The Importance of Temporal Resolution in Evaluating Residential Energy Storage

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***Abstract*—Much research is being conducted into the potential value of residential energy storage. The temporal resolution of the analyses carried out in these studies is typically driven by the available data, which is often only at 30-minute or 1-hour intervals. This study uses higher temporal resolution data to examine the effect of input time-series resolution on the value determined for residential storage. In the case study considered, an analysis carried out at a 30-minute interval underestimates the cost-saving delivered by 5kWh of residential energy storage by 17% on average, compared to the same battery analyzed at a 1-minute interval. The sensitivity of storage value to temporal resolution is found to vary significantly from one customer to the next. A method for improving estimates of the real-time value of energy storage using coarser time-series data is introduced. Finally the impact of temporal resolution on storage technology selection is also evaluated.**

***Index Terms*—Energy storage, optimal operation, temporal resolution**

I. Introduction

A. Motivation

Many existing studies (see Table I) use relatively low resolution temporal data in their analyses of the value of residential energy storage. Whilst this is a pragmatic approach, given that a majority of data-sets are only available at 30-minute or 1-hour intervals, it risks an incorrect assessment of the true value of residential energy storage when operated in real time. This paper seeks to determine how significant this value estimation problem is, by carrying out an empirical study using a dataset of the household demand and rooftop solar photovoltaic (PV) output of several hundred homes from a dataset sourced in Texas [1] that we consider a good representation of residential demand and generation.

Considering a realistic Australian scenario in which a residence has a two-part time-of-use tariff (say, of $[1]0.40/kWh during peak times and $0.20/kWh at other times), and a low fixed export tariff (say, of $0.05/kWh), a householder with a PV system might be able to derive value from a behind-the-meter battery by maximizing solar self-consumption (*i.e*. minimizing export of energy for minimal return), and tariff optimization (*i.e*. minimizing imports during peak-price times). For a 30-minute interval during which a residence's demand and PV output match (on average over the interval), a study carried out on 30-minute resolution data would determine that the battery would not be operated, and so would not deliver value during that interval. However, if during this interval PV output was fluctuating significantly (for example due to passing clouds, or repeated inverter drop-outs as a result of local voltage rise) a study completed at a higher temporal resolution would result in the battery being charged and discharged repeatedly, and delivering some saving to the household. This study evaluates how significant this difference is, as the input data (local demand and PV output) is aggregated from an initial 1-minute resolution, up to a 1-hour interval.

[1]Throughout this paper $ refers to Australian Dollars

B. Contributions & Paper Organization

This work addresses some shortcomings of existing research which evaluates residential battery energy storage systems. The contributions are to:

(i) Identify the empirical relationship between temporal resolution of input data, and the valuation of residential energy storage, for real 1-minute demand and PV data [1] (Section III-A);
(ii) Present an approach to approximating the true real-time operational value of energy storage using coarser time-series data (Section III-C);
(iii) Evaluate the impact of temporal resolution on the most appropriate energy storage technology choice for an application (III-D).

C. Literature Survey

Smart electricity meters which are being installed by utilities the world over are often capable of recording domestic electricity consumption at 1-minute intervals, or finer, but often this data is not kept or made available to researchers for a variety of reasons:

TABLE I: Time Intervals of studies on IEEE Xplore matching search: {(value OR evaluation) AND (residential OR domestic) AND (battery OR "energy storage")}.

Time Interval of Demand/RES Data [minutes]	No. of References	References
≤ 1	5	[2]–[6]
10	4	[7]–[10]
15	9	[11]–[19]
30	5	[20]–[24]
60	30	[25]–[54]

1) Bandwidth limitations mean that it is not always feasible to communicate the higher resolution data to the outside world (but only the lower resolution data required for billing);
2) High temporal resolution data presents a privacy risk, as it is possible to determine a great deal about a household from their 1-minute consumption data;
3) Data-warehousing and management costs increase with higher temporal resolution, as a result of the increased data-volume and throughput rates.

As a result much of the publicly available consumption data is at 30-minute or 1-hour temporal resolution. For example, Table I presents all of the references found on IEEE Xplore by using the search terms {(value OR evaluation) AND (residential OR domestic) AND (battery OR "energy storage")} for which discrete interval data was used in analyses[2]. It suggests that the majority (66% in a sample size of 53 papers) of studies use data with 30-minute intervals or longer.

A number of existing studies consider the question of how the temporal resolution of input data can affect the conclusions of analyses; these are reviewed briefly here. In [55] Urquhart *et al*. consider the change in copper-loss estimates in the distribution network, when simulations are carried out at varying levels of temporal aggregation. They find that between simulations at 1-minute, and those at 30-minute intervals, a 40% underestimation of losses can occur; and that the level of underestimation varies significantly between customers. Kools and Phillipson, [56], study the impact of data temporal granularity on the optimal planning (sizing) of distributed energy resources, concluding that for the planning problem 1-hour resolution data is sufficient. In [57] Hawkes *et al*. evaluate the importance of temporal resolution when determining the optimal sizing of a micro-combined heat-and-power system, concluding that using 5-minute data produces substantially different results to the 1-hour interval data used in many other studies.

The low temporal resolution used in many studies considering the value of residential energy storage, and the significant sensitivity to temporal resolution seen in closely related research, suggests the sensitivity of residential energy storage valuation to temporal resolution is worthy of further study.

[2]Applying this search to papers' meta-data returned 151 papers. The relevant ones using discrete interval data are included in Table I.

II. Method

A. Analysis

We consider a battery that is owned by, and operated in the interests of, a residential electricity customer who has a rooftop PV system. The battery is operated using a simple rule-based controller which seeks to charge the battery with any excess solar PV output (subject to state-of-charge and rate-of-charge constraints). This control law, and the resulting value-estimation of the battery, are described in Algorithm 1. We choose a PV-self-consumption-maximizing controller for two reasons: (i) It is typical of the capability and configuration of storage systems being installed in Australia today and (ii) With prevailing Australian tariff structures, minimizing exports is the most financially attractive value proposition. This simulation and analysis is then repeated at multiple temporal resolutions, *i.e.* we complete this analysis at the finest resolution possible given an available data-set, and then accumulate that data into coarser intervals to mimic the data-set only being available at a coarser resolution.

The simulation is detailed in Algorithm 1. The inputs required are: $\{\boldsymbol{d}, \boldsymbol{p}\}$ the time-series of demand and PV output for the household being considered, suitably aggregated to the interval-length of interest; $\{P_t^i, P_t^e\}$, the tariff structure (see Table II); and the properties of the battery $\{C_{\text{rate}}, B, \eta_c, \eta_d\}$ (see Table III). For each interval we calculate the excess demand ($\hat{d} \leftarrow d_t - p_t$), and if it is positive we satisfy it by discharging the battery (subject to the battery's rate-of-charge and state-of-charge constraints), and if it is negative (*i.e.* we have excess PV output during the interval) we charge the battery so that no energy is exported to the grid (again subject to battery operational constraints). During the simulation we keep track of the net cost (cost of grid imports less money received for grid exports) of operation with a battery, C, and also what the cost would be if no battery were available, C^{NB} (*i.e.* if excess demand is satisfied directly by grid imports). The cost-saving for a particular {customer, battery, interval length} instance is then estimated as $C^{\text{NB}} - C$.

The Matlab code used to simulate the battery's operation is available in a public repository to allow other researchers to reproduce our results [58]

B. Case Study Data

The following specific data is used for our case-study:

1) The Tariff Structure: for this study is given in Table II and is typical of those available to homes connected to the National Electricity Market in Australia.

2) Battery Properties: are given in Table III, and are representative of commercially available home-storage offerings in Australia.

Algorithm 1 Set-Point Operation & Value Estimation

Require: $\boldsymbol{d}, \boldsymbol{p}$ ▷ Demand/PV time-series
Require: P_t^i, P_t^e ▷ Import and export tariffs
Require: $C_{\text{rate}}, B, \eta_c, \eta_d$ ▷ Battery properties
$b \leftarrow B/2$ ▷ Initialize battery to half-full
$C \leftarrow 0$ ▷ Variable to count cost with battery
$C^{\text{NB}} \leftarrow 0$ ▷ Variable to count cost without battery
for $t = 1 \ldots N_{\text{intervals}}$ **do**
  $\hat{d} \leftarrow d_t - p_t$ ▷ Excess demand
  $C^{\text{NB}} \leftarrow C^{\text{NB}} + \min(\hat{d}, 0)P_t^i - \min(-\hat{d}, 0)P_t^e$
  if $\hat{d} > 0$ **then**
    $e \leftarrow \min(\hat{d}/\eta_d, C_{\text{rate}}, b)$ ▷ Energy from battery
    $g \leftarrow \hat{d} - e\eta_d$ ▷ Energy from grid
    $b \leftarrow b - e$ ▷ Update battery state-of-charge
    $C \leftarrow C + gP_t^i$
  else
    $e \leftarrow \min(-\hat{d}\eta_c, C_{\text{rate}}, B - b)$ ▷ Energy to battery
    $g \leftarrow -\hat{d} - e/\eta_c$ ▷ Energy to grid
    $b \leftarrow b + e$ ▷ Update battery state-of-charge
    $C \leftarrow C - gP_t^e$
return $C^{\text{NB}} - C$ ▷ Value estimate of battery

TABLE II: Tariff Structure

Tariff	Symbol	Value
Export (all times)	P_t^e	$0.05/kWh
Import (7am - 10pm)	P_t^i	$0.40/kWh
Import (other times)	P_t^i	$0.20/kWh

TABLE III: Battery Properties

Property	Symbol	Value	[units], Notes
Usable capacity	B	{1.0, 5.0, 10}	[kWh]
Charging rate	C_{rate}	1.0	[hr^{-1}], kW charging rate divided by B
(Dis)Charging efficiency	η_c, η_d	0.96	[]

3) Demand and PV Generation Data: for this study are taken from the Pecan Street Dataport database [1], which we consider a representative dataset for residential demand and generation. 71 customers had complete data for 2013-2014 (525,600 one-minute readings per year), and are included in this study. The source data is recorded as kW power for the 1-minute metering period. This is converted into kWh consumed/produced over the minute (scaling by 1/60). To study the battery valuation determined at different temporal resolutions, the data was then aggregated over several interval lengths: {1, 2, 5, 10, 30, 60} minutes, by summing over an appropriate number of 1-minute intervals.

III. Results

A. Impact of Interval Length on Battery Value

Fig. 1 illustrates the reduction in observable battery value with increasing temporal aggregation level (*i.e.* reducing temporal resolution). Two conclusions can be drawn: (i) For some customers, reducing temporal resolution can significantly affect the battery value determined (by over 40%); and (ii) The extent to which the resolution of the input data affects the resulting battery value varies significantly between customers. Similar plots were produced for 1 and 10 kWh batteries, and the percentage value hidden at reduced temporal resolution is greatest for smaller batteries, as might be expected.

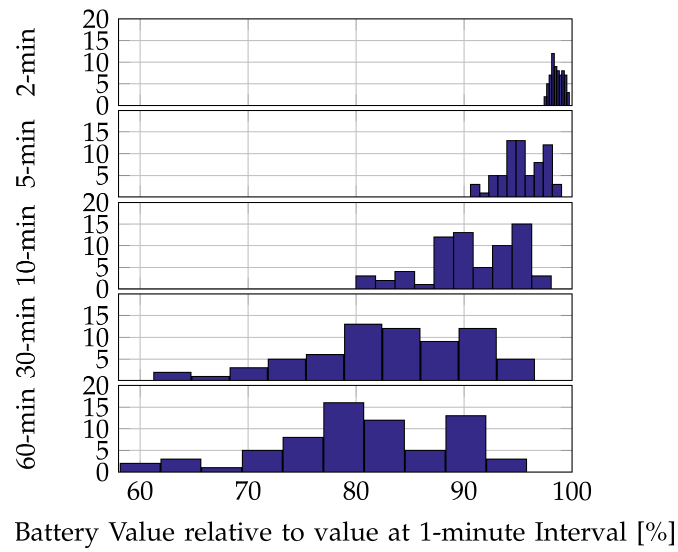

Fig. 1: Histogram of values for a 5kWh battery with data aggregated to increasing interval lengths. Source data from [1].

B. Interval-Length Sensitivity Between Customers

To determine what characteristics of an individual customer's demand/PV profile cause a high or low sensitivity of storage value estimate to temporal resolution, we look at the time series PV and demand data for the customers with greatest and least sensitivity. These are plotted in Fig. 2 which shows that, as might be expected, the customer with most value hidden at higher temporal resolution has a demand signal with significant high frequency content, and that with the least hidden value has a relatively smooth demand profile.

C. Estimating real-time Value from Coarser Data

Fig. 1 demonstrates that a significant number of customers would underestimate the value which energy storage might offer them, if they considered coarser temporal resolution data only. This raises two questions:

1) Is 1-minute data fine enough?: It is not possible to address this question definitively without access to finer temporal resolution data. However, looking at the curves in Fig. 3 they appear to be smooth, and approximately linear for the finest {1, 2, 5}-minute resolutions. This is consistent with the results found in [55] using a dataset of UK households. If we extrapolate these linear trends

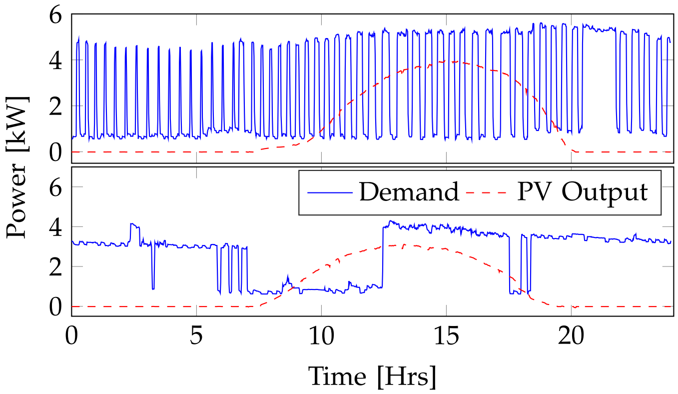

Fig. 2: Time series of demand and PV output for the customer with the most (top) and least (bottom) value hidden at higher temporal resolution. Data from [1].

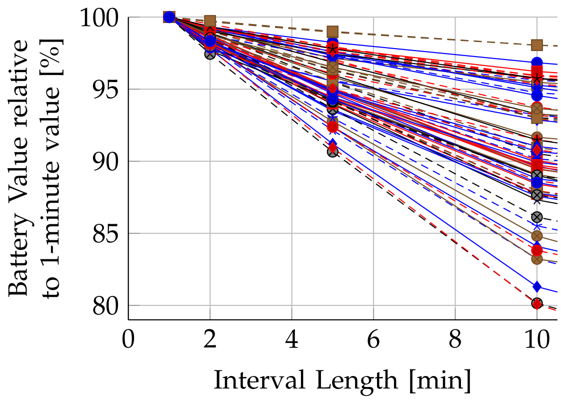

Fig. 3: Value of 5kWh battery with data aggregated to {1, 2, 5, 10}-minute intervals. Source data from [1].

to an interval length of zero minutes (*i.e.* the value of a battery operated in continuous time) for a 5kWh battery we get a value of between 1% and 3% greater than the value determined at a 1-minute interval.

2) Can a better estimate of the fine-resolution value be made from coarse data?: In many settings only coarser temporal data is available, motivating an attempt to estimate the true value of energy storage from coarse data. To attempt this we randomly divide the data into a training set of 45 customers, with the remaining being used as a test-set. We then treat the value determined using data at {30, 60}-minute intervals as regressors (*i.e.* assuming 30-minute input data is available), and the value determined at a 1-minute resolution as the regressand, and use least-squares linear regression to determine the coefficients of a model (using the training set). Finally, for the test customers we estimate the 1-minute value of the battery in two ways; firstly using a simulation with data at 30-minute intervals, and secondly by estimating value at {30, 60}-minute intervals (aggregating the input data before running the analysis as required) and then using

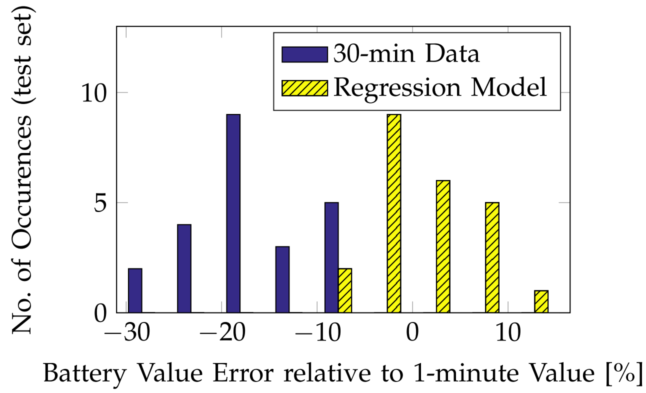

Fig. 4: Histogram of errors of 1-minute value of 5kWh battery using value-estimates from 30-minute data only (solid), and from the linear regression model using {30, 60}-minute interval performance as inputs (hatched). Source data from [1].

the linear regression model. The battery value errors are then normalized to the true 1-minute battery value and are plotted in Fig. 4. The results from 30-minute interval data consistently underestimate the battery value (consistent with the results from the fourth panel of Fig. 1), with a mean error of -17% and a standard deviation of 6.4%. Using the regression model results in relative errors with a mean of +1.1% and a standard deviation of 5.5%. Using the regression model has reduced bias without increasing the variance of errors in trying to estimate the continuous-time value of a battery based on only 30-minute interval input data.

D. Impact of Temporal Resolution on Technology Selection

The main thesis of this paper is that the value estimate of residential energy storage is sensitive to the temporal resolution of the data used. A related question is whether the resolution of data might affect the choice of energy storage technology. To examine this we consider a simple analysis of the cost-saving of an energy storage asset, relative to its purchase cost. Table IV gives properties for a particular battery and supercapacitor energy storage product. We assume that the degradation of an energy storage asset is driven only by the cumulative charging and discharging kWh as it is operated. In practice, battery degradation is more complex, and a proper treatment needs to consider many more factors (see for example [20]). In Table IV we see that neither technology strictly dominates. The battery has a lower cost per kWh-capacity, whereas the supercapacitor has a higher charge/discharge rate, and a lower cost per kWh-throughput, if its large number of cycles can be utilized.

To assess the impact of temporal resolution on technology selection we simulate the operation of an energy storage asset with the properties outlined in Table IV and compare the cost-saving offered by the storage device,

TABLE IV: Battery & Supercapacitor Properties

Parameter	Battery	Supercapacitor
Reference device	BMZ ESS3.0	Eaton XLR-48R6167-R
Data Source	[59]	[60], [61]
B	5.4 kWh	0.041 kWh
Cycle Life	5,000	1,000,000
C_{rate}	1.5	2880
Cost	$7,700	$1,700
Cost/kWh-capacity	$1,426	$41,463
Cost/kWh-throughput	0.143 $/kWh	0.021 $/kWh

TABLE V: Battery & Supercapacitor Performance at Different Temporal Resolutions

	Interval [min]				
Battery	1	2	5	10	30
Value [$]	579	572	554	528	486
Throughput [kWh]	3678	3632	3525	3376	3131
Degradation []	0.068	0.067	0.065	0.063	0.058
Depreciation [$]	525	518	503	481	446
Net value [$]	55	54	51	47	40
ROI [%]	0.71	0.70	0.66	0.61	0.52
	Interval [min]				
Capacitor	1	2	5	10	30
Value [$]	35	32	27	19	7.2
Throughput [kWh]	211	190	158	111	43
Degradation []	0.0026	0.0023	0.0019	0.0014	0.00053
Depreciation [$]	4.4	3.9	3.3	2.3	0.9
Net value [$]	31	28	23	16	6.3
ROI [%]	1.8	1.6	1.4	0.96	0.37

to the costs implied by its degradation. These results are summarized in Table V. This analysis shows that the net return on investment (ROI: the cost saving delivered by operating the storage for 1-year, less the annual depreciation of the asset, divided by the asset's initial capital cost) is higher for the battery at lower temporal resolutions, and for the capacitor at higher resolutions. It is important to note that this is a preliminary analysis, and does not consider the 'calendar' degradation of the battery or capacitor, inclusion of which might result in a higher ROI of the battery at all resolutions (due to the relatively short service life of capacitors). Nonetheless this analysis is of interest, as it shows that using input data with sufficient temporal resolution is important in selecting the right energy storage technology.

IV. Conclusion & Further Work

We have demonstrated that the temporal resolution of input data can significantly affect the value determined for residential energy storage, at least for the empirical case of the users considered in the present study. We have shown that analyses carried out with data at 30-minute or 1-hourly intervals can significantly underestimate the cost-saving which energy storage is able to deliver. An assessment carried out using 30-minute interval data underestimates the cost-saving potential of a 5kWh battery by 17% on average, compared to a study using 1-minute data. We have also presented an approach to improving the estimation of the real-time value of energy storage, when only coarser data is available. Finally, we have demonstrated that the temporal resolution of input data can affect the relative assessment of different storage technologies. It is important that existing and future studies which are completed with coarser resolution data (which is more readily available to researchers) are interpreted in light of these findings. The operational optimization techniques studied in the literature also need to be reviewed for their suitability of application at higher temporal resolutions. A finer temporal resolution will increase the complexity of many predictive optimization approaches whilst reducing the time available for computation in an on-line setting.

The findings in this paper are inherently empirical, therefore will not necessarily apply in other settings; where energy storage is operated for different objectives, with different tariff structures, and for users with different load patterns. Indeed, a key finding from this study is that the sensitivity of energy storage value estimates to temporal resolution of input data varies significantly from customer to customer, even within a single dataset.

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