

**Residential Battery Perspectives Article Appendix - Methodology,  
Assumptions and Detailed Results**

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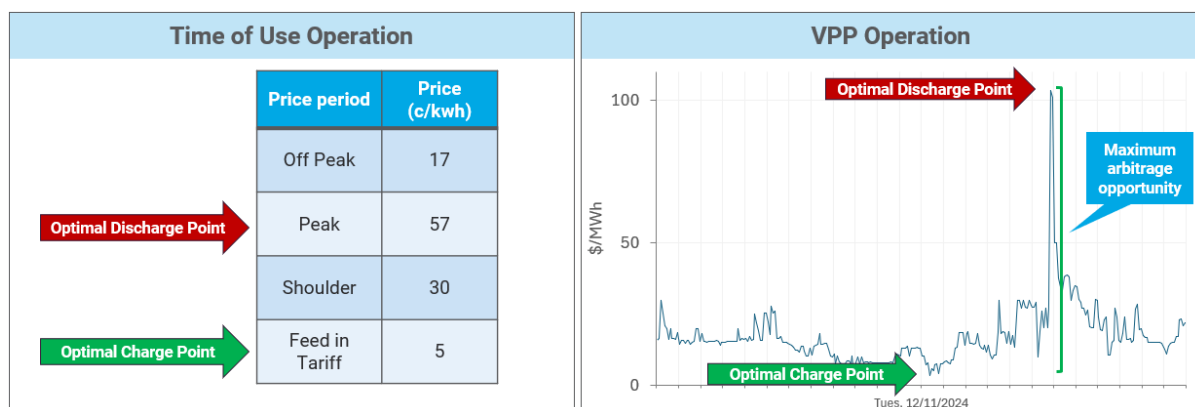
# 1. Methodology

## 1.1. How batteries make money

Batteries make money by arbitraging energy costs – charging when the price is low and discharging when the price is higher. For consumers with import tariffs and solar export feed-in tariffs (FiTs), the maximum arbitrage amount is the difference between peak pricing and the feed-in tariff. This is because by charging the battery from excess solar generation, you forego the additional revenue from solar exports. For example, if the peak price under a time-of-use tariff is 50c/kWh, and the solar feed-in tariff is 10c/kWh, the arbitrage revenue of the battery is 40c/kWh. However, batteries cannot always charge and discharge at these points and may have to settle for a lower, sub-optimal arbitrage. These occur when there is either not enough solar generation to completely charge a battery or not enough consumption during the peak to be displaced by stored energy.

Alternatively, some electricity retailers allow consumers to be directly exposed to the wholesale electricity price. These prices are significantly more variable, which means that the potential maximum arbitrage opportunity is much higher. For example, in NSW on 12/11/2024, the maximum arbitrage opportunity was approximately 100c/kWh. However, these opportunities are much more difficult to take advantage of, as they are typically short-duration, fleeting, and hard to accurately predict.

**Figure 1: Wholesale price exposure can create greater arbitrage opportunities, but is difficult to capture and harder to predict**



## 1.2. We made a number of assumptions

For our model inputs, we made various assumptions that impacted the results. At a high level, we:

- Used NSW-based customer load profiles
- Aggregated all data and behaviour at an hourly level
- Assumed each customer had an existing solar system
- Analysed NSW price offers, focusing on one time-of-use tariff, one flat rate tariff, and NSW spot prices
- Assumed all batteries degrade in the same manner and have a round trip efficiency of 85%
- Assumed all NSW customers claim the government rebates available to them
- Used a 3% discount rate

- Narrowed in on ten residential batteries, five premium options and five top-performers by our metrics
- Split the load profiles into three customer archetypes.

The largest of our assumptions centred around consumption profiles. We focused on 1,000 real customer load profiles from the NSW region only, sourced from the Essential Energy, Endeavour Energy, and Ausgrid networks. These profiles provided us with a year's worth (FY24) of hourly native demand data and varied in annual loads, shape, and seasonality. To accompany this consumption data, each individual was assumed to have an existing solar system. In the NSW Ausgrid region, the average solar system size in FY24 was 7.1kW, and so we provided each consumer trace with an average yearly solar profile for Sydney that corresponded to a 7kW system. This system results in an annual PV output of 10,640kWh and was sourced from the U.S. Department of Energy National Renewable Energy Laboratory [PVWatts calculator](#). The consumer pricing structure was taken from the Origin Go Variable tariff for the Ausgrid distribution region. The ToU prices varied slightly throughout the day, as well as weekdays vs. weekends and the time of the year. The flat tariff price remained constant throughout time, however, both structures had the same FiT rate.

Our battery assumptions relating to cost, capacity, and rated power were sourced from [SolarQuotes](#), with an inverter requirement adding an additional \$2,000 to the battery cost. In terms of battery engineering and degradation effects, we assumed battery storage capacity degraded by 4% per year (in line with cycling once per day on average), and this did not affect the battery's rated power. For batteries that cycled more or less than once per day, degradation was scaled linearly. Additionally, we assumed that batteries lose a small amount of energy during operation, having a round-trip efficiency of 85%.

In November 2024, NSW introduced an incentive to encourage battery uptake, however, since then this subsidy has been amended to promote Virtual Power Plant (VPP) participation as opposed to assistance with upfront battery costs. Individuals who connect their battery to a VPP are estimated to receive an incentive of \$55/kWh. Additionally, the Commonwealth Government has implemented a Solar Battery Rebate. This subsidy also depends on a battery's capacity, with estimates of \$370/kWh. Both subsidies have been included in our modelling. The two subsidies can be added on top of each other for consumers in NSW, we have referred to this as a "Stacked" subsidy scheme. Finally, a discount rate of 3% was used for all our NPV calculations. This discount rate was chosen to approximate a real mortgage rate and reflects the fact that households may trade-off between additional mortgage repayments and residential battery capital expenditure.

Due to the large number of batteries available in the NEM, we conducted preliminary analysis to reduce the model runtime. For all 70 residential batteries, we applied a simplistic battery behavioural algorithm (as described in Section 1.4.1) onto the load profile provided in the AER's default market offer (DMO), scaled to different annual loads and across five networks. This allowed us to compare the relative performance of the batteries, and from this choose a list of ten batteries for further analysis. These included the five top-performing batteries and five premium batteries. A wide range of battery costs and capacities was maintained within this small sample, but importantly, all ten batteries had the same warranty period of ten years.

**Figure 2: Batteries can have a wide range of costs and storage capacities**

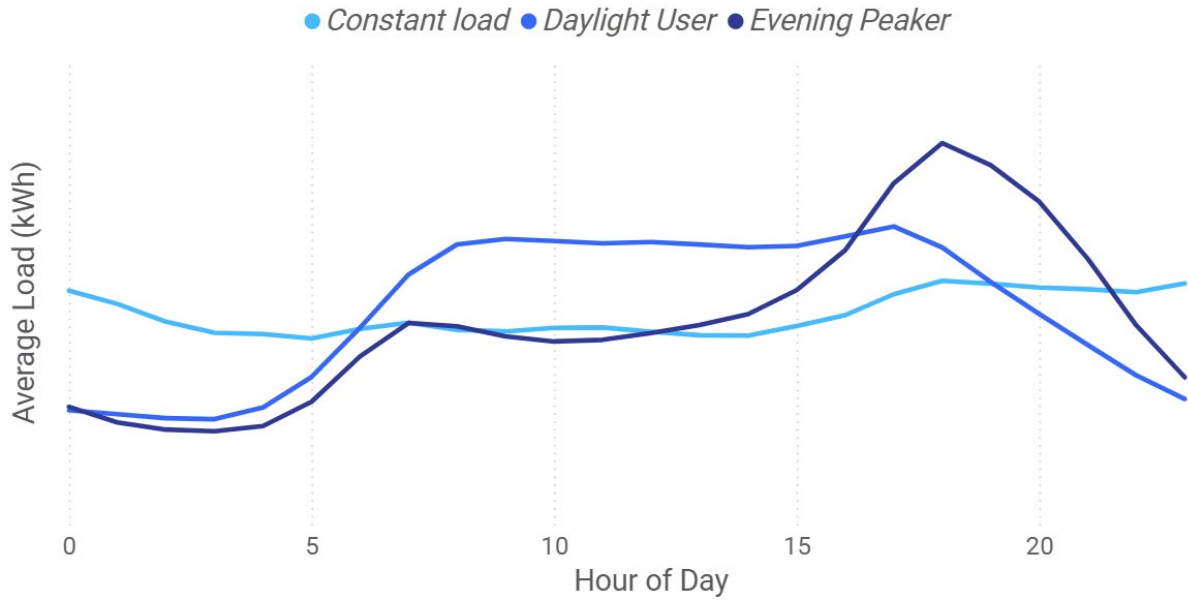
Battery Name	Capacity (kWh)	Cost (\$)	Type
Tesla Powerwall 3	14.00	13,600	Premium
BYD Battery Box Premium HVM 13.8	13.80	14,500	Premium
BYD Battery Box Premium HVM 8.3	8.3	10,500	Premium
SunGrow SBR HV 9.6	9.6	9,550	Premium
SunGrow SBR HV 16	16.00	13,340	Premium
LG Chem RESU 12	13.10	8,800	High Performing
Delta BX 6.3AC	6.32	5,280	High Performing
Alpha-ESS SMILE5 13.3	13.34	9,372	High Performing
Alpha-ESS SMILE5 10.1	10.08	7,458	High Performing
Alpha-ESS SMILE5 B3-PLUS	5.04	4,000	High Performing

From the 1,000 NSW customer load profiles that were analysed, typical customer archetypes were found. Average diurnal profiles were calculated for each individual, which were then normalised and clustered into three different groups using k-means clustering.

It should be noted that we used native load profiles for this analysis, with solar impacts added at a later stage. As such, the solar duck curve does not appear in **Figure 3** below. The customer archetypes were defined as follows:

- **Constant Load** – relatively consistent load across all hours of the day – 28% of consumers
- **Daylight User** – relatively consistent load during daylight hours, and low load otherwise – 30% of consumers
- **Evening Peaker** – high load during evening hours, as well as a smaller bump in the morning (consistent with the typical load of a 9-5 worker) – 42% of consumers

**Figure 3: There are three consumption profiles that are most common amongst NSW consumers**



### 1.3. Financial metrics analysed

Our analysis revolves around comparing the energy bills of each consumer under a solar and battery system to the bill under a solar-only system. The savings, or cashflow, are defined as the difference between these two bills and are used to calculate two metrics, 10-Year Net Present Value (NPV) and battery Payback Period. The NPV is the cumulative total of a consumer's yearly cashflow (with battery degradation and discount rate factored in) minus the battery's upfront cost, or capital expenditure (CAPEX). This is calculated at the end of battery warranty, which for all batteries analysed was ten years.

$$NPV(\$) = \left( \sum_{i=0}^{10} \frac{C_i}{1 + d^i} \right) - CAPEX$$

where  $d$  = discount rate and  $C_i$  = cashflow for year  $i$

It should be noted that we have not assumed any resale value for the battery asset at the end of the 10-year period in the NPV calculation. This is a conservative assumption that was chosen because the project team is not currently aware of any widespread second-hand battery market that could lead to reliable estimates of this asset value. Furthermore, it is likely that the battery would exist as part of the property, and so the value would be included in the property value, making it very difficult to disentangle.

The Payback Period is the amount of time, in years, a battery takes to pay off its CAPEX (i.e. the point when NPV equals zero). These financial metrics are calculated consistently for each of the battery algorithms and operation modes described below.

### 1.4. How batteries operate

A battery's behaviour (or charge and discharge pattern) must be determined in order to calculate the benefits gained from its inclusion. We have done this using two algorithms: a simplistic approach that operates based on available solar generation and a complex algorithm that optimises behaviour with perfect foresight. This has been done to create a lower and upper bound of outcomes for the time of use tariff operation results. We then

have an additional complex algorithm for wholesale passthrough. A more in-depth description of the different algorithms is as follows.

#### 1.4.1. Tariff Operation – The Simple Algorithm

The simple algorithm uses heuristics to govern the battery's behaviour and is similar to many default battery controllers. It charges the battery using excess solar generation and discharges the battery as soon as consumption increases beyond that which solar can provide. In other words, it charges when the sun is shining, and discharges once it begins to set, rather than specifically maximising the arbitrage revenue. Importantly, under this algorithm, the battery does not interact directly with the grid and so cannot charge using grid-sourced electricity. This means it also cannot discharge and feed back into the grid.

#### 1.4.2. Tariff Operation – The Complex Algorithm

The complex algorithm utilises a linear programming algorithm that determines a battery's behaviour at every hour of the year based on a 24-hour lookahead period. Linear programming is a Data Science technique that optimises for an objective statement, in our case to minimise consumer energy bills, subject to a set of constraints, which define where energy can flow to and from. To ensure realistic behaviour, our objective statement also includes a cost for battery degradation, discouraging excessive cycling.

**Figure 4: The goal of the complex algorithm to minimise bills plus other costs for the consumer**

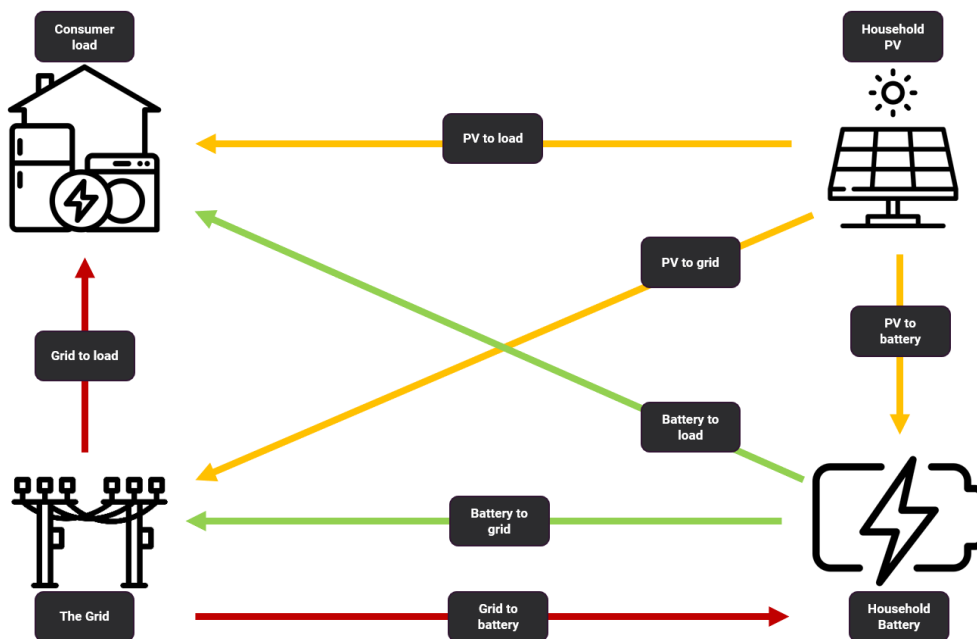
*Minimise*

$$obj = (imports * import price) - (exports * export price) + (degradation * degradation cost)$$

*w.r.t. flow and other constraints*

Flow constraints for the complex algorithm are given in **Figure 5** below.

**Figure 5: Allowed flow constraints in the consumer system**



Each of the consumer profiles are exposed to an Origin Go Variable tariff, with a battery able to interact with the solar, load and grid. This information is then fed into the algorithm, and the optimal hourly charge and discharge battery behaviour based on 24 hours of perfect foresight is calculated. This method may slightly over-estimate cashflow since there is perfect foresight on the solar production and demand consumption. However, we found that results were relatively similar to those of the simple algorithm, which assumes no perfect foresight, indicating that the impacts of perfect foresight are likely minimal. In reality, weather and demand forecasts would be used as an indicator for this modelling approach. Unless mentioned, any ToU analysis/results in this paper were determined using the Complex Algorithm approach.

#### *1.4.3. Wholesale Pass-through – The Complex Algorithm*

A similar linear programming algorithm was used for the wholesale pass-through analysis. However, the consumer and battery were now exposed to the wholesale market with added network pricing. The simple algorithm was not appropriate for wholesale analysis as it does not account for the volatile nature of spot prices. We deliberately avoided perfect foresight of wholesale prices as this is unrealistic and likely to significantly overestimate results. Instead, we used publicly available pre-dispatch data as an indicator which signalled when to charge or discharge the battery in coordination with the known solar and load. The battery behaviour was then evaluated on actual dispatch prices plus network costs post hoc to determine the energy bill. Whilst it is known that pre-dispatch prices vary compared to dispatch prices, we found that using pre-dispatch prices is a good enough indicator for the batteries to still make reasonable profits.

### **1.5. What are the limitations of our modelling**

Our modelling and corresponding analysis are subject to limitations, mainly centred around data availability and characteristics. These are detailed as follows:

- Consumer load profiles and prices are sourced from NSW customers only. Other jurisdictions will have different consumption profiles, tariffs, wholesale prices, and battery incentive programs, however, we expect many of our findings to be state agnostic.
- We focused on a single ToU and flat tariff plan in our analysis, and it is likely that battery NPV and payback periods will vary under different pricing structures. Additionally, we have assumed that tariff pricing stays the same for the next 10 years.
- Data and battery behaviour were assumed at an hourly level, which impacts results, predominantly on the wholesale pass-through operation, where prices are set at a 5-minute granularity. This stifles the battery's ability to capture sudden price spikes.
- As seen in many battery modelling exercises, the complex algorithm requires perfect foresight, with 24 hours of solar and load known ahead of time. This may not be a realistic assumption, but it is likely to only have a small impact on the results, given that real commercial algorithm providers would likely utilise weather forecasts and historic load patterns to provide this information with reasonable accuracy.
- This analysis is a theoretical exercise around customer financial gain. We have not considered other aspects, such as safety concerns, compatibility with other CER resources, and technical standards.

## 2. Results

### 2.1. Tariff Operation

#### 2.1.1. Subsidies reduce the upfront cost of batteries significantly

It is important to note that the following results assume that each of the NSW consumers chooses the “best-performing battery” for their given profiles. We have defined that a battery’s performance is rated on its 10-year NPV, which is the value it provides to the household after the battery’s warranty has been reached. Hence, the battery that will achieve the maximum possible NPV after 10 years is chosen for each individual. If a consumer were to choose a battery based on minimising its payback period, this best-performing battery would change slightly (and we will touch on this further later in section 2.1.3).

We found that subsidies are the single most impactful contributor to reducing battery payback periods. In most cases, without them, batteries struggle to recoup their capital cost. On average, NSW consumers did not break even on the investment after 10 years, with the payback period being 14.5 years. However, when subsidies were introduced into the equation, which could reduce a battery’s CAPEX by over 50%, the benefits of a battery increase significantly. The recently announced federal Solar Battery Rebate can halve the payback period of a battery down to seven years for cost-efficient batteries, with a 10-year NPV of over \$2,000.

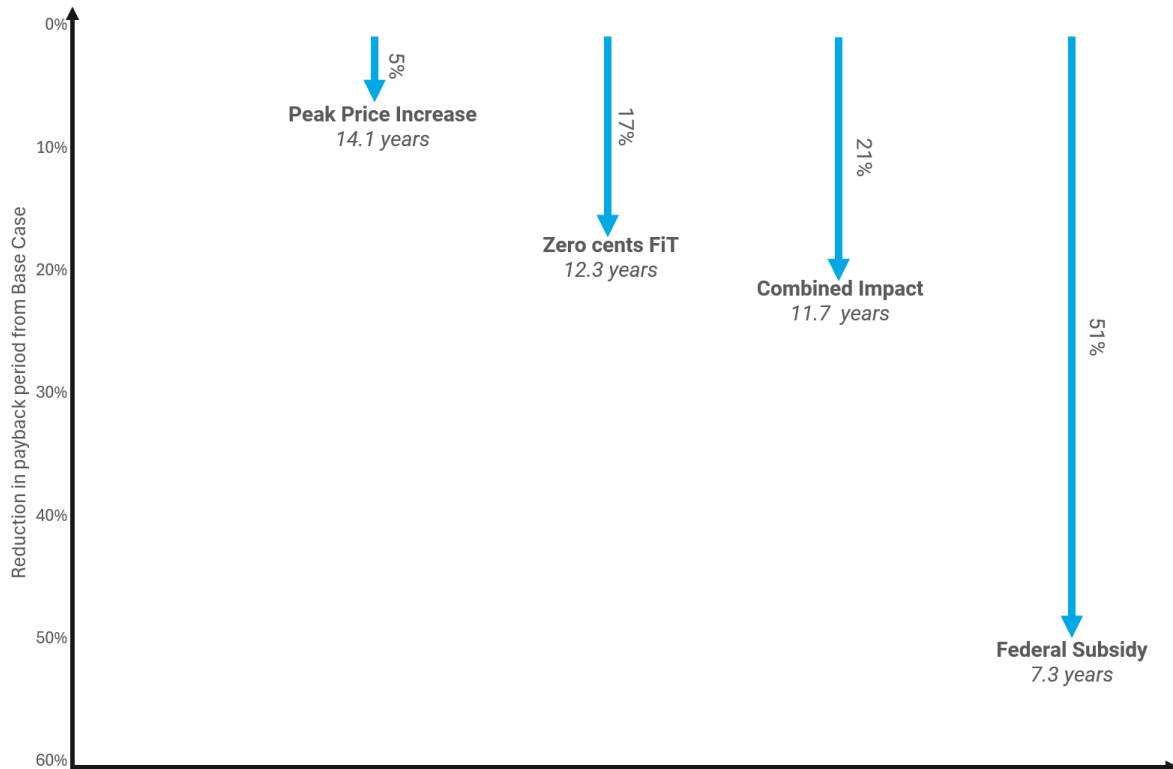
**Figure 6: The new federal rebate can halve payback periods for the average NSW consumer**

	10-Year NPV (\$)	Payback Period (years)
No Subsidy	-488.1	14.5
Federal Subsidy	2,308.2	7.3

#### 2.1.2. Price movements can impact battery economics

We performed sensitivity analysis, looking at a smaller subset of 100 NSW load profiles and investigated how price movements could affect battery performance. These sensitivities included increases to the peak ToU price and reductions in the FiT price, with a combined scenario relating to joint price changes. This analysis was designed to increase the arbitrage potential for batteries and see how this would impact their performance. It was found that these price movements can make a difference in payback periods, but it is only minor when compared to the impacts of subsidies.

**Figure 7: If import and export price gaps widen, battery performance improves**



Additionally, with this smaller subset, we compared the battery benefits under two different pricing schemes. Customers on a ToU tariff structure typically have higher arbitrage opportunities compared to Flat tariff customers, who have no time of day or seasonal variation in price. This analysis focused on Origin Go Variable tariffs, looking at their Single Rate (Flat) and ToU pricing structures. Both tariffs had an export FiT of 5 c/kWh; the ToU option had a peak price of 57.17 c/kWh with a maximum arbitrage potential of 52.17 c/kWh compared to the Flat Tariff's import price of 33.52 c/kWh with a maximum arbitrage potential of 28.52 c/kWh. Interestingly, this almost halving of maximum arbitrage only resulted in slightly shorter payback periods, with a reduction of around 5%. This can be explained by the following factors:

- Although constant, flat tariff pricing is relatively high, typically higher than shoulder prices for ToU structures (the sub-optimal ToU discharge point for batteries). A lot of the time, the battery needs to discharge at least some of its energy in the shoulder period.
- ToU structures consist of days with no peak price, such as all days in shoulder months (April, May, September, October for the Origin Go Variable tariff), and weekend days.

This combination of factors results in both tariffs having comparable average yearly arbitrage opportunities, which could explain the similar performance in batteries seen in **Figure 8** below.

**Figure 8: ToU tariffs show only a modest reduction in payback periods compared to flat tariffs.**

	<u>ToU Tariff</u>		<u>Flat Tariff</u>	
	<u>10-Year NPV (\$)</u>	<u>Payback Period (Years)</u>	<u>10-Year NPV (\$)</u>	<u>Payback Period (Years)</u>
<b>No Subsidy</b>	-625.4	14.9	-1,157.8	15.9
<b>Federal Subsidy</b>	1,981.3	7.3	1,370.7	7.7

### *2.1.2. We found that certain consumer behaviours can boost battery profitability*

Our analysis suggests that some individuals stand to gain more from purchasing a battery. On average, consumers with the Evening Peaker profile have a higher NPV after battery warranty has ended and produce shorter payback periods when compared to other consumers (see **Figure 9** below). By definition, the optimal way to use a residential battery is to shift consumption in peak price periods (which typically occur in the evenings) into shoulder or off-peak times. As such, consumers with a higher proportion of their load in these evening peak periods have a greater potential for arbitrage, resulting in higher battery benefits. On the other hand, consumers with higher loads throughout the day, like the Constant Load and Daylight User profiles, tend to perform slightly worse on average. They have larger relative load during daylight hours. This resulted in fewer opportunities for the battery to charge off excess PV output, relying more frequently on grid charging. This also results in fewer opportunities to offset more costly load in the evenings. Both of these effects lower arbitrage and, as such, stifles battery benefits.

We found that increasing a consumer's annual load directly reduces payback periods. With more consumption to shift, an individual gets more use out of their battery and yields higher returns on the investment. Our analysis found that Evening Peaker consumers with high annual consumption could see payback periods of just over three years on average and an NPV just shy of \$7,000 after 10 years. Conversely, Constant Load and Daylight User individuals with low annual consumption saw a negative 10-year NPV and payback periods outside of battery warranty.

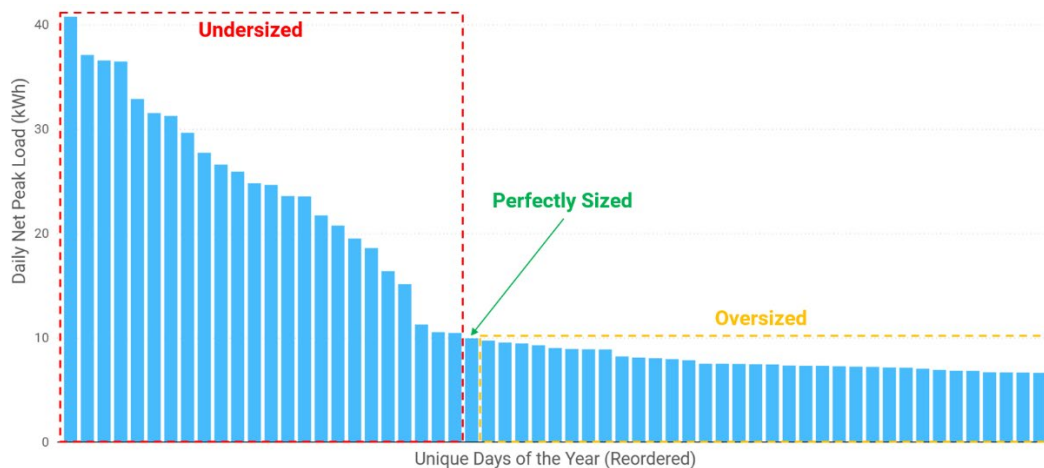
Another interesting artefact was that consumers with extremely high annual loads (24,000+ kWh/year) had a downtick in NPV and payback periods. This went against the monotonic relationship between annual load and battery benefits, with increasing load linked to higher benefits. This was because the consumer's 7kW solar system was being drowned out by the large amount of consumption in the middle of the day. With no excess solar available to charge the battery, its usage was restricted and, as such, the benefits.

**Figure 9: High-consuming Evening Peaker customers show shorter payback periods. Results are determined under a federal rebate scheme.**

	<u>Constant Load</u>		<u>Daylight User</u>		<u>Evening Peaker</u>	
	10-Year NPV (\$)	Payback Period (Years)	10-Year NPV (\$)	Payback Period (Years)	10-Year NPV (\$)	Payback Period (Years)
1,000 kWh – 4,000 kWh	-270.3	12.9	-164.5	12.7	71.4	10.8
4,000 kWh – 8,000 kWh	1,488.4	7.7	1,719.4	7.4	2,370.6	6.4
8,000 kWh – 12,000 kWh	3,465.8	5.2	3,804.2	5.2	4,732.6	4.5
12,000 kWh – 16,000 kWh	4,401.0	4.6	5,264.6	4.3	6,041.0	3.9
16,000 kWh – 20,000 kWh	5,691.5	4.1	5,524.0	4.0	6,529.8	3.8
20,000 kWh – 24,000 kWh	5,814.6	4.0	5,700.0	4.1	6,847.1	3.4
24,000+ kWh	5,048.1	4.7	4,781.1	4.8	6,482.3	4.0

Very rarely are batteries perfectly sized to meet the daily load requirements of a consumer. On days when an individual's consumption in the peak period isn't large enough compared to the storage capacity, battery behaviour patterns must shift to sub-optimal discharge points, and it is considered too big. Alternatively, when this peak consumption is high and outsizes storage capacity, potential shifting is missed, and the battery is then too small. **Figure 10** displays the days in a year when a 10kWh battery would be under, over, and perfectly sized for a sample individual. Perfectly sized would result in 1 cycle a day with 10kWh of energy shifted from the daily net peak load.

**Figure 10: Batteries are very rarely perfectly sized to meet peak load. Results are indicative of a sample consumer with 14,500kWh annual load.**



This means that consumers with low seasonal variation and consistent consumption, typically in peak price periods, achieve high value from a battery purchase. These individuals can choose a more suitable battery to meet their consumption needs and have fewer days with an oversized or undersized battery.

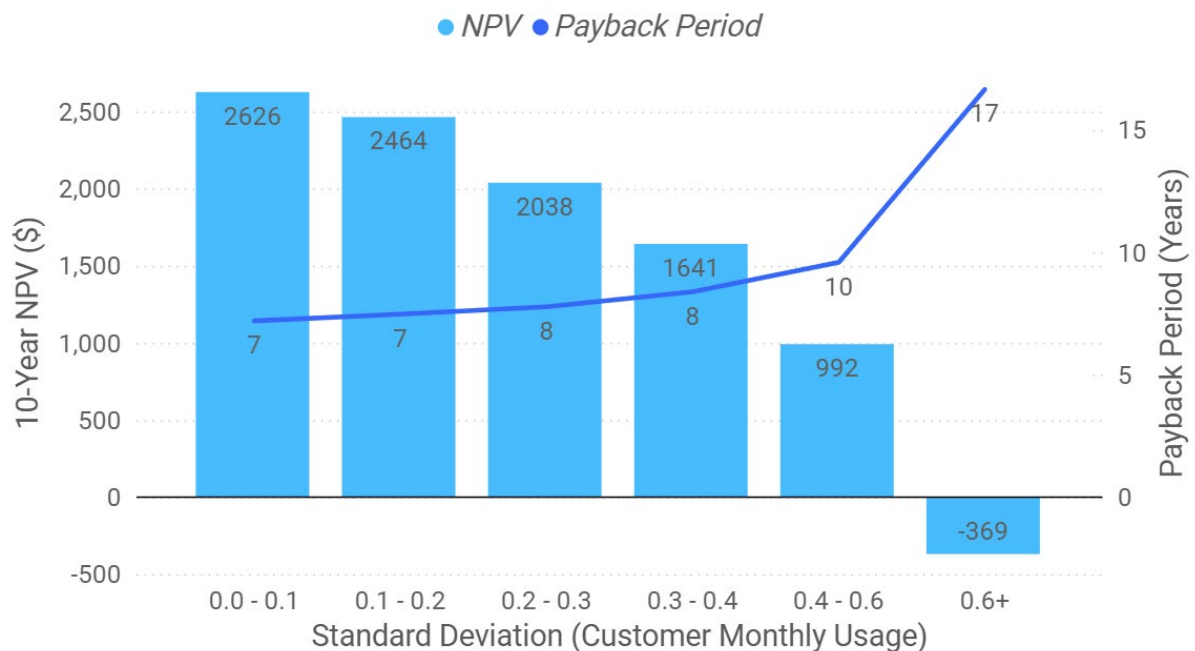
In **Figure 11** below, we see that consumers with a more consistent usage month to month have better battery payback periods. This variability is calculated per consumer using the following formulas:

$$x = Std(M_1, M_2, M_3, \dots, M_{12})$$

$$M_i = \frac{|\alpha_i - \beta|}{\beta}$$

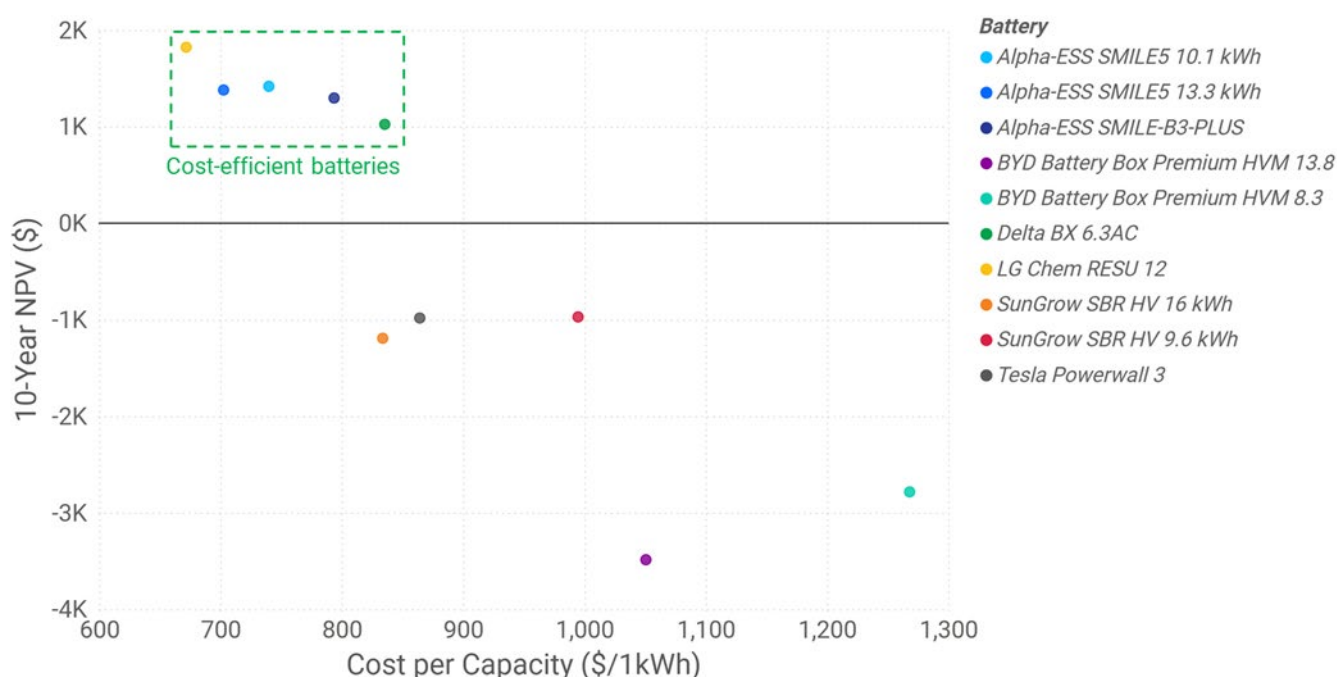
Where,  $\alpha_i$  is the daily average load for month  $i$  and  $\beta$  is the daily average load for the entire year. The calculation of  $x$  is conducted independently for each consumer in the sample, and these values are placed in bins to create the x-axis below.

**Figure 11: Consumers with more consistent usage across the year have better battery paybacks. Results are determined under a federal rebate scheme.**



As previously discussed, our analysis was conducted on a list of ten batteries, half of which are premium brands, and the other half were top performers from our preliminary analysis. This analysis focuses on financial metrics, and safety or integration issues that are harder to quantify were outside of the scope. We found that the "top performers" are typically overseas-built batteries, which are less well-known, and because of this, are more cost-efficient. What this means is that they have a lower cost per kWh of capacity. As shown in **Figure 12**, the cost-efficient batteries provided greater benefits to NSW consumers, with payback periods a fraction of the premium batteries and an additional two to three thousand dollars in the customer's pocket after warranty had expired. In fact, by our metrics, the premium batteries were never the highest-performing battery for any NSW consumer, and all had a negative average NPV after 10 years. This is reflective of the current change in battery popularity in Australia. [Recent trends](#) show that the longtime customer favourite, Tesla Powerwall, has dropped down the ranks, pushed out to fourth place, and cost-efficient batteries like Alpha-ESS are jumping up the ranks, when analysing number of systems in Australia.

**Figure 12: Cost-efficient batteries produce higher financial benefits than their premium counterparts. Results are determined under a federal rebate scheme.**

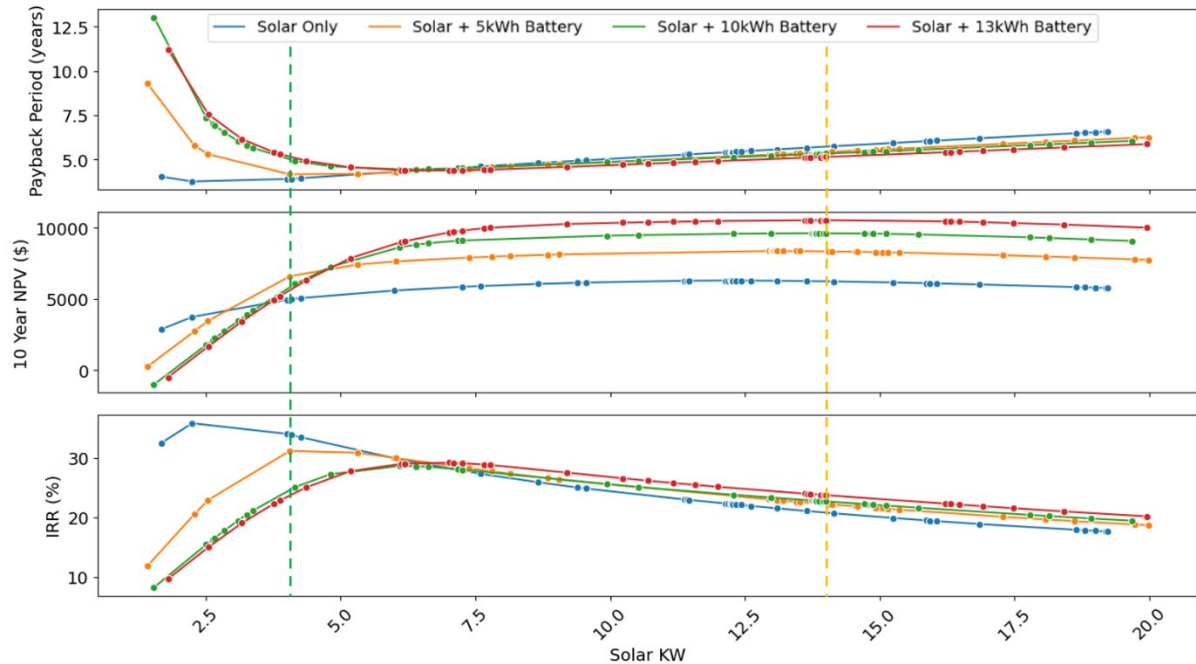


### 2.1.3. Individuals who size their solar and battery together could yield superior returns

Our analysis showed that those who co-optimize for their solar and battery purchase decision will achieve better financial outcomes. We performed this co-optimization through a Data Science technique called Bayesian Optimisation. This efficiently finds a strong system combination using a probabilistic model to intelligently balance exploration and exploitation within the feasible region of solutions. Essentially, given a consumer's consumption profile, this technique will find an aptly sized solar system and battery to maximise financial returns. However, this begs the question of which financial metric an individual optimises for, payback period, NPV, or other. Each decision can lead to a different optimal solar and battery pairing, a situation we have coined "The Buyer's Dilemma".

If a consumer were to minimise for the payback period of a battery, this would often stunt NPV benefits in the long run. Alternatively, maximising for 10-year NPV could produce higher returns, but with an associated higher initial investment and longer payback periods. As seen for an example customer in **Figure 13** below, minimising payback (green dotted line) leads the individual to purchase a smaller battery and solar system when compared to the decision to maximise 10-year NPV (orange dotted line). Favouring one metric limits the potential for another, a good investment decision should consider all relevant financial metrics.

**Figure 13: Battery and solar sizing shows trade-off between fast payback and long-term gain. Results are indicative of a NSW consumer with 14,500kWh annual load under the federal rebate scheme.**



It is important to note that when purchasing solar only, oversizing the solar can lead to longer payback periods with little value added. However, when purchasing solar with a battery, oversizing the solar system would often greatly increase the 10-year NPV with minor increases in the payback period. In both cases, undersizing the solar can stunt benefits in the long run, and oversizing solar remains a sensible investment decision only when it is accompanied by a battery, with the law of diminishing returns taking effect.

## 2.2. Wholesale Pass-through

### 2.2.1 Wholesale-linked offerings can produce better paybacks, but care needs to be taken so that the battery does not cycle too frequently

Consumers who are exposed to wholesale prices rather than ToU pricing structure can roughly double their benefits from purchasing a battery. Due to the volatile nature of wholesale prices, the arbitrage opportunity under this structure is far higher, with a battery able to cash in on sudden price spikes. However, because of this jumpy behaviour, the batteries can cycle twice as much (even with a degradation cost factor), charging and discharging more frequently to follow low and high prices.

As discussed in Section 1.4.2, we introduced a cost for battery degradation in our algorithm. Despite this, the optimal wholesale pass-through behaviour was to cycle the battery roughly twice as much as ToU operation. It should be noted that some commercial models may constrain this further to reduce cycling. Although increased cycling leads to higher results, with a four-year payback on average, and roughly \$5,000 in value added after ten years, it also results in a battery's warranty diminishing and could be expected to expire after five years.

A warranty period is calculated based on the number of years, cycles, or total energy throughput (whichever is reached first), and the manufacturer will cover a battery against defects within this window. Due to the increased cycling, if a problem with the battery were

to arise after five years it may not be eligible for a replacement and this would pose a greater risk to the financial returns of the investment. Realistically, one could apply additional penalties for excessive cycling to increase the warranty period whilst still keeping payback periods reasonably low.

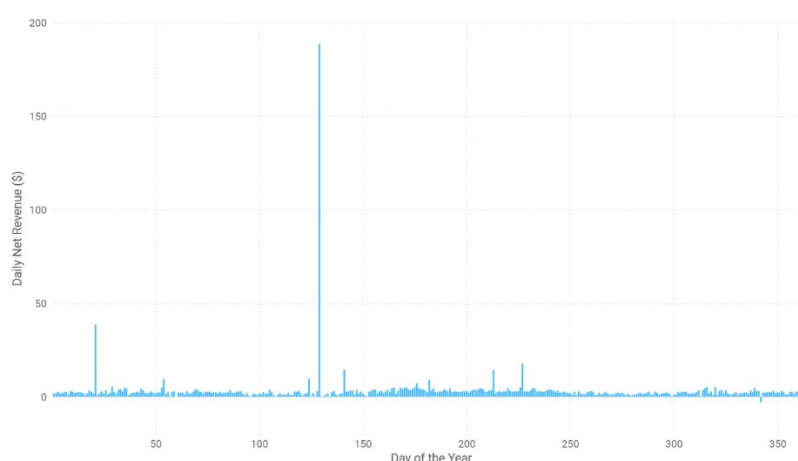
**Figure 14: Wholesale pass-through can slash payback, but can halve battery warranty. Results are determined by averaging 1,000 NSW consumers.**

	<u>Wholesale Pass-through</u>			<u>ToU</u>		
	<i>10-Year NPV (\$)</i>	<i>Payback Period (years)</i>	<i>Estimated Warranty (years)</i>	<i>10-Year NPV (\$)</i>	<i>Payback Period (years)</i>	<i>Battery Warranty (years)</i>
<b>No Subsidy</b>	268.9	11.4	5	-488.1	14.5	10
<b>Federal Subsidy</b>	4,870.2	4.3	5	2,308.2	7.3	10

### 2.2.2. Batteries in wholesale-linked households could produce a large amount of revenue from a small number of days per year

Our Wholesale Pass-through analysis found that around 30% of a battery's benefits come from just 10 days of the year. This is illustrated in **Figure 15** below, which shows the daily net revenue or difference in cashflow between consumers with solar and consumers with solar and a battery. With wholesale prices being highly volatile, a substantial amount of revenue can come from a single day (or even hour). Batteries can capitalise on these price spikes and thus can provide high revenue. As discussed previously, the battery algorithm is calculated on pre-dispatch prices and then evaluated on dispatch prices. The high net revenue day in **Figure 15** corresponds to a dispatch price spike that was most accurately predicted by pre-dispatch prices, with this single day relating to 16% of the total yearly benefits. This explains why there are offers on the market where Virtual Power Plants (VPPs) control household batteries for just 50 days of the year.

**Figure 15: High net revenue can come from just a single day. Results are determined by averaging 1,000 NSW consumers.**



### 2.2.3 VPP participants could see the fastest payback periods

As of 10 June 2025, the NSW Government amended its state-based subsidy, removing the battery installation incentive and promoting VPP participation with an increased VPP rebate. Under this new subsidy, NSW consumers who connect their solar battery to a VPP are rewarded with an upfront payment depending on the size of their battery (roughly \$55/kWh). Importantly, this incentive is stackable with the recently introduced federal rebate, meaning NSW consumers can receive benefits from both schemes. Furthermore, additional benefits are available under [VPP participation](#), with a household receiving a sign-up bonus from the provider (which on average equates to \$267) and annual benefits of roughly \$195/year.

We analysed batteries under these conditions and found that VPP participants could nearly double their benefits. As seen in **Figure 16** below, these NSW consumers on average had a 10-year NPV of over \$4,000, with a battery payback period just under 4 years (a 46% reduction compared to consumers without VPP participation). As stated in the previous section, VPPs can control a residential battery for 50 days a year, with the battery missing out on any potential revenue during these days. However, the provider's annual rewards appear to more than offset these losses, and with the additional benefits from the NSW subsidy, VPP participating individuals, on average, end up better off.

**Figure 16: VPP participation reaps similar benefits to wholesale pass-through without the reduction in warranty period.**

	10-Year NPV (\$)	Payback Period (years)
<b>No VPP participation</b> (Federal subsidy)	2,308.19	7.33
<b>VPP participation</b> (Federal + NSW subsidy)	4,303.98	3.96