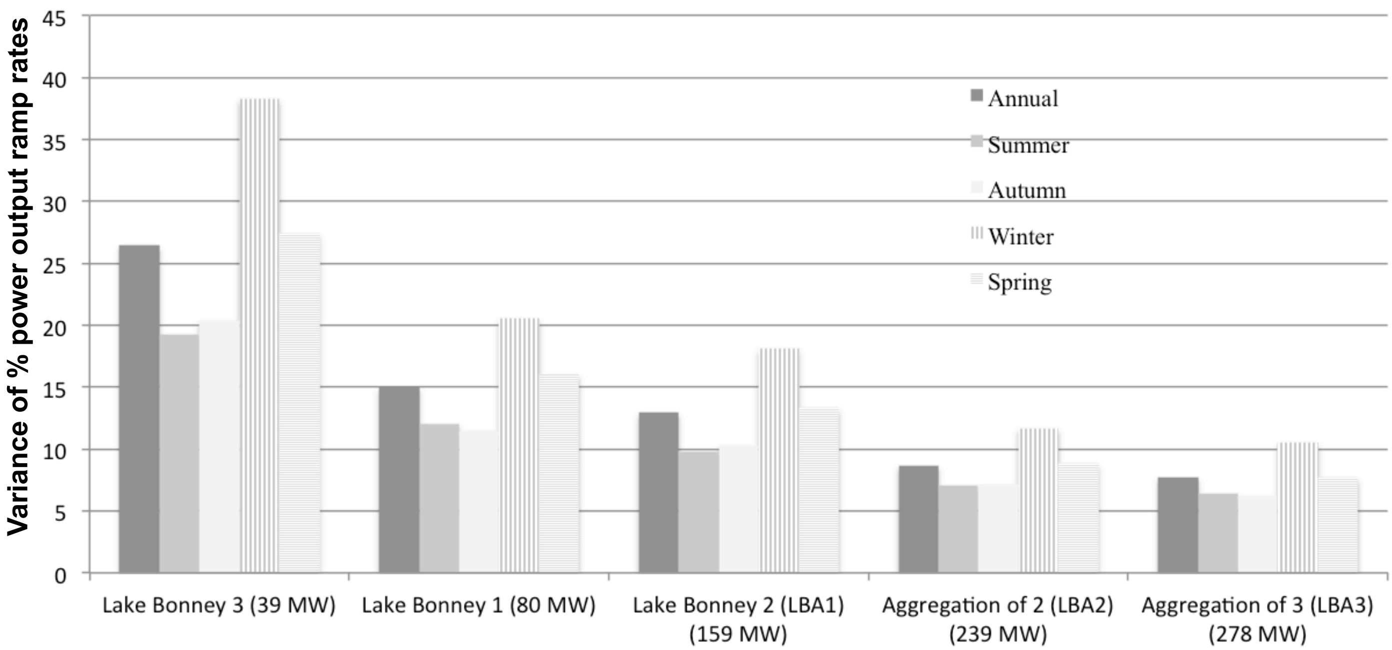

Figure 2: Variance analysis of % power output ramp rates corresponding to *Lake Bonney Area* wind farms (individual and aggregated)

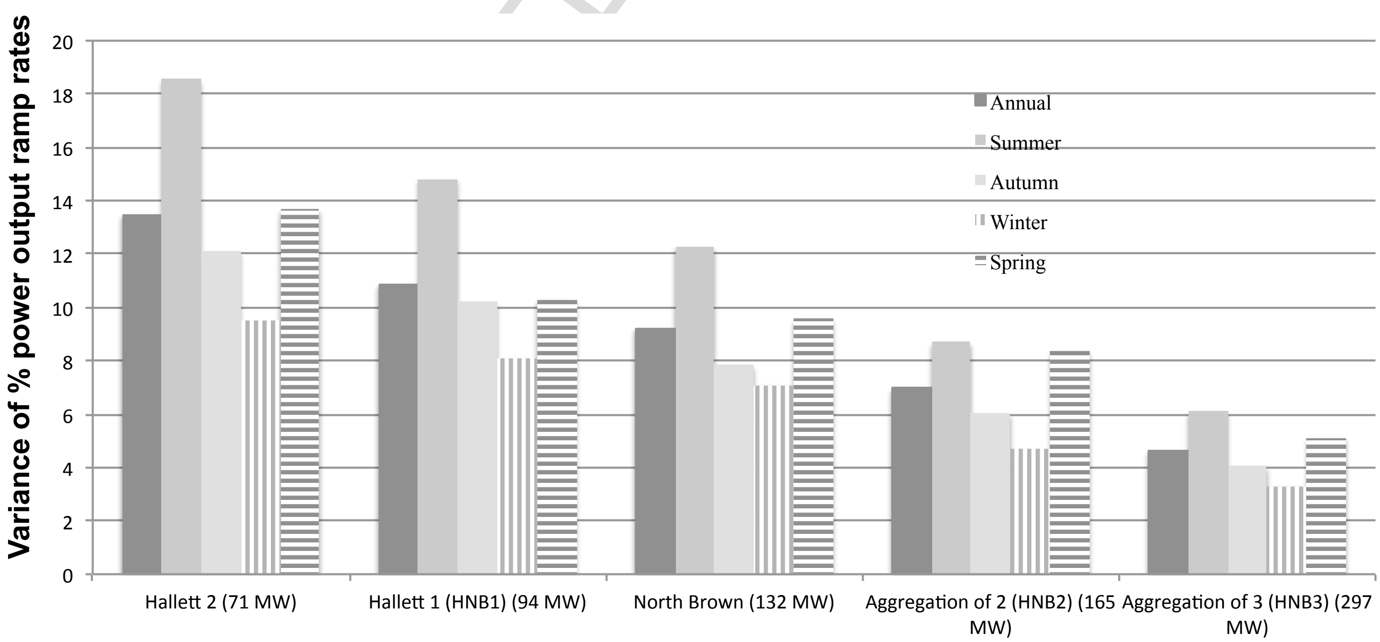

Figure 3: Variance analysis of % power output ramp rates corresponding to *Hallett and North Brown Area* wind farms (individual and aggregated)

3.2 Correlation coefficient analysis

This section evaluates the correlation between power output ramp rates corresponding to various wind farms. The correlation between any two wind farms is expressed in terms of the correlation coefficient (CC). CC calculation is done using Excel's 'Correl' function that uses the following (commonly referred to as Pearson correlation coefficient) formula:

$$CC_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \tag{1}$$

where $CC_{X,Y}$ refers to the correlation coefficient calculated for wind farms X and Y (calculated using their ramp rate datasets), cov denotes covariance and σ represents the standard deviation. The overall objective is to analyse the relationship between the values of CC of any two wind farms and the geographical distances. For this purpose, individual wind farms Lake Bonney 2 and Hallet 1 are selected as the base wind farms from each of the two wind farm clusters. All the CC calculations are performed relative to Lake Bonney 2 and Hallet 1. The results are summarised in Table 3.

Table 3: Correlation coefficients (CC)

	Lake Bonney 1	Lake Bonney 3	Hallett 1
CC with Lake Bonney 2	0.205459	0.243817	0.001238
Distance from Lake Bonney 2	Adjacent ($\approx$ 0 km)	Adjacent ($\approx$ 0 km)	509.4 km

	North Brown	Hallett 2	Lake Bonney 2
CC with Hallett 1	0.20011	0.119465	0.001238
Distance from Hallett 1	8.0 km	29.5 km	509.4 km

Table 3 shows that the outputs of LBA wind farms, due to their close proximity to each other, are highly correlated. As a result, aggregation in LBA wind farms deliver a minimal reduction in intermittency. On the other hand, the LBA wind farms are found to become very weakly correlated with Hallett 1 wind farm (located nearly 500 km apart from LBA wind farms). This provides a quantitative perspective to the possible reduction in intermittency in wind generation through aggregation in Australia. Comparing the values in bottom two rows with the values in first two rows of Table 3 confirm this trend that greater distance corresponds to lower correlation. Although the correlation between HNB farms is lower than the correlation between LBA farms, it is important to note that although LBA wind farms are adjacent to each other, they still span large areas resulting in different individual turbines experiencing different wind conditions.

4 Techno-economic modelling

This section presents a generic techno-economic modelling approach to evaluate different storage types for appropriateness in wind power smoothing applications. The developed techno-economic model is used in the next section to determine best possible storage sizes and types for the Australian wind farms considered in this paper.

4.1 General model

The proposed techno-economic model comprises of three models, namely, application model, storage model and cost model, described as follows.

Application Model

The purpose of *Application model* is to estimate the power required by an ESS to mitigate ramp rate violations. Application model requires wind farm dataset and the grid code specifications. Let the total number of samples contained in the available dataset is denoted as N. Wind farm power output data is used to determine ramp-rates per i^{th} sample (RR_i) where $i \in [1, N]$. The grid code specifications provide the ramp-rate limit (θ_T MW/minute). Denoting the penalty rate as α (\$/MW/minute) ramp rate violation, the overall penalty can be estimated as

$$\mathcal{P} = \Sigma_{i=1}^{N} \Delta RR_i \times \alpha \tag{2}$$

where $\Delta RR_i = RR_i - \theta_T, \forall\ RR_i \geq \theta_T$ and $\Delta RR_i = 0 \ \ \forall\ RR_i < \theta_T$. θ_T is taken as the capacity of the wind farm (MW) multiplied by the chosen ramp rate limit of 4%. α is estimated in section 4.2. Let x_{ESS} denotes the desired power to be delivered by an ESS unit in order to partially or totally mitigate ramp rate violations. With ESS, in (2) θ_T gets replaced with $\theta_{T,ESS} = \theta_T + x_{ESS}$. Then, (2) can be used to estimate overall penalty ($\mathcal{P}_{ESS}$) after ESS is used for ramp rate violation mitigation. Accordingly, the penalty savings achieved through the deployment of ESS can be estimated using the following equation as a function of x_{ESS}:

$$\Delta\mathcal{P} = \mathcal{P} - \mathcal{P}_{ESS} \tag{3}$$

Equation (3) can be used to tune x_{ESS} to achieve desired levels of $\Delta\mathcal{P}$. The results of this model are therefore x_{ESS}, (the desired power requirement of the ESS), and $\Delta\mathcal{P}$ (desired penalty savings).

Storage Model

Having determined x_{ESS} the next task is to determine the ESS desired capacity (Q_{ESS} in MWh). This entails the estimation of the maximum length of time (τ_{ESS} in hours) that an ESS has to discharge or charge. All ESS options are assumed to have a 1C rating (that is, discharges/charges rate of ESS is equal to its manufacturer-specified Ah rating). This assumption is consistent with many grid-connected storage systems currently installed in Australia and is often imposed by network operators. The effective desired Q_{ESS} of each ESS options can be estimated as follows:

$$x_{ESS} \times \tau_{ESS} = Q_{ESS} \tag{4}$$

where τ_{ESS} represents the maximum time required for *prediction*, τ_p, (such as discharging in preparation for absorbing a power ramp), time required for *charging* τ_c or *discharging* τ_d, during a ramp-rate interval or time required for *recovery*, τ_r (returning to a balanced energy state in time for the next ramp-rate period). Accordingly, the following equation is used to estimate τ_{ESS}:

$$\tau_{ESS} = \max(\tau_p, \tau_r, \tau_c, \tau_d) \tag{5}$$

In order to facilitate these prediction and recovery periods, it is assumed that an appropriate control system and an accurate weather forecasting system are in place. Using an annual wind dataset, in this paper, a control approach is implemented to emulate control of ESS charging/discharging. This uses x_{ESS} as the ESS power rating and involves ESS charging/discharging to mitigate ramp rate violations. The corresponding charge and discharge times are used to evaluate τ_{ESS} as per condition (5). Furthermore, let the available forecasting horizon is denoted as $\tau_{forecast}$. In order for a control system to operate reliably, $\tau_{forecast}$ should be sufficiently large such that

$$\tau_{forecast} > \tau_p + \tau_r + \tau_{c/d} \tag{6}$$

Given a dataset, the conditions (5)-(6) are to be checked over the full dataset (an illustration is presented in section 5.2). In Australia, AEMO uses Australian Wind Energy Forecasting System (AWEFS) that is capable of delivering hourly forecasts with a forecast error of no greater than 4% [40]. Consequently, in this analysis $\tau_{forecast}$ is chosen as 1 hour.

Once the desired Q_{ESS} has been determined, given the practical specifications of each j^{th} ESS type, actual capacities $Q_{ESS,j}$ are calculated as $Q_{ESS,j} = \frac{Q_{ESS}}{\eta_j}$ where η_j represents the cycle efficiency of j^{th} ESS type.

Cost Model

$Q_{ESS,j}$ estimated using storage model is used in *Cost Model*. Cost model is used to calculate the overall cost associated with the use of j^{th} ESS type after y years of use with wind farms and to estimate the payback times associated with each ESS type so that the most economically viable ESS option can be determined. Let $J_j(y)$ represents the net cost associated with j^{th} storage type after y years of use. Then, $J_j(y)$ can be evaluated using the following equation:

$$J_j(y) = Q_{ESS,j} \times P_{CAP,j} + \sum_{k=1}^{y} [Q_{ESS,j} \times P_{j,k} + \Delta\mathcal{P}_k + \Gamma_{curtail,k}] \quad y \in [1, Y_j] \tag{7}$$

where $P_{CAP,j}$ and $P_{j,k}$ represents the capital cost (\$/MWh) and annual operational cost (expressed as \$ per MWh of storage capacity in k^{th} year) for j^{th} ESS type, respectively. $\Delta\mathcal{P}_k$ is the penalty payment savings achieved through the mitigation of ramp-rate violations in k^{th} year. Y_j is representative of the lifetime of j^{th} ESS type. $\Gamma_{curtail,k}$ represents the additional revenue generated through the use of ESS in k^{th} year obtained from mitigation of wind power generation curtailment which otherwise may be necessary during network congestion. Sample calculations for estimating $\Gamma_{curtail,k}$ are given in section 5.2. Taking into account inflation, the $J_j(y)$ is subject to the present value of cash flow after y years:

$$\text{Present Value of } J_j(y) = \frac{J_j(y)}{(1+d)^y} \tag{8}$$

where d represents the discount rate which is taken as 6% [41, 42]. Accordingly, the payback time for the j^{th} ESS type can be estimated by solving the following equation for y:

$$\sum_{k=1}^{y} \frac{J_j(k)}{(1+d)^k} = 0, \quad k \in [1, Y] \tag{9}$$

4.2 Ramp rate violation fee

In section 2.3 a permissible ramp rate limit of 4% of installed wind farm capacity per minute is assumed. In order to economically size ESS options, this section estimates the corresponding penalty (α), expressed in \$/MW/minute, for ramp-rate violations. In Australia, currently, generators are used to compensate for the grid fluctuations caused by renewable energy inputs such as those from wind farms. In order to estimate the economic value of a wind farms ramp-rate violations, the payments made to the operators of these generators are used. In particular, the amount of capital spent in compensating for a wind farm is determined to estimate the cost associated with wind farm's ramp-rate violations.

The first step in this calculation is to determine the amount of money spent to compensate for the mismatch between generation and the load, for a wind farm of a given size. AEMO holds digitally accessible figures from previous years' payments [43]. In addition, the percentage of this payment made on behalf of a specific company is also recorded via NemWeb [44]. The wind farm and AEMO 'causer pays' datasets used in this analysis correspond to the year 2011. For the purposes of this analysis, the ramp-rate violation costs are found using the LBA wind farms and the respective company 'Lake Bonney Wind Power Pty Ltd'. This penalty is calculated as \$80,400 (it is assumed that output variations below the ramp-rate have no significant effect on this penalty).

The second step is to calculate the corresponding power in ramp-rate violation of LBA. This is evaluated using the aggregated data of the three LBA wind farms, (LBA3). If the 4% ramp rate violation is used then over the course of 2011, (the year used for all wind farm data, with data in 5 minute intervals), taking all ramp rates in excess of 4% of this aggregated plant's 278 MW size 9042 MW are found to be in excess. The final step is to combine the \$80,400 penalties and the 9042 MW excess to calculate an approximate penalty of $\alpha = \$8.89/\mathrm{MW}/\mathrm{Minute}$. This pricing will be used for all ramp rate violation penalty calculations later in this paper.

5 Results

The proposed techno-economic methodology is implemented in establishing the battery storage requirements for the two wind farm clusters (LBA and HNB).

5.1 Application model

In order to establish power and energy requirements to be delivered by energy storage systems to partially or totally eliminate ramp-rate violations, wind farms aggregations for LBA and HNB are considered (as per Table 2). Figures 4 and 5 summarise the distribution of ramp rates for different power levels.

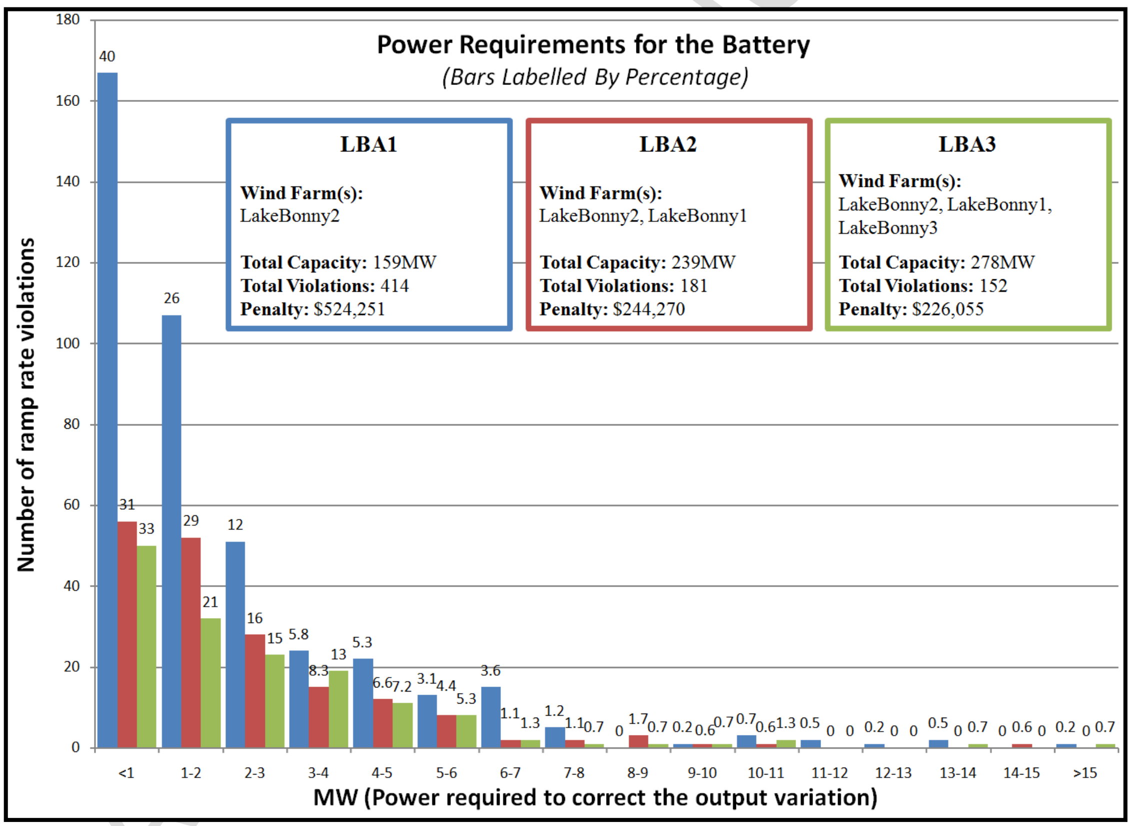

Figure 4: Histogram - power requirements from the battery (Lake Bonney Area - LBA)

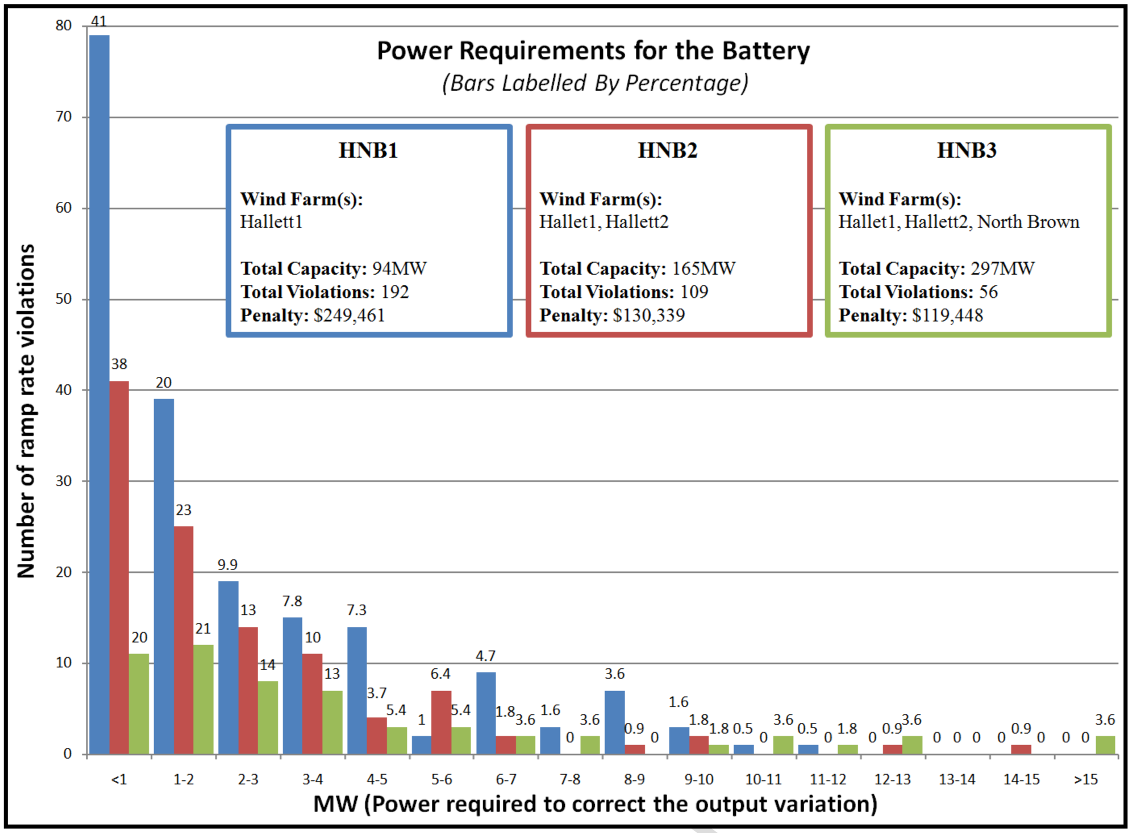

Figure 5: Histogram - power requirements from the battery (Hallett & North Brown Area - HNB)

Figure 4 shows that as the wind farms are aggregated the effects of wind variability tends to smoothen. This is evident from the reduction of ramp-rate magnitudes as well as the frequency of their occurrence as the wind farms are sequentially aggregated. Furthermore, aggregation is more prominent in reducing smaller violations, which can be observed from the decreasing percentage of smaller violations. Similar trends are observed in the second wind farm aggregation HNB (shown in Figure 5). Again, it is observed that aggregation of wind farms results in overall reduction in ramp rate violations. Although the number of wind violations for LBA is far greater than HNB, we still find in both areas that smaller wind violations are more frequently eliminated through aggregation and that aggregation results in reductions in the penalty costs.

5.1.1 Determination of x_{ESS}

As can be concluded from analysing Figures 4 and 5, the majority of violations fall under 2 MW while some are >15 MW. As accounting for 100% of the violations would require a very large (>15 MW) and expensive power rating, the analysis considers a 4 MW power rating to account for most of the violations. Analysing the distribution of power output violations in LBA1-Figure 4 it is concluded that most (84.3%) of the violations are under 4 MW. Similarly, in HNB1-Figure 5 most (79.2%) of the violations are concentrated below 4 MW. With 4 MW storage power rating, The percentage violations mitigated by 4 MW of effective storage power rating in different wind farm cluster aggregations are summarised in Table 4.

Table 4: Percentage and number of violations prevented by a 4 MW ESS

Aggregation number (i)	LBAi	HNBi
1	349 (84.3%)	152 (79.2%)
2	151 (83.4%)	91 (83.5%)
3	124 (81.6%)	38 (67.9%)

Table 4 reveals that a greater percentage of violations are above 4 MW in more aggregated farms. Although this means the prevention of ramp rate violations by an ESS is possibly less profitable in a large wind farm, due to the penalty already avoided through aggregation. Nevertheless, for the sake of analysis, it is best that all wind farms and aggregations have the same ESS size. Therefore, x_{ESS} (used in (3)) is chosen as 4 MW.

It may be noted that the primary criterion for selecting ESS size(s) that businesses (wind farm owner/operator in this case) would adopt would be the size that gets the most Return On Investment (ROI). Most businesses have a minimum threshold ROI required to invest in something, and sometimes that threshold depends on the level of perceived risk. Although the risk analysis is not explicitly performed, it is perceived that the criterion of shortest payback, as used in this paper, is roughly equivalent.

5.1.2 Estimation of $\mathcal{P}$ and $\mathcal{P}_{ESS}$

The use of a 4 MW ESS reduces the number of violations by a given percentage as observed in Table 4. However, as the penalty rate is calculated by violation power rather than simply by the number of violations, the magnitude of power in violation provides the best economically quantified measure of intermittency. Using α = \$8.89/MW/Minute, overall capital savings ($\Delta\mathcal{P}$) achieved through the use of ESS can be estimated. Table 5 shows the amount of capital saved by using $x_{ESS} = 4$ MW energy storage system installation through avoided ramp rate penalty. There is a consistent trend between the ‘percentage of capital saved’ and the percentages in Table 4.

Table 5: Ramp rate violation fees before and after a 4MW energy storage system is installed (\$AUD)

	LBA1	LBA2	LBA3	HNB1	HNB2	HNB3
Penalty Before Installation ($\mathcal{P}$) (\$)	186,453	86,876	80,398	88,722	46,377	42,482
Penalty After Installation ($\mathcal{P}_{ESS}$) (\$)	33,002	11,866	12,778	19,563	7,975	16,986
Capital Saved due to ESS ($\Delta\mathcal{P}$) (\$)	153,451	75,011	67,620	69,159	38,402	25,497
Percentage of Capital Saved	82.3%	86.3%	84.1%	78.0%	82.8%	60.0%

5.2 Storage model

Having chosen $x_{ESS} = 4$ MW as the desired power rating, τ_{ESS} must be found so as to estimate the value of Q_{ESS} (MWh). Assuming the existence of a ramp-rate mitigating control system to charge/discharge ESS, Table 6 lists the longest observed charge/discharge times and the recovery/preparation times. The most common continuous charge/discharge time is observed as 10 minutes. Accordingly, to account for the effects of assumptions made in this analysis, a maximum time of 15 minutes is chosen for LBA1's wind farm calculations. Similarly, a 10-minute requirement is chosen for the other aggregate models, reflecting their maximum requirement. Therefore, in order to accurately compare the different aggregation outputs, a maximum charge/discharge requirement of $\tau_{ESS} = 15$ minutes is used for LBA1 and a maximum charge/discharge requirement of $\tau_{ESS} = 10$ minutes is used for LBA2, LBA3, HNB1, HNB2 and HNB3. With $x_{ESS} = 4$ MW, desired ESS capacity is obtained as $Q_{ESS} = 1$ MWh for $\tau_{ESS} = 15$ minutes (corresponding to LBA1) and $Q_{ESS} = 0.67$ MWh for $\tau_{ESS} = 10$ minutes (corresponding to other five wind farm aggregations).

Table 6: Estimation of τ_{ESS}

Wind Farm	HNB1	HNB2	HNB3	LBA1	LBA2	LBA3
Maximum Consecutive Discharge (Minutes) τ_d	10	5	10	15	10	10
Maximum Consecutive Charge (Minutes) τ_c	10	10	10	10	10	10
Maximum Consecutive Time Periods Required (Minutes) (τ_r and τ_p)	5	10	10	10	10	10

Furthermore, using Table 6, the validity of condition (6) can also be verified:

$$\tau_p + \tau_r + \tau_{c/d} = 15 + 15 + 15 = 45 \ minutes < \tau_{forecast} \ (= 1 \ hour) \tag{10}$$

5.3 Cost model

Using the effective capacity requirement of 0.67 - 1 MWh and the effective power requirement of 4 MW, (at 1C), the actual ESS sizes and prices are calculated. This cost is calculated from the values in Table 7, allowing \$/kW or \$/kWh figures to be used. From the ESS types listed in Table 7, the specifications listed in Table 7 are used for calculating the CAPEX and OPEX associated with different ESS types.

Table 7: ESS Specifications used for Price Modelling [45, 46, 47, 48, 49, 50, 51, 52, 53, 54]

j^{th} ESS type	$Q_{ESS,j}$ for $Q_{ESS} =$ 0.67 MWh	$Q_{ESS,j}$ for $Q_{ESS} = 1$ MWh	Roundtrip Efficiency η_j (%)	ESS CAPEX, $P_{CAP,j}$ (\$/kWh)	Lifetime (years) Y_j	Annualised Operational Expenditure, $P_{j,k}$, $\forall k$ (\$/kW/year)
Flywheel	0.70	1.05	95	1600	20	11.6
Lithium-ion battery	0.78	1.18	85	400	10	8
Na-S battery	0.89	1.33	75	350	10	22
Supercapacitor	0.70	1.05	95	10000	20	13
Vanadium Redox Flow Battery	1.03	1.54	65	600	20	5

Payback calculations

Using Tables 5, 7 and equation (9), the ESS payback times for each of the ESS types and wind farm aggregations is calculated. The results are summarised in Table 8. Table 8 uses capital saved from avoided ramp-rate penalties only, (curtailment avoidance is not accounted for in these payback time). From Table 8 it is observed that lithium-ion batteries are the most economically viable with sodium-sulphur and redox flow batteries also providing a payback time. Despite LBA1 (the smallest and most volatile farm in its aggregation set) requiring a larger capacity, it still yields shorter payback times. Hence it can be seen that smaller and more importantly, more volatile wind farms, typically benefit the most from an ESS despite requiring a larger and therefore more expensive ESS.

Table 8: ESS Payback Times (Benefit from Ramp-Rate Penalty Avoided Only)

Wind farm, (Q_{ESS})	Flywheel	Lithium-ion	Na-S	Super-capacitors	Vanadium Redox Flow
LBA1, (1 MWh)	No Payback	4.548	9.588	No Payback	9.206
LBA2, (0.67 MWh)	No Payback	9.882	No Payback	No Payback	19.091
LBA3, (0.67 MWh)	No Payback	No Payback	No Payback	No Payback	No Payback
HNB1, (0.67 MWh)	No Payback	No Payback	No Payback	No Payback	No Payback
HNB2, (0.67 MWh)	No Payback	No Payback	No Payback	No Payback	No Payback
HNB3, (0.67 MWh)	No Payback	No Payback	No Payback	No Payback	No Payback

Energy curtailment profit calculations ($\Gamma_{curtail,k}$)

Although ESSs are specified to account for ramp rate violations they could simultaneously be used to account for curtailed energy generation. The negation of this curtailment is expected to negate curtailment by 2% [55]. This is based on the assumption that an ESS can significantly negate curtailment. However, in this analysis, the power rating of the wind farms (94-297 MW) is significantly larger than the power rating of the ESSs (4 MW). As a result, with an 'effective' 1 MWh capacity, the amount of energy that can be charged or discharged is limited by the specifications of the ESS.

Due to the maximum ESS charging/discharging rate of 0.33 MW per 5 minutes, the ability to prevent curtailment losses will be limited by this specification. Assuming an electricity price of \$50/MWh (revenue/MWh), the financial benefit from curtailment power loss prevention is estimated to be approximately $\Gamma_{curtail,k}$ =\$35,040 per year $\forall\ k$ [56].

Clearly, the inclusion of the financial benefit of curtailment power loss prevention increases the total capital savings. The corresponding payback times are summarised in Table 9 (considering both the ramp-rate violation avoidance and curtailment benefits). As expected, financial benefits from curtailment prevention have a positive effect in obtaining shorter payback times.

Table 9: ESS Payback Times (Benefit from Ramp-Rate Avoided & Curtailment Loss Mitigation)

Wind farm, (Q_{ESS})	Flywheel	Lithium-ion	Na-S	Super-capacitors	Vanadium Redox Flow
LBA1 (1 MWh)	No Payback	3.422	5.612	No Payback	6.844
LBA2 (1 MWh)	No Payback	4.742	No Payback	No Payback	9.057
LBA3 (0.67 MWh)	No Payback	5.323	No Payback	No Payback	10.161
HNB1 (0.67 MWh)	No Payback	5.189	No Payback	No Payback	9.908
HNB2 (0.67 MWh)	No Payback	No Payback	No Payback	No Payback	No Payback
HNB3 (0.67 MWh)	No Payback	No Payback	No Payback	No Payback	No Payback

6 Discussion

The analysis presented in section 5 shows that of all the ESS types considered the Lithium-Ion and Redox ESS types are the only economically viable options. The Lithium-Ion ESS type is found to deliver the fastest payback time. Furthermore, the Li-ion ESS options are seeing faster technological advancements that can potentially lead to significant price reductions in the near future. Consequently, the Li-ion ESS type is selected for discussion.

Table 10 collectively shows the relationship between wind farm/aggregation sizes, ESS capacity requirements, variance values and payback times. The overall trend is that a higher ESS capacity requirement is the result of a higher variance, while the wind farm/aggregation size generally is associated with low variance. Further insight into this trend can be gained from Figures 6-8.

Table 10: Power Plant Size, (Effective) Capacity, Variance and Payback Time

	Power Plant Size (MW)	Power Plant Variance	Q_{ESS} (MWh)	Payback Time (Years), without curtailment	Payback Time (Years), with curtailment
Lake Bonney 3	39	26.43717	1	2.88	2.392
Lake Bonney 1	80	15.1	1	6.49	4.41
LBA1	159	12.93	1	4.55	3.42
LBA2	239	8.69	0.67	9.88	4.74
LBA3	278	7.72	0.67	No Payback	5.323
Hallett 2	71	13.46	0.67	No Payback	4.99
HNB1	94	10.86	0.67	No Payback	5.189
North Brown	132	9.22	0.67	No Payback	6.1
HNB2	165	6.96	0.67	No Payback	No Payback
HNB3	297	4.65	0.67	No Payback	No Payback

From Figure 6, a relationship of the negative correlation between size and variance is observed. Although most data points correlate to the projected trend-lines, the second to left LBA data point has the greatest variation from this trend, potentially representing an outlier point. As this data point's variance falls below the trend-line, it suggests that wind conditions are weaker than typically expected for the Lake Bonney 1 wind farm. Figure 7 displays the relationship between variance in power output ramp-rates and ESS payback times of Li-ion batteries. In this case, the trend identifies that higher variance (and intermittency) results in quicker payback on an ESS investment. The trend is consistent for both without and with the inclusion of curtailment benefits. Finally, in Figure 8, the relationship between the wind farm aggregation sizes and ESS payback times is plotted. Figure 8 shows that the length of payback time is directly proportional to the size of a wind farm aggregation. Larger the wind farm/aggregation longer is the expected ESS payback time, potentially making the use of ESS less attractive in large wind farms or wind farm clusters.

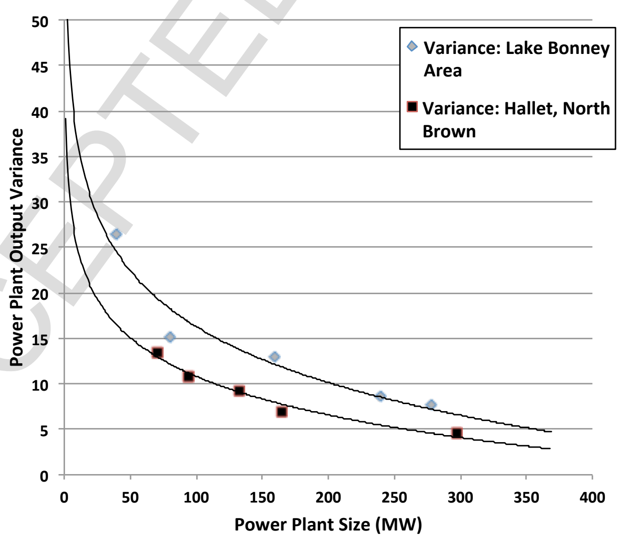

Figure 6: Power Output Variance vs Power Plant Size characteristics of LBA and HNB wind farm aggregations

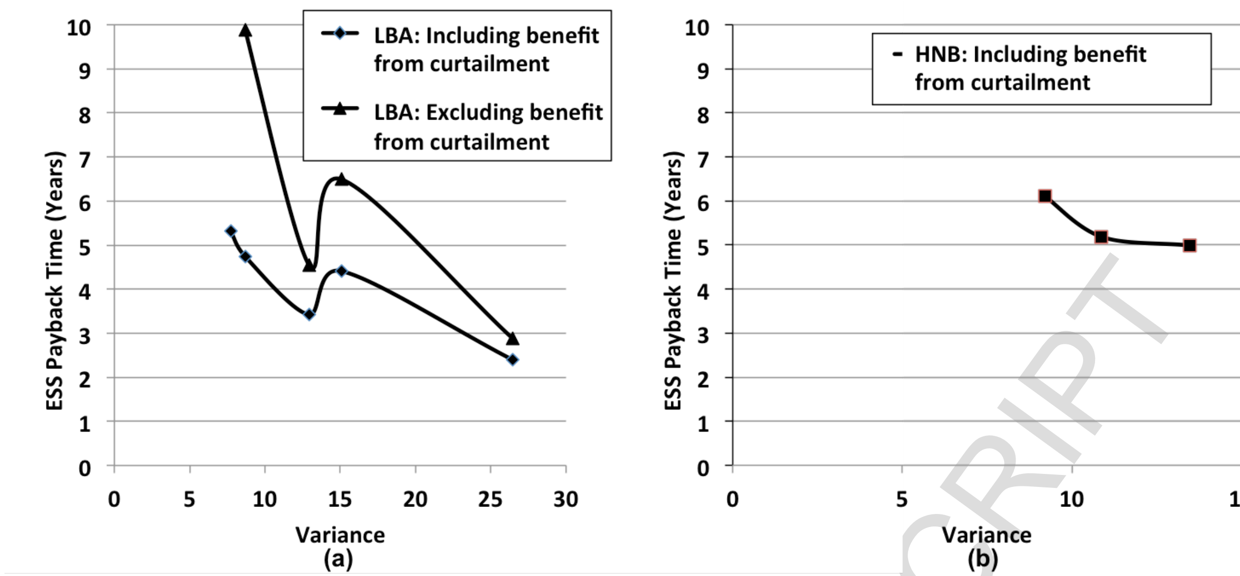

Figure 7: Payback Time vs. Variance

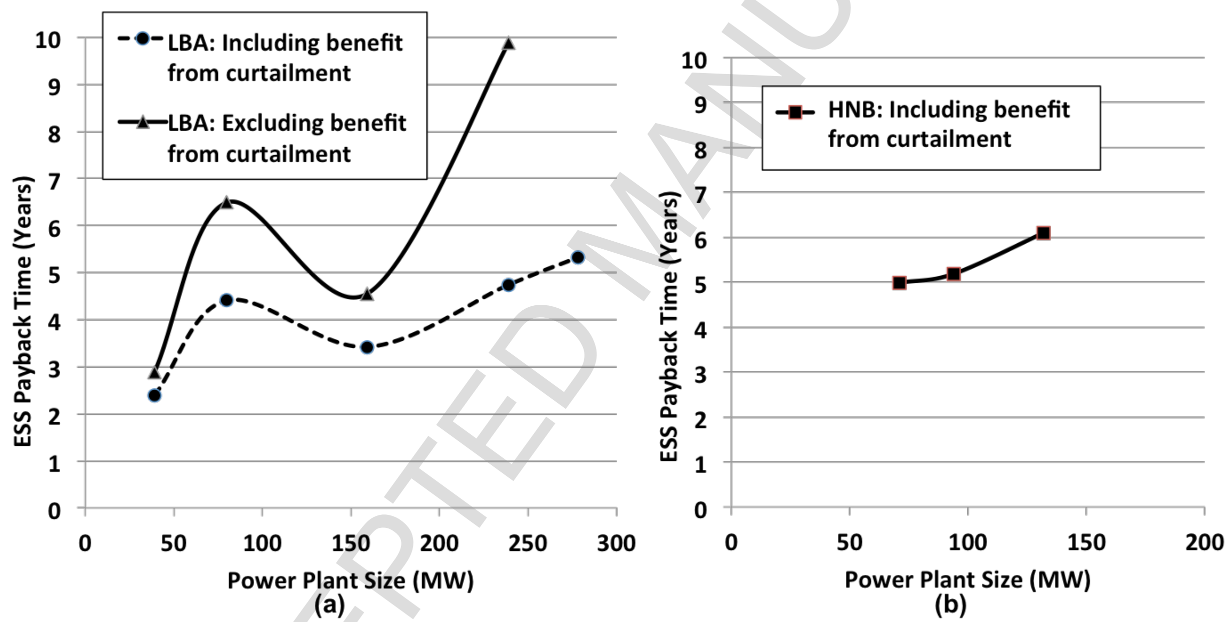

Figure 8: Payback Time vs. Power Plant Size

The overall trends in the relationship between wind farm sizes, ESS payback and variance levels is collectively displayed in Figure 9 using the LBA wind farm aggregations (excluding the Lake Bonney 1 data points as it is an outlier). Figure 9 demonstrates a very clear trend - an ESS's payback time is shorter for smaller wind farms. This is due to the greater variance of smaller wind farms that leads to a greater economic contribution of an ESS. The actual slopes of the curves will vary for different wind farm scenarios, but support the general relationships between size, variance and payback discussed earlier. Although these trends are known to be most accurate when considering only the aggregate models, greater specific analysis of why Lake Bonney 1 can be verified as an outlier, is also performed.

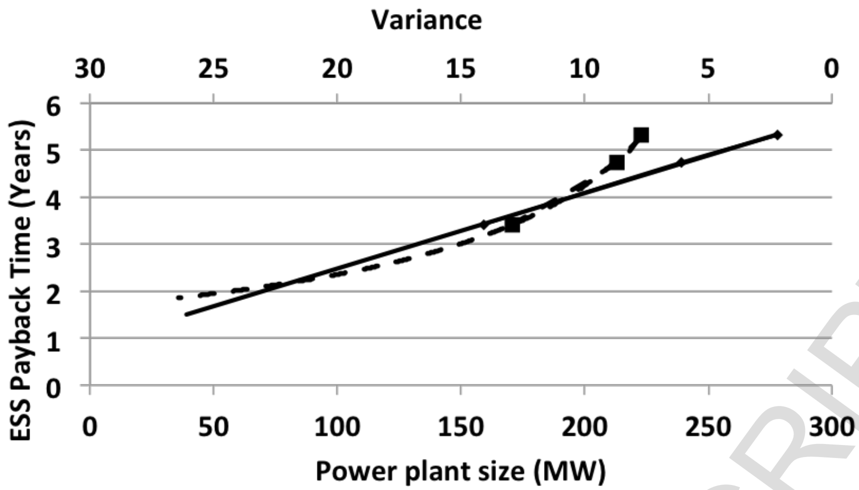

Figure 9: LBA (Benefit from Mitigated Ramp-Rate Violations & Curtailment Power Losses) Payback Times of Aggregate Models Only (solid - wind farm size vs payback time, dashed - variance vs payback time)

The Lake Bonney 1 Outlier

From Figures 6, 7 and 8, it is observed that Lake Bonney 1 breaks from an otherwise consistent trend. The reason for this anomaly lies in considering the variance of the ESS energy levels throughout the year. This is explained through Table 11 which shows the variance in wind farm power output and ESS power output for various Lake Bonney wind farms and aggregations. The important point of consideration is that while annual variances uniformly reduce from left to right (with size), ESS variance for Lake Bonney 1 is disproportionately lower, which points to Lake Bonney 1 wind conditions atypical in comparison to other wind farms. On the other hand, all the HNB wind farms and aggregations consistently decrease in ESS variance while increasing in size, making Lake Bonney 1 a unique case.

Table 11: ESS Payback Times (Benefit from Ramp-Rate Avoided & Curtailment Loss Mitigation)

Wind Farm	Lake Bonney 3	Lake Bonney 1	LBA1	LBA2	LBA3
Annual Variance	26.43717	15.0697	12.92883	8.68784	7.7233
ESS Variance	0.000839	0.000413	0.000437	0.0002	0.000166

Overall trends

Considering Lake Bonney 1 as an outlier overall conclusions can be drawn. From Figure 7 a negative correlation between variance and payback time is deduced while Figure 8 supports the conclusion that a greater size results in a shorter payback time due to the effects of aggregation. These two trends are further supported by Figure 6, which displays a lower variance to be the result of greater wind farm size. Finally, these relationships are validated by the data graphed in Figure 9, which, using the most reliable data points, confirms these trends, also suggesting the correlation between size and payback time is more linear than the negative correlation between variance and payback time. Thus, ESS power smoothing is typically more economically viable in smaller wind farms despite requiring a larger ESS capacity.

7 Sensitivity Analysis

This section presents a sensitivity analysis with respect to battery price and ramp-rate limit violation penalty. Both these parameters heavily govern the outcomes of the analysis and are like to change in future as net wind penetration increases and technological developments continue to drive down battery prices. The sensitivity analysis is performed using the LBA cluster as the test case.

7.1 Battery pricing (upfront capital investment)

With the continuing research and developmental efforts, lithium-ion battery prices are expected to drop in future. The 25% and 50% reductions in battery price are chosen. These choices are consistent with the target of \$100/kWh to \$150/kWh set by 'US Advanced Battery Consortium [57].

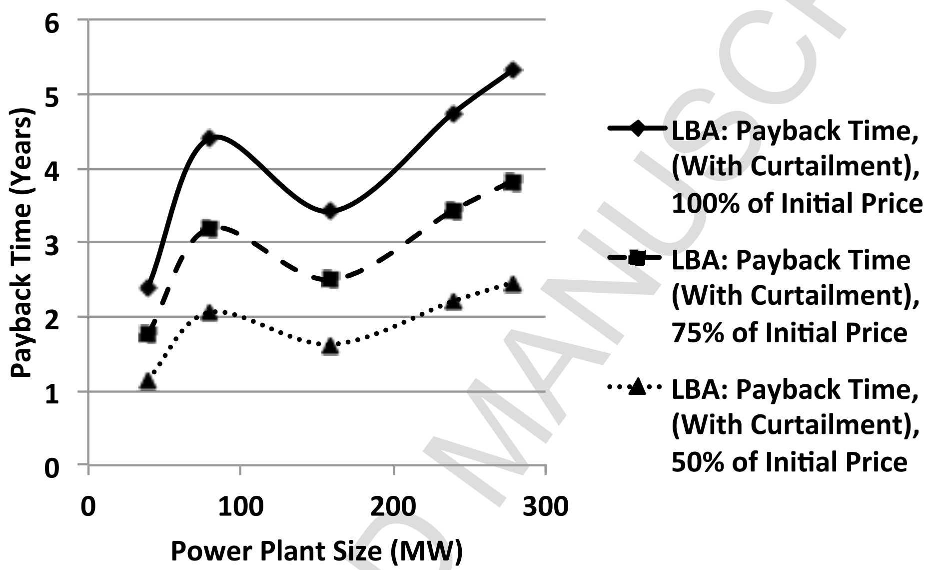

Figure 10: Effect of a Reduction in Price for Lithium-Ion Batteries by 25% and 50% on Payback Time

Observed in Figure 10 are the payback times which result from a 0%, 25% and 50% reduction in the initial capital investment required for a lithium-ion battery. This price reduction has a significant effect on the payback time. In the case of LBA3, for example, the payback time reduces from 5.32 years initially at \$400/kWh to 3.83 years at \$300/kWh to 2.46 years at \$200/kWh. Therefore, future price reductions in lithium-ion batteries will have a significant effect on the financial viability of ESS power smoothing systems wind energy applications.

7.2 Ramp-rate violation penalty

Based on AEMO's 'causer pays' data, the current average ramp-rate violation penalty is approximated as \$8.89/MW/min. As the grid's energy from wind penetration and other, (variable) renewable energy sources increases, a greater penalty may be required to prevent an overly variable grid power levels. To investigate this, the payback times of an ESS (lithium-ion), are calculated using 1.5 times and 2 times the originally assumed ramp-rate violation penalty.

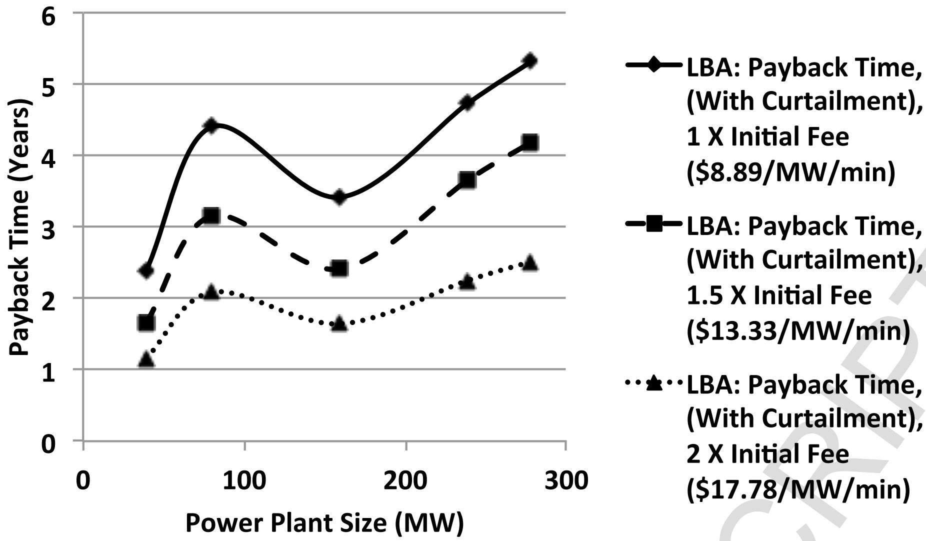

Figure 11: Effect of an increase in the ramp-rate penalty by 1.5× and 2× on ESS payback times

The payback times based on these increased ramp-rate violation fees are graphed in Figure 11. Taking the example of LBA3, as this fee is increased payback time decreases from 5.32 years at \$8.89/MW/min to 4.19 years at \$13.33/MW/min to 2.52 years at \$17.78/MW/min. Again, the reduction is over 50% at a 2× increase in the ramp-rate violation fee, although the reduction is slightly less than a 50% reduction in the initial capital investment price considered in Figure 10. The combination of these factors is expected to make ESSs, (specifically lithium-ion batteries), even more viable in future years.

8 Conclusions

This paper performs a techno-economic analysis to evaluate the cost of wind farm variability and presents a value proposition for using various ESS types in wind farm power ramp rate mitigation. The paper collectively considers the wind farm sizes and locations in conjunction with the regulatory framework in terms of ramp rate violation penalties. A techno-economic modelling framework is presented and implemented on a large number of wind farms in Australia. The sensitivity of payback times on investment on ESS is analysed with respect to capital expenditure and regulatory framework changes.

The results demonstrate that in addition to capital expenditure, regulatory framework can have a profound effect on the suitability of energy storage for wind farm applications. It is found that doubling of the ramp rate penalty fee tends to reduce the ESS payback time by nearly two-thirds. Considering that growth in wind generation entails an increase in ramp rate penalties (to maintain power system security), the analysis indicates that the growing wind generation penetration is likely to benefit economic feasibility of ESS. Secondly, based on the analysis presented in the paper, it can also be concluded that larger wind farms generally have smaller ESS requirements. This is because variance decreases as wind farm size or penetration levels increase in a given geographical location. The power outputs of wind farm clusters at a distance of 500 km are found to be almost completely uncorrelated whereas the correlation is found to reduce by nearly half for wind farms with a geographical separation greater than 20 km. This indicates that as the wind generation penetration levels gradually increase in geographically dispersed locations, beyond a certain level of wind generation penetration the power system stability issues arising due to wind variability may alleviate to some extent and, thus, requiring lower ramp rate mitigation mechanisms such as ESS. On the other hand, the analysis also indicates that although the smaller wind farms generally have higher ESS requirement, smaller wind farms tend to have a faster ESS payback times (despite the larger capacity requirement) due to their associated higher degree of variability.

Future work will involve extension of this analysis with modern market clearing approaches (such as [19]) and advanced ESS management algorithms to evaluate collective effect of market clearing mechanisms and choice of ESS control algrithms on the appropriateness of ESS in mitigating wind/renewable generation related variability. Future work will also look into the aggregation between different renewable sources as opposed to the existing method of aggregating a single source (e.g. hybrid aggregation of wind and solar generators) and identify the associated ESS capacity requirements.

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Highlights

1. Wind generation intermittency analysis and smoothing using storage is analysed.
2. Technical, economic and regulatory factors with wind farm sizes are considered.
3. A techno-economic model is proposed to evaluate available storage options.
4. Smaller wind farms require larger storage but yield faster payback on investments.
5. Growth in wind generation is likely to favour storage through regulatory reforms.