University of Hong Kong

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Final Year Project

A New Pricing Scheme for Controlling Energy Storage Devices in Smart Grid

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Abstract

Improvement of the overall efficiency of energy infrastructure is one of the main anticipated benefits of the deployment of smart grid technology. Advancement in energy storage technology and two-way communication in the electric network are indispensable components to achieve such a vision, while efficient pricing schemes and appropriate storage management are also essential. In this final year project, a universal pricing scheme is proposed which permits one to indirectly control the energy storage devices in the grid to achieve a more desirable aggregate demand profile that meets a particular target of the grid operator such as energy generation cost minimization and carbon emission reduction. Such a pricing scheme can potentially be applied to control the behavior of energy storage devices installed for integration of intermittent renewable energy sources that have permission to grid connection and will have broader applications as an increasing number of novel and low-cost energy storage technologies emerge.

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Symbols

Symbol	**Meaning**
$\mathcal{H} = [1, H]$	Time period
h	Time slot
$\mathcal{N} = \{1, ..., N\}$	Set of users
x_n^h	User n's load during time slot h
$\mathcal{M} = \{1, ..., M\}$	Set of energy storage devices
e_m	Capacity of energy storage device m
a_m	Charge efficiency of energy storage device m
b_m	Discharge efficiency of energy storage device m
s_m^h	Storage profile of m
s_m^{h+}	Charging profile of energy storage device m
s_m^{h-}	Discharging profile of energy storage device m
s_+	Charging volume
s_-	Discharging volume
v_m^h	Energy generation from the renewable energy sources connected with device m at time slot h
$S_m^h = s_m^h - v_m^h$	True energy exchange profile between energy storage device and grid
e_m^0	Initial energy storage at the beginning of $\mathcal{H}$
$\mathcal{S}_m$	Set of valid storage profiles for energy storage device m
$\times$	Cartesian product of vector spaces
$\mathcal{S} = \times_{m \in \mathcal{M}} \mathcal{S}_m$	Cartesian product of valid storage profiles of all energy storage devices in $\mathcal{M}$
l^h	Aggregate demand in the grid at time slot h
$\sum_{h=1}^{H} C^h$	Objective function
p^h	Pricing function
B_m	Amount to be charged from energy storage device m
c	Constant set by grid operators to adjust the ratio of arbitrage benefit to grid benefit

$\tilde{l}^h$	Current aggregate demand profile
$\tilde{s}_m^h$	Current storage profile
$X^h = \sum_{n \in \mathcal{N}} x_n^h$	Total user load profile
$\acute{X}^h$	Prediction for the next day on total user load profile
$\acute{v}_m^h$	Prediction for the next day on renewable energy generation
ε_p	Error of prediction

Dedicated to my parents

Chapter 1

Introduction

This chapter discusses about project background, problem investigated in the project, objectives of the project and project results.

1.1 Project Background

Currently, fossil fuels provide about 80% of world energy supply. As can be seen in Table 1.1, from 1990 to 2008 although energy generation from renewable power and nuclear power kept increasing, the world became more and more dependent on fossil fuels.

Table 1.1: World Energy Consumption

	Energy use (PWh)			
	Fossil	Nuclear	Renewable	Total
1990	83.374	6.113	13.082	102.569
2000	94.493	7.857	15.337	117.687
2008	117.076	8.283	18.492	143.851
Change 2000-2008	22.583	0.426	3.155	26.164

Oil, coal and natural gas are the three major forms of fossil fuel, each of which has a share of more than 20% in the world energy consumption (Fig.1.1). Reserves-to-production (R/P) ratios (the reserve portion of the ratio is the amount of a resource known to exist in an area and to be economically recoverable and the production portion of the ratio is the amount of resource used in one year at the current rate) and distribution of proven reserves of the three main fossil fuels are shown in Fig.1.2, Fig.1.3, Fig.1.4, Fig.1.5, Fig.1.6, Fig.1.7.

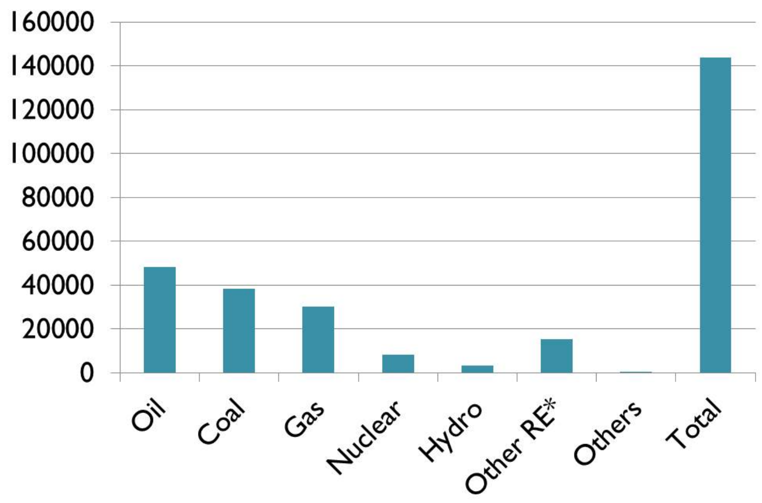

FIGURE 1.1: Energy consumption by power source in 2008.

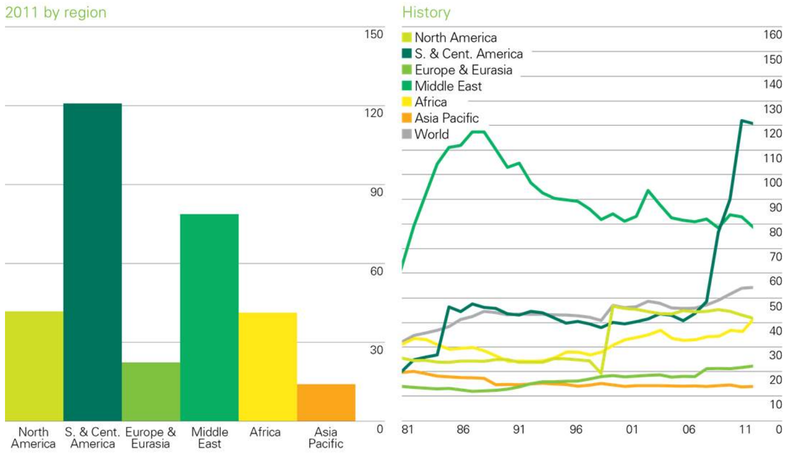

FIGURE 1.2: Oil reserves-to-production (R/P) ratios [24].

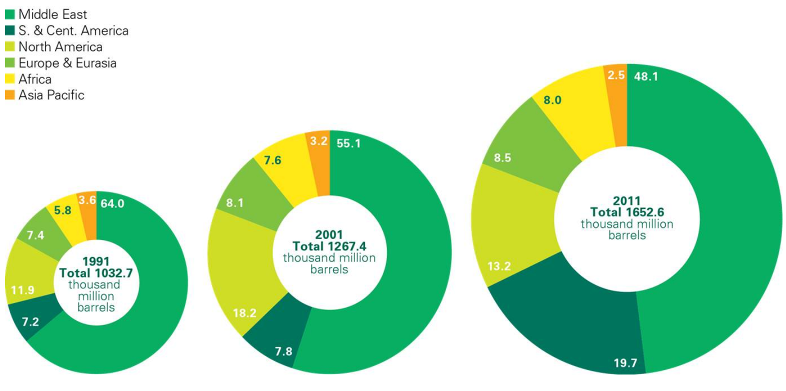

FIGURE 1.3: Distribution of proven oil reserves in 1991, 2001 and 2011 [24].

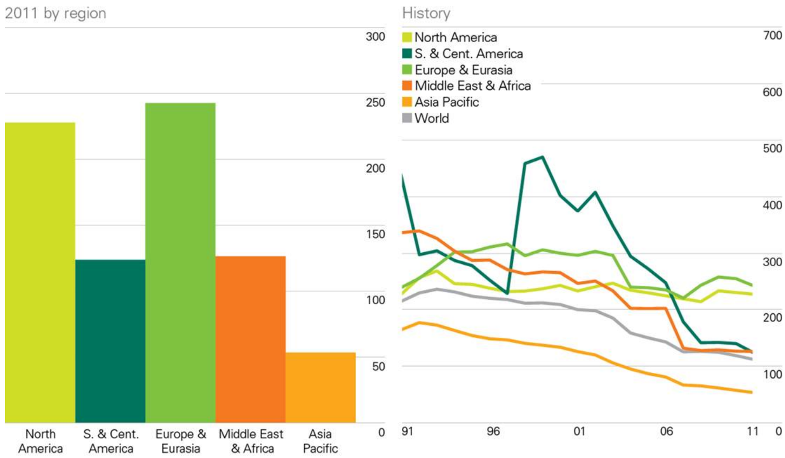

FIGURE 1.4: Coal reserves-to-production (R/P) ratios [24].

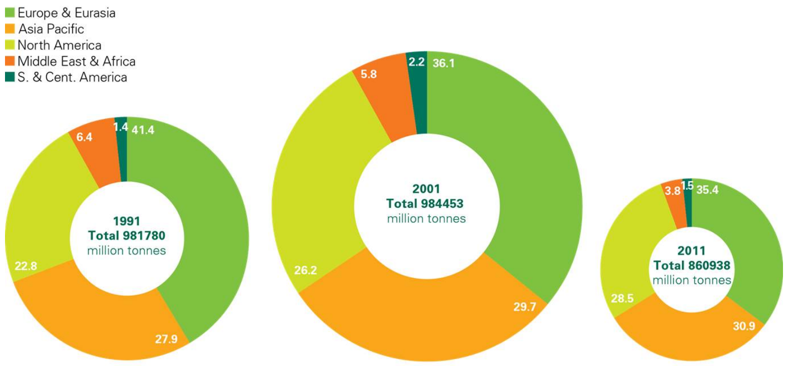

FIGURE 1.5: Distribution of proven coal reserves in 1991, 2001 and 2011 [24].

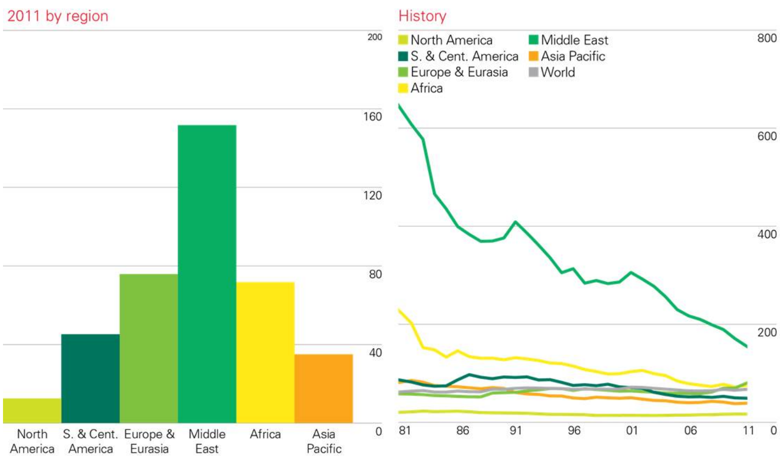

FIGURE 1.6: Natural gas reserves-to-production (R/P) ratios [24].

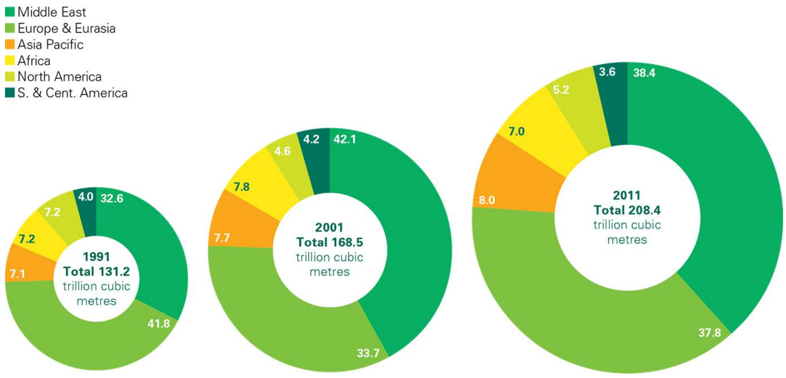

FIGURE 1.7: Distribution of proven natural gas reserves in 1991, 2001 and 2011 [24].

It is estimated that world proven oil reserves at the end of 2011 reached 1652.6 billion barrels, which were sufficient to meet 54.2 years of global production. World proven reserves of coal in 2011 were sufficient to meet 112 years of global production which is the largest R/P ratios for any fossil fuel. For natural gas, world proven reserves at end-2011 could meet 63.6 years of production.

Although current fossil fuel reserves can meet world demand for several decades and new reserves are still being discovered as is shown in the statistical review of world energy, there are still reasons to care about energy efficiency and develop renewable energy at present.

The first issue is that investment in the development of renewable energy has to be made long before all the fossil fuel resources are depleted. Secondly, fossil fuel resources are not evenly distributed. For example, the majority of oil reserves are in Middle East, whose share is more than 48% in 2011. It is of strategic importance for countries which depend largely upon resource imports to fuel their economic growth to develop renewable energy. And fluctuation of resource price (Fig.1.8) can have tremendous negative impact to real economy, which can be alleviated by becoming less dependent on non-renewable resources. Moreover, environmental problems such as air pollution and global warming caused by burning of fossil fuels are getting more and more serious and have aroused increasing public concern.

Energy price volatility, supply uncertainties, and environmental concerns are leading many countries to consider renewable energy to provide affordable energy services that enhance energy security and reliability. China, in its 12th Five-Year Plan for Renewable Energy Development, plans to increase its installed capacity of renewable power from less than 300 GW in 2011 to more than 600 GW by 2020 (Fig.1.9). In 2010, energy from renewable sources was estimated to have contributed 12.4% of gross final energy

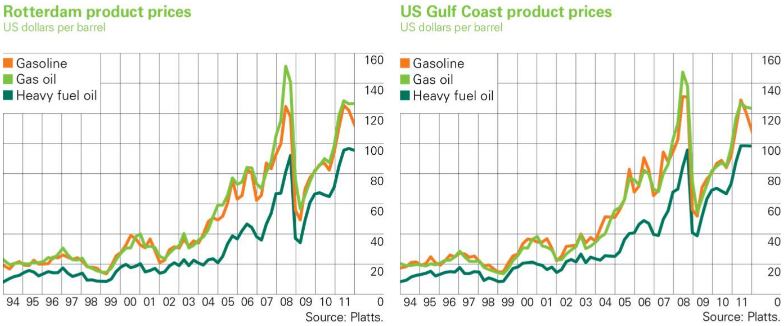

FIGURE 1.8: Rotterdam & Gulf Coast product prices history [24].

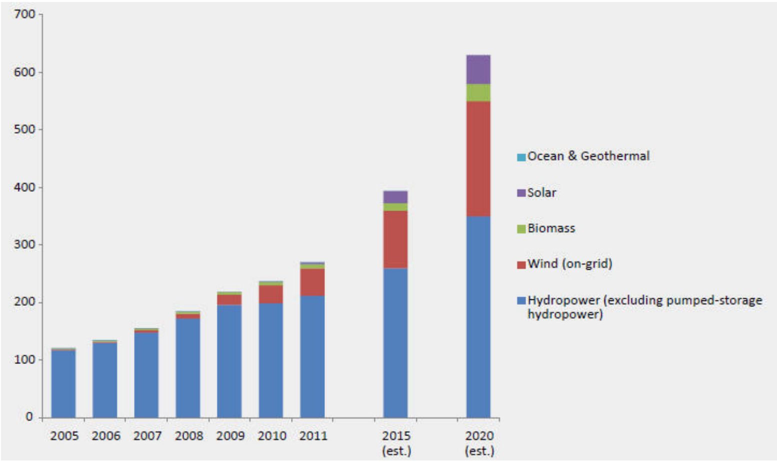

FIGURE 1.9: Installed capacity of renewable power (GW) in China [1].

consumption in the EU27. The 2009 Directive on renewable energy set individual targets for all Member States, such that the EU will reach a 20% share of total energy consumption from renewable sources by 2020 (Fig.1.10).

Therefore renewable energy sources, such as photovoltaic solar systems and wind turbines, will have growing importance in future power generation systems. However, exploitation of renewable energy resources can be problematic as renewable power generation is usually intermittent and variable (Fig.1.11), which could impair power quality and reliability of the whole grid.

Energy storage systems are increasingly being used to help integrate renewable power generation into the grid [10–12, 19, 21]. For instance, some battery energy storage systems are capable of absorbing and delivering both real and reactive power with sub-second response times, which mitigates the adverse effect on system stability due to the introduction of renewable power. And different energy storage technologies—for example, pumped-hydro energy storage, electrochemical energy storage and supercapacitor—can be combined in order to give full play to their own characteristics and advantages

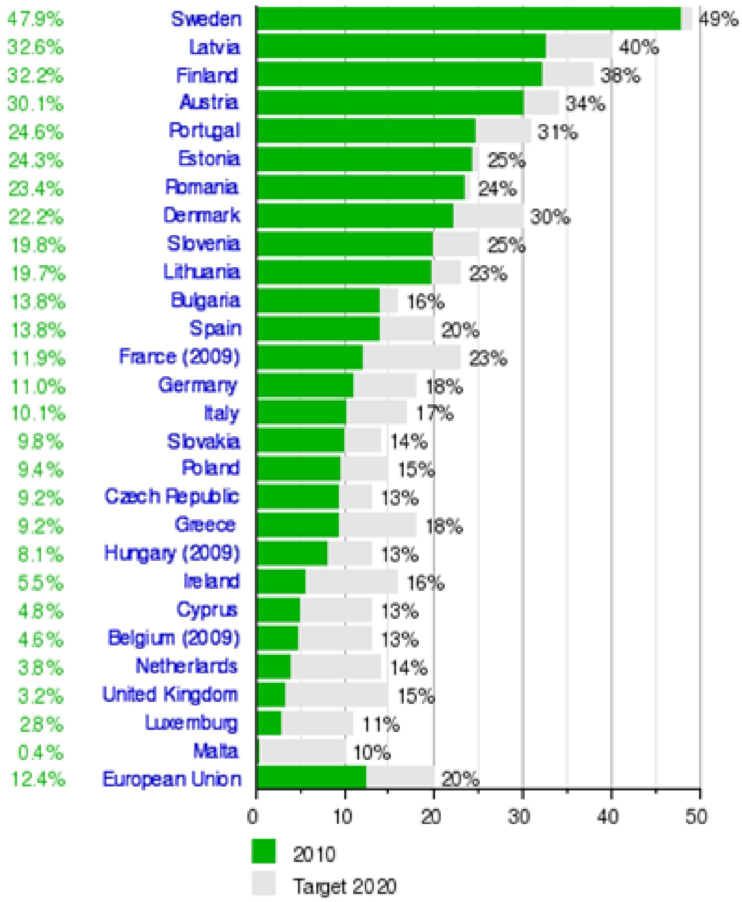

FIGURE 1.10: Share of total energy consumption from renewable sources in European countries [2].

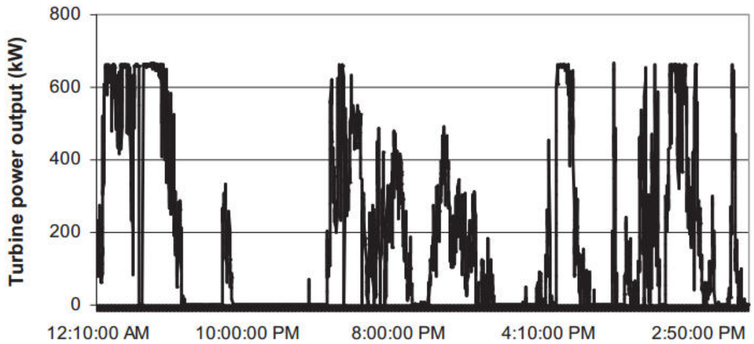

FIGURE 1.11: Real power output of a 650kW wind turbine.

(Table 1.2). Also, energy storage control systems can be integrated with energy markets to make more economical use of energy. The purpose is to lower the peak load, which requires the support of expensive and also carbon intensive peaking power plant generators, so that both carbon emissions and energy generation costs are lowered. The end users will definitely benefit as electricity price decreases.

TABLE 1.2: Advantages and Disadvantages of Ten Energy Storage Technologies

Technology	Advantages	Disadvantages
Flooded Cell Lead-Acid Batteries	Mature and inexpensive; readily available	Short life cycle; low energy density; high maintenance costs
Valve Regulated Lead-Acid Batteries	Lower maintenance costs than traditional flooded cell lead-acid batteries; mature technology	Less reliable and higher costs than traditional flooded cell lead-acid batteries
Lithium Ion Batteries	Higher energy and power density; high efficiency	Relatively early stage technology; special handling requirements; high production cost
Vanadium Redox Batteries	Energy capacity and power can be sized independently; low maintenance; long cycle life	Relatively early stage technology; high cost; low energy density
Flywheels	High power density; high cycle life; quick recharge; independent energy capacity and power sizing	Not applicable for long duration storage applications; high costs
Superconducting Magnetic Energy Storage	High power capacity; high efficiency	Low energy density; large parasitic losses; high production cost
Supercapacitors	High power density; high cycle life; quick recharge	Low energy density; high cost
Compressed Air Energy Storage	Huge energy and power capacity; long lifetime	Geographically limited; requires fuel input; low efficiency
Pumped Hydro	Huge energy and power capacity; long lifetime	Geographically limited; expensive to site and build
Hydrogen Fuel Cells	High energy density; scalable	Low efficiency; parasitic losses

Note, however, that it is still at too early a stage for widespread adoption of small-scale consumer storage devices, even though the potential has been foreseen [6, 13, 14]. And

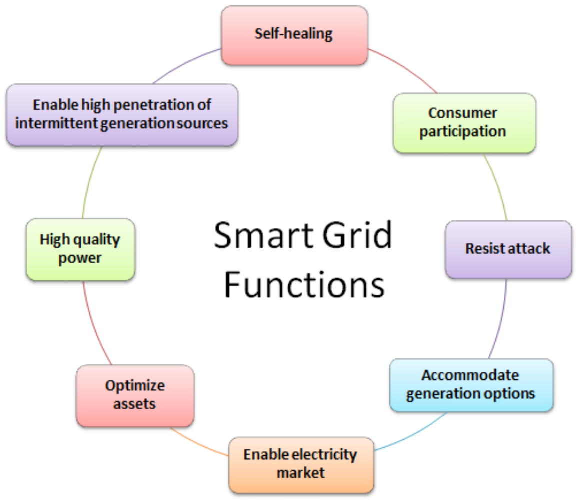

FIGURE 1.12: Some main functions of smart grid.

cost-effectiveness of energy storage as an arbitrage instrument depends on capital costs, operations and maintenance costs as well as price incentives from the grid. In most cases up to now, energy arbitrage as a sole revenue source does not appear to be economically viable. Additional high-value ancillary services such as smoothing the volatile power output and voltage regulation need to be bundled [12, 20] while at the same time, more attractive and efficient pricing schemes have to be provided by the grid [21].

In recent years there has been growing interest in the development of intelligent electricity network technologies, collectively called the smart grid, which meet the needs for future energy provision [3]–[9]. A smarter grid is expected to fully accommodate renewable and traditional energy sources. Moreover, it will make the grid work far more efficiently by applying tools and technologies available now [4] and potentially reducing carbon footprint. Fig.1.12 shows some main functions of smart grid.

One of the most important topics in the areas of smart grid is peak curtailment/leveling based on advancement in energy storage technology and two-way communication in the electric network. Our project mainly focuses on peak curtailment in the future smart grid.

1.2 Problem Investigated

Fig.1.13 shows a typical demand profile in the electricity grid. The daytime load is almost double the night time load. As we can imagine, after the large-scale integration of renewable power generation, the aggregate profile could be even more irregular.

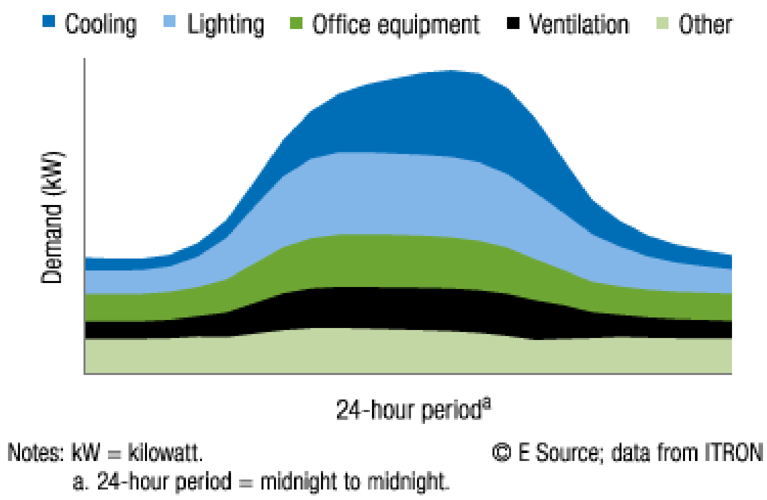

FIGURE 1.13: Electricity demand profile in a 24-hour period.

Peak in demand can bring about many problems. All the facilities in the grid, such as transformers and transmission lines, have their own capacity. At a peak in demand, capacity of facilities could be challenged which possibly endangers the reliability of the grid, and transmission as well as distribution losses are disproportionately high. To meet the peak demand, peaking power plant generators have to be put into use which are usually expensive and also carbon intensive. And occasionally the electricity demand is so high that in order to keep the grid system stability and power quality grid operators have no choice but to cut off the service. Therefore, it is beneficial and necessary to flatten the demand.

1.3 Project Objectives

In this project, we focus on the pricing scheme set by grid owners and operators, which indirectly controls energy storage devices in the grid so that the aggregate demand profile could be flattened and reliability as well as economics and efficiency of the grid is improved. Advancement in energy storage technology and two-way communication in the electric network are necessary preconditions for achieving such a vision.

1.4 Project Results

We propose a new universal pricing scheme for controlling energy storage devices in the grid, which also takes integration of renewable energy into consideration. It guarantees convergence to the optimal aggregate demand profile which minimizes the convex objective function defined by grid operators when user load and renewable energy generation profile keep constant and each energy storage device is operated optimally in terms of income maximization. In the situation where user load and renewable energy generation change from day to day, it can still efficiently reduce the value of the objective function, which means satisfactorily meeting a particular target of grid operators. This pricing scheme can be applied to energy storage devices installed for integration of intermittent renewable energy with permission to grid connection. They are more economically feasible at current stage as they are used for multiple functions. And as an increasing number of novel and low-cost energy storage technologies emerge, which will possibly justify the use of either large-scale or small-scale consumer energy storage as an arbitrage instrument, our pricing scheme will have much broader applications in the future.

Chapter 2

Literature Review

There are many pricing schemes available in the smart grid literature [6, 14]−[18], most of which assume that users or other agents such as energy storage devices in the grid are all self-interested and try to minimize their payment to grid or maximize their income.

2.1 Mohsenian-Rad *et al.*'s Billing Model

Mohsenian-Rad *et al.*'s billing model in [15, 16] assumes that users are charged proportional to their daily energy consumption and total daily charges to the users are proportional to total daily energy generation costs. It is proved that the Nash equilibrium of such a game always exists and is unique. Moreover, the unique Nash equilibrium is the optimal solution of energy cost minimization problem. Algorithm 1 is executed by energy consumption scheduler (ECS) of each user in the grid in order to reach the Nash equilibrium. x_n denotes energy consumption schedules of user n.

This model does not welcome the introduction of energy storage devices since they always increase energy consumption. And shift of load from peak to off-peak periods brings little immediate gains to load shifters themselves although it benefits the grid and other users, which implies share of interest.

2.2 Real-Time Pricing Schemes

In [14], price of electricity at certain time interval depends on aggregate demands in the grid at that time interval. Since aggregate demand profile in the coming day cannot be known in advance, prediction of market prices is needed for demand side management. In [17] a price signal for the next 30 minutes time slot is provided at the current time. In

Algorithm 1 : Executed by each user in the grid.

Randomly initialize daily energy consumption.
repeat
    At random time instances **Do**
        Solve local optimization problem using interior point method.
        if x_n changes compared to current schedule **then**
            Update x_n according to the new solution.
            Broadcast a control message to announce the new schedule to the other ECS units across the system.
        End if
    End
    if a control message is received **then**
        Update the vector containing the scheduled daily energy consumption for all other users accordingly.
    End if
until no unit announces any new schedule.

order to avoid the situation where agents all switch on their electrical appliances which results in a peak in demand when they are signalled a low electricity price, an adaptive mechanism for decentralised demand side management is introduced. First, an agent i gradually adapts its energy consumption profile d^i towards the optimal $d^{i,*}$ as follows: $d^i(t+1) = d^i(t) + \beta^i(d^{i,*} - d^i(t))$ where $\beta^i \in (0,1]$ defines the learning rate (that is, how fast the agent reacts to changing conditions). Second, an agent reoptimises its energy consumption profile on any particular day, with a probability of $\alpha \in (0,1)$.

2.3 Voice *et al.*'s Pricing Scheme

In [6], Voice *et al.* propose that at the end of each day price profile for the coming day based on current loads is announced so that energy storage devices do not need to speculate on future prices in order to optimize their storage profile in terms of income maximization in the coming day. As explicit incentives are provided by the pricing function, a damping term is added to the bill to ensure stability. It is proved that under this pricing scheme with some strictly increasing differentiable pricing function, aggregate demand profile converges to a unique equilibrium. A specific example of the pricing scheme is also provided with pricing functions designed to recover supplier costs. The behavior of energy storage devices in the grid under this model is more predictable and controllable for the grid operator. Our pricing scheme adopts the same mechanism but we mainly focus on the optimality and efficiency of the pricing scheme in terms of meeting objectives of the grid.

Chapter 3

Model Description

This chapter describes the model used. Consider a smart power system which contains several users and energy storage devices. We are interested in the storage management during the time period $\mathcal{H} = [1, H]$. Without loss of generality, we can assume that time granularity is one hour and $H = 24$.

3.1 User

Let $\mathcal{N} = \{1, ..., N\}$ denote the set of users and let x_n^h denote user n's load during time slot h. Our pricing scheme is only applied to energy storage devices that have permission to grid connection. Users can be charged according to other simpler pricing scheme such as flat pricing or peak load pricing and control of their load profile is not discussed in this project.

3.2 Energy Storage Device

Let $\mathcal{M} = \{1, ..., M\}$ denote the set of energy storage devices. Assume that they are all self-interested and try to minimize their own payment or maximize the income. Each energy storage device m has a capacity of e_m, charge efficiency of $a_m < 1$ and discharge efficiency of $b_m < 1$. If q amount of energy is consumed to charge the device, only $a_m q$ can be stored. Similarly, if q amount of energy is stored, only $b_m q$ can be discharged. Let s_m^h denote the storage profile of m. We have $s_m^h = s_m^{h+} - s_m^{h-}$, $s_m^{h+} \cdot s_m^{h-} = 0$, $\forall h \in \mathcal{H}$, where s_m^{h+} is the charging profile and s_m^{h-}, the discharging profile. $0 \leq s_m^{h+} \leq s_+$, $0 \leq s_m^{h-} \leq s_-$, $\forall h \in \mathcal{H}$, where s_- is the discharging volume and s_+ is the charging volume of the device for one time interval. Let v_m^h denote possible energy generation from the renewable energy sources connected with device m at time slot h. Renewable energy can be stored into energy storage devices for a later sale or sold to the grid directly. Assume that energy storage in each device at the end of each day comes back to the same level as the beginning of the day, $a_m b_m \sum_{h=1}^{H} s_m^{h+} = \sum_{h=1}^{H} s_m^{h-}$. Apparently $\sum_{h=1}^{H} s_m^h \geq 0$. Moreover, energy that can be stored or discharged at time slot h satisfies $s_m^{h-}/b_m \leq e_m^0 + \sum_{j=1}^{h-1}(a_m s_m^{j+} - s_m^{j-}/b_m)$, $a_m s_m^{h+} \leq e_m - e_m^0 - \sum_{j=1}^{h-1}(a_m s_m^{j+} - s_m^{j-}/b_m)$, $\forall h \in \mathcal{H}$, where e_m^0 is the initial energy storage at the beginning of $\mathcal{H}$. Let $\mathcal{S}_m$ represent the set of valid storage profiles for m, and set $\mathcal{S} = \times_{m \in \mathcal{M}} \mathcal{S}_m$ where $\times$ denotes the Cartesian product of vector spaces. The true energy exchange profile between energy storage device and grid is $S_m^h = s_m^h - v_m^h$.

3.3 Grid Operator

Let l^h denote the aggregate demand in the grid at time slot h and by definition $l^h = \sum_{m \in \mathcal{M}} S_m^h + \sum_{n \in \mathcal{N}} x_n^h$, $\forall h \in \mathcal{H}$. Grid operators usually have particular targets for aggregate demand profile. One common design objective in a power distribution system is energy generation cost minimization: $\underset{s \in \mathcal{S}}{\textbf{minimize}} \sum_{h=1}^{H} C^h(l^h)$. Cost function C^h is assumed to be strictly increasing and convex. Usually, we have $C^h(L) = a_k L^2 + b_k L + c_k$, where $a_k > 0$ and $b_k, c_k \geq 0$ are predetermined parameters. According to the target and corresponding objective function, grid operators can adjust pricing scheme to steer energy storage devices in the grid.

Chapter 4

Pricing Scheme

Our work in this project mainly focuses on finding the most efficient pricing scheme, under which value of the convex objective function defined by grip operator is minimized when each energy storage device strives to maximize their income.

Assume that the grid operator announces the pricing scheme for the next day at the end of each day. Under this assumption, energy storage devices do not need to make predictions on future market prices in order to optimize their storage profile. And they are allowed to sell electricity to the grid at the same price as the grid sells electricity according to the pricing scheme announced.

4.1 Constant User Load Profile and Renewable Energy Generation

We first consider a situation where the user load profile is constant (user load profile may vary little from day to day if there is no sudden weather change taking place or other events which may change user behavior significantly) and so is the renewable power generation. Define a pricing function p^h indicating the price for electricity at time slot $h \in \mathcal{H}$ set by the grid operator. Consider the situation where the grid operator announces the price p^h for each h of the coming day. As energy storage devices in the grid all react to the same price signals in the way that their income is maximized, the aggregate behavior can be unstable. Fig.4.1 shows the evolution of objective function value after such price signals are given. The system becomes extremely unstable and the objective function value oscillates at a higher level after application of the pricing scheme, which implies that the objectives of grip operator have not been met.

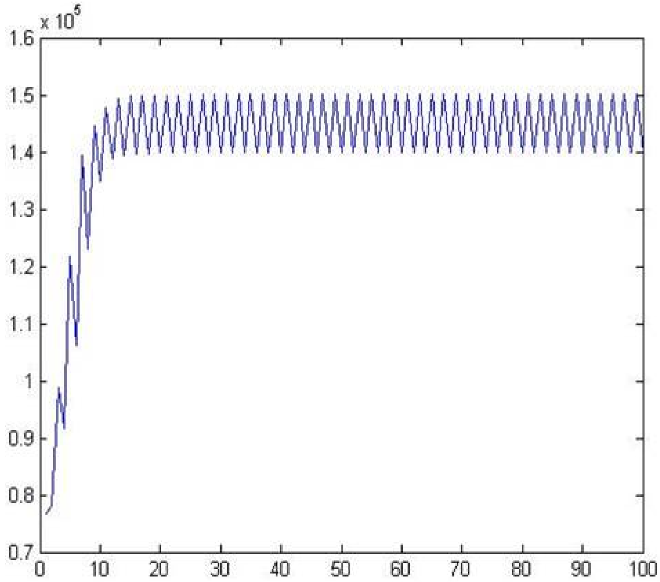

FIGURE 4.1: Evolution of objective function value after price signals are given.

In [6], Voice *et al.* propose a pricing mechanism which introduces a damping term to guarantee stability. That is, each energy storage device $m \in \mathcal{M}$ is charged an additional fee of $\sum_{h=1}^{H} \mathcal{K}(s_m^h - \tilde{s}_m^h)^2$, where $\tilde{s}_m^h$ is the storage profile of the day before and $\mathcal{K} > 0$. We employ the same mechanism in our pricing scheme when the objective function takes the form of $\sum_{h=1}^{H} C^h(l^h) = \sum_{h=1}^{H}(a_k {l^h}^2 + b_k l^h + c_k)$, where $a_k > 0$ and $b_k, c_k \geq 0$. For each energy storage device $m \in \mathcal{M}$, let B_m denote the amount to be charged for $\mathcal{H}$. If $B_m < 0$, device m earns revenue through the daily operation. At the beginning of each day, every device m makes optimal decision on its storage profile which yields to all the constraints mentioned before using convex optimization methods so that the aggregate income in the coming day is maximized.

We propose that at the end of each day, pricing scheme for the next day is announced and

$$B_m = \sum_{h=1}^{H} S_m^h p^h + \mathcal{K}(s_m^h - \tilde{s}_m^h)^2 \tag{4.1}$$

where B_m is the amount to be charged in the coming day, $p^h/(2a_k\tilde{l}^h + b_k) = \mathcal{K}/a_k M = c > 0$, c is a constant set by grid operators to adjust the ratio of arbitrage benefit to grid benefit and has no influence on storage profile, a_k, b_k come from the objective function $\sum_{h=1}^{H} C^h(l^h) = \sum_{h=1}^{H}(a_k {l^h}^2 + b_k l^h + c_k)$, M is the total number of energy storage devices, and $\tilde{l}^h$ is the aggregate demand profile in the day before.

We first show that with such a pricing scheme, the objective function is non-increasing from day to day if all the energy storage devices are operated optimally in terms of income maximization.

Theorem 4.1. *Given objective function* $\sum_{h=1}^{H} C^h(l^h) = \sum_{h=1}^{H}(a_k {l^h}^2 + b_k l^h + c_k)$ *where* $a_k > 0$ *and* $b_k, c_k \geq 0$, *the objective function is non-increasing if pricing scheme (4.1) is applied and each energy storage device* $m \in \mathcal{M}$ *adopts the following optimal storage profile* $s_m = \underset{s_m \in \mathcal{S}_m}{\arg\min} B_m$.

Proof. If device m does not change its storage profile in the coming day, $B_m(\tilde{s}_m) = \sum_{h=1}^{H} p^h(\tilde{s}_m^h - v_m^h)$, where $\tilde{s}_m$ is the storage profile of m in the day before.

Assume that the new storage profile $s_m = \tilde{s}_m + \Delta s_m$ is adopted. If device m is operated optimally in terms of income maximization, Δs_m will at least keep B_m the same or possibly decrease B_m.

$$B_m(\tilde{s}_m + \Delta s_m) = \sum_{h=1}^{H} p^h(\tilde{s}_m^h + \Delta s_m^h - v_m^h) + \mathcal{K}\sum_{h=1}^{H} {\Delta s_m^h}^2$$

$$B_m(\tilde{s}_m + \Delta s_m) - B_m(\tilde{s}_m) = \sum_{h=1}^{H} p^h \Delta s_m^h + \mathcal{K}\sum_{h=1}^{H} {\Delta s_m^h}^2 \leq 0$$

$$\sum_{m\in\mathcal{M}} (\sum_{h=1}^{H} p^h \Delta s_m^h + \mathcal{K}\sum_{h=1}^{H} {\Delta s_m^h}^2) \leq 0$$

By definition $l^h = \sum_{m\in\mathcal{M}}(s_m^h - v_m^h) + \sum_{n\in\mathcal{N}} x_n^h$ and $\Delta l^h = \sum_{m\in\mathcal{M}} \Delta s_m^h$,

$$\Delta {l^h}^2 \leq M \sum_{m\in\mathcal{M}} {\Delta s_m^h}^2$$

where M is the total number of energy storage devices, which implies

$$\sum_{h=1}^{H} p^h \Delta l^h + \frac{\mathcal{K}}{M}\sum_{h=1}^{H} \Delta {l^h}^2$$

$$\leq \sum_{h=1}^{H} p^h \sum_{m\in\mathcal{M}} \Delta s_m^h + \mathcal{K}\sum_{h=1}^{H}\sum_{m\in\mathcal{M}} {\Delta s_m^h}^2 \leq 0$$

We have $p^h = \frac{\mathcal{K}(2a_k\tilde{l}^h + b_k)}{a_k M}$, then

$$\sum_{h=1}^{H} \frac{\mathcal{K}(2a_k\tilde{l}^h + b_k)}{a_k M}\Delta l^h + \frac{\mathcal{K}}{M}\sum_{h=1}^{H} \Delta {l^h}^2 \leq 0$$

$$\sum_{h=1}^{H}(2a_k\tilde{l}^h + b_k)\Delta l^h + a_k\sum_{h=1}^{H} \Delta {l^h}^2 \leq 0$$

$$\sum_{h=1}^{H} C^h(\tilde{l}^h + \Delta l^h) - C^h(\tilde{l}^h)$$

$$= \sum_{h=1}^{H} 2a_k \tilde{l}^h \Delta l^h + a_k {\Delta l^h}^2 + b_k \Delta l^h \leq 0$$

where $\tilde{l}^h + \Delta l^h$ is aggregate demand profile in the coming day and the value of the objective function is reduced or kept the same with the new profile. $\square$

It is reasonable to expect that $l^h > 0,\ \forall h \in \mathcal{H}$ and $C^h(l^h) > 0$. Therefore, $\sum_{h=1}^{H} C^h(l^h)$ is lower bounded. Since it is non-increasing from day to day, we may conclude that the objective function and storage profile of each device $m \in \mathcal{M}$ will all converge to an equilibrium.

The optimal storage profile solution to the objective function minimization problem and the minimum objective function value can be achieved in a centralized manner with convex optimization algorithm such as Interior Point Method with all the parameter known. We then prove that under our pricing scheme, the objective function will converge to the minimum value calculated centrally.

Theorem 4.2. *Given objective function* $\sum_{h=1}^{H} C^h(l^h) = \sum_{h=1}^{H}(a_k {l^h}^2 + b_k l^h + c_k)$ *where* $a_k > 0$ *and* $b_k, c_k \geq 0$*, the objective function converges to* $\min\limits_{s \in \mathcal{S}} \sum_{h=1}^{H} C^h(l^h)$ *if pricing scheme (4.1) is applied and each energy storage device* $m \in \mathcal{M}$ *adopts the following optimal storage profile* $s_m = \arg\min\limits_{s_m \in \mathcal{S}_m} B_m$.

Proof. Assume that $\tilde{l}^h$ is the current aggregate demand profile, $l^{h\prime}$ the optimal aggregate demand profile, which minimizes the objective function and ${s_m^h}'$ the corresponding storage profile of each device m when optimal aggregate demand profile is achieved.

$$\sum_{h=1}^{H} C^h(l^{h\prime}) - C^h(\tilde{l}^h) = \epsilon < 0$$

Let $\lambda^h = l^{h\prime} - \tilde{l}^h = \sum_{m \in \mathcal{M}}({s_m^h}' - \tilde{s}_m^h)$

$$\sum_{h=1}^{H} 2a_k \tilde{l}^h \lambda^h + a_k {\lambda^h}^2 + b_k \lambda^h = \epsilon$$

$$\sum_{h=1}^{H} p^h \lambda^h + \frac{\mathcal{K}}{M} {\lambda^h}^2 = \epsilon \frac{\mathcal{K}}{a_k M}$$

$$\sum_{h=1}^{H} p^h \lambda^h \leq \epsilon \frac{\mathcal{K}}{a_k M}$$

Therefore, $\exists m$ such that $\sum_{h=1}^{H} p^h \Delta \check{s}_m^h = \epsilon' < 0$, where $\Delta \check{s}_m^h = {s_m^h}' - \tilde{s}_m^h$.

Let $\Delta \hat{s}_m^h$ denote the valid Δs_m^h which minimizes $\sum_{h=1}^{H} p^h \Delta s_m^h + \mathcal{K} \sum_{h=1}^{H} {\Delta s_m^h}^2$. As storage profile converges, for all $\varepsilon > 0$ there exists a day such that the absolute value of $\Delta \hat{s}_m^h$ after this day is smaller than ε.

$$|\sum_{h=1}^{H} p^h \Delta \hat{s}_m^h + \mathcal{K} \sum_{h=1}^{H} {\Delta \hat{s}_m^h}^2| \leq \sum_{h=1}^{H} |p^h| \varepsilon + \mathcal{K} H \varepsilon^2$$

Thus,

$$\min(\sum_{h=1}^{H} p^h \Delta s_m^h + \mathcal{K} \sum_{h=1}^{H} {\Delta s_m^h}^2) = \sum_{h=1}^{H} p^h \Delta \hat{s}_m^h$$

$$+\mathcal{K} \sum_{h=1}^{H} {\Delta \hat{s}_m^h}^2 \geq -\sum_{h=1}^{H} |p^h| \varepsilon - \mathcal{K} H \varepsilon^2$$

For each $m \in \mathcal{M}$, which satisfies $\sum_{h=1}^{H} p^h \Delta \check{s}_m^h = \epsilon' < 0$, $\exists \alpha_0 = -\frac{\epsilon'}{\mathcal{K} \sum_{h=1}^{H} {\Delta \check{s}_m^h}^2} > 0$ such that $\sum_{h=1}^{H} p^h \Delta \check{s}_m^h + \mathcal{K} \alpha_0 \sum_{h=1}^{H} {\Delta \check{s}_m^h}^2 = 0$. If $\alpha_0 \geq 1$, let $\Delta s_m^h = 0.5 \Delta \check{s}_m^h$ so that Δs_m^h is surely valid. $\sum_{h=1}^{H} p^h \Delta s_m^h + \mathcal{K} \sum_{h=1}^{H} {\Delta s_m^h}^2 = (0.25 - 0.5\alpha_0) \mathcal{K} \sum_{h=1}^{H} {\Delta \check{s}_m^h}^2$. Or if $\alpha_0 < 1$, let $\Delta s_m^h = 0.5 \alpha_0 \Delta \check{s}_m^h$, $\sum_{h=1}^{H} p^h \Delta s_m^h + \mathcal{K} \sum_{h=1}^{H} {\Delta s_m^h}^2 = -\frac{\alpha_0^2}{4} \mathcal{K} \sum_{h=1}^{H} {\Delta \check{s}_m^h}^2$. Thus, $\min(\sum_{h=1}^{H} p^h \Delta s_m^h + \mathcal{K} \sum_{h=1}^{H} {\Delta s_m^h}^2) \leq \begin{cases} -\frac{\alpha_0^2}{4} \mathcal{K} \sum_{h=1}^{H} {\Delta \check{s}_m^h}^2 & : \quad 0 < \alpha_0 < 1; \\ (0.25 - 0.5\alpha_0) \mathcal{K} \sum_{h=1}^{H} {\Delta \check{s}_m^h}^2 & : \quad \alpha_0 \geq 1. \end{cases}$

As a result, $\sum_{h=1}^{H} |p^h| \varepsilon + \mathcal{K} H \varepsilon^2 \geq \begin{cases} \frac{\alpha_0^2}{4} \mathcal{K} \sum_{h=1}^{H} {\Delta \check{s}_m^h}^2 & : \quad 0 < \alpha_0 < 1; \\ (-0.25 + 0.5\alpha_0) \mathcal{K} \sum_{h=1}^{H} {\Delta \check{s}_m^h}^2 & : \quad \alpha_0 \geq 1. \end{cases}$
If $\alpha_0 \to 0$, then $\epsilon' \to 0$ for each $m \in \mathcal{M}$ satisfying $\sum_{h=1}^{H} p^h \Delta \check{s}_m^h = \epsilon' < 0$ since $0 \leq \mathcal{K} \sum_{h=1}^{H} {\Delta \check{s}_m^h}^2 < \mathcal{K} H (s_+^2 + s_-^2)$. Otherwise, $\Delta \check{s}_m^h$ converges to 0 and so is ϵ' for each $m \in \mathcal{M}$ satisfying $\sum_{h=1}^{H} p^h \Delta \check{s}_m^h = \epsilon' < 0$. Since $\sum_{h=1}^{H} \sum_{m \in \mathcal{M}} p^h \Delta \check{s}_m^h = \sum_{h=1}^{H} p^h \lambda^h \leq \epsilon \frac{\mathcal{K}}{a_k M} < 0$, ϵ converges to 0. $\square$

The pricing scheme can be further generalized for other convex objective functions. For grid operators, they may first approximate their own convex objective function by using a finite number of terms. For example, the function

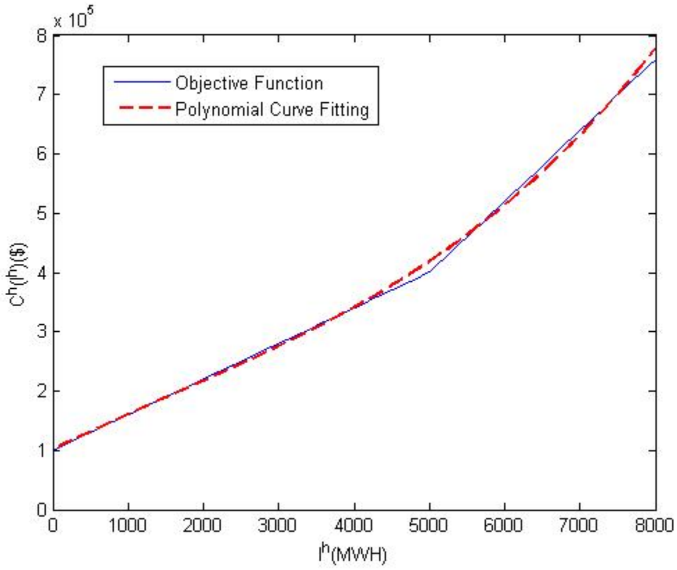

FIGURE 4.2: Objective function and corresponding polynomial curve fitting.

$C^h(l^h) = \begin{cases} 1 \times 10^5 + 60l^h & : \quad 0 < l^h < 5000 \ ; \\ 4 \times 10^5 + 120l^h & : \quad 5000 \leq l^h < 8000 \end{cases}$ shown in Figure 4.2 can be approximated as $C^h(l^h) \approx 8.7264 \times 10^{-7} {l^h}^3 - 0.0043 {l^h}^2 + 63.4167 l^h + 1.0101 \times 10^5$, $0 < l^h < 8000$ by polynomial curve fitting.

Then, more generally, $\sum_{h=1}^{H} C^h(\tilde{l}^h + \Delta l^h) - C^h(\tilde{l}^h)$ takes the form of $\sum_{h=1}^{H} A_1^h \Delta l^h + A_2^h {\Delta l^h}^2 + A_3^h {\Delta l^h}^3 + A_4^h {\Delta l^h}^4 + \cdots$.

$$\sum_{h=1}^{H} C^h(\tilde{l}^h + \Delta l^h) - C^h(\tilde{l}^h) \leq \sum_{h=1}^{H} A_1^h \Delta l^h + A_2^h P_2(A_2^h, \Delta l^h)$$

$$+ A_3^h Q_3(A_3^h, \Delta l^h) + A_4^h P_4(A_4^h, \Delta l^h) + \cdots$$

where

$$P_n(A_n^h, L) = \begin{cases} L^n & : \quad A_n^h \geq 0 \ ; \\ 0 & : \quad A_n^h < 0 \ . \end{cases} \quad n > 0, \ n \text{ is even,}$$

$$Q_n(A_n^h, L) = \begin{cases} 0 & : \quad L < 0, A_n^h \geq 0 \ ; \\ L^n & : \quad L \geq 0, A_n^h \geq 0 \ ; \\ 0 & : \quad L \geq 0, A_n^h < 0 \ ; \\ L^n & : \quad L < 0, A_n^h < 0 \ . \end{cases} \quad n > 1, \ n \text{ is odd.}$$

Figure 4.3 shows some examples of $P_n(A_n^h, L)$ and $Q_n(A_n^h, L)$ with comparison to L^n. Note that $A_n^h P_n(A_n^h, L)$ and $A_n^h Q_n(A_n^h, L)$ are all convex.

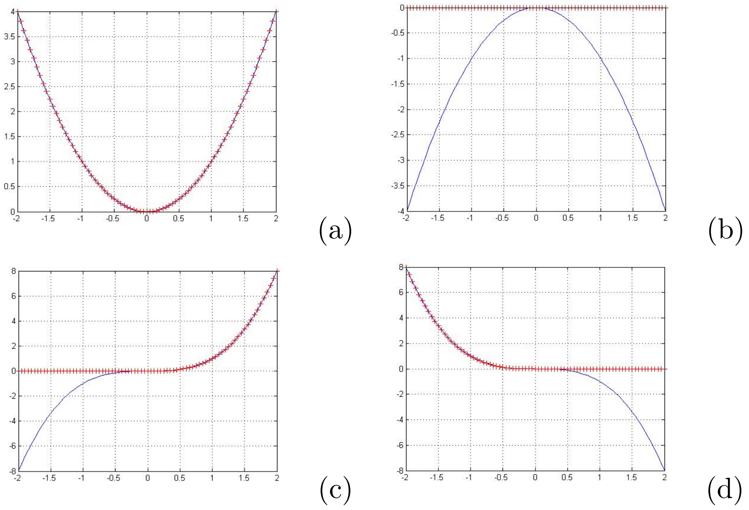

FIGURE 4.3: $P_n(A_n^h, L)$ and $Q_n(A_n^h, L)$ compared with L^n: a) $P_2(A_2^h, L)$ and L^2 where $A_2^h \geq 0$. b) $-P_2(A_2^h, L)$ and $-L^2$ where $A_2^h < 0$. c) $Q_3(A_3^h, L)$ and L^3 where $A_3^h \geq 0$. d) $-Q_3(A_3^h, L)$ and $-L^3$ where $A_3^h < 0$.

The universal pricing scheme should be:

$$B_m = \sum_{h=1}^{H} S_m^h p^h + \mathcal{K}_1^h P_2(A_2^h, s_m^h - \tilde{s}_m^h) + \mathcal{K}_2^h Q_3(A_3^h, s_m^h - \tilde{s}_m^h)$$

$$+ \mathcal{K}_3^h P_4(A_4^h, s_m^h - \tilde{s}_m^h) + \cdots \tag{4.2}$$

where $p^h/A_1^h = \mathcal{K}_1^h/A_2^h M = \mathcal{K}_2^h/A_3^h M^2 = \mathcal{K}_3^h/A_4^h M^3 = \cdots = \mathcal{K}_n^h/A_{n+1}^h M^n = c > 0$, M is the total number of energy storage devices in the grid. Constant c is set by grid operators to adjust the ratio of arbitrage benefit to grid benefit and has no influence on storage profile.

We then prove that with such a pricing scheme, the convex objective function is non-increasing from day to day if all the energy storage devices are operated optimally in terms of income maximization.

Theorem 4.3. *Given convex objective function $\sum_{h=1}^{H} C^h(l^h)$, the objective function is non-increasing if pricing scheme (4.2) is applied and each energy storage device $m \in \mathcal{M}$ adopts the following optimal storage profile $s_m = \underset{s_m \in \mathcal{S}_m}{\arg\min} B_m$.*

Proof. Assume new storage profile $s_m = \tilde{s}_m + \Delta s_m$ is adopted, where $\tilde{s}_m$ is storage profile of m in the day before. Then,

$$B_m(\tilde{s}_m + \Delta s_m) - B_m(\tilde{s}_m) = \sum_{h=1}^{H} \Delta s_m^h p^h + \mathcal{K}_1^h P_2(A_2^h, \Delta s_m^h)$$

$$+\mathcal{K}_2^h Q_3(A_3^h, \Delta s_m^h) + \mathcal{K}_3^h P_4(A_4^h, \Delta s_m^h) + \cdots \leq 0$$

$$\sum_{h=1}^{H} C^h(\tilde{l}^h + \Delta l^h) - C^h(\tilde{l}^h) \leq \sum_{h=1}^{H} A_1^h \Delta l^h + A_2^h P_2(A_2^h, \Delta l^h)$$

$$+A_3^h Q_3(A_3^h, \Delta l^h) + A_4^h P_4(A_4^h, \Delta l^h) + \cdots$$

$$\leq \sum_{h=1}^{H} A_1^h \sum_{m\in\mathcal{M}} \Delta s_m^h + A_2^h M \sum_{m\in\mathcal{M}} P_2(A_2^h, \Delta s_m^h)$$

$$+A_3^h M^2 \sum_{m\in\mathcal{M}} Q_3(A_3^h, \Delta s_m^h) + A_4^h M^3 \sum_{m\in\mathcal{M}} P_4(A_4^h, \Delta s_m^h)$$

$$+\cdots \leq 0$$

This completes the proof. □

Similarly, the convex objective function $\sum_{h=1}^{H} C^h(l^h)$ converges to $\min\limits_{s\in\mathcal{S}} \sum_{h=1}^{H} C^h(l^h)$. The proof is omitted here.

4.2 Changing User Load Profile and Renewable Energy Generation

For the situation where user load profile and renewable energy generation change from day to day, we can slightly revise the pricing scheme introduced previously to accommodate the changes. Assume that grid operators and energy storage devices have perfect prediction respectively on the total user load profile $X^h = \sum_{n\in\mathcal{N}} x_n^h$ and renewable energy generation v_m^h in the coming day. That is, perfect prediction for the next day on total user load profile $\acute{X}^h$ or renewable energy generation $\acute{v}_m^h$ is achieved at the end of each day. Each device will send their prediction $\acute{v}_m^h$ to grid operator (Algorithm 3), which will be used as part of the pricing scheme later (Algorithm 2).

For objective function $\sum_{h=1}^{H} C^h(l^h) = \sum_{h=1}^{H}(a_k {l^h}^2 + b_k l^h + c_k)$, where $a_k > 0$ and $b_k, c_k \geq 0$, we change the pricing scheme to

$$B_m = \sum_{h=1}^{H} S_m^h p^h + \mathcal{K}(s_m^h - \tilde{s}_m^h)^2 \tag{4.3}$$

where $p^h/\{2a_k[\acute{X}^h + \sum_{m\in\mathcal{M}}(\tilde{s}_m^h - \acute{v}_m^h)] + b_k\} = \mathcal{K}/a_k M = c > 0$ and $\tilde{s}_m^h$ is storage profile of m in the day before.

In the situation where user load and renewable power profile are constant, we actually make prediction that user load and renewable generation in the coming day will keep the same as in the previous days. Thus to accommodate the changes, we need to replace $\tilde{l}^h$ with $\acute{X}^h + \sum_{m\in\mathcal{M}}(\tilde{s}_m^h - \acute{v}_m^h)$.

Since each energy storage device m is assumed to be operated optimally in terms of income maximization, if $\tilde{s}_m + \Delta s_m$ is adopted as storage profile of next day, $B_m(\tilde{s}_m + \Delta s_m, \acute{v}_m) - B_m(\tilde{s}_m, \acute{v}_m) \leq 0$. It is easy to show that

$$\sum_{h=1}^{H} C^h[\acute{X}^h + \sum_{m\in\mathcal{M}}(\tilde{s}_m^h - \acute{v}_m^h + \Delta s_m^h)]$$

$$-C^h[\acute{X}^h + \sum_{m\in\mathcal{M}}(\tilde{s}_m^h - \acute{v}_m^h)] \leq 0$$

where $\acute{X}^h + \sum_{m\in\mathcal{M}}(\tilde{s}_m^h - \acute{v}_m^h + \Delta s_m^h)$ is exactly the aggregate demand profile of the coming day if all the predictions are accurate.

Therefore, under the control of our pricing scheme, value of the objective function can always be reduced or kept the same when new aggregate demand profile is reached by the changes of storage profile made according to price signals compared with the situation where no changes of storage profile are made, if perfect predictions of total user load and renewable energy generation together with optimal operation of storage devices are assumed. In most cases the better the prediction made by grid operators on next day total user load profile, the lower value of objective function can be achieved. However under this pricing scheme, energy storage device operators have no incentive to make efforts for accurate prediction of renewable power generation profile in the coming day. Thus, our pricing scheme can be further revised to

$$B_m = \sum_{h=1}^{H} S_m^h \frac{\mathcal{K}\{2a_k[\acute{X}^h + \sum_{m\in\mathcal{M}}(\tilde{s}_m^h - \acute{v}_m^h)] + b_k\}}{a_k M}$$

$$+ \mathcal{K}(s_m^h - \tilde{s}_m^h)^2 + \mathcal{J}(v_m^h - \acute{v}_m^h)^2 \tag{4.4}$$

where $(v_m^h - \acute{v}_m^h)$ is the difference between the true renewable power generation and the predicted renewable power generation, $\mathcal{J} > 0$ and $\mathcal{J}(v_m^h - \acute{v}_m^h)^2$ provides the incentive for more accurate prediction.

For more general convex objective functions,

$$\sum_{h=1}^{H} C^h[\acute{X}^h + \sum_{m\in\mathcal{M}}(\tilde{s}_m^h - \acute{v}_m^h + \Delta s_m^h)] - C^h[\acute{X}^h + \sum_{m\in\mathcal{M}}(\tilde{s}_m^h - \acute{v}_m^h)]$$

takes the form of

$$\sum_{h=1}^{H} A_1^{h'} \sum_{m\in\mathcal{M}} \Delta s_m^h + A_2^{h'}(\sum_{m\in\mathcal{M}} \Delta s_m^h)^2 + A_3^{h'}(\sum_{m\in\mathcal{M}} \Delta s_m^h)^3$$
$$+A_4^{h'}(\sum_{m\in\mathcal{M}} \Delta s_m^h)^4 + \cdots$$

Similarly, to ensure that $\sum_{h=1}^{H} C^h[\acute{X}^h + \sum_{m\in\mathcal{M}}(\tilde{s}_m^h - \acute{v}_m^h + \Delta s_m^h)] - C^h[\acute{X}^h + \sum_{m\in\mathcal{M}}(\tilde{s}_m^h - \acute{v}_m^h)] \leq 0$, let

$$B_m = \sum_{h=1}^{H} S_m^h p^h + \mathcal{K}_1^h P_2(A_2^{h'}, s_m^h - \tilde{s}_m^h) + \mathcal{K}_2^h Q_3(A_3^{h'}, s_m^h - \tilde{s}_m^h)$$
$$+ \mathcal{K}_3^h P_4(A_4^{h'}, s_m^h - \tilde{s}_m^h) + \cdots \tag{4.5}$$

where $p^h/A_1^{h'} = \mathcal{K}_1^h/A_2^{h'}M = \mathcal{K}_2^h/A_3^{h'}M^2 = \mathcal{K}_3^h/A_4^{h'}M^3 = \cdots = \mathcal{K}_n^h/A_{n+1}^{h}{}'M^n = c > 0$. And the incentive for more accurate prediction is provided by the additional term $\mathcal{J}(v_m^h - \acute{v}_m^h)^2$.

4.3 Profit Guarantee

In some cases where user load profile changes dramatically, $B_m > 0$ even when the energy storage device is operated optimally in terms of income maximization. To guarantee profit for each energy storage device, our pricing scheme can be extended further. Assume that B_m is the amount to be charged for $m \in \mathcal{M}$ in a whole day according to the pricing scheme introduced in previous sections. Let $\max(B_m^+)$ denote the maximum positive daily charge of all $m \in \mathcal{M}$. If all the daily charges $B_m \leq 0$, then $\max(B_m^+) = 0$. Our new pricing scheme gives

$$B_m{}' = B_m - \max(B_m^+) \quad \forall m \in \mathcal{M} \tag{4.6}$$

where $B_m{}'$ is the amount to be charged in the new pricing scheme. Apparently $B_m{}' \leq 0$ which guarantees a profit and storage profile of each $m \in \mathcal{M}$ that minimizes $B_m{}'$ is exactly the same as the profile minimizing B_m. Thus the change in pricing scheme only affects revenue of each energy storage device but has no influence on their decision on storage profile.

4.4 Summary

We propose a new pricing scheme on the base of Voice *et al.*'s pricing mechanism [6]. It is proved that in the situation where user load and renewable energy generation profile keep constant and each energy storage device is operated optimally in terms of income maximization, value of the convex objective function defined by grid operator is non-increasing from day to day and aggregate demand profile is convergent to the optimal profile which minimizes the convex objective function value under our pricing scheme. When both user load and renewable energy generation are changing, we tailor the previous pricing scheme and have proved that value of the convex objective function is always reduced or kept the same when new aggregate demand profile is reached by the changes of storage profile made according to the revised pricing scheme compared with the situation where no changes of storage profile are made, if perfect predictions of total user load and renewable energy generation together with optimal operation of storage devices are assumed. Profitability of optimal energy storage operation can also be guaranteed by an extension of our pricing scheme which does not affect energy storage devices' decision on storage profile.

Chapter 5

Simulation Results

In this chapter, we present some simulation results and evaluate the performance of our pricing scheme in different situations. In our simulations, we use the hourly demand data of Ontario, Canada from the IESO Public Reports [22] for user load profile. Average hourly demand is approximately 15400 MWH. Also, we use hourly output data of the 9 wind generators in Ontario for renewable power generation profile. Most of these wind generators have rated hourly output below 150MWH. And we assume that each of these generators is equipped with energy storage device whose charging and discharging volume is 400% rated power of the generator and has 4-hour charge/discharge time. We make this assumption to show the performance of our pricing scheme at higher levels of energy storage penetration. In reality economically viable charging and discharging volume as well as capacity of energy storage device connected with renewable energy source at current stage are much less than the sizes in our assumption. Each energy storage device has charge efficiency $a = 0.95$ and discharge efficiency $b = 0.95$. At the beginning of each day (also the end of each day), state of charge of each energy storage device is 50%. The objective function (daily energy generation cost) is defined as $\sum_{h=1}^{H} C^h(l^h) = \sum_{h=1}^{H}(0.003{l^h}^2 + 10l^h + 100000)$.

5.1 Simulation Results for Constant User Load Profile and Renewable Energy Generation

Simulation results of the objective function value and aggregate demand profile for the situation where user load and renewable power generation keep constant from day to day are shown in Fig. 5.1 and Fig. 5.2. Hourly demand data of Ontario on Sept. 1, 2009 are used as the constant user load profile and hourly output of the 9 wind generators on Sept. 1, 2009, the constant renewable power generation profile. On the first day

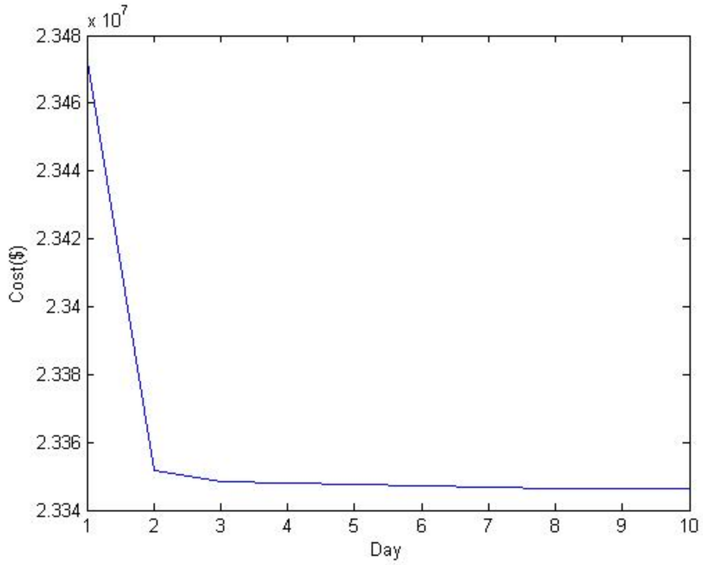

FIGURE 5.1: Evolution of objective function value (energy generation cost) in the situation where user load and renewable power generation are all constant.

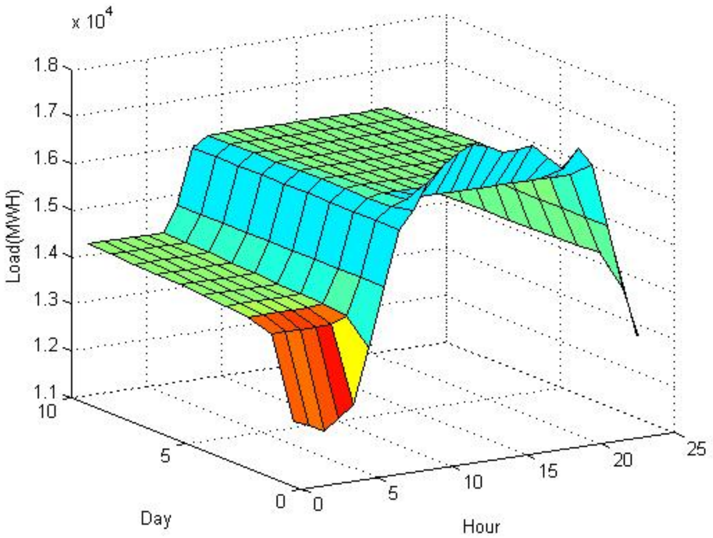

FIGURE 5.2: Evolution of aggregate demand profile in the situation where both user load and renewable power generation are constant.

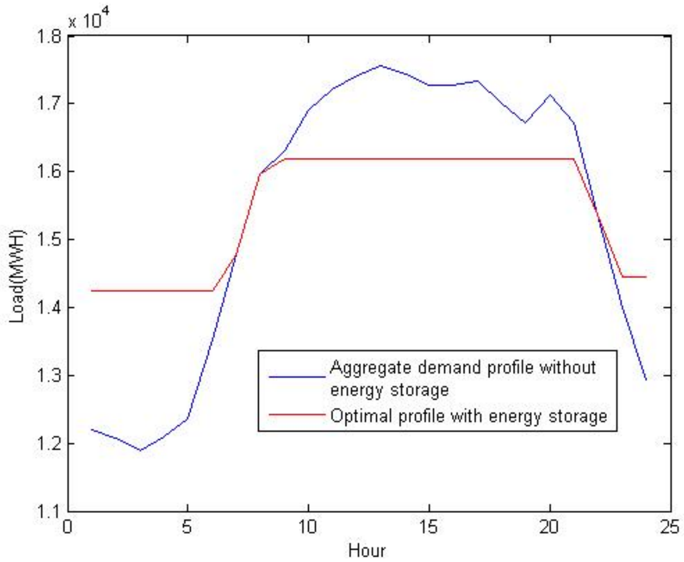

FIGURE 5.3: Comparison of aggregate demand profile without energy storage to optimal aggregate demand profile with energy storage.

$s_m^h = 0 \ \ \forall m \in \mathcal{M} \ \ \forall h \in \mathcal{H}$. Fig. 5.3 compares the aggregate demand profile without energy storage to optimal aggregate demand profile with energy storage that is solved in a centralized manner. As is shown in Fig.5.1, objective function value is non-increasing under our pricing scheme. From Fig. 5.2 and Fig. 5.3, it can be observed that under our pricing scheme, aggregate demand profile converges to the optimal profile. The majority of decrease in the objective function value is made on the first day.

5.2 Simulation Results for Changing User Load Profile and Renewable Energy Generation

For the situation where both user load and renewable power generation are changing, simulation results are shown in Fig. 5.4, Fig. 5.5, and Fig. 5.6. We use hourly demand data of Ontario and hourly output of the 9 wind generators in Sept. 2009 for our simulation. Predicted user load profile and renewable power generation profile are exactly user demand profile and generator output profile in the next day. On Aug. 31, 2009, $s_m^h = 0 \ \ \forall m \in \mathcal{M} \ \ \forall h \in \mathcal{H}$. It can be observed from Fig. 5.4 that the value of the objective function is reduced every day either compared with the situation where no energy storage is used or if previous day storage profile is kept. And by comparing Fig. 5.5 and Fig. 5.6, we can see that the aggregate demand profile is efficiently flattened. Ideally, as shown in Fig. 5.7, with ideal charge and discharge efficiency, sufficient charging and

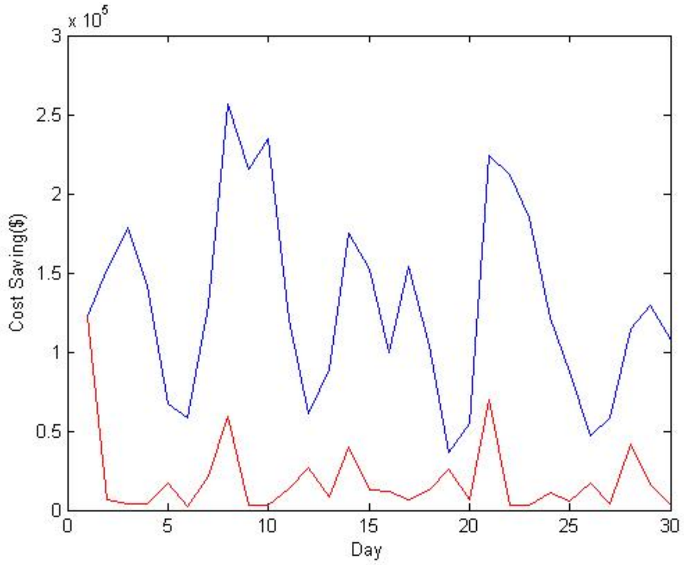

Figure 5.4: Evolution of cost saving: blue line shows cost difference between no energy storage participation and with energy storage participation under our pricing scheme; red line shows cost saved by energy storage changes made to previous day storage profile under our pricing scheme.

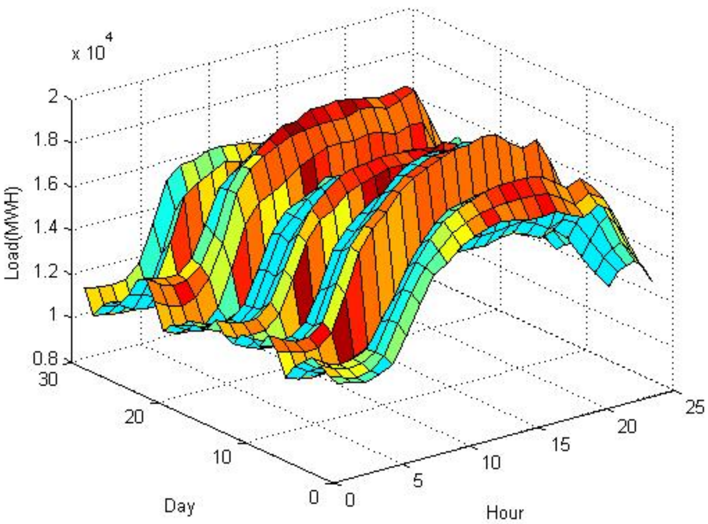

Figure 5.5: Evolution of aggregate demand profile without energy storage in the situation where both user load and renewable power generation are changing.

discharging volume as well as energy storage capacity, fully flattened aggregate demand profile can be achieved every day.

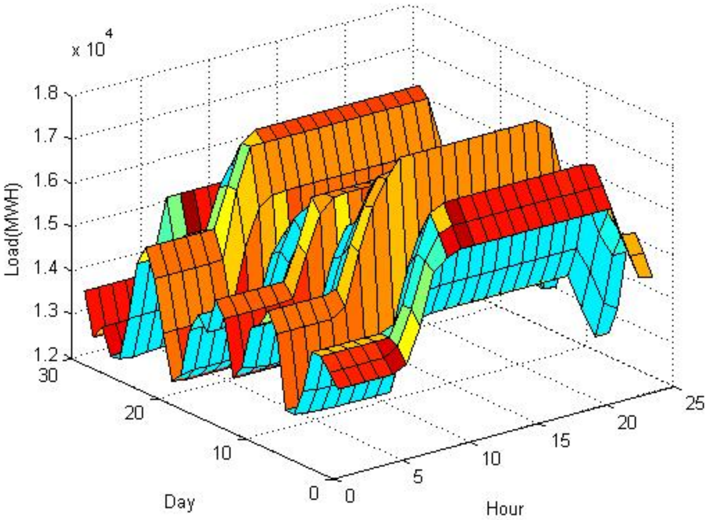

FIGURE 5.6: Evolution of aggregate demand profile with energy storage in the situation where both user load and renewable power generation are changing.

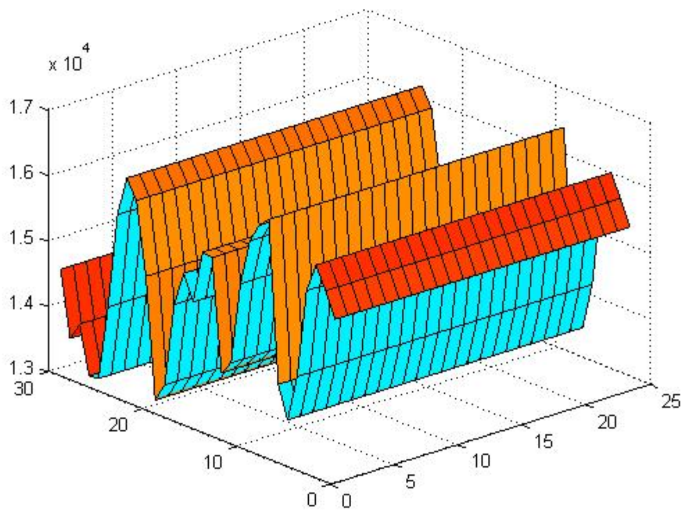

FIGURE 5.7: Evolution of aggregate demand profile with ideal efficiency, sufficient charging and discharging volume as well as energy storage capacity.

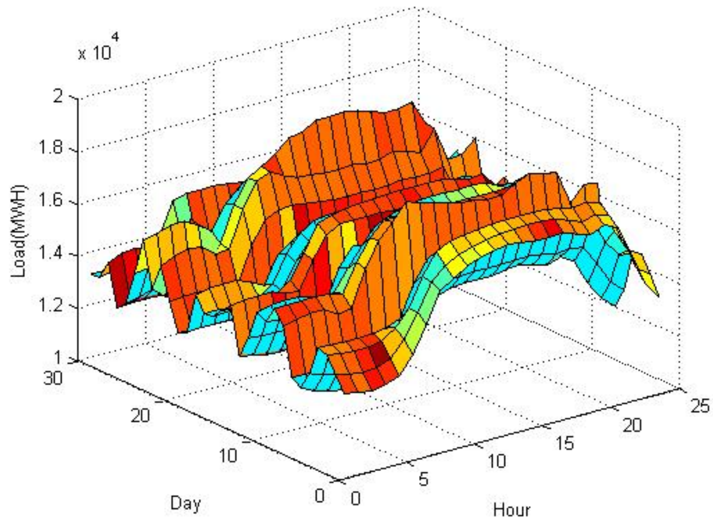

FIGURE 5.8: Evolution of aggregate demand profile when standard deviation of the normal distribution ε_p yields to equals 0.4.

5.3 Simulation Results after Introduction of Prediction Errors

However, prediction error is inevitable in reality. As is shown in Fig. 5.5, the shape of daily aggregate demand profile without energy storage is similar from day to day, but the magnitude varies significantly. Therefore what grip operator needs to predict every day is mainly the magnitude of daily aggregate demand profile without energy storage. We now introduce errors into the prediction, which yield to normal distribution. If error ε_p is incurred, the true aggregate demand profile without energy storage in the coming day will be $(1 + \varepsilon_p)(\acute{X}^h - \sum_{m \in \mathcal{M}} \acute{v}_m^h)$ where $\acute{X}^h$ and $\acute{v}_m^h$ are perfect predictions for the next day on total user load profile and renewable energy generation respectively. ε_p yields to normal distribution whose mean is 0.

Evolution of aggregate demand profile and cost saving in the situations where standard deviation of the normal distribution ε_p yields to equals 0.1, 0.2 and 0.4 is shown in Fig. 5.8, Fig. 5.9, Fig. 5.10, Fig. 5.11, Fig. 5.12 and Fig. 5.13. After prediction errors are introduced, profitability of our pricing scheme can not be guaranteed when prediction errors are too large which is rare but possible (Fig.5.9). But in general, our pricing scheme still reduces the value of objective function efficiently and the more accurate the predictions are, the better the objectives are met.

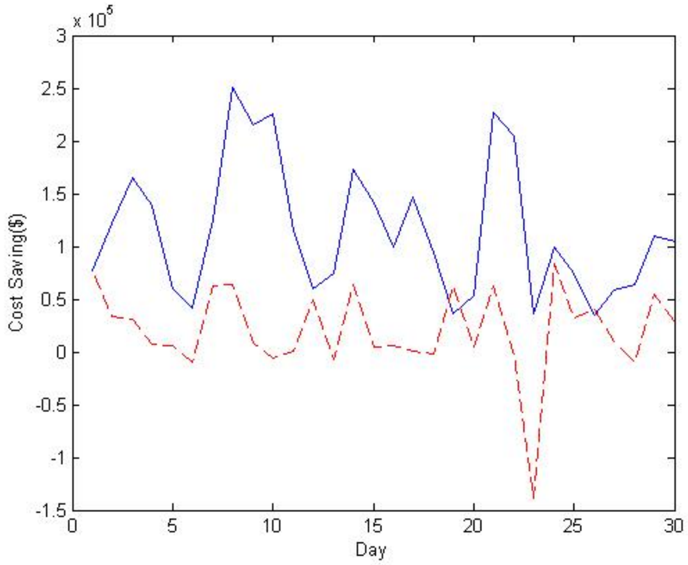

FIGURE 5.9: Evolution of cost saving when standard deviation of the normal distribution ε_p yields to equals 0.4: blue line shows cost difference between no energy storage participation and with energy storage participation under our pricing scheme; red line shows cost saved by energy storage changes made to previous day storage profile under our pricing scheme.

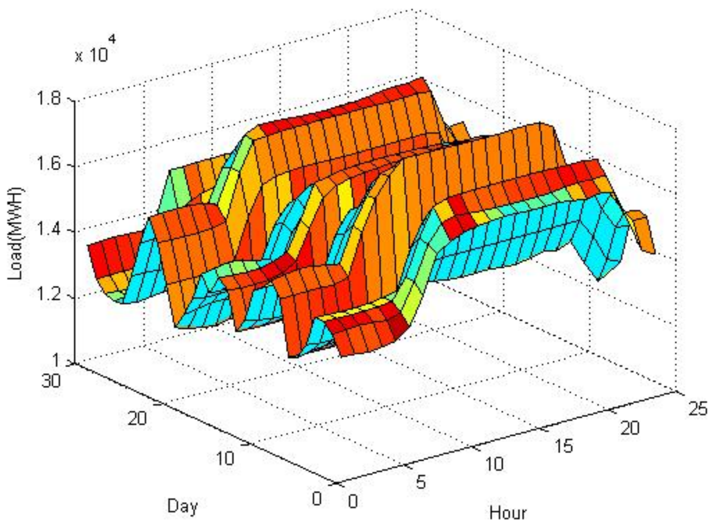

FIGURE 5.10: Evolution of aggregate demand profile when standard deviation of the normal distribution ε_p yields to equals 0.2.

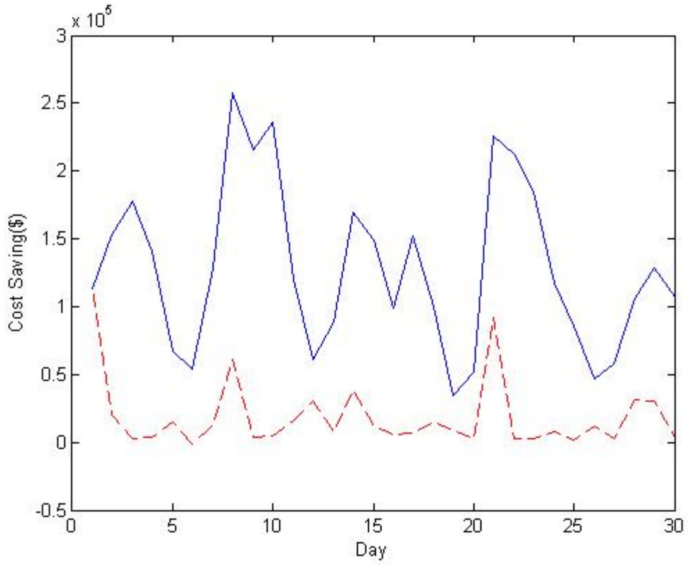

FIGURE 5.11: Evolution of cost saving when standard deviation of the normal distribution ε_p yields to equals 0.2: blue line shows cost difference between no energy storage participation and with energy storage participation under our pricing scheme; red line shows cost saved by energy storage changes made to previous day storage profile under our pricing scheme.

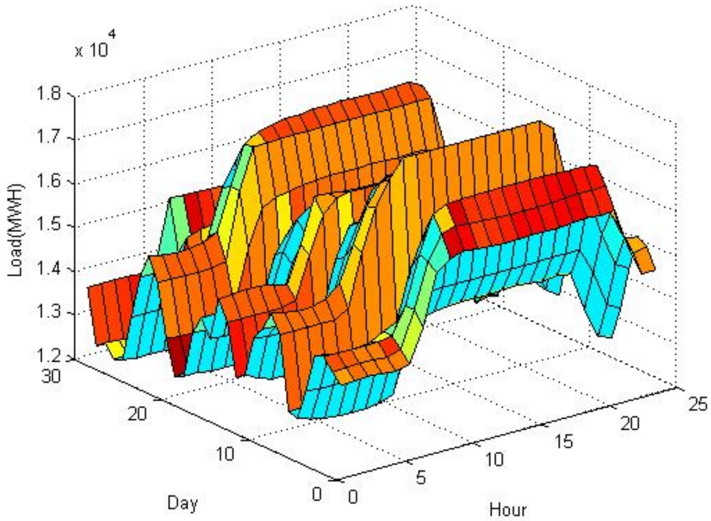

FIGURE 5.12: Evolution of aggregate demand profile when standard deviation of the normal distribution ε_p yields to equals 0.1.

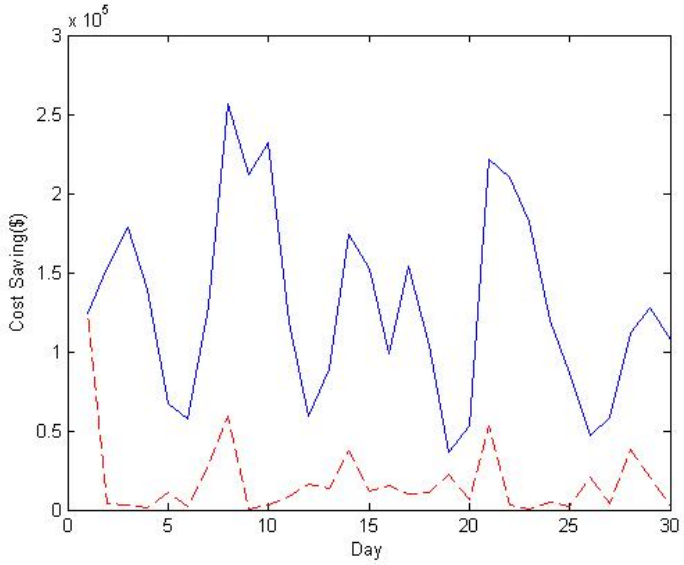

Figure 5.13: Evolution of cost saving when standard deviation of the normal distribution ε_p yields to equals 0.1: blue line shows cost difference between no energy storage participation and with energy storage participation under our pricing scheme; red line shows cost saved by energy storage changes made to previous day storage profile under our pricing scheme.

5.4 Summary

As is shown by the simulation results, when user load profile and renewable energy generation are constant, value of the convex objective function defined by grid operator is non-increasing under our pricing scheme and aggregate demand profile in the grid converges to the optimal profile. The majority of decrease in the objective function value occurs on the first day. In the situation where user load profile and renewable energy generation are changing, profitability of our pricing scheme is guaranteed if perfect prediction is assumed. Even when prediction errors are introduced, in general our pricing scheme still reduces objective function value efficiently and the more accurate the predictions are, the better the objectives of grid operator are met.

Chapter 6

Conclusion

In this project, a new universal pricing scheme was proposed to indirectly control energy storage devices in smart grid. It was designed to efficiently reduce the value of any convex objective function defined by grid operators. We proved that in the situation where user load and renewable energy generation profile keep constant and each energy storage device is operated optimally in terms of income maximization, aggregate demand profile is convergent to the optimal profile which minimizes the convex objective function value under our pricing scheme. When both user load and renewable energy generation are changing from day to day, our pricing scheme can still efficiently reduce the value of the objective function. Profitability of optimal energy storage operation can also be guaranteed. Simulation results assuming high level of energy storage penetration were provided to demonstrate the stability and profitability of our pricing scheme. Our pricing scheme can be applied to control the behavior of energy storage devices installed for integration of intermittent renewable energy at current stage and is believed to have much broader applications in future.

Appendix A

Pseudocodes for System Operation

Algorithm 2 : Executed by grid operator.

At the end of each day **Do**
    Predict total user load profile.
    repeat
        Collect renewable energy generation predictions.
    until receive predictions from all renewable energy sources.
    Set price based on the objective function, predictions of total user load profile and renewable energy generation as well as current total storage profile.
    Send updated pricing scheme for the next day to all energy storage devices in the grid.
End

Algorithm 3 : Executed by each energy storage device in the grid.

At the end of each day **Do**
    if there are renewable energy sources connected **then**
        Make prediction on renewable energy generation profile in the coming day and send it to grid operator.
    End if
    At receiving pricing scheme for the next day **Do**
        Optimize energy storage profile in the coming day according to the received pricing scheme so that income is maximized.
    End
End
Charge and discharge itself according to the scheduled energy storage profile in the coming day.

Bibliography

[1] China National Energy Administration, China National Renewable Energy Centre, "Key information at a glance: China 12th five-year plan for renewable energy development," 2012.

[2] Eurostat News Releases, June 2012 [Online].
Available: http://epp.eurostat.ec.europa.eu/cache/ITY_PUBLIC/8-18062012-AP/EN/8-18062012-AP-EN.PDF.

[3] S. M. Amin and B. F. Wollenberg, "Toward a smart grid," *IEEE Power Energy Mag.*, vol. 3, no. 5, pp. 34–41, 2005.

[4] U. S. Department of Energy, "The Smart Grid: An Introduction," 2009.

[5] M. Pipattanasomporn, H. Feroze, and S. Rahman, "Multi-agent systems in a distributed smart grid: Design and implementation," *Proc. IEEE Power Systems Conf. and Expo.*, pp. 18, 2009.

[6] T. Voice, P. Vytelingum, S. Ramchurn, A. Rogers, and N. Jennings. "Decentralised control of micro-storage in the smart grid," *AAAI Conference on Articial Intelligence*, 2011.

[7] K. T. Tan, X. Y. Peng, P. L. So, Y. C. Chu, and M. Z. Q. Chen. "Centralized control for parallel operation of distributed generation inverters in microgrids," *IEEE Trans. on Smart Grid*, vol. 3, no. 4, pp. 1977–1987, 2012.

[8] K. T. Tan, P. L. So, Y. C. Chu, and M. Z. Q. Chen, "Coordinated control and energy management of distributed generation inverters in a microgrid," *IEEE Trans. on Power Delivery*, to appear.

[9] C. W. Potter, A. Archambault, and K. Westrick, "Building a smarter smart grid through better renewable energy information," *Proc. IEEE/PES Power Systems Conf. and Exposition*, pp. 1–5, 2009.

[10] C. A. Hill, M. C. Such, D. Chen, J. Gonzales, W. M. Grady, "Battery Energy Storage for Enabling Integration of Distributed Solar Power Generation," *IEEE Trans. on Smart Grid*, vol. 3, no. 2, pp. 850–857, 2012.

[11] N. Miller, D. Manz, J. Roedel, P. Marken, and E. Kronbeck, "Utility scale battery energy storage systems," *Proc. IEEE Power Energy Soc. Gen. Meeting*, Minneapolis, MN, 2010.

[12] M. Kintner-Meyer, P. Balducci, C. Jin, T. Nguyen, M. Elizondo, V. Viswanathan, X. Guo, and F. Tuffner, "Energy Storage for Power Systems Applications: A Regional Assessment for the Northwest Power Pool (NWPP)," PNNL-19300, Pacific Northwest National Laboratory, Richland, WA, 2010.

[13] S. Ramchurn, P. Vytelingum, A. Rogers, and N. Jennings, "Agent-based homeostatic control for green energy in the smart grid," *ACM Transactions on Intelligent Systems and Technology*, vol. 2, no. 4, article 35, 2011.

[14] P. Vytelingum, T. D. Voice, S. D. Ramchurn, A. Rogers, and N. R. Jennings, "Agent-based micro-storage management for the smart grid," *Proc. of the Ninth International Conference on Autonomous Agents and Multiagent Systems*, pp. 39–46, 2010.

[15] H. Mohsenian-Rad, V. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE Trans. on Smart Grid*, vol. 1, no. 3, pp. 320–331, 2010.

[16] C. Wu, H. Mohsenian-Rad, J. Huang, and A. Y. Wang, "Demand side management for wind power integration in microgrid using dynamic potential game theory," *Proc. of IEEE GLOBECOM Workshop on Smart Grid Communications and Networking*, Houston, TX, 2011.

[17] H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," *IEEE Trans. on Smart Grid*, vol. 1, no. 2, pp. 120–133, 2010.

[18] P. Samadi, H. Mohsenian-Rad, R. Schober, V. Wong, and J. Jatskevich, "Optimal real-time pricing algorithm based on utility maximization for smart grid," *Proc. of IEEE Conf. on Smart Grid Communications*, 2010.

[19] N. S. Wade, P. C. Taylor, P. D. Lang, and P. R. Jones, "Evaluating the benefits of an electrical energy storage system in a future smart grid," *Energy Policy*,vol. 38, no. 11, pp. 7180–7188, 2010.

[20] S. Teleke, "Energy Storage Overview: Applications, Technologies and Economical Evaluation," *Quanta Technology Technical Papers*, [Online]. Available: http://www.quanta-technology.com/sites/default/files/doc-files/Energy-Storage-Overview.pdf.

[21] J. Eyer and G. Corey, "Energy storage for the electricity grid," *Sandia National Labs Publications*, 2010 [Online]. Available: http://prod.sandia.gov/techlib/access-control.cgi/2010/100815.pdf.

[22] IESO Public Reports: http://reports.ieso.ca/public/.

[23] S. Boyd and L. Vandenberghe, "Convex Optimization," *Cambridge Univ. Press*, Cambridge, 2004.

[24] BP Statistical Review of World Energy June 2012 [Online]. Available: http://www.bp.com/liveassets/bp_internet/globalbp/globalbp_uk_english/reports_and_publications/statistical_energy_review_2011/STAGING/local_assets/pdf/statistical_review_of_world_energy_full_report_2012.pdf.