PV Generation and Demand Mismatch: Evaluating the Potential of Residential Storage

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***Abstract*—Favourable conditions in recent years have led to significant uptake of residential rooftop solar photovoltaic generation in many parts of the world. However, the cost-effectiveness of such systems is reducing due to declining subsidies, falling feed-in tariffs, and the typical timing mismatch between solar generation and local demand. In this paper, we investigate how this mismatch can be addressed by installing a customer-end storage system that provides an opportunity to maximally exploit the value of existing solar generation. The value of such storage depends on the extent of the coincidence of demand and generation, the size of the storage system, the pricing structure for both energy used and energy generated, any available feed-in tariffs, and the cost of the storage itself. An optimal storage operational strategy using dynamic programming is introduced and a variety of storage system sizes and price scenarios are evaluated and compared. Our study shows that under certain conditions customer-end storage could become economically attractive to consumers in the near future, opening the door for disruptive retail electricity business models in the years to come.**

I. Introduction

In recent years, many regions of the world have seen a significant uptake of rooftop photovoltaic (PV) solar generation in residential areas. Australia is a prime example: the favourable combination of high levels of insolation, rising electricity prices, and attractive feed-in tariffs has led to installation of more than a million residential PV systems – an uptake equivalent to 14% of households, and one of the highest rates in the world [1].

The economic value of residential PV is determined by the initial system cost, the cost structure of importing energy from the grid, the payment structure of exporting energy to the grid, and the coincidence of demand and generation. Domestic households typically have periods of high power demand in the morning and evening, with less power demand during the day. PV generation, however, tends to generate the majority of its energy in the middle of the day. This means that houses with PV systems frequently end up exporting energy to the grid in return for a payment in the middle of the day, and purchasing energy at standard electricity rates in the morning and evening.

Until recently, exporting energy to the grid has been encouraged in many parts of the world by feed-in-tariffs that have typically been greater than the electricity rate. This allowed consumers having low demand during the day to benefit from feeding generated energy into the grid and purchasing required energy back in the evening, at a net benefit. Recently however, feed-in tariffs in many locations have been significantly

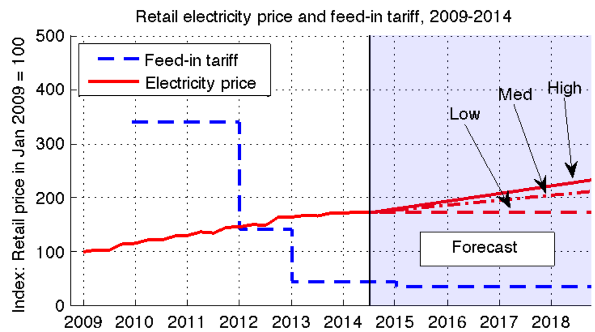

Fig. 1: Trends in retail electricity price and renewable energy feed-in tariff, Victoria, Australia

reduced, often to rates lower than the electricity price. For example, in the period from 2009 to 2014, feed-in tariffs in the state of Victoria, Australia were reduced by 87% while retail electricity costs rose by 73% [2], [3]. These trends are shown in Fig. 1.

When the credits for generating electricity are smaller than the cost of buying electricity, there is no longer an incentive to feed back into the grid; rather, the greatest net benefit can be derived from using as much of the locally generated energy to satisfy local demand as possible. A simple way to do this is to perform demand response, *i.e.* to schedule time-shiftable loads (washing machines, dishwashers, etc.) to times of day when generation is likely. A more refined way to achieve this would be to monitor relevant local conditions in real or near-real time, and to intelligently schedule loads dynamically in response to available generation.

Either of these approaches can be well supported with the integration and intelligent control of customer-side energy storage. Until recently, high battery prices and minimal incentives for load-shifting meant that customer-side energy storage was neither economical, nor widely available. However, battery costs are falling: the costs of compact lithium-ion battery packs, for example, are estimated to have reduced by 25% between 2009 and 2014, and are expected to fall further [4]. At the same time, rising electricity prices and falling feed-in tariffs are strengthening the incentive for local load shifting.

Given all of these trends in the industry, the following question naturally arises: is there a value case for residential storage *in combination with* an existing PV generation system?

Towards this objective, in this paper we first explore the typical coincidence between solar generation and household demand. We then present an approach for optimal operation of battery storage, which is used to investigate the electricity cost savings for different storage system sizes. We finally evaluate the payback of storage systems under a variety of cost and sizing assumptions. We answer the above question in the affirmative and show that in the coming years there will likely be a significant value proposition for introducing residential storage in combination with existing PV generation systems.

II. Coincidence Analysis

Residential demand and PV generation profiles vary significantly from one house to another and from one month to the next. Fig. 2 presents typical demand and generation profiles for a suburban household in Melbourne, Australia for a day in summer. The generation profile represents a 2.5kW system (most popular residential size) generating on a cloudless day, and the demand profile represents average load as measured at a distribution transformer having 114 residences connected. As can be seen, excess generation (diagonally shaded between 9:00 - 16:00) could be stored in a battery, and used to offset excess demand at a later time of day (diagonally shaded between 16:00 - 20:00). In the summer, such a relatively small PV system could almost cover peak demand. In the winter (when demand is higher due to heating, and there is reduced generation) this offset decreases.

An important point to note is that Fig. 2 presents smoothed profiles that are averaged over large numbers of customers. In reality, with instantaneous switching of loads and intermittent cloud cover, the coincidence is quite different. Fig. 3 shows data measured at one specific household on a summer day over fourteen hours – the impacts of a thermostat controlled air conditioner on demand, along with the impacts of variable cloud cover on generation can clearly be seen. Given that electricity prices are typically calculated according to net grid import / export over discrete time intervals, the coincidence across these intervals becomes important. In Victoria, where mandatory smart meter installation has taken place, these intervals can be as small as five minutes.

This study uses the following datasets:

Demand: to model residential demand, we use 88 individual user profiles, logged at customers' smart meters in half-hour intervals over the course of a full year (June 2012 - May 2013). The average daily demand is presented in Fig. 4.

Generation: to model generation, we use data logged at a residential PV installation. This dataset was only available from January 2014-August 2014, and for the remaining months data from similar months (according to standard insolation levels) was replicated to fill the gap. This generation profile is presented in Fig. 5. As can be seen, the measured data set matches standard annual insolation values for Melbourne well.

To examine the coincidence in our datasets, an interval-by-interval comparison (in 30min intervals) of all 88 demand datasets to the generation profile was conducted. The results are also shown in Fig. 5. Areas shaded in red represent generation that occurs in excess of present demand (in other words, generation that is fed back into the grid). Areas shaded

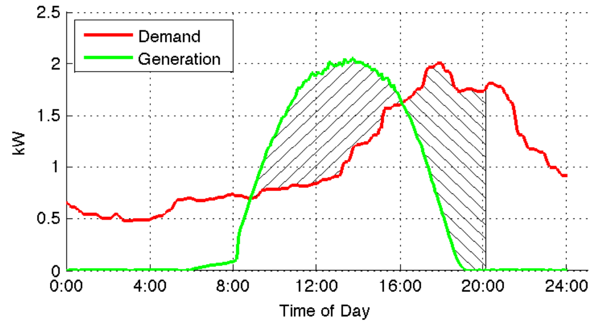

Fig. 2: Coincidence of averaged demand and generation for a household in Victoria, Australia. Excess generation can be stored and used to offset later demand.

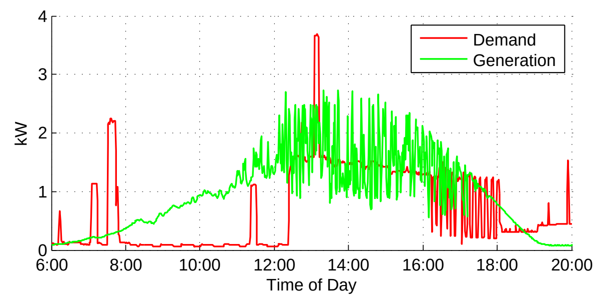

Fig. 3: Coincidence of specific demand and generation for a household in Victoria, Australia. In reality, high variability in both generation and demand must be taken into account when determining coincidence.

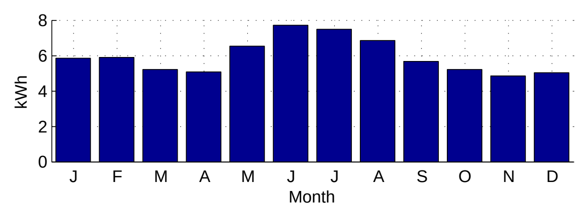

Fig. 4: Average daily demand, as averaged over 88 individual consumer datasets measured at 30-minute intervals.

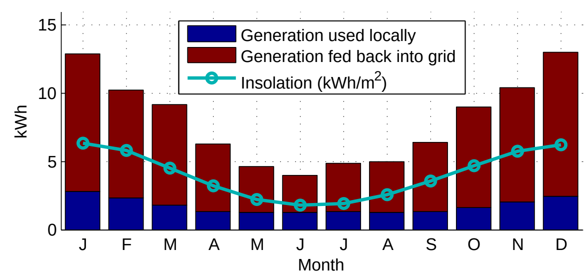

Fig. 5: Average daily generation for a 2.5kW PV system, with coincidence averaged over 88 customers. 78% of local generation does not coincide with local demand when comparing across 30-minute intervals.

Algorithm 1 Calculating the smallest storage system size S that will capture all local generation across time period T, where g(t) and d(t) are generation and demand at time t, respectively.

cSum(0) = 0
for t = 1 to T **do**
  cSum(t) = max(0, cSum(t-1) + $\frac{g(t)-d(t)}{\Delta t}$)
end for
S(T) = max(cSum)

in blue represent generation that is used to offset local demand directly. As can be seen, the mismatch between generation and demand is significant: across the full year, 78% of generated energy is fed back into the grid, with only 22% being used to offset local demand.

The highly intermittent nature of both demand and generation (as shown in Fig. 3) means that a storage system may alternate between charging and discharging at many points throughout the day. On the one hand the additional cycling leads to faster battery degradation, but on the other hand, typically a smaller system size is required to fully capture all available generation than is often thought. It is straightforward to calculate this smallest required storage system size: it is simply the maximum of the cumulative sum of coincidence across all intervals in the time period of interest (see Algorithm 1). For the profiles shown in Fig. 2, a battery of size 5.0kWh would be sufficient to ensure that all generation is used (and none is exported to the grid); for the profiles shown in Fig. 3 a battery of size 3.3kWh would be sufficient.

III. Optimal Storage Operation

To understand what the impact of storage might be for residential customers, and to draw some conclusions regarding the financial viability, it is necessary to understand the storage system's operation – in other words, its charge/discharge strategy. Storage operation has already been extensively discussed and trialled in several studies around the world. Most studies to date have focussed on large scale storage as operated by the network operator, for example for peak load shifting or voltage control [5], [6]. Only recently has there been more interest in the possible operation of storage systems on the customer side [7], [8]. For the analysis conducted in this paper we use a simple method based on dynamic programming.

For convenience of notation, let the time-varying net impact on the electricity grid of a customer be represented by $n(t)$. This net impact is simply the sum of demand, generation, and storage charge / discharge: $n(t) = d(t) - g(t) - b(t)$. (Note that battery discharge is modelled as a positive quantity, with battery charging negative). The cost paid at any time t by the consumer depends on the electricity pricing structure $c^-(t)$ that is paid when demand exceeds generation, and the feed-in tariff $c^+(t)$ that is received when generation exceeds demand:

$$c(t) = \begin{cases} n(t)\ c^-(t) & \text{if } n(t) \geq 0 \\ n(t)\ c^+(t) & \text{if } n(t) < 0 \end{cases}$$

The full cost over a horizon T is therefore: $\sum_{t=0}^{T} c(t)\Delta t$.

Our goal is to minimise the total cost of electricity use. The lowest possible cost over the horizon (along with the associated charge/discharge strategy for the battery) can be determined using dynamic programming. This is achieved by discretising all possible levels of charge of the storage system into S intervals, and all points in time in the horizon of interest into T intervals, a state space of $S \times T$.

The dynamic program is operated with a forward pass and a backward pass. In the forward pass, for every time $t \in T$ the best possible way of reaching all states of charge $s \in S$ is determined. Upon reaching the final time interval, the best final state is chosen and a backwards pass ensures that the optimal operational strategy that led to this best final state is recovered.

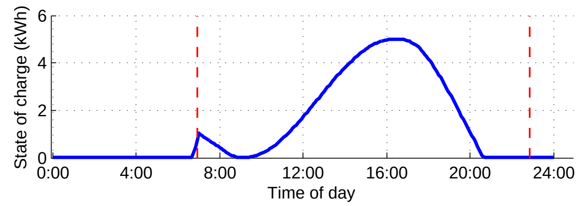

Fig. 6: Optimal storage operation for a 5kWh system size, as applied to the demand and generation profiles in Fig. 2.

This method relies on predicting demand and generation in future intervals. For the analysis conducted in this paper, we used the available datasets (in other words, perfect prediction), so the results present an upper limit on the possible benefits of storage. In reality, such prediction is difficult and the likely benefit would be lower. However, we do not expect it to be significantly lower since there is a certain amount of flexibility in when a battery can charge and discharge, and since updated predictions could be established in a receding horizon manner on a real system.

Fig. 6 shows how this optimal storage operation is applied to the demand and generation profiles shown earlier in Fig. 2. Peak pricing in this case applies to the time period from 7:00 to 23:00 as marked by the dashed red lines. In the lead up to the changeover from off-peak pricing to peak pricing, the battery charges in order to shift load from peak to off-peak. However, it only charges as much as is required to offset demand before the PV system starts to generate (since it is desirable to use as much of the storage system's capacity to store generation as possible). As soon as generation exceeds demand, the storage system charges. Once demand exceeds generation, the storage system discharges – using as much excess generation to offset peak demand as possible.

IV. Storage Benefit Analysis

In this section we examine the electricity cost savings that a customer can expect to receive for a variety of storage system sizes. While there may also be a case for lead-acid batteries (as well as other chemistries) for customer side storage, we examine here only Li-ion batteries. This is partly due to their high cycle life, projected cost decreases, and high energy density [4], and partly due to projected availability of large numbers of used Li-ion electric vehicle batteries in the near future that may be of value in second-life applications [9].

The same datasets described in Section III are used to model demand and generation, and the remaining assumptions used to generate the following results are based on typical conditions in Victoria, Australia, and are presented in Table I. An optimal charge / discharge strategy as described in Section III is assumed.

Fig. 7 shows the savings that a 5kWh storage system can provide over the course of a year. After 1 year of operation, \$307 of savings are available for the customer. The operation of the same storage system over 20 years is presented in Fig. 8 (assuming an electricity price fixed at June 2014 levels).

PV generation	The generation dataset corresponds to output from a 2.5kW system. Degradation of the PV system is modelled as 0.5%/year.
Battery	Only 80% of nominal maximum capacity is utilised as to protect against excessive battery degradation [10]. The charging and discharging rates are limited to a maximum of 3.45kW. Regarding degradation, maximum capacity reduces at a rate of 20% capacity for every 1500 charge-discharge cycles of nominal maximum capacity [10]. Partial cycling is assumed to cause degradation proportional to cycling depth.
Electricity cost	For the first year of generation we assume on- and off-peak prices of 36¢/kWh (7am-11pm) and 22¢/kWh (11pm-7am), respectively. For subsequent years, electricity price follows the respective trends shown in Fig. 1. The low forecast assumes prices remain at June 2014 levels; the medium forecast assumes prices grow at the fitted average slope over the past two years; and the high forecast assumes prices grow at the fitted average slope over the past five years.
Feed-in tariff	A feed-in tariff of 8¢/kWh is assumed for 2014, reducing to 6.2¢/kWh from 2015 onwards [11].
Storage cost	Studies assume storage costs of either $600, $310, or $150 per kilowatt-hour, corresponding to estimated costs in 2014, 2020 and 2030, respectively [4]. Furthermore, a size-independent fixed cost of $1500 is assumed to cover inverter and installation. No ongoing maintenance costs were considered.
Interest, inflation	No interest rates are considered in this work. All dollar values are in 2014 terms.

TABLE I: Assumptions

At the end of this period, $4323 would have accumulated for the customer (and for an increasing electricity price this would be greater). Over the lifetime of the storage system, its useable capacity decreases in response to the increased number of cycles it undergoes (Fig. 9). In this case, the storage system would have undergone a total of 4356 cycles, leading to a useable capacity of only 1.1kWh after 20 years.

Finally, a range of different storage sizes are compared in Fig. 10. As can be expected, larger systems provide greater returns. However, in proportion to battery capacity, smaller systems generate more savings than larger systems due to a higher utilisation. This utilisation also results in increased battery degradation, which leads to the notable reductions in annual cost savings in later years for smaller systems.

V. Payback Analysis

In this section, we conduct an analysis of the payback period of batteries. The payback period can be determined from the results of the prior benefit analysis and the assumptions listed in Table I.

Fig. 11 shows the average impact of future electricity price trends on battery system payback period for various battery sizes at 2020 estimated prices ($310). Regardless of which electricity cost trend is considered, the 6kWh system is found to have the shortest payback period. Smaller and larger systems have higher payback periods due to the size-independent cost component for smaller systems, and the limited utilisation for larger systems for the 2.5kW PV generation considered.

If electricity prices remain flat at 2014 levels (low forecast), on average over the 88 house demand sets evaluated, the cost

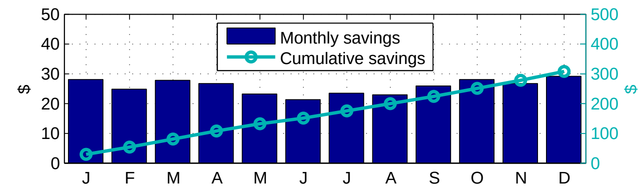

Fig. 7: Electricity cost savings for a 5kWh storage system over one year

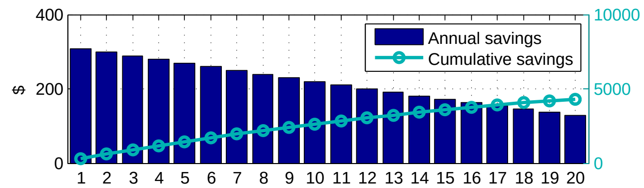

Fig. 8: Electricity cost savings for a 5kWh storage system over 20 years

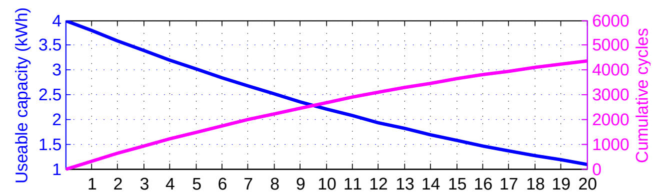

Fig. 9: Modelled battery degradation of a 5kWh storage system over 20 years

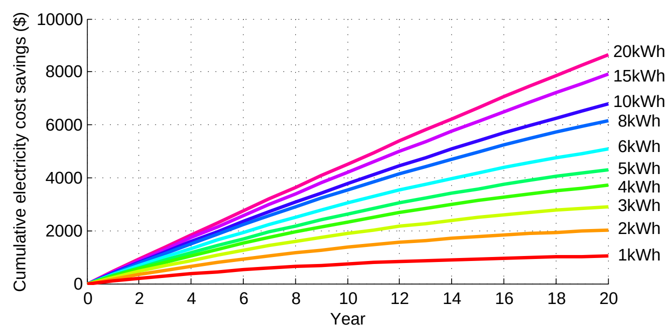

Fig. 10: Comparing the benefits for different sizes of storage systems

of an 8kWh system is recouped in 11.4 years. If prices rise as steeply as they have these past 5 years (high forecast), the system pays itself back in 8.2 years on average. And if prices rise albeit more slowly as they have the past two years (medium forecast), then the system will take around 9.0 years to pay itself back.

The impact of battery prices on payback period assuming a continuation of the electricity price trend of the past 5 years (high forecast) is shown in Fig. 12. A lower battery cost has an obvious impact on payback period, with the payback period of 5kWh system reducing from 11.6 years at current battery prices to 8.2 years and 6.2 years for battery costs forecasted for 2020 and 2030, respectively.

The results also indicate that for lower battery prices, the optimal system size increases. While for current battery cost estimates a 5kWh system offers the shortest payback

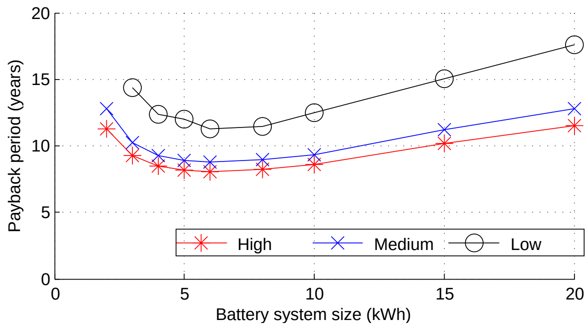

Fig. 11: Comparing the payback time for a battery cost of $310/kWh and three different electricity price forecasts.

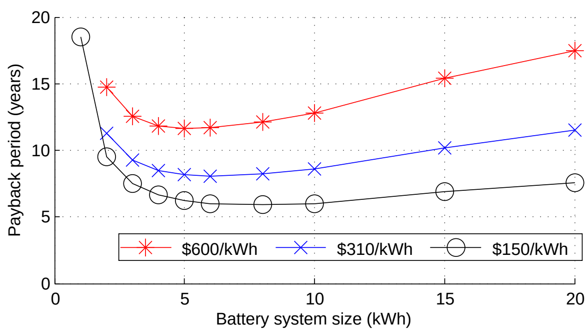

Fig. 12: Comparing the payback time for the high electricity price forecast and three different battery costs

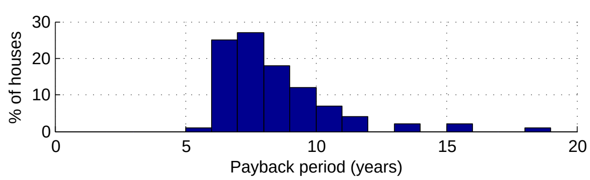

Fig. 13: Payback period histogram of 88 houses for 6kWh system, high electricity forecast and battery cost of $310/kWh.

period, for 2020 and 2030 battery costs, the optimal system sizes are 6kWh and 7kWh, respectively. This suggests that with passing time, there is incentive for consumer to buy increasingly large battery systems. This may be of concern for power companies as increasing battery sizes allow consumers to bridge increasing time delays in generation and inch ever closer to being self-sufficient from an energy perspective. Note that this consider only the battery price to be at future levels, not the electricity price. If by the time the system is first installed the initial electricity cost is already at a higher level than presently, the payback period reduces further yet.

In addition to the average payback results for 88 houses, payback distributions among these houses were also investigated. Fig. 13 shows the payback period histogram for a 6kWh storage system, the high electricity price forecast and the estimated 2020 battery cost. Out of the 88 houses simulated, 83 houses have a payback period of less than 10 years, and all but one recover the initial costs in less than 20 years. This tight clustering of payback periods suggests that once customer-side storage starts becoming financially viable for the first few households, viability for the large majority of houses may not lag far behind.

VI. Conclusion

There has been a surge in residential rooftop solar installations in recent years. However, waning subsidies, reducing feed-in tariffs, and timing mismatch between solar generation and local demand are raising questions about the cost-efficacy of these systems. Li-ion batteries are emerging as promising candidates for residential energy storage units owing to rapidly declining costs. Motivated by this trend, we (1) investigated the coincidence between solar generation and local demand (using real smart meter data sets from 88 households), and examined how it can be effectively managed by means of local storage, (2) proposed a dynamic programming based optimal charge/discharge policy for storage operation, and (3) conducted a cost analysis to evaluate possible dollar-savings in electricity as a result of introducing residential storage, and what the return on this storage investment would be. Our results indicate that there is significant potential for integrating local battery storage with existing residential PV generation systems. This proposition is likely to become financially viable with attractive payback periods in the near future.

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References

[1] G. Parkinson, “People power: Rooftop solar PV reaches 3GW in Australia,” Online: http://reneweconomy.com.au/2013/people-power-rooftop-solar-pv-reaches-3gw-in-australia-99543, 4 December 2013.

[2] Australian Bureau of Statistics, “Consumer price index for electricity (category 6401.0),” March 2014.

[3] T. Wood and L. Carter, “Fair pricing for power,” Grattan Institute, July 2014.

[4] V. Muenzel, J. de Hoog, I. Mareels, A. Vishwanath, and S. Kalyanaraman, “Affordable batteries for green energy are closer than we think,” The Conversation, July 2014.

[5] G. Bao, C. Lu, Z. Yuan, and Z. Lu, “Battery energy storage system load shifting control based on real time load forecast and dynamic programming,” in *Automation Science and Engineering (CASE), 2012 IEEE International Conference on*, Aug 2012, pp. 815–820.

[6] H. Sugihara, K. Yokoyama, O. Saeki, K. Tsuji, and T. Funaki, “Economic and efficient voltage management using customer-owned energy storage systems in a distribution network with high penetration of photovoltaic systems,” *Power Systems, IEEE Transactions on*, vol. 28, no. 1, pp. 102–111, Feb 2013.

[7] T. Tashiro, K. Tamura, and K. Yasuda, “Modeling and optimal operation of distributed energy systems via dynamic programming,” in *Systems, Man, and Cybernetics (SMC), 2011 IEEE International Conference on*, Oct 2011, pp. 808–813.

[8] Z. Wang, C. Gu, F. Li, P. Bale, and H. Sun, “Active demand response using shared energy storage for household energy management,” *Smart Grid, IEEE Transactions on*, vol. 4, no. 4, pp. 1888–1897, Dec 2013.

[9] G. Lacey, G. Putrus, and A. Salim, “The use of second life electric vehicle batteries for grid support,” in *EUROCON, 2013 IEEE*, July 2013, pp. 1255–1261.

[10] B. Stiaszny, J. C. Ziegler, E. E. Krau, J. P. Schmidt, and E. Ivers-Tiffe, “Electrochemical characterization and post-mortem analysis of aged LiMn2O4Li(Ni0.5Mn0.3Co0.2)O2/graphite lithium ion batteries. Part I: Cycle aging,” *Journal of Power Sources*, vol. 251, no. 0, pp. 439 – 450, 2014.

[11] Department of State Development Business and Innovation, “Victorian Feed-In Tariff Schemes,” Online: http://www.energyandresources.vic.gov.au/energy/environment-and-community/victorian-feed-in-tariff-schemes, Accessed Aug 2014.