Real-Time Battery Management Algorithm for Peak Demand Shaving in Small Energy Communities

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***Abstract*—One of the solutions to tackle the problems of high peak demand and grid instability due to high photovoltaic (PV) power penetration is to deploy a battery storage system. This paper presents a real-time battery management algorithm (BMA) for peak demand shaving in small energy communities with grid-connected PV systems. The BMA aims to control the charge/discharge of the community battery storage using measurement of the instantaneous power consumption of the community. Historical data records of community daily energy consumption and available renewable energy are taken into account to manage the charge/discharge of the battery. Simulation results show the effectiveness of the BMA which is able to reduce the peak energy consumption by 35%, increase PV self-consumption by 47% and reduce transmission line losses during the peak period by 56% when compared to a PV system without the battery storage.**

***Index Terms*—Peak shaving, Battery management algorithm, PV system, Battery storage, Time of use tariff.**

I. INTRODUCTION

World electricity demand almost doubled from 1990 to 2011 and seems set to grow further by 81% from 2011 to 2035 (from 19,004 TWh to 34,454 TWh) [1]. In order to respond to this growth, new power stations particularly coal-fired and natural gas power plants need to be built. This could result in a rise in electricity price and greenhouse gas emissions. To cope with these issues, sustainable energy sources such as solar power, wind power and biomass energy are receiving increased attention. In the UK, the government has been encouraging households to install PV panels by offering the Feed-in Tariff scheme. This has resulted in significant growth of PV installations at a domestic level from a cumulative 77 MW in 2010 to over 1500 MW in 2012 [2], [3]. A PV system has several key advantages such as easy installation (requiring only an electrical connection) plus it generates no noise and has a very low maintenance cost [2]. However, in some locations, grid problems have been observed where high levels of PV generation are injected into the distribution system during days with strong solar irradiance and low load demand. This can cause serious issues to the distribution system such as high system losses, voltage regulation and electricity blackout [4], [5]. Moreover, the grid infrastructure may need to be upgraded in order to carry such high power flows and hence substantial investment could be required in certain locations. One solution to maintain gird voltage stability and to avoid grid reinforcements is to deploy an energy storage device to store the excess generated power and then this stored energy can be utilized during periods of high demand [3].

This paper presents a proposed BMA based on empirical system models. The major benefits of the battery storage systems employed are to shave the peak power demand and to increase renewable self-consumption, and therefore, increase grid stability and reduce distribution system losses. It should be noted that a time-of-use (ToU) tariff with significant price differential between peak and off-peak consumption periods also needs to be applied to enable value to be captured through energy cost saving for the consumers when deploying this system.

The paper is organized as follows. In section II the data sources used for the case study are discussed including information on the power converter used as an interface and the battery system model obtained from the experiment. Section III presents the BMA. Section IV presents the outputs of simulations that illustrate the results of battery operation, peak shaving capability and PV self-consumption. Finally, section V presents conclusions drawn out of this work.

II. DATA SOURCES AND MODELLING

A. *Residential Community Model*

The community model considered in this paper is based on seven residential dwellings at the University of Nottingham campus. A simulation of domestic demand was created using a model from the Centre for Renewable Energy Systems Technology (CREST) created by Richardson and Thompson [6]. This CREST tool was used to generate seven residential profiles with a time resolution of one minute. Occupants are assumed to be students and workers.

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B. Renewable Energy Sources

Each house in the community is assumed to have a 1.65 kW (peak) PV array for local generation. A total generation capacity of 11.6 kW is therefore assumed. The input for the simulation is obtained from data recorded at 10-minute intervals made publicly available on www.pvoutput.org and the location of the PV panels is in Oxford and had been scaled to give a peak power of 11.6 kW to match the modeled community

C. EnergyTariff

The economic case for adding a battery to a smart energy community cannot be made using existing energy tariffs: there needs to be a significant price differential between peak and off-peak consumption periods. For the purposes of this work, tariff periods have been determined by analysis of New Electricity Trading Arrangements (NETA) data available for 2011 [7]. This data shows the total UK electricity consumption over the year, divided into half hour blocks. The method used to create the tariff times takes this data on a day-by-day basis and calculates the average energy consumed on a specific day (E_{av}). The energy consumption for each half hour block (E_h) is then compared to E_{av}. If $E_h > 1.1 * E_{av}$ then that half hour block is considered to be a “peak” tariff period. If $E_h < 0.9 * E_{av}$ then that half hour block is considered to be an “off-peak” period, other times are assumed to be “average-rate” periods [8].

D. Power Converter Model

The power converter model in this work is obtained from the experiment in the laboratory at the University of Nottingham. The available 12 kW power converter has been tested at different power operation and the input and output power has been measured. As a result, the output power equation of this converter can be expressed as (1).

$$P_{out} = 0.9494 * P_{in} + 323.89 \tag{1}$$

where P_{out} is the output power of the converter and P_{in} is the input power of the converter in watts. It can be found from (1) that the efficiency of the converter becomes extremely poor as the operating power reduces. This would affect the total energy cost saving corresponding to the payback of the system when the charge/discharge decision process was made. To quantify the minimum power converter operation, the round trip efficiency (charge and discharge) and energy price tariff need to be considered. The conservative round trip efficiency of the converter in this work would be more than 50%.

E. Battery Model

The parameters that determine usage of the battery are the instantaneous battery voltage (battery terminal voltage) and battery degradation. The battery voltage evolves with the battery capacity fade and resistance rise. These parameters will determine the maximum charge and discharge power of the battery as well as the maximum battery capacity. In order to determine the instantaneous battery voltage, a simple battery equivalent circuit is considered. Two important battery parameters are the battery open-circuit voltage (V_{oc}) and battery internal series resistance (R_{batt}).

If the battery is charged and discharged at the same current rate, can be expressed as (2):

$$V_{oc} = \frac{V_{ter\min al\_ch} + V_{ter\min al\_disch}}{2} \tag{2}$$

where $V_{ter\min al\_ch}$ is the battery terminal voltage during charging and $V_{ter\min al\_disch}$ is the battery terminal voltage during discharging. R_{batt} can be determined as (3):

$$R_{batt} = \frac{V_{oc} - V_{ter\min al\_disch}}{2} \tag{3}$$

V_{oc} can be determined by experiment. Figure 1 shows the plot of the experimental battery pack terminal voltage as a function of state of charge (SOC) of the 24kWh battery during the battery charging and discharging at 30A.

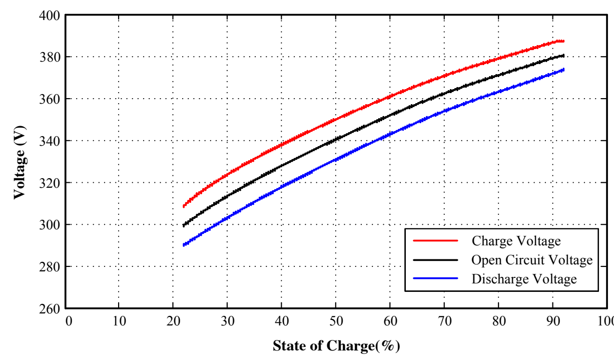

Figure 1. Battery open circuit voltage measued from an experiment.

From the result of Figure 1 and (2), R_{batt} can therefore be plotted in Figure 2.

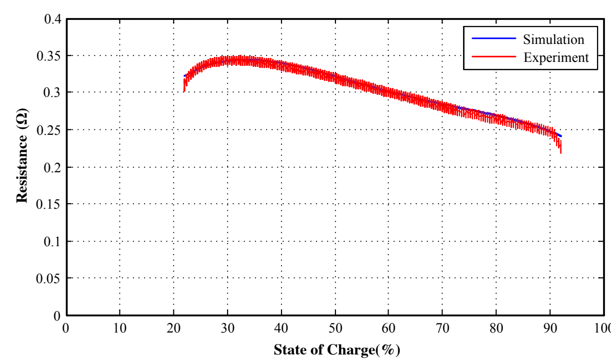

Figure 2. Battery internal resistance Vs state of charge.

In terms of the battery degradation, the battery manufacture data sheet provides the curves of cycle life and calendar life. Unfortunately, the degradation of the internal resistance information of the battery cell is not given on the datasheet. The only available information with which to approximate the internal resistance degradation has been derived the SAFT battery pack [9].

III. Battery Management Algorithm

In its basic form, the BMA controls the battery charge/discharge to minimize daily energy cost and peak demand power for the smart energy community. The algorithm will seek to charge the battery from any excess photovoltaic (PV) panel generation or from the grid during the off-peak period (when the energy price is cheap) and discharge during the peak period (when the energy price is expensive). However, without any discharge power control criterion, the battery was found to run out too early before the evening peak period. The solution to this problem is to set up a Community Power Target (*CPT*) to determine at what power level the battery should be discharged so that the peak demand can be shaved throughout the day. If the actual community power (*CP*) drawn goes below zero (i.e. the community wants to export power) then the battery will charge. If the community power goes above its *CPT*, then the battery will discharge provided certain other criteria are met. The algorithm is designed to work in two stages, namely Prediction, and Control. These stages operate as follows:

A. Prediction

The Community Power Target is forecast each day at midnight, based on predictions of community energy consumption and renewable energy available for the following day, The *CPT* is calculated as (4):

$$CPT = \frac{E_C - E_{ERS}}{2} \tag{4}$$

where E_C is a prediction of the community energy consumed for the next day in kWh and E_{RES} is a prediction of the local renewable energy available in kWh over the next 24 hours. *CPT* can be considered to be the average power that would be drawn from the grid by the community during the next 24 hours, if all the locally-generated renewable energy can be captured and used within the community. The weather conditions for the next day can be accessed from weather forecasting websites and this can help predict the total renewable energy available for the next day. It is assumed that as research progresses in this field a sufficiently accurate prediction one day ahead will be available in the future, certainly for PV systems. The load profile as an hour-by-hour or minute-by-minute prediction is more difficult to forecast accurately. However, the whole day's energy demand can be estimated using energy demand of the equivalent day of the previous week. The available renewable generation may not be sufficient to reduce the peak gird consumption (particularly in the evenings), and therefore charging of the battery from the grid at low cost periods (for example between 0.00 hrs and 05.00 hrs) has been also included in the algorithm. The amount of energy required from the grid can be calculated by predicting the energy demand for the next day, predicting the renewable energy resource available and also using the battery's State of Charge (SOC) at midnight. The required battery pre-charge energy (ΔE_n) required from the grid overnight for day n can be divided into three cases.

Case1: when predicted excess PV energy is less than the battery capacity available, (E_{batt_av}). The pre-charge energy required is determined by (5)

$$\text{if } E_{RES} > (E_C * \delta) \ \&\& [E_{RES} - (E_C * \delta)] < E_{batt\_av}$$

$$\Delta E_n = [SOC_{\max} - SOC_{current}] - [E_{RES} - (E_C * \delta)] \tag{5}$$

where δ is a ratio between the predicted energy use from 09.00 hrs to 18.00 hrs and the predicted whole day community energy demands.

Case 2: when predicted excess PV energy is larger than the battery capacity available. In this case, a prediction of the morning energy demand is required as the battery needs only to be charged for the morning demand, and can be filled to meet the evening peak from PV generation during the day, (6).

$$\text{if } E_{RES} > (E_C * \delta) \ \&\& [E_{RES} - (E_C * \delta)] > E_{batt\_av}$$

$$\Delta E_n = (E_C * \delta_{em}) \tag{6}$$

where δ_{em} is a ratio between the predicted energy use from 06.00 hrs to 09.00 hrs and the predicted whole day community energy demands.

Case 3: there is predicted to be no excess PV energy during the day and therefore the battery is pre-charged to its full battery capacity (7)

$$\text{if } E_{RES} < (E_C * \delta)$$

$$\Delta E_n = E_{batt\_av} \tag{7}$$

δ and δ_{em} can be obtained from a statistical analysis of the community's historical energy usage data. There values vary depending on whether the day is weekday or weekend day.

B. Real-Time Control

As mentioned earlier, the BMA operates by comparing the actual instantaneous community power (*CP*) and with the community power target (*CPT*). The difference between *CP* and *CPT* is calculated: ideally if *CP* goes below zero then the battery will charge, and if the *CP* is greater than the *CPT* then the battery will discharge. Furthermore, the battery system and its grid interface are not ideal components and therefore system losses must be considered when determining battery behavior.

IV. CASE STUDY AND SIMULATION RESULTS

The proposed BMA is verified through simulations using MATLAB software. The case study is based on seven houses linked as a small energy community which also has an 11 kWp PV array and a 24 kWh community energy storage system. The simulation parameters and conditions are listed in Table I.

TABLE I. SIMULATION PARAMETERS & CONDITIONS

Items	Parameters & Conditions
Minimum Charge Power	600W
Minimum Discharge Power	1,200W
PV Prediction	kWh generated on previous day
Load Prediction	Data from the same day in the previous week
Discharge algorithm	Discharge during peak and average period
Charge algorithm	Charge during off-peak period
Battery SOC Operation	10%-90%
Battery End of Lifetime Criterion	Battery State of Health less than 30%

The results of operating the battery management system using the BMA are given in the various plots in Figure 3 showing a typical winter day (first year of running). Figure 3 (a) shows the underlying community power demand (black), and the community demand when optimally suing the PV generation and the battery (red). *CPT* is shown in blue for reference. Figure 3(b) is similar to Figure 3(a) but shows a system not implementing *CPT* control, where the charge in the battery is exhausted by about 16.30 in the afternoon. Figure 3(c) shows the PV power provided to the community. Figure 3(d) shows the ToU tariff where a value of '1' represents the off-peak tariff, '2' represents the average tariff and '3' represents the peak-price tariff. Figure 3(e) shows the battery state of charge. Similar graphs for summer will also be presented in Figure 4.

It can be seen in Figure. 3 that in winter when there is less PV energy available, the battery is charged over night according to the prediction approach, to support power requirements during the day and evening period. With the *CPT* control algorithm, the battery can be utilized throughout the evening peak period while without use of the *CPT*, the battery runs out too almost as soon as the PV array stops generating, at 16.30 hrs. This results in large amount of peak energy consumption and corresponding high peak demand during the evening time. In summer, as shown in Figure 4, the battery pre-charges a small amount of energy between midnight and 02.15 hrs which can be utilized during the early morning. Then the battery starts to charge from about 11.00 hrs using the excess PV energy up until it is full (at 90% SOC) when the PV generation nearly ends for the day. The BMA with the *CPT* also provides better peak energy and power demand shaving through the whole day. However, the BMA with non-*CPT* control has an advantage in terms of increasing PV self-consumption because the battery is utilized more in the early morning and therefore allowing more space to charge.

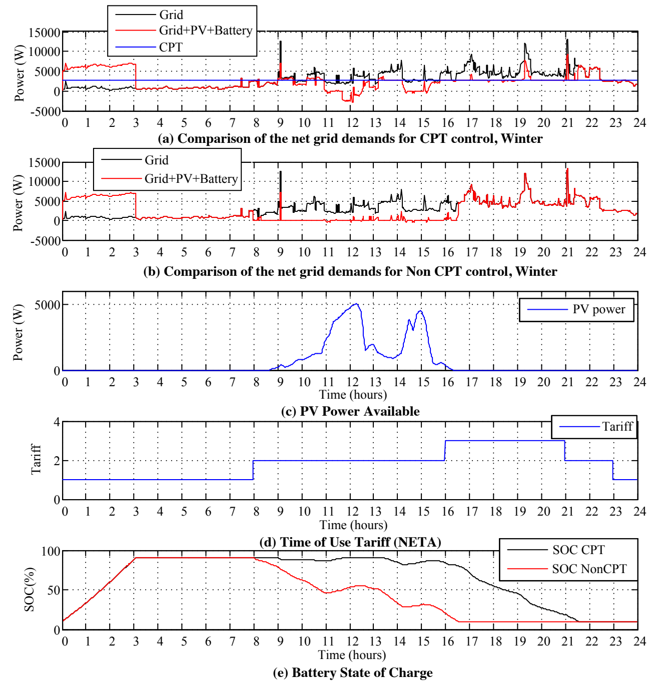

Figure 3. Example simulation results in winter: (a) Community grid demand with *CPT*, (b) Community grid demand without *CPT*, (c) PV power available, (d) Time of use tariff, (e) Battery state of charge.

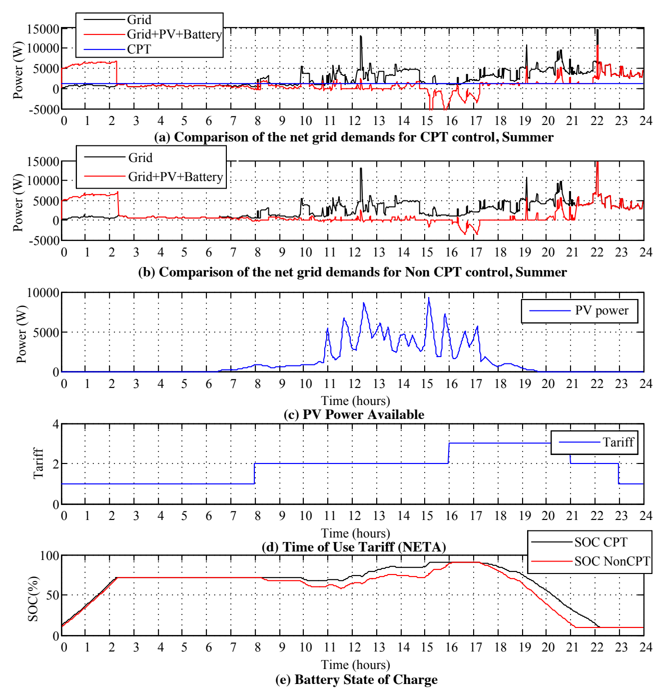

Figure 4. Example simulation results in winter: (a) Community grid demand with *CPT*, (b) Community grid demand without *CPT*, (c) PV power available, (d) Time of use tariff, (e) Battery state of charge.

The overall performance of the BMA can be quantified by assessing how the battery changes energy consumption patterns – particularly its ability to move consumption from peak to off-peak periods. Figure 5 shows the total community energy consumption over the battery lifetime at each tariff, for the four scenarios considered. The battery lifetime for the BMA without the *CPT* approach is 12 years, which is one year shorter than when using the *CPT* approach due to greater usage of the battery. A 12-year lifetime is used as a basis for the following comparison. For the case of grid-only supply (green) the peak rate consumption is very large (around 43% of the total consumption) whilst the low-rate, off-peak consumption is small 14%. By contrast, when adding a PV array and battery (blue for the BMA with *CPT* control and red for the BMA with non-*CPT* control) much of the peak-rate consumption is moved to the off-peak rate (increasing to around 40% of total community demand). The battery also considerably reduces the amount of PV energy exported (i.e. increases self-consumption).

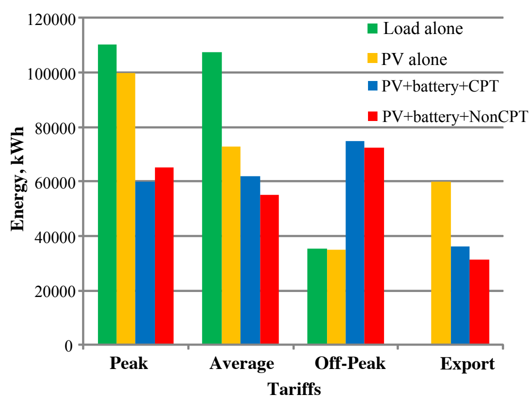

Figure 5. Total community energy consumption at different tariff periods for four scenarios over 12 years.

In order to quantify the benefit of peak power demand reduction, the energy losses from the grid system such as transmission line losses can be assessed. The line resistance is assumed to be 1Ω to simplify the calculation. Figure 6 shows the total transmission line energy losses during the peak period for four scenarios. It is obvious from Figure 6 that the PV array and the battery with the non CPT approach are able to reduce the transmission line losses by 33% in comparison with the PV array alone. The better improvement by 20% more can also be seen when applying the CPT.

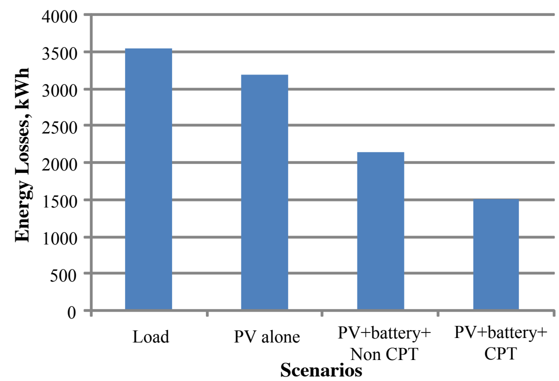

Figure 6. Total transmission line energy losses during the peak period for four scenarios over 12 years.

V. Conclusions

This paper develops a real-time battery management algorithm to reduce the peak energy and power demand within small communities through use of a community battery system. The proposed BMA uses historical load (previous week, same day) and PV data (previous day) as input variables to determine the battery charge/discharge decision through creation of a community power target (*CPT*) set point. The simulation study reveals that without intelligent control the battery often runs out early before fully peak-shaving the evening peak period. Furthermore, it was observed that the battery degrades more quickly due to greater battery usage and its lifetime is shorter than when using *CPT* control. The effectiveness of the BMA indicates that the consumption of energy in the peak period can be reduced by 35% with an increase in the PV self consumption by 47% as well as a reduction of the transmission line losses during the peak period by approximately 56% when comparing to a similar community with PV but without a battery.

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