The Innovation Hub

for Affordable Heating and Cooling

Report #001

Battery sizing analysis for NSW schools: Nimbin, Jamison and Singleton High

April, 2021

CSIRO

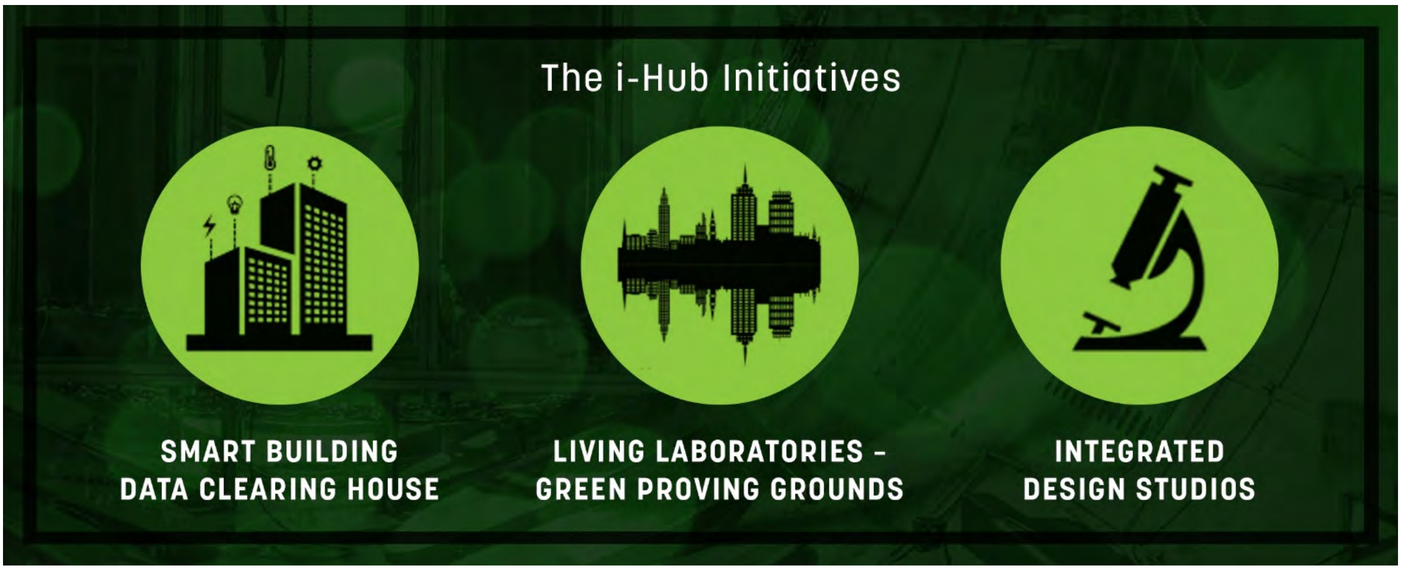
About i-Hub

The Innovation Hub for Affordable Heating and Cooling (i-Hub) is an initiative led by the Australian Institute of Refrigeration, Air Conditioning and Heating (AIRAH) in conjunction with CSIRO, Queensland University of Technology (QUT), the University of Melbourne and the University of Wollongong and supported by Australian Renewable Energy Agency (ARENA) to facilitate the heating, ventilation, air conditioning and refrigeration (HVAC&R) industry's transition to a low emissions future, stimulate jobs growth, and showcase HVAC&R innovation in buildings.

The objective of i-Hub is to support the broader HVAC&R industry with knowledge dissemination, skills-development and capacity-building. By facilitating a collaborative approach to innovation, i-Hub brings together leading universities, researchers, consultants, building owners and equipment manufacturers to create a connected research and development community in Australia.

This Project received funding from ARENA as part of ARENA's Advancing Renewables Program.
The views expressed herein are not necessarily the views of the Australian Government, and the Australian Government does not accept responsibility for any information or advice contained herein.

Primary Project Partner



Project title: **CSIRO Senaps data platform demonstration and development of the Data Clearing House**

This project will oversee development of the Data Clearing House (DCH), a cloud based building data management and application enablement platform. The DCH connects Internet of Things (IoT) systems from buildings and supports complex data analytics. The DCH will underpin the development of applications that improve renewable energy integration in buildings and unlock new opportunities for delivering Buildings to Grid (B2G) services.

This project will investigate features of the CSIRO Senaps data platform and their suitability for the DCH. It will combine these findings with results from the DCH2 Switch data platform subproject to develop the Data Clearing House.

Lead organisation

CSIRO

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1. SUMMARY

1.1 Executive summary

This report describes modelling to calculate the annual electricity cost savings from installation of lithium ion battery storage systems in three NSW schools; Nimbin High School, Jamison High School, and Singleton High School. Each school has an existing solar photovoltaic system and approximately 1 year of electricity net export data was provided along with electricity tariff information for the analysis.

Two different battery control strategies are compared alongside the base case (no battery storage system). The first strategy is a fixed daily charge/discharge schedule specifically tailored to minimise the electricity costs of each school. This schedule is intended to be pre-programmed during initial battery installation and be used as a 'fall-back' control. The second strategy uses a smart adaptive controller to re-compute the daily optimum (lowest cost) battery charge/discharging in response to actual electricity consumption and generation at each school. The analysis considers batteries capacities in the range 10kWh to 200kWh.

Two different electricity tariff scenarios are analysed; i) an existing tariff scenario based on the tariffs specified in electricity bills provided for each school, and ii) a wholesale electricity price scenario based on the NSW regional reference (i.e. spot) price. The wholesale electricity price scenario is only evaluated with the adaptive control strategy as implementing a pre-determined (fixed) schedule to minimise a fluctuating spot price was found to result in highly variable and sometimes perverse outcomes (e.g. higher electricity costs than the base case).

The analysis is based on the existing PV array at each school. That is, it does not model varying PV array sizes since it is difficult to accurately decouple the school's consumption and generation from the supplied net metering data alone. In addition, possible future changes in the school's load and/or generation, for example due to PV degradation, are not included. The influence of air-conditioning controls is also outside the scope of this work.

Both battery control strategies make use of a battery degradation model that accounts for the cost of using (i.e. degrading) the battery. Hence, along with the output annual electricity cost saving values, the analysis also outputs an estimate of the percentage reduction in battery lifetime. Together these two output values for each scenario may be used in subsequent financial analysis to evaluate longer term economics.

Key findings include

- Load and generation are well-aligned for all three schools. This limits the opportunity to use batteries to maximise solar self-consumption.
- Annual cost savings using the adaptive controller are 4.5% (Singleton), 5.2% (Jamison) and 8.3% (Nimbin). For the sites with demand/capacity charges (Jamison and Singleton), the majority of the saving is due to reducing these charges.
- Percentage savings are highest for Nimbin due to higher savings from maximising solar self-consumption and from energy arbitrage. This is a result of there being excess PV generation for Nimbin, and a greater difference between peak/shoulder and off-peak energy prices.
- The schedule-based control does not adapt to changing load, generation or prices. The greater the battery capacity, the more likely this will result in adverse outcomes.
- Calculated battery degradation rates are approximately 0.9% per year across all scenarios with approximately 1 charge—discharge cycle per day. Assuming an end-of-life capacity of 80% suggests battery lifetimes on the order of 20 years. However, it is suggested that a more conservative 15-year operating life be assumed in any subsequent financial analysis.

2. METHODOLOGY

2.1 Data preparation

Data used is summarised in Table 1. Because all analysis is historical (i.e. no consumption and generation forecasts were required) it was possible to directly use the net metering interval data supplied. For all three schools, cost savings were based on 1 year of data. However, for Singleton, the rolling 12-month capacity charge meant that the resulting battery control was applied to the full data-set (i.e. 2 years), with cost savings based only on the savings in the 2nd year. This was necessary to account for the cost saving from reducing the capacity charge. Battery model parameters were the same for all three schools and are summarised in Table 2.

As a cross check of the calculation of costs given the supplied tariff data, each time-of-use energy and cost component was calculated and compared to the provided electricity bills for Jamison and Singleton for the billed month. (This was not possible for Nimbin as the electricity data did not cover the date of the electricity bill supplied.)

For Singleton calculated overall and retailer time of use values were in close agreement with those on the provided bill. However, the calculated amount of energy assigned to the network peak period was 37% less than the value on the bill provided (with the non-peak period higher such that the total energy was the same). Here we used the network peak/shoulder/off peak period timing for business customers as described in the Ausgrid network price guide (1), and so the reason for this difference remains unresolved.

In the case of Jamison, the calculated overall and retailer time-of-use values were also in close agreement with the bill. However, the network peak period energy value calculated here was 22% higher than the value on the bill provided. Once again, we used the network peak/off-peak period timing as specified in the relevant network price guide (2) and so the reason for this difference also remains unresolved.

Table 1 Summary of electricity and tariff data

School	Electricity & PV data set	Period for savings calculation	Mean daily net energy (kWh)	Tariff data
Nimbin	NEM12 data 1/3/2020 to 28/2/2021. Aggregated to half-hourly.	Mar 2020 to Feb 2021 (inclusive)	178.7 kWh	Origin electricity invoice (July 25 to Oct 25 2019). 3 tier time-of-use structure with solar feed-in credit and no demand or capacity charges. 6% greenpower
Jamison	NEM 12 data 26/2/2019 to 25/2/2021. Aggregated to half-hourly.	2020 calendar year	711 kWh	ERM invoice (July 2019). 3 tier time of use (retail), 2 tier (network). Monthly demand charge. Network prices updated to 2020. Retail tou times determined from data.
Singleton	NEM12 data 26/2/2019 to 25/2/2021. Aggregated to half-hourly.	2020 calendar year	1151 kWh	Invoice (Nov 2019). 3 tier time-of use (network & retail). Capacity charge (12 month).

2.2 Adaptive controller

A model predictive control (MPC) algorithm was used to determine best-case battery operation leading to the lowest cost (electricity cost and battery degradation cost) for the period covered by the data. Model parameters are listed in Table 2.

To replicate the behaviour of the real controller, the algorithm was implemented in a semi-recursive fashion, but without forecasting. That is, the optimum charge/discharge pattern was determined for successive 3-day periods, advancing 1 day at a time so that only the first 24 hours of the charge/discharge solution was 'saved'. This mimics how the controller operates in practise, albeit without the additional complexity associated with forecasting load and generation.

The algorithm uses linear constrained quadratic optimisation to minimise either; i) the sum of network costs (time of use, feed-in, demand and capacity charges) and estimated battery degradation costs or; ii) the sum of wholesale and degradation costs over the analysis window. Demand/capacity charges are accounted for via a cost penalty applied when the power demand from the grid over a half-hour period within the demand charging window is greater than a pre-set fraction of the current demand/capacity charge level which is assumed constant over each 3 day period. Battery charge/discharge inefficiencies and constraints on charging limits, rates of charge and rates of change of charge are applied.

A linearised form of the lithium-ion phosphate battery degradation model of Schimpe et al. (3) was used. This model accounts for the influence of state of charge, charge/discharge rates and calendar time on battery degradation. The financial cost of degrading the battery was accounted for based on the proportional reduction in lifetime that results from using it assuming a fixed battery capital cost with no residual value at end-of-life.

Demand and capacity charges were calculated from real power values only (i.e. assuming a power factor of 1 at peak demand).

Table 2 Battery modelling parameters

Parameter	Value
Capacity	Varied between 10kWh to 200kWh
Max. charge/discharge rate	0.5 x capacity (kW)
Charge/discharge efficiency	88%, 98%
Max/min state of charge	98%, 20%
Max. charge ramp rate	16% of max/min
Capital cost[1]	$1200/kWh
Capacity @ end of life	80%
Battery calendar age at start of analysis	5 years[2]

2.3 Method to determine fixed battery charging schedule

The optimisation algorithm used in the adaptive controller was applied to determine two fixed (static) 24-hour patterns of target battery charge/discharge power that; i) lead to the lowest possible annual cost for the provided data-set, and ii) require no external input signals other than the date and time to be implemented.

Imposing the same charging pattern on set days while ensuring battery physics are modelled correctly, demand/ capacity charges are accounted for, and annual costs and battery degradation are minimised, is a non-trivial problem. Here, instead of performing a single global (annual) optimisation, the problem was divided into two steps; finding the optimum pair of charging patterns for each day type, and determining which pair of charging patterns led to the lowest annual costs when replicated over the full year.

[1]Results here are not strongly depending on the assumed capital cost value. This value is not used in financial calculations here and only has a moderate influence on the computed charge/discharge pattern because the battery degrades even when it is not cycled (i.e. calendar degradation), and, in the case where demand charges are present, because reduction of demand charges is assumed to always provide a net benefit for the purposes of the control algorithm.

[2] Battery performance was evaluated for a 5-year old battery to be more representative of average battery performance over its life and factoring in that degradation is faster for a new battery.

Specifically, this involved:

1) Dividing the year of data into school days and non-school days
2) For each day of data, an optimal charge/discharge schedule was computed using the linear constrained quadratic optimalisation model. To ensure that the subsequent charging pattern for any given day could be applied to any day of the same type, an additional constraint setting the battery state of charge at the start and end of each day to 60%[3] was applied. This resulted in approximately 200 school day charge/discharge profiles and 160 non-school day charge/discharge profiles.
3) Combinations of school day and non-school day charge profiles were applied to the entire data set and the pair that lead to the lowest total annual electricity and battery degradation cost when the same two profiles were applied to every day of the year was determined. That is, the best pair of profiles was the one that performed well on average across the whole year.

This procedure is not *guaranteed* to deliver the absolute lowest annual cost for the particular data-set because the overall optimum solution may not correspond to the optimum solution calculated for any given day. However, it is likely to be very close to it. Of more relevance is the fact that the solution has been optimised with complete knowledge of the entire year of energy values. In practice, real-world savings are likely to be less than those presented here because the schedule was optimised to the same data-set used to calculate savings.

3.0 RESULTS

3.1 Net energy demand characteristics (no battery)

Figure 1 (left plots) are boxplots of the half-hourly net real power export (positive corresponding to energy supplied from the grid) for the three sites (without a battery) as a function of the hour of the day for school days. Figure 1 (right plots) are frequency distributions of the half-hourly net export power for all hours, also for school days.

All three sites have a regular daily pattern of net export with minimal demand overnight and increased load between approximately 7 am and 3pm consistent with typical school attendance hours. Nimbin High has a much lower total demand and a PV system that is comparatively larger; hence there are regular periods of net import (power feed to the grid) during the day even on school days but particularly on non-school days. Singleton has more than six times the average demand of Nimbin and 60% higher demand than Jamison. For Jamison and Singleton there are typically almost no periods of net import.

The frequency distributions show all three sites have a long ‘right-tail’; that is, comparatively large half-hourly demand values that occur for only a very small proportion of the year. This suggests significant potential for reducing any demand/capacity charges (noting that Nimbin does not have a demand or capacity charge) though these plots correspond to all times on school days, not specifically to demand charging periods.

Although separate load and generation data was not available, based on the export values that are higher during the middle of the day it is clear that load and generation are well-aligned for all three schools. This limits the opportunity to use batteries to maximise solar self-consumption.

[3] This value was chosen after some experimentation. It allows the optimisation process to either add or remove charge from the battery at both the start and end of the day, but is weighted toward ensuring sufficient charge is available for the afternoon peak period.

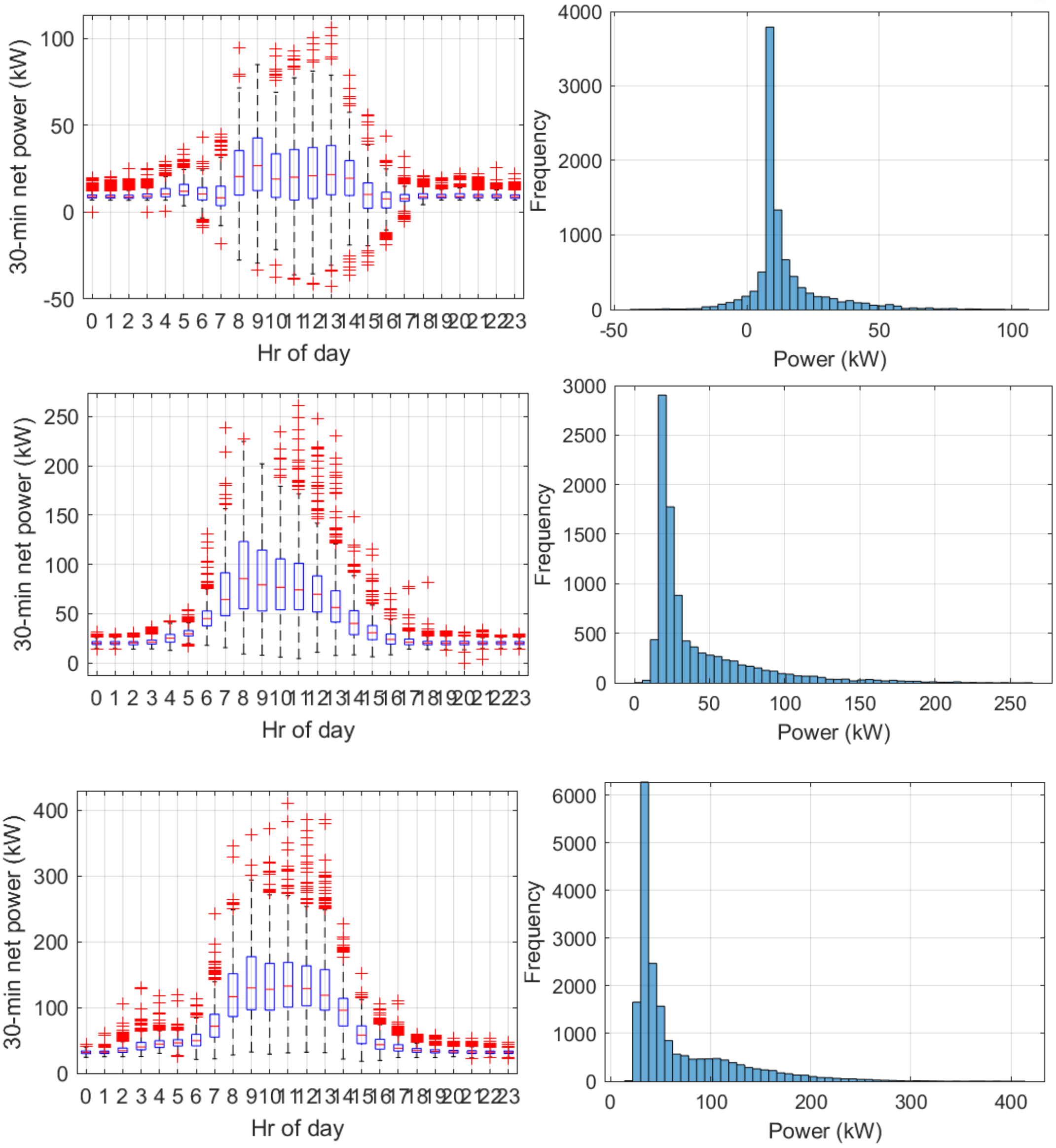

Figure 1 Left: boxplots of net power as a function hour of the day. Right: distributions of net power. Base case. Nimbin (top), Jamison (centre), Singleton (bottom).

3.2 Overall results 60kWh battery

Results are first presented for a battery capacity of 60kWh. Table 3 summarises the cost savings under the existing tariffs and Table 4 those under a wholesale-based tariff. Additional plots showing the average net export amount as a function of hour of the day with and without the battery are shown in the appendix (Figure 5).

Annual cost savings using the adaptive controller are 4.5% (Singleton), 5.2% (Jamison) and 8.3% (Nimbin). For the sites with demand/capacity charges (Jamison and Singleton), the majority of the saving is due to reducing these charges. Energy arbitrage (shifting net export from high to low energy price periods) gives minimal savings.

For both Jamison and Singleton retailer peak and shoulder charges are the same and hence the school day is entirely within the same retail energy cost period. In addition, the difference between off-peak and peak retailer and network energy charges is only a few cents which limits the opportunity for energy arbitrage.

For Nimbin time of use energy charges are much higher (almost 2 to 3 times higher) and so using the battery to shift net export to off-peak times provides much greater savings. However, the fact that shoulder and peak charges are almost the same (27.4c/kWh vs 28.9c/kWh) limits the benefit somewhat. For Nimbin there is also a feed-in credit of 9c/kWh which provides cost recovery from excess solar generation. This reduces (though does not remove) the benefit of using the battery to maximise solar self-consumption and this can be seen in the reduction in the feed-in credit that occurs for the battery cases. For Nimbin, the PV system is also believed to have been installed in May 2020, approximately 2 months into the analysis period. This is estimated to have resulted in a small (approximately 10%) reduction in the calculated battery electricity savings reported here.

Despite the above factors, and the absence of demand or capacity charges, the overall percentage savings remain higher for Nimbin largely because the savings from the demand and capacity charge reductions for Jamison and Singleton are not as high as might be expected for two reasons outlined below.

Firstly, for both Jamison and Singleton the net export is highest outside the demand/capacity charging window. For Jamison this begins at 4pm and for Singleton 2pm; in both cases after the highest demand period.

Secondly, for Singleton in particular, the capacity charge (~220kVa) is large in comparison to the maximum battery discharge rate for the 60kWh battery which is only 30kVa. Hence, the most that the capacity charge can be reduced using this battery is 30/220 or approximately 14%. Further cost reductions might be obtain using a specialised battery with higher peak discharge (e.g. a 1C battery delivery 60kVA discharge from a 60kWh capacity). For Jamison the demand charge is based on the highest value per month so the penalty from an unusually high demand value is less than for Singleton where the highest demand value can persist for up to a year.

Cost savings under a fixed battery control schedule and consistently significantly lower than those with the adaptive control as expected. Even so, in practise, because the fixed schedule was tailored specifically to the data-sets here, the resultant savings for other years are likely to be lower. That is, the key difference between the fixed and adaptive control is that that latter can adjust according to actual net export (consumption and generation) which is especially important for minimising demand and capacity charges. The calculated fixed schedules for the three locations are shown in Figure 4 with values listed in Table 8 in the appendix.

For all sites and all scenarios, it’s important to note that no battery changes either the total net export over the year or the fixed energy costs such as daily charges, metering charges, access charges and environmental charges. Hence there is only a portion of the base electricity bill that can be reduced using one of three savings mechanisms; i) arbitrage, ii) demand/capacity charge reduction and iii) maximising self-consumption (a form of arbitrage).

Table 3 Summary of results with 60kWh battery (existing tariff)

	Nimbin		Jamison		Singleton	
	Fixed	Adaptive	Fixed	Adaptive	Fixed	Adaptive
Base electricity cost	$21414		$52924		$96505	
Overall saving with 60kWh battery	**$698 (3.3%)**	**$1779 (8.3%)**	**$1769 (3.3%)**	**$2774 (5.2%)**	**$3889 (4.0%)**	**$4374 (4.5%)**
Energy cost saving	$832 (3.9%)	$2507 (11.8%)	$262 (0.67%)	$469 (1.2%)	$286 (0.5%)	$703 (1.2%)
Import energy revenue change	-$134 (-6.1%)	-$727 (-33.5%)	N/A		N/A	
Demand charge cost saving	N/A		$1507 (30.3%)	$2305 (46.3%)	$3604 (12.2%)	$3671 (12.4%)

Base electricity costs under a purely wholesale (spot price) based tariff are approximately one quarter of those under the existing tariffs. In practise it is likely that additional, presumably fixed charges would be applied to bring the overall electricity bill cost closer to the cost under the existing tariff. Because these have not be included here percentage cost savings with a 60kWh battery are much higher by a factor of approximately three times. If these fixed costs are known it would be a simple exercise to include them and recalculate percentage savings.

Figure 2 shows the cumulative cost saving of the year under a wholesale-based tariff for Jamison. Here it is apparent that approximately half the annual saving arises from just three short periods of very high spot price where the battery has minimised the net export amount. This highlights why it is not possible to achieve reliable savings under a pre-determined fixed charging schedule; that is, the savings are highly sensitive to the precise occurrence of these high prices, and so an adaptive controller with forecasting capability is required to predict and response appropriately when they occur.

Table 4 Summary of results with 60kWh battery (wholesale tariff)

	Nimbin	Jamison	Singleton
Base electricity cost	$4388	$16292	$24900
Overall saving with 60kWh battery	$1025 (23.4%)	$2822 (17.3%)	$3520 (14.1%)

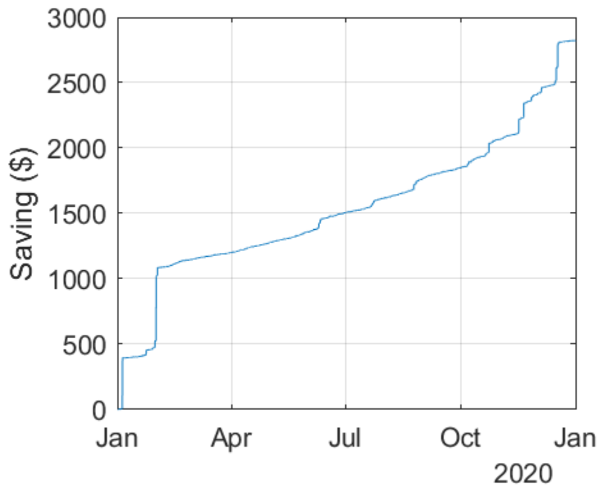

Figure 2 Cumulative electricity cost saving under a wholesale tariff scenario for Jamison (60kWh battery).

3.3 Results with varying battery capacity

The above analysis was repeated with battery capacities between 10kWh and 200kWh. Annual cost saving and percentage battery degradation values for each case are listed in Tables 5,6 and 7 in the Appendix. Figure 3 summarises the relative cost saving (i.e. the annual electricity cost with the battery divided by the annual electricity cost without the battery) as a function of battery capacity. Fixed schedule control cases are shown by the solid lines and the adaptive control cases by the dashed lines.

In general, it would be expected that cost saving would increase as battery capacity increases, and this is indeed the case with the adaptive control. However, for the schedule-based control for Nimbin electricity cost increases slightly for the largest battery sizes. This is a consequence of the fixed schedule which fails to adapt to the changing net export (load and generation) day to day. For small battery sizes these differences are less likely to cause adverse cost outcomes, whereas for larger battery sizes the errors are magnified.

Calculated battery degradation rates are approximately 0.9% per year across all scenarios with approximately 1 charge—discharge cycle per day. Assuming an end-of-life capacity of 80% suggests battery lifetimes on the order of 20 years. These is at the upper end of typically quoted lifetimes and longer than most battery warranted periods. Given the substantial uncertainties involved in estimating battery degradation, and battery life-times, and factoring in that battery performance is significantly reduced near end-of-life, it is suggested that a more conservative 15-year operating life be assumed in any subsequent financial analysis, with residual value accounted for if required.

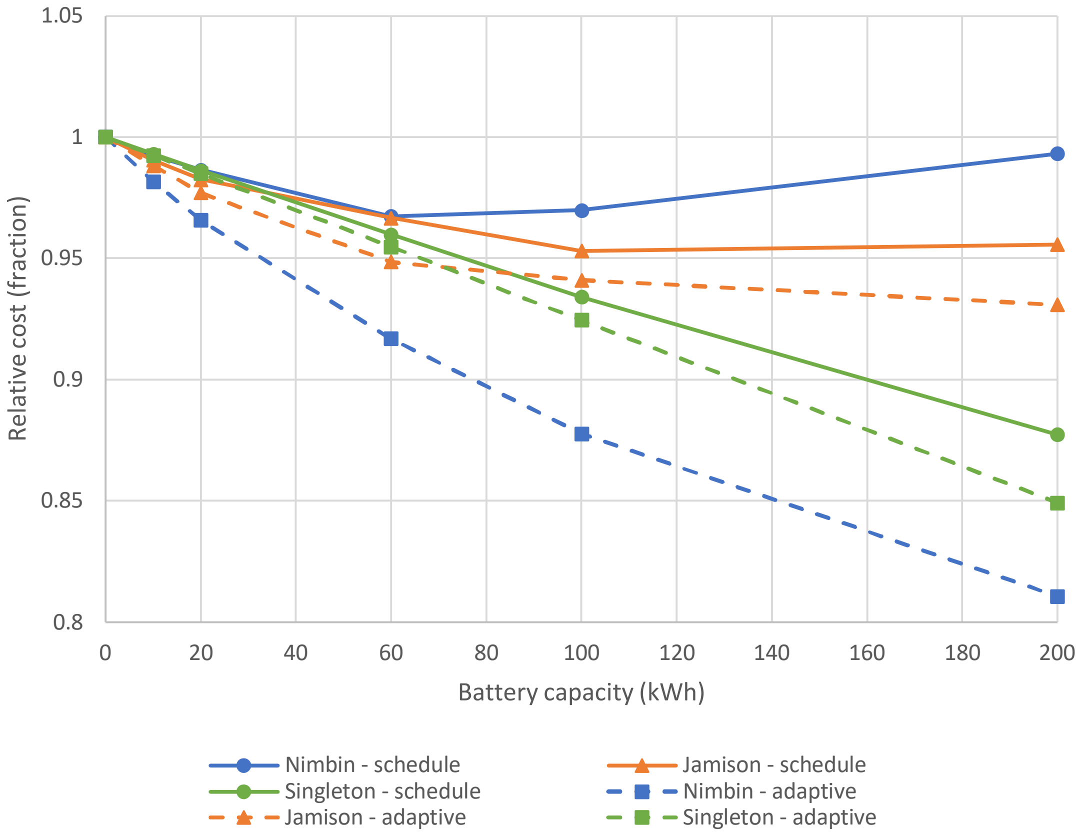

Figure 3 Relative electricity cost saving as a function of battery capacity under existing tariffs for three schools. Scheduled based control (solid lines) and adpative control (dashed lines).

3.4 Fixed schedules

The two calculated target fixed charge/discharge schedules for each school for a 60kWh/30kVa are shown in Figure 5. Data values are given in Table 8 in the appendix.

On school-days consumption is generally lower. For Nimbin, a net solar generation *usually* occurs during the middle of the day, and so the battery schedule suggests charging during these times as well as late at night during the off-peak period. Discharging is scheduled in the late afternoon on both school days and non-school days during the peak tariff period. There is also a discharge in the early morning on non-school days to ensure that the battery has sufficient capacity to soak up the excess solar generation.

For Jamison the charge/discharge is scheduled entirely to minimise demand charges. This leads to a discharge from 4pm to 8pm and charging overnight from 10pm. A very similar pattern is applied to both school days and non-school days since demand charge periods occur during both. (For Jamison demand charges apply to ‘business days’ or essentially all days within set months that are not gazetted public holidays. For Singleton capacity charges apply to ‘working weekdays’ or all weekdays that are not public holidays.)

For Singleton the calculated schedule suggests minimising the capacity charge as the sole aim. This leads to a rapid discharge from 2pm to 4pm to cover the peak in net demand, followed by overnight charging. Because the capacity charge potentially occurs on a single half-hourly interval in the year which is likely to be a school day when loads are higher, the optimisation calculation has suggested no battery use on non-school days, despite the fact that the capacity charging period will apply on some of these days.

This highlights an important point; because these schedules are fixed there is no guarantee that they will lead to cost effective operation on any given day. For example, in the case of Nimbin, if a non-school day is overcast, the battery will still attempt to charge during the middle of the day based on the schedule, and this may lead to expensive grid charging. Likewise, for Singleton, discharging over the specified afternoon period is not guaranteed to reduce the demand/capacity charge since the highest demand could occur later in the afternoon after the battery is already depleted. Based on the historical data analysed this is unlikely but not specifically prevented.

An addition consideration is that these schedules represent target charging/discharging behaviour under the assumed battery performance parameters used in the modelling. If they are implemented in practise it is essential that additional logic is included to ensure state of charge remains within acceptable bounds. For example, top-up charging overnight may be required to ensure the battery is not gradually depleted. It is also assumed that the battery has in-built mechanisms for precenting over/under charge, maintaining cell voltages and temperatures.

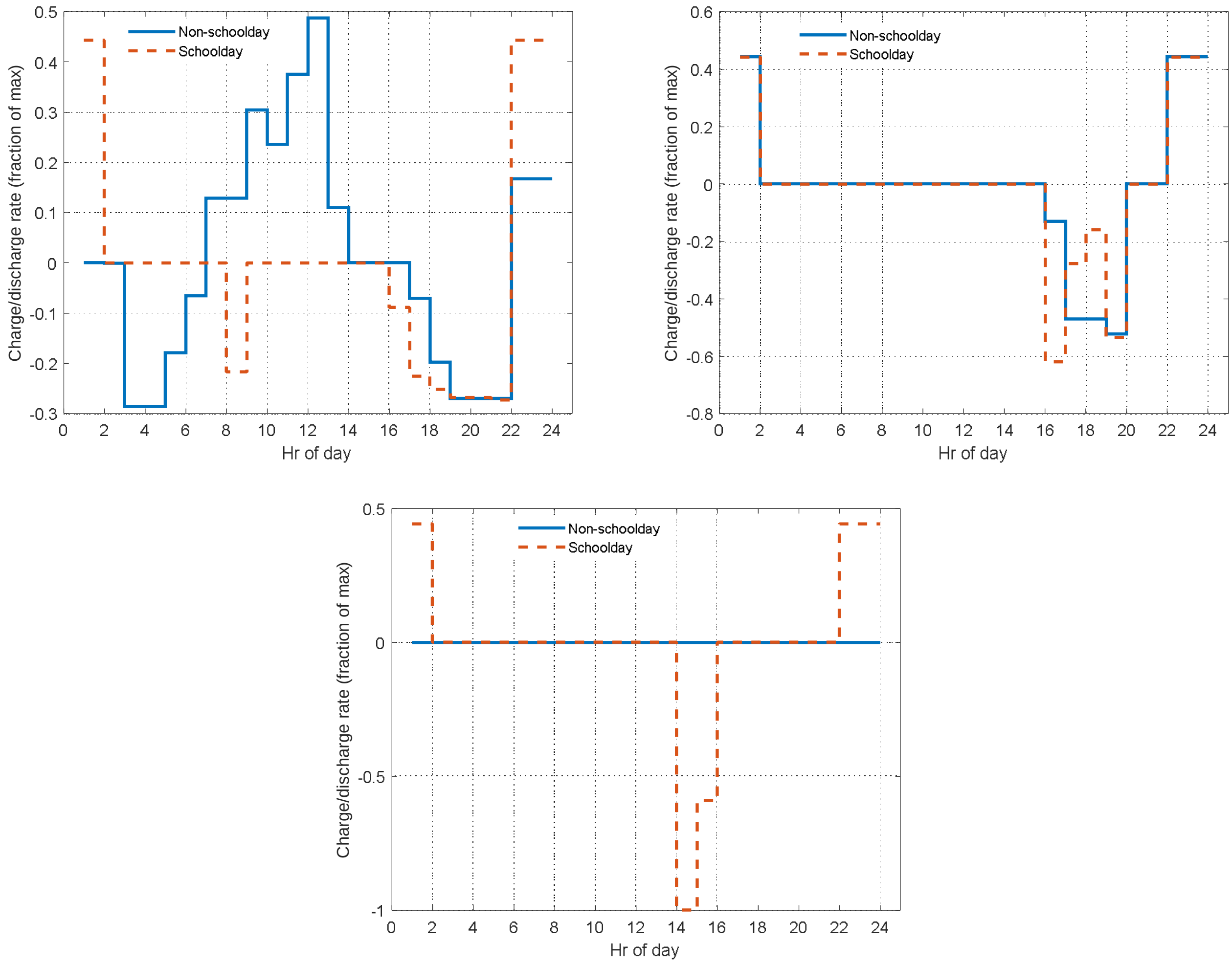

Figure 4 Calculated fixed battery charge/discharge schedules for Nimbin (top left), Jamison, (top right) and Singleton (bottom) for a 60kWh/30kVa battery. Positive values are charging. A value of 1 indicates charging at the full rate (i.e. 30kVa).

4.0 Summary

The analysis described here is expected to be combined with financial modelling to assess overall economics of the battery systems considered. To facilitate this, annual electricity cost saving and annual percentage battery capacity loss values for each case are given in the Appendix.

Key findings from this analysis are;

1) The load profile for all three schools is well-aligned with the solar generation, and the PV capacity is not large compared to the load. This means a battery is not essential to maximise solar self-consumption with the existing PV arrays. In addition, Nimbin has a significant solar feed in credit which disincentivises maximising of self-consumption.

2) The capacity charge for Singleton is very large and represents a significant potential for cost reduction from either demand response strategies or from battery control. However, the 60kWh/30kVa battery is simply too small to substantially reduce this charge. Although not evident in the single year analysis here, guaranteeing this saving from year to year requires an adaptive controller.

3) For all three schools there is only a small or negligible difference between shoulder and peak energy charges. Only Nimbin has a significant (>10c/kWh) difference between peak/shoulder and off-peak charges. This limits the potential for using the battery for energy arbitrage.

4) Although adaptive control delivers greater cost savings, the differences compared to a fixed schedule are not as dramatic as might be expected. One of the reasons is that the battery capacity is small compared to the load which means that its optimum day-to-day operation is more consistent.

   However, the most important factor is that the adaptive control effectively guarantees the best possible outcome because it responds to changes in the load and generation, whereas a fixed schedule works well if that schedule just happens to match the load and generation well. Because the best fixed schedule was calculated from the same data used to evaluate the cost saving, the resultant savings represent a best-case scenario for fixed schedule control. If the same schedule is applied year-on-year, average savings are likely to be lower. Savings may also potentially decrease over time due to gradual changes in the under-lying load and generation. For Singleton, most of the saving was due to the reduction in capacity charge over a single half-hour event in the year which the fixed schedule successfully captured because the exact occurrence of this event was known when determining the schedule. This level of foresight would not be present in a practical deployment of a fixed schedule.

5) Given the above issues, the fixed schedules calculated here are intended to be used as a fall-back control option only. It is further recommended that the fixed schedules be re-calculated periodically, particularly if there are substantial changes in the load, generation, tariff structure or relative tariff charges.

5.0 Works cited

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3. *Comprehensive modeling of temperature-dependent degradation mechanisms in lithium iron phosphate batteries.* **Schimpe, M., et al.** 2, s.l. : ECS, 2018, Journal of the Electrochemical Society, Vol. 165, pp. A181-A193.

APPENDIX

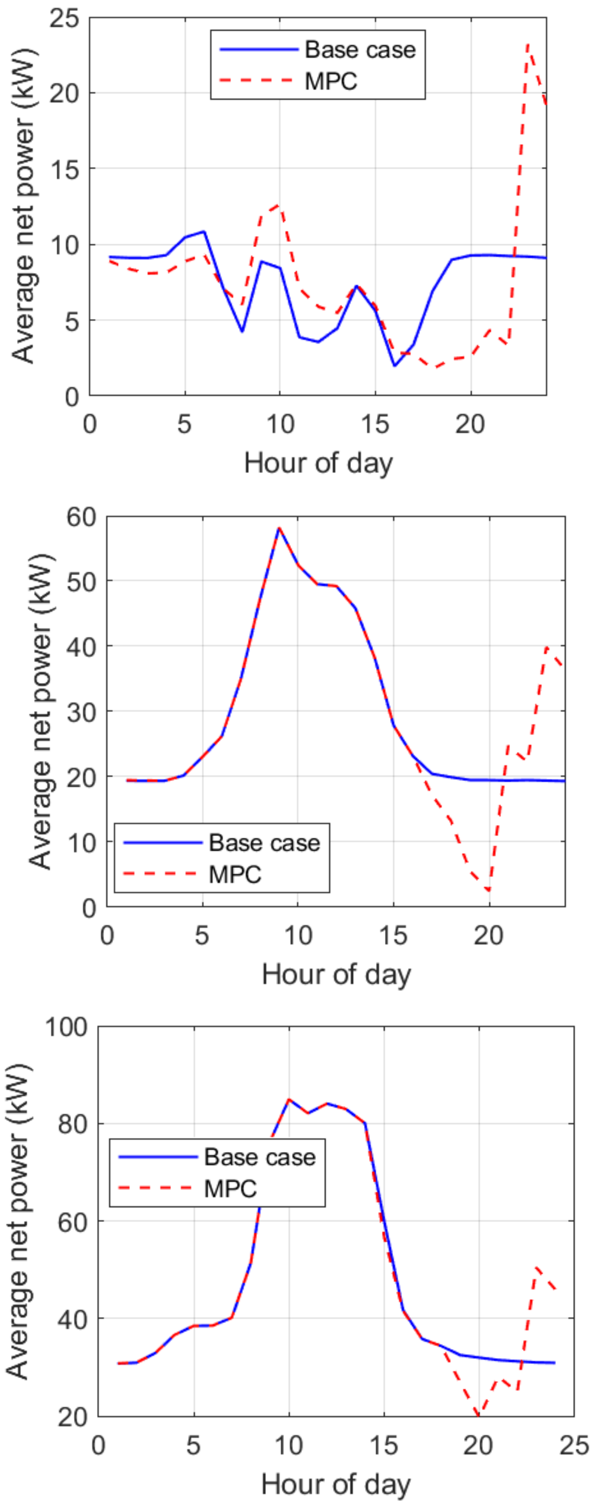

Figure 5 Average net power for base case (no battery) and adaptive control case (labelled 'MPC') with 60kWh battery for Nimbin (top), Jamison (centre) and Singleton (bottom).

Table 5 Results table – existing tariff, schedule control

Battery capacity (kWh)	Nimbin		Jamison		Singleton	
	Electricity cost ($)	Degradation (%)	Electricity cost ($)	Degradation (%)	Electricity cost ($)	Degradation (%)
0 (base case)	21414	N/A	52924	N/A	96505	N/A
10	21250	0.89	52419	0.90	95835	0.91
20	21123	0.89	51995	0.90	95170	0.91
60	20716	0.91	51156	0.90	92616	0.91
100	20766	0.93	50435	0.90	90139	0.91
200	21267	0.93	50577	0.91	84664	0.92

Table 6 Results table – existing tariff, adaptive control

Battery capacity (kWh)	Nimbin		Jamison		Singleton	
	Electricity cost ($)	Degradation (%)	Electricity cost ($)	Degradation (%)	Electricity cost ($)	Degradation (%)
0 (base case)	21414	N/A	52924	N/A	96505	N/A
10	21020	0.90	52300	0.88	95776	0.86
20	20679	0.90	51706	0.87	95047	0.86
60	19634	0.90	50200	0.87	92131	0.86
100	18793	0.91	49804	0.87	89216	0.87
200	17359	0.91	49266	0.87	81955	0.87

Table 7 Results table – wholesale tariff, adaptive control

Battery capacity (kWh)	Nimbin		Jamison		Singleton	
	Electricity cost ($)	Degradation (%)	Electricity cost ($)	Degradation (%)	Electricity cost ($)	Degradation (%)
0 (base case)	4388	N/A	16292	N/A	24899	N/A
10	4073	0.90	15692	0.91	24304	0.91
20	3822	0.90	15099	0.91	32709	0.91
60	3363	0.90	13471	0.90	21379	0.91
100	3062	0.90	12667	0.90	19848	0.90
200	2793	0.88	11302	0.89	18177	0.89

Table 8 Calculated fixed battery charging schedules for three schools. Note: the sum of charging energy is greater than the sum of discharging energy due to battery inefficiencies.

Hour of the day (AEDT)	Target Charge amount (kW) (positive = charge, negative = discharge) based on a 60kWh/30kVa battery					
	Nimbin		Jamison		Singleton	
	School days	Non-school days	School days	Non-school days	School days	Non-school days
12 midnight to 1am	13.3	0.0	13.3	13.3	13.3	0
1am to 2am	13.3	0.0	13.3	13.3	13.3	0
2am to 3am	0.0	0.0	0.0	0.0	0.0	0
3am to 4am	0.0	-8.6	0.0	0.0	0.0	0
4am to 5am	0.0	-8.6	0.0	0.0	0.0	0
5am to 6am	0.0	-5.4	0.0	0.0	0.0	0
6am to 7am	0.0	-2.0	0.0	0.0	0.0	0
7am to 8am	0.0	3.9	0.0	0.0	0.0	0
8am to 9am	-6.5	3.9	0.0	0.0	0.0	0
9am to 10am	0.0	9.1	0.0	0.0	0.0	0
10am to 11am	0.0	7.1	0.0	0.0	0.0	0
11am to 12noon	0.0	11.3	0.0	0.0	0.0	0
12noon to 1pm	0.0	14.6	0.0	0.0	0.0	0
1pm to 2pm	0.0	3.3	0.0	0.0	0.0	0
2pm to 3pm	0.0	0.0	0.0	0.0	-30.0	0
3pm to 4pm	0.0	0.0	0.0	0.0	-17.7	0
4pm to 5pm	-2.7	0.0	-18.6	-3.9	0.0	0
5pm to 6pm	-6.8	-2.1	-8.3	-14.1	0.0	0
6pm to 7pm	-7.5	-5.9	-4.8	-14.1	0.0	0
7pm to 8pm	-8.0	-8.1	-16.1	-15.7	0.0	0
8pm to 9pm	-8.0	-8.1	0.0	0.0	0.0	0
9pm to 10pm	-8.2	-8.1	0.0	0.0	0.0	0
10pm to 11pm	13.3	5.0	13.3	13.3	13.3	0
11pm to midnight	13.3	5.0	13.3	13.3	13.3	0