MATEC Web of Conferences 70, 10011 (2016) DOI: 10.1051/matecconf/20167010011
*ICMIT 2016*

# Rule-based Energy Management System in an Experimental Microgrid with the Presence of Time of Use Tariffs

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**Abstract.** This paper aims to investigate a method of peak load shaving through the utilization of solar PV and battery energy storage whilst creating a cost effective Energy Management System (EMS). This is achieved by utilizing a rule-sets to manage and optimize a scheduling system with a forecasting algorithm. As Time of Use (ToU) tariffs change throughout the day, a cost benefit can be achieved when a smart energy storage system is appropriately employed. The EMS operation is tested on an experimental microgrid with commercial load considering payback period calculation.

## 1 Introduction

Microgrids are integrated energy systems comprising loads, storage systems, Distributed Energy Resources (DERs) and Renewable Energy Sources (RESs) [1]. The wide global adoption of renewable energy sources (RES) as distributed generation has led to an improved efficiency of microgrids and provided a reduction in carbon dioxide emissions on a global scale. One of the most common forms of RES is solar photovoltaics (PV), with a larger number of installations occurring on commercial and residential buildings [2]. Even though solar PV produces power with a normalized curve similar to that of the majority of commercial buildings, the intermittent nature of solar energy production makes grid management harder.

The utilization of a battery energy storage system (BESS) has the potential to remove the intermittency of solar PV energy production and can give the capability to shave the peak loads [3]. Due to high cost of BESS, the most effective size of energy storage and solar PV can be ascertained to minimize capital costs but provide enough storage to benefit the building load [4]. Different software and algorithms are used to increase the stability and the interconnection of microgrids [5].

Thus, to attain the full benefits of BESS, a forecasting and scheduling algorithm is a necessity. The optimal operating schedule of the storage device is obtained by maximizing an objective function which corresponds to the maximum benefit for the storage owner [6]. A forecasting algorithm for a BESS is used to determine when a peak load is likely to occur, how long that peak load will be occurring for and what the power requirement of that peak load is [7]. This is important information for a scheduling system that is required to best utilize the energy stored within the BESS. In order to create an optimized energy storage schedule, peak shaving, financial effects of peak and off peak tariffs and solar PV production have to be taken into account. Looking at the market, there are two main policies to charge the customers, Real Time Pricing (RTP) and Time of Use (ToU) tariffs. ToU tariffs provide two or three price levels for the customer (peak, shoulder and off peak prices). On the other hand, there is RTP which deals with retail electricity prices and whole sale electricity prices [8].

In the literature, different methods for optimal energy management in a microgrid has been proposed. In [9], a smart energy management system is proposed which is similar to the method used in this paper. However, the authors look at market prices and use complex optimization algorithms. Papers [2] and [3] present optimal energy management systems for PV and BESS systems. Paper [2] looks at the market price s and employs dynamic programming to optimize the objective function. The authors in paper [3] utilize model predictive control method to optimize the PV and BESS system operation.

The objective of this paper is to shave the demand peak in a commercial load and obtain the maximum benefit out of the PV and BESS scheduling in presence of ToU tariffs. In order to achieve this goal, an optimized cost effective Energy Management System (EMS) is proposed. This EMS reduces the peak demand and volume charges while optimally charges and discharges the BESS to get more benefits.

The rest of the paper is organized as follows; in section 2 the Energy Management System with forecast algorithm is explained. Section 3 represents the scheduling system and the objective function. In section 4, the case study of the experimental microgrid is investigated and the results of peak shaving and cost

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benefit analysis are represented. Section 5 concludes the paper.

## 2 Energy management system

The objectives of Energy Management Systems (EMS) are to shave the peak demand charges and optimally schedule the BESS to charge and discharge economically in the presence of time of use tariffs. Due to intermittency of renewable energy sources, a forecasting algorithm is required to compensate for uncertainties and provide high accuracy data for load and generation characteristics. As it is illustrated in Fig. 1, the EMS employs PV as the main generation source. Because of variation in PV generation, EMS cannot guarantee effective peak shaving with PV alone. Thus, a BESS is utilized in order to aid the system in shaving the peak demand in conjunction with solar PV. The optimal use of BESS requires a scheduling system which defines the time and amount of charging and discharging of BESS through the grid supply and solar PV where applicable. In the presence of ToU tariffs, the scheduling system charges the BESS when the tariffs are low and discharges when tariffs are high. By doing so, a cost beneficial system which accomplishes the objectives is created.

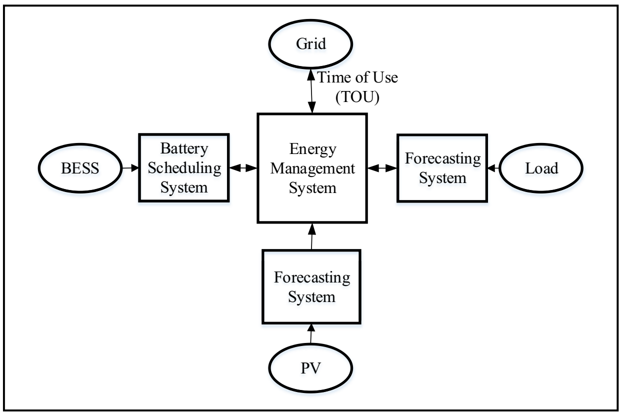


**Figure 1.** Energy Management System

### 2.1 Forecasting algorithm

The operation of the scheduling is aligned with uncertainties. In order to reduce the uncertainties, the forecasting system plays an important role. Load profile forecasts are used as input information in order to calculate an initial charge and discharge schedule for the current day in the scheduling algorithm. A load profile is the shape of the consumption of electricity or load throughout a 24 hour period.

The load profile forecasting approach used in the test site University building N44 control system follows the general method of [7] with forecast models modified to suit commercial building scenarios.

The average load forecast model is constructed according to the autoregressive moving average (ARMA) approach. The ARMA modelling approach incorporates variables that are lags of the time series being forecasted and lags of the historical forecast error [10]. The average load forecast model is depicted in Equations 1 and 2:

$$\hat{y}_t = \beta_0 + \sum_{i=1}^{n} \beta_i y_{t-i} + \hat{\varepsilon}_t + \varepsilon_t \qquad (1)$$

where $y_t$ is load at time t, $\hat{y}_t$ is the load forecast, $\beta_0$ is the y-intercept, $\beta_i$ is the coefficient for time lag i, there are n number of time lags and $\varepsilon_t$ is the forecast error and $\hat{\varepsilon}_t$ is the error forecast for time t and is expanded upon in (2):

$$\hat{\varepsilon}_d = \gamma_0 + \sum_{j=1}^{m} \gamma_j \varepsilon_{d-j} \qquad (2)$$

where $\gamma_0$ is the y-intercept of the model, $\gamma_j$ is the coefficient for the error time lag $\varepsilon_{t-j}$ and m is the number of lags. After forecasting the peak load, the first stage in forecasting the load profile for the day is to forecast the load profile $LPF_{d,t}$ for the current day. The next stage in load profile forecast algorithm is the manipulation of $LPF_{d,t}$ to adjust it to be in accordance to the peak load forecast. The final stage in the forecasting the load profile for current day is to add the historical error forecast to the load profile forecast:

$$L\widehat{PF}_{d,t} = \widehat{LPF}_{d,t} + \hat{\varepsilon}_{d,t}, \quad for\ 1 \leq t \leq 96 \qquad (3)$$

$$\hat{\varepsilon}_{d,t} = \gamma_0 + \gamma\varepsilon_{d-1,t}, \ for\ 1 \leq t \leq 96 \qquad (4)$$

where $\gamma_0$ is the constant, $\gamma$ is a vector of coefficients, j is the lag number and there are m number of lags. For more detailed explanation, papers [11, 12] are recommended.

## 3 Scheduling system

The main challenge in EMS is to develop a scheduling system for BESS to determine the optimal charge/discharge of battery considering ToU tariffs and peak demand shaving targets. A rule-base scheduling algorithm is designed to determine the charge/discharge of BESS. In order to apply the scheduling system to the battery and obtain a cost effective scheduling system, a model of BESS, an objective function and the constraints are defined. The main purpose of the objective function is to maximize the benefits of scheduling system by charging the BESS at low ToU tariffs and discharging at high ToU tariffs. Thus, a peak shaving algorithm is proposed to gain highest possible benefits from BESS scheduling.

The rule sets for scheduling are defined in Table 1. These rules define the charge/discharge characteristics of the BESS. As can be seen, the scheduling depends on the battery State of Charge (SOC), load demand and ToU tariffs.

**Table 1.** Scheduler Rule-Set
a) SOC Low

| Scheduler | ToU (Off-peak) | ToU (Peak) |
|---|---|---|
| **Load demand low** | Charge | Charge |
| **Load demand high** | Standby | Discharge |

DOI: 10.1051/matecconf/20167010011

b) SOC High

| Scheduler | ToU (Off-peak) | ToU (Peak) |
|---|---|---|
| **Load demand low** | Charge | Standby |
| **Load demand high** | Discharge | Discharge |

## 3.1 BESS modelling

The BESS is modelled as follows:

- BESS charging mode ($P_{BESS}(t) < 0$):

$$E(t) = E(t - \Delta T) - \eta_c P_{BESS}(t - \Delta T)\Delta T \quad (5)$$

- BESS discharging mode ($P_{BESS}(t) > 0$):

$$E(t) = E(t - \Delta T) - \frac{P_{BESS}(t - \Delta T)}{\eta_d}\Delta T \quad (6)$$

where $P_{BESS}(t)$ is the battery power (kW), E(t) is battery energy (kWh), $\eta_c$ is battery charging efficiency, $\eta_d$ is battery discharge efficiency, $\Delta T$ is the scheduling time step which is set at 15 min intervals in this study.
The BESS has some constraints which needs to be meet:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (7)$$

$$P_{BESS}^{min} \leq P_{BESS}(t) \leq P_{BESS}^{max} \quad (8)$$

where SOC(t) is battery state of charge, $SOC_{min}$ is minimum SOC of battery which is equal to *DOD* Depth of Discharge of battery, $SOC_{max}$ is maximum SOC of battery which is upper bound of battery capacity. In this study, DOD is 80% and $SOC_{max}$ is 100%.

## 3.2 Objective function

In order to maximize the benefits of the scheduling system, the objective function is expressed as:

$$\max f(t) = \max \sum_{t=t_0}^{T} \{P_{BESS}(t) \times ToU(t) \times \Delta t - P_{Load}(t) \times ToU(t) \times \Delta t\} \quad (9)$$

The goal of the objective function is to maximize the savings through utilizing the optimally scheduled BESS and minimize the costs by shaving the peak demand and volume.

## 3.3 Constraints

In this study the focus is in peak shaving and battery scheduling. While buying energy from grid, the policy is to charge when $ToU(t)$ is low and discharge when $ToU(t)$ is high. To achieve this, there are some constraints that should be meet. The other requirement for scheduling is the constraints definition which is as below;

Power balance:

$$P_{Load}(t) = P_{PV}(t) + P_{BESS}(t) + P_{Grid}(t) \quad (10)$$

BESS constraints:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (11)$$

$$P_{BESS}^{min} \leq P_{BESS}(t) \leq P_{BESS}^{max} \quad (12)$$

$$E_{min} \leq E(t) \leq E_{max} \quad (13)$$

$$\eta_c P(t) \leq C_{max} \quad (14)$$

$$\frac{P(t)}{\eta_d} \leq D_{max} \quad (15)$$

Peak shaving:

$$P_{Grid}(t) \leq P_{Grid}^{max} \quad (16)$$

where $C_{max}$ is the max charge rate and $D_{max}$ is the max discharge rate of battery which in this study is the same as the Statcom maximum charge and discharge rate (30kVA).

## 3.4 Peak shaving algorithm

In order to shave the peak demand, the BESS scheduling system requires a discharge algorithm which optimally discharges the battery and shaves the peak demand. The algorithm implemented in this study is as follows:

Step 1: The scheduling system sets the discharge level at the highest rate which is Statcom max discharge rate (30 KVA) in this case.

Step 2: If the BESS reduces the peak during the peak period in a way that the new peak is the same in the whole peak period, the discharge level is appropriate, otherwise;

Step 3: The discharge level is reduced one kW each time to reach to a level that the peak in peak period is created by battery, i.e. the battery has enough capacity to discharge during the peak period thoroughly not discharging the complete battery capacity for just a portion of peak period.

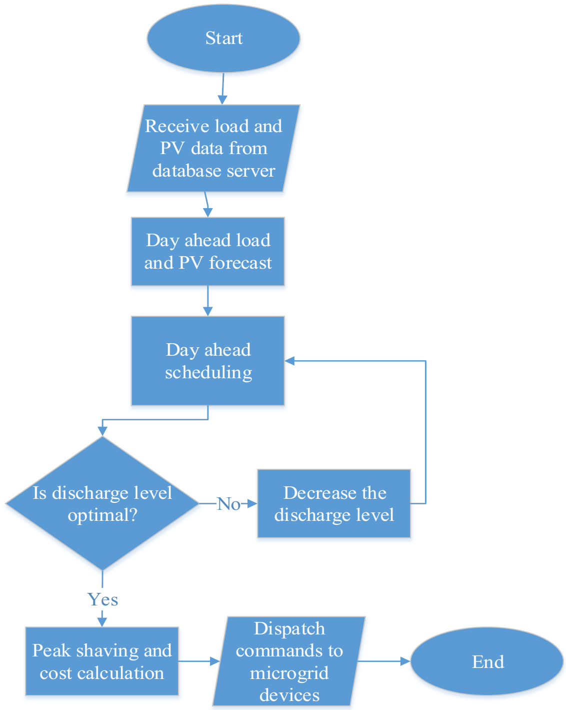


**Figure 2.** Scheduling algorithm

By going through the peak shaving algorithm, the optimal discharge level and consequently the maximum benefit out of peak shaving is achieved. The complete scheduling system is displayed in Fig. 2. As it can be seen, the forecasting algorithm is employed to do the initial scheduling and the peak shaving and cost calculation is derived out from real time scheduling.

# 4 Case study

## 4.1 Experimental Microgrid

To test the scheduling system performance, it is implemented on a Microgrid testing facility with commercial load characteristics. The Microgrid Testing Facility (MGTF) has been designed and implemented at Griffith University's Nathan Campus as a unique test bed for investigating all aspects of a Microgrid and Smartgrid network. One aspect of the MGTF incorporates distributed generation in the form of solar PV cells connected to a DC bus via parallel connected DC/DC converters. This DC bus connects the common DC components together to reduce the need for multiple power conversion stages; the energy storage tank and the Statcom inverter. 60kWh of Lithium-ion based energy storage is utilised to create the backbone of the bus. A 30kVA Distributed-Statcom provides the AC connection to the building and grid which also serves as the control mechanism for the energy storage solution.

The testing facility is equipped with a communication, monitoring and data management system. The main purpose of communication system is to facilitate data collection and measurement and also dispatch control commands to Microgrid devices. The system installation and communication details is explained in [13] and [14]. The complete experimental system in this study is shown in Fig. 3 with the BESS parameters specified in Table 2.

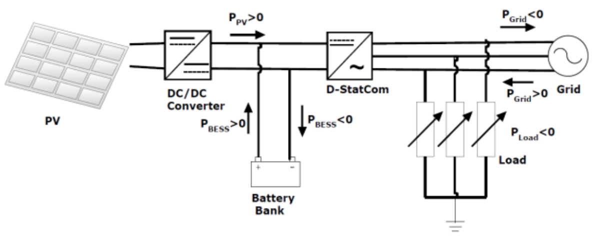


**Figure 3.** Microgrid structure with PV and BESS

**Table 2.** Battery parameters

| BESS parameters | characteristics |
|---|---|
| BESS technology | Li-Ion |
| Rated capacity | 60 kWh |
| Cycles (80% DOD) | 7500 |
| $C_{Capital}$ | $60000 |

## 4.2 EMS operation

The Microgrid EMS performance is investigated observing PV, BESS and BESS scheduling system influence on peak load shaving and system cost reduction. The ToU tariffs for commercial loads are shown in Table 3 and 4. The tariffs are defined based on Australian energy tariffs in Queensland State. There are two tariffs (peak and off peak) for volume charges and one tariff for demand charges.

**Table 3.** Energy charges ToU

| ToU tariffs | Price | Time |
|---|---|---|
| Peak | 9.7 c/kWh | 7 am - 8 pm |
| Off-peak | 6.6 c/kWh | 8 pm – 7 am |

**Table 4.** Demand charges ToU

| ToU tariffs | Price | Time |
|---|---|---|
| Peak | 24.14 $/kW | Whole day |

The results for the day ahead scheduling for a day in January 2016 is illustrated in Fig. 4 and 5, with a scheduling time step of 15 min. It can be seen in Fig. 4 that PV can reduce the peak demand and how BESS optimal scheduling increases the peak demand shaving and reduces the volume charges costs.

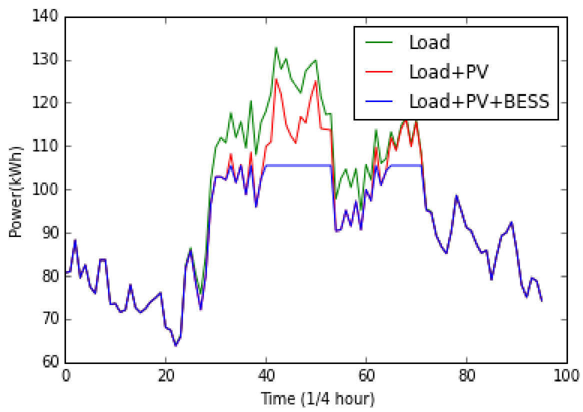


**Figure 4.** a) Load profile b) load profile with PV c) load profile with PV and BESS

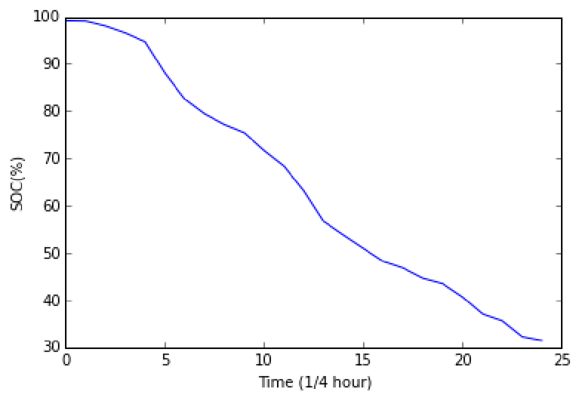


**Figure 5.** Battery SOC during peak period

In Fig. 5, the SOC of BESS during peak period is shown. The SOC is supposed to be high from 100 to 30 and low from 30 to 20. The BESS is not fully discharging during the peak period as it depends to the discharge level defined by scheduling system.

### 4.3 Cost benefit analysis

In order to analyse the economics, the payback period (PBP) of investment is investigated. Using PBP, the minimum time to recover the amount of investment of battery in estimated.

The battery investment and installation cost is calculated as:

$$C_{capital} = C_E E_{max} \tag{17}$$

$E_{max}$ is the BESS energy capacity and $C_E$ is BESS installation and production cost per kWh which is $1000 for the chosen battery technology. The PBP is calculated as follows:

$$\sum_{t=t_0}^{PBP} S_{annual} * (1 + \mathrm{i})^{n-1} \geq C_{capital} \tag{18}$$

where $S_{annual}$ is the annual savings from peak shaving, $n$ is the year, $C_{capital}$ is the battery investment and installation cost, i is the interest rate per year which is 15% in this study.

The PBP of PV and BESS is calculated for the experimental Microgrid. As it can be seen in table 5 and 6, the BESS has a higher PBP but it brings more benefits to the system as well. Furthermore, PV and BESS provide a cost effective system for peak shaving applications.

**Table 5.** PBP for PV

| | |
|---|---|
| **Annual revenue** | $6132 |
| **Capital cost** | $40000 |
| **PBP** | 4.9 years |

**Table 6.** PBP for BESS

| | |
|---|---|
| **Annual revenue** | $8227 |
| **Capital cost** | $61100 |
| **PBP** | 5.4 years |

## 5 Conclusion

In this paper, an energy management system employing PV and BESS is proposed. The EMS aims to shave the peak load and achieve a cost beneficial solution for the experimental Microgrid. The rule-base scheduler is operating in a way that tries to get the most of energy form battery energy storage system and purchase the least form the grid. On the other hand, the forecasting module is employed in order to strengthen the accuracy of results of the energy management system.

Furthermore, the operation of EMS has been investigated for the following cases: load, load and PV as well as load and PV including BESS. The payback period for the PV and BESS system has been calculated considering the annual saving of the system and total system price. The performance of the scheduling system has been optimized for commercial operation which resulted in maximized benefits.

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