A Receding Predictive Horizon Approach to the Periodic Optimization of Community Battery Energy Storage Systems

Peter Wolfs
Centre for Smart Grid and Sustainable Power Systems
Curtin University
Perth, Australia
p.wolfs@curtin.edu.au

G.Sridhar Reddy
Centre for Smart Grid and Sustainable Power Systems
Curtin University
Perth, Australia
Gsridhar.Reddy@curtin.edu.au

Abstract— **Community scale battery energy storage systems can improve the utilization of network assets and increase the uptake of intermittent renewable energy sources. This paper presents an efficient algorithm for optimizing the cyclic diurnal operation of battery storages in a low voltage distribution network with a high penetration of PV generation. A predictive control solution is presented that uses neural networks to predict the load and PV generation at hourly intervals for twelve hours into the future. The load and generation forecast, and the previous twelve hours of load and generation history, is used to assemble a 24 hour load profile. A diurnal charge profile can be compactly represented by a vector of Fourier coefficients allowing a direct search optimization algorithm to be applied. The optimal profile is updated hourly allowing the state of charge profile to respond to changing future forecasts in load and PV generation.**

Keywords-battery energy storage system, receding horizon control, periodic optimisation

I. INTRODUCTION

Energy storage has significant advantages for any distribution grid, [1-2]. Storage is frequently presented as the solution to the integration of intermittent generation sources into the grid, [3,4]. The deployment of batteries in the power system at a residential or commercial scale has been uneconomic, [5]. The battery cycle life costs, the costs of charging and discharging new batteries, ranges between $AUD0.05c and $AUD1.00/kWh exclusive of additional capital costs for inverters and grid connections. Generally this will exceed the costs of providing a traditional supply solutions such as conductor replacement or reconstruction. Remote and rural systems are neither well serviced nor well interconnected and are an important exception. Many utilities have programs of research aimed at supporting the edge of the rural distribution grid, [6].

Retired electric vehicle batteries will provide a lower-cost storage opportunity. Electric vehicles (EVs) and pluggable hybrid electric vehicles, (PHEVs) will represent a battery market of $USD30-40 billion by 2020, [7,8]. Batteries will be removed from vehicle service once their capacity degrades to design end point which is typically 80% of their original amp-hour charge capacity. Once removed from a vehicle a battery has a scrap value for recycling. It also has a second-use value if it can be sold into an alternative market place. The second-use of electric vehicle batteries for grid support was first proposed for lead acid batteries, [9,10]. Baseline projections have electric vehicle sales in the US reaching 3% of total sales in 2015, 18% in 2020 and 45% of total sales in 2025, [11]. One manufacturer, A123, has opened a production facility in Livonia Michigan that will expand its manufacturing capacity by up to 600MWh annually, [12].

This paper examines the integration of storage into the low voltage distribution network at a micro-grid or community level. There are various models of ownership. Distribution network services providers may locate storages with distribution transformers to provide local support in networks with capacity or voltage regulation constraints. Collectives such as gated communities or housing collectives may operate storage to reduce energy prices. In either case the operation of the storage must be optimized with respect to the timing of energy purchases or releases and ultimately the battery state of charge.

II. COMMUNITY SCALE ENERGY STORAGE

The battery optimization problem can be framed at the distribution network level. Figure 1 shows hourly data collected at a 200kVA 400/230Vac distribution transformer supplying a low voltage three-phase four-wire LV feeder within the Perth Solar City High Penetration Trial. This feeder supplies 77 residential houses where 29 residences have roof top photovoltaic systems. The total PV generation is 54kWp. Power flow reversals are observed at the distribution transformer at times of low load and high PV generation which often occur at noon on week days. A power flow reversal example is seen between 144 and 167 hours and this corresponds to noon on a Monday.

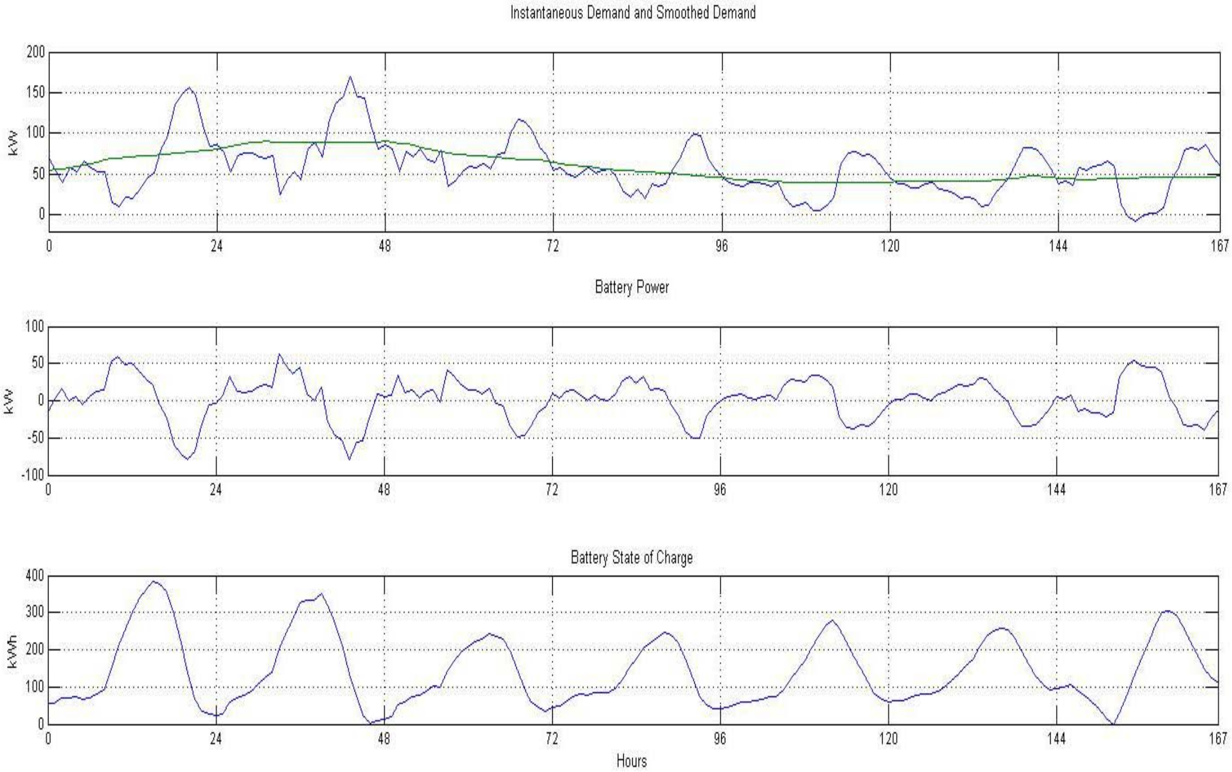

Figure 1. LV Grid Hourly Data for Midnight 30th January to 11.00PM 6th February

An ideal community level battery storage system will modify the transformer loading to optimize the energy supply cost. If a high peak demand charge is levied the transformer loading should approach the non-causal averaged load:

$$p_{24}(t) = \frac{1}{T}\int_{t-T/2}^{t+T/2} p_g(t)dt \quad [1]$$

Where

$p_{24}(t)$ is the 24 hour averaged load
$p_g(t)$ is the power drawn from the grid
T is the averaging period, 24 hours.

A non-causal average is calculated over the period (t-T/2, t+T/2) and introduces no phase delay. The battery energy storage system would be managed to charge or discharge at rates, allowing for battery and conversion losses, which result in the total transformer load that follows the averaged power. In figure 1 the green trace in the top subplot shows the resulting transformer loading with a battery system that has a 90% round trip energy storage efficiency. The corresponding battery power and battery state of charge are shown in the lower two subplots. This control approach requires the future knowledge of the transformer loading to calculate the non-causal moving average described in equation 1. The method focuses on the minimization of peak demand but does not inherently include the other factors affecting the energy cost such as time of use tariffs or battery capital and operating expense costs. A practical control system requires two additional components:

- A method to incorporate predictions of the future loading which will have a degree of uncertainty;
- An optimization step that can find the minimum 24 hour energy cost.

III. Periodic Optimisation

The State of Charge (SoC) of a community battery energy storage system, operating with uniform daily patterns of energy demand and generation, will follow a uniform periodic cycle. A stable periodic solution requires that the SoC at the end of each day is constant. Any discrepancy in charge would accumulate over time leading to over-charging or over-discharging. Both power and SoC are periodic functions:

$$p_b(t) = p_b(t+T) \quad [2]$$

$$s_{oc}(t) = s_{oc}(t_0) + \int_{t_0}^{t} p_b(t)\, dt \quad [3]$$

$$s_{oc}(t) = s_{oc}(t+T) \quad [4]$$

Equation 4 implies that the battery power has a daily average of zero. Figure 2 shows a highly simplified battery SoC variation. The battery storage operates over a cycle time T which is often a single day. The battery discharges at relatively high power, $P_{discharge}$, during a period of peak energy demand or high tariff. The battery is recharges over the remainder of the cycle at a power of P_{charge}. The state of charge is the integral of power and varies between SoC_{min} and SoC_{max}. The optimization of a battery energy storage system will require that an optimal daily profile is determined for the battery state of charge. If the daily state of charge is known, the instantaneous charging power is determined and ultimately the daily energy cost can be determined. The solution could be a sequential list of the state of charge values during the day as shown in Equation 5.

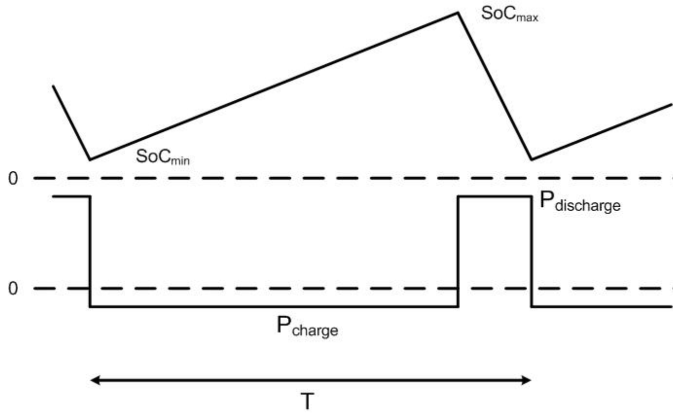

Figure 2. A Simplified SoC Cycle

$$C_T = \begin{bmatrix} SoC_1 \\ \vdots \\ SoC_n \end{bmatrix} \quad [5]$$

Numerical optimisation processes rely upon the repeated evaluation of a cost function for a proposed solution vector. The proposed solution vectors are generated with knowledge of problem-specific constraints. A charging power limitation imposes an absolute value constraint on the difference between each adjacent SoC value within the solution vector or n constraints, where n is the order of the SoC vector. This introduces a computational burden that will slow any optimization algorithm.

A charging power constraint might be more easily applied by framing the solution vector as a list of average charging powers over each time interval. This has another disadvantage. Power can be a discontinuous function and the daily charging power frequency spectrum has increased higher frequency components relative to the SoC spectrum. As such a power vector is resistant to efforts to compactly represent a solution. A compact representation can reduce the dimensionality of the optimization problem.

A superior approach is to represent the periodic state of charge solution utilizing a vector of Fourier coefficients such that:

$$C_F = \begin{bmatrix} a_1, b_1 \\ \vdots \\ a_n, b_n \end{bmatrix} \quad [6]$$

$$s_{oc_i}(t) = a_0 + a_1 \cos\left(\frac{2\pi t}{T}\right) + b_1 \sin\left(\frac{2\pi t}{T}\right) + \dots\dots + a_n \cos\left(\frac{2\pi n t}{T}\right) + b_n \sin\left(\frac{2\pi n t}{T}\right) \quad [7]$$

The coefficient a_0 does not contribute to battery power and can be set to ensure a positive minimum state of charge. The optimization problem becomes the selection of the Fourier coefficients for the state of charge equation to minimize the daily energy cost function:

$$J = C_{peak} + C_{energy} + C_{wear} \quad [8]$$

Where the daily peak energy charge is expressed in terms of a peak demand rate, R_{max} and the peak grid power P_{gmax}:

$$C_{peak} = P_{gmax} R_{max} \quad [9]$$

And the daily energy purchase cost is determined by the time varying tariff rate, r(t) and the grid power $p_g(t)$:

$$C_{energy} = \int_{t_0}^{t_o+T} p_g(t)\, r(t) dt \quad [10]$$

And the daily battery wear cost is determined by the battery power and a cyclic wear factor K_{wear}, which is determined by the operational and capital costs:

$$C_{wear} = \frac{K_{wear}}{2} \int_{t_0}^{t_o+T} |p_b(t)|\, dt \quad [11]$$

Subject to the following constraints:

$$S_{ocmin} \le s_{oc}(t) \le S_{ocmax} \quad [12]$$

$$|p_b(t)| \le P_{bmax} \quad [13]$$

Where the S_{ocmin} and S_{ocmax} are minimum and maximum limits on the battery state of charge and P_{bmax} is a maximum battery power.

IV. Receding Horizon Predictive Control

Figure 1 shows that the power in a practical distribution network has a strong diurnal variation but is not strictly periodic. The daily energy consumption and peak demand is a strong function of exogenous variables especially temperature, relative humidity and the day of the week. This paper presents a receding horizon control method as shown in Figure 3. The approach relies to two operating time scales: a twelve hour receding horizon prediction time scale and a one hour control update time scale. The key features are:

- At hourly intervals a set of neural networks forecast the future load values for $p_l\left(t + \frac{iT}{24}\right); i \in (0,12]$;
- The future forecasts, covering the following twelve hours at hourly intervals, are supplemented with previous values of $p_l\left(t - \frac{iT}{24}\right); i \in [0,11]$; extending eleven hours into the past to produce a 24-hour net load profile;
- For that 24-hour net load profile, a direct search optimization is applied to find the battery state of charge profile, $C_{Fnew}(t)$, that minimizes daily energy cost;

- This new charge profile, $C_{Fnew}(t)$, is used to update the previous state of charge profile, $C_{Fold}(t)$.

The charge profile update process is performed hourly as follows;

$$C_{Fnew}(t) = (1 - a)C_{Fnew}(t) + a\,C_{Fold}(t) \qquad [14]$$

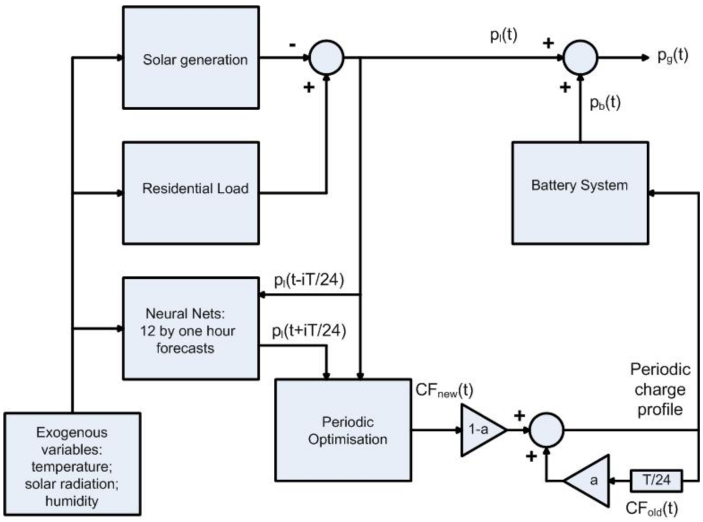

Figure 3. Receding Horizon Periodic Control

V. RECEDING HORIZON PREDICTIVE CONTROL

Load forecasting is performed using a set of twelve neural networks which are individually trained to provide load forecasts at one hour intervals into the future. The network inputs are:

- Dry bulb temperature;
- Relative humidity;
- Solar radiation;
- Hour of the day;
- An integer representing the day of the week;
- An integer flag indicating if the day is a working day or holiday;
- The current load;
- Load 24 hours previously;
- Load 168 hours previously;
- Average load in the past 24 hours.

The network has ten inputs and a hidden layer of 20 neurons. Training was undertaken using a Mean Absolute Error , (MAE) performance metric with the default MATLAB toolbox Levenburg-Marquardt algorithm, [13]. A training set of 14,451 points was assembled using data records collected between 17th October 2011 and 29th January 2012. A test set of 4032 points was assembled from a data records collected from the 30th January 2012 to 26th February 2012. The training set included the annual peak load day and a broader climatic range than found in the test set. The MAE performance metric for each of the twelve forecasts are given in Table 1.

TABLE I. FORECAST ERROR

Forecast period (hours)	MAE (kW)
1	8.3
2	9.3
3	10.3
4	10.9
5	10.8
6	10.7
7	11.0
8	10.6
9	10.6
10	11.3
11	10.9
12	10.7

Figure 4 shows the output of two of the twelve neural nets. The top traces show the load profile, in green, and the forecast, in blue, made with data available an hour earlier. The lower subplot shows the load, green, and the forecast load, blue, made from data available twelve hours earlier. Clearly forecast errors accumulate with the prediction duration.

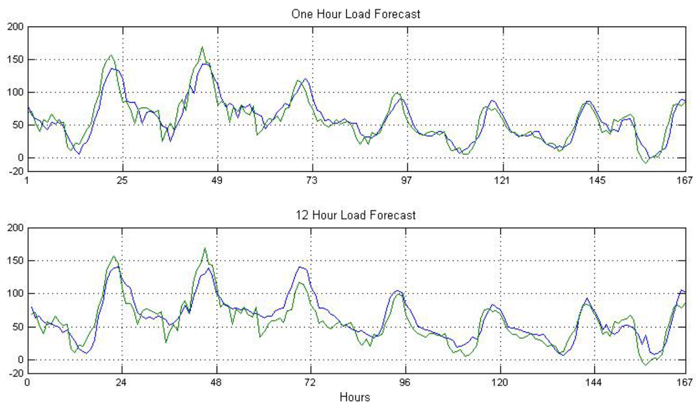

Figure 4. Neural Net based One and Twelve Hour Load Forecasts

VI. SIMULATION RESULTS

Figure 5 shows the response of the receding control periodic optimization system with forecast load data for the week from 30th January to 6th February. To allow comparisons against the ideal smoothed demand response the cyclic operating cost of the battery was set to zero as was the energy charge. A peak demand tariff of \$1.0178/kWh, which corresponds to the peak demand charge of a local utility, was levied. These settings cause the algorithm to focus on demand reduction. The battery cyclic energy efficiency was 0.9 and the exponential weighting factor, *a* in equation 14, was set to 0.9. Figure 5 shows the results.

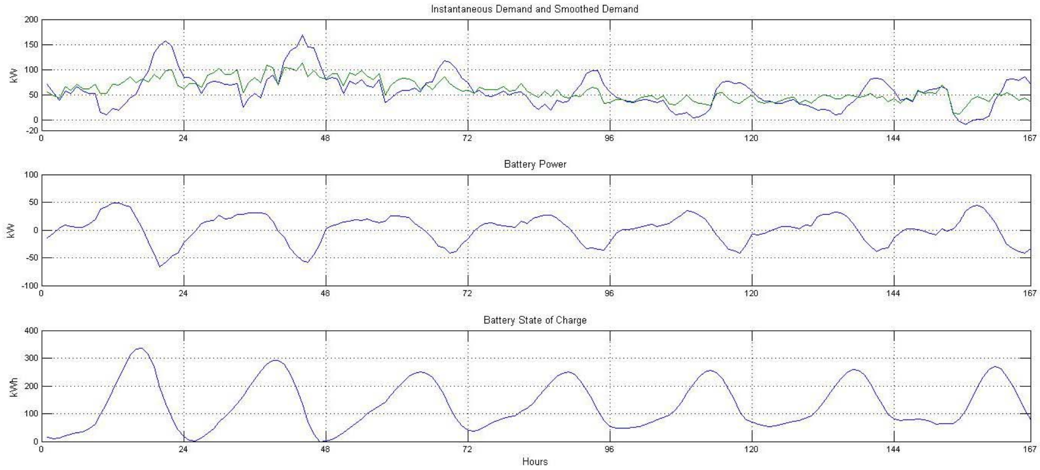

Figure 5. LV Receding Horizon Control Response - 30th January to 11.00PM 6th February

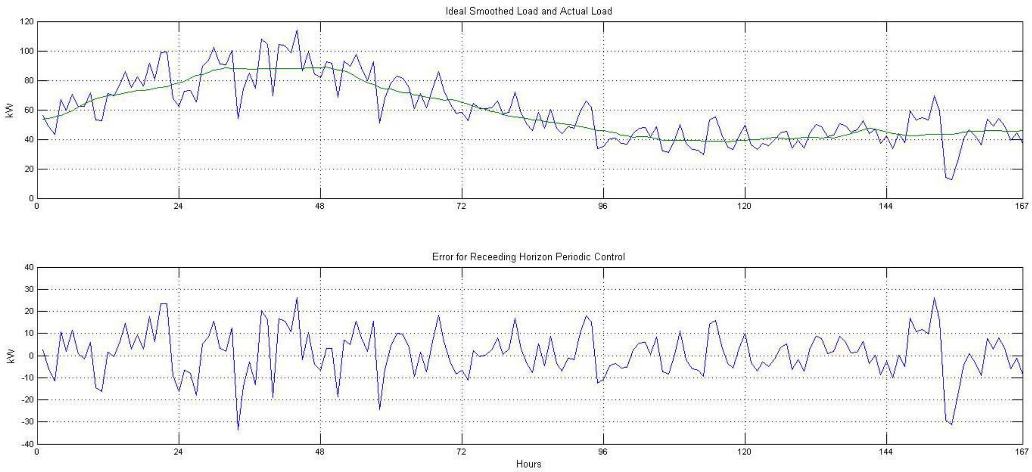

Figure 6. LV Receding Horizon Response Compared to Ideal Response

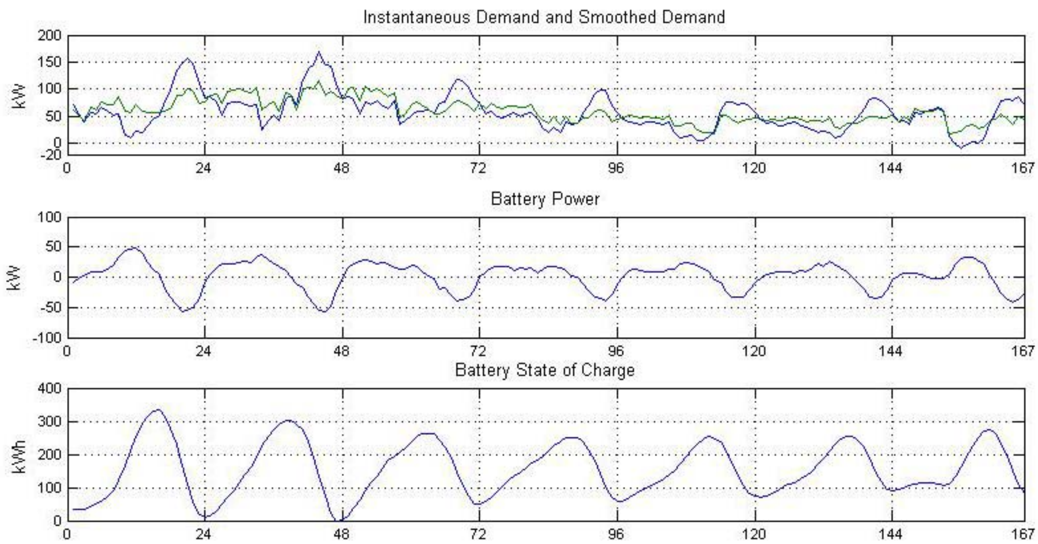

Figure 7. TOU and Peak Demand Optimization 30th January to 11.00PM 6th February

The lower trace is the battery state of charge profile over the 168 hour period which is produced by the sequential processes of hourly load forecasts, a 24-hour cyclic optimization to produce and weighted charge profile updating process. The resulting state of charge profile closely matches the ideal profile shown in figure 1. The resulting battery power is shown as the second trace in Figure 5 while the resulting smoothed grid power is compared to the unsmoothed profile in the top traces.

Figure 6 provides a more detailed comparison of the ideal and actual responses. The maximum value for the unsmoothed peak demand is 169.3kW. The ideal smoothed demand is 89.0kW. This is a reduction to 53% of the uncontrolled peak but requires a perfect future knowledge of the load. The proposed control method achieved 113.9kW or a reduction to 67% using a forecast model that includes prediction uncertainty. The lower trace shows the variation between the proposed method and the ideal smoothed load. The Mean Absolute Error (MAE) is 8.1kW which is comparable to MAE prediction measures observed with the neural network forecast models.

Figure 7 shows the result of an optimization for a combined time of use tariff and peak demand tariff based on an existing West Australian structure. A peak energy charge of 14.56c/kWh applies between 8.00am and 10.00pm, the off peak charge is 9.21c/kWh and the peak charge is $1.0178. Currencies are expressed in Australian dollars. The battery cyclic cost is 2.6c/kWh which is set to half the differential between the off peak and on peak rates. This is low relative to the expected cost for new batteries but might be achieved with second use batteries, [9,10]. The cyclic energy efficiency is 0.9 and the update smoothing factor a=0.9. It can be observed that small changes occur in the state of charge and the battery power to allow increased purchases of energy during the off peak time. The weekly energy cost is the optimized system is $1,787 with peak charges contributing $575. Without a battery storage the weekly charges are $1,978 with a peak charge contribution of $791.

VII. CONCLUSIONS

This paper has used load data extracted from a low voltage distribution feeder with a high penetration of photovoltaic generation to demonstrate the feasibility of applying a periodic optimization method to the management of state of charge for in a battery energy storage system. Receding horizon forecasts of load net of PV generation were successfully made using neural nets. These allowed rolling 24 hour load profiles, with future predictions and previous load data to be constructed. These became inputs to an optimum periodic charge profile calculation which produced hourly updates for an optimum charge profile. The hourly profiles were then added using a moving exponential weighting to give a final battery target profile. The method was successfully tested using historical feeder data.

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