Electrical Power and Energy Systems 77 (2016) 337–344

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Energy management at the distribution grid using a Battery Energy Storage System (BESS)

Ehsan Reihani [a], Saeed Sepasi [b,*], Leon R. Roose [b], Marc Matsuura [b]

[a] Renewable Energy Design Laboratory, Department of Mechanical Engineering, University of Hawaii at Manoa, 2540 Dole St., Holmes Hall 347, Honolulu, HI 96822, USA
[b] Hawaii Natural Energy Institute, School of Ocean and Earth Science and Technology, University of Hawaii at Manoa, 1680 East-West Road, POST 110, Honolulu, HI 96822, USA

ARTICLE INFO

Article history:
Received 19 December 2014
Received in revised form 16 September 2015
Accepted 17 November 2015

Keywords:
Battery energy storage system
Peak shaving
Power smoothing
Voltage regulation
Grid optimization

ABSTRACT

In 2008, the State of Hawaii initiated a clean energy initiative that set an ultimate goal of 70% clean energy by 2030 (40% from renewable energy and 30% from energy efficiency). A controllable Battery Energy Storage Systems (BESSs) can be used to manage intermittent renewable resources on a power system to address both circuit and system level issues. Simulation and experimental results of applying a novel algorithm for the charging and discharging of a BESS are presented, using actual grid data for controlling a BESS for the purpose of peak load shaving, power curve smoothing, and voltage regulation of a distribution transformer. Two optimization objectives for peak shaving are presented in which proposed load forecasting methods are used. The application of a BESS for voltage regulation is examined and analyzed with different tests, and the observed results are discussed.

Introduction

The addition of renewable energy resources to power grids in the U.S. has grown rapidly in recent years. Photovoltaic (PV) devices are the fastest growing renewable category with a 60% growth rate, followed by wind power at 27% and biofuels at 18% [1]. The inherent intermittent nature of renewables poses some challenges to the continued expansion of their use due to limitations of existing conventional generation facilities that are designed more for efficiency than flexibility and existing transmission and distribution systems that are designed for one-way power flows and load connection rather than generation interconnections.

Energy storage is one of the ways to deal with the variability of renewable resources. Energy storage devices can harvest excess energy during periods of low demand and inject the stored energy when needed during peak usage periods. The storage devices can also play the role of reserve power plants, providing extra energy in case of power system contingencies or a rapid change in demand. A popular use of energy storage is for system peak demand shaving, which involves absorbing energy when there is excess energy, generated either by renewables or base power plants, during off-peak times and injecting the stored energy back into the distribution system during system peak load times. As a result, renewable generation curtailment is reduced, and expensive fast generating units can be avoided. Energy storage can also be used for peak demand shaving on a particular distribution feeder transformer, with the objective to reduce the peak power demand on the transformer and extend its useful life. The Battery Energy Storage System (BESS) is a battery equipped with bidirectional converters which can absorb or inject active and reactive power at the designated set points. In this paper, an algorithm is developed to manage stored energy and storage capacity effectively for peak shaving and load leveling purposes and which considers estimates of future hourly pricing and renewable generation output.

There is a growing number of research works which employ different storage technologies for dealing with the intermittency of renewables. In [2], different technologies used in battery energy storage systems deployed at the grid level are introduced. The optimal power and size of a hybrid energy storage system consisting of BESS and a high-speed superconducting flywheel energy storage system are investigated in [3] for the purpose of stabilizing the power system. In [4], a real-time State of Charge (SOC) based control method is proposed to reduce the fluctuations in the power system in response to a high level of integration of variable energy sources such as PV and wind. The sizing of energy storage for micro-grids is examined in [5], where a neural network is used to forecast the PV and wind power generation levels, and the optimal size of BESS is determined with and without connection to the main grid. In [6,7], a scheme consisting of wind generation in combination with a BESS is proposed for scheduling short-term power dispatch to maximize the energy harvested from wind generation.

* Corresponding author. Tel.: +1 808 956 0767; fax: +1 808 956 2373.
E-mail address: sepasi@hawaii.edu (S. Sepasi).

http://dx.doi.org/10.1016/j.ijepes.2015.11.035
0142-0615/

Different methods have been proposed for battery operation optimization and leveling the load profile.

In [8,9], dynamic programming techniques are used to find the optimal battery energy storage and power levels for peak load shaving applications. Battery storage is examined in [10] for reducing transmission and distribution losses, and a set of normalized charts are provided to quantify the benefit of BESS for leveling the utility load. Finally, in [11], BESS is used to regulate active and reactive power according to SOC limits, and the control signals are fed into the switches using a current control loop.

BESS

Here, a grid scale BESS (1 MW, 1 MWH) is connected to a distribution feeder via a 1 MVA step-up transformer and is used for peak shaving of the distribution grid circuit shown in Fig. 1.

A 69 kV transmission grid provides the energy balancing needs of the distribution circuit and BESS collectively via a 69/12.47 kV distribution transformer. The goal of peak shaving is to optimally control the BESS to reduce the peak load of the circuit.

The BESS consists of twelve Li-ion battery racks and a master control rack. A single battery rack contains 22 trays (2 columns of 11) each populated with 38 prismatic flat pack cells and one Battery Management System (BMS) tray at the top. Together, these components form a 1 MW, 1 MW h energy storage system. The BESS is connected to a 1 MW bidirectional three phase inverter with 12,470 V AC output. The battery management system has a SOC estimation algorithm, which estimates the amount of usable electrical energy stored in the battery pack [12]. The SOC is limited to an operating range of 0.2–0.8 in which the battery is neither fully depleted nor fully charged [13,14], in order to avoid adversely impacting the battery life. Control modes, set points, and active and reactive power commands are sent from the dispatch room to the BESS controller using the Maui Electric supervisory control and data acquisition (SCADA) system utilizing the DNP3 protocol.

In the context of a deregulated energy market system, a Distribution System Company (DISCO) can offer peak load shaving and load smoothing services with optimal operation of a BESS under its control at a market based price to the Independent System Operator (ISO). The ISO can in turn then utilize this DISCO provided resource to meet its system operational objectives, such as peak demand shaving and operational reserves.

Peak shaving

Peak shaving is used to reduce the peak demand on a power system, either at the balancing area as a whole or on a subsystem such as a distribution feeder. This can be accomplished in several ways depending on the needs of the system and the objectives of the strategy used. An example of this is to shift curtailed renewable energy or lower priced energy generated during times of low demand to periods of high demand to increase the utilization of renewable energy or reduce the use of more expensive peak generating units. BESS are one of the emerging grid level options for shifting generation to when it is needed and smoothing the power fluctuations. In order to schedule the battery operation for the next 24 h, a forecast of the circuit power profile is needed. A linear regression method is used for obtaining the power profile needed in the forecasting optimization algorithm.

Linear regression method

In this method, the predicted value for each time step for n collected samples is calculated based on the least square fitting polynomial. A general fitting for a straight line to a first degree polynomial statement is as follows [15]:

$$y = a_0 + a_1 x \tag{1}$$

The residual is the difference of forecast and actual values:

$$R^2 = \sum_{i=1}^{n} [y_i - (a_0 + a_1 x_i)]^2 \tag{2}$$

Taking the partial derivative with respect to each coefficient a_i and arranging in matrix form we get the Vandermonde matrix as follows:

$$\begin{bmatrix} \mathbf{1} & \mathbf{x_1} & \cdots & \mathbf{x_1^k} \\ \mathbf{1} & \mathbf{x_2} & \cdots & \mathbf{x_2^k} \end{bmatrix} \begin{bmatrix} \mathbf{a_0} \\ \mathbf{a_1} \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} \mathbf{y_i} \\ \sum_{i=1}^{n} \mathbf{x_i y_i} \end{bmatrix} \tag{3}$$

Rearranging Eq. (3) for y_i gives the following:

$$\begin{bmatrix} \mathbf{y_1} \\ \mathbf{y_2} \\ \vdots \\ \mathbf{y_n} \end{bmatrix} = \begin{bmatrix} \mathbf{1} & \mathbf{x_1} \\ \mathbf{1} & \mathbf{x_2} \\ \vdots & \vdots \\ \mathbf{1} & \mathbf{x_n} \end{bmatrix} \begin{bmatrix} \mathbf{a_0} \\ \mathbf{a_1} \end{bmatrix} \tag{4}$$

The matrix shown in Eq. (4) can be written as follows:

$$y = Xa \tag{5}$$

Then the "a" coefficients can be calculated with a simple manipulation:

$$a = \left(X^T X\right)^{-1} X^T y \tag{6}$$

The paper discusses a parallel load forecasting method which is required for peak shaving of the load curve. The advantage of the proposed load forecasting method is its light computation burden. Two BESS control use cases are then evaluated and presented. The first use case focuses on a peak shaving method which presents fairly accurate performance since the magnitude of load uncertainty is low during the primary periods of BESS charging and discharging in the early morning and early evening hours. The method, however, may not perform as well in time periods when PV generation variability is high. The second BESS use case builds upon the first case by adding a power smoothing algorithm that utilizes an improved reference power curve to address periods when PV production and power output variability is high, while maintaining the capability of peak shaving.

BESS experiments

In order to develop a good understanding of BESS operation on the power grid, several charge/discharge experiments are performed, and the electrical measurements from SCADA equipment at the distribution transformer are plotted.

Active power flow

In this experiment, BESS is charged with 50 kW steps. This test is done to figure out the impact of charging on the voltage level and transformer Load Tap Changer (LTC) operation. The step changes are kept small for safety purposes and also to see the effect of incremental power changes on the grid. BESS and circuit active power and transformer voltage level and BESS SOC graphs are depicted in Figs. 2 and 3, respectively.

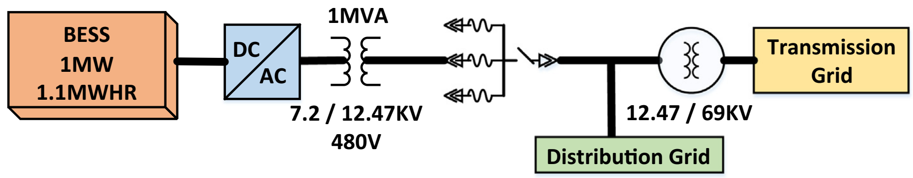

Fig. 1. BESS connection to distribution grid system.

In Figs. 2 and 3, [1]blue and red graphs in the power measurements represent active and reactive power, respectively. In the voltage measurement plot, phases A, B and C are indicated by blue, red, and green colors, respectively. Charging BESS draws current from the main grid, and there is a gradual voltage drop sensed by the LTC. As a result, the transformer compensates for the voltage drop by increasing its tap position, as observed in the abrupt changes in the voltage graph.

Reactive power flow

In order to analyze the impact of reactive power flow from the BESS on the voltage level, reactive power tests are performed in which reactive power is injected and absorbed in 200 KVAR increments. Results from reactive power injection tests and the corresponding measurements are plotted in Figs. 4 and 5.

Voltage level changes measured at the lower side of the 69/12.47 kV distribution transformer of approximately 0.015 kV for each incremental 200 KVAR injection and 0.06 kV for the total 800 KVAR test are recorded. Based on the observed test results, reactive power flow by the BESS does not have a significant impact on voltage regulation in the presence of the transformer LTC which serves as the primary voltage regulation equipment for the distribution circuit. Thus, it is preferred to utilize the BESS capacity for active power management. Remaining BESS capacity can, however, be used to regulate the distribution circuit power factor.

Optimization algorithm

The optimization algorithm finds the optimum active power flow of the BESS at each time step. The objective function for peak shaving consists of two components, SOC cost and load cost which are to be minimized. The SOC cost at time step $k+1$ is defined as follows:

$$J_{SOC(k+1)} = \frac{P_k \Delta t}{E_{tot}} + SOC_k - SOC_{max} \tag{7}$$

In the above equation, P_k denotes discharged power and SOC_k is the value of the SOC of the BESS with capacity E_{tot} at time step k. The cost of SOC, represented by J_{SOC}, includes the updated SOC value minus the maximum SOC value, SOC_{max}. The SOC cost is added to keep the battery full for as long as possible and incur a cost for battery operation. The total cost at step $k+1$ can be described as a weighted load flowing through the distribution transformer L_k plus the SOC cost:

$$J_{k+1} = J_{SOC(k+1)} + (L_k + P_k)W_k \tag{8}$$

The weight component W_k is a quadratic function of load, which penalizes the high load passing through the distribution transformer:

$$W_k = (L_k + P_k)^2 \tag{9}$$

[1] For interpretation of color in Figs. 2 and 3, the reader is referred to the web version of this article.

Combining Eqs. (8) and (9) into a single objective function, we arrive at the following equation:

$$J_{k+1} = \frac{P_k \Delta t}{E_{tot}} + SOC_k - SOC_{max} + (L_k + P_k)W_k \tag{10}$$

Minimizing the objective function leads to taking a partial derivative with respect to P_k and summing over the planning horizon gives the following result:

$$\mathrm{Min}\left(\sum_{k=1}^{N} \frac{\Delta t}{E_{tot}} + 3(L_k + P_k)^2\right) \tag{11}$$

Subject to SOC constraints:

$$\frac{1}{\Delta t}[SOC_{min}E_{tot} - E_K] < P_k < \frac{1}{\Delta t}[SOC_{max}E_{tot} - E_K] \tag{12}$$

$$E_{k+1} = E_k + P_k \Delta t \tag{13}$$

where E_k denotes BESS stored energy level at time step k. The objective function is nonlinear with a sequential quadratic programming method which is used to obtain the BESS optimal points. If there is an effective forecast of renewable energy generation available, such as a wind forecast, the objective function can be revised to make use of renewable generation for charging the battery rather than curtailing it in the off-peak time. This can be done by defining a reference power curve, P_{ref}, at the distribution transformer with the electricity price and renewable energy generation assumptions embedded in the reference power curve. The revised objective function minimizes the error of active power flowing from the transformer and the reference power curve using the battery capacity subject to SOC constraints:

$$\mathrm{Min}\left[\sum_{k=1}^{N} (L_k + P_k - P_{ref(k)})^2\right] \tag{14}$$

It is up to the utility to define the reference power curve. A typical reference power curve consists of two parts, peak time and off-peak time. The off-peak power profile makes use of a renewable energy forecast for charging the BESS. The peak time profile follows setpoints obtained from optimal power flow. The overall flowchart of the algorithm is shown in Fig. 6.

The algorithm presented in Fig. 6 describes the peak shaving method that is implemented in the BESS in Fig. 1. In the above flowchart, Q_{res} denotes the remaining reactive power injection capability of the BESS after it has dispatched active power determined by the optimization objective function. If this value is greater than the reactive power demand of distribution grid Q_L, available reactive power capacity from the BESS is used to raise the power factor of the circuit to the desired level. Although the optimization algorithm takes into account SOC changes on the horizon, the real value of SOC is read from SCADA to account for losses and inaccurate dispatch of the BESS. By following this technique, we make sure that the BESS is maintained within its desired SOC range.

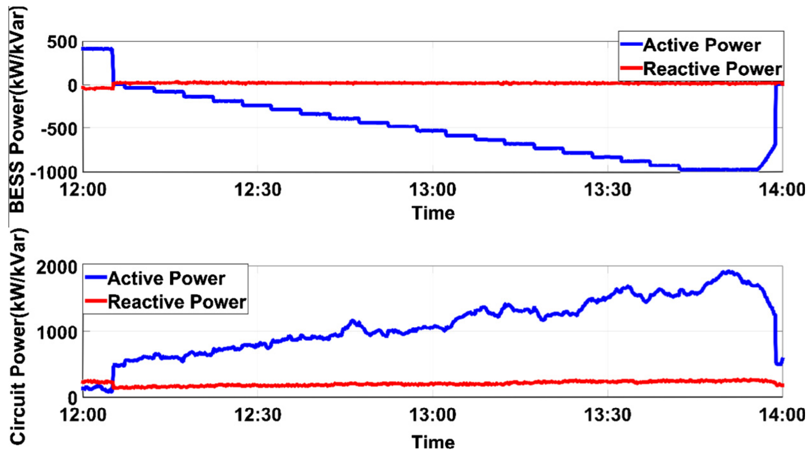

Fig. 2. Circuit and BESS measurements in 50 kW active power flow test.

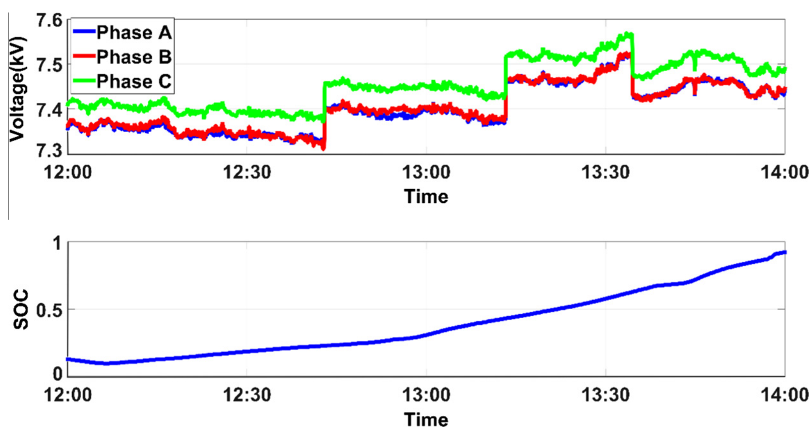

Fig. 3. Circuit voltage and BESS SOC measurements in 50 kW active power flow test.

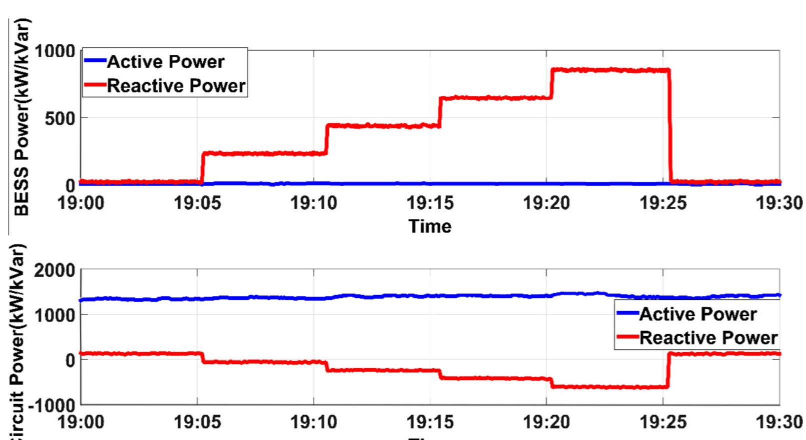

Fig. 4. Circuit and BESS measurements in 200 kVAR reactive power flow test.

A potential concern of load shifting performance by a BESS is the impact of the power flow changes on the regulation of grid frequency. In the case of the BESS evaluated here, the amount of power injected or absorbed is insignificant from a perspective of overall system generation load balance. Thus, any minor frequency deviations that result from the BESS charging and discharging cycles are easily managed by the system Load Frequency Control (LFC) function through dispatch of the conventional generators. Moreover, a frequency error signal can be embedded in the optimization algorithm, by which part of the deviation can be corrected by the BESS power flow.

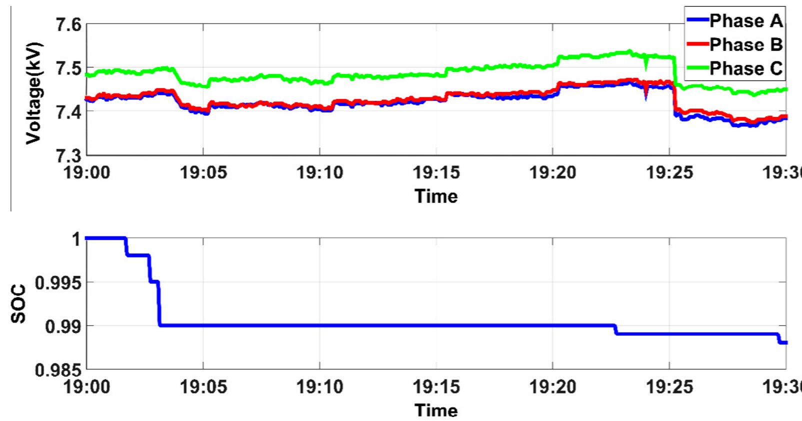

Fig. 5. Circuit voltage and BESS SOC measurements in 200 kVAR reactive power flow test.

Simulation and results

Load forecasting simulation results

Linear regression method for next day load forecasting is applied to 108 days of historical data with 1 min resolution. The forecast data point (y) for each time step (X) is obtained by inserting the given time step in Eq. (5). If the load curve for 24 h is given with 1 min resolution, the above equation should be executed 1440 times to obtain a forecast value for the next day. The load forecasting algorithm is performed on 14 weeks of data and the predicted weekday in the 15th week is compared with the actual value. The load forecast and the corresponding actual load for a weekday at the distribution transformer are shown in Fig. 7.

It can be seen in Fig. 7 that the linear regression approach does not perform well in predicting the fluctuation caused by PV resources in the circuit around 12:00 PM to 3:00 PM when PV production is highest. However, we are not concerned about the deviation of the forecast value from the actual value during this time period when PV fluctuations are high because the load shifting function of the BESS does not occur during these hours. The forecast value is very close to the actual load during the BESS load shifting charge and discharge cycles which coincide with times of low to no PV generation on the grid. The Root Mean Square Error (RMSE) for this forecast is 49.36.

Peak shaving simulation and infield test results

The optimization algorithm is applied to a 1 MW/1 MW h BESS in the circuit shown in Fig. 1. The time step is taken once every 15 min for a total of 96 steps in a 24 h planning horizon. The first optimization algorithm shown in Eqs. (11)–(13) is applied to the forecast load for both smoothing and shaving the peak of the power curve. The shaved peak, load, BESS, optimized active power profile, and BESS SOC are depicted in Figs. 8 and 9, respectively. The output of a PV inverter in the circuit is plotted in Fig. 10.

The optimization simulation is done with an initial SOC of 70%. Due to lack of communication with SCADA until 12:00 PM, the BESS is operated according to optimization points after this time, and thus SOC goes above 80% for a short time to comply with the obtained power points. As can be seen from Fig. 10, there is a small amount of power generation from PV resources causing the load curve to ramp up from 12:00 PM. The load forecast cannot predict the stochastic variations caused by weather conditions (e.g. cloud movement) on the power profile. However, the optimized and shaved power profile curves are very close after 5:00 PM, and the peak is shaved even better than the expected curve.

The SOC trajectories also have some discrepancies due to some nonlinearities of the BESS and also some errors from the SOC estimation subsystem in the BESS. In order to prolong the battery life, SOC_{min} and SOC_{max} parameters are set to 0.2 and 0.8, respectively. The objective function defined in Eq. (11) tries to flatten the overall power curve by finding the BESS power setpoints considering the forecasted load. As a result, the BESS is charged when the load is low (early morning) and discharged when the load is high (early evening). In the case of conducting our test, the BESS SOC is near 80% at the start of the test, there is not a significant power flow into the BESS until 6:00 AM. Then, from approximately 6:00 AM to 9:00 AM, the peak shaving algorithm called on the BESS to discharge a little to reduce an early morning peak demand on the feeder and approach the optimized profile. PV fluctuations change the load profile between the hours of 9:00 AM and 6:00 PM when the forecast and actual loads vary quite significantly. The evening circuit peak demand is then shaved well from 6:00 PM until about 11:00 PM.

Another scenario can also be considered where for some reason the BESS is unavailable to shave the peak circuit load. In this case, normal dispatch of thermal generation by the grid Energy Management System (EMS) operates to pick up the load. Other peak shaving methods implemented in an EMS such as load management can also be dispatched to reduce circuit peak demand in coordination with action of the BESS.

In order to effectively address the high variability of the load profile during periods when there is high PV production and fluctuation, a real time smoothing scheme can be used. Since real-time measurements of active power in the transformer are available in the dispatch room, an active power setpoint is defined for the BESS. Any deviation from this setpoint is compensated for by charging/discharging the difference in power to maintain the defined level. The charge/discharge of the BESS away from this level should be almost equal to keep the SOC level needed in early evening for peak shaving. However, to ensure that the BESS SOC is at its desired level based on the peak load shaving algorithm, power smoothing capability is suspended at 5:00 PM, one hour in advance of the start of anticipated peak shaving, to allow the BESS an opportunity to recharge. Simulations of this power smoothing algorithm are performed. The load curve, accompanied by PV fluctuations, along with the BESS active power setpoint, is depicted for a sample day in Fig. 11.

This feature is useful for reducing the system regulating reserve to the degree that the BESS can flatten the fluctuation and thus minimize the operational and cost burden on thermal generation regulating grid frequency. In order to find the optimum number of smoothing levels, the maximum and average SOC error for 10 smoothing levels is plotted in Fig. 12.

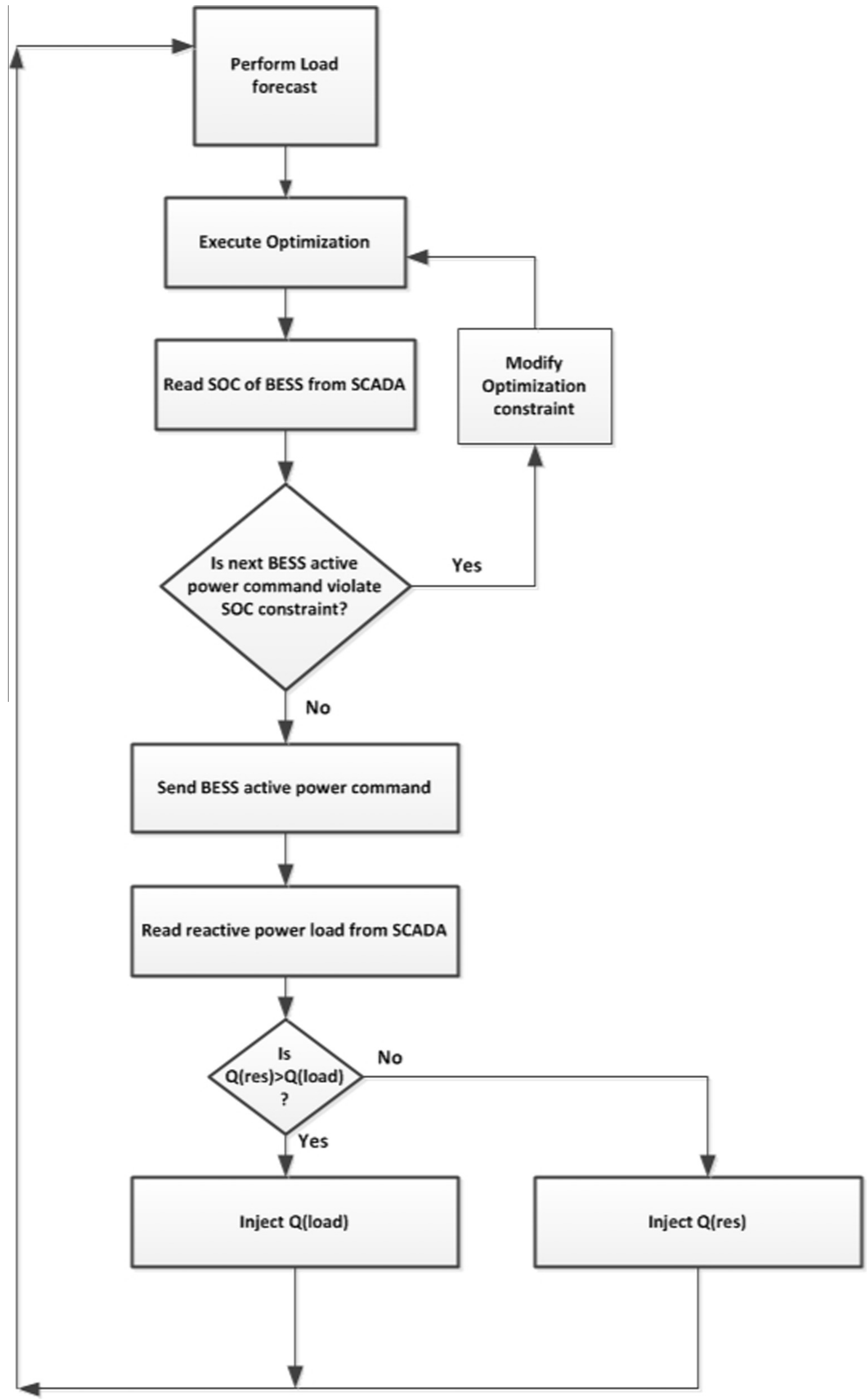

Fig. 6. Flowchart of peak shaving method.

The average value for the above 10 active power setpoints is 771.67 kW. If this value is applied across an entire week, the maximum SOC error at 7:00 PM, one hour into the peak shaving period, is 13%. The BESS can effectively compensate for this 13% shortfall in SOC by charging for approximately 40 min with minimal impact to the overall effectiveness of the peak shaving objective. The optimization algorithm for the second method in Eq. (14) is applied to the circuit, for which a reference power curve is provided. The BESS tries to follow the reference power curve considering SOC constraints. For example, it is preferred to charge the BESS at a

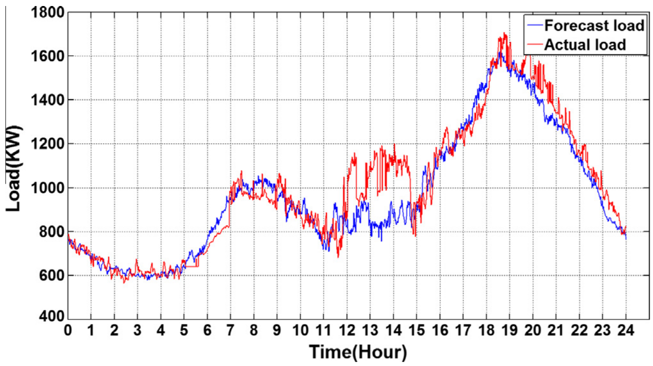

Fig. 7. Actual and forecast load curves using linear regression method.

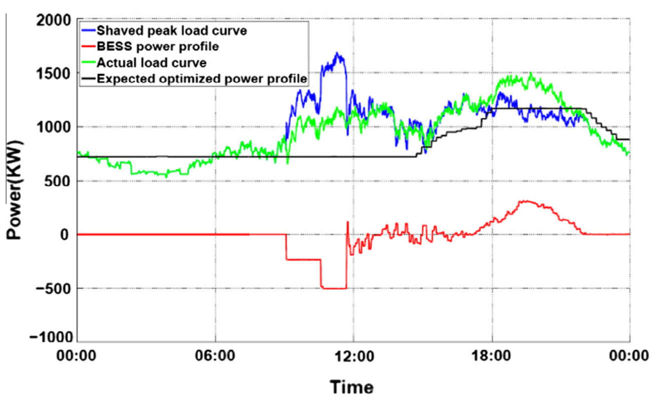

Fig. 8. Power curves for first optimization algorithm.

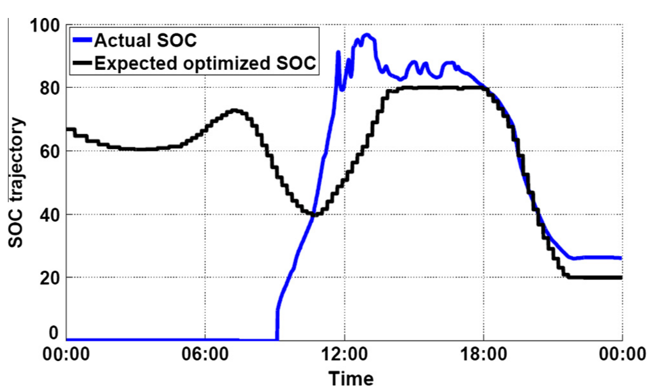

Fig. 9. Actual and forecast SOC curve for first optimization method.

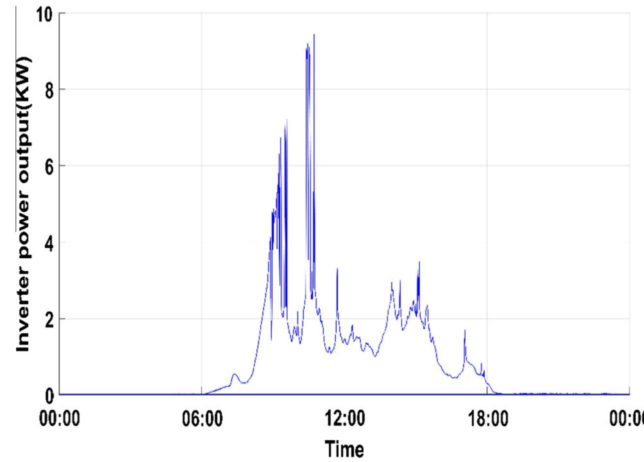

Fig. 10. Power output of an inverter in the circuit.

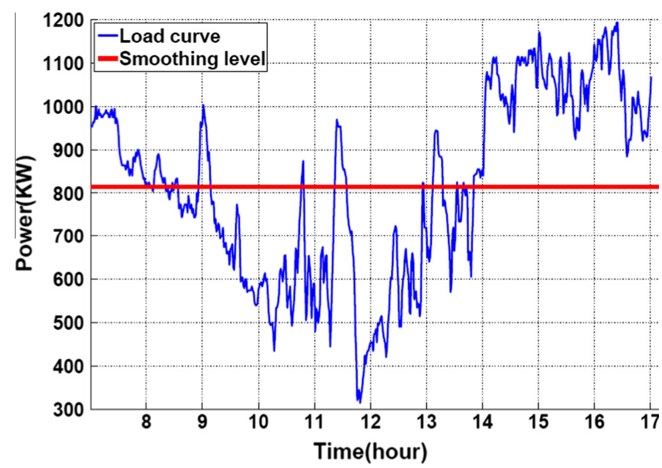

Fig. 11. Distribution circuit load curve with PV production and BESS active power setpoint.

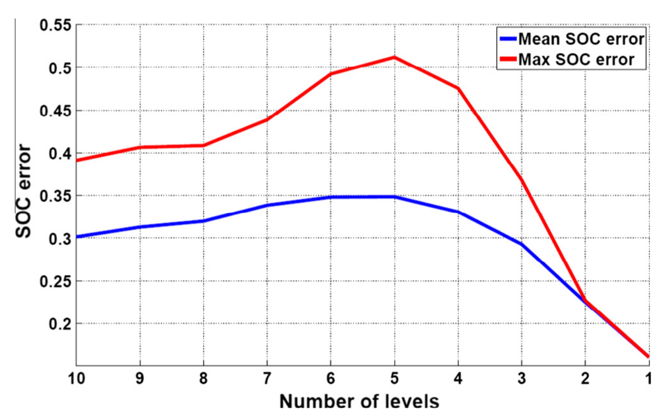

Fig. 12. Maximum and average SOC error for 10 smoothing levels.

constant rate from 2:00 AM to 5:00 AM and discharge it from 6:00 PM to 11:00 PM. The utility can define the reference power curve based on the optimal power flow in the grid. The BESS power output and SOC values are depicted in Figs. 13 and 14, respectively.

The SOC value rises up in the charging time interval based on the duration defined and drops sharply in the peak time interval to meet some of the demand. It remains constant in other time intervals as the reference power curve is defined as the forecast load.

This approach uses a reference load following algorithm in which operational and planning constraints can be embedded and used for defining the reference power curve. Considerations such as load forecast, demand response, and reserve scheduling can be easily integrated into the reference power curve and thus make it a better approach. On the other hand, charging and discharging of the BESS can decrease its lifetime, which makes the first approach more desirable [16]. Moreover, after getting real data from SCADA, the planning can be updated for the next time horizon. The objective of the first method is to flatten the load curve with the BESS considering the imposed constraints. The disadvantage of the first method is its vulnerability to growing

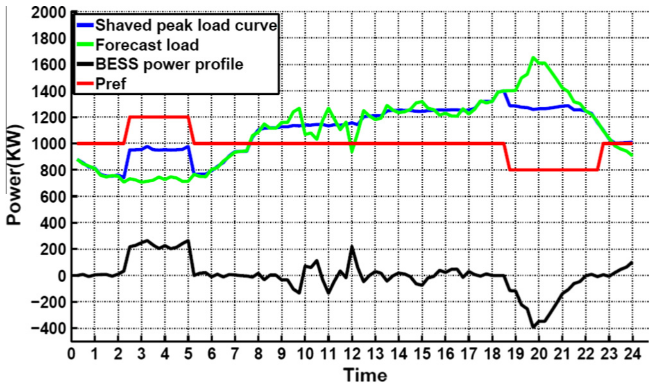

Fig. 13. Power curves for second optimization algorithm.

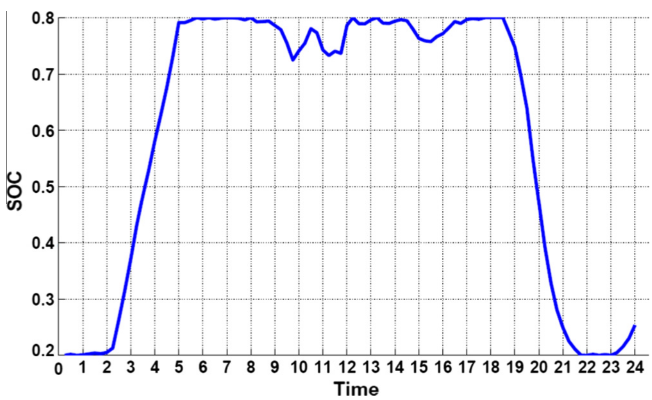

Fig. 14. Actual and forecast SOC curve for second optimization method.

uncertainty in the grid especially with higher integration of distributed renewable generations.

Conclusion

In this paper, BESS is investigated for use in peak shaving and voltage regulation of a distribution feeder. Several experiments are carried out on the BESS and measurements obtained by SCADA are analyzed. Application of BESS for peak shaving, voltage regulation, and power smoothing is studied and it is shown that the BESS capacity can be used effectively for peak shaving and power smoothing. In this application (bulk storage at the substation end of a feeder), the BESS does not have much impact on the feeder voltage, but can be used to serve the VAr load on the circuit and reduce the VAr load on the system. Two optimization methods for peak shaving are introduced and the resulting power curves are discussed.

Acknowledgement

The authors would like to gratefully and sincerely thank Chris Reynolds for his assistance, patience, time, and, most importantly, his friendship during BESS tests at the Maui Electric Company.

References

[1] Sioshansi FP. Smart grid: integrating renewable, distributed and efficient energy. Academic Press; 2011.
[2] Sparacino A, Reed G, Kerestes R, Grainger B, Smith Z. Survey of battery energy storage systems and modeling techniques; 2012.
[3] Lee H, Shin B, Han S, Jung S, Park B, Jangi G. Compensation for the power fluctuation of the large scale wind farm using hybrid energy storage applications. IEEE Trans Appl Supercond 2012;22(3).
[4] Xiangjun L, Hui D, Xiaokang L. Battery energy storage station (BESS)-based smoothing control of photovoltaic (PV) and wind power generation fluctuations. IEEE Trans Sustain Energy 2013;4(2):464–73.
[5] Chen S, Gooi H, Wang M. Sizing of energy storage for microgrids. IEEE Trans Smart Grid 2012;3(1):142–51.
[6] Teleke S, Baran M, Bhattacharya S, Huang A. Optimal control of battery energy storage for wind farm dispatching. IEEE Trans Energy Convers 2010;25(3):787–94.
[7] Yao D, Choi S, Tseng K, Lie T. Determination of short-term power dispatch schedule for a wind farm incorporated with dual-battery energy storage scheme. IEEE Trans Sustain Energy 2012;3(1):74–84.
[8] Oudalov A, Cherkaoui R, Beguin A. Sizing and optimal operation of battery energy storage system for peak shaving application; 2007.
[9] Riffonneau Y, Bacha S, Barruel F, Ploix S. Optimal power flow management for grid connected PV systems with batteries. IEEE Trans Sustain Energy 2011;2(3):309–20.
[10] Nourai A, Kogan V, Schafer C. Load Leveling reduces T&D line losses. IEEE Trans Power Deliv 2008;23(4):2168–73.
[11] Grid-connected lithium-ion battery energy storage system for load leveling and peak shaving; 2013.
[12] Sepasi S, Ghorbani R, Bor Yann L. SOC estimation for aged lithium-ion batteries using model adaptive extended Kalman filter; 2013.
[13] Sepasi S, Ghorbani R, Bor Yann L. Improved extended Kalman filter for state of charge estimation of battery pack. J Power Sources 2014;255(1):368–76.
[14] Sepasi S, Ghorbani R, Bor Yann L. A novel on-board state of charge estimation method for aged Li-ion batteries based on model adaptive extended Kalman filter. J Power Sources 2014;245(1):337–44.
[15] Ostertagová E. Modelling using polynomial regression. Procedia Eng 2012;48:500–6.
[16] Sepasi S, Roose LR, Matsuura MM. Extended kalman filter with a fuzzy method for accurate battery pack state of charge estimation. Energies 2015;5(6):5217–33.