LOAD FORECASTING AND DEMAND RESPONSE MANAGEMENT IN DISTRIBUTION
GRID WITH HIGH RENEWABLE ENERGY PENETRATION

A DISSERTATION SUBMITTED TO THE GRADUATE DIVISION OF THE
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By

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To my family
Acknowledgments

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Abstract

With increasing distributed renewable energy penetration, new tools are necessary to cope with variability and intermittency of these resources. Demand response and battery energy storage system (BESS) have emerged as potential solutions which provide more flexibility to the power system operator. In this paper, several active and reactive power experiments are performed on the BESS to find out the impact of BESS power flow on the voltage level. A day ahead load forecasting approach is developed which is used for the BESS power optimization. Moreover, twenty minute ahead load forecasting method is also proposed which utilizes the day ahead load forecast. Using the day ahead load forecasting method, a load following formulation is developed by which utility can shape the power curve with the help of BESS. In order to remove the power curve fluctuations, a smoothing approach is utilized in which a power line is defined and power fluctuations around the line are removed by the BESS. SOC of battery and ramp rating of generators can be used to update the slope of the power line.

Operation of storage devices such as residential battery storage and water heater are optimized using dynamic programing. A method for scheduling of storage devices is proposed where a given risk function is decomposed to a given number of devices. Operation of each device is then optimized based on the obtained cost function.

The demand response resources in the distribution grid can be managed either in a vertical environment or in a market environment. In the vertical structure, utility is directly controlling the available devices to come up with an optimized load curve. Customers are paid compensation for providing this flexibility to the utility. In the market environment, aggregators who manage the distributed demand response resources compete with each other to sell demand response quantity to the utility. Utility provides an inverse demand function by performing optimal power flow at
each node so that the function between the price and quantity of power at each distribution node is determined. Two models for clearing price in the market is introduced and the contribution of each aggregator as well as market price is calculated for each model.
Chapter I: Energy Management at the Distribution Grid Using a Battery Energy Storage System (BESS)

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 (BESS) 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.

Index Terms:

Battery energy storage system, Peak shaving, Power smoothing, Voltage regulation, Grid optimization.
I.1 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 collect 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 chapter, 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. 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.

### I.1.1 Forecasting review

Kaur [13] defines load forecasting as the “way of estimating what future electric load will be for a given forecast horizon based on the available information about the state of the system.” Forecasting is significant because it affects trading in the electricity market, allows one to follow
the load, provides real time dispatch, shows the operating reserves, and can work in conjunction with smart grid-automation and control [12]. The types of forecasting depend on time with short term forecasting ranging from one hour to one week, mid-term forecasting ranging from one week to one month, and long term forecasting ranging from one month to years [13]. Short term forecasting predicts upcoming power demand based on historical data and predicted weather conditions. Typically, short term forecasting is used for unit commitment, scheduling energy transfer, and dispatching load [15].

The four main factors that affect load are weather conditions, the time of the day, the economy, and random unpredicted errors. The weather conditions have a high impact on the net load especially when penetration of renewable energy generation is high. A cloudy can increase the load significantly and requires more reserve. Likewise, a windy day can produce more energy and less power is required from conventional generators. Time of day plays an important role in the load shape. Usually there is high load in the beginning of night and a lower amount on early morning. The economy can increase the load based on the running machines who consume a big chunk of energy. Faults can affect the load by disconnecting part of distribution or a sever case part of transmission system. In such contingencies, the net load is dropped and the feeding generators have to decrease the amount of generation to match with reduced load. Metaxiotis states that the efficient forecasting methods include causality, reproducibility, functionality, sensitivity, and simplicity [15]

I.1.1.1 Traditional forecasting methods

In Analysis and Evaluation of Five Short-Term Load Forecasting Techniques, Moghram and Rahman used multiple linear regression, stochastic time series, general exponential smoothing, state space method, and a knowledge-based approach. They tested each method during the winter
and summer seasons to determine hourly forecasts. Based on their analysis, for the peak summer days, the transfer function approach gave the best results whereas for the peak winter days the transfer function approach resulted in the next to the worst accuracy. [16].

I.1.1.2 Multiple linear regression

Multiple linear regression contains several independent variables such as dry bulb temperature, dew point temperature and wind speed. They estimated regression coefficients by the least square estimation and determined if the coefficients were significant by using statistical tests such as the F-statistic test. They also used t-ratios to determine the significance of the coefficients related to the independent variables [16].

I.1.1.3 Stochastic time series

The stochastic time series is a popular technique that has several different types of processes and models such as the autoregressive (AR) process, the moving-average (MA) process, the autoregressive moving-average (ARMA) process, the autoregressive integrated moving-average process (ARIMA), seasonal process, and transfer function (TF) modeling. The AR process linearly relates time, previous times, and random noise along with a backshift operator. The MA process linearly relates current and previous times to noise from errors or residuals, and the oldest noise value is needed in order to make the regression perform accurately with a backshift operator as well. The ARMA process uses the oldest noise value and oldest previous value with a backshift operator to make a load prediction. The ARIMA process uses a differencing process by having a series that is differenced a certain number of times and contains AR and MA components. Seasonal processes look at periodic trends throughout the day, week, or year by modeling as an AR, MA, ARMA, or ARIMA seasonal process. Seasonal processes can even take two seasons into account using a second seasonal time series. The transfer function model takes white noise into consideration and implements the noise with the load history to predict the load [16].
I.1.1.4 General exponential smoothing

General exponential smoothing (GES) uses a fitting equation with a fitting function vector, a coefficient vector, white noise, and a transpose operator. The mean square error method estimates the coefficients to minimize the fitting equation. Minimizing it creates an estimate vector and a forecast of the series, which can be updated after combining them together. Then a transition matrix can be created, which then relates back to the fitting function [16].

I.1.1.5 State space and Kalman filter method

The state space and Kalman filter (SSKF) method considers the load as a state variable and contains system state equations and measurement equations. The variables involved are the process state vector at a given time, the state transition matrix when no forcing function exists, white noise with known covariance, load measurements at a given time, a matrix relating the process state vector and load measurements without noise, and a load measurement error considering white noise with known covariance. The process noise and the measurement noise are treated separately and unrelated to each other. The apriori estimate is used to make estimates on the process based on prior knowledge up to the most recent data. After error vectors are calculated, the posteriori estimate is created from the apriori estimate and measurement noise. Finally, a blending factor or Kalman gain is used recursively in the Kalman filter, so the forecast is based off the latest model. This means that the model needs to be determined before this recursion [16].

I.1.1.6 Knowledge-based expert system

The knowledge-based expert systems (KBES) approach uses artificial intelligence through computer programming. The program can “reason, explain, and have its knowledge base expanded as new information becomes available to it” by following an if-then statement approach in combination with mathematical formulas [16]. These expert systems have “a wide base of
knowledge in a restricted domain, and uses complex inferential reasoning to perform tasks, which
a human expert could do.” This means that an ES can solve problems that a human expert can
solve, so this saves the human expert time to do another task, which increases the human expert’s
efficiency. In the context of load forecasting, artificial neural networking and reinforcement
learning methods can be utilized to train a network to forecast future load values based on several
inputs. Rahman and Bhatnagar as well as Jabbour, Riveros, Landsbergen, and Meyer were among
the first to start working with ES back in 1988 [15].

I.1.1.7 Analysis of five traditional short-term load forecasting methods

From Moghram and Rahman’s comparative analysis of the five short-term load forecasting
methods, they found surprising results. They noticed that the transfer function approach provided
the best results on a peak summer day but “next to worst” for a peak winter day. They reasoned
that the transfer function approach depended heavily on past data and could not accurately take
current weather factors into its analysis causing it to be less accurate than other methods such as
the KBES. They found that the multiple linear regression found correlations between load, dry
bulb temperature, dew point temperature, and wind speed, however the transfer function approach
did not express any correlation between the load and those same variables. They found that
significant weather changes would drastically affect the results causing nonlinearities. Therefore,
the models and analysis based solely off historical data would be highly inaccurate because they
did not take these weather changes into account. However, an expert system would be capable of
taking these weather changes into consideration. Therefore, an expert system with learning
capabilities and “potential for improvement in the load forecast with greater knowledge” is critical
in producing accurate forecasting predictions [16]. The following table compares five load
forecasting methods: Multiple Linear Regression (MLR), Autoregressive Integrated Moving-
Average (ARIMA), Transfer Function (TF), general Exponential Smoothing (GES), State Space (SS), Stochastic Time Series (STS) and Knowledge Based Expert Systems (KBES) in the summer and winter respectively.

Table I.1 forecast percent error for summer using the five load forecasting algorithms

<table>
<thead>
<tr>
<th>Time</th>
<th>Load</th>
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<th>ARIMA</th>
<th>TF</th>
<th>GES</th>
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Table I.2 forecast percent error for winter using the five load forecasting algorithms

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### I.1.1.8 Artificial neural networks

Artificial neural networks (ANN) are “information processing techniques” modeled from biological nervous systems. ANN started with Lee, Cha, and Ku in 1990 [15]. The two main selection methods are experience and statistical experience. The experience method is based on some correlation between load points at different temperatures. The statistical method relies on auto-correlation analysis of historical load data to determine input variables. Some networks even contain auto-correction analysis to make more accurate predictions based on previous load data. The network contains numerous units or neurons that have input and outputs and can be developed by learning and training though data classification and recognizing familiar patterns. ANN typically has four input variables: historical loads, historical and future temperatures, hour of the
day, and day of the week. These four input variables produce sufficient results for normal weather conditions. For extreme-weather conditions, four more variables, wind-speed, sky-cover, rainfall, and if the day is wet or dry, are needed due to the non-linear relationship between load and weather conditions [17].

A huge advantage of ANNs is that they can perform accurate predictions. Training must be selected based on the characteristics of the day that will be forecasted or else the training will be useless. However, training the ANN with multiple pairs at once does not work because the loads have different patterns and vary throughout the week. For instance, a weekday’s load prediction will definitely be different from a weekend’s load prediction because of activities and power consumption are different on weekdays and weekends. Another reason why multiple training pairs does not work at one time is because recent data is always more accurate than older data. Having recent data will give a more accurate prediction than a large library of old data [17].

There are two ANN methods to obtain good forecasting results. One requires several ANNs for different days and then giving each ANN the training for that particular day. The other method is have one ANN with the “day type information in the input variables.” The first method has a large network but multiple ANNs, but the second method has smaller networks in one ANN. Each method has its own advantages and disadvantages. Another factor to consider is that training selection can drastically affect the ANN’s prediction, so typically a “least distance criteria” method is used to select the best training [17].

There are two main types of ANN classification methods. One observes and compares data, while the other type is unsupervised (self-organization) and selects the training set independently from human intervention. It is important to note that day of the week classification is system dependent, and typically there are five different categories of loads throughout the week: Monday,
Tuesday-Thursday, Friday, Saturday, and Sunday/Public holidays. Another method of classification not as common is gathering the data and then combining it with data from five days before to make a training set [17].

I.1.1.9 Genetic algorithms

Another forecasting method uses genetic algorithms. This method is based off of evolution and adaptation as organisms gradually improve and develop over time by survival of the fittest. In genetic algorithms, there are several strings comprised of bits, and these strings then evolve. An example of a success is Srinivasan’s work titled Evolving artificial neural networks for short term load forecasting where he evolved a neural network structure and connected weights for tomorrow’s load to make a forecasting prediction [15]

I.1.1.10 Combining forecasting methods

Currently, there have been at least three studies of combining methods, and it is important to note that a combination of multiple forecasting methods produces more accurate forecasting predictions. For instance, in 1995 Kim K., Park, Hwang, and Kim S. developed a hybrid short-term forecasting system using both ANN and fuzzy ES. A few years later in 2000, Tamimi and Egbert combined fuzzy logic with ANN to create a more accurate short term load forecast [15]. In 2011, Borges, Penya, and Fernández analyzed a combination of methods and found fascinating results.

Borges, Penya, and Fernández conducted such a study in combining short-term load forecasting methods and determining the best forecasting method. They noticed that the short-term load forecasting often utilized one of two methods: statistical methods, such as regression, or artificial intelligence. Of the statistical methods and linear models, they consider ARIMA the best because it “achieves promising results.” Artificial intelligence is excellent for dealing with non-
linear characteristics of the load data. Each method presents “different information and precision.” As a result, choosing a method with less error in one specific situation may not produce accurate results in general and we might some information which are necessary to consider in the algorithm for a larger variety of situations. Therefore, combining methods solves this problem, so they placed the outputs of the simple forecasting methods as the inputs of a model to determine how to combine the results [18].

When combining methods and creating a model, some conclusions were made. One conclusion states “that combining forecasts reduces the error compared to the average error of the component forecasts,” while the other states “that a simple average…performs as well as more sophisticated statistical approaches.” They found that the neural network learned the best algorithm for short-term load forecasting. The Neural network model works very well during the weekends but poorly during the weekdays, which affects the average results. Therefore, they concluded that “the rule-based model learns to use the NN in weekends and the polynomial in weekdays. When combining methods, they concluded that rule-based and simple average methods work better than more complicated methods such as neural network and support vector machines [18]. The following table shows a result of day ahead load forecast for four data sets for four algorithms:

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Data set 1</th>
<th>Data set 2</th>
<th>Data set 3</th>
<th>Data set 4</th>
</tr>
</thead>
</table>

*Table I.3 Mean absolute percentage error (MAPE) results in day-ahead forecasting (%). in brackets results with bias correction post-process*
Taylor and McSharry also conducted a study on short-term load forecasting. They compared ARIMA, periodic AR modeling, Holt-Winters exponential smoothing method, and principal component analysis (PCA). They modified the Holt-Winters method to include two seasonal cycles in load by considering several variables such as smoothed level seasonal indices for intraday and intraweek seasonal cycles, smoothing parameters, and a step-ahead forecast made from the forecast origin. They said that compared to ARIMA, the double seasonal Holt-Winters method is just as simple and robust, which makes it a great method to choose. They found that the ARIMA and PCA forecasting methods were accurate, but the Holt-Winters method exponential smoothing method performed even better, making it the best method. [19].

Based on the above survey, simple load forecasting methods can be as accurate as the sophisticated approaches and thus a linear fitting method is sued to forecast the day ahead load value for battery control.

I.1.2 Battery energy storage system (BESS)

Here, a grid scale BESS (1 MW, 1 MWH) which is already installed in Maui island, 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. 1-1.
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 MWh energy storage system. The BESS is connected to a 1 MW bidirectional three phase inverter with 12,470 Volt AC output. The battery management system has a SOC estimation algorithm, which estimates the amount of usable electrical energy stored in the battery pack. The SOC is limited to an operating range of 0.2 - 0.8 in which the battery is neither fully depleted nor fully charged [20],[21], 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.

I.1.3 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 sub-system 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 hours, a forecast of the circuit power profile is needed.

I.1.4 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 [22]:

\[ E_{tot} = \sum_{i=1}^{n} E_i = \sum_{i=1}^{n} (\frac{1}{\Delta t} \int_{t_i}^{t_{i+1}} P_i dt) \]

\[ E_{tot} : \text{Total energy stored in BESS at time } t \text{ (kWH).} \]
\[ E_i : \text{Energy stored at battery at time } t \text{ (kWH).} \]
\[ P_i : \text{Power flow into the battery at time } t \text{ (kWH).} \]
\[ \Delta t : \text{Time resolution for BESS power flow optimization.} \]
\[ y, x, a_0, a_1 : \text{The parameters of affine fitted function.} \]
\[ R : \text{The error between fitted line value and actual value.} \]
\[ y = a_0 + a_1x \] (1-1)

\[ E_{t+1} = E_t + P\Delta t \]

\[ SOC_{t+1} = SOC_t + \frac{P\Delta t}{E_{tot}} \]

The residual is the square-root of the some squares of difference of forecast and actual values:

\[ R^2 = \sum_{i=1}^{n} [y_i - (a_0 + a_1x_i)]^2 \] (1-2)

Taking the partial derivative with respect to each coefficient \( a_i \) and arranging in matrix form the Vandermonde matrix is obtained as follows:

\[
\begin{bmatrix}
1 & x_1 & x_1^2 & \cdots & x_1^k \\
1 & x_2 & x_2^2 & \cdots & x_2^k \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
1 & x_n & x_n^2 & \cdots & x_n^k
\end{bmatrix}
\begin{bmatrix}
a_0 \\
a_1 \\
\vdots \\
a_k
\end{bmatrix} =
\begin{bmatrix}
\sum_{i=1}^{n} y_i \\
\sum_{i=1}^{n} x_iy_i
\end{bmatrix}
\]

(1-3)

Rearranging equation 1-3 for \( y_i \) gives the following:

\[
\begin{bmatrix}
y_1 \\
y_2 \\
\vdots \\
y_n
\end{bmatrix}
= \begin{bmatrix}
1 & x_1 \\
1 & x_2 \\
\vdots & \vdots \\
1 & x_n
\end{bmatrix}
\begin{bmatrix}
a_0 \\
a_1
\end{bmatrix}
\]

(1-4)

The matrix shown in equation 1-4 can be written as follows:

\[ y = Xa \] (1-5)

Then the “a” coefficients can be calculated with a simple manipulation:
The chapter discusses the linear fitting method which is required for peak shaving of the load curve. The linear fitting or parallel method is required to have a load curve to compare with the reference load curve and optimize the battery operation to follow the reference curve. The advantage of the linear fitting forecasting method is its light computation burden. More accuracy can be reached with more sophisticated approaches with higher computational burden and more historical days. 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.

I.2 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.

I.2.1 Active power flow

In this experiment, BESS is charged with steps of 5% of the battery 1 MW power capability. 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. 1-2 and 1-3, respectively.

Fig. 1-2. Circuit and BESS measurements in 50 KW active power flow test

Fig. 1-3. Circuit Voltage and BESS SOC measurements in 50 KW active power flow test
In Figs. 1-2 and 1-3, 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. As shown in Fig. 1-3, SOC has discrete slopes or charging rates that correspond to much larger power steps. This can be explained by nonlinear behavior of battery cells in which each individual cell SOC might not have a linear relationship with the power flow.

1.2.2 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. 1-4 and 1-5.

---

![Image of power flow graphs]

**Fig.1-4.** Circuit and BESS measurements in 200 KVAR reactive power flow test
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.

I.3 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.
$P_k$: Power of BESS at time k

$P_{\text{ref}}$: Reference power curve

$SOC_k$: Time resolution for BESS power flow optimization.

$E_{\text{tot}}$: Total capacity of BESS

$SOC_{\text{max}}$: Maximum allowed SOC of BESS (0.8)

$SOC_{\text{min}}$: Minimum allowed SOC of BESS (0.2)

$SOC_k$: SOC of BESS at time step k

$L_k$: Distribution active power load at time k

$W_k$: Coefficient of penalty function for excess power flow through the distribution transformer

$J_k$: Cost to go in dynamic programming formula at time k

The SOC cost at time step $k+1$ is defined as follows:

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

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:

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

The weight component $W_k$ is a quadratic function of load, which penalizes the high load passing through the distribution transformer:
\[ W_k = (L_k + P_k)^2 \]  

(1-9)

Combining equations 1-8 and 1-9 into a single objective function, the following equation is obtained:

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

(1-10)

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:

\[
\text{Min} \left( \sum_{k=1}^{N} \frac{\Delta t}{E_{tot}} + 3(L_k + P_k)^2 \right)
\]

(1-11)

Subject to SOC constraints:

\[
\frac{1}{\Delta t} [SOC_{min} E_{tot} - E_k] < P_k < \frac{1}{\Delta t} [SOC_{max} E_{tot} - E_k]
\]

(1-12)

\[
E_{k+1} = E_k + P_k \Delta t
\]

(1-13)

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.
\[
\text{Min}\left[ \sum_{k=1}^{N} \left( L_k + P_k - P_{\text{ref}(k)} \right) \right]^2
\]  

(1-14)

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. 1-6.
Fig. 1-6. Flowchart of peak shaving method
The algorithm presented in Fig.1-6 describes the peak shaving method that is implemented in the BESS in Fig. 1-1. 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, it is ensured that the BESS is maintained within its desired SOC range.

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. Part of the frequency deviation can be corrected by the BESS power flow. This part can obtained by a cost analysis between the cost of reserve and cost of battery operation. In fact, since the frequency correction is vital for the health of power system, it is more desirable to correct the frequency deviation with LFC loops which are more reliable than batteries.

I.4 Simulation and results

I.4.1 Load forecasting simulation results

Linear regression method for next day load forecasting is applied to 108 days of historical data with 1 minute resolution. The forecast data point (y) for each time step (X) is obtained by
inserting the given time step in equation (1-5). If the load curve for 24 hours is given with 1 minute resolution, equation (1-6) 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. 1-7.

![Fig. 1-7. Actual and forecast load curves using linear regression method](image)

It can be seen in Fig. 1-7 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, the deviation of the forecast value from the actual value is not a concern during this time period when PV fluctuations are high because the load shifting function of the BESS does not occur during these hours. As the penetration of renewable generation is increasing, the magnitude of these fluctuations will increase accordingly. A high discrepancy of actual and forecast load, the battery will have a higher error of operation since it is following the forecast load curve. At day of forecast, there was not much PV generation. Therefore, in addition
to the fluctuations, there is an offset between actual and forecast load. The value of mean absolute percentage error (MAPE) for seven days of forecast is 2.1 for the linear fitting method which is better than values reported in [18]. 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 kW.

I.4.2 Peak shaving simulation and infield test results

The optimization algorithm is applied to a 1 MW/1 MWh BESS in the circuit shown in Fig. 1-1. The time step is taken once every 15 minutes for a total of 96 steps in a 24 hour planning horizon. The first optimization algorithm shown in equation. (1-11) to (1-13) 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. 1-8 and 1-9, respectively. The output of a PV inverter in the circuit is plotted in Fig. 1-10.

![Fig. 1-8. Power curves for first optimization algorithm](image)
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. 1-10, 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, \( \text{SOC}_{\text{min}} \) and \( \text{SOC}_{\text{max}} \) parameters are set to 0.2 and 0.8, respectively. The objective function defined in equation (1-11) 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.1-11.
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. 1-12.

![Fig. 1-12. Maximum and average SOC error for 10 smoothing levels](image)

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 minutes with minimal impact to the overall effectiveness of the peak shaving objective. The optimization algorithm for the second method in equation (1-14) 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 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. 1-13 and 1-14, respectively.

![Power curves for second optimization algorithm](image1)

Fig. 1-13. Power curves for second optimization algorithm

![Actual and forecast SOC curve for second optimization method](image2)

Fig. 1-14. Actual and forecast SOC curve for second optimization method
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 [23]. 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 uncertainty in the grid especially with higher integration of distributed renewable generations.

1.5 Conclusion

In this chapter, 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. In the next chapter, two forecasting approaches are discussed and used to come up with peak load shaving and power smoothing of distribution load curve.
In the next chapter, peak shaving and power smoothing of an actual distribution system load curve is explained which uses two load forecasting method. The first method forecasting method is a simple linear fitting method and the second method benefits from the information obtained by first method and predicts twenty minuet ahead load value. Using the forecast points, peak shaving and smoothing of power curve is performed.

I.6 Summary and Contributions

1 Several experiments are performed on BESS. The goal of these experiments was to determine the impact of BESS on the voltage level of distribution transformer. In the first set of test, BESS is used to absorb active power from the transmission system. It is shown that tap changer of the distribution transformer can regulate the voltage. In the next set of experiment, reactive power is injected to the grid. The reactive power does not have a significant impact on the voltage and its affect is lower than active power. A load following method is proposed in which BESS power flow is used so that aggregate power flowing the distribution transformer follows a reference power curve. Several constraints such as SOC constraints are considered for the optimization problem.

2 A day ahead load forecasting problem is introduced which used historical data to predict the load value for the next 24 hours. The historical load are categorized into day weeks. A linear function is fit into the data and the forecast point for the next day is obtained. The advantage of this method is its light computational burden

3 Power smoothing is done using the function available in the GUI of the BESS system. SOC deviation is measured using several smoothing levels and it is shown that single smoothing level has the minimum SOC error.
An algorithm is developed for power factor correction of distribution load. Part of the BESS capacity which is not used for active power correction can be utilized to inject reactive power load of distribution grid.
Chapter II: Load Commitment of Distribution Grid with High Penetration of Photovoltaics (PV) Using Hybrid Series-Parallel Prediction Algorithm and Storage

Abstract

Battery Energy Storage System (BESS) is one of the promising solutions to deal with intermittency of renewable generation. In this chapter, BESS is used for peak shaving and smoothing the distribution load curve of an actual circuit on the island of Maui in Hawaii. The distribution circuit has about 850KW of installed rooftop PV generation. This amount of PV and future expansion raises some concerns about potential impacts on the transmission system. This chapter aims to mitigate these effects. Two load forecasting methods are presented. The forecast load data is then used to control BESS for two main purposes, peak shaving and smoothing. To achieve these goals, two approaches are explained. In approach I, a nonlinear programming method is utilized and equations for simultaneous load shifting and smoothing are derived. In the next approach, a real time control is developed which performs smoothing and peak shaving simultaneously. These methods are applied on 108 days of historical data and pros and cons of each approach is discussed.

II.1 Introduction

Hawaii clean energy incentive (HCEI) shows the roadmap for relieving the economy from fossil fuels by achieving 70% clean energy by 2030 with 30% from efficiency measures, and 40% coming from locally generated renewable resources. With strong public support for renewable
energy in the state [24], researchers are investigating new methods to increase renewable energy penetration mostly in the form of solar, wind and wave energy. One of the most tangible issues in renewable integration is its intermittency which makes it hard to rely on for meeting the load demand. As a result, having a more predictable renewable energy source, gives a leverage for incorporating more of this type into the power grid. BESS is one of the most straightforward solutions for reducing the fluctuations and thus coming up with a more predictable power source. With charging and discharging capability, not only it can harness the fluctuations in the power output of renewables, but also can be used as a means for peak shaving purpose. In other words, BESS can be used to store the excess renewable energy in off-peak time periods and dump it back into the grid in the high load demand time periods [25]. In this chapter, BESS is used for both purposes. A short survey of BESS application for above goals is presented here. BESS is used in [26] to smooth out the fluctuations caused by PV and wind generation in power system using real time State Of Charge (SOC) based control strategy. In this chapter’s proposed method, SOC changes around 50% while alleviating the fluctuations. SOC is a quantity that represents the ratio of available BESS capacity to its fully charged capacity [27]. Wind power smoothing is done by ramp control in [28]. In [29], a model predictive control strategy is utilized to have BESS mitigate the wind power fluctuations so that the windfarm can be dispatched in hourly basis. Dual BESS is used in [30] to maximize energy harvest from the wind without lowering grid power quality. The two BESS units try to provide wind power as a short term dispatchable unit which can be coordinated with other units for active power scheduling. Embedding reliability criteria into objective function would add to the credibility of solution. Dynamic programming is used in [31] for designing an optimal power management mechanism for peak shaving in grid connected PV systems at lowest cost. The predictive optimization applied in the chapter, save 13% on the
electricity cost for the planned period of study. The results of the proposed method would improve with higher accuracy in load forecasting. In [32], the author investigates PV integration challenges and cites BESS as one of the most promising solutions available to deal with intermittency of PV resources. It is reported that deployment of hybrid BESS and Distribution level Static COMpensator (STATCOM) provides 13% return on $25M investment on ancillary services such as frequency regulation, delayed capital investments, minimizing resource curtailment and reactive power support. In [33], different moving average algorithms are applied to smooth out PV power curve. BESS is used for residential electricity peak demand shaving in [34]. Peak shaving between 42% and 49% is reported in 5 regions in Canada except Quebec which is about 28%. It is concluded that peak shaving system is unsuitable for houses with electric heating which needs a higher storage capacity. A brief introduction of smart grid project at Public Service Company of New Mexico (PNM) is reported in [35]. The main objective of this chapter is analyzing the cost effectiveness of BESS for smoothing, peak shaving and/or other ancillary services. In [36], profitability of BESS deployment ability and residential scale is investigated. Different BESS chemical type are analyzed for six business cases and it is shown that molten salt batteries are the most promising type. Moreover, it is claimed that utility scale BESS have a higher profit potential compared with distributed storage. Peak shaving and load smoothing are discussed in [37] where it is shown that peak shaving using BESS at community level in Queensland, Australia saves about 18% in a weekly energy cost. Sizing of distributed BESS is discussed in [38]. It is shown that with current BESS price, economic profits are not likely but might improve if multiple functions are considered for BESS operation. Peak shaving and electricity cost minimization are discussed in [39] with a proposed load forecasting method suited for residential storage controller. The proposed storage controller algorithm saves cost about 80% with respect to baseline algorithm.
However, none of the cited papers have discussed simultaneous peak shaving and smoothing on the distribution transformer load. Thus, this report presents algorithms and methods to accomplish this goal so that the transmission system is relieved from the aggregate fluctuations of rooftop PV generations. Next section presents the circuit and explains more about interconnection of BESS and the distribution system under study. The system model and problem statement is covered in section II and proposed approaches are explained in section III. Simulation results are discussed in section IV. Finally, conclusion and future work is given in section V.

II.2 System model and problem statement

The system model is defined in an island environment where several generators are meeting the load demand. The information flow diagram is depicted in Fig. 2-1. Several BESSes are managing the distribution load. All of the BESSes, generators and other controllable devices send the measured data to Energy Management System (EMS) which lies at the heart of data processing and command optimization. Hybrid Forecast and Load Commitment (HFALC) program is amended to EMS to manage the BESS operation.
HFALC is briefly described in Fig. 2-2 where parallel and series-parallel load forecasting data is utilized for optimizing BESS performance. Information flows from EMS to forecasting algorithms and optimized command is sent back to EMS. User preference is also provided for optimization and forecast algorithms. After finding the improved operation points, the required data is sent back to EMS where this information is processed more and the required commands are sent to control units. A more detailed explanation of HFALC is given in later sections.
The electrical circuit of the BESS in the distribution is depicted in Fig. 2-3. A 1100KWH/1MW BESS is connected to a power converter whose output voltage is increased via a step-up transformer. The power of BESS goes to a distribution circuit which has 850KW rooftop PV generation which causes some stochastic variability in the power curve. The circuit is also fed from a distribution transformer with the ratio of 69KV/12.47KV. BESS SOC along with some other health parameters are transmitted via SCADA system to dispatch room where an operator can control BESS operation via a GUI. The distribution transformer power flow is also measured by SCADA and is available via a database in the utility. The aim of BESS control is to mitigate the variability in the power of distribution transformer and also reduce the amount
of committed generating units for meeting the demand. This can be done by charging BESS with excess renewable energy and dumping back the stored energy in the grid in the peak load time, thus replacing the conventional generating units which are not mostly environment friendly. BESS can also provide smoothing function in midday when load intermittency is pretty high due to distributed PV generation in the distribution circuit. The overall problem can be divided into two categories namely, peak shaving and smoothing. The solution approaches for the mentioned objectives is covered in the next section.

II.3 Peak shaving and smoothing

Two approaches are followed in this report to achieve the mentioned goals. First method uses nonlinear programming and second approach is a simple algorithm which controls BESS SOC in real time. Both methods rely on forecasting of load curve and thus a separate subsection discusses forecasting in detail which comes subsequently. The first method uses a forecast load curve and yields a SOC trajectory for peak shaving and also smoothing. By injecting/absorbing the power determined by SOC trajectory, peak shaving and/or smoothing goals are reached. Next, a simple algorithm which makes use of real time control of BESS SOC is covered. This method benefits from a better forecasting method and is easy to implement. It also includes some user-interactive parameters which can be set by the operator or fed from another power system application.

II.3.1 Forecasting

Forecasting plays an important role in both methods and therefore forecasting method is covered here. As startup time of rapid start generators such as diesel and gas turbines are less than 20 minutes [40], any shortage of power not provided by BESS can be met by these types of
generators. Therefore, prior knowledge of load behavior is necessary to cope with abrupt drop of intermittent generations. Besides, for the next day planning of BESS, an approximate load curve is essential. Consequently, the forecasting is performed for the next 24 hours ahead and also 20 minutes ahead to be able to optimally control charge/discharge of BESS. A total number of 108 days of historical load data points are used for forecasting. Two methods are used in forecasting namely, parallel and series-parallel.

II.3.2 Series-Parallel forecasting

In this method, in addition to the historical load data, past data of each day is used. The past data spans from twenty minutes ago until the present moment. Moreover, the load data point calculated by parallel forecasting is also required. As a result, a set of data is prepared which includes the past data and a point from future forecast. A spline interpolation is fit into this set of data. In the next step, the new points produced by spline interpolation, are averaged. The generated point comprises one component of the final forecast value. This point is compared with the actual value when the future time spot is reached. Then, a weighted value of this error is added to the averaged value and makes the final forecast value. Apparently, in the first forecast point, this error does not exist and the above steps work for forecasting after the first point. This process is refereed as PI control shown in Fig. 2-4 since it mimics the PI control mechanism. The twenty minute interval can be changed to suit user preference. At this point, the required future behavior of load curve is known to some certainty. This information is employed for optimal control of BESS to accomplish the defined objectives.
II.3.3 Peak shaving and smoothing: first approach

In approach one, peak shaving and smoothing objectives are handled separately. First of all, a SOC trajectory is found by solving the peak shaving problem and BESS power is determined to follow the obtained trajectory. Next, fluctuations in the midday are curbed while sticking to the planned SOC trajectory as much as possible. In the next subsection, the peak shaving problem is explained and SOC trajectory for next 24 hours is obtained.

II.3.4 Peak Shaving

For peak shaving, it is desired to charge BESS in early morning when there is excess renewable energy production usually from wind turbines and discharge it to replace the expensive units which pick up the peak load. In other words, BESS power flow tries to flatten the load curve considering imposed constraints. Therefore, cost function is defined as minimization of total load deviation from a straight line. This line is determined based on the forecast load curve already obtained. The total load consists of forecast load and BESS power. In other words, the BESS tries to maintain the load curve as straight line given the nominal capacity. Based on this explanation, the mathematical objective function is written as follows:
\[ e(t) = L(t) + P(t) \]  
\[ \text{Min} \left( \sum_{t=1}^{N} (e(t))^2 \right) \]

where \( N \) is the number of time steps in forecasting horizon. Parameters \( L(t), P(t) \) and \( e(t) \) stand for forecast load, BESS power and error between the two power values at time stage \( t \). The above equation can be derived from a different perspective as well. Suppose objective function at time step \( t \) is defined as the total load flowing the distribution transformer times a time variant coefficient:

\[ J(t) = [L(t) + P(t)] W(t) \]

where \( W(t) \) represents load coefficient at time step \( t \). In order to penalize the high load flowing through the distribution transformer, \( W(t) \) is chosen as square of overall power flow:

\[ W(t) = (L(t) + P(t))^2 \]

Plugging (2-3) into (2-4), taking first derivative and summing up over the horizon results in relation (2-1). SOC constraints are described as:

\[ P_t < \min \left\{ \left( \frac{SOC_{\text{max}} E_{\text{tot}} - E_t}{\Delta t} \right) P_{\text{nom}} \right\} \]

\[ P_t > \max \left\{ \left( \frac{SOC_{\text{min}} E_{\text{tot}} - E_t}{\Delta t} \right), -P_{\text{nom}} \right\} \]

SOC of BESS is updated by:

\[ SOC_{t+1} = SOC_t + \frac{P_t \Delta t}{E_{\text{tot}}} \]

In the above equations, \( SOC_{\text{min}} \) and \( SOC_{\text{max}} \) denote the minimum and maximum allowable SOC. \( E_{\text{tot}} \) and \( E(t) \) show the capacity of BESS and stored energy at time step \( t \) respectively. \( \Delta t \) represents
the planning time resolution. The same relation can be achieved by flattening the load curve using the BESS:

$$\sum_{t} (L(t) + P(t))^2$$

(2-7)

The problem in (2-7) is a routine constrained nonlinear programming which can be tackled with regular solvers in Matlab® or other commercial or non-commercial programs such as GAMS® and AMPL®. Solving cost function (2-7) gives the BESS active power flow at each time step and also the resulting SOC.

**II.3.5 Smoothing**

Smoothing is an add-on function amended to peak shaving problem to harness the stochastic variability in the load curve. The underlying concept is the same as peak shaving. That is, at each time interval, a level is determined and BESS tries to keep this straight total line. In other words, BESS is optimized to shave the peak while maintaining the smoothing level during each interval. This level should be determined in a way that SOC deviation is minimum at the end of each time interval. Therefore, smoothing level is defined as the average of current and forecast load. Consequently, the amount of BESS charge and discharge should be almost equal and thus SOC deviation is kept at minimum level. The more forecast is equal to the actual value, less SOC deviation occurs at the end of each period.

$SOC_e(t)$: SOC error at time $t$.

$SM_e(t)$: Smoothing error at time $t$.

$SL(t)$: Smoothing level at time $t$. 
$P_x(t)$: BESS supplemental power provided for SOC correction.

$\alpha$ and $\beta$: coefficients for each component of cost function

SOC error, $SOC_e$, at time step $t$ is defined as:

$$SOC_e(t) = \left( SOC(t-1) + \frac{(P(t) + P_x(t))\Delta t}{E_{tot}} + SOC(t) \right)^2$$ (2-8)

Smoothing error, $SM_e$ at step $t$ is expressed as:

$$SM_e(t) = (L(t) + P(t) + P_x(t) - SL(t))^2$$ (2-9)

Where smoothing level is a combination of following terms:

$$SL(t) = \frac{L(t) + f(t + \Delta t)}{2} + SOC(t + \Delta t) - SOC(t)$$ (2-10)

The two first components comprise the average of current and series-parallel forecast value. The remaining terms, which represent SOC deviation from a preplanned point, are added to make up for the SOC deviation. In addition to that, $f$ which denotes twenty minute ahead load forecast, is responsible for calculating the smoothing level. Smoothing level is updated at the end of each period. Total cost is weighted sum of SOC and smoothing error:

$$Cost = \sum_{t=0}^{N} (\alpha SOC_e(t) + \beta SM_e(t))$$ (2-11)

Optimal BESS power is obtained by minimizing the cost function:

$$P_x = \arg \min_{P_x} Cost$$ (2-12)

After finding $P_x$, BESS power is updated by $P_x$: 


\[ P(t) = P(t) + P_s(t) \] (2-13)

SOC is also calculated by 11 accordingly.

II.3.6 Peak shaving and smoothing: second approach

In the second method, BESS operation is divided into three time sections namely, charging, smoothing and discharging. However, smoothing is embedded in charging and discharging functions serving peak shaving goal. In spite of some fluctuation in SOC caused by smoothing implementation, BESS is kept almost full during smoothing period to be able to dump back stored energy in the discharging period. The goal of smoothing which is present in all time periods is to filter out the load stochastic variability. The smoothing level is approach one, changes to an inclined line whose slope is based on the startup time of rapid start generators such gas turbines and diesel generators. In other words, fast generators can make up any load discrepancy within allowed time. Moreover, BESS removes the fluctuations around the line while maintaining the SOC level. It is assumed that BESS is empty with SOC of about 20% and needs to be charged until early morning. Usually, there is higher generated power form windfarm before sunrise and the load is pretty much low at the same time. As a result, some of the generated power has to be curtailed. Therefore, it is preferred to charge BESS with the curtailed power. Even if there is no generated power from windfarm, BESS can be charged from base load generators. Apparently, the stored energy will meet the peak demand at early night which would be otherwise met with gas turbines and diesel generators. In order to come up with line equation for the inclined reference power line, two points are required. The first point is the current load and the next point comes from the twenty minute ahead forecast load. BESS is counteracting the load around the defined line so that total load is an inclined line regardless of what is happening in the circuit. Regardless of whether the load fluctuations are from PV or abnormal load value at peak and off-peak time
periods, BESS sticks to the define power line following plan. Consequently, the power line at each time step $t_k$, $P_k(t_k)$, is written below:

$$P_k(t_k) = (P(t) + L(t)) + m(t_k - t)$$  \hspace{1cm} (2-14)

where $m$ is the slope of the power line and is calculated by:

$$m = \frac{f(t + \Delta t) + g(SOC(t)) - (P(t) + L(t))}{\Delta t}$$  \hspace{1cm} (2-15)

To add power system operator preference, slope of the power line is updated by $g(SOC(t))$. For instance, the operator observes an increase in wind power generation and thus updates the slope accordingly. For charging, the slope needs to be adapted for charging given the current SOC of battery. Therefore, the slope is higher than smoothing state. Charging continues until SOC reaches almost 80% to be considered full. Apparently, for discharging the reverse action should be followed. The smoothing function begins when BESS is almost full and continues when the peak load level is detected. BESS power flow is determined like 18 except SOC deviation is corrected in the slope of smoothing:

$$f(t + \Delta t): \text{Distribution load curve active power forecast at time } t+\Delta t.$$

$$g(SOC(t)): \text{Correction function to compensate for SOC deviation.}$$

$$P_k(t_k) = (P(t) + L(t)) + (m - \Delta SOC(t))m(t_k - t)$$  \hspace{1cm} (2-16)

$$y = a_0 + a_1x$$  \hspace{1cm} (2-17)

$$m = \frac{f(t + \Delta t) + g(SOC(t)) - (P(t) + L(t))}{\Delta t}$$  \hspace{1cm} (2-18)

where $\Delta SOC$ is given as:
Besides correction embedded in $m, g(SOC(t))$ can be also utilized for the same purpose. When the peak load level is measured, BESS starts to discharge the stored energy and will continue until it is almost empty, i.e., SOC reaches nearly 20%.

II.4 Simulation results

The proposed approaches are used to control BESS power flow using 108 days of actual distribution system active power data. Firstly, results of forecast methods are given and compared with actual load curve. Then, impact of BESS on peak shaving and smoothing of load curve for both approaches is investigated.

II.4.1 Forecasting results

Parallel and series-parallel methods are applied on the historical load data for coming up with an approximate behavior of load curve in the future. The data and the algorithm are processed in Matlab environment. In parallel method, 103 historical days are used to forecast the 104th day. The forecast load curve obtained from set of equation (1-2) to (1-6) along with actual load data is depicted in Fig. 2-5. When the amount of fluctuation is high, especially in midday, the actual and forecast load curves differ significantly while in other parts of the day, the two curves are fairly close to each other. The parallel forecast data is used for forecasting 20 minutes ahead of 104th day using series-parallel method. The forecast result accompanied with actual data sampled at 20 minutes interval is depicted in Fig. 2-5. As shown in Fig. 2-6, the discrepancy in data has reduced significantly even in midday time compared to sheer parallel method.
II.4.2 Peak shaving and smoothing approach I results

In the first simulation, peak shaving is performed on the 104th day using equation (2-7) to (2-10) where the load is obtained using parallel forecast method expressed in equations 1-6. Pure peak shaving method tries to keep the load curve as flat as possible based on the predicted curve and SOC constraints. Solving equations (2-1) to (2-6) gives the target SOC trajectory shown in Fig. 2-7 which BESS will follow by absorbing or injecting active power to the distribution circuit. Looking at the forecast load in Fig. 2-5, it is easy to see how SOC trajectory in Fig. 2-7 is obtained.
Fig. 2-7. SOC trajectory obtained from approach

As shown in Fig. 2-7, SOC is increasing to shift the load curve by charging from midnight until 6 a.m. As the concavity of the load curve changes around 6 a.m., BESS discharges some of the stored energy until about 9 a.m. to lower the load curve. After the local minimum in SOC trajectory which happens around 9 a.m., BESS charges up to 2 p.m. to increase the load.
Fig. 2-8. Circuit load corrected by BESS operation calculated by approach which is a little below the flat line around 800 KW. After 2 p.m. until 6 p.m., BESS keeps the stored energy and starts to discharge to shave the peak. The compensated load flowing through the transformer is depicted in Fig. 2-8.
As it can be seen in Fig. 2-8, the corrected load is almost flat until 8 a.m. but will differ a little due to error in forecasting. Moreover, since the forecast and actual load are different significantly around noon, the corrected load is even higher than actual load. BESS discharges the stored energy in the evening and flattens the load curve. Applying smoothing expressed in equations (2-12) to (2-16) to the load curve yields the curve shown in Fig. 2-9. Smoothing period is taken as 15 minutes. In other words, BESS tries to dampen the fluctuations around a smoothing level. This level is the average of current load and 15 minutes ahead predicted load. Smoothing function is decreasing fluctuations while following target SOC closely. The reached SOC after smoothing is pretty much close to target SOC trajectory depicted in Fig. 2-10. Still, the same problem exists with the increase in load in midday caused by forecast error.
II.4.3 Peak shaving and smoothing approach II results

The second approach benefits from real time control of BESS power using series-parallel forecast. BESS follows the power trajectory which is an inclined line between the current load and 20 minutes load forecast. The function \( g(SOC(t)) \) in (2-18) is chosen as a simple constant 150KW for charging, 0 for smoothing and \(-SOC(t-1)*390\) for discharging period. Therefore, BESS will charge following the line whose slope is increased by power of 150KW above the forecast value. In the smoothing period, BESS tries to decrease the fluctuations by creating a power line where the forecast value is kept unchanged. The slope of discharging line depends on the available energy. That is, as the stored energy reduces, the slope of line decrease and thus discharging functions approaches the smoothing function. The reached SOC and corrected load are depicted in Figs. 2-11 and 2-12 respectively.
As shown in these figures, this method does not suffer from the shortcomings of previous approaches in smoothing period. However, the absolute value of SOC change in the smoothing time, i.e. the time duration between SOC of 0.8 at the end of charging period and SOC of 0.8 in the beginning of discharging period is 0.8147. It means that there is complete cycle of zero to 0.8 of BESS. BESS tries to smooth out the fluctuations with minimal change in SOC. As a result, BESS remains almost full in the beginning of discharging period and dumps back stored energy to shave the peak load. It is also clear from Fig. 2-12 that BESS has removed the fluctuations in the load and the corrected load has changed to piecewise linear curve. In short, BESS has removed the variability of load curve without much affecting SOC and has shifted the load to make use of renewables generated in early morning for meeting the demand at night.
In this chapter, two approaches for controlling BESS power flow are introduced. These methods serve two purposes, peak shaving and smoothing. Two forecasting methods are investigated and results are compared with actual load. In the first method, BESS follows a SOC trajectory which is obtained by parallel forecast approach. This method suffers from inaccurate forecast load which leads to unsuitable charge/discharge of BESS which at some time aggravates the circuit loading. Further research for more accurate load prediction with high PV penetration might pave the way for better understanding of circuit behavior. Smoothing function is added to reduce the fluctuation while performing the peak shaving task. This method also relies on the same forecasting method while adds smoothing to the shaved peak load curve. In the second approach, a simple algorithm based on series-parallel forecasting is investigated. This method takes advantage of fairly accurate load forecast and performs both tasks. This method not only shifts the
load but also damps the load stochastic fluctuations mostly caused by PV generation. There are some user interactive parameters which can be coordinated with other variables in power system for an optimal operation. With more deployment of BESS, the amount of variability in transmission decreases and this leads to more integration of renewables, especially rooftop PV generations.

In the next chapter, we will talk briefly about how we control the storage devices such as water heater and AC and also residential battery storage. We solve this problem by modeling these devices in a stochastic environment and find the optimum trajectory using dynamic programming.

II.4.5 Summary and Contributions

1 A very short term load forecasting method is proposed. The time horizon of this forecasting method can be adjusted based on the system operator’s preference. Since the rapid startup generators come online in about twenty minutes, the forecasting horizon is chosen as twenty minutes. Historical data as well as load data of the same day is used to produce the load forecast point.

2 Simultaneous peak shaving and power smoothing is done on actual load curve. In this approach, peak shaving and smoothing of load curve is done simultaneously using the developed forecast methods. A linear load curve is defined and all the fluctuation around this linear power curve is removed by the BESS. The slope of the power line is updated by the SOC error so that BESS has enough stored energy to shift the load energy to shave the peak load.

3 Another load smoothing curve is also introduced in which a flat smoothing line is used as a reference line and BESS removes the fluctuations around this line while following a reference load curve for peak shaving.
Chapter III: Scheduling of Price Sensitive Demand Response Resources in a Distribution Grid

Abstract

Utility can alleviate some of the issues caused by the penetration of intermittent renewable energy resources such as distribute solar generation by demand repose. Battery storage devices and water heaters make up a significant part of demand response by which utility can plan their operation according to the optimal power flow results. Dynamic programming is used to give the optimum operation plan for each individual storage device which includes water heater and battery storage device. Scheduling of all units across the distribution is discussed given a rigid price signal. The algorithms are applied on storage devices and water heater and obtained results are analyzed.

III.1 Introduction

Demand response (DR) management is considered a significant asset in optimizing energy flow at the consumer level. With increasing distributed renewable energy generation, DR can help the power system operator alleviate the negative impacts of volatile resources on the grid stability. Adding intelligence to the residential loads is a crucial step to the smart grid paradigm. Interaction of smart loads using widespread communication infrastructure turns DR into a useful resource for power system operators. The bidirectional power and information flow in the emerging utility environment paves the way for utilizing DR elements such as thermal storage, distributed battery storage systems and air-conditioner (AC) for providing services such as peak load shaving, load smoothing and reserve procurement. Sufficient DR is a major contributing factor for sustainable
operation power system markets [40]. Smart pricing encourages the consumers to manage their loads voluntarily [41]. Thermal, AC and distributed as well utility scale storage comprise a significant portion of responsive demand at residential and utility scale respectively. Demand response is utilized to procure reserve in [42] using a short term stochastic security constrained unit commitment (SCUC) model. Utility must provide the necessary reserve using the available resources in spite of large variations from renewable resources and load demand in the distribution grid. Optimal scheduling of residential appliances and BESS is investigated in [43] and [44] considering operational and planning constraints. The joint influence of price and Co2 signals on DR behavior is presented in [45]. The consumer inconvenience levels are also considered in the proposed model. The 6th Northwest power plan [46] states based on the experience in the region and elsewhere that the achievable technical potential for demand response in the region is around 5 percent of peak load over the 20-year plan horizon. The DR resources in this programs include direct load control for air conditioning, space heat and water heat, irrigation scheduling, aggregators, demand buyback, interruptible contracts and dispatchable generators. The load change in DR can be realized into two categories priced-based demand response and incentive-based demand response [47]. Real time pricing, critical peak pricing and time-of-use tariffs provide customers with time varying rates which reflect the price of electricity in different time periods. Incentive-based demand response programs pay participating customers to reduce their loads at times requested by the program sponsor. The price signal can entail different factors such as cost of reserve procurement, reliability studies, operational planning and load forecast [48]. Time-sensitive pricing lies in the non-dispatchable class of demand response according to the definition in [49]. Experiments performed in [50] and [51] show that large tank heat pump (HPWH) as well as electric resistor water heaters (ERWH) are capable of providing demand response services such
as peak load reduction and ramping rate regulation. ERWH provides more dynamic response and higher magnitude of power flow while HPWH is at least 10% more available than the ERWH in the very short-term response scenario, similar to the peak load reduction and short-term response scenarios. The reported results can be utilized for defining an improved price signal which considers the attitude of consumers in addition to financial incentives. Reliability standards working group ancillary service study [52] performed by General Electric (GE) through Hawaii Natural Energy Institute (HNEI) points out that storage as well as DR should be allowed to provide primary frequency response and spinning reserve. The mentioned DR services are frequency response, regulation, spinning reserves, non-spinning reserves and replacement reserves. Load commitment is addressed in [53] proposing a framework to minimize the household payment. The problem resources are responsive devices, storage and plug-in hybrid vehicle. Since water heater and battery storage have a high impact on overall contribution of a house in DR program, special attention should be paid to optimize this portion of DR. A distributed system wide DR management scheme is presented in [54] to flatten the load curve while minimizing the customer electricity costs. Reliable communication infrastructure within house appliances and utility is necessary for implementing the proposed algorithm. DR scheduling in deregulated environment is presented in [55] where a new market concept called DR Exchange (DRX) is introduced. The different DR types need to be studied in the proposed market structure to comply with existing service requirements. In this chapter, Battery Energy Storage System (BESS) and water heater energy planning is investigated. Scheduling of all units of thermal and battery storage devices according to a desired reference profile in the distribution grid is addressed.
III.2 Dynamic Programming

Dynamic programming is a planning tool which addresses decision making of an agent in a stochastic environment. Each agent finds the best course of actions not only by present environment information but also considering future stages. This tradeoff relieves the problem from myopic attainments among set of interactive actions and presents an efficient sacrifice between immediate and future costs. The mathematical model of dynamic programming is built around finite-discrete-time Markov decision processes. This process is characterized by several elements; states, environment, actions and cost. An agent has a finite set of actions at each state. Taking an action follows a certain cost at discrete times. The history of agent interaction with the environment is summarized in agent’s current state which comprises one of the decision making elements, the other being immediate action cost. The transition probability from state $i$ to state $j$, denoted by $p_{ij}$ solely depends on the current state $i$ and the taken action $u$ which is a Markov property:

$X_k$ : State of the system at time step $k$.

$U_k$ : Action taken at time step $k$.

$U(X_k)$ : Set of allowed actions at state $X_k$.

$N$ : Number of time steps.

$p_{ij}$ : Probability of moving from state $i$ to state $j$.

$\omega_k$ : Noise of the system at time step $k$.

$g(i,u)$ : Immediate cost incurred following taking action $u$ at state $i$. 
\[ p_{ij} = f(i,u) \]  \hspace{1cm} (3-1)

A discrete time dynamic system is defined as:
\[ x_{k+1} = f_k(x_k, u_k, w_k) \]  \hspace{1cm} (3-2)

The state \( x_k \) goes to state \( x_{k+1} \) following action \( u_k \in U(x_k) \) with probability \( \omega_k \in P(x_k, u_k) \).

The class of control laws make up an admissible set of policies \( \pi = \{\mu_0, \ldots, \mu_{N-1}\} \) where \( \mu_k \) maps states \( x_k \) into control laws \( u_k = \mu_k(x_k) \). For every initial conditions \( J_0(1), \ldots, J_0(n) \), the sequence \( J_k(i) \) proceeds backward in time from period \( N-1 \) to period \( 0 \) generated by the iteration:
\[
J_{k+1}(i) = \min_{u_k \in U(i)} \left\{ g(i,u) + \sum_{j=1}^{n} p_{ij}(u) J_k(j) \right\} \]  \hspace{1cm} (3-3)

In other words, \( J_k(i) \) gives the optimal cost starting from state \( i \) of a \( k \) stage problem with cost per stage given by \( g \) and a special cost free termination state. This problem is called stochastic shortest path problem in which the objective is to reach the terminal state with minimum expected cost. Deterministic shortest path problem is a special case where the transition probability is equal to 1 for each state-control pair \( (i,u) \). Therefore if a control action \( u \) is applied at state \( i \), there is a move to state \( j \) with probability 1. The state transition probability will improve by observing the environment behavior over time which includes some sort of learning algorithm. This leaning mechanism tries to drive the problem into deterministic area which in turns leads to more optimum solutions.
### III.3 BESS power flow equation

Battery is used as a storage for transferring energy with grid at different time intervals. Since there is little control on generation of electrical energy from renewable resources, storage is employed to add flexibly for dispatch of electrical power from intermittent resources. Battery energy storage system at utility scale can be utilized for different purposes such peak load shaving, load smoothing, frequency control and voltage stability [56], [57], [58], [59]. Utility scale storage consists of a number of small cells which are connected in an appropriate configuration to generate a given voltage and current. The equation governing the operation of a battery are the same for utility scale and small units and are given by:

\[
E_{t+1} = E_t + P_t \Delta t 
\]  
\[ 
SOC_{t+1} = SOC_t + \frac{P_t \Delta t}{E_{tot}} 
\]

The power flow at each time step is constrained by the nominal power and SOC constraints:

\[ P_{nom} : \text{Nominal power of BESS} \]

\[
P_t < \min \left\{ \frac{(SOC_{max} E_{tot} - E_t)}{\Delta t}, P_{nom} \right\} \]  
\[
P_t > \max \left\{ \frac{(SOC_{min} E_{tot} - E_t)}{\Delta t}, -P_{nom} \right\} \]

### III.4 Water heater model

The water heater is modeled as a single heating element which heats up a nominal mass of water in the tank shown in Fig. 3-1 [60].
The water temperature changes according to the heat applied via the thermal element:

\[ M \cdot S H_w \cdot \frac{dT}{dt} = U A (T_{amb} - T) + Q \]  \hspace{1cm} (3-8)

- \( M \) = Mass of water in the tank (lb)
- \( S H_w \) = Specific heat of water (BTU/lb/°F)
- \( T \) = Temperature of the water in the tank (°F)
- \( t \) = Time (hour)
- \( U A \) = Standby heat loss coefficient times area of the storage tank (BTU/°F/hr)
- \( Q \) = Rate of heat input to tank from the heater (BTU/hr). Zero when the heater is off.

When water is drawn from the outlet, same volume of inlet water with temperature of \( T_{inlet} \) refills the tank and the final temperature is given by
\[ T_{\text{new}} = \frac{T_{\text{curr}} M_{\text{curr}} + T_{\text{inlet}} M_{\text{inlet}}}{M_{\text{curr}} + M_{\text{inlet}}} \]  

(3-9)

### III.5 Storage device optimal control

#### III.5.1 BESS

At each state of SOC in the BESS, several charging and discharging actions with different magnitudes can be taken which will lead to their respective previous states. The cost at each state is the summary of immediate cost and past experience of agent which is calculated by Bellman DP equation (3-3) in which the probabilities are all set to one due to deterministic nature of storage.

![Diagram](image)

Fig. 3-2. Actions and costs at each state

The state propagation is calculated by (3-2) and set of allowable actions at each state is limited by (3-3) and (3-4). The immediate cost \( g(i, u) \), depends on the electricity cost at time \( t \). After the values of all states are calculated for all time stages, the optimal trajectory is found by following the optimal action from the state in the last stage with the minimum cost.
\[ SOC_{opt}(N) = \arg \min J_N(j) \quad j = 1,2,\ldots,n \]  
\[ SOC_{opt}(t-1) = SOC_{opt}(t) + \frac{P_{opt}(t) \Delta t}{E_{tot}} \]  

III.5.2 Water Heater

Water heater is considered a storage device which can absorb excess electrical energy and store it in the form of thermal energy. The energy flow can be optimized to avoid renewable energy curtailment and contribute in alleviating extra loading on expensive generators in the peak time. Almost every customer in the distribution grid is equipped with water heater and thus can provide some flexibility to the grid. The aggregate impact of water heater units consists a significant part of demand response and thus considered an important asset from power system operation standpoint. Water heater is modeled as an agent which operate in accordance with a finite-discrete-time Markovian decision process. Water temperature evolves probabilistically with user hot water draw. Allowable set of actions are turn on and off which do not violate temperature constraints. Electricity use cost is incurred once the agent takes an action. The states, actions and costs are all observed at discrete times. The temperature at each time step has sufficient information for the agent to take an action in the stochastic environment. Therefore, the water heater past experience with the environment is summarized in the current temperature state realizing a Markov property. After laying the mathematical foundation for water heater planning problem acting as an agent, dynamic programming is utilized to provide the optimal sequence of actions in an elegant and principled manner. The value at each state is a probabilistic minimization obtained by (3-3) shown graphically in Fig. 3-3.
The probabilistic nature of state changes arises from stochastic hot water draw. Once all
the state values for all time stages are obtained, the optimal trajectory is found by following the
optimal action at each time step moving backwards. The following equations present the optimal
state at final and other time stages.

\[ T_{opt,N} = \arg\min J_N(j) \quad j = 1, 2, \ldots, n \]  
\[ T_{opt}(t-1) = \sum_{j \in T_{opt}(t)} p(j, u_{opt}(t)) T_{opt}(t) \quad t \neq N \]  

III.5.3 Storage device scheduling

The cost function which is provided by the utility can be decomposed into nodal parts for
each house. The aggregate cost function is built upon a recursive probabilistic formula borrowed
from reliability engineering:

\[ P(X) = (1 - O)P'(X) + O.P'(X - C) \]  

Where
\( \hat{P}(X) \): Cumulative probability of \( X \) kW of water heater capacity in OFF state before a storage is added

\( P(X) \): Cumulative probability of \( X \) kW of water heater capacity in OFF state after a storage is added

\( O \): Probability of storage being in OFF state

The above formula is initialized by setting the following conditions:

\[
P(X) = 1 \text{ for } X \leq 0 \quad (3-15)
\]

\[
P(X) = 0 \text{ Otherwise} \quad (3-16)
\]

The storage in the above equation refer to either water heater or distributed battery storage systems. The table calculated by (3-14) for different values of \( X \) is called Storage Status Probability Table (SSPT). SSPT is similar to Capacity Outage Probability Table (COPT) used in power system reliability studies [61]. An example of SSPT for OFF state probability of 0.1 each is shown in table 1. The cumulative probability of 3 and 4 units in OFF state is .0037.

<table>
<thead>
<tr>
<th>State</th>
<th>WH CAP Working</th>
<th>WH CAP Not Working</th>
<th>Cumulative Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>16</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>12</td>
<td>4</td>
<td>.3439</td>
</tr>
<tr>
<td>2</td>
<td>8</td>
<td>8</td>
<td>.0523</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>12</td>
<td>.0037</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>16</td>
<td>.0001</td>
</tr>
</tbody>
</table>
The status probability of each water heater unit will change according to the given cumulative probability of in-service water heater units. In other words, the utility provides an aggregate probability function for 24 hours ahead. We are looking for the probability of each individual storage unit in OFF state at each time step. The obtained probability function is considered as the cost function for dynamic programming problem. Decomposition of the cost function is easily performed by minimizing the error in the following equation:

\[
O_{i,t} = \arg \min \left\{ \left( R(\text{SSPT}(o_{i,t})) - r_i \right)^2 \right\}
\]

(3-17)

\(O_{i,t}\) and \(o_{i,t}\) denote optimal and initial status of device \(i\) at time step \(t\). The status of each device is optimized to minimize the difference between calculated risk value from SSPT and given risk value \(r_i\) at each time step. The above equation is solved using sequential quadratic programming illustrated by Fig. 3-4:

![Sequential Quadratic Programming](image)

**Fig. 3-4: Cost function decomposition**

The status of each individual storage during 24 hours is considered as cost function for the dynamic programming to plan for its operation in the 24 hours ahead.
III.6 Discussion and results

In this section, application of dynamic programming is investigated on distributed storage and water heater operation planning. Next, scheduling of storage devices is discussed using the cited approaches in previous part. Scheduling of the storage devices is done without considering grid model. It is assumed that distribution grid can handle variations caused by power flow of storage devices.

III.6.4.1 Storage planning results

A 15 kW/30 kWh battery storage is used to provide the optimal power given a cost function. The states span from -15kW to 15kW during 24 hours with time step taken as 15 minutes. The SOC states are between [0.2 0.8] which will help the battery last longer. The cost function is similar to aggregate load curve at the substation point. The cost function is considered rigid but can be updated in receding horizon. The cost function shown in Fig. 3-5 incentivizes the storage to charge at low load times and discharge when the cost is high.

![Cost function for planning battery storage](image)

Fig. 3-5: Cost function for planning battery storage

The optimal and smoothed state trajectory is shown in Fig. 3-6. The smoothed SOC
trajectory $s(x)$ is obtained from minimizing (3-19) given smoothing parameter $p$, the weights $w_i$ and the input data $x$ and $y$:

$s(x)$: Smoothed trajectory

$p$: Smoothing parameter

$w_i$: Smoothing weights

$x$ and $y$: Input data

$$p \sum_i w_i (y_i - s(x))^2 + (1 - p) \int \left( \frac{d^2 s}{dx^2} \right)^2 dx$$  \hspace{1cm} (3-18)

The smoothing parameter and the weights are assumed to be .099 and 1 respectively. The smoothing is performed to reduce the stress on the battery and increase its lifetime. There are two charge and discharge cycles which is caused by two valleys in the cost function. Charging occurs during around 4 to 6 a.m. when the load the cost function has the minimum value. The first discharge starts around 9 a.m. which the first price peak happens. There are small fluctuations on SOC value which stem from the price variations. The second charge starts around 2 p.m. and discharge happens around 7 p.m. when the price is at its peak.
Fig. 3-6. Optimal SOC trajectory

The power flow of the battery obtained from smoothed spline SOC trajectory is shown in bar graph in Fig. 3-7 where it shows the optimal power of battery storage at each time step. The positive and negative values represent charging and discharging of battery respectively.

Fig. 3-7: Optimal power flow of battery storage

The optimal power flow is constrained to -15kW to 15kW which is the nominal power of the battery.

III.6.4.2 Water heater planning

A 5.5 kW, 50 gallon water heater with ignorable loss is considered for dynamic programming planning. The temperature states span from $100^\circ F$ to $140^\circ F$. The ambient temperature is $75^\circ F$ and if cold water fills the tank as soon as hot water is drawn. The hot water draw at each time step is modeled as a Gaussian distribution function with standard deviation of 0.7. These values can changed based on the measurements from each unit and historical data. Forecasting of water draw might help come up with a better water consumption profile.
The water draw profile is considered by which the water heater is turned on 4 time steps during 24 hours. The price, temperature and ON/OFF time steps are shown in Figs. 3-5, 3-9 and 3-10 respectively.
Fig. 3-10. ON/OFF status of water heater

The water heater is turned on during low price and remains OFF while the price is high keeping the temperature in the allowed range.

III.6.4.3 Cost function decomposition results

A given risk function is decomposed into 4 units of risk functions using (3-17). The capacity of the units are with capacities of 5, 7, 10, 14 kW. The risk functions and corresponding optimum trajectories after smoothing are shown in Fig. 3-11 and 3-12 respectively.
Storage 2 and 3 SOC curves overlap in Fig. 3-12. Each storage device is contributing to the overall risk function so that each device in a grid can follow its corresponding optimum trajectory to fulfill the overall risk function provided at the substation. Sum of the battery storage power flow is depicted in Fig. 3-13. This power flow compensates the variations in the aggregate load curve by shifting the energy from the peak time into light load time steps.
The water heater aggregate load is shown in Fig. 3-14 where the load of water heaters overlap due to identical water draw profile and capacity.

III.6.4.4 Price signal sensitivity analysis

In this section, the sensitivity of battery storage SOC trajectory to price signal variation is discussed. In the first example, the price signal comes with slow variations shown in Fig. 3-15. The SOC of battery is sensitive to each local extrema and tries to charge and discharge around the point. The water heater is turned on between 3 and 4 a.m. when the price is in its global minimum. Due to hot water draw in subsequent hours, water heater is turned on around 7 and 8 a.m. to keep the temperature in the allowed range.

The next signal price is similar to the price signal in Fig. 3-15 without the small variations. There is a mild slope from 4 a.m. until around 7 p.m. during which SOC does not change. The charging and discharging happen at the minimum and maximum points around 3 a.m. and 7 p.m. respectively. The water heater ON/OFF times did not change and the ON times occur on the global minimum and later.
In order to investigate the effect of local extrema, a sinewave price function is used in Fig. 3-17. The battery SOC shows a periodic pattern following the sinewave behavior. The water heater turns on at the local minima which has a zero cost. The final temperature at the end of planning horizon is higher than the case in Fig. 3-15 and 3-16.

In the next example in Fig. 3-17 and 3-18, the impact of damping price signal on SOC and water heater performance is analyzed. The battery SOC has the same behavior and changing the magnitude of price signal does not change the power flow of battery. The water heater is also turned on at the local minima where the price signal value is zero.

Fig. 3-15. SOC trajectory for price signal 1
Fig. 3-16: Price signal 2 with two local extrema

Fig. 3-17. Price signal 3 with several extrema
In this chapter, optimal storage device operating points are obtained given a rigid price function using Bellman’s dynamic programming equation. The storage devices considered are battery and water heater. The model of the devices is explained and their optimal operating points are shown and discussed. Moreover, a cost function decomposition approach is introduced to calculate consisting cost functions for each device by which the device will optimize its operation. Finally, dynamic programming algorithm is applied to the storage devices with different signal prices and it is shown that the storage device runs a cycle around each inflection point in the price signal. In the next chapter, implementation of demand response market is discussed in which aggregators sell their available amount of demand response to the utility. Based on the amount of cleared quantity, the aggregator does an optimization to optimally allocate the amount of DR into the signed up houses.
III.8 Summary and Contributions

1 Dynamic programming is used to optimize the operation of water heater and battery storage given a price function. Water heater on/off decision making is done in a stochastic environment where the hot water draw changes probabilistically. In case of battery storage, the optimal power flow at each time step is obtained. The SOC limits are chosen to prolong the life cycle of the battery. In case of water heater, the water heater on/off time steps are determined in order to keep the temperature in the allowed range and also minimize the aggregate cost. The cost function can be the cost of electricity usage or other planning criteria can be also embedded in the price signal.

2 Price function decomposition is done using an approach borrowed from power system reliability study. A given price function is decomposed to several price signals and each storage device operation is optimized based on the obtained price signal.

3 A sensitivity analysis is performed on the price signal to see how the storage devices react to the price signal changes. It is shown that battery storage is sensitive to a change in the convexity of the price signal and charge/discharge cycle is done during convexity change. In the case of water heater, the water heater is turned on the local minima of the price signals. If the amount of hot water draw is little so that the temperature is not changing significantly, the water heater is tuned on only one local minima to increase the temperature to the upper limit.
Chapter IV: A Novel Approach Using Flexible Scheduling and Aggregation to Optimize Demand Response in the Developing Interactive Grid Market Architecture

Abstract

The development of an effective, stable, and economical power grid depends largely upon the system’s ability to maintain the critical balance between generation and demand. With the increasing presence of intermittent renewable energy generation sources, variable control over loads, and energy storage devices on the grid becomes even more important to maintaining this balance. Much work has already been done to come up with more effective ways to implement these control systems. Utilizing an integrated approach that combines consumer requirements into aggregate pools, and provides a dynamic response to market and grid conditions, a mathematical model is developed, which can quantify parameters for optimum demand response. In this model, optimization is achieved as a function of cost vs. comfort.

\( C_i \): Compensation of firm \( i \) in DR market

\( DRA \): Demand response aggregator

\( DRP \): Demand response provider

\( P_i \): Load reduction of \( i \)th DRA

\( D(t) \): Total distribution system demand
CHAPTER 4

\( N \): Total number of committed generating units

\( LR_i \): Load reduction of \( i \) th DRA

\( K(t) \): Total number of DRAs at time step \( t \)

\( \Gamma_i \): Maximum load reduction of \( i \) th DRA

IV.1 Introduction

In the absence of widespread battery storage systems, thermal energy storage has been considered to be a resource already in place, which with little modification or investment, would be able to add far more control to the supply and demand requirements of the active power grid. The control over these decentralized thermal energy storage systems such as domestic water heaters and air conditioning provide grid operators with a powerful tool for the optimization of grid efficiency. Human consumption of thermal energy in the form of hot water for example, comprises 40-60\% of the monthly domestic electricity bill in Hawaii [62], [63]. The energy required for water heating can be stored in the hot water tank for later use by the consumer, making these loads an ideal candidate to stagger throughout the day during off-peak times of grid power demand. The effective control and scheduling of these storage devices in the distribution grid gives operators the ability to more effectively harness the inherently variable power generation from distributed renewable energy sources such as photovoltaic arrays.

In this way the utility gains these services:

- Load leveling: Controllable loads may be shifted to times of off-peak demand or to make use of available renewable energy generation.
- Grid Stability: Dynamically switching loads helps to improve the transient and steady states stability of the grid.

Improvements in IT infrastructure have provided the tools to communicate with and control grid-tied devices in a cheap and reliable way. The utility or the system operator can easily access real-time data about availability of DR resources and with the application of a quick heuristic or algorithm, add or shed loads from the system to achieve the above specified goals.

Demand response can be classified into two general categories, direct load control (DLC) and incentive based control. In the DLC program, utilities have remote access to switch controllable loads such as water heaters and air conditioners. DLC has been implemented successfully in several areas including Hawaii, where Hawaiian Electric has a total of 34,000 DLC customers, collectively providing 15 megawatts of controllable peak demand power [62]. By participating in the program customers receive $3 every month as a bill credit on their electric bill, whether or not an event is triggered.

Incentive based control is implemented by dynamically adjusting the price of energy, ideally as a real-time reflection of the marginal cost of production. The idea is that given this
financial incentive, consumers will adjust their usage [64]. This

Figure 4-1: Aggregate control and local optimization of DR resources in the interactive grid market
is sometimes referred to as “time of use pricing”, where utilities adjust prices during several periods throughout the day [65]. In its simplest form, this involves only two time steps—peak, and off-peak. With the advent of reliable, cheap, and efficient means of communication and monitoring systems, a far greater resolution may be achieved; especially when coupled with real-time cost analysis. Smaller time steps can be used with pricing that reflects actual real-time marginal cost of production more accurately [66]. Distributed equipment connected to the grid that is capable of participating in demand response can be programmed to process received RTP information and react autonomously based on user-defined policies [67]. These smart agents are able to communicate with, and interact with each other [67] to achieve an optimum aggregate response. Multi-agent systems (MAS) have been successfully applied to several power distribution systems [68], [69], [70], and [71]. Smart agents respond to RTP data and act to maximize profit, but RTP is also a direct reflection of grid conditions. Acting in concert to maximize profit, smart agents naturally stabilize grid conditions for optimal efficiency. This concept can also be viewed as power matching [68] which can be especially beneficial in a grid with a large presence of intermittent generation sources.

Fotuhi uses a stochastic model to study DR [69], where reserve resources are scheduled in a way that optimizes the use of DR resources [77], and [78]. Response to specific price signals can be used to schedule switching of home appliances to maximize cost savings [70]. Strategies for price signaling can take into account different factors such as economic, reliability, comfort and security.

We have developed a model to optimize individual storage device control in response to price signals as a function of consumer-defined cost or comfort parameters [71]. In our model, individual device nodes are combined into aggregate microgrid groups [69]; simplifying agent
interaction by adding a layer of abstraction. The autonomy of each aggregate group to optimize its own pooled resources is desirable, especially with the presence of distributed, intermittent, renewable energy generation. Each group first makes most efficient use of local resources, then participates in the larger grid market based on the supply or demand of its pooled resources. Each smart agent involved is in charge of controlling the resources of its own partition aggregate.

We determined that there are two factors each smart agent must maintain for optimum performance. They must simultaneously maximize cost savings for all participants while maintaining the minimum comfort parameters set by consumers. Really, the only control these smart agents have is to switch on and off controllable loads within their pool—thermal, mechanical, or chemical storage—so of course the output of this mathematical model is in terms of change in controllable load. Each smart agent optimizes load switching within its own pool.

In order to quantify optimum parameters based on cost, market analysis was carefully considered. There are several imperfect competition models available to quantify market conditions including: the Cournot, supply function equilibrium (SFE), Bertrand, and monopoly models [72]. The monopoly model was unsuitable for conditions with consumer owned distributed renewable energy generation throughout the grid. The Bertrand model assumes a market that has producers that have identical marginal cost curves. This is ideal for modeling several competing large utilities however, not representative of distributed renewable generation that has widely different marginal cost of production. This leaves us with the Cournot and supply function equilibrium models which have flexibility to account for different marginal costs of production between competing firms on the market. There exists contention as to which model is more effective. The Cournot models costs based on demand while the SFE uses price. Simulations using
both models have been performed and the results of the comparative analysis are shown in the following sections.

With effective means of communication and control, and the ability to process large amounts of data, mathematical models provide a means to quantify and implement grid optimization. We will describe the combination of these methods into an effective strategy for DR.

IV.2 DR Scheduling

Water heating energy use is about 240 to 400 KWH/month which comprises 40% to 60% of the monthly electricity bill in Hawaii [63], [73]. Most demand response comes in the form of remotely switchable loads that have a capacity for energy storage. Tank style water heaters that are able to store thermal energy for later use make up the majority of these loads. Air conditioning can also store thermal energy to a lesser degree within conditioned space at the cost of comfort. There are some systems, which are able to store thermal energy in the form of ice for later use. Battery storage banks are the most direct and obvious form of energy storage. In the cases of datacenter UPS systems and electric vehicles, which are not currently utilized, it is possible to efficiently add these items to our pool of DR resources [76].

Consider an individual storage device such as a water heater. Each device—a heater in this example—may be programmed according to an owners desired parameters of cost and comfort. Comfort in the form of having their hot water heater on at a specific desired time may be sacrificed for a cost savings and vice versa. The owner of each device retains this prerogative of choosing where to set this boundary condition. This condition is represented as a price signal that is broadcast. Utilities simultaneously broadcast their own price signals determined by their marginal cost of production. In our model, groups of devices are controlled by demand response aggregators,
which process these signals to optimize control of each demand response resource within the aggregate pool. Dynamic programming (DP) provides a tool to find the optimal control signal at demand response resources for each time step throughout the day [75]. In an effort to effectively quantify optimization, these price signals are processed by DP and a cost is associated with each DR control signal sent (on/off DR switch signal) and with each state of current DR resources (DR resource on/off state).

Consider the case of a domestic water heater. Volume and timing of hot water draw follow stochastic trends [75]. Determining an appropriate price signal for the device depends on several factors. Current tank temperature must be considered and then weighed against comfort settings. A heater tank with a current temperature below the owner-set comfort level for that time slot will have a high cost associated with switching the unit off. In comparison, a tank that is currently heating water, yet above the temperature threshold for comfort will have a lower cost associated with it. The water heater is just one example of DR resources that can be optimized in a similar fashion using DP. Optimal control signals for battery storage banks, air conditioning, and other types of DR resources can be found using this method. Battery storage is easier to model because the programming state space is completely deterministic. Battery banks are not subject to the same external factors that influence charge state such as water draw in a water heater. Charge/discharge/off control signals coupled with the communication of current state of charge allow complete control over timing of these DR resources [76].

The ultimate goal of DR is to minimize cost by keeping the load curve throughout the day as stable as possible. The total energy use throughout the day must remain the same. In order to estimate the appropriate optimum value for the load value for any given day, historical data is used to give a good approximation of the load curve for that date; possibly load data from the previous
year. For load curves with DR present, the load contribution by DR is subtracted to give us the load curve that would have resulted should there have been no DR. Total area under the load curve for the entire day is found and converted into a rectangle to find the estimated optimum value for the load. We can then use this approximation to estimate the needed DR at any time throughout the day using the following method:

\[ \Delta L(t) : \text{DR contribution to load curve at time } t. \text{ (}\ast \text{ optimum)} \]

\[ L(t) : \text{Distribution system load at time } t. \]

\[ L_{opt} : \text{Estimated optimum value for load.} \]

\[ \Delta L'(t) = \arg \min \left\{ L_{opt} - (\Delta L(t) + L(t)) \right\} \]  \hspace{1cm} (4-1)
Figure 4-2: Example distribution grid with 500 4 kW water heaters connected as scheduled DR resources. Sample load curve data before scheduling retrieved from actual distribution grid load data.

Figure 4-3: Water heater load data from example in Fig. 4-2. Power is shifted from times of peak demand to off-peak times.

The marginal cost of production is related in a non-linear fashion to the needed amount of DR contribution to shift the distribution system load back to the estimated optimum level. That is, there is an additional cost associated with operating the distribution grid at non-optimal load values, where the needed DR is the quantity by which the system deviates from its optimum levels. For example, at a certain value of needed DR contribution, the load may be such that another peak generator must be switched on at that particular point. The marginal cost of production and thus the utility price signal will make a jump at this value. All costs are related to the utility price signal which is in turn related to the required DR for load optimization. Using the Bellman equation, a method is developed for DP to optimize control signals for individual DR resources as follows:

\[ u_{t+1}(i) \]: Optimal control signal at state \( i \) at time step \( t+1 \).
CHAPTER 4

\[ g(i, u) : \text{Cost incurred by applying control signal } u \text{ at state } i. \]

\[ p_{ij}(u) : \text{Probability of moving from state } i \text{ to state } j \text{ after applying } u. \]

\[ J_i(j) : \text{Optimal cost of state } J \text{ at time step } t. \]

\[ u_{t,i}(t) = \arg \min_{u_i \in U(t)} \left\{ g(i, u) + \sum_{j=1}^{n} p_{ij}(u) J_i(j) \right\}, \quad t = 1, \ldots, N \tag{4-2} \]

Control signals to switch DR resources are thus scheduled in a manner that minimizes the total cost. Cost functions are of course related to the amount of DR needed to bring the total system load closer to the estimated optimum value and the comfort settings of the owner of the DR resource itself. If the needed DR is an increase in load, the cost of an off signal may be greater than an on signal and vice versa. Costs are calculated using a combination of the required amount of DR and the comfort settings of the consumer unit. All of the costs can be converted in a same unit using the software such as ESware to calculate the indices such as return on investment and other economic indices. Cost is also affected by the unit's current system state. If the unit in question was a water heater for example, the current tank temperature would be reflected in its price signal. If the tank were below the desired temperature, the cost of an off signal would be high and vice versa.

IV.3 DR Market

IV.3.1 Optimal Power Flow

The standard AC Optimal Power Flow (OPF) equations minimize cost of overall real and reactive power injections by a generator [77]. These optimal values of active and reactive power for each generator are calculated using the methods described by [77]. The cost functions used to
arrive at the optimal active and reactive power generation for each individual generator are constrained by:

- Balance of power generated with power consumed—active and reactive.
- The limit of power flow at each end—to and from—of each supply branch (branch flow limits are calculated using non-linear functions of bus voltage angles and magnitudes).
- The set value for maximum deviation from reference voltage angle.
- The minimum and maximum allowable voltage at each bus.
- Maximum and minimum amount of power generation for each generator.

The minimization problem can be expressed as follows:

\[
P_g : \text{Set of values for active generation at each generator.}
\]

\[
Q_g : \text{Set of values for reactive generation at each generator.}
\]

\[
\Theta : \text{Set of bus voltage angles.}
\]

\[
V_m : \text{Set of voltage magnitudes at each bus.}
\]

\[
f_{P_i} \left(p_{s_i}\right) : \text{Cost function of active power generation for generator } i.
\]

\[
f_{Q_i} \left(q_{s_i}\right) : \text{Cost function of reactive power generation for generator } i.
\]

\[
\text{Min}_{\Theta, V_m, P_g, Q_g} \sum_{i=1}^{n_g} f_{P_i} \left(p_{s_i}\right) + f_{Q_i} \left(q_{s_i}\right)
\]  

(4-3)

From a DR perspective, it is concluded that the total energy of the system is remaining constant. The sum of the power contribution from demand response and contribution from power generators remains the same. What can be adjusted is the amount of contribution from one or the other at any given time period. We define the location marginal price (LMP) as the cost of power at given values of DR and generator contributions. The LMP is proportional to the power draw and therefore inversely proportional to the amount of DR contribution. For any given time period
with its own unique set of values for power draw and available DR resources, OPF is performed at each possible level of DR contribution to obtain an LMP value at each point. Performing, the method of least squares on the output to obtain linear regression, an approximation for inverse demand function is obtained with this set of values.

The calculated inverse demand function in Fig.4-4 becomes:

\[ \pi : \text{Price given per unit of demand response received (}/MWh). \]

\[ \Phi : \text{Offset of inverse demand function.} \]

\[ \xi : \text{Rate of change of price with respect to demand response contribution.} \]

\[ \pi(\Delta L) = \Phi - \xi \Delta L \]  \hspace{1cm} (4-4)

**IV.3.2 Demand response market**

Financial incentive is offered to motivate consumers to actively participate in the management of load distribution through demand response. As mentioned previously, increases in the presence of intermittent renewable energy generation throughout the grid make the ability to
effectively distribute loads throughout the day even more important. The DR market consists of
two entities: Utility who acts as a buyer of demand response, and distribution system consumers
that own demand response capable equipment who act as sellers. The product being purchased and
sold is demand response load. A nice feature of this model is that the exact amount of demand for
the product is known, which is given by equation 1. Each consumer therefore bids a price to sell
their share of the available demand for distribution grid load adjustment in the form of demand
response. The final market price depends on the bids of all participants. A layer of abstraction can
be added by breaking the grid up into microgrids, each controlled by a demand response aggregator
(DRA). The DRA optimizes its own section of the grid and bids on the demand response market
on behalf of its available units. The DRA optimizes its available resources and estimates the market
price to place a bid that will maximize its profit on the demand response market. Several
assumptions are made in developing this model:

- No party has the power to influence the market.
- Residential DRAs have almost the same capacity of DR.
- No single DRA controls a significantly large proportion of the overall DR quantity.

At each time step, each house bids discomfort price with the goal of maximizing its profit
without cooperating with other agents. Utility buys the aggregate amount of load adjustment DR
from DRAs with the lowest bids or the bids within the determined acceptable range in order to
minimize its purchasing costs. Thus an equilibrium point is found and the market share is cleared.
The utility is able to minimize cost of turning on peak generators relative to the amount correction
from non-optimal load values obtained by purchasing demand response. Such interaction between
the entities is modeled in the game theory concept as a non-cooperative game. The market
equilibrium or Nash Equilibrium is obtained in an imperfect competition environment using Cournot and supply function equilibrium models.

IV.3.3 Cournot model for two competing DRA

In the Cournot model, the DRAs are competing with each other independently to sell their share of DR. In determining the cost attached to providing demand response, the DRA may use the quadratic cost function as shown below for approximation. The discomfort cost associated with deploying each individual DR resource unit’s available DR load is determined by the unit’s system state-temperature in the case of a water heater-and the unit’s comfort setting. Using the inverse demand function as a reference point, the maximum price per unit of demand response is \( \pi \) expressed in equation (4-4). Assuming that this is the highest price that available demand response load may be sold for, units set at the maximum comfort setting within the aggregate will take on this value for discomfort cost. Other available units will take on costs relative to their comfort settings and status which will be reflected in the coefficients \( u \) and \( v \) of the quadratic cost function below:

\[
C_i(\Delta L_i) = \frac{1}{2}u_i\Delta L_i^2 + v_i\Delta L_i
\]

In order to find the coefficients of cost function, the aggregator needs to perform an optimization among its customers to come up with an optimal cost curve. Using the method of least squares, it is possible to fit a quadratic equation to the cost curve and determine the coefficients \( u \) and \( v \) for the aggregator. Each customer provides a quadratic cost function with known coefficients to the DRA within its available power (equation 6). The overall cost per unit of DR for every DRA becomes the output of the minimization of the sum of the cost of each
customer’s demand response. Solving equation (4-7) for a given set of DR values produces the optimal cost curve for the aggregator:

$$C(h_i) : \text{The amount the aggregator pays house } i \text{ based on the DR house } i \text{ will provide } (\$/h).$$

$$S_{T_k}^{max} : \text{Nominal power of transformer at lateral distribution branch } K.$$  

$$C(h_i) = \frac{1}{2} u_h \Delta L_{h_i}^2 + v_h \Delta L_{c_i} + w_h$$  

$$C_j(\Delta L_j) = Min \left\{ \sum_{i \in A_k} C(h_i) \right\}$$  

Subject to the following constraints:

$$\Delta L_{h_i, min} \leq \Delta L_{h_i} \leq \Delta L_{h_i, max}$$

$$\sum_{i \in K} \Delta L_{h_i} \leq S_{T_k}^{max}$$

In addition to the above constraints a voltage regulation constraint can be also embedded in the above formulation. This constraint helps to give outputs which control the voltage variation along the distribution system. This is especially important with the presence of large amounts of intermittent renewable energy generation which may follow stochastic trends. Consider the simple radial [80].

$$P_{G_i}, Q_{G_i} : \text{Active and reactive power generated by renewable energy sources at location } i.$$  

$$P_{L_i}, Q_{L_i} : \text{Active and reactive load at location } i.$$
The power flow and voltage equations on the above radial distribution system ignoring line losses are as follows:

\[ P_m : \text{Available power at bus location } m. \]
\[ r_i, x_i, V_i : \text{Resistance, reactance, and voltage at bus } i. \]
\[ N_b : \text{Number of busses in the radial distribution grid.} \]

\[ P_m = \sum_{k=m+1}^{N_b} P_{L_k} - \sum_{k=m+1}^{N_b} P_{G_k} - \sum_{k=m+1}^{N_b} \Delta L_k, \quad m = 0, 1, \ldots, N_b - 1 \]  \hspace{1cm} (4-8) 

\[ V_m^2 = V_{m-1}^2 - 2(r_m P_{m-1} + x_m Q_{m-1}) + \frac{(r_m^2 + x_m^2)(P_{m-1}^2 + Q_{m-1}^2)}{V_{m-1}^2} \quad m = 0, 1, \ldots, N_b - 1 \]  \hspace{1cm} (4-9) 

Starting from \( N = 1 \), it is assumed that service transformer voltage \( V_0 \) is given and \( V_1 \) to \( V_N \) are obtained by successively plugging in the upper voltage value in the above equation. The nonlinear constraint of the optimization problem which addresses the voltage control constraint is given as follows:

\[ \sum_{i} (V_i - 1.0)^2 = 0 \]  \hspace{1cm} (4-10) 

In the Cournot model, each DRA analyzes the availability of its DR resources at each time step,
and bids a quantity of load reduction, $\Delta L_i$. The profit earned by each DRA is the difference between what the utility is willing to offer and the discomfort cost of the DRA:

$\Omega_i : \text{Profit of aggregator } i \, (\text{S/h}).$

$$\Omega_i = \pi(\Delta L)\Delta L_i - C_i(\Delta L_i) \quad (4-11)$$

Taking partial derivative of each DRA with respect to its contribution in demand response load gives the optimal value:

$$\frac{\partial \Omega_i}{\partial \Delta L_i} = \pi(\Delta L) - u_i \Delta L_i - v_i + \Delta L_i \frac{d\pi}{d\Delta L} \frac{d\Delta L}{d\Delta L_i} = 0 \quad i = 0,1,\ldots,m \quad (4-12)$$

Expanding the above equations for $m$ DRAs yields a set of equations:

$$\Phi - \xi \sum_{i \in A_i} \Delta L_i - (u_i + \xi)\Delta L_i - v_i = 0 \quad i = 1,\ldots,m \quad (4-13)$$

The value of DR contribution in load for each DRA is calculated from the above set of equations. Each DRA then optimizes its resources based on the amount of DR it has won on the market.

Thus finding the optimal cost from zero DR up to the maximum available from registered customers in the circuit gives us a list of points for our optimal cost curve. The method of least squares is applied and a quadratic cost function is fit to the points. This determines the cost function coefficients $u$ and $v$ in equation 4-5.

**IV.3.4 Supply function equilibrium**

It has been indicated that the Cournot model may have several limitations. The amount of power produced by each aggregator at Cournot model is very sensitive to the bidding price ($\varepsilon_i$) and small changes in the cost coefficient leads to sharp changes at the amount of demand repose
quantities [72]. Some say that a better model to predict market behavior is the supply function equilibrium model however, this method requires more work because both supply and cost functions must be determined. In contrast to the Cournot model the SFE considers that the amount of DR provided by each aggregator is dependent upon the market price and total DR quantities. Using these values as input, the Nash equilibrium point is reached which is shown by:

\[ \Delta L(\pi) = \sum_a \Delta L_a \]  

(4-14)

The profit for each aggregator is the difference between the revenue from DR sold and the discomfort cost of implementation:

\[ \Omega_i = \pi \Delta L_i - C_i(\Delta L_i) \]  

(4-15)

\[ \Omega_i = \pi \left( \Delta L(\pi) - \sum_{-i} \Delta L_{-i}(\pi) \right) - C_i \left( \Delta L(\pi) - \sum_{-i} \Delta L_{-i}(\pi) \right) \]  

(4-16)

Taking the first derivative of each aggregator’s profit with respect to the price of DR, the aggregator’s contribution to the total DR is calculated as follows [81]:

\[ \Delta L_i(\pi) = \left( \pi - \frac{dC_i(\Delta L_i)}{d\Delta L_i} \right) \left( \frac{d\Delta L}{d\pi} + \sum_{-i} \frac{d\Delta L_{-i}(\pi)}{d\pi} \right) \]  

(4-17)

We express the supply and cost function as affine and quadratic functions [81]:

Supply:

\[ \Delta L_i(\pi) = \beta_i (\pi - \alpha_i) \quad \forall i \in A_b \]  

(4-18)

Cost:

\[ C_i(\Delta L_i) = \frac{1}{2} u_i \Delta L_i^2 + v_i \Delta L_i \quad \forall i \in A_b \]  

(4-19)

Coefficients u and v, for the cost function are determined using the same methods described for the Cournot model in the previous section. Once u and v are known, alpha and beta
in the supply function are calculated. Substituting the demand (equation 4), supply (equation 18) and cost (equation 19) functions into equation 17, then using the methods described by [82], Green’s equation is obtained:

\[ \beta_i = (1 - u_i \beta_i) \left\{ \frac{1}{\xi_i} + \sum_{j \in A_i, j \neq i} \beta_j \right\} \quad \forall i \in A_b \]  

(4-20)

\[ \alpha_i = v_i \quad \forall i \in A_b \]  

(4-21)

The solution starts with \( u_a = 1/\beta_a \) in the first iteration. Each aggregator updates its value of \( \beta_a \) given the values of \( \beta_i \) for the other firms from the previous iteration. The sequence will converge to one non-negative solution. Market price of DR is also calculated in the following manner:

\[ \pi = \frac{\Phi + \xi \sum_{i} \alpha_i}{1 + \xi \sum_{i} \beta_i} \]  

(4-22)

**IV.4 Numerical example And Comparison SFE vs Cournot**

**IV.4.1 Cournot model Results (Two DRAs)**

OPF is performed on bus number 30, IEEE 30 bus test [78, [79]. The LMP for electrical energy at different levels of DR contribution is given shown in Fig. 4-4. The equation for inverse demand function obtained by OPF becomes:

\[ \pi = 4.05 - 0.026 \Delta L \quad \$ / MWh \]  

(4-23)

\( \Delta L_1 = 0.5338 MW \)

\( \Delta L_2 = 0.5883 MW \)
The market price is \( \sim 4 \, \text{$/MWh} \). The aggregator can get a percentage of the overall profit and give the rest to the houses.

**IV.4.2 SFE results (Two DRAs)**

Suppose that DRA1 and DR2 have the following cost functions:

\[
C_1(\Delta L_1) = 3.186\Delta L_1^2 + 0.63\Delta L_1
\]
\[
C_2(\Delta L_2) = 3\Delta L_2^2 + 0.5\Delta L_2
\]

From equation 18, the following values for each aggregator’s DR contribution are calculated:

\[ \Delta L_1 = 0.5338 \text{MW} \]

\[ \Delta L_2 = 0.5883 \text{MW} \]

The market price is \( \sim 4 \, \text{$/MWh} \).

**IV.4.3 Comparison**

The price and obtained amount of DR for each aggregator using Cournot and SFE models are shown in the following figures.
Figure 4-6: Comparison of price using Cournot and SFE.

Figure 4-7: Contribution of DRA 1 in different price elasticities using Cournot and SFE market mechanisms
Suppose aggregator 1 wants to optimize 0.5338 MW of DR from the available resources in the circuit. It can optimize it based on the cost function provided by each house and also the constraints given in relations 7 and 10. Given the following table of coefficients and maximum DR capacity, aggregator comes up with the following contribution of each house or provider (DRP). The constant coefficient is zero for all providers.

![Figure 4-8: Contribution of DRA 2 in different price elasticities using Cournot and SFE market mechanisms](image)

<table>
<thead>
<tr>
<th>DRP number</th>
<th>$u_{h_i}$</th>
<th>$v_{h_i}$</th>
<th>$ub_{h_i}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>58.1</td>
<td>0.63</td>
<td>0.0588</td>
</tr>
<tr>
<td>2</td>
<td>24.4</td>
<td>0.63</td>
<td>0.14</td>
</tr>
<tr>
<td>3</td>
<td>35.88</td>
<td>0.63</td>
<td>0.0952</td>
</tr>
<tr>
<td>4</td>
<td>24.9</td>
<td>0.63</td>
<td>0.1372</td>
</tr>
<tr>
<td>5</td>
<td>35.88</td>
<td>0.63</td>
<td>0.0952</td>
</tr>
</tbody>
</table>
### IV.5 Contributions

A demand response market is proposed in which demand response quantity is traded. Demand response aggregators collect the available amount of DR in the circuit and propose a cost function to the utility. Based on the market clearing structure, market price as well as contribution of each aggregator is determined.

---

<table>
<thead>
<tr>
<th>House</th>
<th>Power (MW)</th>
<th>DR Contribution</th>
<th>Cost Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>45.2</td>
<td>0.63</td>
<td>0.0756</td>
</tr>
<tr>
<td>7</td>
<td>30.5</td>
<td>0.63</td>
<td>0.1120</td>
</tr>
<tr>
<td>8</td>
<td>27.11</td>
<td>0.63</td>
<td>0.1260</td>
</tr>
<tr>
<td>9</td>
<td>34.86</td>
<td>0.63</td>
<td>0.098</td>
</tr>
<tr>
<td>10</td>
<td>25.42</td>
<td>0.63</td>
<td>0.1344</td>
</tr>
</tbody>
</table>

Figure 4-9: Contribution of each house for providing the obtained DRA 1 DR contribution
Cournot and supply function equilibrium market clearing mechanisms are discussed and the obtained results are compared. It is shown that the price and the DR contributions converge to the same value as the elasticity of the price is increasing.

Conclusion

In the first chapter, impact of active and reactive power of BESS on voltage level of distribution system transformer is investigated. Based on the experiments, reactive of BESS does not have a high impact on the voltage level and it is better to use the BESS capacity to regulate the active power flow of the transformer. Voltage of transformer can be easily regulated by changing the tap or injecting reactive power from generators. Based on the capability of BESS software, a smoothing method is designed to remove the power fluctuations at the transformer so theses fluctuations do not put a high burden on the generators. A load flowing algorithm is also developed to correct the active power flow.

In chapter II, two load forecasting methods are developed to predict the overall load of distribution grid for the next day and next twenty minutes. The day ahead load forecasting method is not accurate in midday which might originate from the PV fluctuations. The second method, benefits from previous twenty minute load data and produces better results. The forecasting methods are utilized to develop a power curve smoothing algorithm for removing the load fluctuations caused by PV intermittency. The smoothing algorithm keeps the SOC of battery in a defined range during the smoothing period so that BESS can perform peak shaving later.

In chapter III, dynamic programming is used to find the optimal control signals of storage devices such as battery storage and water heater. Scheduling of the storage devices is performed using two different methods, regular scheduling and cost decomposition. For regular scheduling, storage devices inject (in case of battery) or absorb power to follow a reference curve. Cost
function decomposition is used where a reference risk function is decomposed to contributing cost functions using an optimization algorithm. Sensitivity of control signals to the price signal is investigated and optimal heuristics are found. It is shown that control signals are sensitive to a change in convexity of price signal and a charge/discharge cycle will occur in case of a battery.

In chapter IV, a demand response market is designed in which DR aggregators are selling their load change to the utility. Aggregators can profit from the revenue they get from selling DR quantity and the cost of providing DR which is paid to customers. An inverse demand function is obtained using a continuous optimal power flow at aggregators’ bus. The cost function for each aggregator is obtained by finding the optimal cost for each unit of demand response from the registered providers. Cournot and SFE models are discussed and their results are compared. It is shown that two models produce the same results for high elasticity demand function.
CHAPTER 4

References


CHAPTER 4


CHAPTER 4


CHAPTER 4


