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Financial Optimization of Industrial PV-Battery Storage Systems

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Abstract

The purpose of this research is to develop a financial model of an industrial grid-connected PV-battery storage energy system operating either as a retailer's customer or as a NEM integrated entity capable of purchasing and selling electricity at varying spot market prices. The model was used to formulate an objective cost function, necessarily including battery's LCOE. A concept of dynamic LCOE was proposed and trialed. The model was used to optimize electricity dispatch schedules of Transgrid's iDemand facilities.

1. Introduction

While most PV systems in Australia are small-scale roof-top installations, commercial PV installations with capacities of 100kW or more are becoming increasingly common. The profitability of such installations depends on the ability to maximize local consumption of solar electricity and, most critically, to reduce demand charges that constitute a large proportion of commercial/industrial electricity bills. These objectives can be achieved by combining PV with optimally-controlled local energy storage.

Commercial PV-storage systems can operate either 'behind the meter' or as a 'merchant' - selling power back into the National Electricity Market (NEM). In the former, forecasted solar generation and local demand are used to derive battery schedules minimizing an electricity bill i.e. to achieve passive savings. The latter approach offers much more substantial financial flexibility and profitability through additional active earnings available to a peaking generator. While market and regulatory mechanisms currently do not support this mode of operation for industrial clients, there are a number of trials currently progressing with the expectation that this will soon change. However, this implementation depends on the ability to forecast wholesale electricity prices (Maisano *et al*, 2016).

Typically battery charging/discharging schedules are predetermined, so a battery is charged overnight and discharged during office hours. It is often assumed that battery storage, once purchased, should be fully utilized. This is often not correct. Whilst PV electricity is generated at a zero marginal cost, this is not true for the batteries. Lifetime and efficiency of the battery is limited, and each stored kWh adds to marginal costs. Therefore, financial optimization of PV/storage system should balance costs of storage with NEM prices and network charges.

This paper focuses on improving financial performance of PV-storage based industrial-scale demand management systems by:

(i) Constructing an objective cost function that comprises all costs associated with local generation, storage and purchases of electricity plus demand or capacity charges that constitute a substantial portion of electricity bills of commercial customers;
(ii) Integrating advanced techniques for short to medium-term forecasting of NEM spot prices into the system's operation.

The research optimises battery charging/discharging schedules to maximise benefits of energy storage both in supporting local demand and in exporting electricity during periods of expected high market prices. The primary goal of the research was to develop an optimization model which integrates market price forecasting into the control of TransGrid's iDemand installation[1] and provide comparative benefit analysis of 'on the tariff' and 'merchant'-type operation.

The model compared behind-the-meter and NEM trading scenarios. It has been demonstrated that in both cases electricity costs can be reduced by 20-30% when battery LCOE is assumed to be in the range $0.1-0.2/kWh.

2. The Method

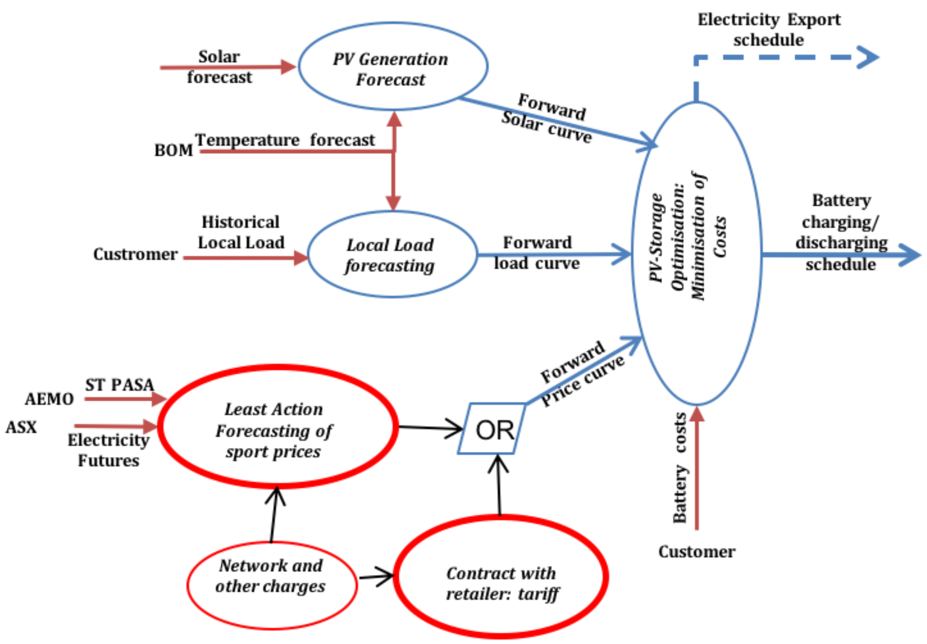


Figure 1. Research Method: forward solar, load and price curves are combined to derive battery charging and electricity export schedules minimising overall cost of consumed electricity.

[1] iDemand is TransGrid's pilot demand management project encompassing lithium ion battery system, photovoltaic generation source, and LED based energy efficiency measures. Refer to case study. Website is: http://idemand.transgrid.com.au/LiveMonitor

The cost-efficient utilisation of PV-battery storage depends on the availability of three independent data sets (Fig.1): Forward Solar Curve, Forward Load Curve, and Forward Price Curve. The Forward Solar Curve comprises predicted Solar Generation based on solar and ambient temperature forecasts available elsewhere. The Forward Demand Curve is highly predictable for industrial customers. We used calendar adjusted historical data.

Depending on the mode of operation, the Forward Price Curve is either a tariff set in a contract with a retailer, **or** a forecast of NEM spot prices.

The goal of PV storage optimisation is to minimise total costs over the billing period T by finding optimal battery charge/discharge schedules.

The total cost is represented by the following objective function:

$$C_{Total} = C_{Grid} - V_{Grid} + C_{BatteryDischarge} + C_{Solar} + C_{Demand}\ , \tag{1}$$

each term of which is described below.

2.1. Cost of imported electricity:

$$C_{Grid} = \vec{P}_C \bullet (\vec{X}_1 + \eta \vec{X}_2) \tag{2}$$

Here $\vec{X}_1$ is a portion of grid electricity used to support local demand, and $\vec{X}_2$ is a portion of grid electricity used to charge the battery[2]. Vector $\vec{P}_C$ represents the time series of the Forward Price Curve (FPC). In the 'behind the meter' scenario the FPC is the electricity retail tariff plus network and other (auxiliary, 'green', etc.) charges as shown in Fig.2. In the case of trading with the NEM the Forward Price Curve is spot market half-hourly prices (Maisano *et al*, 2016, Maisano, Radchik and Ling, 2016) plus network and other charges.

The loss factor η represents the financial losses associated with operating a battery storage defined similarly to the AEMO MLF methodology employed in the NEMDE optimisation engine[3]

$$\eta = 1 + \mu \tag{3}$$

where total loss coefficient μ is:

$$\mu = 1 - (1 - \mu_1)(1 - \mu_2)(1 - \mu_3) \tag{4}$$

and $\boldsymbol{\mu_1}$ is the losses in an inverter, $\boldsymbol{\mu_2}$ - the internal cell losses within the battery, and $\boldsymbol{\mu_3}$ -the losses in the cabling within the system. The $\boldsymbol{\eta}$ exhibits financial penalties due to the system's physical losses.

2.2. Value of electricity exported into the grid

Exported electricity is sourced from solar X_3 and battery X_4 .

$$V_{Grid} = \vec{P}_S \bullet (\vec{X}_3 + \frac{1}{\eta} \vec{X}_4) \tag{5}$$

[2] From here onwards symbol "●" means scalar product

[3] *TREATMENT OF LOSS FACTORS IN THE NATIONAL ELECTRICITY MARKET*, AEMO, 1-Jul-2012, p.23.

Vector $\vec{P}_S$ is the time series of electricity sales prices. Note that $P_C > P_S$ because network and other charges always act as transaction costs, i.e. against the participant.

2.3. Cost of battery discharge

$$C_{BatteryDischarge} = \vec{P}_{LCOE}(y) \bullet (\frac{1}{\eta}\vec{X}_4 + \eta \vec{X}_5) \tag{6}$$

Here $\vec{X}_5$ is battery power supporting local demand, and $\vec{P}_{LCOE}(y)$ is the Depth-of-Discharge (***DOD* = *y***) dependent dynamic battery LCOE[4] , which will be determined as part of system optimisation in section 2.7.4.

2.4. Cost of locally used solar electricity

$$C_{Solar} = P_{Solar}\vec{1} \bullet (\vec{X}_6 + \vec{X}_7) \tag{7}$$

Where P_{Solar} is the LCOE of solar panels (assumed value 6c/kWh), $\vec{X}_6$ is solar energy used by the site and $\vec{X}_7$ is solar energy charging the battery. $\vec{1}$ is a unit vector of length: $\dim \vec{1} = N$

2.5. Demand charge

The penalty for excessive use of the electricity network over the time ***T*** is represented by:

$$C_{Demand} = \frac{T}{PF} P_D X_{Demand} \tag{8}$$

Here power factor **PF**- power factor, $\boldsymbol{P_D}$ – capacity (or demand tariff) and X_{Demand} is the maximum system demand over the period ***T***.

2.6. Model constraints

2.6.1. Energy Conservation

If $\vec{E}_S$ is the Forward Solar Curve (kW/m^2) and X_S is the scaling parameter (m^2) for the size of solar nominal output, then:

$$\vec{X}_3 + \vec{X}_6 + \vec{X}_7 = X_S \vec{E}_S \tag{9}$$

The Forward Load Curve $\vec{E}_L$ must be met by the discharging battery, solar PV generation for local use and the energy taken from the grid:

$$\vec{X}_1 + \vec{X}_5 + \vec{X}_6 = \vec{E}_L \tag{10}$$

2.6.2. Battery Constraints

The battery charge $\boldsymbol{U_i}$ (kWh) at tick[5] i - here elements of vector $\left\{\vec{I}_i\right\}_k = \begin{Bmatrix} 1 & k \le i \\ 0 & i < k \le N \end{Bmatrix}$:

[4] Levelised cost of electricity

[5] We use the term ‘tick’ to mean a single half-hourly period

$$U_i = (\vec{X}_2 - \vec{X}_4 - \vec{X}_5 + \vec{X}_7) \bullet \vec{I}_i \quad (11)$$

That battery charge limits are constrained by maximum and minimum depths of discharge:

$$DOD_{\min} \le \frac{U_i}{U_{\max}} \le DOD_{\max} \quad (12)$$

where $\boldsymbol{U_{max}}$ is the max{U_i}.

The total energy going into/out of the battery at the current time-step ***i*** plus the energy stored in the battery at the previous time-step ***i-1***, cannot exceed max/min battery charge[6]:

$$\begin{cases} \left\{\vec{X}_2 + \vec{X}_7\right\}_{i,k} \delta_{i,k} + U_{i-1} \le DOD_{\max} U_{\max} \\ U_{i-1} - \left\{\vec{X}_4 + \vec{X}_5\right\}_{i,k} \delta_{i,k} \ge DOD_{\min} U_{\max} \end{cases} \quad (13)$$

Energy flow in and out of the battery is also limited by ramping up ($\boldsymbol{R_{up}}$) and down ($\boldsymbol{R_{down}}$) rates as:

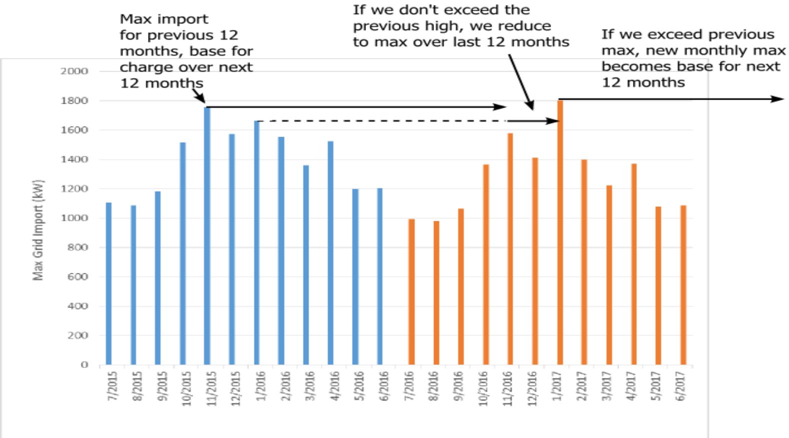
$$\begin{cases} \vec{X}_2 + \vec{X}_7 \le R_{up} \vec{I} \\ \vec{X}_4 + \vec{X}_5 \ge R_{down} \vec{I} \\ R_{down} \le \left| U_i - U_{i-1} \right| \le R_{up} \end{cases} \quad (14)$$

2.6.3. Peak demand

By introducing a minimisation variable $\boldsymbol{X_P}$ representing the peak consumption over the current billing period and a billed max demand $\boldsymbol{D_{max}}$ from the last bill (see Fig. 2) we can write:

$$\vec{X}_1^{peak} + \vec{X}_2^{peak} < X_P \vec{I}^{peak} < D_{\max} \vec{I}^{peak} \quad (15)$$

Here superscript 'peak' means peak ticks subset of vectors $\vec{X}_1$, $\vec{X}_2$ and $\vec{I}$. The peak demand is allowed to 'float' and, therefore, will be set by the model to the optimal maximum grid import level that minimises costs (by way of reducing all charges, including demand charges).



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6 Here $\delta_{i,k}$ -kroneker delta

Figure 2. Setting and recalculation of the demand charge

2.6.4. Dynamic LCOE

Since LCOE depends on the depth of discharge it is strongly linked to the operational pattern of the storage.

Battery manufacturers provide a discretised dependence of average number (***N***) of charge/discharge cycles the battery can sustain for a given DOD. By fitting these data points with a continuous function we can plot the curve ***N(y)*** where y is DOD (Fig.3 , left)

Dynamic LCOE is defined as follows:

$$P_{LCOE}(y) = \frac{Cost\,/\,kWh}{Efficiency \times y \times N(y)} \qquad (16)$$

By using the same typical discrete dataset ***(DOD, N)*** we fit it with quadratic function shown on (Fig.3, right)

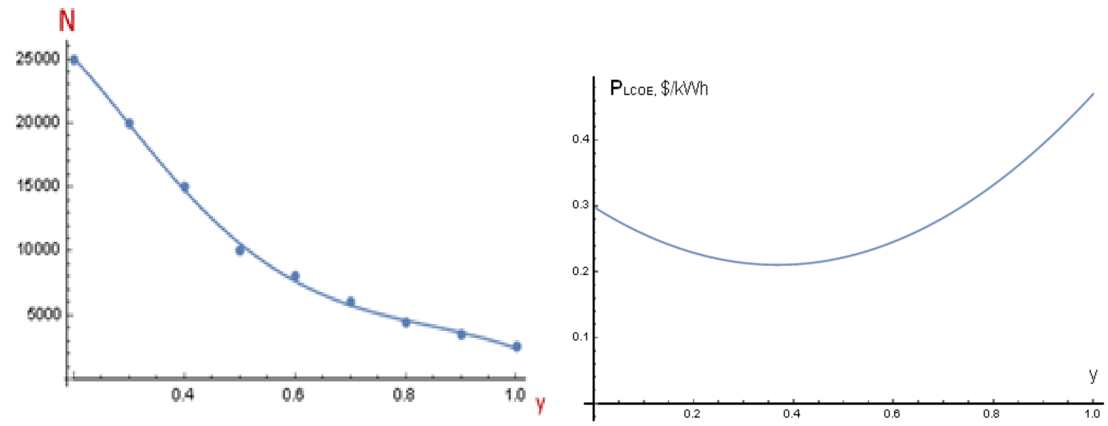


Figure 3. Number of cycles as a function of DOD (left) and Dynamic LCOE as a function of DOD (right)

Determination of the optimal battery schedule includes the following steps:

1. Using a historical NEM price (or tariff) curve, a historical solar curves and a historical demand curve minimise (1):

$$\underbrace{Min\{C_{Total}\}}_{\{\vec{X}_1\ \vec{X}_2\ \vec{X}_3\ \vec{X}_4\ \vec{X}_5\ \vec{X}_6\ \vec{X}_7\ X_{Demand}\ y\ X_S\}\geq 0} \qquad (17)$$

subject to constraints described above.

2. Construct the probability distribution ***f(y)*** out of obtained from minimisation time series of Depth-of-Discharge ***y.***
3. Calculate mean LCOE within the battery's operational range $(y_{\min}, y_{\max})$:

$$\bar{P}_{LCOE} = \frac{1}{y_{\max} - y_{\min}} \int_{y_{\min}}^{y_{\max}} dy\, f(y) P_{LCOE}(y) \qquad (18)$$

4. Substitute $\bar{P}_{LCOE}$ into (17) and solve for the operational schedule, employing the Forward Price Curve, the Forward Solar Curve and the Forward Load Curve.

3. Model Application : Transgrid iDemand

3.1. System and site details

The iDemand system features a 435 kWh battery storage system and 98.4 kW of solar PV, as well as both DC and AC LED lighting. The solar PV system consists of two primary arrays, one which is made of 53kW of polycrystalline silicon panels, and the other has 45.4 kW of thin-film cadmium telluride modules.

The iDemand facility monitors electricity imported from the distribution grid. It also monitors local demand. The overall local demand is defined as the total power consumed by lighting and electricity required by the rest of the iDemand facility. For the purposes of financial optimisation of this paper, all loads were combined in a total demand, and the cost of electricity supporting the total demand has to be minimised.

Presently, the iDemand does not participate in any National Electricity Market (NEM) trading. Under current National Electricity Rules, such trading by transmission utilities in the spot market or in ancillary services markets is not permitted and an arms-length arrangement with an electricity retailer would be required to enable utilities to extract these value streams.

The only component of iDemand system that can be varied to reduce electricity charges is the battery operational schedule. iDemand's battery system is currently controlled by a fixed pre-set dispatch schedule based on two years of historical load and solar generation. Critically, the pre-set schedule used on the site does not take into account costs associated with purchasing batteries.

3.2. Financial optimisation of iDemand

Our goal was twofold:

(i) To derive battery dispatch schedule minimising all costs associated with purchasing and on-site storage of electricity.

(ii) Analyse and quantify benefits potentially arising from a merchant-type operations of industrial sites similar to iDemand.

3.2.1. Tariff based Forward Price Curve

The first goal implies minimisation of iDemand's electricity bills taking into account costs of the battery storage. For this purpose, the January 2015 Transgrid electricity bill from was analysed and reconstructed. Since the battery N(y) curve wasn't available, we have used 3 different values of battery LCOE: 0, 20 and 60 c/kWh. The results are summarised in Table 1.

Table 1. Comparison of expenses between current operational schedule and optimised schedules, both on fixed tariff.

LCOE c/kWh	0		20		60	
Expense Type	**TransGrid pre-set schedule**	**Optimised**	**TransGrid pre-set schedule**	**Optimised**	**TransGrid pre-set schedule**	**Optimised**
Grid	$ 6,063.45	$ 5,929.36	$ 6,063.45	$ 6,211.82	$ 6,063.45	$ 6,211.82
Demand	$ 3,430.27	$ 2,147.92	$ 3,430.27	$ 2,449.95	$ 3,430.27	$ 2,449.95
Battery Usage	$ 0.00	$ 0.00	$ 4,966.90	$ 249.04	$ 4,966.90	$ 249.04
Total Cost	$ 9,493.72	$ 8,077.28	$ 14,460.62	$ 8,922.96	$ 14,460.62	$ 8,922.96
Maximum Grid Import	224.38 kW	140.50 kW	224.38 kW	151.90 kW	224.38 kW	160.26 kW
Battery Usage	7,176 kWh	8,908 kWh	7,176 kWh	1,289 kWh	7,176 kWh	360 kWh

For non-zero LCOE the optimised schedule discharges the battery far less often, the optimisation ensures that the battery is being discharged at the most effective time. As where LCOE exceeds the peak tariff use of the battery when it is not affecting peak demand for the month is actually counter-productive. However, use of the battery to reduce the monthly peak demand is very effective- *$1,108 saving (32%) in the demand charge* (LCOE=20c/kWh). We have solved for the maximum grid import that will be the case at the optimum cost (given the expected demand and solar profiles). Therefore we have a target threshold over which we discharge the battery. Such a figure could be set in an automated control system such that any grid import exceeding 151.90kW (or slightly lower, depending on response times) would trigger battery discharge until the grid import falls below this figure (again, possibly with a margin to cover fluctuating demand). The actual energy cost should be similar to the optimised result unless solar is on average less than expected, and the actual demand charge should be similar to the optimised result, provided that the battery contains enough charge to meet longer than expected peaks. In both cases, the better the forecasts that the optimisation is based on, the closer the actual cost figures will be. For 60 c/kWh LCOE 60c LCOE there is far less battery usage, nevertheless the battery can still be used to reduce the maximum grid import (max demand) to 160kW, and therefore still drive a 38% total saving over the default profile.

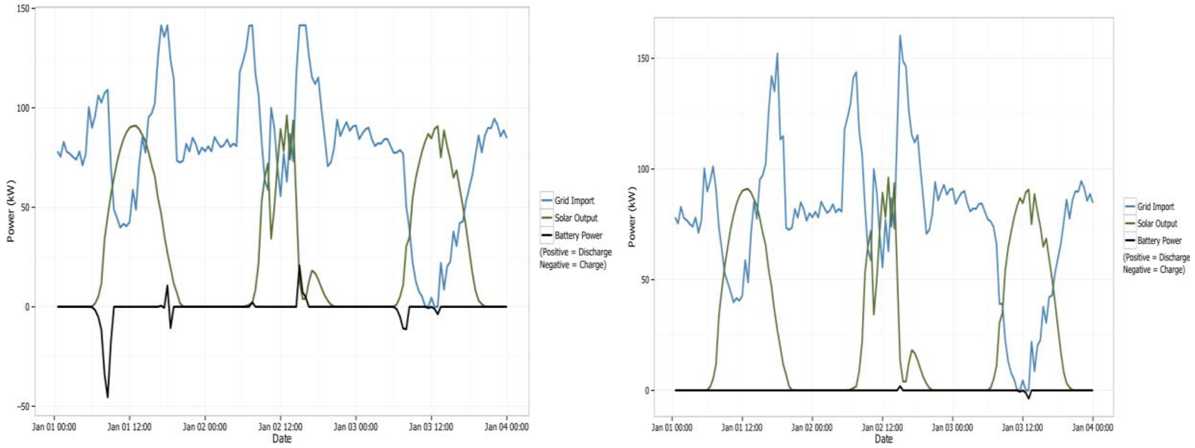
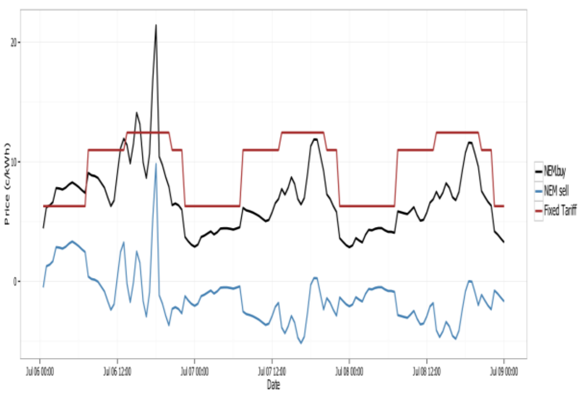


Figure 4. Optimum battery schedule with retail tariff and 20 (left) 60 (right) c/kWh LCOE

3.2.2. Market based Forward Price Curve

In order to simulate a NEM trading scenario, the LAP principle was used to generate an expected price curve for NSW for July – September 2016. The average of this curve was calibrated to the Q3 2016 NSW quarterly futures price, which as at settlement on 20 June 2016 was $51.40. **Fig. 5** shows LAP price forecast for July 2016 with respect to the existing retail tariff. For the demand and solar forecasts for July 2016, we have used the actual data from July 2015 as a proxy. We have compared this against TransGrid's July 2015 discharge schedule with a retail tariff. A typical profile resulting from this is shown in tariff. Figure 6.



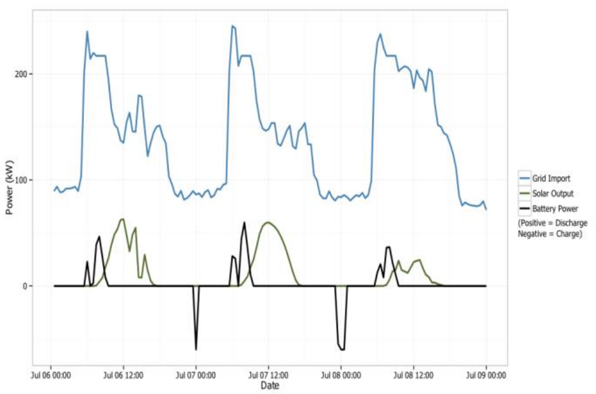


Figure 5. NEM prices and fixed tariff. **Figure 6. Optimum battery schedules**

Table 2 shows a total saving of $2,531 for the month (19%) with the optimised profile, which reduces peak demand down to 245kW.

Table 2. Comparison of the pre-set and optimised profiles (LAP forecasted Forward Price Curve)

Expense Type	Idemand business as usual	This research
Grid	$ 7,082.67	$ 6,470.64
Demand	$ 4,398.61	$ 3,749.41
Battery Usage	$ 1,588.94	$ 318.72
Total Cost	**$ 13,070.22**	**$ 10,538.77**
Maximum Grid Import	287.7 kW	245.26 kW
Battery Usage	1,589 kWh	1,381 kWh

4. Conclusions

A mathematical model of PV+storage which incorporates demand charges and dynamic LCOE was formulated and trialled on Trasngrid's iDemand industrial site. It has been shown that the implementation of the proposed approach along with detailed forecasts of forward solar, load and price curves can produce significant savings through the implementation of operational schedules minimising the proposed cost objective function. Trading into the NEM may provide additional benefits in comparison with a conventional 'behind the meter' operation, depending on the prevailing market prices. The Forward Price Curve was derived for the NEM spot prices using the Least Action pricing principle also developed by the authors. Depending on the LCOE of batteries, the proposed operational schedules allow for 15-30% saving in electricity costs when forecasts of local demand, PV generation and spot market prices are available.

References

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