CUSTOMER COST MINIMIZATION FOR ENERGY CONSUMPTION SCHEDULING IN SMART GRID

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ABSTRACT

The world has been on a fast track of industrial development thanks to human activities. On the back of the same coin is the fact that people are consuming more and more energy to support the fast-paced development. Studies have pointed out an increasing consumption on traditional, non-renewable energies such as coal and oil, while the application of renewable energies, such as wind power and solar power, are still quite far away from mass application because of various restrains. Therefore, it is essential to search for a better way for people to consume energy, especially electricity since it is a necessary every-day energy and it is overwhelmingly generated with non-renewable resources.

Researches about smart grid have been quite fruitful with demand response being the most promising research area. A large number of previous studies have been done in the area of real-time pricing schemes and fairness in bill and cost for theses schemes, but real-time demand response using energy consumption scheduling algorithms did not attract much attention until recently because of the two-way communication capacity of smart grid and fair delay problem of the energy scheduling. Also, using optimal stopping rule to model these problems has yet to be studied. Solution to these problems will essentially make demand response program more flexible or even smart grid participation a more attractive choice to customers.

This dissertation looks at three problems. The first problem is the cost minimization problem with real-time demand response using energy consumption scheduling modeling in a neighborhood area network. We simulate this problem with discrete event simulation with different sets of parameters, and provide the results analysis under several circumstances. The

second problem explores the importance of fairness in terms of delay. A formal concept of delay is defined using the energy scheduling model, and then the problem is formed based on a cost minimization problem with a fairness boundary constraint. The proposed algorithm solves the cost minimization while bounding the delays of all customers. The simulation results show that the algorithm with fair delay has much better performance than the algorithm without fair delay in terms of fairness index metric. In the third problem, we adopt the optimal stopping rule method to model the energy consumption scheduling problem. Then a cost minimization problem with comfortable delay is presented, and an optimal stopping rule based energy consumption scheduling algorithm is proposed to solve this problem. The simulation results show that the optimal stopping rule algorithm has better performance in terms of total cost than a greedy algorithm while satisfying the comfortable level constraint.

DEDICATION

This dissertation is dedicated to everyone who helped me and guided me through the trials and tribulations of creating this manuscript. In particular, my family and close friends who stood by me throughout the time taken to complete this masterpiece.

LIST OF ABBREVIATIONS AND SYMBOLS

DoE	Department of Energy
IBP	Incentive based price
PBP	Price based program
TOUP	Time of use pricing
CPP	Critical peak pricing
RTP	Real time pricing
SCADA	Supervisory Control And Data Acquisition
SQL	Structured Query Language
RTU	Remote terminal unit
PLC	Programmable logic controller
MTU	Master terminal unit
HMI	Human machine interface
LAN	Local area network
WAN	Wide area network
IP	Internet protocol
IED	Intelligent electronic device
PAC	Process automation controllers
ICCP	Inter-control Center Communications Protocol
OCP	Odyssey commutation processor
SNMP	Simple network management protocol

MCC	Master control center
NIST	National Institute of Standards and Technology
AMI	Advanced metering infrastructure
NETL	National energy technology laboratory
IC	Integrated communication
HAN	Home area network
BAN	Building area network
IAN	Industrial area network
HEMS	Home energy management system
BACnet	Building automation and control network
DSM	Demand side management
ADHDP	Action dependent heuristic dynamic programming
PAR	Peak average ratio
PHEV	Plug-in hybrid electric vehicle
DAP	Day-ahead pricing
N	Total customer number
j	Timeslot number
Δt	Unit time per timeslot
i	Customer number
$l_i(j)$	Demand of power load for customer i at timeslot j
$o_i(j)$	Actual energy consumption of customer i at timeslot j
$b_i(j)$	Instantaneous bill payment for customer i at timeslot j
$B_i(j)$	Accumulative bill payment for customer i at timeslot j

$a(j)$	Instantaneous aggregate load of the power provider at timeslot j
$A(j)$	Accumulative aggregate load of the power provider at timeslot j
$e(j)$	Instantaneous aggregate load demand of the power provider at timeslot j
$E(j)$	Accumulative aggregate load demand of the power provider at timeslot j
$\gamma(j)$	PAR of the power provider at timeslot j
l^{peak}	Instantaneous peak load threshold of a power provider
$B_{Avg}(j)$	Average bill of N customers over timeslot j
$r_i(j)$	Accumulated delayed remainders for customers I at timeslot j
$c_i(j)$	Remainder load cost at timeslot j for customer i
ρ	A price function of $r_i(j)$
$c_{Avg}(j)$	Average remainder of N customers over j timeslots
α	Weighted parameter for customers total cost function
$c_{Tot}(j)$	Accumulative total cost for customer I at timeslot j
$p(j)$	RTP power price at timeslot j
η	A parameter defined by the power provider
ε	A parameter defined by the power provider
$p_i^{threshold}(j)$	Power price threshold for customer i at timeslot j
$p_i^{avg}(j)$	Average power price for customer i at timeslot j
μ	Mean of normal distribution
σ	Standard deviation of the normal distribution

$d_i(j)$	Accumulative delay for customer i over j timeslots
δ_0	A fair delay boundary parameter
$\pi(j)$	Average normalized delay at timeslot j
$\delta_i(j)$	Normalized delay deviation for customer i at timeslot j
$\Delta r_i(j)$	Consumed remainder load by the carry-on operation
$p_i^{feedback}(j)$	The power provider's feedback parameter for customer i at timeslot j
λ	Predefined parameter by each customer for power threshold
$\mathrm{I}[d_1(j), d_2(j), ..., d_N(j)]$	Fairness index of N customers' delays at timeslot j
$P(j)$	Price random variable for timeslot j
n	Scheduled timeslot for load demand $l_i(j)$
c	Delayed cost per timeslot
$y_{i,j}(n)$	Reward function for load demand $l_i(j)$ if it is scheduled to timeslot n
$X_{i,j}(n)$	Random variable of final bill payment's negation
$\phi_n[x_{i,j}(j), x_{i,j}(j+1), ..., x_{i,j}(n)]$	Probability of stopping after observations from timeslot j to n
$\Phi(i, j, n)$	A stopping rule for load $l_i(j)$
$n_i(j)$	The timeslot that yields the maximum reward
$\Psi_n[X_{i,j}(j), ..., X_{i,j}(n)]$	The random variable of stopping occurs
$\psi_n[x_{i,j}(j), x_{i,j}(j+1), ..., x_{i,j}(n)]$	Probability of $l_i(j)$ stops at timeslot n
$V[\Phi^*(i, j, n)]$	Optimal stopping rule reward value
E	The mean expectation of the random variable

z^*	Solution value of optimal price threshold
$E[]^+$	Math expectation mean value which is larger than zero
$[p_a, p_b]$	Uniform distribution
ΔO_i	Acceptable comfortable level of consumed energy for customer i for a day
K	Number of timeslots for a day
$\lambda_i(j)$	Boolean value of whether there is a load request from customer i at timeslot j
$S_i(j)$	The set of the load demands scheduled to timeslot j
$c_{i,j}$	Comfortable cost per timeslot
$c_{i,j}^{total}$	Total cost per timeslot of delay cost and comfortable cost

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CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 INTRODUCTION

1.1 Motivation

The world is developing fast. In the last decade, due to the fast growth of human population, the amount of energy consumption has increased rapidly. What also went up together with the number of population was the price of fossil fuels [2]. As Lior wrote in his 2012 report [2], energy resources and consumption are "immediately related to environmental quality and other vital resources such as water and food". The scarcity of the fossil fuels, in return, pushes the price to a higher level. To most countries, a stable national economy is the cornerstone of steady and healthy development. Therefore, it is undeniably important for the industry to maintain a low energy bill for industrial, commercial, and domestic electricity consumptions.

Apart from economic issues, environmental conservation is yet another reason to work on the energy consumption problem. Although the research of renewable energies, such as wind, geothermal and solar power, have made some impressive breakthroughs, it is admittedly still quite far away for renewable energies to be widely applied to the world as a replacement for traditional energy generation resource because of reasons such as noise, lack of wind, or low efficiency [3]. In the paper on optimization problem of "Green" buildings, researchers pointed out sometimes "the availability of a specific resource depends on the specific season and varies during the day" [4]. In fact, in Lior's latest reports on the present situation of sustainable energy development, the combined energy production of all renewable energies only counted towards 3% of the world's primary energy consumption in 2009, and that number decreased to 1.8% in 2011

[2]. The consumption of fossil fuels, such as coal and oil, on the contrary, has been rising continuously.

In 2010, oil was still the dominating fuel for world primary energy consumption with a 33.6% share [5]. On the other hand, coal also occupied a 29.1% share in 2010. Regardless of minor fluctuations in world energy consumption, simply by adding the two numbers together, as much as 62.7% of world primary energy consumption can be located into the category of fossil fuel consumption [5]. Not only have fossil fuels been the dominant fuel, their consumption amount has been growing throughout years as well. The combined consumption changed from below 7500 million tones oil equivalent in 2008 to more than 7500 million tones oil equivalent in 2010 with the consumption of coal continues to grow [5]. The situation, therefore, can be described as growing consumption versus limited reserve. It is then of top priority for people to preserve fossil fuels as much as possible until replacement becomes available.

Environmental pollutions have also become a confronting challenge in last decade. According to the "Living Planet Index" and "Ecological Footprint", we seem to be "running out of environment much faster than out of resources" [5], [6].

The environmental pollution concern, together with the conservation of fuels and economic concern all point to the direction that human race need a more efficient way to consume energy. Most countries in the world have started ongoing researches on energy cost and pollution reduction [3]. In the fruitful results of these researches, smart grid is by far the most promising one.

1.2 Current Power Grid Issues and Smart Grid

The electrical power grid has contributed greatly to our daily life and industry. Currently, however, the power grid system has many issues, which must be resolved. First, more voltage

sags, blackouts, and overloads have occurred in the past decade than over the past 40 years [7]. Second, as the population size has increased, the current grid is becoming old and worn out; thus adding new appliances into customer's houses and buildings gives more instability to the current power grid [7] . Third, the current electrical network contributes greatly to carbon emissions. The United States' power system alone produces 40% of all nationwide carbon emissions [8].

Considering both economic and environmental interests, changes must be made to such an unstable and inefficient system. It requires reliability, scalability, manageability, and extensibility, but also should be interoperable, secure, and cost-effective. This electric infrastructure is called "Smart Grid".

A smart grid is "an intelligent electricity network that integrates the actions of all uses connected to it and makes use of advanced information, control, and communication technologies to save energy, reduce cost and increase reliability and transparency" [9]. Targeting at these issues makes smart grid an ally of both the earth and the community. In fact, as Fuselli et al. stated in their paper, smart grid aligns the interests of "electric utilities, consumers and environmentalists'" all at once [3]. Furthermore, with the help of smart grid, electricity supply industry has been able to make a lot of improvements. For instance, the philosophy of operation changed from "to supply all the required demand whenever occurs" to "the system will be most efficient if fluctuations in demand is kept as small as possible" [10].

The new philosophy can be fully addressed when smart grids reach their 100% potential for they will be able to intelligently address all the customers' energy needs without pressuring the grid and cause damage. The realization of this goal will then reinforce the reliability of the electricity system since a perfect balance between the supply and the load requests is what makes a system reliable [10]. The improved energy efficiency can also save a lot of energy. After all, "a

Joule saved is worth significantly more than a Joule earned", because it takes much more than 1J of energy to generate 1J of power [6]. Moreover, the flexibility of smart grid also makes it quite favorable because it can be adapted to a large variety of grid environments that varies from micro scenarios (i.e. individual houses) to large scale systems (i.e. energy generation and distribution plants) [3]. With such reliability, scalability, manageability, extensibility, and other beneficial characteristics of smart grid's (Fig. 1.1) the confronting challenges the world faces, i.e. the decrease of fossil fuels, increasing prices, and pollution, will slowly fade away [11].

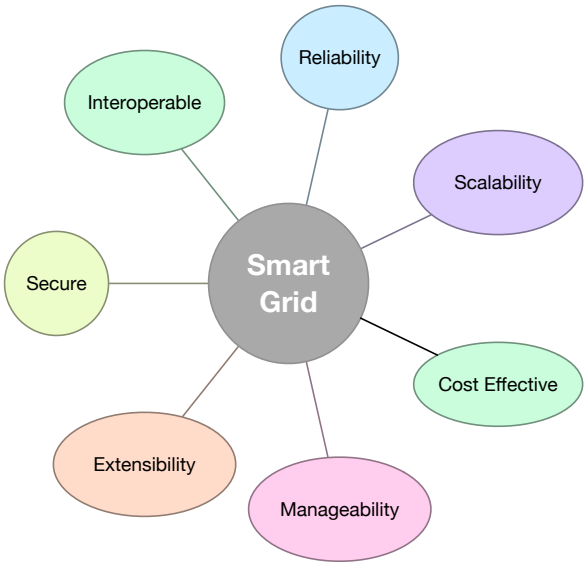

Fig. 1.1 Smart Grid Characteristics [2]

Having said that, it is not easy to maintain a perfect balance of supply and load request. The possible rapid changes of both supply and load request levels are influential factors to the balance, no matter if they are caused by various outages or sudden load changes [10]. According to the literature, demand side response, which is also known as demand response, is the cheaper

resource that not only capable of operating the system, but also in accordance with the new philosophy [10].

1.3 Demand Response and Issues

Demand response programs are defined similarly by various researchers, yet they all slightly differ from one another. For instance, Vuppala defined demand response programs as "various voluntary schemes offered by energy utility and distribution companies to their customers for curtailing their energy usage, particularly during periods of peak-load" [12]. Albadi's definition for demand response is "the changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time" [10]. In this dissertation, the definition of demand response cites the one provided by the U.S. Department of Energy (DoE), which describes demand response as "a tariff or program established to motivate changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over the time, or to incentive payments designed to induce lower electricity usage at times of high wholesale market prices or when system reliability is jeopardized" [1]. Unlike Vuppala's definition, which emphasizes on voluntary participation from customers, the definition given by Albadi focuses more on the purpose of demand response, which is to encourage and motivate the customers to alter their consumption pattern in response to the change of price. The DoE definition summarizes these two important features of demand response, and, on top of that, also outlines the common method to motivate customers, which is through monetary incentives. Finally, it evaluates demand response as a method that saves customers a lot of dollars and at the same time ensures the reliability of the energy generating system. Based on what is included in DoE's

definition, it appears to be a very well rounded summary of all the important features of demand response.

Demand response has many advantages that benefit both energy suppliers and customers. The diverse benefits offered by demand response include monetary savings, power efficiency improvements, flexibility, and reliability improvements [10], [12]. A detailed illustration of various demand response benefits can be found in Chapter II Literature Review (Fig. 2.15). Regardless of the convenience and improvements demand response has to offer, researchers have found the adoption rate of demand response programs has been unexpectedly slow [12]. Vuppala et al.'s paper [12] shined some light into the leading causes. One of the reasons is that customers become hesitant when they find out about penalties related to contract breach. In addition, the unpredictable nature of peak load duration is not especially encouraging as well. Finally, the fact that even if customers participate in demand response programs they still have to pay high prices for must run services, such as lighting during peak hours makes the advantages of demand response programs less impressive.

Demand response programs, as discussed, have huge potentials that may bring current smart grid to the next level and benefit the world as a whole. However, the interactive nature of demand response requires much more input than the effort of just researchers. It is the involvement of end-use customers that can eventually push demand response forward. Their participation will generate data that are crucial for the advancement and debugging of demand response programs and even smart grid. Without them, *Demand Response* programs will have nothing to respond to, let alone make the grid smarter or make the world greener. Therefore, it becomes urgent for demand response programs to become attractive enough to attract more participants.

Demand response programs can be categorized into two groups: incentive based programs (IBP) and price based programs (PBP) [10]. In IBP, participants receive credits or monetary rebates for their participation in demand response programs, whereas in PBP participants do not receive any rebate but are able to shift the load management to smart meters that have the automation functionality, or even become a power supplier by selling their extra load back to the power grid.

PBP can be further divided into five categories: Time of Use Pricing (TOUP), Critical Peak Pricing (CPP), Extreme Day Critical Peak Pricing, Extreme Day Pricing, and Real Time Pricing (RTP) [10]. These PBP programs all aim at flatten the demand curve by offering a higher price during peak hours and lower price at off-peak hours [10], yet they offer different per unit consumption prices at different time blocks of the day. TOUP rates is the most commonly implemented PBP program. It offers two time blocks in the simplest model, which are peak and off-peak rates. The most efficient PBP program, even the most efficient demand response program is RTP program as a large number of economists believe [13]. Not only will RTP be reducing expenditures for end users, but also lead to economic and environmental advantages [14].

As implied by its name, RTP programs charge customers hourly fluctuating prices that "reflect the real cost of electricity in the whole sale market" [14]. Usually the programs inform customers about the prices on a "day-ahead" or "hour-ahead" basis. This characteristic of RTP leads economists to the conclusion that RTP programs fit for competitive electricity markets and should be paid more attention by policymakers [15]. In fact, Zhang et al. [16] found that RTP, and other demand response programs, did encourage and enable customers to take a much more

active role in scheduling their own energy consumptions to save energy, reduce cost, and in return benefit the power grid operation.

1.4 Energy Consumption Scheduling and Fair Delay

After the publication of Albadi and El-Saadany's paper, smart grid has had more developments and advancements as a result of the vigorous studies done by researchers. Thanks to current available RTP-alike schemes, each and every customer within the smart grid now has the opportunity to dynamically schedule its loads at each time. Most of the scheduling at customers' end is performed by the energy consumption scheduling system. The energy consumption scheduling system can be as simple as a single smart meter, which is programmed to start, suspend, resume and stop one or many smart appliances [15]. On top of controlling and monitoring the smart devices, the energy consumption scheduling system also coordinates the communication between appliances and the power supplier. A graph illustration of the energy consumption scheduling system is presented in the Introduction section of Chapter 3. It is also important to realize that the available schemes are all performing fragments of RTP's functionality after all. Therefore, RTP is still in need in order to largely improve the efficiency of smart grid. But the challenge of RTP, that is the fact the customers might not be able to know the future power price, remains.

In this dissertation, algorithm aiming at minimizing energy cost for customers is proposed. The algorithm adopts energy consumption scheduling and optimal stopping rule respectively to try and solve the cost minimization problem. The energy consumption scheduling algorithm is discussed in a neighborhood area network level. In addition, the approach with optimal stopping rule also considers the comfortable level of delay as a variation.

Fairness is another sub-topic of demand response's that has been vigorously researched in past years. Vuppala et al.'s paper [15] looked into the definition of fairness. For demand response participants, the lack of fairness features makes demand response programs much less attractive. In fact, having understood the importance of having as many participants as possible to get involved with demand response is the key to future advancements. Vuppala et al. explored the definition and criteria of a fair demand response. They proposed a fairness-incorporated pricing model and compared it against flat rate schemes and price-based schemes. Their simulation results supported their expectation that their model achieved better fairness than the other models for it not only flattened the demand curve, but also was able to create a win-win situation for both customers and power provider.

The price-based foundation of Vuppala's scheme puts it under the category of fair bill. However, fair bill is not the only way to achieve fairness. In this dissertation, fair delay is explored and discussed as another option to offer fairness to the customers. The key idea is to avoid unfair delays during peak hours and keep delays fairly distributed among consumers. This dissertation proposes an energy consumption scheduling based algorithm to realize the above-mentioned goal.

The rest of this dissertation is organized as follows. Chapter II reviews a collection of current literatures that are related to the topics discussed in this dissertation and highlight the opportunities to contribute to the area. Real-time demand response in smart grid distribution using energy consumption scheduling methodology is explored and thoroughly discussed in Chapter III. In Chapter IV, fairness in the form of fair delay is studied to further engage the customers with demand response and smart grid. Following that, Chapter V studies and provides the solution to customer cost minimization problem using energy consumption scheduling with

optimal stopping rules in RTP demand response program. Finally, this dissertation concludes in Chapter VI, with a summary of this dissertation and an outline for possible future work directions.

2 LITERATURE REVIEW

2.1 Power Grid Overview

Power grid has changed quite a lot in the last couple of decades because of technological advancements in both industries and academics [15]. Although power grids are getting “smarter”, the basic function of grids never changed. Their main function is still generating electricity and supporting energy consumption. Understanding the way a traditional power grid functions is still quite important for researchers who are dedicated to accelerate the evolvement of power grids and make them “smarter”.

An electrical grid system has four main elements. They are electricity generation plants, transmission substations, distribution substations, and end users. Fig. 2.1 is a graphic overview of an electrical grid system [15]. As shown in the figure, as it moves downward, more elements start to appear, which represents the service structure of a power plant very well since one plant supports the energy consumption of a large number of customers’.

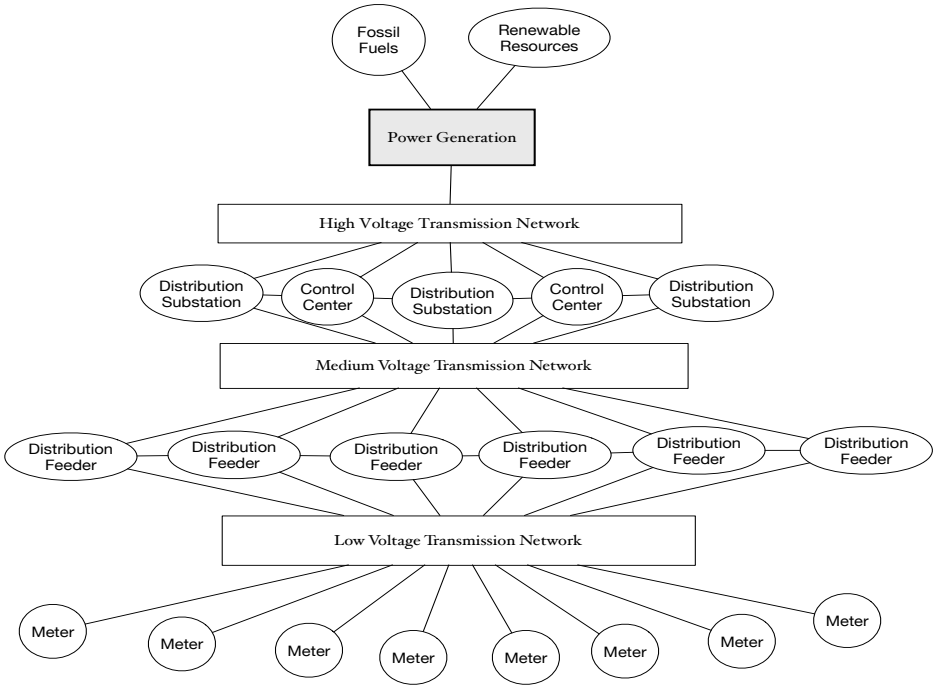

Fig. 2.1 Overview of Electrical Grid System [15]

An important part of power grid is Supervisory Control And Data Acquisition (SCADA). SCADA systems are known for their diverse functionalities that include real-time monitoring, logging/archiving, report generation, and automation for smart grid [14]. Because of their function set, SCADA systems are widely used to monitor and control industrial processes. In the U.S., SCADA systems were developed among power delivery systems, and have already been in use for five decades. To date, many such advanced systems and their applications have been developed worldwide.

In the past 10 years, an interest in improving the national power grids to make them "smart" and productive has cropped up. This means, closed, isolated, and single user-based architectures will be changed into interlinked, standardized systems that support new functionalities, and they are also user friendly and cost efficient. SCADA being an important

feature of power grid will be required to become more robust and secure for the sake of the smart grid. Gao et al. studied the SCADA communication and security issues in their 2014 paper [20].

Gao et al. [20] started their paper with a detailed overview of the functionalities of SCADA's. As mentioned, SCADA's main functionalities include monitoring, logging/archiving, report generation, and automation. In addition to these functions, SCADA is also features access control, multimedia interface, trending, and alarm handling. These functions are explained below and shown graphically in Fig. 2.2.

Access control: users are allocated among groups that have defined read/write access privileges to the process parameters in the system and often to specific product functionality [17].

Multimedia interface: multimedia interface supports multiple screens, which can display combinations of synoptic diagrams and text [18].

Trending: most of the SCADA products provide trending facilities, and one can use it to summarize the common capabilities in a chart or a figure [18].

Alarm handling: alarm handling is based upon limit and status checking, and it is performed centrally in the data servers [19]. In other words, the information only exists in one place, all users see the same status (e.g., the acknowledgement), and multiple alarm priority levels (in general many more than three levels) are supported. It is usually possible to group alarms and to handle these as aggregation. E-mails can be generated, and predefined actions can be executed automatically in response to alarm conditions.

Logging/archiving: logging can be described as the medium-term storage of data on a disk, and archiving can be described as the long-term storage of data either on a disk or on another permanent storage medium [19]. Logging is typically performed on a cyclic basis. In other words, once a certain file size, period, or number of points is reached, the data are

overwritten [19]. Logging of data can be performed at a set frequency, or it can be initiated only if the value changes or if a specific predefined event occurs. Logged data can be transferred to an archive once the log is full. The logged data is time stamped and can be filtered when viewed by a user. The logging of user actions is, in general, performed together with either a user ID or station ID.

Report generation: one can send reports by using Structured Query Language (SQL) type queries to the archive, real-time database, or logs [19].

Automation: many of the products allow actions to be triggered automatically by events [19].

Fig. 2.2 SCADA Functionality [20]

SCADA systems have been evolving since they were created. The paper [21] summarized that distributed architecture and multimedia are two dominate techniques that would influence the SCADA systems. The paper [19] reviewed that SCADA was adopting Web Technology, ActiveX, and Java in the products and also adopting object linking and embedding for process control as a means of communication between client and server modules. The paper [22] argued that the future SCADA is not a stand-alone system, but rather, it is incorporated with a deep level implementation of information flows within the substation system featuring the advanced communication technologies.

Recent SCADA systems have shown a feature that many new technologies have applied into systems to make them more real-time, productive, robust, and secure. For example, those new technologies include advanced systems such as SCADA systems based on Internet [23]-[25], Intranet-based SCADA [26], web-based SCADA [27], industrial Ethernet-based SCADA [28], web-based SCADA display system via Internet [29], and so forth.

In order to have a better understanding of the power grid, or even smart grid, the researchers analyzed the structure of the SCADA system as well.

The traditional SCADA system is composed of a central host computer and a number of remote terminal units (RTUs), the operator terminals, and/or programmable logic controllers (PLCs) [30]. Some key components are as follows [30]:

SCADA meter: used for gathering data from a plant (acquiring) and sending commands (control) to a plant.

RTU: used for connecting to sensors in the plants, converting sensor signals to digital data, and sending digital data to the supervisory system.

PLCs: used as field devices because they are more economical, flexible, and configurable than special- purpose RTU.

Communication infrastructure: used for connecting the supervisory system to the RTUs and/or PLCs.

A proper understanding of SCADA is necessary to analyze the various security threats that need to be addressed. A SCADA system is a centrally controlled master system that commands terminal RTUs, and these RTUs include relay devices, actuators and sensors, circuit power breakers, voltage regulators, and so forth. Master terminal units (MTUs) are higher-level units, including supporting applications, human machine interfaces (HMIs), data storage, and acquisition systems. PLCs are used as control sensory devices and RTUs. Programmable automation controllers are used as the basic controlling unit.

There are three generations of SCADA system architectures. The first generation uses the WAN for communication between MTUs, which execute decision-making, and RTUs, which serve the end users. The second generation uses local area networks (LANs) to communicate between MTUs and RTUs. The third generation uses wide area network (WAN) and Internet protocol (IP).

The components of the SCADA architecture include the following: (i) on-field devices, for example, RTUs, PLCs, intelligent electronic devices (IEDs), and Process Automation Controllers (PACs); (ii) monitoring and controlling equipment, for example, HMI, historian, controller for SCADA, and real-time data processor; and (iii) communications, for example, Inter-Control Center Communications Protocol (ICCP), Odyssey Commutation Processor (OCP), Ethernet, wireless networks, serial network connections, and Modbus and DNP3 protocols. The terminal controller unit is responsible for communicating, analyzing the data, and displaying the

occurring events to the users as well as the service providers. The devices are generally controlling and controlled devices, which run on embedded operating systems to communicate data using various controlling protocols, such as Modbus and DNP3.

To ensure that SCADA systems are well maintained, security measures should be given special importance [31]. Attacks on the SCADA system can cause threat to people's safety, a loss of productivity, and even some environmental damage [31]. Some basic network systems (e.g., ports, hubs, switches, routers, firewalls, and the Simple Network Management Protocol (SNMP)) are also general, electrical power grid components that are at risk of being attacked.

The interconnection of microprocessors used in SCADA has been an increasing trend in recent times, and this interconnection makes the SCADA system less secure [31] PLCs and DCSs used as process controllers have been replaced by IEDs, which are generally applied to control power meters, to control power stations, and to trace heat [31] Power meters, wireless LANs, IEDs, relay networks, and Master Control Centers (MCCs) are interconnected in SCADA when setting up power grids [31]. With all these devices being interconnected, the network of a SCADA system is becoming less isolated and, thus, becoming prone to attacks [31].

- Hardware architecture

One is able to distinguish between two basic layers in a SCADA system: the client layer, which caters to the human–machine interaction and the data server layer, which handles most of the process data control activities. The data servers communicate with devices in the field through process controllers. Process controllers (e.g., PLCs) are connected to the data servers either directly or via networks or fieldbuses that are proprietary (e.g., Siemens H1) or nonproprietary (e.g., Profibus) [19]. Data servers are connected to each other and to client

stations by means of an Ethernet LAN. The data servers and client stations are NT platforms, but for many products, the client stations may also be Win95 machines.

- Software architecture

The products are multitasking and are based upon a real-time database that is located in one or more servers. Servers are responsible for data acquisition and handling (e.g., polling controllers, alarm checking, calculations, logging, and archiving) on a set of parameters, which are typically those to which they are connected [19].

- Communication infrastructure

A typical SCADA communication system generally consists of a master station and many other distributed RTUs [30]. The RTUs are interconnected to the master station through a variety of communication channels, such as radio links, leased lines, fiber optics, and others [30]. However, one of the greatest communication challenges is that the channel limits the speed of data acquisition and control that can be performed. Furthermore, random noise on the channel is another challenge that has hindered SCADA communication [30].

These security threats that SCADA faces alerts smart grid researchers about potential security issues that smart grid might face. Upon understanding the system, structure, and even potential threats that the traditional grid deals with, it is appropriate to move on to smart grid for more discussion related with this dissertation now.

2.2 Current Infrastructures and Future Direction of Smart Grid

2.2.1 Smart Grid

One main objectives of the update from traditional grid to smart grid is to become more energy-efficient [32]. To realize this goal, smart grid takes advantages of latest technologies,

including intelligent and autonomous controllers, advanced software for data management, and two-way communications between power utilities and consumers. Before the discussion of smart grid goes further, it is necessary to clarify what smart grid is.

In Chapter I, the definition of smart grid has been explored. Here in Chapter II, more in depth discussion can be carried out with the help of current literature.

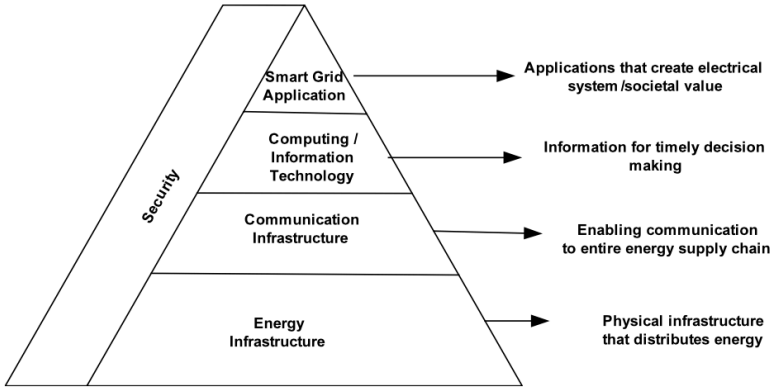

Fig. 2.3 Definition of Smart Grid [1]

The U.S. DoE has an official definition of smart grid, which is presented in the format of a pyramid graph (Fig. 2.3) [11]. As the graph shows, essential components of a smart grid from bottom up are energy infrastructure, communication infrastructure, computing or information technology, and smart grid application. The bottom layer is physical energy infrastructure that distributes energy. Communication infrastructure is defined on the very top of the physical energy infrastructure to entire supply chain. Computing/information technology is above the communication infrastructure for timely decision-making. Smart grid applications are on the top to create electrical system/societal values. Security is in another dimension and covers all layers, so that the importance of security can be highlighted.

Generally, Smart grid is a data communications network integrated with the electrical grid that collects and analyzes data captured in near-real-time about power transmission, distribution, and consumption [33]. Based on these data, smart grid technology then provides predictive information and recommendations to utilities, their suppliers, and their customers on how best to manage power [33]. From another perspective, smart grid is a complex system of systems, and therefore National Institute of Standards and Technology (NIST) has developed a conceptual architecture for the entire smart grid [2]. This conceptual architectural reference model provides a means to analyze use cases, to identify interfaces for which interoperability standards are needed, and to facilitate the development of a cyber security strategy [2].

Though it emerged from the recent power grid system, smart grid has more requirements to meet and new characteristics to attain. The synthesized requirements of the desired smart grid are as follows:

(1) Advanced Metering Infrastructure (AMI): It is designed to help customers know the real-time prices of power and optimize power usage accordingly [2] [34]. Also, consumers become informed participants, and they can choose different purchasing patterns based on their needs and the grid's demand, which can ensure the reliability of the electric power system [35].

(2) Wide area Situational Awareness: It is intended to monitor and manage all the components of the electric power system. For example, their behaviors and performance can be modified and predicted to avoid or to address potential emergencies [2].

(3) IT Network Integration: The smart grid scopes (generation, transmission, distribution, consumption, and control center) [7] and sub-scopes will use a variety of communication networks which are integrated from IT networks.

(4) Interoperability: The smart grid will have the capability of two or more networks, systems, devices, applications, or components to exchange and readily use information securely, effectively, and with little or no inconvenience to the user [2]. The smart grid will be a system of interoperable systems. That is, different systems will be able to exchange meaningful, actionable information. The systems will share a common meaning of the exchanged information, and this information will elicit agreed-upon types of responses. The reliability, fidelity, and security of information exchanges among smart grid systems must achieve requisite performance levels [2].

(5) Demand Response and Consumer Efficiency: Utilities and customers will cut their usage during peak times of power demand. Mechanisms will also be made for consumers to smartly use their power devices to lower their cost [2].

Hence, we can conclude that smart grid, by definitions and requirements, will have the characteristics of being more efficient, reliable, intelligent, etc. There are many challenges and issues involved in the smart grid communication fields. Essentially, there is an effort to make the power generation and consumption more flexible, to allow dynamic pricing, the collection of energy from small, reusable energy producers and so on. To implement this, the electric grid needs to be upgraded with communication and computation devices. Moreover, with integrating information networks into the current power grid system will come many security and privacy issues, which must be addressed. Obvious vulnerabilities are introduced by IT networks. For example, hackers can steal customers' power without any trace being left their metering devices. The NIST therefore has released a guideline for addressing cyber security and privacy issues in the Smart Grid [36].

To achieve the characteristics of the desired Smart Grid addressed in the previous subsection, National Energy Technology Laboratory (NETL) described five key technology

areas that are integrated communication (IC), sensing and measurement, advanced components, advanced control methods, and improved interfaces and decision support [34], [35] as shown in Fig. 2.4.

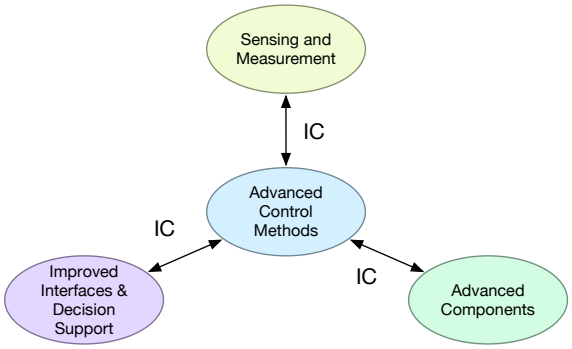

Fig. 2.4 Five Key Technology Areas in Smart Grid [34], [35]

These key technologies will later be added onto the smart grid architecture to make it functional like muscles on bones. An overview of smart grid architecture is able to assist the understanding of smart grid in return.

There are three major sources of smart grid architecture proposals:

(1) Government & Organizations: Provisioned requirements and blueprints of smart grid.

(2) Industrial: Proposals of communication infrastructure implementations.

(3) Academia: Greater focus on defining communication architecture requirements and solutions.

The architectures proposed above are focused on parts of the smart grid system, which are intended to address specific requirements that must be met. However, several conceptual architectures of the smart grid have now been proposed by national organizations and companies, such as the DoE [7], the State of West Virginia [34], NIST [2], etc.

The DoE's Smart Grid System Report [7] proposed that a smart grid's architecture should include the following scopes: Market Operators, Reliability Coordinators, Gen/Load Wholesalers, Transmission Providers, Balancing Authorities, Energy Service Retailers, Distribution Providers, and End Users (Industrial, Commercial, and Residential).

West Virginia's white paper [34] proposed that smart grid architecture should be composed of the following four elements: Sensing and Measurement, Advanced Control Methods, Improved Interfaces & Decision Support, and Advanced Components.

NIST proposed in the NIST Framework and Roadmap for Smart Grid Interoperability Standards [2] that smart grid architecture should include the following: Customers, Markets, Service Providers, Operations, Bulk Generation, Transmission, and Distribution. This is one the most fully described architectures proposed in recent smart grid literature. As depict in Fig. 2.5, Customers area can be further categorized into three types: Home Area Networks (HANs), Building Area Networks (BANs), and Industrial Area Networks (IANs). They can be either wired or wireless networks on customer premises (home, building and industry areas respectively) that support messaging among appliances, smart meters, electronics, energy management devices, applications, and consumers. Applications and communications in these networks may be driven by Home Energy Management Systems (HEMS), Building Automation and Control Networks (BACnet), or other energy management systems [37].

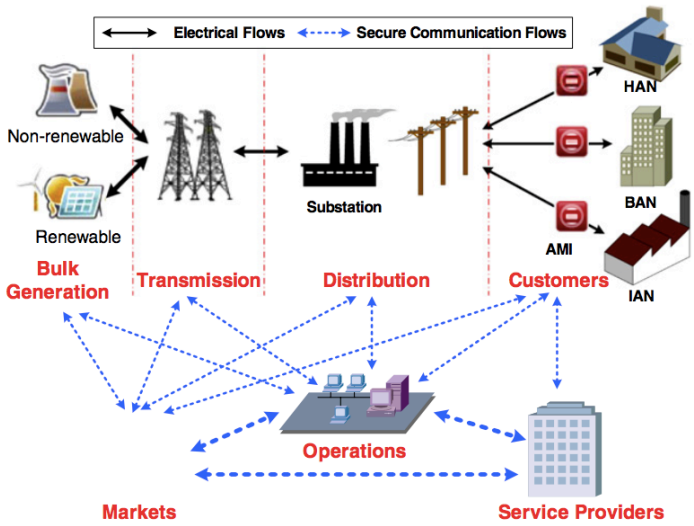

Fig. 2.5 Smart Grid Architecture [38]

After reviewing the existing organization-proposed smart grid architectures [2], [7], [34], [35], [39], I conclude that a smart grid architecture must address the following critical issues as also shown in Fig. 2.6 [33]: (1) transmitting data over multiple media; (2) collecting and analyzing massive amounts of data rapidly; (3) changing and growing with the industry; (4) connecting large numbers of devices; (5) maintaining reliability; (6) connecting multiple types of systems; (7) ensuring security; and (8) maximizing return on investment.

Fig. 2.6 Critical Issues in Smart Grid [33]

NIST further broke down smart grid into seven domains according to collections of interconnected networks. The details of seven domains are shown graphically in the figure below Fig. 2.7 [2].

Fig. 2.7 Seven Domains of Smart Grid [2]

As these networks are interconnected, the way they communicate with each other is much more complicated and intertwined than the traditional "generation-transmission-distribution-customer" way. Fig. 2.8 is an illustration of the ongoing communications between these seven domains. The compact structure of the graph represents the frequent communications between these domains with operation at the center of communication network. However, it is important to realize that although several domains are communicating with more than one other domain, not all domains are communicating with same number of other domains. The domain of service provider only communicates with and connects markets, operations, and customers (including residential, commercial, and industrial) because of the role it plays in a smart grid only requires communication with these three other domains [2], [32]. An example from the other side of the scale is operations. It is in constant connections with all other six domains because its managerial role in electricity movement means it need to get the latest updates about what is going on in the grid and what needs to be done all the time.

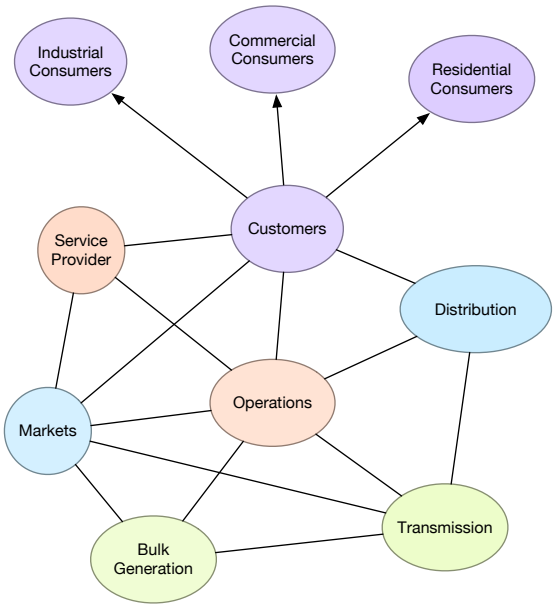

Fig. 2.8 Communication Network Between Seven Domains [2], [32]

2.2.2 Microgrid

Microgrid is a variation of smart grid's among many. It is a combination of customer and operation domain because of its function set. Microgrids usually operate in disparate locations and may not be connected with the national grid [40]. It is "composed of a set of distributed energy resources and is considered as an alternative energy providing system to the current centralized energy generation" [41]. In other words, microgrids coordinate distributed energy resources, energy storage devices and electric loads in a decentralized manner [32]. Possible electricity generating sources of microgrid's include renewable energies, such as wind power, solar energy, biomass, tidal energy etcetera, among traditional electricity generating methods. Microgrid is an example of the customer domain because of its capability of generating, storing, and managing energy. The resemblance shared between microgrid and operation is the management of energy movement. The operation cycle of microgrid's is shown graphically below in Fig. 2.9.

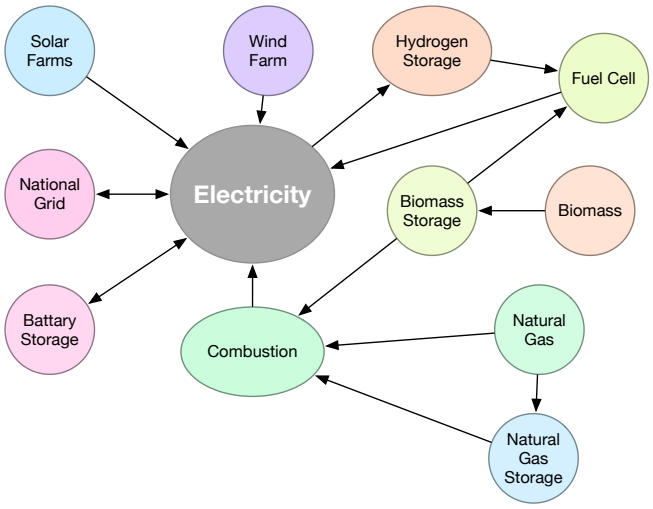

Fig. 2.9 Microgrid Operation Cycle [32]

Mohamed and Kovio proposed an online management genetic algorithm of microgrid for residential application [42]. They adopted a power management strategy proposed by Ramanathan and Gupta, which turned out need to be completed online. Mohamed and Kovio included not only operation and maintenance costs, but also emission costs into their cost function. They modified the algorithm presented in their previous work by shifted the focus to cost optimization. They also considered the possibility of selling electricity back to the main grid when microgrid has extra energy stored.

Naraharisetti et al. studied the scheduling problem in microgrid [40]. They proposed a mathematical model known as “Mixed Integer Linear Programming”, which aimed at advancing the scheduling operations for microgrid that are connected with the national grid.

2.2.3 Smart Homes

Smart homes is another trendy topic that refers to residential buildings equipped with smart grid technology, which can be as basic as a smart meter with communication capability

that aims at benefiting the end users [41], [43], [44]. To be specific, the benefits of smart homes include simplify the life of its inhabitants, reduce energy usage, and provide comfort and security [44]. In 2012, smart homes were already quite popular thanks to their ability to lower energy bills, allow flexibility on energy consumption, and benefit the environment. However, considering the difficulty of incorporating "dumb" appliances into smart homes, smart home technologies were generally limited to demonstration projects.

In Sun and Huang's paper, they reviewed a large range of energy optimization methods for smart home appliances. A smart home usually has a set of devices that include those seen in following Fig. 2.10. Also in a smart home, all smart devices are "typically linked to a home network to which they report their states or from which they receive instructions" [44].

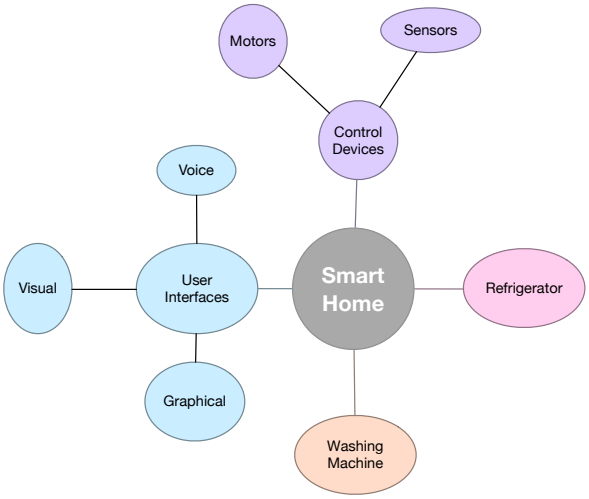

Fig. 2.10 Smart Home Devices [45]

The major energy optimization methods under analysis in Sun and Huang's paper are fuzzy logic, neural networks, heuristic methods, and evolutionary algorithms. This paper covered

a number of previous researches and experiments that adopted above-mentioned method(s) in hope for the realization of the goal of optimizing the power scheduling in smart homes.

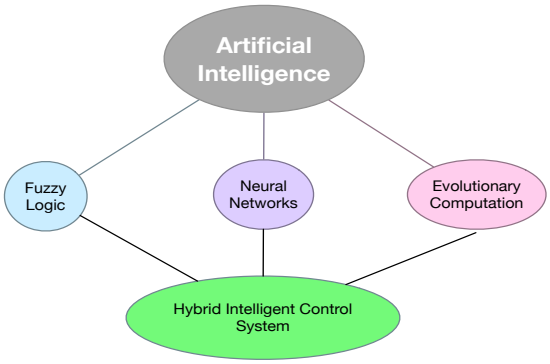

Fig. 2.11 Major Energy Optimization Methods

The above reviewed information about smart grid, microgrid, and smart homes makes it clear that smart grid is indeed a wonderful system with a lot of potential. With different variations, such as microgrid and smart homes, smart grid will be able to change the world to the better in a lot of ways. However it is restricted in various aspects because of technological incompetence and lack of customer participation among other reasons. The following subsection will discuss DSM and demand response, the improvement of which will make smart grid more attractive to the customers.

2.3 Demand Side Management & Demand Response

A concept that is quite important in smart grid is called Demand Side Management (DSM). DSM is a concept that includes all activities that aim at altering the customers' energy consumption file, no matter it is the time and/or shape, in order to match the supply while incorporating renewable energies efficiently [32]. In addition, DSM also works wonders in the

integration of distributed generation and reduces costs in both energy generation and transmission.

A lot of researchers believe DSM is an umbrella term for the collection of energy-efficiency, conservation program and demand response program [12], while other researchers and practitioners see DSM and demand response as interchangeable equals [47], [48]. In this dissertation, they are treated as synonyms.

The paper written by Albadi and El-Saadany gave a very well-rounded overview of demand response in electricity markets [10]. Their paper started by offering descriptions of demand response. They highlighted three ways in which customers can take action. These actions are reducing only peak-hour electricity usage, shifting load demand from peak hours to off-peak hours, and using onsite generation, which is also known as "customer owned Distributed Generation". The paper went on by looking into the different groups of demand response programs. However because of the stance their paper was written from, they mainly looked at demand response programs based on offered motivations. In another demand response survey presented by Vardakas et al. [32], they also mentioned demand response programs based on control mechanism and demand response programs based on decision variables. A graphical presentation of these programs can be found here in Fig. 2.12.

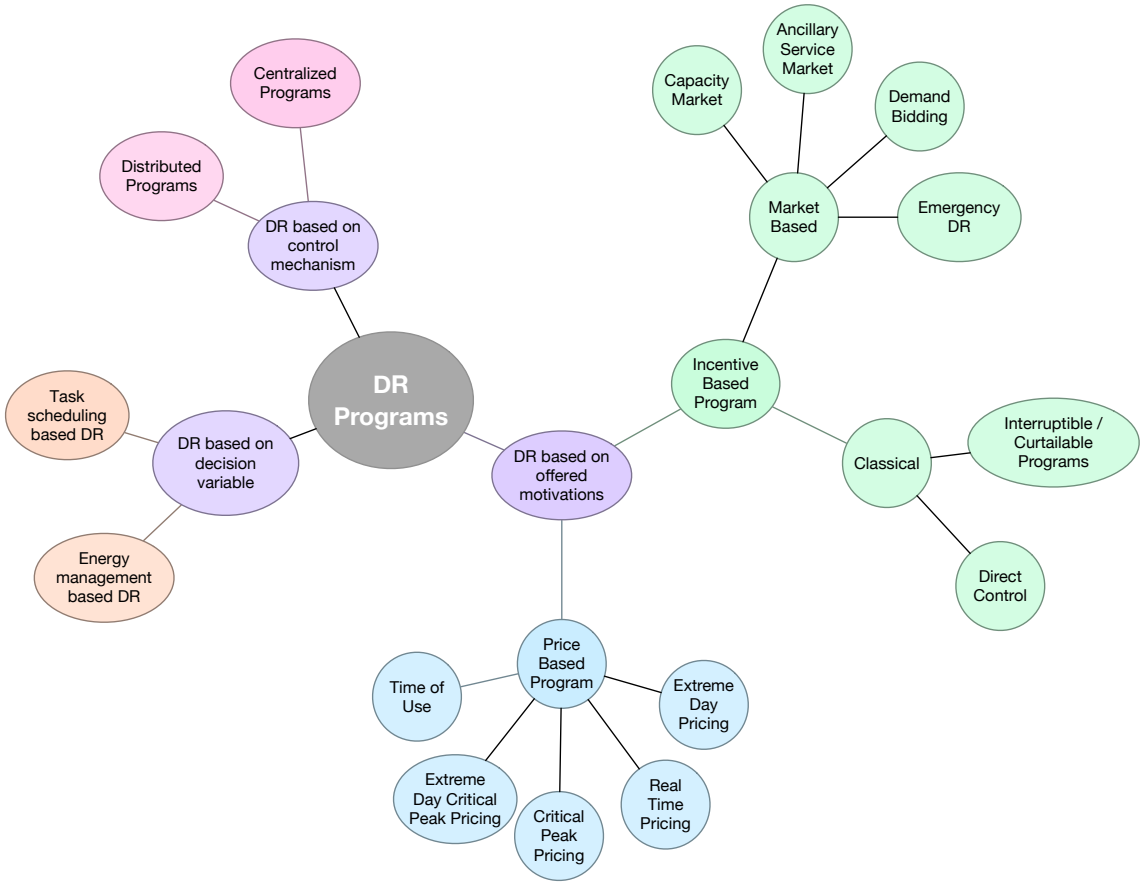

Fig. 2.12 Collection of Demand Response Programs [32]

Another difference between Albadi and El-Saadany's survey and Vardakas' survey is that they grouped demand response programs based on offered motivations differently. A graphical illustration of how Vardakas grouped demand response programs can be found below in Fig. 2.13 [32].

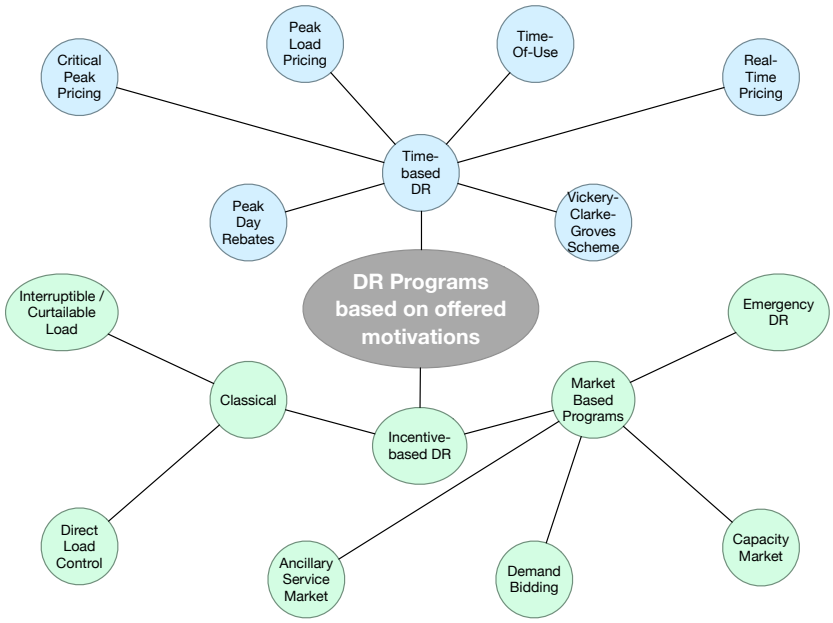

Fig. 2.13 Vardakas' Version of Demand Response Programs Based on Offered Motivations [32]

The differences between the two groupings are mainly found in non-incentive-based demand response programs. Instead of calling the non-incentive-based programs "price-based programs", Vardakas named them "time-based programs". In both groups, there are time-of-use pricing scheme, RTP, and critical peak pricing scheme. In Vardakas' paper, peak load pricing scheme divided a day into a number of periods and different electricity rate was applied to each period. Peak day rebates scheme allows customers to make their own decision on whether or not they want to respond to a critical event. Vickrey-Clarke-Groves scheme was based on customers' voluntary participation on providing their power demand information to a centralized mechanism for price calculation. On the other hand, in Albadi and El-Saadany's survey, extreme day pricing scheme has a higher price for electricity, which is in effect for the whole 24 hours of the extreme day that will be known one day ahead [10]. Finally, extreme day critical peak pricing is the scheme that critical peak pricing is adopted for peak and off-peak periods during extreme days whereas a flat rate is used for other days. The differences between the definitions highlighted the

differences between the focuses of the two groups, which in return explained why they were grouped in such ways.

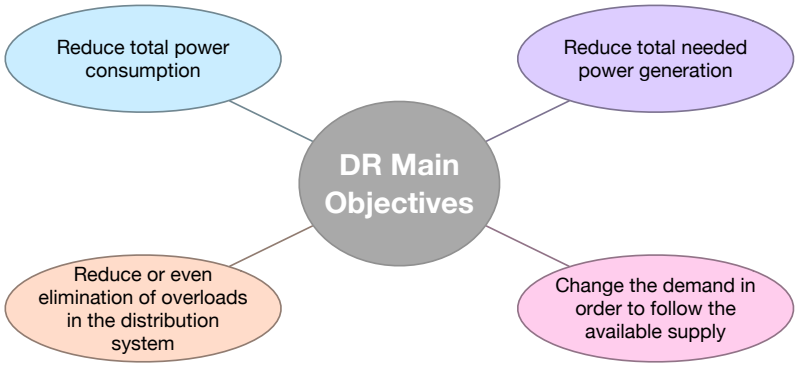

Fig. 2.14 Main Objectives of Demand Response [32]

The various demand response programs, regardless of their different designs, all aim at achieving one or many of main objectives. Fig. 2.14 illustrates the objectives of demand response schemes [32]. In fact, various demand response programs were created based on these objectives. Usually, above-mentioned demand response programs aim at fulfilling more than one objective with their algorithm to increase its implementation rate. For instance, the primary objective of price-based programs is to reduce or even elimination of overloads or to change the demand in order to follow the available supply depends on the consumption profiles of the customers. On top of that, there is also a secondary objective that these programs are aiming to achieve, which can be both to reduce the total power consumption and to reduce total needed power generation, since these two objectives are somehow interconnected.

Albadi and El-Saadany [10] also evaluated the benefits and costs of demand response programs, which are also shown graphically in Fig. 2.15 and 2.16, respectively.

On top of merits and costs evaluation, this paper also highlighted the most common indices used for demand response evaluation, which are the actual peak demand reduction and the variations of this factor. The indices decision was made based on the ultimate goal of demand response that is to reduce the peak demand for smart grid. To make the indices more suitable for making comparisons between different demand response programs, the actual peak demand reduction factor was also normalized into percentage. Because of the different characteristics and functionality of various demand response programs, demand price elasticity, which was found by calculating the ratio of the percent change in demand to the percent change in price ($E=\Delta Q/\Delta P$). Apart from measuring the achievements made by demand response programs in a numeric manner, the authors also noted that customer acceptance and enrolment were also important factors that make considerable impacts on demand response programs.

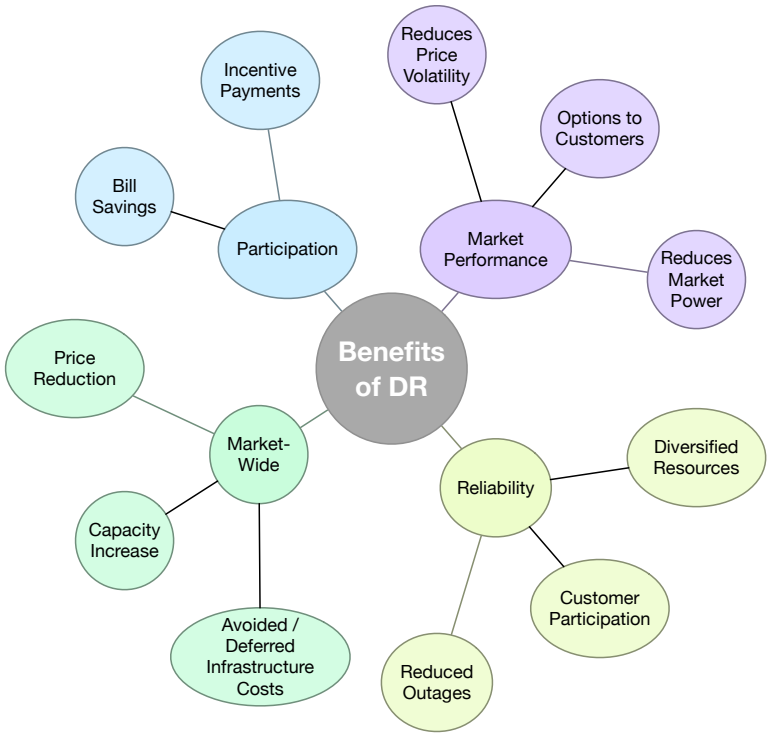

Fig. 2.15 Benefits of Demand Response [10]

Fuselli et al. [3] experimented with home energy resource scheduling with the method of action dependent heuristic dynamic programming (ADHDP). Fuselli and his team used ADHDP as an optimization technique to realize cost saving and energy waste minimization. ADHDP was consisted of two parts that were Action and Critic Network, and the program was able to minimize a given utility function over a certain time horizon. The researchers used both a historical set of solar irradiation and the main grid in their simulation. The results confirmed their expectation that the proposed method was able to reduce the overall energy cost.

2.4 Energy Consumption Scheduling and Optimization

2.4.1 Energy Consumption Scheduling

As previously mentioned, energy consumption scheduling performs as the communication coordinator between smart appliances and the power provider. It helps to assure

the smart appliances will function when the power price is ideal for the customers and as a result minimizes power bills. Because of the important role energy consumption scheduling performs in smart grid and bill minimization, researchers have conducted various researches to exploit as much potential as possible from the energy consumption scheduling.

Targeting at improving demand response efficiency in residential power usage, Chen et al. [45] proposed a RTP-based algorithm that adopted a Stackelbrg game model. In their model, the leader level game was played by the power provider for it sets the real-time price of electricity, and the follower level game was played by energy consumption scheduling for it schedules the power consumption of smart appliances at the customers' end. Instead of working on the minimization of customers' bills, the algorithm proposed was more focused on the benefits of the power provider's. According to their simulation result, the algorithm was able to balance the difference between customers' actual demand and planned supply, as well as reduce the peak load [45].

Lee et al. [49] proposed program that can be embedded in the energy consumption scheduling with a focus on peak load reduction in homes and buildings. Their design works best in the scenario where appliances are no more than 10, the power load profile is practical, and the search space size is reasonable. Although the limitations can pose a question regarding the practicality of this proposed scheme, they are a reflection of the complex nature of the energy consumption scheduling.

From the above reviews, it is clear that a large number of projects done on the energy consumption scheduling are actually aiming at optimization as their goal. A revision of optimization-related works can be found below.

2.4.2 Optimization

Optimization is an important part of smart grid and demand response because it is the process that makes smart grid and demand response as perfect, effective, and functional as possible. The objectives of demand response-based optimization models usually fall into one of five categories that are 1. minimization of electricity cost, 2. maximization of social welfare, 3. minimization of aggregated power consumption, 4. minimization of both electricity cost and aggregated power consumption, and 5. both the maximization of social welfare and minimization of aggregated power consumption [32].

In Samadi et al.'s [50] paper, the authors looked into a real-time energy consumption scheduling algorithm with load uncertainty that aims at bill minimization for individual residential customers. The load-scheduling problem was formulated as an optimization problem. The researchers adopted an approximate dynamic programming approach to make the computing simpler. They also studied the difference between must-run appliances (such as lighting) and controllable appliances that are much more flexible. Instead of assuming the demand response algorithm understands customers' energy needs perfectly, the algorithm proposed in this paper survives on only some estimates of future demand. Their algorithm combined RTP with inclining block rates to balance residential load in order to achieve a low peak average ratio (PAR) [50].

Chen et al. [18] evaluated real-time price-based demand response through applications installed in energy consumption scheduling with a focus on Stochastic Optimization and Robust Optimization. Their research was strictly conducted with residential appliances, which is the same with Samadi et al.'s study. On top of considering bill minimization as their main goal, Chen et al. also took energy efficiency into consideration when designing their model. In order to achieve their goal, the proposed demand response program would automatically determine "the

optimal operation in the next 5-minute time interval while considering future electricity price uncertainties" [18]. In addition, the researchers also employed the risk aversion formulation to control the financial risks that comes with real-time price uncertainties.

The success of optimization will highlight the benefits of demand response, and as a result makes demand response more attractive to the customers and pushes up the participation rate. The increasing participation rate will then become the motivation of further technological advancements in smart grid. Eventually, smart grid will find the optimal balance point between human electricity consumption and environmental costs. All this described train reaction happens with the urge of striving for a better future.

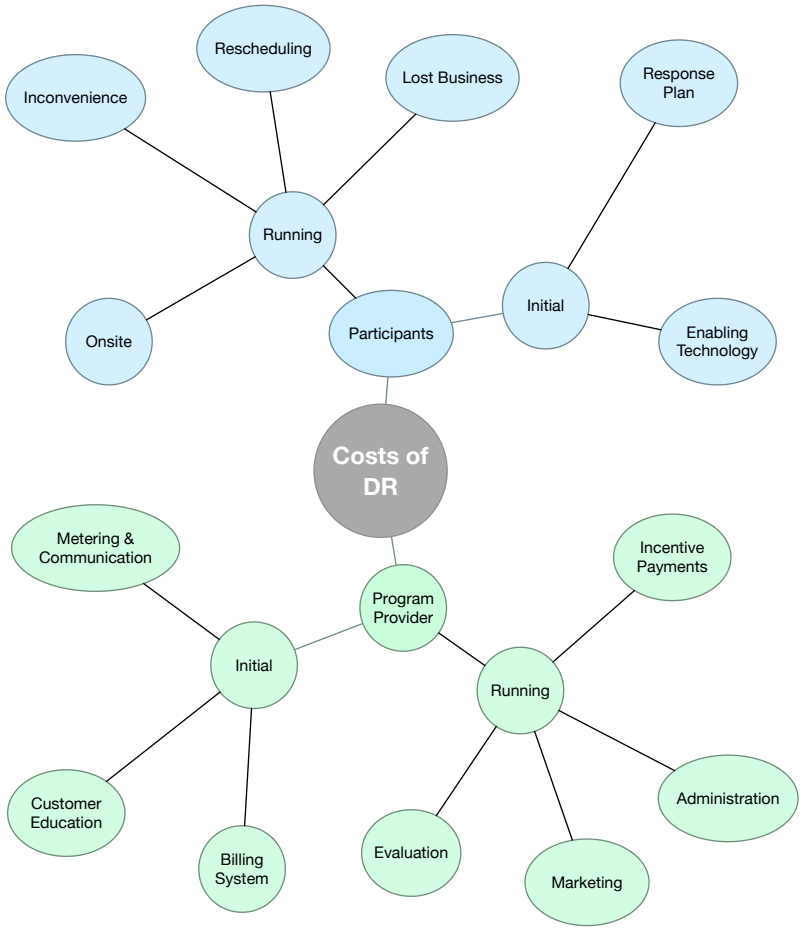

Fig. 2.16 Costs of Demand Response [10]

2.5 RTP and Fairness

2.5.1 RTP

Albadi and El-Saadany's paper [10] also discussed customers' experience with various demand response programs. According to their findings, RTP programs relied on opportunities for bell savings as their major customer motivation. However, because of poor marketing and limited technical assistance that was available to the participants, some RTP programs' penetration level was quite low. In addition, the fact that some participants were not very responsive to different prices also contributed to the unsuccessful result of some of the RTP

programs. The findings presented in Albadi and El-Saadany's paper offer valuable insights for future researches in terms of available room left for improvements. Having said this, it is important to remember their research was conducted in 2007. A lot more achievements and advancements have been made in the field since then.

Mohsenian-Rad and Leon-Garcia conducted research on the topic of optimal residential load control with price prediction in RTP [14]. The researchers identified a couple of barriers that were blocking RTP from getting fully utilized based on literature. The barriers were: 1. the lack of knowledge among customers about how to respond to the time-varying prices and 2. the lack of effective building automation systems that can provide assistance to the customers. The solutions that researchers came up with were an optimal and automatic residential energy consumption scheduling framework which targeted at achieving a desired trade-off between minimizing the electricity payment and minimizing the waiting time for each appliance in the resident subject to customers special needs [14].

Their proposed solutions were embedded in a scenario that includes a smart meter for every household, which connects to a smart meter, and an energy consumption scheduling device in every smart meter. Also they adopted a price predictor unit which was an addition to the energy consumption scheduling and estimated future price by applying a weighted averaging filter to past price [14]. By taking advantage of the actual hourly-based rates adopted by Illinois Power Company from January 2007 to December 2009 and a weighted average price prediction filter, the researchers found the optimal coefficients for different days of the week. The simulation results confirmed the merits of combining energy consumption scheduling and price predictor, especially in terms of reducing energy bills for end users.

An interesting note about smart meter is that in Vardakas' paper [32] he confirms the advantage of smart meter installation for it allows the implementation of more dynamic pricing schemes that can trigger peak-demand reduction, while on the other hand he mentioned some consumer groups may have different reactions. According to [51], the lower level of price-elasticity of low-income consumer group makes it quite difficult for customers in that group to respond to the changing electricity rates. This is just one implication among many when various pricing schemes applied to a wide range of customers.

2.5.2 Fairness

Vuppala et al.'s paper also discussed the issue of fairness in demand response programs, with an emphasis on fairness principles that customers regard highly of [12]. To decide what kind of demand response program is "fair", they considered the criteria listed as following. For must–run appliances, such as lighting, power price will be fixed [12]. On the other hand, power consumed by non-must-run appliances will be charged at multi-dimensional prices [12]. User category, income level, and appliance category will be taken into consideration when determining the exact power price [12]. A graphical illustration of the criteria can be found as Fig. 2.17.

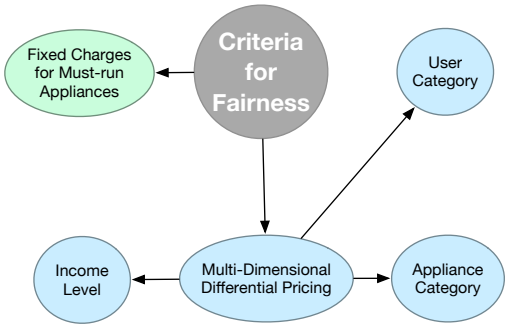

Fig. 2.17 Criteria for Fairness [12]

If a deal meets all the described criteria, it was then labeled as fair. However, after comparison, none of the available programs was able to meet all criteria. Even RTP was considered "unfair" because the differences between appliances and income levels were not important variables of RTP's. They then established the lack of fairness principles in demand response programs for current programs only address part of the criteria. .

The fair demand response scheme they proposed promised to address all the above criteria [12]. They made sure that the price of must-run services was time irrelevant, and that price varies according to different user types, appliances and income levels. The simulation results supported their expectation and, as a result, achieved a higher level of customer satisfaction. The result also showed a loss of economic efficiency as a side effect.

Zhang et al. looked at fair cost in smart homes with microgrid [41]. Sometimes a number of smart homes share one microgrid, and this sharing feature would eventually lead to competition between homes, especially when local distributed energy resources cannot respond to all load requests.

In this paper, fairness was achieved through fair cost and it was defined differently from Vuppala et al.'s. Instead of coming up with their own definition, the authors cited Mathies and Gudergan's definition, which described fairness as "the reasonable, acceptable or just judgment of an outcome which the process used to arrive" [52]. Zhang et al. proposed and experimented with a mathematical programming formulation that aims at maintaining the fair cost during such competition between smart homes that share the same microgrid. They utilized lexicographic minimax method with a focus on mixed integer linear programming approach to minimize one-day forecasted energy cost for each smart home. They studied two groups of 10 and 50 smart homes with their distributed energy resource operation and output examined. The simulation

result showed a 30% and 24% cost saving for the two groups respectively and a fair cost distribution among smart homes in their scenario.

Fan [53] proposed a distributed demand response program and user adaptation in smart grid. The proposed program and adaptation was established with a reference to the congestion pricing in IP networks. In Kelly et al.'s [54] work on proportionally fair pricing scheme, it was concluded that additive increase and multiplicative decrease rate control can achieve proportional fairness. The criterion for fairness was a willingness to pay parameter, which held the belief that customers who are willing to pay more should get more. Fan's work was established on top of Kelly et al.'s work and the simulation showed pricing could indeed help with shifting the load leveling burden from power supplier to the customers while maintaining proportional fairness [53].

Baharlouei et al. also introduced their criteria for fairness which was defined as "the variational distance between normalized billing vector for billing mechanism and normalized billing vector for billing mechanism" [55]. Based on this fairness index, Baharlouei et al. proposed a billing model that aims at not only improve the optimal general system performance, but also improve the fairness of the billing system [55].

2.6 Related Work Conclusion

This section reviewed the broad context where this dissertation is working in by zooming in from the big picture to more specific areas. First, it introduced the structure and functionality of traditional grid and details of SCADA, which is an important part of traditional power grid. Upon understanding what smart grid is built on, the discussion proceeded into the next section. The revision moved onto current situation of smart grid, system structure, and the seven domains

of smart grid. As the part with most potential, demand response was then reviewed, in terms of various current available demand response programs and the difference between various grouping principles. energy consumption scheduling and optimization problems were also discussed as the introduction to the next section. A series RTP and fairness related works were also reviewed and commented to gain insights on the specific areas that this dissertation will build on.

From this review of related work, it is quite obvious that although a lot of research has been done in smart grid, especially in terms of demand response and RTP, according to our research none of them dealt with real time demand response with fair delay as a constraint, which is how we contribute to the field with this dissertation.

The next chapter looks at the first problem this dissertation studies – how to achieve real time demand response using energy consumption scheduling.

3 SCHEDULABLE ENERGY SCHEDULING ALGORITHM IN SMART GRID DISTRIBUTION

3.1 Introduction

In recent years, there has been a rapid development of technologies in smart grid. One the most popular and promising area within it is the field of demand response. In this research area hides the potential key to the next stage of a more efficient smart grid. It also offers possibilities for the customers to receive a smaller and more reasonable bill, which in return will further encourage current and potential customers to utilize their smart-grid-compatible appliances.

After several years of vigorous research and experimentations, the most up-to-date demand response in smart grid has had the capability of lowering the peak time load consumption and reducing the utility and customer's cost. Along with the development of smart meter and two-way communication schemes are also developed methods for *near* real-time energy consumption scheduling.

Regardless of the mentioned achievements, there are still problems and challenges remain yet to be solved, such as real-time demand response, automation with energy consumption scheduling, and fairness issues. Among them the main problem that requires a timely solution in demand response is the real-time demand response issue.

Demand response issue has a couple of challenges to it, with the first being customers' participation [32]. According to the definition given by the DoE, demand response refers to "a tariff or program established to motivate changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over the time,

or to incentive payments designed to induce lower electricity usage at times of high wholesale market prices or when system reliability is jeopardized" [1]. This definition makes it clear that end-use customers' power usage preferences have the possibility of benefiting the power grid on top of benefiting themselves [32]. In other words, it is the customers who are at the center of successful demand response. Therefore, it is vital to design real-time demand response schemes in a way that customers can easily perceive the benefits of the demand response program, so that the customers' active participation will ensure the normal functionality of the power grid.

The improvements on real-time demand response, in return, concern the customers as well. With the introduction of the Plug-in Hybrid Electric Vehicle (PHEV) into smart grid, a regular customer can now be both a power consumer and/or a power supplier. That is to say, when real-time market power price is lower than the expectation of the customer, it has the opportunity to download the power load and store it locally as a consumer. When the real-time power price is greater than the expectation, the customer has the choice of either consume the power that had been downloaded earlier, or sell the extra amount of load back to the grid as a power supplier. Thus, to make the transition between the two roles a much smoother experience for the customer, real-time demand response is much needed for it offers the consumer much more choices and flexibility on its own power consumption.

The second challenge of the demand response issue is RTP. Thanks to current available RTP-alike schemes, each and every customer within the smart grid now has the opportunity to dynamically schedule its loads at each time. That is to say, schemes, such as TOUP scheme, CPP scheme, and Day-Ahead Pricing (DAP) scheme, that performs part/parts of RTP's function have enabled the customers to lower their power costs and have more flexibility with their power usage. It is also important to realize that regardless of how these available schemes have their

own advantages, they are all performing fragments of RTP's functionality after all. For instance, DAP scheme estimates the power price one day ahead, which creates unnecessary deviations from the real price. As a result, customers might actually be paying more for their power consumption. The merits of the mentioned schemes only make their lacking of systematic wholeness more obvious. Therefore, RTP is still in need in order to largely improve the efficiency of the smart grid. But the challenge of RTP, that is the fact the customers might not be able to know the future power price, remains. In this paper, this challenge is referred to as the "delay challenge".

In real-time demand response system, price prediction challenges are preventing the system from minimizing customers' bills using the RTP scheme [32].

In a scenario where the customer can manage its smart appliances energy consumption using smart home console while the demand response program is transparent to it, instead of having the customer worry about how to optimize the load management to reduce the bill payment, the demand response program will provide the automatic energy scheduling functionality to it. In this scenario, at time t1, the customer wants to do laundry and tells the washer to wash using real-time demand response program. Then the washer communicates with the smart home automation console with a desired task schedule based on the customer's predefined settings on the washer and the smart home console.

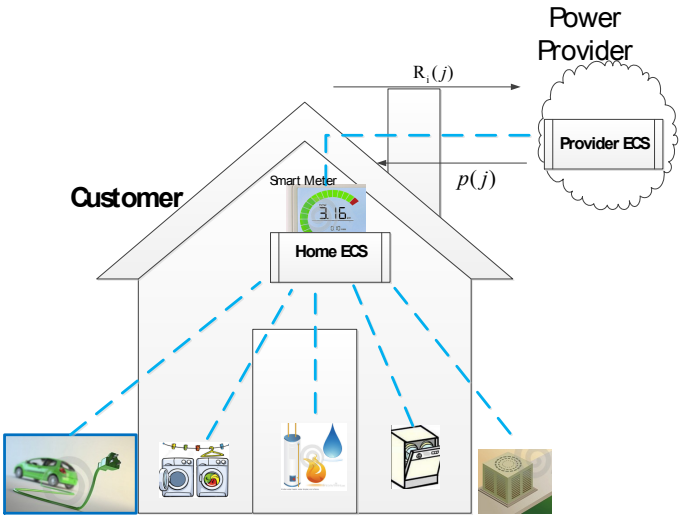

Fig. 3.1 Real-Time Demand Response Architecture (Partially From) [56]

As seen in Fig. 3.1, all the appliances are controlled by the energy consumption scheduling console system. This is the system that assists the customers with their scheduling for energy consumption. A good schedule of energy consumption will not only save the customer a lot of dollars, but also reduce possible pressure that the power grid receives during peak hours.

Here we assume that only the schedulable energy is considered in this chapter. This scenario assumes the energy consumption scheduling system has the ability to pause or resume. Here is a description of the setup of the energy consumption scheduling console.

•The smart meter shows the current real-time power price and displays on the energy consumption scheduling console.

•energy consumption scheduling console shows the load request status: how much has been consumed, and how much should the consumer pay, etc.

•Price Threshold that allows consumption will also be displayed.

•energy consumption scheduling automatically schedules all the loads for all the smart appliances.

In order to reduce the cost for power providers while deducting the customers' bills, energy consumption scheduling researchers attempts to provide a new way to the realization of this goal. This chapter proposes a real-time demand response system and its matching distribution energy consumption scheduling algorithms that aim at solving the total cost minimization problem. Forthcoming discussion about the problem and its solutions are hosted in the above-mentioned energy consumption scheduling system setup. A simulation is conducted to find the experimental-optimal results based on different parameter setups. The simulation results are analyzed to shine some light to the energy consumption scheduling problem from a new angle. The paper's goal is to focus on the customers' cost minimization. The cost is not only composed of the money that each customer pays for the bill, but also of the cost that incurs when customer does not get to consume the energy in time. Also, unlike focusing on the energy consumption scheduling of appliances within a customer's HAN level, this chapter focuses on the energy consumption scheduling with each customer considered as an entity at neighborhood area network level.

In the upcoming passages, this chapter discusses a number of related works that have been done previously in the field of energy scheduling. Then, it proceeds into section 3.3 System Model and section 3.4, in which section the problems under discussion are defined in detail. After this, proposed solutions to the problems, i.e. total cost minimization strategies, are presented in section 3.5 Simulation Setup and analysis is found in section 3.6. Finally, section 3.5 concludes this chapter.

3.2 Related Works

Traditional demand response is achieved through SCADA infrastructure, but it is not as real-time as in smart grid environment. Real-time demand response requires the power provider to update retail power price at each time-slot level for all the customers. It also obliges each and every customer to report load consumption to the power provider at each timeslot.

In most researches the methods of achieving demand response through energy consumption scheduling can be grouped into two categories: task scheduling and energy based scheduling [32]. The task scheduling is focused on scheduling the fixed load requests throughout the timeline, while the energy based scheduling focuses on scheduling flexible load requests throughout the timeline [32]. The flexible load requests means that load requests can be partially consumed and rescheduled throughout the timeline. It gives more flexibility to the customers on the energy consumption scheduling. The following work is an example.

The paper [57] proposed an autonomous DSM framework to solve the optimization problem of reducing the utility's operational cost, using the energy consumption scheduling algorithm. The author assumes that the energy consumption scheduling devices that are assumed built in smart meters would facilitate the two-way communications in the smart grid infrastructure, and find the optimal energy consumption schedule for each customer. Their aim was to reduce the total energy cost and the PAR at the same time for the utility. They also provided a pricing mechanism to reduce customer's bill payment using game theory as the incentive to encourage the usage of energy consumption scheduling devices. But the framework faces several challenges. Firstly, their paper assumed that customers use other customers' load information to optimize a game. But in reality sometimes customers do not fully trust each other, especially those within the same network, due to potential privacy leaking issues [1]. Moreover,

it is important to realize that in their study, incentives were offered to the participants as the proposed pricing scheme to encourage the use of the energy consumption scheduling devices. However, this pricing scheme is linearly proportional to the load that each customer uses, but in reality the power price is not always proportional to the customers load consumption, especially during the peak-time of the utility. In addition, the work in [1] focused on the energy consumption scheduling of the appliances within a household instead of that of the whole neighborhood area network.

Caron and Kesidis [15] also introduced an energy consumption scheduling framework, with optimal solutions in their paper. They proposed an algorithm that can reduce the total cost and PAR of the system when all the customers share their complete load profile. On the other hand, they also took the customers' concern about privacy into consideration and came up with distributed stochastic strategies that will extract partially enough information to improve the overall load profile. The strategies offered [15] are considering how to minimize the power provider's cost and PAR without trying to motivate the customers. Their schemes may have some insights into modeling of customers autonomous energy consumption scheduling within neighborhood area network distribution network and optimal goal of minimizing the utility's operational cost. But if one considers how the customers, instead of the power grid, are playing the center role of successful demand response, the challenges would be the lack of methods focusing on reducing customers' cost.

The following sections looks into the details of the problem of reducing customers' cost, in terms of the model of the system and the outline of the problems.

3.3 System Model

3.3.1 Customer Model

Assume that there are N customers, denoted as $1,2,...,i,...N$. Assume that time is divided into timeslots, and therefore let timeslot j denote the time period $[j\Delta t,(j+1)\Delta t)$, where $j=1,2,...$, and Δt is a unit time per timeslot.

Assume that all the load demands from customers are schedulable power loads and they are known at the beginning of each timeslot. For customer i, its *demand of power load* at timeslot j is defined as $l_i(j)$, where $j=1,2,...$ and $0 \le l_i(j) < l_i^{\max}(j)$, and let $l_i^{\max}(j)$ denote the *maximum load capacity* that the customer i can handle, which is normally a constant defined by each customer's setup of its own power system.

At each timeslot, all the customers send their load demand request to the power provider. Then they wait for the power provider's response of the current power price. In the RTP scheme, each customer has the opportunities to dynamically schedule its load at each timeslot. Assume the energy consumption scheduling algorithm exists and it uses load demand $l_i(j)$ and RTP power price as inputs and how much load it consumes as output.

Let $o_i(j)$ denote the *actual energy consumption* of customer i at timeslot j, and it's defined as

$$0 \le o_i(j) \le l_i(j) \quad \text{or} \tag{3.1a}$$

$$o_i(j) > l_i(j) \tag{3.1b}$$

If customer i consumes the energy within the *load demand* of j timeslot $l_i(j)$, then (3.1a) satisfies. On the other hand, if customer i actually consumes not only all the *load demand* of j timeslot $l_i(j)$, but also the delayed load demand from previous timeslots, then (3.1b) satisfies.

Let $b_i(j)$ denote the *instantaneous bill payment* for customer i at timeslot j, and it is calculated as follows.

$$b_i(j) = o_i(j) \cdot p(j) . \tag{3.2}$$

Let $B_i(j)$ denote the *accumulative bill payment* of customer i during time period $[0, j\Delta t)$ and it is calculated as follows,

$$B_i(j) = \sum_{k=1}^{j} o_i(k) \cdot p(k) . \tag{3.3}$$

3.3.2 Power Provider Model

Assume there is only one power provider within the power distribution system. For the power provider, it receives the *load requests* $l_1(j), l_2(j), ..., l_N(j)$ from all the customers at timeslot j.

Let the $a(j)$ denote *instantaneous aggregate load* of the power provider and is defined as

$$a(j) = \sum_{i=1}^{N} o_i(j) . \tag{3.4}$$

Let $A(j)$ denote the *accumulative* agg*regated power load* of the power provider at timeslot j and it is defined as

$$\begin{aligned} A(j) &= \sum_{k=1}^{j} a(k) \\ &= \sum_{k=1}^{j} \sum_{i=1}^{N} o_i(j) \end{aligned} . \tag{3.5}$$

Above is the actually consumed aggregated load $A(j)$, but the aggregated original load demand also needs to be defined. Let $e(j)$ denote the *instantaneous aggregated load demand* of the power provider requested by all the customers $\{1,2,...,i,...N\}$ at timeslot j. It can be calculated as

$$e(j) = \sum_{i=1}^{N} l_i(j) . \tag{3.6}$$

Let $E(j)$ denote the *accumulative aggregated load demand* for the duration from timeslot 1 to timeslot j. It can be calculated as

$$\begin{aligned} E(j) &= \sum_{k=1}^{j} e(k) \\ &= \sum_{k=1}^{j} \sum_{i=1}^{N} l_i(j) \end{aligned} . \tag{3.7}$$

Let $\gamma(j)$ denote the *Peak-Average load Ratio (PAR*) of the power provider at timeslot j, and is defined as follows,

$$\gamma(j) = \frac{\max_{k \in \{1,2,...,j\}} \{a(k)\}}{\frac{A(j)}{j}} , \tag{3.8}$$

where $\max_{k \in \{1,2,...,j\}} \{a(k)\}$ is the *peak instantaneous aggregate load* during the time duration $[0, j\Delta t)$ and $\frac{A(j)}{j}$ is the *average load* during the same time period. Note that [14] also defined this ratio, but the definition of this ratio is not exactly the same due to different load representation.

The paper [17] defined a two-step conservation rate model for calculating the *accumulative cost function* for the utility of a 6-hour time duration, which was adopted by the BC Hydro company [17]. The time variable in paper [58] is a continuous variable instead of a

discrete variable in the model in [58]. Also the paper [15] provides an energy consumption scheduling problem with a fixed time duration T = 6 hours, while our scheduling problem is a real-time demand response problem in this chapter. However, the real-time demand response system is not a fix-time system. Therefore, we use the same concept, and apply its global threshold cost model into the instantaneous cost model in discrete timeslots to make it more realistic.

Let $\omega(j)$ denote the *instantaneous cost* of the power provider. Based on the paper [15], $\omega(j)$ can be calculated as

$$\omega(j)=\begin{cases} K_1 \cdot a(j)+\varphi_1, & if\ \ a(j)<l^{peak}; \\ K_2 \cdot a^2(j)+\varphi_2, & if\ \ a(j)\geq l^{peak}. \end{cases} \tag{3.9}$$

where l^{peak} is the instantaneous peak load threshold of a specific power provider, which is the constant known to the power provider. K_1, K_2, φ_1, and φ_2 are the power provider's *preset constant parameters* by based on its own situation measured in \$/kW, \$/kW, and \$, \$. This equation shows that the *instantaneous operational cost* $\omega(j)$ for the power provider will be a linear function of *the instantaneous aggregate* load $a(j)$, if $a(j)$ is lower than the *peak load* threshold l^{peak}, and $\omega(j)$ will be an increasing quadratic function of the $a(j)$, if $a(j)$ is higher than the *peak load* threshold l^{peak}.

Then let $\Omega(j)$ denote the *accumulative cost* of power provider at timeslot j and is defined as in [15]

$$\Omega(j)=\begin{cases} \Omega(j-1)+\omega(j), & if\ \ j=2,3,...; \\ \omega(j), & if\ \ j=1. \end{cases} \quad . \tag{3.10}$$

3.4. Total Cost Minimization Problem in RTP Demand Response Program Using Energy Consumption Scheduling

3.4.1 Problem Statement

In a demand response system, the power provider always seeks to lower its load demand during peak time stage. In terms of measurement, the power provider seeks to minimize its *PAR* $\gamma(j)$ in (3.8). To achieve that, the power provider tries to persuade its customers to decrease their load consumption from the peak time or shift the load to non-peak time. But to incentivize the customers to lower the load consumption during peak time, the power provider employs the RTP scheme so that every customer uses the provider's real-time power price to adjust the load consumption accordingly.

Assume that all the *load demand* $l_i(j)$ for each customer i at timeslot j may be schedulable. Assume that at timeslot j, the customer i has the ability to automatically assign certain tasks to its household's appliances. Then all the appliances can automatically schedule the appliances' load based on the tasks that customer has assigned them to accomplish. Then the smart home console will have a load demand $l_i(j)$ known before the beginning of timeslot j for each customer.

In order for the power provider to measure the performance of energy consumption scheduling algorithm in terms of reducing the bill of the customers, we introduce the following metric to measure the performance. Let $B_{Avg}(j)$ denote the average bill of N customers over j timeslots. It is calculates as

$$B_{Avg}(j) = \frac{\sum_{i=1}^{N} B_i(j)}{N \cdot j} . \tag{3.11}$$

Since $B_{Avg}(j)$ is the accumulative value of the average bill of N customers over j timeslots, the above normalization makes more sense than just an accumulative bill over j timeslots.

We assume that the energy consumption scheduling algorithm exists, and that it can help the customers to make decisions on how to consume the energy request at each timeslot. Assume that at each timeslot, the energy consumption scheduling makes decision on $o_i(j)$. If the load demand $l_i(j)$ is partially consumed as $o_i(j)$, there will be an instantaneous load remainder $l_i(j)-o_i(j)$ delayed for the later consumption scheduling. At j^{th} timeslot, customer i may have multiple previously accumulated delayed remainders and they are all waiting for consumption scheduling. Let $r_i(j)$ be the accumulated delayed remainders for customer i at j^{th} timeslot. Then $r_i(j)$ can be calculated as

$$r_i(j)=\begin{cases} r_i(j-1)+[l_i(j)-o_i(j)], \\ \quad if\ \ o_i(j)\le l_i(j),\ j=2,3,...; \\ r_i(j-1)-[o_i(j)-l_i(j)], \\ \quad if\ \ o_i(j)>l_i(j),\ j=2,3,...; \\ l_i(j)-o_i(j),\quad if\ \ j=1. \end{cases} \tag{3.12}$$

Based on this accumulative load remainder, there is a case that the customers want to avoid. That is, some of their load requests are kept in the remainder for such relatively long time that they don't get used. Besides, for the power provider, if the customers put too much load requests in the load remainder, it makes it difficult for the power provider to calculate and announce the real-time power price. Therefore, the unused part of load request stored in the load remainders means some cost for the customers. Let $c_i(j)$ denote the remainder load cost at timeslot j for customer i, and it can be calculated as

$$c_i(j)=\rho[r_i(j)], \tag{3.13}$$

where ρ is a function of $r_i(j)$ in terms of $\$/kWh$. It means the price function for unused load requests. Let $c_{Avg}(j)$ denote the average remainder cost of N customers over j timeslots, and it is calculated as

$$c_{Avg}(j) = \frac{\sum_{i=1}^{N} c_i(j)}{N \cdot j} \tag{3.14}$$

In order to measure the performance of using the energy consumption scheduling algorithm to schedule the power consumption, a weighted performance is needed. Let $c_{Tot}(j)$ denote the accumulative total cost for customer i at j^{th} timeslot. It can be calculated as

$$c_{Tot}(j) = \alpha \cdot B_{Avg}(j) + (1-\alpha) \cdot c_{Avg}(j)\,. \tag{3.15}$$

Therefore, it can be assumed that all the customers may respond to the RTP price scheme with load shifting operation when they find out the price is higher than how much they are willing to pay.

Customer's Total Cost Minimization Problem:

Objective:

$$\min c_{Tot}(j) \tag{3.16}$$

3.4.2 Real-time Pricing (RTP) Scheme

Let $p(j)$ denote the *retail power price* at timeslot j. According to the paper [15], $p(j)$ is defined by the power provider, either based on the wholesale power market price [14], or based on the aggregated load [15]. In practice, the paper [14] adopted the power price prediction methods for the customers to make decisions on scheduling energy consumption. On the other

hand, instead of using price prediction, the paper [17] pointed out that for power prediction, no matter it is off-peak or peak hour, estimation accuracy is very poor, especially for the off-peak with its accurate rate lower than 30% in most months. Therefore, a non-prediction-dependent RTP scheme is required for the customers in the demand response program. Based on the paper [18], a practical and polynomial real-time power price, $p(j)$ can be calculated as a function of the *instantaneous aggregated load demand* [18],

$$p(j) = \eta \cdot e(j)^{\varepsilon} \tag{3.17}$$

where η and ε are the parameters that defined by the power provider. In general, η is a constant and $\varepsilon \geq 1$, $e(j)$ is the *instantaneous aggregated load demand* in (3.6). To enable the power provider to persuade customers to use less power during the peak time, ε can be calculated as

$$\varepsilon = \begin{cases} 1, & if \;\; e(j) \leq l^{peak}; \\ \dfrac{e(j)}{l^{peak}}, & if \;\; e(j) > l^{peak}. \end{cases} \tag{3.18}$$

Now that the power price is calculated by the power provider based on (3.17), and then RTP price information is broadcasted to all the customers at the beginning of each timeslot. Based on the price information, customer's energy consumption decision $o_i(j)$ can be determined based on optimal strategies to minimize the bill payment $b_i(j)$.

Then the problem can be further broken down into customer side and the power provider side. Subsection C will illustrate the two parts respectively.

3.4.3 Distributed Energy Consumption Scheduling on Bill Minimization

On the customer side, energy consumption scheduling is responsible for making the decision of its own energy consumption at each timeslot. The decision result will impact its *bill payment* individually. Thus all the customer's decisions at each timeslot will impact the whole distribution system's performance.

Solving the problem of minimizing customer's bill is an optimal process of decision-making on choosing $o_i(j)$ over the j timeslots for customer i. Meanwhile, flattening the system's overall load demand is a byproduct of this optimal process.

For each timeslot, the decision of choosing $o_i(j)$ is made by the customer i based on the real-time power price and a power price threshold. The threshold is dynamically calculated at each timeslot based on the RTP, so that it will help the customer to minimize its bill payment. In a real-time demand response power system, each customer optimally consumes or schedules its *load demands* $o_i(j)$ based on the power price of each timeslot using the energy consumption scheduling. Each customer minimizes its *bill payment* calculated in (3.2).

In order to let the customer's energy consumption scheduling to make decisions that will benefit the customers' bill minimization, we introduce the power price threshold as the (3.19) to assist the customers to make decisions on $o_i(j)$.

$$p_i^{threshold}(j) = p_i^{avg}(j) \tag{3.19}$$

- $p_i^{threshold}(j)$ is the threshold of power price that the customer i's energy consumption scheduling will use to manage all their appliances.
- $p_i^{avg}(j)$ is the average power price that customer i has been observed over the j timeslots, and it is a customized parameter for customer i.

Remark I: Here we assume that every customer use the same time window to observe the average power price $p_i^{avg}(j)$, which means that each customer starts to observe RTP price from timeslot 1 until timeslot j.

We develop a strategy based on the threshold defined in (3.19). The idea behind the strategy is, if the RTP price is not expensive, each customer seeks to schedule more energy for consumption, and if the RTP price is expensive, each customer tends to schedule less energy for consumption. Thus the strategy is each customer uses a stationary policy y to decide how much remainder to consume if the $p(j) > p_i^{threshold}(j)$. Each customer uses a stationary policy x to decide how much remainder to consume if the $p(j) > p_i^{threshold}(j)$. Therefore, the decision of actually consumed energy at j^{th} timeslot $o_i(j)$ can be calculated as

$$o_i(j) = \begin{cases} x \cdot l_i(j), & if \;\; p(j) > p_i^{threshold}(j); \\ l_i(j) + y \cdot r_i\,(j), & if \;\; p(j) \le p_i^{threshold}(j). \end{cases} \tag{3.20}$$

where $0 \le x < 1$ and $0 \le y \le 1$.

From (3.20), the solution to problem in (3.16) is now to find the optimal stationary policy (x, y) in (3.20) that will give the customer the minimized total cost in (3.16). Here we use simulation to find out the optimal policies for all the customers.

3.4.4 Simulation

3.4.4.1 Simulation Design

Assume that at every timeslot each customer generates a load request, but the request could be zero. Assume every timeslot there is a load request, but the request could be zero. Also assume that the amount of each customer's load demand follows the same normal distribution as seen in Table 3.1.

Table 3.1 Stream Table

Stream	**Purpose**
1	load requests time is constant and requests at each timeslot
2	load request of a customer follow the above normal distribution

Note that all the time in the simulation is integer, marked as timeslots such as 1,2,3, …. Here time of 1 means that it's the 1st timeslot. Initially, every customer schedules its first load request at the beginning of the 1st timeslot and sends the request to the power provider. Assume the communication overhead and delay between all the customers and the power provider are ignored. Then the power provider updates the real-time power price for the current timeslot after receiving the load requests. Finally, each customer makes its own energy consumption decision on how much load to consume and how much load to delay at current j^{th} timeslot.

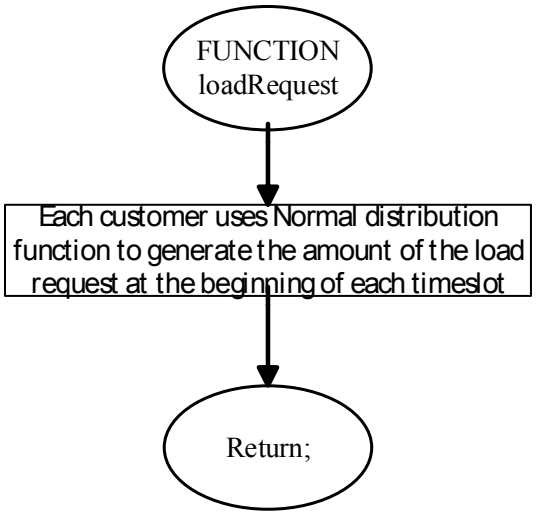

Fig. 3.2 Flow Chart of Load Request Function

As seen in Fig. 3.2, the flow chart of load request function is at the beginning of each timeslot, each customer uses normal distribution function to generate the certain amount of load request. The normal distribution function's definition is given next subsection.

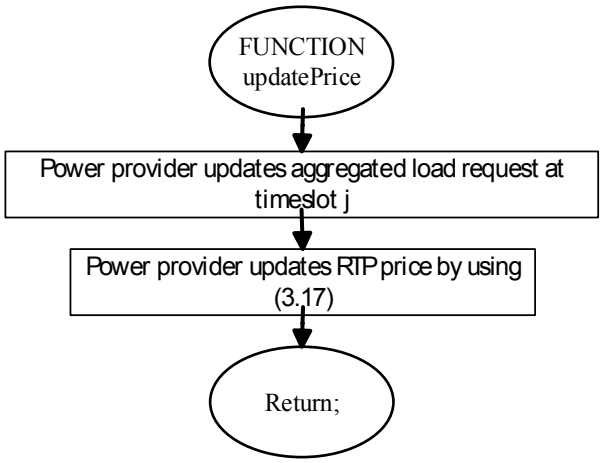

Fig. 3.3 Flow Chart of Updated Price Function

As seen in Fig. 3.3, after the load requests are generated by all the customers, the power provider aggregates all load requests at current timeslot, and then use the real-time price function (3.17) to calculate the power price for the current timeslot and let all the customers know the price.

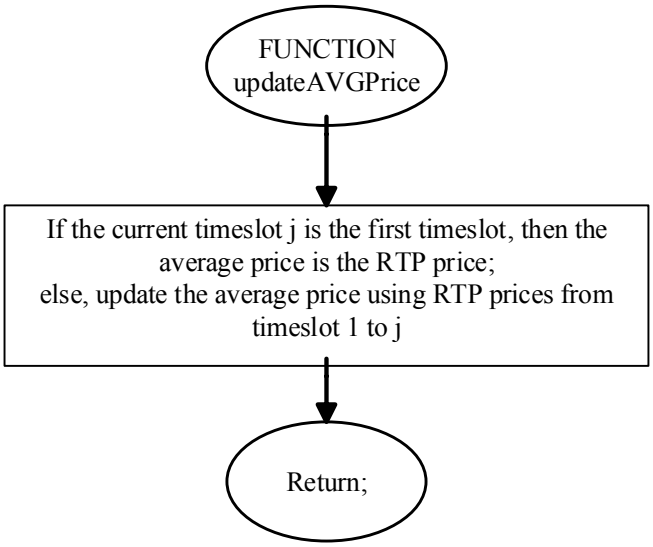

Fig. 3.4 Flow Chart of Updated AVGPrice Function

As seen in Fig. 3.4, after the customer receives the real-time power price for the current timeslot, it will make the decision on whether the current power price is expensive enough to delay the consumption or cheap enough to consume the load request. Therefore, this update average price function is called by each customer at each timeslot to determine whether the current power price is cheap or not by comparing it with the average power price.

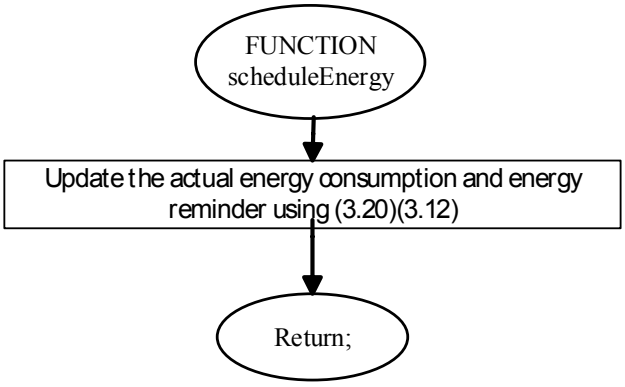

Fig. 3.5 Flow Chart of Schedule Energy Function

As seen in Fig. 3.5, since each customer has the power price of current timeslot and the updated average power price, it makes the decision of consuming or delaying load request based on equation (3.20) and update the energy remainder based on equation (3.12). The output of the simulation is the total cost of all the customers (3.15) at each timeslot, which is the performance metric of energy consumption scheduling algorithm.

3.4.4.2 Simulation Input Design

As seen in Fig. 3.6, let μ denote the peak load defined by power provider. Let the normal distribution $N(\mu,\sigma^2)$ be $N(\mu/N,(\mu/3N)^2)$, and this will guarantee the values of 99.7% of observations fall in the interval $[0,2\mu/N]$, as seen in Fig. 3.6 [59]. Even though the possibility of generating negative number is small, this design still eliminates them by regenerating another normal distribution number when it happens. N is the number of customers within the distribution network. As seen in Fig. 3.6, the *mean* of normal distribution is μ/N and the *standard deviation* is $\mu/3N$.

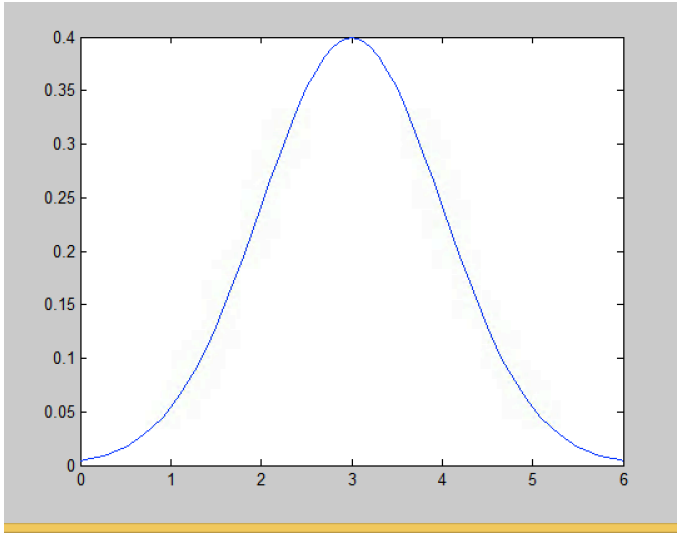

Fig. 3.6 Load Requests Following Normal Distribution $N(\mu / N,(\mu / 3N)^2)$ by Each Customer

3.4.4.3 Non-peak Input Setup

The above subsection shows a simulation setup with stable input of load requests , which produces a convergent average bill.

However, in this simulation setup, to make the aggregated input load request less intense, we setup a dynamic way of generating normal distribution load request for each customer at each timeslot. If setting up input as letting each customer follow a normal distribution of $N(\mu / N,(\mu / 3N)^2)$, it will make the $e(j) = \sum_{i=1}^{N} l_i(j)$ in (3.6) stable as high as μ. But in order for the $e(j)$ to fluctuate within $[0,\mu]$, we let the aggregate load requests follow the normal distribution of $N[\mu / 2,(\mu / (2*3))^2]$. In this way, a random aggregated load requests is generated at current timeslot j, which is denoted as e_j^{rand}. Then, the aggregate load requests follow the normal distribution means that $e_j^{rand} \sim N[\mu / 2,(\mu / (2*3))^2]$.

Then let each customer generate the load requests based on this random aggregated load request. We still use the normal distribution to let each customer generates its load request at

each timeslot. But the normal distribution $N(\mu,\sigma^2)$ follows $N(e_j^{rand}/N,(e_j^{rand}/3N)^2)$. Since e_j^{rand} is a random value of the range$[0,\mu]$, each customer follows a varying normal distribution to generate its own load request at different timeslot. In this way, both the aggregated load request and the individual load request follow the normal distribution to generate load request at each timeslot, as seen in Fig. 3.7.

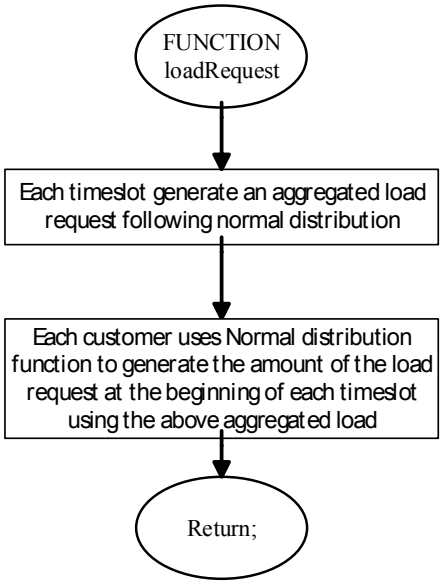

Fig. 3.7 Intermittent Setup-Flow Chart of Load Request Function

As seen in Fig. 3.8, from 1st timeslot 1 to 1000th timeslot, the aggregated load requests fluctuate approximately from above 0 to load peak range.

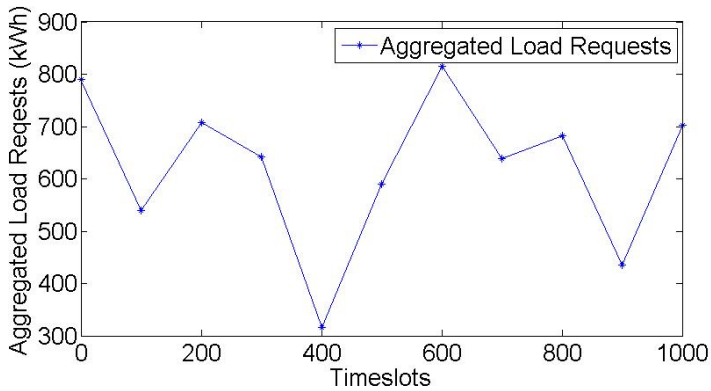

Fig. 3.8 Fluctuate Setup- Input Sample of Aggregated Load Request

Based on this input, the following experiment is subcategorized two setups, based on the α value in equation (3.15), which is the weight value to determine the total cost for the customer, with $\alpha = 0.5$ and $\alpha = 0.1$. Also, we assume that $\rho[r_i(j)] = 10 \cdot r_i(j)$ in equation (3.13), which is linear.

3.4.4.3.1 Simulation Setup One-- α =0.5

Table 3.2 Simulation Parameters

Experiment Parameters	**Values**
Load Peak	1000kWh
N	100
Sim_time	1000
α	0.5
η	1E-2
μ	500kWh

Using the set of parameters in Table 3.2, as seen in Fig. 3.9 and Fig. 3.10, they show that the total cost based on different x values, the lowest total cost is when x=0 or x=0.1 and y is approximately at [0.8, 1.0] area.

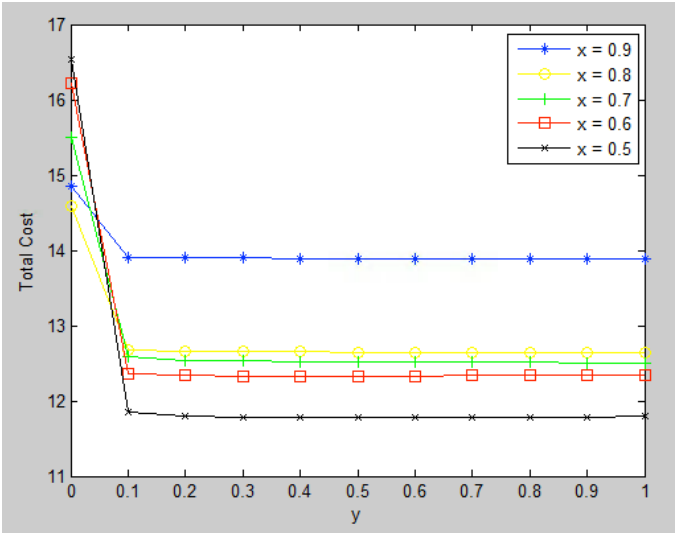

Fig. 3.9 Total Cost for fixed x=0.5, x=0.6,… x=0.9.

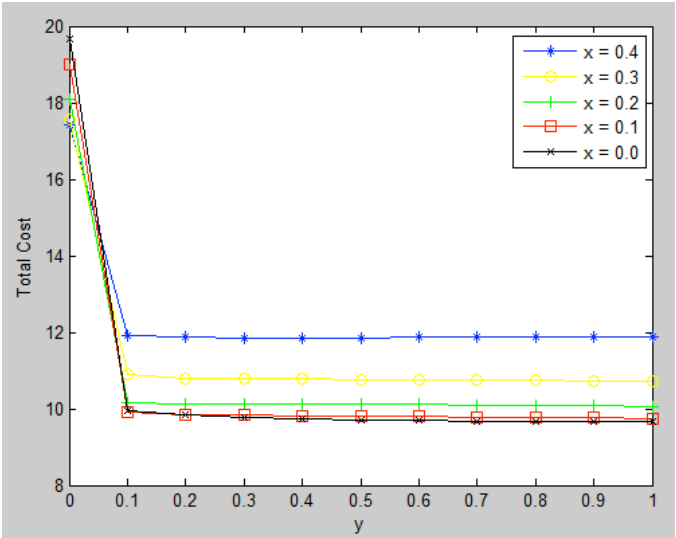

Fig. 3.10 Total Cost for fixed x=0, x=0.1,… x=0.4.

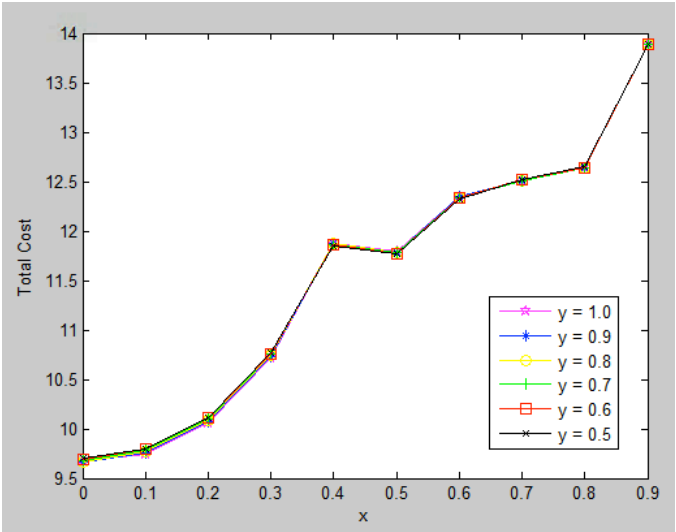

Fig. 3.11 Total Cost for fixed y=0.5, y=0.9, …, and y=1.

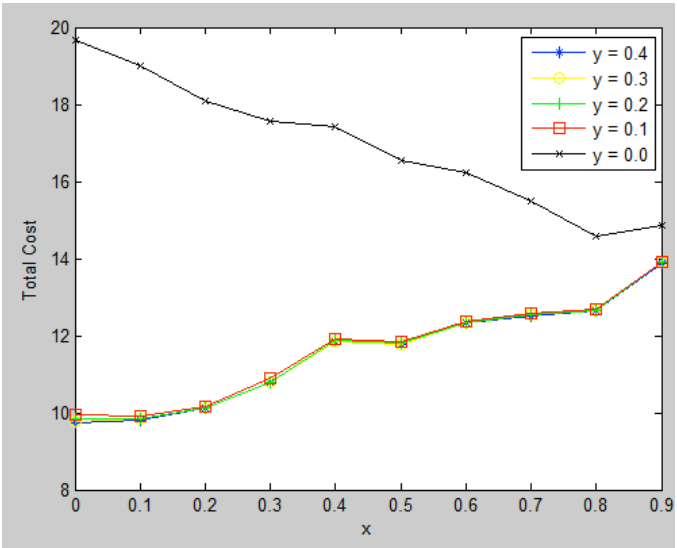

Fig. 3.12 Total Cost for fixed y=0.0, y=0.1,… ,and y=0.4.

Fig. 3.11 and Fig. 3.12 show that the total cost based on different y values, and the lowest total cost is when y is approximately at [0.5,1.0] area, and the x=0.0. Also in Fig. 3.12, when y = 0.0, the total cost has the largest values. This means if the load requests are delayed, they will

never be used even when the real-time price is cheap. Therefore, the remainder load cost keeps growing.

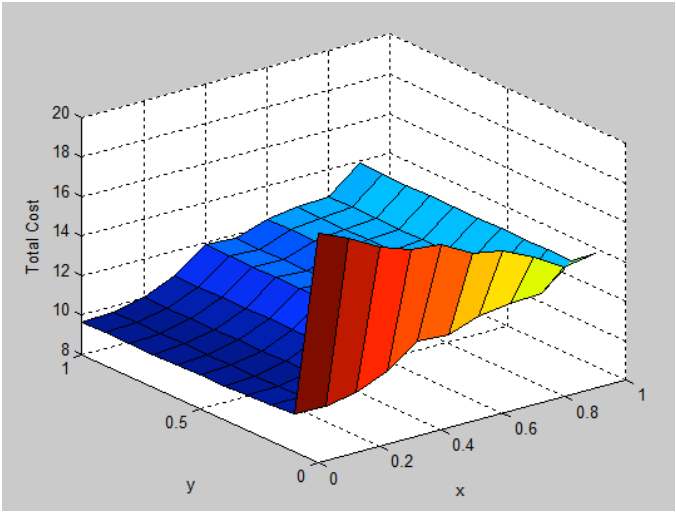

Fig. 3.13 Total Cost

As seen in Fig. 3.13, it is seen that the total cost has the largest value when x = 0 and y = 0, this is because that there is no load requests consumed that the large cost incurred by the customers waiting has dominate the total cost. For the smallest value of the total cost is when x = 0 and y = 1. This means the best policy for customers is not to consume at all when the real-time price is expensive and delay them to the next timeslot as a load remainder, then try to consume more of the remainder in the next possible cheap timeslot.

3.4.4.3.2 Simulation Setup Two-- α =0.1

Using the set of parameters in Table 3.3 and adopting the previous setup, Fig. 3.14 and Fig. 3.15 show the total cost based on different x values, the lowest total cost is when x=0 or

x=0.1 and y is approximately at [0.8, 1.0] area, but with a lower minimal total cost comparing to the previous setup.

Table 3.3 Simulation Parameters

Experiment Parameters	**Values**
Load Peak	1000kWh
N	100
Sim_time	1000
α	0.1
η	1E-2
μ	500kWh

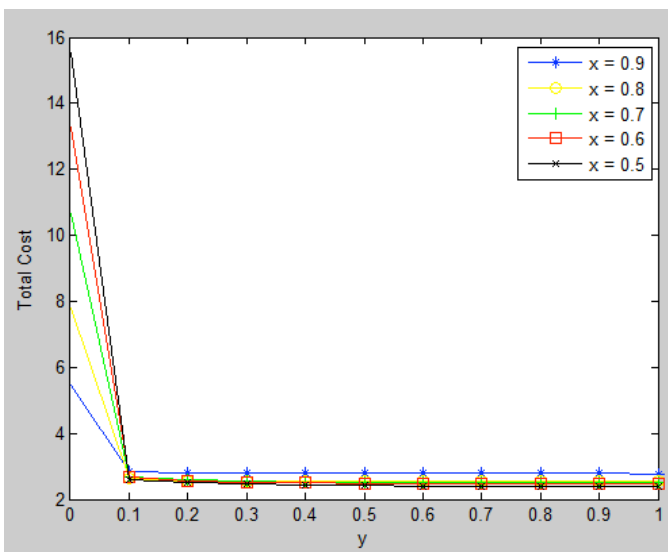

Fig. 3.14 Total Cost for fixed x=0.5, x=0.6,… x=0.9.

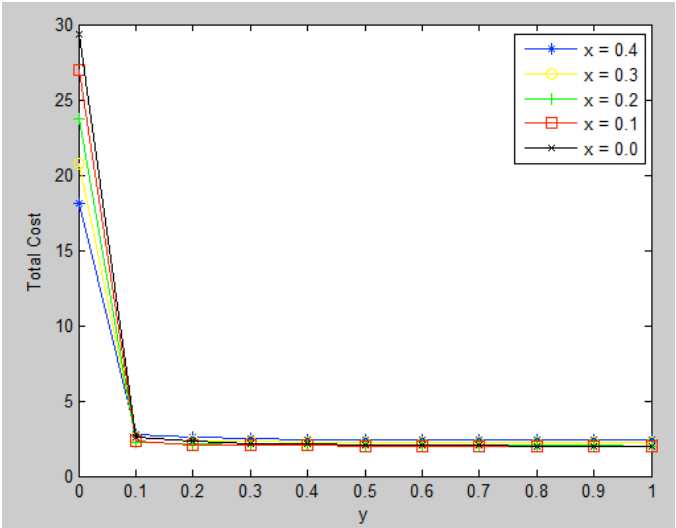

Fig. 3.15 Total Cost for fixed x=0, x=0.1,… x=0.4.

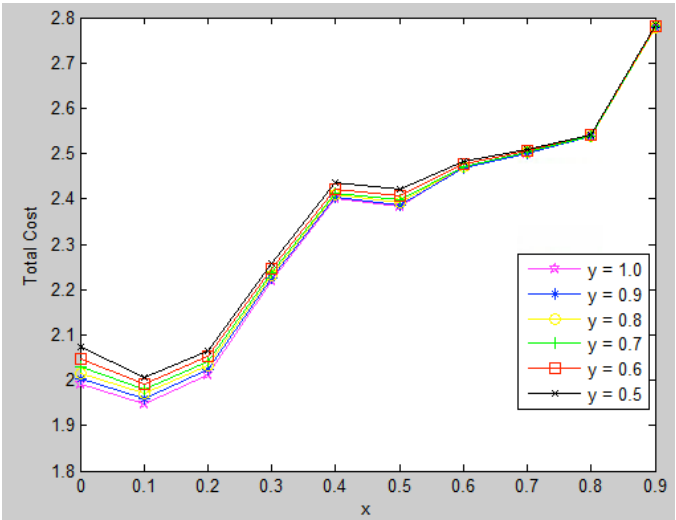

Fig. 3.16 Total Cost for fixed y=0.5, y=0.9, and y=1.

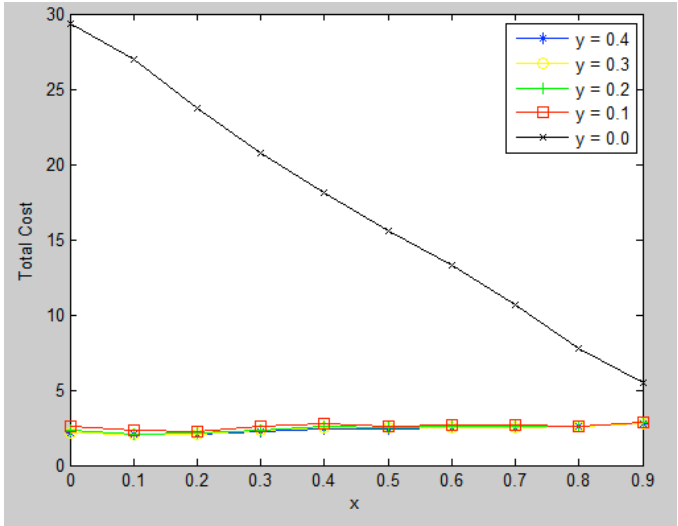

Fig. 3.17 Total Cost for fixed y=0.0, y=0.1,… ,and y=0.4.

Adopting the previous setup, Fig. 3.16 and Fig. 3.17 show that the total cost based on different x values, the lowest total cost is when x=0.1 and y is approximately at [0.8, 1.0] area, but with a lower minimal total cost comparing to the previous setup.

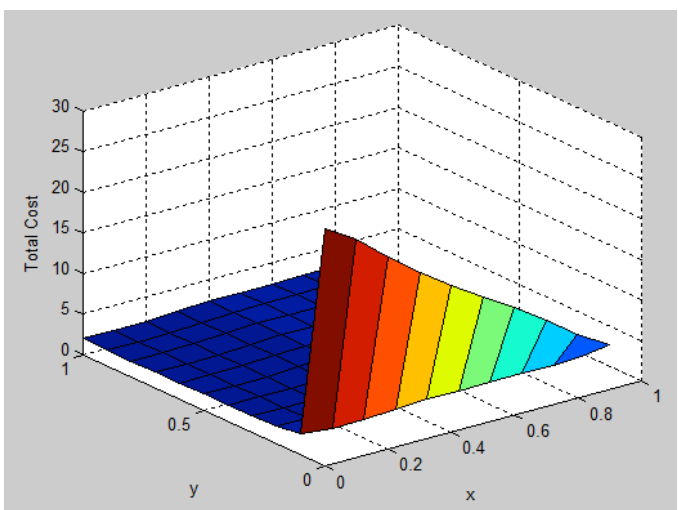

Fig. 3.18 Total Cost

As seen Fig. 3.18's 3D plot, the results of α =0.1 are similar to the last setup α =0.5. The largest value of total cost is still when x= 0 and y =0, and that is when the customers don't

consume energy at all. But the smallest value are quite similar, which is when x=0.1 and y =1. Therefore, the best policy for the customers for the smallest total cost at this setup is to lower the consumption of load requests generated at the current timeslot as 10% when the real-time price is expensive and delay them to the next timeslot as a load remainder, then try to consume more of the remainder in the next possible cheap timeslot.

To summarize both the setup in Table 3.2 and Table 3.3, for the aggregated load request's average $e(j)$ is fluctuate within [0, μ], the best policy is not to consume or lower the consumption to approximately as low as 0.1 when the real-time price is expensive and delay them to the next timeslot as a load remainder, then try to consume more of the remainder in the next possible cheap timeslot.

Next subsection conducts the simulation experiment of large load request input as a setup.

3.4.4.4 Large Load Request Input

Since the $e(j)$ defined in last subsection as the aggregated load fluctuate within $[0,\mu]$, a large peak load request input is introduced in this subsection, which make the $e(j)$ stable at the μ level, and let the μ= Load Peak, as seen in Fig. 3.19.

3.4.4.4.1 Large Load Request and α =0.1

Let every customer generate a load request following the normal distribution $N(\mu / N,(\mu / 3N)^2)$ at each timeslot, where μ is equal to Load Peak. Load Peak is the parameter set by the power provider. Because the timeslot here is considered to be a very small unit time, it is assumed that the Load Peak is 1000kWh by the power provider. Also assume that the total simulation running time is 1000 timeslots. Assume that there are 100 customers within the power provider's distribution network. The rest of the experiment parameters are shown in Table 3.4.

Table 3.4 Simulation Parameters

Experiment Parameters	**Values**
Load Peak	1000kWh
N	100
Sim_time	1000
α	0.1
η	1E-2
μ	1000kWh

As illustrated in Fig. 3.19, from 1st timeslot 1 to 1000th timeslot, the aggregated load requests $e(j)$ maintains closely with of the Load Peak of the power provider. This means that the aggregated load requests are quite stable at the peak load level for the power provider throughout all timeslots.

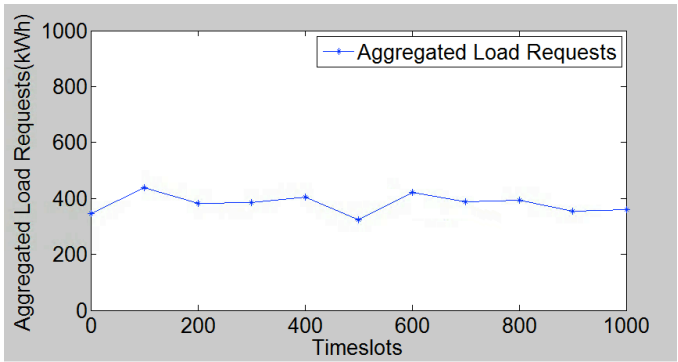

Fig. 3.19 Large Load Request Setup-Aggregated Load Requests

As seen in Fig. 3.20 and Fig. 3.21, they show that the total cost performance based on the large peak load requests when α=0.1. Based on different x values the lowest total cost is when x=0.

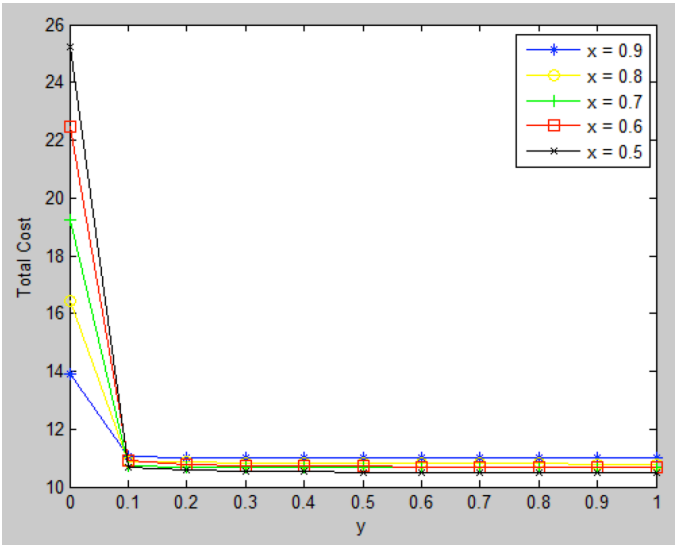

Fig. 3.20 Total Cost for fixed x=0.5, x=0.6,… x=0.9

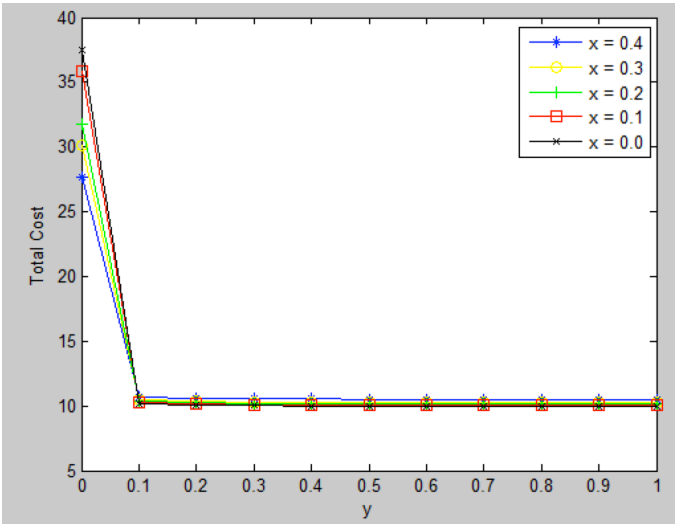

Fig. 3.21 Total Cost for fixed x=0, x=0.1,… x=0.4.

Fig. 3.22 and Fig. 3.23 show the total cost based on different y values, and when y is approximately at the area [0.5,0.9], the total cost has the lowest values.

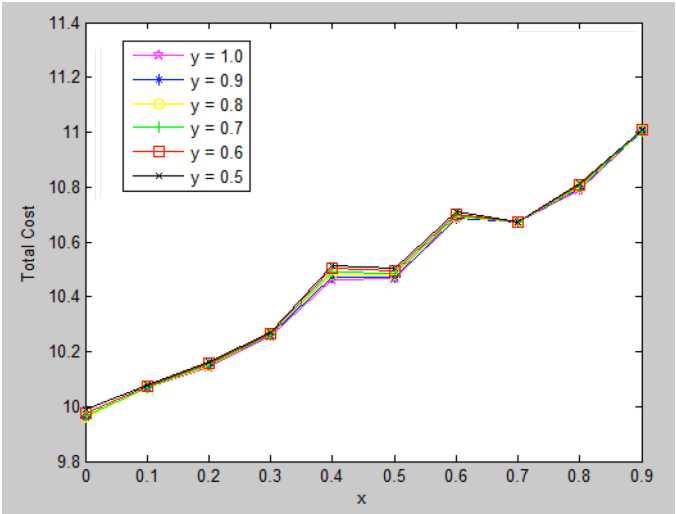

Fig. 3.22 Total Cost for fixed y=0.5, y=0.9, and y=1.

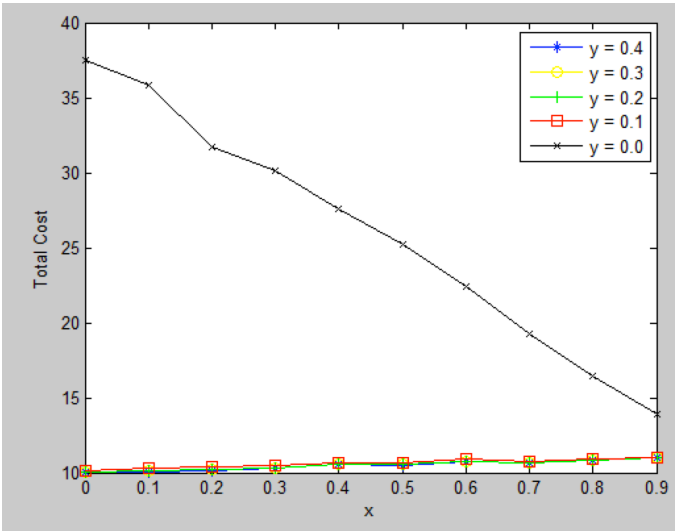

Fig. 3.23 Total Cost for fixed y=0.0, y=0.1,… ,and y=0.4.

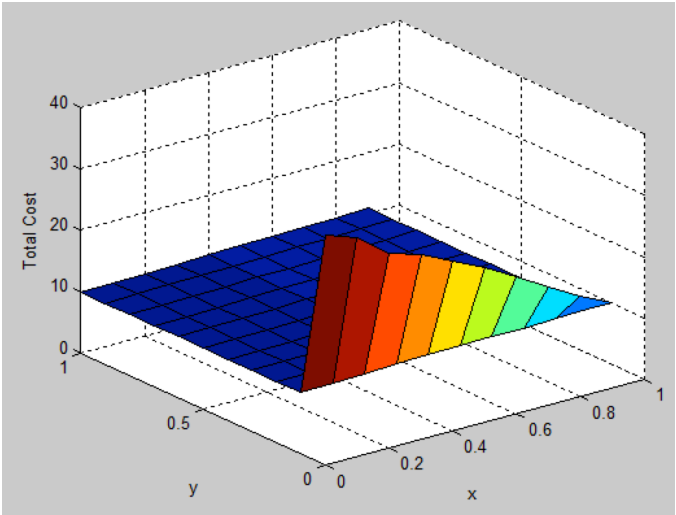

Fig. 3.24 Total Cost

Based on Fig. 3.20 to Fig. 3.23 and the Fig. 3.24's 3D plot, it can bee seen that the largest value of the total cost is still when x =0 and y=0. But for the smallest total cost is when x is from 0 and y is approximately at the area [0.5,0.9]. That is to say, when policy is within the (x,y) area, the smallest total cost can be found.

But for each customer, it runs its own energy consumption scheduling algorithm based on RTP power price. Given this relatively large and intense aggregated load requests, the power provider will impose high RP power price. Consequently, the policy of consuming load remainder when real-time price is cheap, which is the y value, moves from previous setup of 1 to [0.5,0.9].

3.4.4.4.2 Simulation Setup Three—Large Load Requests and α =0.5

The experimental parameters are shown in Table 3.5 with large load requests and α =0.5.

As seen in Fig. 3.25 and Fig. 3.26, the total cost based on different x values is demonstrated. When x=0, it has the lowest total cost.

Table 3.5 Simulation Parameters

Experiment Parameters	**Values**
Load Peak	1000kWh
N	100
Sim_time	1000
α	0.5
η	1E-2
μ	1000kWh

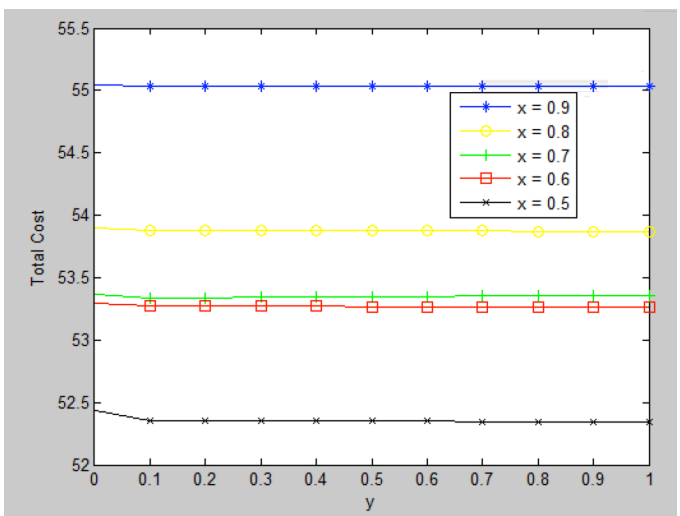

Fig. 3.25 Total Cost for fixed x=0.5, x=0.6,… x=0.9.

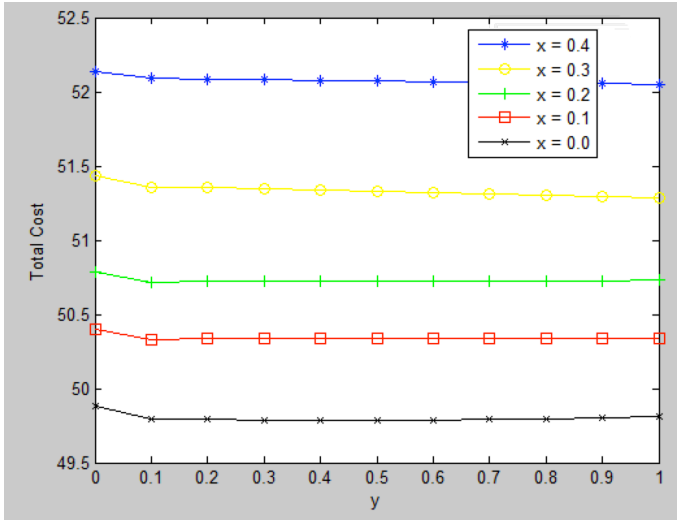

Fig. 3.26 Total Cost for fixed x=0, x=0.1,… x=0.4.

As seen in Fig. 3.27 and Fig. 3.28, the total cost based on different y values is illustrated. But in these two Figures, the lines with different y values are so closely laid out that it is hard to tell which y is the lowest. But as seen Fig. 3.26, when y is at the area [0.3,0.6] and x=0, the total cost has the lowest value.

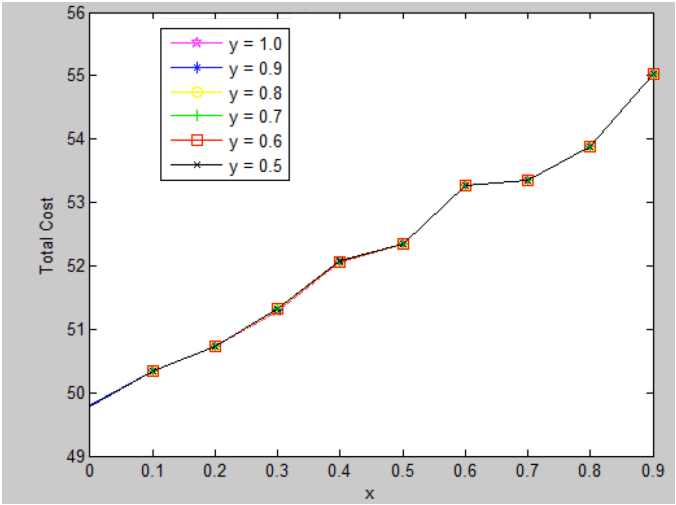

Fig. 3.27 Total Cost for fixed y=0.5, y=0.9, and y=1.

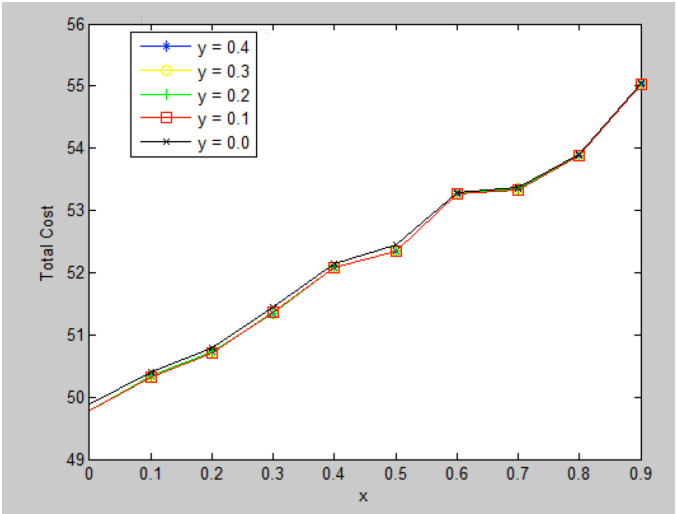

Fig. 3.28 Total Cost for fixed y=0.0, y=0.1,… ,and y=0.4.

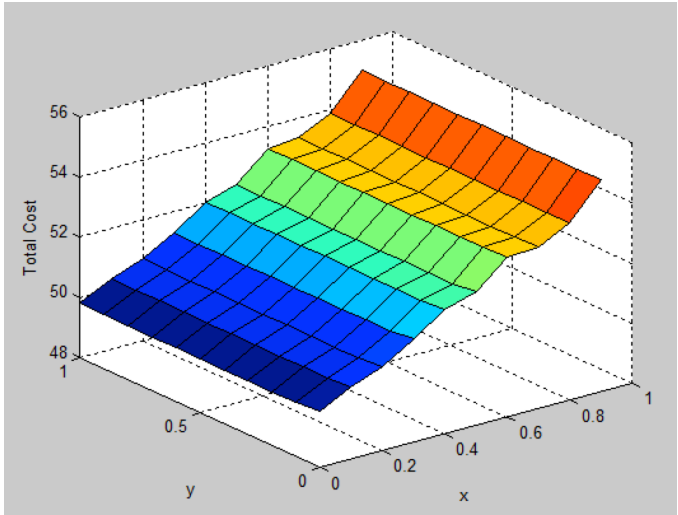

Fig. 3.29 Total Cost

In Fig. 3.29, it can be seen that the largest value of the total cost is when x =0.9 and y =0, which mean every customer consumes 90% of the load request at current timeslot when the real-time power price is expensive and don't consume the load remainder at all even if the real-time power price is cheap.

For the smallest total cost, it is within the area of x=0, y ranges [0.3, 0.6]. It means that each customer don't consumes load request at current timeslot if the real-time power price is expensive and wait to consume them at next cheap timeslot with a remainder using y belongs to [0.3, 0.6].

3.4.4.4.3 Simulation Setup Three—Large Load Requests and α =0.9

The simulation experimental parameters are shown in Table 3.6, when α =0.9. For this α value, the weighted total cost in (3.15) is more preferable to the load consumption bill.

Fig. 3.30 and Fig. 3.31 show the total cost based on different y values. It is when x=0 total cost has the lowest value and when x =0.9 total cost has the largest value. This means that when the customers want to lower the total cost, they need to focus on lower the consumption of power when the real-time price is expensive.

Table 3.6 Simulation Parameters

Experiment Parameters	**Values**
Load Peak	1000kWh
N	100
Sim_time	1000
α	0.9
η	1E-2
μ	1000kWh

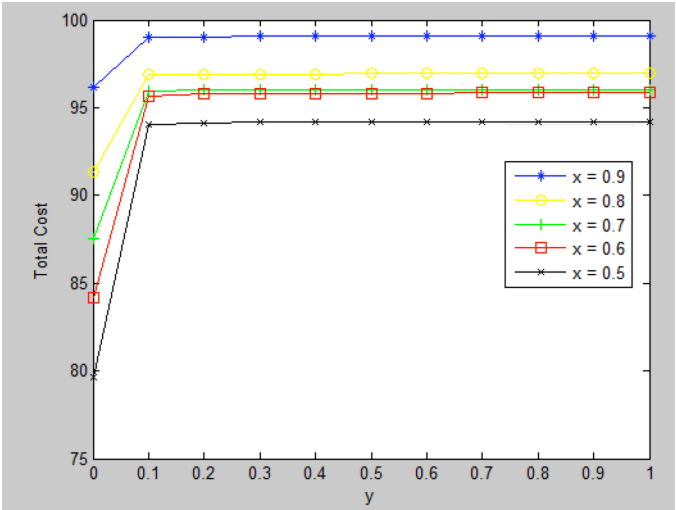

Fig. 3.30 Total Cost for fixed x=0.5, x=0.6,… x=0.9.

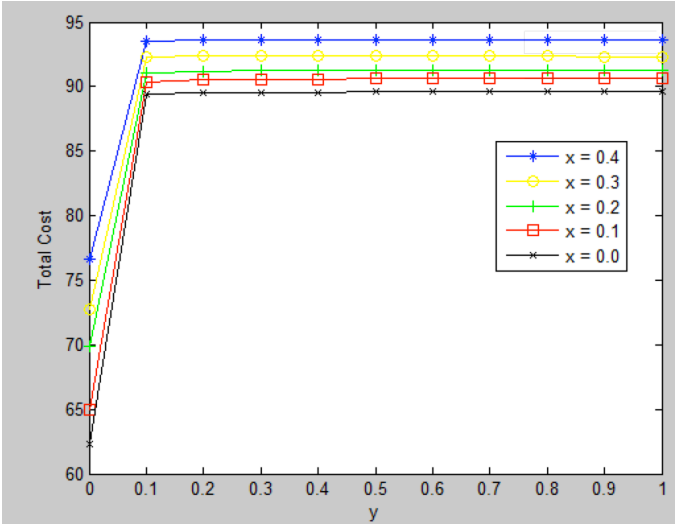

Fig. 3.31 Total Cost for fixed x=0, x=0.1,… x=0.4.

Fig. 3.32 and Fig 3.33 show the total cost based on different y values. When y=0, the total cost has the lowest value. This means that even if the real-time power price is cheap, the customers still just consume the load requests generated the current timeslot, and ignore the load remainder consumption, in order to lower the total cost.

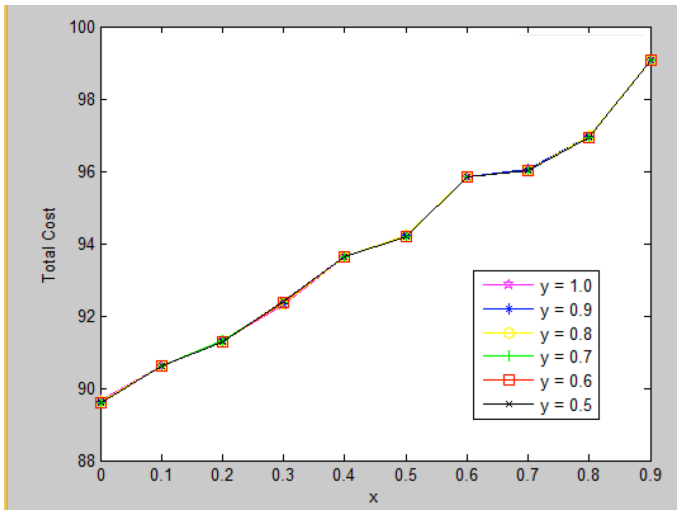

Fig. 3.32 Total Cost for fixed y=0.5, y=0.9, and y=1.

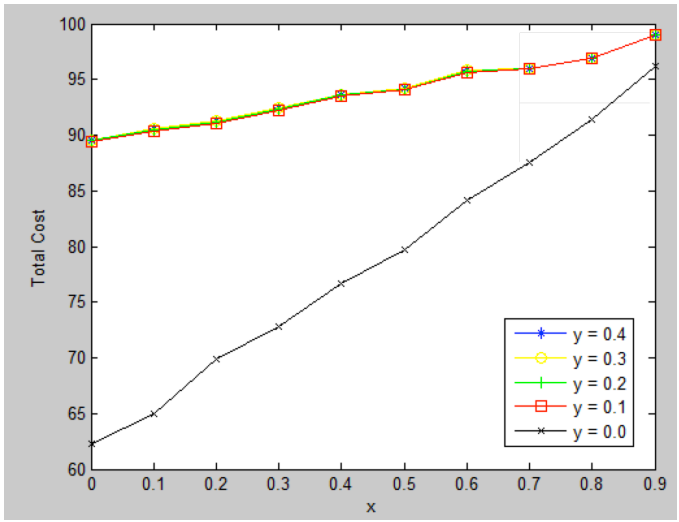

Fig. 3.33 Total Cost for fixed y=0.0, y=0.1,… ,and y=0.4.

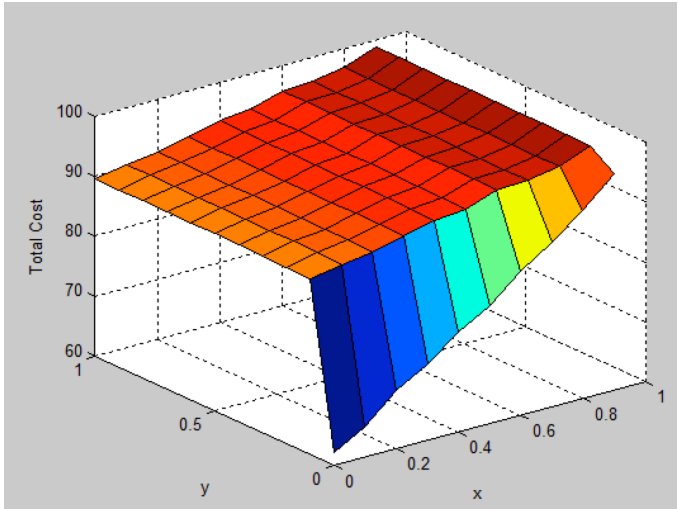

Fig. 3.34 Total Cost

It can be seen in Fig. 3.34 that the largest total cost is when x =0.9 and y ranges within [0.1,1]. The smallest total cost is when x =0 and y =0, which means that each customer doesn't consume energy at all. It is practically unreasonable for the customers to not consume load requests at all. The reason to that is when α =0.9, it makes the bill cost, which is part of the weighted total cost (3.15), so dominating that the cost incurred by the delay of energy consumption is neglected.

Remark II: All the above simulation result is based on N=100 customers. But in reality, the customers' number is dynamic instead of a fixed number.

3.5 Conclusion & Future Work

This chapter has proposed a problem of how to minimize the total cost for customers who participate in the operation of smart grid by using demand response and real-time pricing scheme. Mathematical formation of the system and the problem statement is provided. To solve the problem, a new real-time price scheme is proposed, and based on which, the algorithm to find total cost minimization is proposed. But in order to find the minimal total cost, the method is to

use discrete event simulation to conduct experiments based on different sets of parameters. The simulation experiments are divided into two major categories: 1. Average Load Requests Input, which means that the aggregated load requests fluctuate within [0, peak load] following Gaussian distribution with a mean value of half of the peak load; 2. Large Load Requests Input, which means that the aggregated load requests maintains stable at the peak level. In the 1st category, since the load requests are not very large, the best policy for the customers is to use as low of load request as possible when the real-time price is expensive. When the real-time power price is cheap, based on different weighted parameter α in (3.15), customers may adjust the corresponding y value based on the simulation results, in order to get the lowest total cost. In the 2nd category, the load requests are very large. When α is lower than 0.5, which means bill cost is less or equally important as load remainder cost, the customers can adjust the policy in a similar way as in the 1st category. However, when the α is as high as 0.9 or larger, the billing cost dominates the total cost, which means the customer will have to try not to consume load request to lower the total cost.

The solution and the sets of discrete simulation experimental results may potentially lead to a new angle of energy consumption scheduling problem. Knowing that current literature does not offer much insight in solving the total cost minimization problem using real-time pricing scheme, this chapter has filled another blank space on the big canvas that is smart grid. Hopefully it will encourage more research to be carried on based on the work presented in this chapter.

Apart from focusing the benefit party as the customers, it would also be an interesting journey for future work to consider how to enable the power providers to make the best out of

smart grid, that is to say how to maximize its profit while the customers total cost is also minimized.

4 TOTAL COST MINIMIZATION PROBLEM WITH FAIR DELAY IN SMART GRID DISTRIBUTION

4.1 Introduction

In the last decade, human population increased rapidly. According to the United States Census Bureau, world population increased from nearly 6.5 billion in 2005 to almost 7.3 billion in 2015 [66]. Along with the growth of world population is the growth of world energy consumption. The combined consumption of oil and coal changed from below 7500 million tones oil equivalent in 2008 to more than 7500 million tones oil equivalent in 2010 with the consumption of coal continues to grow [5]. The large growth of energy consumption during a decade can be easily mapped out based on the growth of this two-year period.

Knowing the non-renewable nature of world's primary energy resources, i.e. oil and coal, two choices are available to maintain the sustainability of the world. These choices are the development in renewable energy resources and energy conservation. Renewable energies only counted towards 3% of the world's primary energy consumption in 2009, and that number decreased to 1.8% in 2011 [5], [6]. The shortcomings of the renewable energies, such as noise, lack of wind, or low efficiency [3], make it difficult for them to challenge the primary position of traditional energy resources. On the other hand, energy conservation can be implemented through improving energy efficiency, and smart grid is proven to be a promising research field.

A smart grid is "an intelligent electricity network that integrates the actions of all uses connected to it and makes use of advanced information, control, and communication technologies to save energy, reduce cost and increase reliability and transparency" [9]. The key

functionality of a smart grid lies in communication because it is a network between the customers and the power provider. This key function is known as demand response. According to the Department of Energy (DoE), demand response is "a tariff or program established to motivate changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over the time, or to incentive payments designed to induce lower electricity usage at times of high wholesale market prices or when system reliability is jeopardized" [1].

Successful demand response can benefit both energy suppliers and customers. The diverse benefits offered by demand response include monetary savings, power efficiency improvements, flexibility, and reliability improvements [10], [12]. However, researchers have found the adoption rate of demand response programs has been unexpectedly slow [12]. According to the paper [12], possible penalties related to contract breach and the limited flexibility of current demand response programs together with other factors make customers hesitant to adopt demand response programs. This can be a huge barrier to successful demand response.

The interactive nature of demand response and demand response programs determines the vital role of customer participation [32]. Without customer participation, demand response would not be able to gather enough data to further their developments, demand response programs would have nothing to respond to, and smart grid would not be able to improve energy efficiency to conserve the resources. Therefore, to attract more customers to participate becomes a necessary condition for demand response programs.

Current demand response programs have two major concepts of customer attraction. They are real-time and fairness [32]. The program that incorporates the real-time concept is

known as the Real-Time Pricing (RTP) Scheme. This pricing scheme charges customers hourly fluctuating prices that "reflect the real cost of electricity in the whole sale market" [10]. In fact, Zhang et al. [41] found that RTP did encourage and enable customers to take a much more active role in scheduling their own energy consumptions to save energy, reduce cost, and in return benefit the power grid operation. In terms of the fairness concept, current literature suggests different definitions, which are discussed in detail in section 4.2 Relate Works [12], [41], [52]. Researches done in fairness have mainly been done in the area of "fair bill" [12], [60]. Fair bill scheme aims at making the bill fare for different customers according to different grouping criteria. One shortcoming of the fair bill schemes is that customers might have to wait for a long time for their energy request to be answered. However, this waiting time might be too long to tolerate for some customers who need timely respond to their load request. Therefore, instead of fair bill, this chapter proposes an algorithm based on the concept of fair delay.

This concept of fair delay for energy consumption scheduling has yet to be discussed in the literature. Its aim is to maintain the delays among customers are fair with other within a neighborhood area network distribution network in smart grid. As a result, all customers can have their energy requests met in a same timely manner, while having their total cost minimized at the same time. This algorithm is based on switching between out-of-bound control strategy and in-bound cost minimization strategy. The simulation has confirmed that the algorithm proposed in this chapter was able to respond promptly while lower the customer's total cost.

The rest of the chapter is organized as below. Section 4.2 discusses the related works. Section 4.3 describes the system model in which the problem discussion is conducted. Section 4.4 discusses total cost minimization problem with fair delay boundary. The solution to the

problem is presented in section 4.5. Simulation design and results analysis can be found in section 4.6.

4.2 Related Work

Using energy consumption scheduling method to study the demand response system has been in trend for some time now for the RTP demand response problem [45], [46], [18], [15], and [61]. The method provides many RTP solutions to benefit both the customers and the power provider in terms of reducing cost and/or lowering the peak demand load, which in turn makes the power grid more efficient.

The study of demand response in smart grid also started paying more attention to fairness in recent decades [12], [60], [62], [63], and [41]. Vuppala et al.'s paper discussed the issue of fairness in demand response programs, with an emphasis on fairness principles that customers regard highly of [12]. To decide what kind of demand response program is "fair", they considered the criteria listed as following. For must–run appliances, such as lighting, power price will be fixed [12]. On the other hand, power consumed by non-must-run appliances will be charged at multi-dimensional prices [12]. User category, income level, and appliance category will be taken into consideration when determining the exact power price [12].

After almost two decades, fairness now has had its share of in depth discussion among the researchers. The discussion of fairness also developed into different branches with the main one being fair bill.

Zhang et al. looked at fair cost in smart homes with microgrid [41]. Sometimes a number of smart homes share one microgrid, and this sharing feature would eventually lead to competition between homes, especially when local distributed energy resources cannot respond to all load requests. In this chapter, fairness was achieved through fair cost and it was defined

differently from Vuppala et al.'s. Instead of coming up with their own definition, the authors cited Mathies and Gudergan's definition, which described fairness as "the reasonable, acceptable or just judgment of an outcome which the process used to arrive" [52]. The paper [41] proposed and experimented with a mathematical programming formulation that aims at maintaining the fair cost during such competition between smart homes that share the same microgrid. The paper [41] utilized lexicographic minimax method with a focus on mixed integer linear programming approach to minimize one-day forecasted energy cost for each smart home. The paper [41] studied two groups of 10 and 50 smart homes with their distributed energy resource operation and output examined. The simulation result in the paper [41] showed a 30% and 24% cost saving for the two groups respectively and a fair cost distribution among smart homes in their scenario.

Baharlouei et al. also introduced their criteria for fairness which was defined as "the variational distance between normalized billing vector for billing mechanism and normalized billing vector for billing mechanism" [55]. Based on this fairness index, Baharlouei et al. proposed a billing model that aims at not only improve the optimal general system performance, but also improve the fairness of the billing system [55].

Fan [53] proposed a distributed demand response program and user adaptation in smart grid. The proposed program and adaptation was established with a reference to the congestion pricing in IP networks. In Kelly et al.'s [54] work on proportionally fair pricing scheme, it was concluded that additive increase and multiplicative decrease rate control can achieve proportional fairness. The criterion for fairness was a willingness to pay parameter, which held the belief that customers who are willing to pay more should get more. Fan's work was established on top of Kelly et al.'s work and the simulation showed pricing could indeed help

with shifting the load leveling burden from power supplier to the customers while maintaining proportional fairness [53].

In terms of fairness performance, Jain [64] proposed a matrix that determines if users of a system is having a fare share of the resources. In this chapter, we apply the same method to measure the fairness in terms of the delay of load requests among all the customers.

From the above review on current literature, it is established that most of the researches have been done in the fair bill area, where as none has been done to study fair delay. Bearing the different approaches to achieve fairness in existing literature, this chapter attempts to achieve fairness through fair delay.

4.3 Cost Minimization Problem With Fair Delay in RTP Demand Response Program Using Energy Consumption Scheduling

4.3.1 Delay

One challenge for the utility to deploy the RTP demand response system is to attract the customers to participate in the demand response program. Beside the real-time need from the customers, fairness is another important factor to achieve it [32]. Fairness study of the demand response system has incorporate a fairness index into the demand response programs emphasizing on fair bill between customers [12]. To the best of our knowledge, little attention has been paid to fairness delay for the RTP demand response systems.

Let $d_i(j)$ denote the *accumulative delay* for customer i from timeslot 1 to timeslot j. For every timeslot j, we can calculate $d_i(j)$ at the beginning of each timeslot using following iterative procedure,

$$d_i(j)=\begin{cases} d_i(j-1)+\dfrac{o_i(j)-l_i(j)}{l_i(j)}, \; if \;\; j=2,3,4,..., \\ \qquad\qquad\qquad\qquad 0\le l_i(j)<o_i(j)\,; \\ d_i(j-1)+\dfrac{l_i(j)-o_i(j)}{l_i(j)}, \; if \;\; j=2,3,4,..., \\ \qquad\qquad\qquad\qquad 0\le o_i(j)\le l_i(j); \\ 0, \qquad\qquad\qquad\qquad j=1. \end{cases} \tag{4.1}$$

and $o_i(j)$ is calculated by customer i's energy consumption scheduling decision.

However, since in the real-time demand response system, customers are not only concerned about minimizing the *billing payments* but also the *delay of time* that will come with scheduling of their energy consumption. Within a power system, each of the customer will demand its own desired amount of energy, if the power system can handle the load without step into the peak stage, then the power system will let every customer to schedule the energy consumption to fulfill the load demand immediately. But if the power system can't handle a large amount the energy load demand from all the customers, the power provider will need customers to delay some energy for later consumption. Therefore, in order for the customers to feel fair, the individual delays among all the customers are supposed to be bounded at a predefined level. Thus, it is important to deal with the fair delay boundary.

For $\forall\ i_1,i_2 \in \{1,2,...,N\}$, where i_1 and i_2 are any two customers, their *accumulative delays* $d_{i_1}(j)$ and $d_{i_2}(j)$ can be calculated from (4.1). Let $\dfrac{d_{i_1}(j)}{j}$ and $\dfrac{d_{i_2}(j)}{j}$ denote the *normalized delay* for the two customers at timeslot j. Thus the fair delay boundary can be defined as follows,

$$\left|\frac{d_{i_1}(j)}{j}-\frac{d_{i_2}(j)}{j}\right| \le \delta_0 \quad , \qquad (4.2)$$
$$for \ \forall \ i_1, i_2 \in \{1,2,...,N\}$$

where δ_0 is a parameter set by the power provider of demand response system and $\delta_0 \ge 0$. In the extreme case of $\delta_0 = 0$, this indicates that every customer has exactly same level of the delay during the system. But usually, in practice, $\delta_0 > 0$.

4.3.2 Problem Definition

Customer's Total Cost Minimization with Fair delay Problem

Objective:

$$\min C_{Tot}(j) \qquad (4.3a)$$

subject to

$$\left|\frac{d_{i_1}(j)}{j}-\frac{d_{i_2}(j)}{j}\right| \le \delta_0 \quad . \qquad (4.3b)$$
$$for \ \forall \ i_1, i_2 \in \{1,2,...,N\}$$

Remark I: Here we assume that each customer is honest about its load demand $l_i(j)$ at each timeslot j. This problem is the same bill minimization problem as in (4.1) with a fair delay in (4.2). The challenge here is to satisfy the fair delay condition. In order to satisfy the "fair delay", two concepts are introduced in the following subsection: the *average normalized delay* among all the customers and each customer's *normalized delay deviation* from the *average normalized delay* of at each timeslot j.

4.4 Solution

4.4.1 Average Normalized Delay and Delay Deviation

Let $\pi(j)$ denotes the average normalized delay at timeslot j, and it is defined as

$$\pi(j) = \frac{\sum_{i=1}^{N} d_i(j)}{N \cdot j} \qquad (4.4).$$

The power provider at each timeslot j can calculate this *average normalized delay*.

Let $\delta_i(j)$ denote the *normalized delay deviation* between customer i's normalized delay and the *average normalized delay* at timeslot j. In addition, $\delta_i(j)$ is defined as follows,

$$\delta_i(j) = \frac{d_i(j)}{j} - \pi(j) \qquad (4.5)$$

Lemma 1: $\left|\frac{d_{i_1}(j)}{j} - \frac{d_{i_2}(j)}{j}\right| \le \delta_0$ in (4.2) of the problem (4.4) is the same as the following,

$$\left|\delta_{i_1}(j) - \delta_{i_2}(j)\right| \le \delta_0 , \qquad (4.6)$$

where $\delta_{i_1}(j)$ and $\delta_{i_2}(j)$ are the deviations for any two customers i_1, i_2 at timeslot j.

Proof:

$$\begin{aligned}\left|\delta_{i_1}(j) - \delta_{i_2}(j)\right| &= \left|[\frac{d_{i_1}(j)}{j} - \pi(j)] - [\frac{d_{i_2}(j)}{j} - \pi(j)]\right| \\ &= \left|\frac{d_{i_1}(j)}{j} - \frac{d_{i_2}(j)}{j}\right|.\end{aligned}$$

Thus, $\left|\frac{d_{i_1}(j)}{j} - \frac{d_{i_2}(j)}{j}\right| \le \delta_0$ is equal to (4.3b). □

Therefore the problem (4.3) can also be equally expressed as follows,

Objective:

$$\min C_{Tot}(j) \tag{4.7a}$$

subject to

$$\left|\delta_{i_1}(j)-\delta_{i_2}(j)\right| \le \delta_0 \;\; for \;\; \forall \; i_1, i_2 \in \{1,2,...,N\}. \tag{4.7b}$$

Lemma 2: (4.7b) will be satisfied if both conditions are both met,

$$\max_{i=1}^{N} \delta_i(j) \le \pi(j) + \frac{\delta_0}{2} \tag{4.8}$$

$$\min_{i=1}^{N} \delta_i(j) \ge \pi(j) - \frac{\delta_0}{2} \tag{4.9}$$

Proof:

$$\begin{aligned}\left|\delta_{i_1}(j)-\delta_{i_2}(j)\right| &\le \left|\max_{i=1}^{N} \delta_i(j) - \min_{i=1}^{N} \delta_i(j)\right| \\ &\le \left|[\pi(j)+\frac{\delta_0}{2}]-[\pi(j)-\frac{\delta_0}{2}]\right| \\ &= \delta_0\end{aligned}$$

□

4.4.2 Delay Deviation Awareness Operations

Given the above two conditions (4.8) and (4.9), it is possible to bound the fair delay by making sure that each customer i's deviation is bounded as $\delta_i(j) \in [\pi(j)-\frac{\delta_0}{2}, \pi(j)+\frac{\delta_0}{2}]$. But to achieve this, each customer needs to know the *average normalized delay* each time from the power provider before scheduling the consumption of its own energy. This means that every customer need to be aware of whole "delay" situation of the neighborhood area network grid as well as its own delay.

Then taking advantage of this awareness, the energy consumption scheduling can apply a "fair delay" strategy to make decisions on $o_i(j)$ and reschedule $l_i(j)$ if necessary if it is not fully consumed at each timeslot.

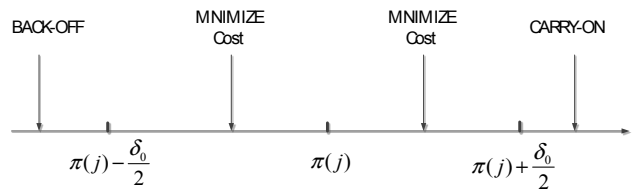

Fig. 4.1 Back-Off and Carry-On Operations for Fair Delay Bounding

As seen in Fig. 4.1, each customer is aware of the average normalized delay and its own delay deviation of the normalized delay. If the delay deviation $\delta_i(j) < \pi(j) - \frac{\delta_0}{2}$, it means the customer i is leading within the N customers on the normalized delay, then in order to achieve the "fair delay", the customer performs a **BACK-OFF** operation at timeslot j. On the other hand, if the deviation $\delta_i(j) > \pi(j) + \frac{\delta_0}{2}$, it means that the customer i's consumption is falling behind among all N customers in terms of the normalized delay, then the customer performs a **CARRY-ON** operation. However, if the deviation satisfies $\delta_i(j) \in [\pi(j) - \frac{\delta_0}{2}, \pi(j) + \frac{\delta_0}{2}]$, then customer i performs regular bill payment minimization through the energy consumption scheduling.

BACK-OFF: if the customer chooses to back-off, it means that customer i makes the decision

$$o_i(j) = 0 \ , \tag{4.10a}$$

and reschedule its $l_i(j)$ by adding it to the $r_i(j)$ at this timeslot, which $r_i(j)$ is defined as follows,

$$r_i(j) = r_i(j-1) + l_i(j) \tag{4.10b}$$

This means that customer i adjusts its leading *normalized delay* $\frac{d_i\,(j-1)}{j-1}$ more back to the *average normalized delay* $\frac{d_i\,(j-1)+1}{j}$.

CARRY-ON: if the customer chooses to carry-on, it means that customer i makes the decision to consume the load demand of this timeslot and some of the remainder load of the previous timeslot. Let $\Delta r_i(j)$ denote the consumed remainder load by the carry-on operation, then

$$r_i(j) = r_i(j-1) - \Delta r_i(j), \tag{4.11a}$$

$$o_i(j) = l_i(j) + \Delta r_i(j), \tag{4.11b}$$

where $\Delta r_i(j)$ is the solution of

$$\frac{\Delta r_i(j)}{r_i(j)} = \delta_i(j) \tag{4.11c}$$

This operation will reduce the *normalized delay* of customer i from $\pi(j) + \delta_i(j)$ to $\pi(j)$.

4.4.3 Balanced RTP Price Threshold

For each timeslot, the decision of choosing $o_i(j)$ is made by the customer i based on a power price threshold. Let $p_i^{threshold}(j)$ be the power price threshold. In a real-time demand response power system, each customer optimally consumes or schedules its *load demands* $o_i(j)$ based on the power price of each timeslot using the energy consumption scheduling. Each customer minimizes its cost calculated in (3.15).

In order to let the customer's energy consumption scheduling to make decisions that will both minimize the bill payment and bound the normalized fair delay of the customers, we introduced the power price threshold in a weighted way in (3.14) to assist the customers to make decisions on $o_i(j)$.

$$p_i^{threshold}(j) = p_i^{avg}(j) + \lambda \cdot p_i^{feedback}(j) \tag{4.12}$$

- $p_i^{threshold}(j)$ is the threshold of power price that the customer i's *energy consumption scheduling* will use to manage all their appliances.
- $p_i^{avg}(j)$ is the average power price that customer i has been observed over the j timeslots, and it is a customized parameter for customer i.
- $p_i^{feedback}(j)$ is the power provider's feedback parameter from the power provider that indicates the delay deviation strategy depending on the neighborhood area network situation.

λ is a predefined parameter by each customer, and $\lambda \in [0,1]$ and it balances the impact between each customer's need of minimizing its bill payment and the power provider's coordination of fair delay.

4.4.4 Power Provider Feedbacks

Each timeslot j, $j = 2,3,...$, the power provider wants to encourage all the customers to help the power provider to flatten its peak. This is executed by the RTP power price in (4.12). But they can also adopt delay strategy to help customers to bound their delays to be fair.

Now that when the customer's delay deviation $\delta_i(j) < \pi(j) - \frac{\delta_0}{2}$ or $\delta_i(j) > \pi(j) + \frac{\delta_0}{2}$, the energy consumption scheduling program will perform Back-Off or Carry-On operations to force restrict the delays of the customers whose delay is out of fair bound to the δ_0 delay deviation level. But at timeslot j for the customers whose delay deviation $\delta_i(j) \in [\pi(j) - \frac{\delta_0}{2}, \pi(j) + \frac{\delta_0}{2}]$, we introduce the Differentiated Delay Feedback for each customer based on their own delay deviation status using $p_i^{feedback}(j)$.

Differentiated Delay Feedback (DDF)

The idea let the power provider compare each customer's delay deviation with the normalized average delay of all the customers at each timeslot j. If the delay deviation is $\delta_i(j)=0$, that means that at timeslot j, customer i's delay is as fair as the average level of all N customers. Then the power provider doesn't give any feedback to impact the customer's energy consumption scheduling decision. If $\delta_i(j)\in[\pi(j)-\frac{\delta_0}{2},0)$, then the power provider gives a feedback $p_i^{feedback}(j)$ to make the customer's price threshold $p_i^{threshold}(j)$ higher than it normally uses to dissuade customer to contribute more delay of the energy consumption scheduling load consumption. If $\delta_i(j)\in(0,\pi(j)+\frac{\delta_0}{2}]$, then the power provider should give the opposite feedback of $p_i^{feedback}(j)$. Therefore, we propose to design the delay-differentiated feedback as follows,

$$p_i^{feedback}(j)=\frac{-\delta_i(j)}{\pi(j)}\cdot p(j) \tag{4.13}$$

Remark I: In (4.13), if the $\delta_i(j)=0$, the $p_i^{threshold}(j)=p_i^{avg}(j)$, this means that the customer only takes the threshold as the normal cost minimization problem. If $\delta_i(j)\in[\pi(j)-\frac{\delta_0}{2},\pi(j))$, then the $p_i^{threshold}(j)=p_i^{avg}(j)+\lambda[\frac{-\delta_i(j)}{\pi(j)}\cdot p(j)]$, this makes the price threshold $p_i^{threshold}(j)>p_i^{avg}(j)$. The larger $p_i^{threshold}(j)$ makes the energy consumption scheduling possibly to schedule more energy for consumption at timeslot j. If $\delta_i(j)\in[\pi(j),\pi(j)+\frac{\delta_0}{2}]$, then the situation is the opposite.

4.4.5 Distributed Energy Consumption Scheduling Algorithm

The idea of the energy consumption scheduling is to set the energy consumption scheduling decision making into 2 stages:

Stage 1: Fair delay Bounding Stage

For each customer i, let the energy consumption scheduling program check the delay situation based on the current normalized delay and the average delay of all the customers given by the power provider. If it runs out of the boundary in (4.8) or (4.9), the energy consumption scheduling performs Back-Off or Carry-On operation.

State 2: Cost Minimization and Fair delay Optimization Stage

For each customer i, the energy consumption scheduling program uses a stationary policy y to decide how much remainder to consume if the $p(j) \le p_i^{threshold}(j)$. Each customer uses a stationary policy x to decide how much remainder to consume if the $p(j) > p_i^{threshold}(j)$. Therefore, the decision of actually consumed energy at j timeslot $o_i(j)$ can be calculated as

$$o_i(j) = \begin{cases} x \cdot l_i(j), & if \;\; p(j) > p_i^{threshold}(j); \\ l_i(j) + y \cdot r_i\,(j)/j, & if \;\; p(j) \le p_i^{threshold}(j). \end{cases} \tag{4.14}$$

where $0 \le x < 1$ and $0 \le y \le 1$.

Energy Consumption Scheduling Algorithm: Executed by Each Customer i

// busy-waiting

1: wait for $\pi(j)$ from the power provider until receiving it;

// This means that this customer i has delayed much less than the average

2: **if** $\delta_i(j) < \pi(j) - \frac{\delta_0}{2}$

3: perform **Back-Off** operation in (4.10)

4: **if** $\delta_i(j) > \pi(j) + \frac{\delta_0}{2}$ **;**

5: perform **Carry-On** operation in (4.11)

6: **if** $\delta_i(j) \in [\pi(j) - \frac{\delta_0}{2}, \pi(j) + \frac{\delta_0}{2}]$

7: using $p_i^{threshold}(j)$ calculated in (4.12) to find the optimal policy (x, y) defined in (4.14).

4.5 Simulation

4.5.1 Simulation Design

Assume every timeslot there is a load request, but the request could be zero. Also assume that the amount of each customer's load demand follows the same normal distribution.

Note that the time in the simulation is integer, marked as timeslots such as 1,2,3, …. Here time of 1 means that it's the 1st timeslot. Initially, every customer schedules its first load request at the beginning of the 1st timeslot and sends the request to the power provider. Assume the communication overhead and delay between all the customers and the power provider are ignored. Then the power provider updates the real-time power price for the current timeslot after receiving the load requests. Finally, each customer makes its own energy consumption decision on how much load to consume and how much load to delay at current j^{th} timeslot using the energy consumption scheduling algorithm in last section.

Table 4.1 Stream Table

Stream	**Purpose**
1	load requests time is

	constant and requests at each timeslot
2	load request of a customer follow the above normal distribution

For the measurement of delay fairness, we borrow the concept of fairness index proposed by Jain [64] as,

$$\mathrm{I}[d_1(j), d_2(j), ..., d_N(j)] = \frac{(\sum_{i=1}^{N} d_i(j))^2}{N \cdot \sum_{i=1}^{N} d_i(j)^2}, \tag{4.15}$$

where $d_i(j)$ is the delay for customer i defined in (4.1), and I denotes the fairness index of a set of N customers' delays. Its result ranges from $\frac{1}{N}$ and 1, which are the worst case and best case respectively.

4.5.2 Simulation Setup

Let every customer generate a load request following the normal distribution $N(\mu / N, (\mu / 3N)^2)$ at each timeslot, where μ is equal to Load Peak. Load Peak is the parameter set by the power provider. Because the timeslot here is considered to be a very small unit time, it is assumed that the Load Peak is 1000kWh by the power provider. Also assume that the total simulation running time is 1000 timeslots. Assume that there are 100 customers within the power provider's distribution network. This means the aggregated load requests $e(j)$ maintains stable at the peak load level.

4.5.2.1 α =0.1 and δ_0 =0.1

Table 4.2 Simulation Parameters

Experiment Parameters	**Values**
Load Peak	1000kWh
N	100
Sim_time	1000
α	0.1
λ	1
δ_0	0.1
μ	1000kWh

The simulation set of parameters are given as shown in Table 4.2, and the weighted parameter α is set to 0.1, to emphasize the importance of the load remainder's delay cost in (3.15). Also, the fair delay boundary is set as δ_0=0.1.

As seen in Fig. 4.2 and Fig. 4.3, they show the total cost plot lines based on different x values. When x=0, the total cost has the lowest value, and the other lines plotted by the rest of x values are quite close with each other. But as seen in Fig. 4.4 and Fig. 4.5, when x=0.1, the total cost is slightly lower than the rest of x values.

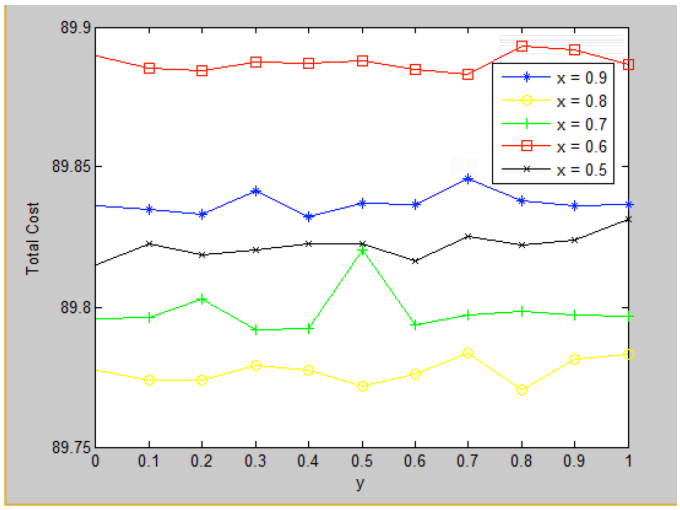

Fig. 4.2 Total Cost for fixed x=0.5, x=0.6,… x=0.9.

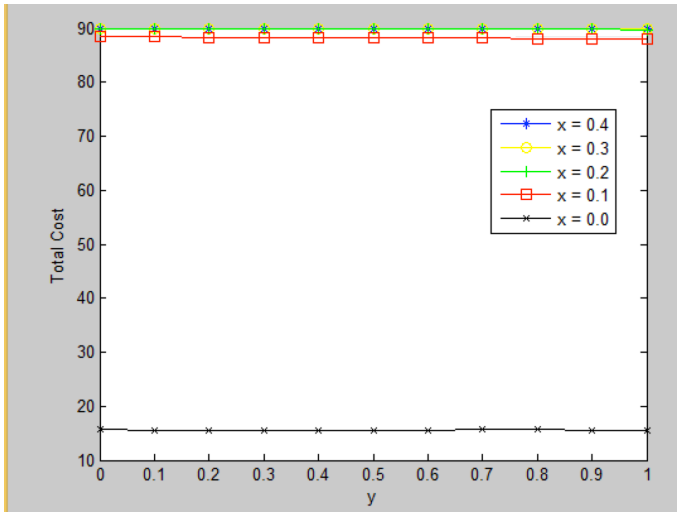

Fig. 4.3 Total Cost for fixed x=0, x=0.1,… x=0.4.

As seen in Fig. 4.4 and Fig. 4.5, they show the total cost plot lines based on different y values. The results show that all the lines with different y values are overlapping with each other. This means that when the y value varies from 0 to 1, the total cost does not change much. This result can also be verified in the Fig. 4.2 and Fig. 4.3.

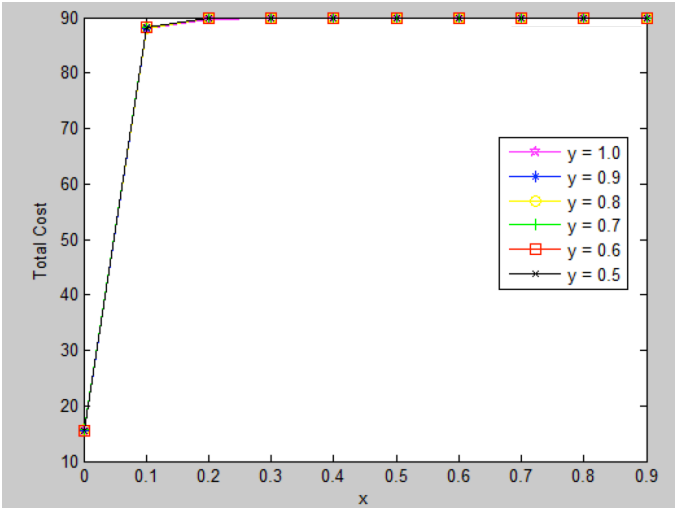

Fig. 4.4 Total Cost for fixed y=0.5, y=0.9, …, and y=1.

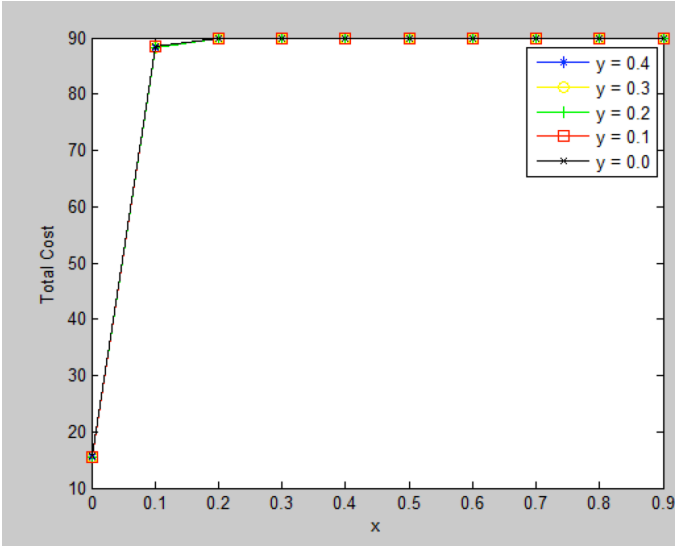

Fig. 4.5 Total Cost for fixed y=0.0, y=0.1, … ,and y=0.4.

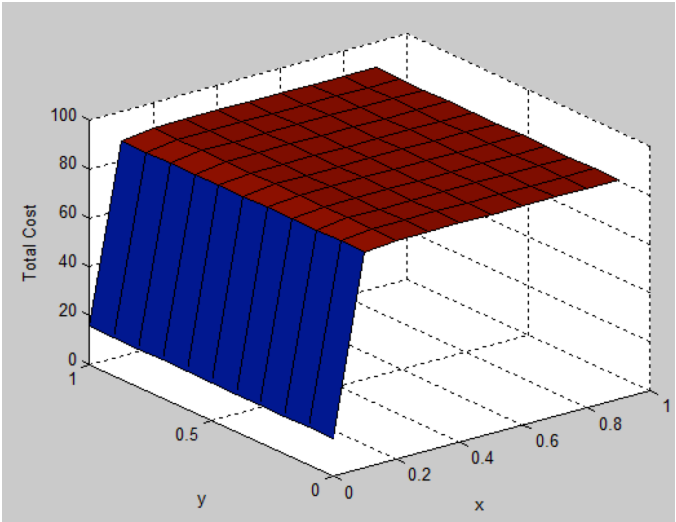

Fig. 4.6 Total Cost 3D

As seen in Fig. 4.6, it shows that the performance of the total cost in 3D plot, and when x=0.0, the total cost has the lowest value. This means that the best policy for the customer to do is not to consume any load requests when the real-time power price is expensive. The varying y value does not have much impact on the total cost, this means if the real-time power price is cheap, the best policy for the customer is consume all the load requests generated at the current timeslot and load remainder is consumption is not relevant in terms of lowering the total cost. But all the above result is not considering the fairness boundary in delay yet. Therefore, the fair delay results are analyzed below.

As seen in Fig. 4.7 and Fig. 4.8, they show the fair delay performance as several lines based on different x values. It is quite obvious that when x=0, the fair delay index is lower than 0.8, which is much lower than the rest of x values, which are higher than 0.99. This means even when x=0, the policy makes the customers have lower total cost, but in terms of the fair delay index, the performance is bad. Therefore, even the total cost is the lowest when x=0, the policy is not acceptable due to its bad fair delay boundary violation.

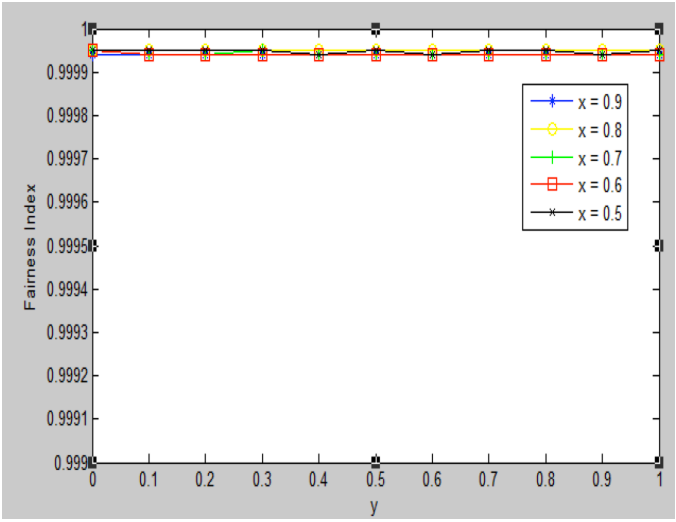

Fig. 4.7 Fairness Index for fixed x=0.5, x=0.6, … x=0.9.

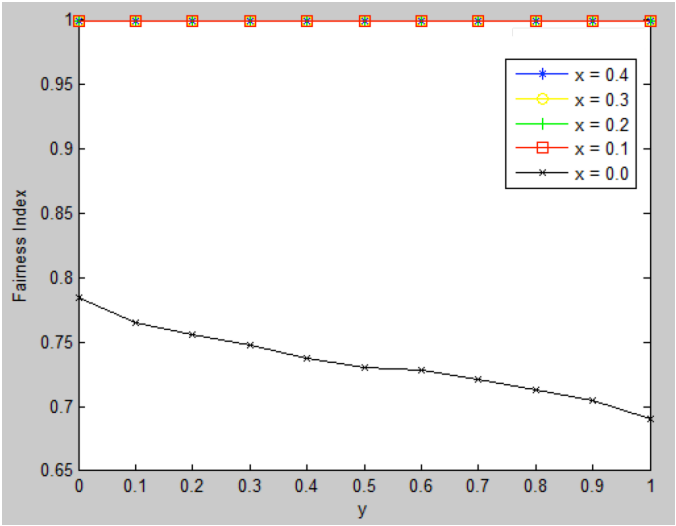

Fig. 4.8 Fairness Index for fixed x=0, x=0.1, … x=0.4.

As seen in Fig. 4.9 and Fig. 4.10, they show the fair delay performance as several lines based on different y values. The results show that the varying y values all have the same good

performance on fairness delay index, which are over 0.99, except for the case when x =0. This means that the y value is not important for making the policy in order to have a high fair delay.

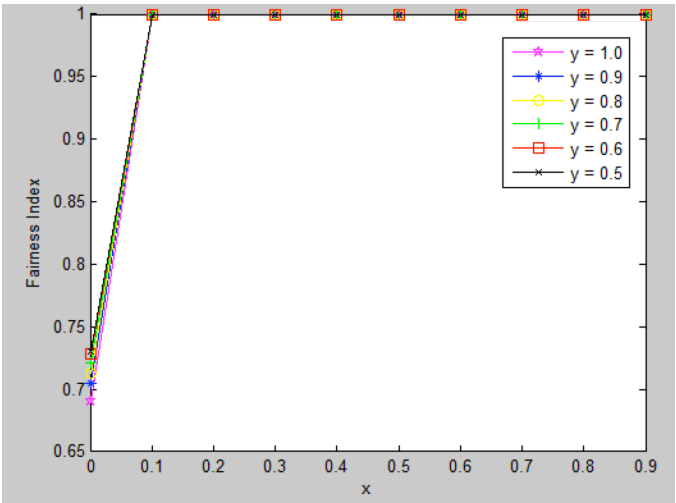

Fig. 4.9 Fairness Index for fixed y=0.5, y=0.9, …, and y=1.

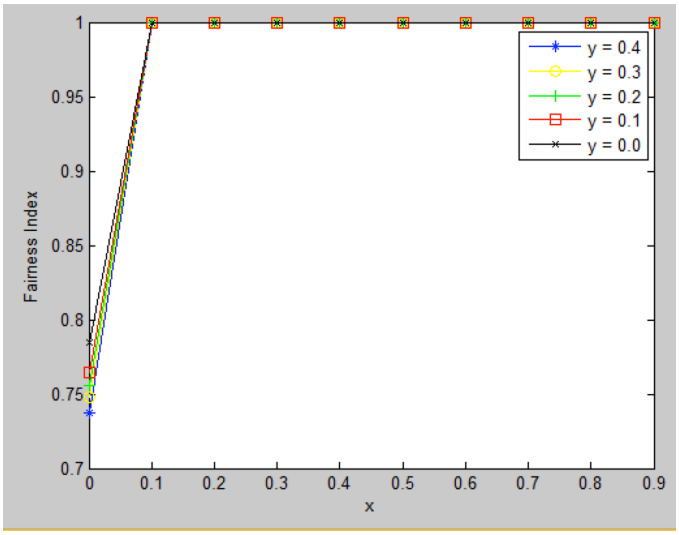

Fig. 4.10 Fairness Index for fixed y=0.0, y=0.1,… ,and y=0.4.

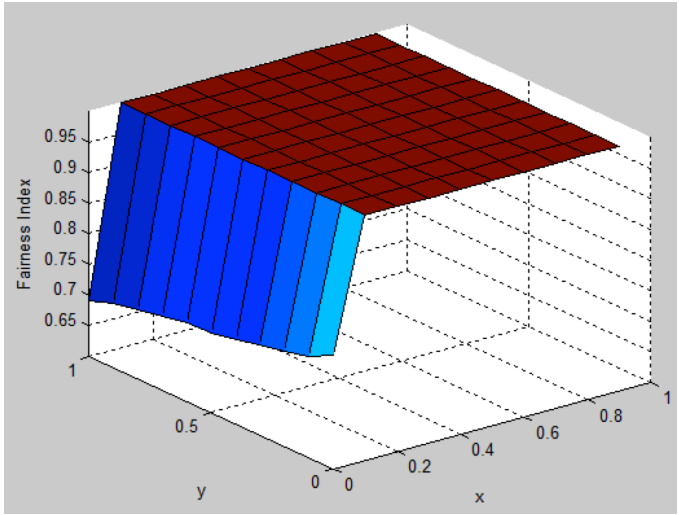

Fig. 4.11 Fairness Index 3D

As seen Fig. 4.11, it shows that most of the fairness delay performance is as good as 0.99, which means that 99% of the customers' delays are maintained at the same level. But when the x=0, it show the fairness index is somehow below 0.8. It is because even when the real-time price is greater than the threshold price, the policy still makes customers to choose to delay all the load requests consumption for cheaper price, which break the fair delay boundary. Therefore, to best policy for the customers to choose to have the lowest total cost while maintaining the fair delay boundary is x=0.1 with all the possible y values.

4.5.2.2 α =0.1 and δ_0 =0.5

This set of simulation parameters is given as shown in Table 4.3. In this setting, the weighted parameter α is still set to 0.1, to emphasize the importance of the load remainder's delay cost in the total cost. Also, the fair delay boundary is set as δ_0=0.5, which has a larger space for all the customers to bound their delay comparing to the previous simulation setup.

Table 4.3 Simulation Parameters

Experiment Parameters	**Values**
Load Peak	1000kWh
N	100
Sim_time	1000
α	0.1
λ	1
δ_0	0.5
μ	1000kWh

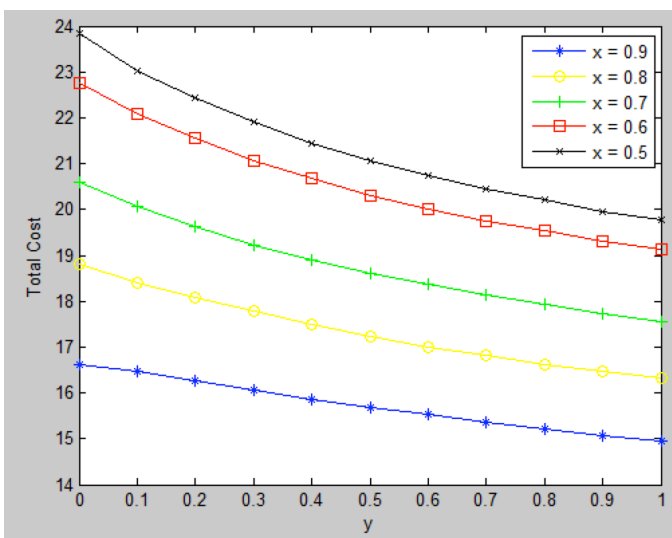

Fig. 4.12 Total Cost for fixed x=0.5, x=0.6,… x=0.9.

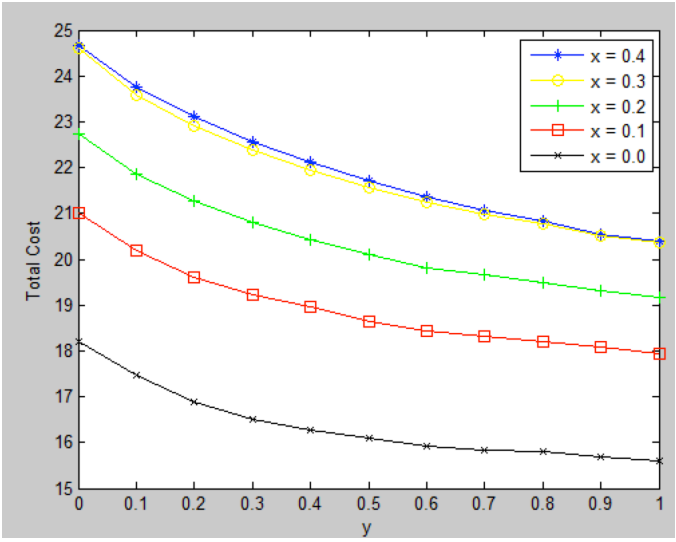

Fig. 4.13 Total Cost for fixed x=0, x=0.1,… x=0.4.

As seen in Fig. 4.14 and Fig. 4.15, they show the total cost plot lines based on different y values. When y=1.0, this total cost has the lowest value throughout the x-axis. This means that when the real-time power price is lower than the threshold price, the best policy for the customers is to consume the load requests generated at the current timeslot, as well as the 100% of the normalized load remainder.

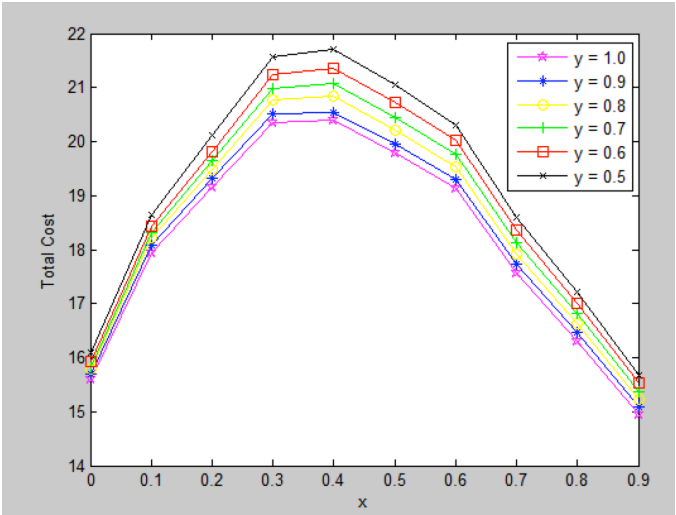

Fig. 4.14 Total Cost for fixed y=0.5, y=0.9, …, and y=1.

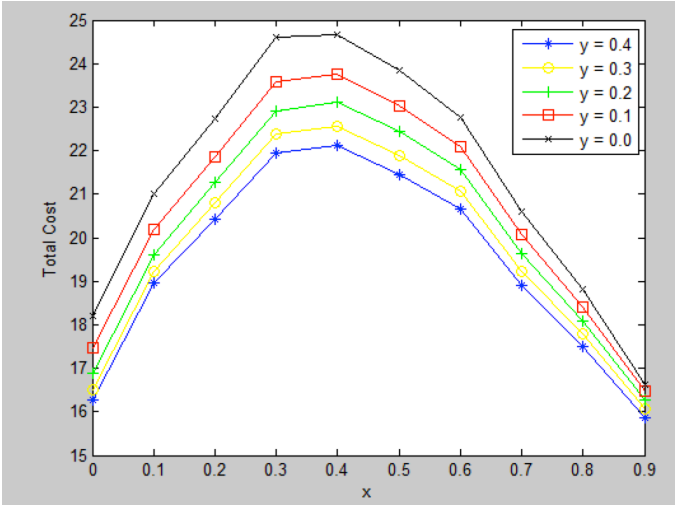

Fig. 4.15 Total Cost for fixed y=0.0, y=0.1, … ,and y=0.4.

As seen in Fig. 4.16, when x=0.9 and x=0 it has 2 lines with the lowest total cost. x=0.9 means that the best policy for the customers is to consume 90% percent of the load requests generated at the current timeslot if the real-time power price is higher than the threshold price. Whereas when x=0, it is best for customers to choose to delay all the load requests generated at the current timeslot if the real-time power price is higher than the threshold price.

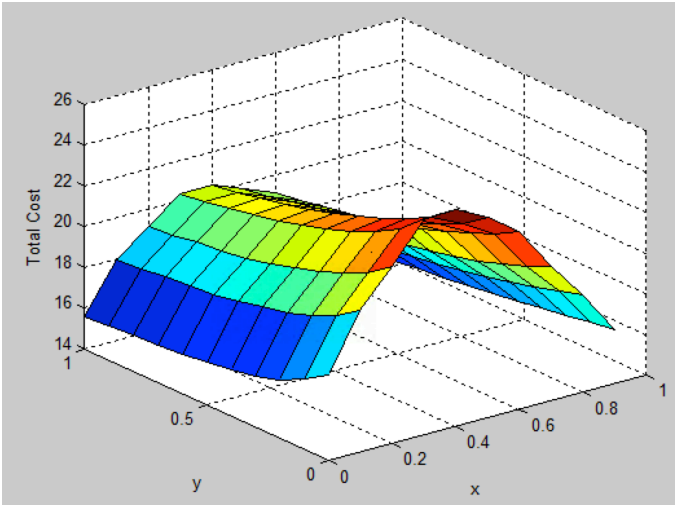

Fig. 4.16 Total Cost 3D

As seen in Fig. 4.17 and Fig. 4.18, they show the fair delay performance as several lines based on different x values. It is quite clear that when x=0, the fair delay index is lower than 0.85, which is obviously lower than the rest of x values. When x=0.1, the fair delay index is at [0.9,0.95]. The x is greater than and equal to 0.2, the fair delay index is higher than 0.95.

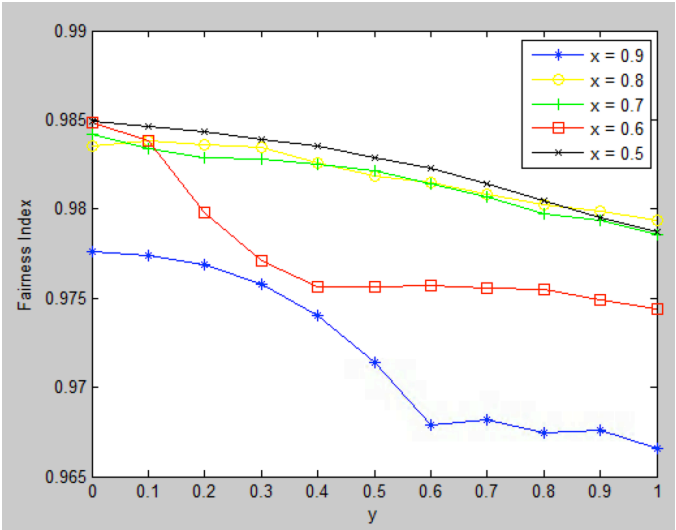

Fig. 4.17 Fairness Index for fixed x=0.5, x=0.6, … x=0.9.

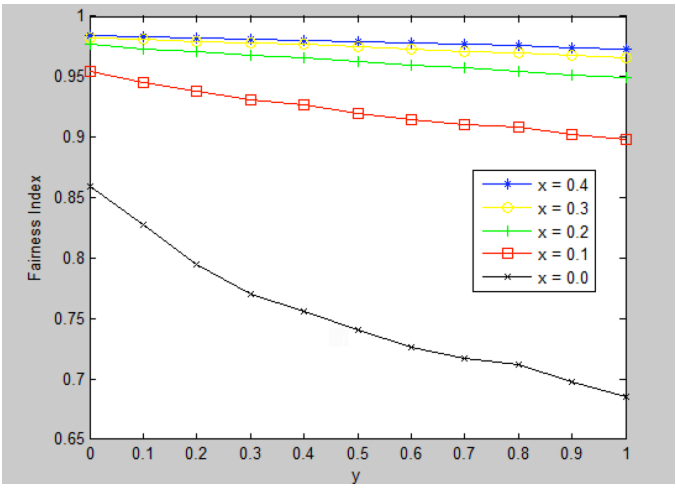

Fig. 4.18 Fairness Index for fixed x=0, x=0.1, … x=0.4.

Fig. 4.19 and Fig. 4.20 show the fair delay performance as several lines based on different y values. It is shown that when x is greater than or equal to 0.2, the y value does not impact the fair delay index much.

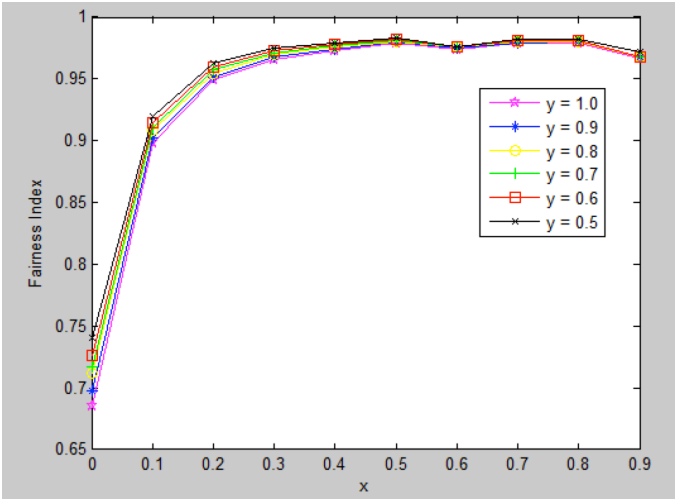

Fig. 4.19 Fairness Index for fixed y=0.5, y=0.9, …, and y=1.

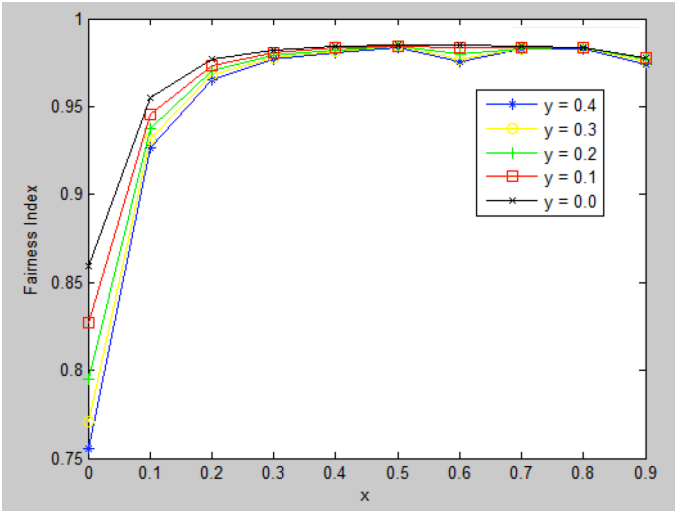

Fig. 4.20 Fairness Index for fixed y=0.0, y=0.1,… ,and y=0.4.

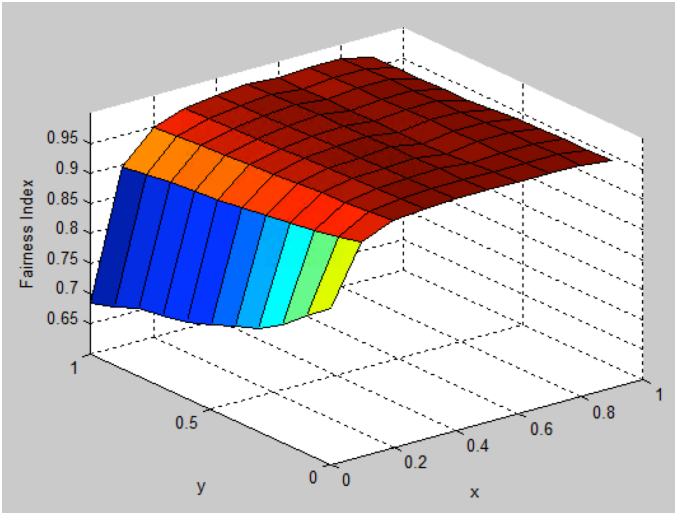

Fig. 4.21 Fairness Index 3D

As seen in Fig. 4.21, it shows that the performance of fair delay, and it shows that the fairness delay index is as good as 0.95 in most cases. This means 95% of the customers' delays are maintained at the same level. Only when the x=0, it shows the fairness index is somehow below 0.85. The reason behind this result is that even when the real-time price is smaller than the threshold price, the customer still chooses to delay for the next timeslot to consume the load requests. Therefore, the best policy for the customers to choose from is to have the lowest total cost while maintaining the fair delay boundary at x=0.9 and y=1.

4.5.2.3 Fairness Index Comparison With Non-Fair Delay Energy Consumption Scheduling

In order to show the effectiveness of the fair delay control algorithm, we compare fair delay performance of the algorithm in this chapter with the energy consumption scheduling algorithm without fair delay control with the same set of simulation parameters listed in Table 4.2.

From Fig. 4.22 it can be seen that the fair delay control algorithm in this chapter has effectively improved the fairness of the delay among all the customers with all the x values comparing to the energy consumption scheduling algorithm without the fair delay control. The algorithm with fair delay control has the fair delay index mostly at the level of 0.99 while the algorithm without fair delay control is mostly below 0.8.

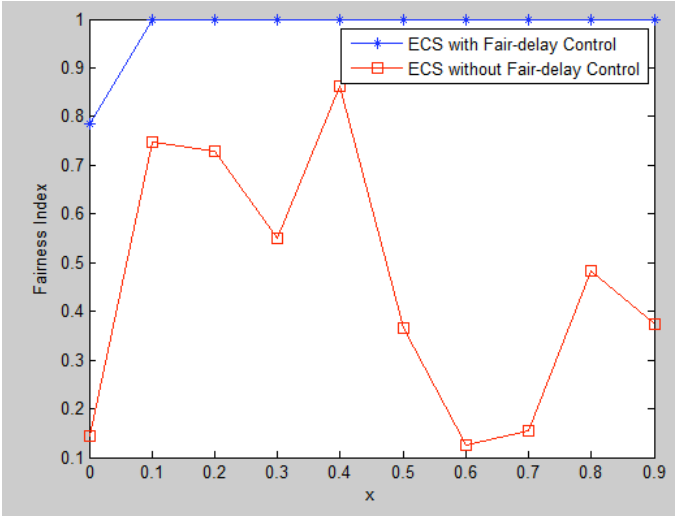

Fig. 4.22 Fairness Index Comparison Between Energy Scheduling algorithms with and without Fair delay control

From Fig. 4.23 it can be seen that the fair delay control algorithm in this chapter has effectively improved the fairness of the delay among all the customers with all the y values comparing to the energy consumption scheduling algorithm without the fair delay control. The algorithm with fair delay control has the fair delay index mostly at the level of 0.99 while the algorithm without fair delay control is mostly below 0.4.

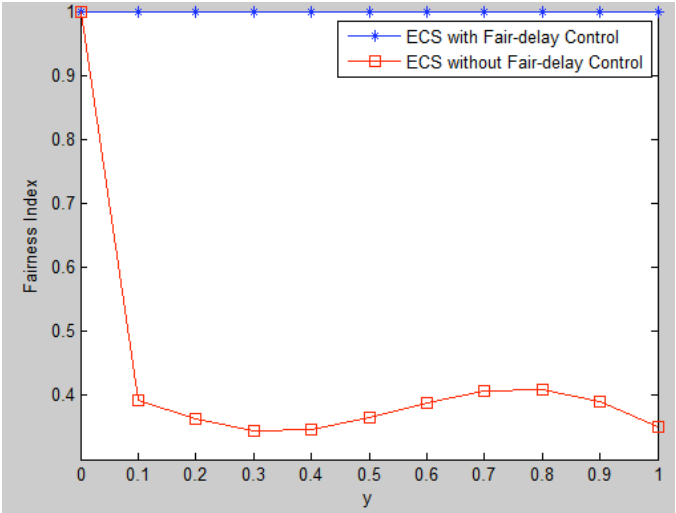

Fig. 4.23 Fairness Index Comparison Between Energy Scheduling algorithms with and without Fair delay control

4.6 Conclusion

This chapter has studied the total cost minimization problem with fair delay constraint using energy consumption scheduling method in smart grid distribution. In order to bound all the customers' delay within a fairness range, an algorithm is proposed with back-off, carry-on and optimize procedures. In order to find the best policy for using this algorithm, discrete event simulation is used to find the best policy in order to lower all the customers' total cost while bounding the customers' delays within a fairness range. In order to let the system reflect the delay impact, the load requests are setup as high as load peak level. Then the simulation is categorized with two setups: 1. Fair delay boundary δ_0=0.1; 2. Fair delay boundary δ_0=0.5. In the 1st simulation setup, the best policy for the customers is to choose is x=0.1 with all the possible y values, in order to have the lowest total cost while maintaining the fair delay boundary. The best policy of the 2nd simulation setup for the customers is to choose to have the lowest total cost while maintaining the fair delay boundary is x=0.9 and y=1. From the above two simulation

setups, it is shown that if the fair delay boundary is too tight, the customers will have to consume less energy while maintaining the fair delay boundary. Therefore, it is vitally important for the power provider to pick up a proper fair delay boundary to let the customers consumes energy at a lower total cost and maintaining the fair delay at the same time.

At last the fair delay index is compared between the algorithm with and without fair delay control function. The results showed that the algorithm without fair delay control has a fair delay index lower than 0.4, while the algorithm with the fair delay control in this chapter has a much better fair delay index performance, which is higher than 0.99.

However, the limitation on the length of the chapter only allowed a certain amount of discussion to be conducted. Future work can look further into fairness problem from fair bill, fair delay, or otherwise.

5 SCHEDULABLE ENERGY SCHEDULING ALGORITHM USING OPTIMAL STOPPING RULE IN SMART GRID DISTRIBUTION

5.1 Introduction

The relationship between people and energy has been changing rapidly in the past several decades. The simple consumption of energy is becoming a more complicated issue because of the growing population and revealing shortage of natural resources. Instead of pure consumption, energy is now being scheduled, conserved, and even sold back to the power grid by consumers as a method to contribute to a more environmentally friendly society.

The emergence of smart grid is a huge step forward for people to use energy in a more efficient manner. A smart grid is known as "an intelligent electricity network that integrates the actions of all uses connected to it and makes use of advanced information, control, and communication technologies to save energy, reduce cost and increase reliability and transparency" [9]. Smart grid is altering the old-fashioned energy consumption pattern slowly. Because of its smart feature, such as flexibility and cost minimization, consumers are now much more educated about their own energy consumption pattern. To ensure the world continues to develop in a sustainable manner, it is essential for smart grid to be further studied and optimized from various angles.

Among all the researchable topics of smart grid, demand response is one of the most promising ones [1]. In fact it has been shown through literature that demand response is capable of delivering significant benefits to not only the customers but also the whole society [9]. The definition of demand response, as cited from the Department of Energy, is, "a tariff or program

established to motivate changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over the time, or to incentive payments designed to induce lower electricity usage at times of high wholesale market prices or when system reliability is jeopardized" [1]. What makes it easier for demand response to accomplish above-mentioned purposes is energy consumption scheduling.

energy consumption scheduling is a trendy topic among the researchers. Using energy consumption scheduling method offers the opportunity to conquer the real-time and automation challenges [14]. In other words, energy consumption scheduling helps with motivating customers to change their consumption pattern. In terms of real-time, there are various types of methods that target at situations when real-time price is not known before the energy consumption scheduling decision is made. One of them is to make RTP price predictions [14]. Customers then make energy consumption scheduling decisions based on the prediction. Another method is to make believable assumptions of the energy consumption scheduling decisions, which are based on other customers' load demands and their energy consumption scheduling decisions [57] or the power provider's cost [15]. Regardless of the various programs that adopts energy consumption scheduling method, there is room left for energy consumption scheduling to advance further.

Optimal stopping rules is an optimization model that minimizes or maximizes solution if conditions are satisfied [65]. The paper [17] applied it to the Home Energy Management (HEM) using it to optimally schedule all the appliances. It has the advantage to schedule each appliance individually, which allows flexibility when peak arrives. It will automatically run some or all the household appliances. Another advantage of optimal stopping rule is that apart from being a model, it also offers mathematical solutions to the model based on it.

In this chapter, optimal stopping rule is combined with energy consumption scheduling to achieve cost minimization. Unlike the paper [17] focusing on scheduling all the appliances within the HAN in the smart grid distribution, this chapter is focusing on the customers' scheduling behavior within the neighborhood area network. Moreover, this chapter also considers comfortable level as a constraint for the cost minimization problem and seeks its solution.

The rest of this chapter is be organized into five sections. Related work is in section 5.2. The system model built upon optimal stopping rule can be found in section 5.3. Section 5.4 is the solution to the problems. Simulation is then conducted in section 5.5. Finally, the chapter concludes in section 5.6.

5.2 Related Work

Using energy consumption scheduling method to study the demand response system has been in trend for some time now for energy consumption scheduling has been widely used in the exploration of RTP demand response programs [15], [18], [45], [46], and [61]. The method provides many RTP solutions to benefit both the customers and the power provider in terms of reducing cost and/or lowering the peak demand load, which in return makes the power grid more efficient. Most residential demand response studies are mainly focused on the appliance scheduling during the RTP environment. This focus has brought many useful designs of energy consumption scheduling techniques into the RTP demand response solution set.

In the paper [50], the authors looked into a real-time energy consumption scheduling algorithm with load uncertainty that aims at bill minimization for individual residential customers. The load-scheduling problem was formulated as an optimization problem. The researchers adopted an approximate dynamic programming approach to make the computing

simpler. They also studied the difference between must-run appliances (such as lighting) and controllable appliances that are much more flexible. Instead of assuming the demand response algorithm understands customers' energy needs perfectly, the algorithm proposed in this chapter survives on only some estimates of future demand. Their algorithm combined RTP with inclining block rates to balance residential load in order to achieve a low PAR [50].

Demand response programs designed in a distributed network have also been discussed. The paper [9] proposed a distributed framework for demand response and user adaptation in smart grid networks. The author in the paper [9] utilized his knowledge in Internet traffic control and transferred the concept of congestion pricing into demand response problem and attempted to shift the burden of load leveling from energy provider to the customers through pricing. Based on the assumption that customers will definitely adapt to the price signals to maximize their own benefits, Fan modeled user preference as a willingness to pay parameter, which was treated as same as an indicator of differential quality of service. Although the analysis and simulation in the paper both demonstrated the convergence of the proposed algorithm, as Fan himself writes in the paper, the model used in this chapter is highly abstract that makes it impractical. In other words, regardless of the success of analysis and simulation, Fan's framework is not practical enough to be adapted into industrial application. But the idea of solving demand response issues with concept originated from the Internet is quite enlightening and will hopefully come in handy for future exploration.

The paper [17] proposed an opportunistic scheduling scheme based on optimal stopping rule as a real-time distributed scheduling algorithm for smart appliances' automation control. They assumed that a smart appliance has the ability to automatically schedule its operation based on RTP, and that the operation of every appliance in the customer's home is independent. Their

scheduling scheme focused on reducing customer's bill while considering the waiting time that the customer has to put up with. Thus Yi et al. [17] assumes that the power price using statistic method following uniform or Gaussian distribution. The single load cost minimization problem defined in [17] is very similar to the house selling model in [58]. Then Yi et al. [17] extends the minimization problem on the single appliance's cost minimization to multiple appliances scheduling with and without maximum load allowance at each timeslot.

The following section explores the problem discussed in this chapter and establishes the system model.

5.3 Single Load Demand Cost Minimization Using Optimal Stopping Rule

5.3.1 System Model

Assume that there are N customers $\{1,2,...,N\}$ within the power distribution system. Assume that time is divided into timeslots, and therefore let timeslot j denote the time period $[j\Delta t,(j+1)\Delta t)$, where $j=1,2,...$, and Δt is a unit time per timeslot.

For each timeslot $j=1,2,...$, the customer i may have a load demand, and let $l_i(j)$ denote the customer i's load demand generated at timeslot j. Then at timeslot j the load demand may be consumed at the very timeslot j or may also be kept waiting and consumed at a later timeslot of a lower price.

Let $P(1),P(2),...P(j),...$ denote a sequence of price random variables; thus, let $p(1),p(2),...,p(j),...$ denote the observations of the sequence of random variables $P(1),P(2),...P(j),...$. Thus, $p(j)$ means the real-time power price at timeslot j.

Let j denote the current timeslot. But how to find the exact timeslot for the load demand $l_i(j)$ to be consumed in order to minimize customer's cost is the problem. Noted that if the

customer waits for a future timeslot for that load consumption, it may have a lower power price later, but then it will pay for the cost of delaying that load demand during the waiting period.

Let's assume there is a scheduling algorithm for each load demand $l_i(j)$ run by each customer, based on the input of load demand and RTP price from server. Let n denote one scheduled timeslot for load demand $l_i(j)$, where $n \geq j$.

Then the $l_i(j) \cdot p(n)$ denotes the *scheduled bill* for load demand $l_i(j)$ if it is consume at timeslot n, and $(n-j) \cdot c$ denote the *delayed cost* for load demand $l_i(j)$. For an arbitrary load demand $l_i(j)$ generated at timeslot j for customer i, we consider two trade-off costs: the scheduled bill payment and the delay cost. Thus the *total cost* of the load demand is expressed as $l_i(j) \cdot p(n) + (n-j) \cdot c$, where c is *the delay cost per timeslot*, which is defined by all customers. Now the problem of minimizing the cost means minimizing the above total cost for the load demand $l_i(j)$.

Let $y_{i,j}(n)$ denote the *reward function* for the load demand $l_i(j)$ if it is scheduled n^{th} to timeslot. It be can defined as,

$$y_{i,j}(n) = -\left[-x_{i,j}(n) + (n-j) \cdot c\right], \tag{5.1}$$

where $n = j, j+1, j+2, \ldots$. Therefore, this reward is the negation of the *total cost* of load demand $l_i(j)$ if it is scheduled at n^{th} timeslot.

To summarize, in order to solve the above single load demand cost minimizing problem, finding the optimal timeslot for the single load demand to minimize the total cost is the key procedure. Fortunately, optimal stopping rule [58], [65] provides a mathematical model that can find the optimal timeslot. The following content introduces how to model this problem in the optimal stopping rule model and how to solve it.

Let $X_{i,j}(n)$ denote the random variable of *final bill payment's negation* if the load demand $l_i(j)$ is scheduled at n^{th} timeslot. It can be defined as

$$X_{i,j}(n) = -l_i(j) \cdot P(n) . \tag{5.2}$$

$X_{i,j}(n)$ is a function of the random variable $P(n)$, and for each n, $l_i(j)$ is a known constant value. Let $x_{i,j}(n)$ denote the observation of $X_{i,j}(n)$. Let $Y_{i,j}(n)$ denote the random variable of the rewards.

Consequently, the equation (1) can be expressed as,

$$Y_{i,j}(n) = -[X_{i,j}(n) + (n-j) \cdot c] . \tag{5.3}$$

Then we can get $y_{i,j}(n) = Y_{i,j}(n)|_{X_{i,j}(n)=x_{i,j}(n)}$.

The optimal stopping rule model of the cost minimization problem for the single load demand $l_i(j)$ can be defined as follows. Let $y_{i,j}(j)$, $y_{i,j}(j+1)$, …, $y_{i,j}(\infty)$ denote a sequence of real valued reward functions. Given a sequence of random variables $X_{i,j}(n)$, $X_{i,j}(j+1)$, $X_{i,j}(j+2)$, …, assume that their joint distribution is known. Therefore, the optimal stopping rule problem is finding the optimal timeslot for the load demand to stop in order to get the maximum rewards. Here the load demand $l_i(j)$ continue observing the bill payment and delaying its consumption, and here stopping means that the load demand $l_i(j)$ stops delaying and starts to consume. For example, this model can be described as an asset-selling problem. If there is a house decided to be sold in the market at timeslot j, then the owner can observe all the price offers since timeslot j. Then the owner has two options to choose at each timeslot. Option I is that the owner can accept the price observation at timeslot j and sell the house. Similar for the load demand, the customer can observe the bill payment $X_{i,j}(j) = x_{i,j}(j)$ that is needed to pay if

the load demand is scheduled at timeslot j. Option II is that the owner can delay the selling at timeslot j and observe the future sequence of house prices but with advertising cost of each timeslot. Similar to the delay cost of the load demand, the customer can observe future bill payments $X_{i,j}(j+1)=x_{i,j}(j+1)$, $X_{i,j}(j+2)=x_{i,j}(j+2)$, … for as long as the customer wish to continuing delay. In general, for each $n=j,j+1,j+2,...$, after observing $X_{i,j}(j)=x_{i,j}(j)$, $X_{i,j}(j+1)=x_{i,j}(j+1)$, …, $X_{i,j}(n)=x_{i,j}(n)$, the customer may stop and receive the rewards.

Let $\phi_n[x_{i,j}(j),x_{i,j}(j+1),...,x_{i,j}(n)]$ denote the *probability of stopping* at each of the following observations are observed from timeslot j to timeslot n, which depends on observations of $X_{i,j}(j)=x_{i,j}(j)$, $X_{i,j}(j+1)=x_{i,j}(j+1)$, …, $X_{i,j}(n)=x_{i,j}(n)$. Then a ***stopping rule*** is defined as a probabilities vector as follows [58],

$$\begin{aligned}\Phi(i,j,n)=\{&\phi_j[x_{i,j}(j)],\phi_{j+1}[x_{i,j}(j),x_{i,j}(j+1)],\\ &...,\phi_n[x_{i,j}(j),x_{i,j}(j+1),...,x_{i,j}(n)]\}\end{aligned}, \tag{5.4}$$

where $n \geq j$.

Let $n_i(j)$ denote *the* $n_i(j)^{th}$ *timeslot that yield the maximum rewards,* and at which timeslot that stopping occurs, and $j \leq n_i(j) \leq \infty$, where $n_i(j)=\infty$ if stopping never occurs, which means that the load demand is never scheduled for consumption. Moreover, it is determined by both the observations $X_{i,j}(j)=x_{i,j}(j)$, $X_{i,j}(j+1)=x_{i,j}(j+1)$, …, $X_{i,j}(n)=x_{i,j}(n)$ and the stopping rule $\Phi(i,j,n)$.

Let $\Psi_n[X_{i,j}(j),...,X_{i,j}(n)]$ denote the random variable of the stopping occurs given a sequence of random variables $X_{i,j}(j),...,X_{i,j}(n)$. Therefore, given observations $x_{i,j}(j)$, …, and $x_{i,j}(n)$, let ψ_n denote the probability of $n_i(j)=n$, and it is defined as

$$
\begin{aligned}
&\psi_n[x_{i,j}(j), x_{i,j}(j+1), \ldots, x_{i,j}(n)] \\
&= P[n_i(j) = n \mid X_{i,j}(j) = x_{i,j}(j), \\
&\qquad X_{i,j}(j+1) = x_{i,j}(j+1), \ldots, \\
&\qquad\qquad X_{i,j}(n) = x_{i,j}(n)]
\end{aligned} \tag{5.5}
$$

for $n = j, j+1, \ldots$, and here P_r stands for probability function.

Based on the Chapter 1 of [58], ψ_n can be calculates using ϕ_n as follows,

$$
\begin{aligned}
&\psi_n[x_{i,j}(j), x_{i,j}(j+1), \ldots, x_{i,j}(n)] \\
&= [\prod_{k=j}^{n-1}(1 - \phi_k[x_{i,j}(j), x_{i,j}(j+1), \ldots, x_{i,j}(k)] \\
&\quad \cdot \phi_n[x_{i,j}(j), x_{i,j}(j+1), \ldots, x_{i,j}(n)]
\end{aligned} \quad . \tag{5.6}
$$

Then optimal stopping rule is the rule that achieves that maximum reward value. Let $\Phi^*(i,j,n)$ denote the optimal stopping rule, and let $V[\Phi^*(i,j,n)]$ denote the *Optimal stopping rule reward value* by choosing the optimal stopping rule $\Phi^*(i,j,n)$, and the reward can be calculated as [58],

$$
\begin{aligned}
V[\Phi^*(i,j,n)] &= E[Y_{i,j}(n_i(j))] \\
&= E\sum_{n=j}^{\infty} \Psi_n[X_{i,j}(j), \ldots, X_{i,j}(n)] \cdot Y_n(X_n)
\end{aligned} , \tag{5.7}
$$

for $n = j, j+1, \ldots$, here E stands for the mean expectation of the random variable.

5.3.2 Single Load Request Of A User Cost Minimization Problem Using Optimal Stopping Rule

Therefore, based on (5.3) the maximum reward of the single load request cost minimization problem can be defined as

$$
\begin{aligned}
&\max_{n=j,j+1,\ldots} E[Y_{i,j}(n)] \\
&= \max_{n=j,j+1,\ldots} E\{-[X_{i,j}(n) + (n-j)\cdot c]\}
\end{aligned} . \tag{5.8}
$$

Noted that when $n = n_i(j)$, the maximum reward is achieved. Based on (5.1), it equals as follows,

$$\begin{aligned} &\max_{n=j,j+1,\ldots} E[Y_{i,j}(n)] \\ &= \min_{n=j,j+1,\ldots} E[P(n)\cdot l_i(j) + (n-j)\cdot c] \end{aligned} \tag{5.9}$$

We can derive the following theorem based on the Theorem in Chapter 4 of book [58].

Theorem 1: if $\{P(n)\}$ is an i.i.d. process, then the optimal stopping rule which solves the single timeslot cost minimization problem in (5.8), exists, and is calculated as

$$n_i(j) = \min\{n \geq j : p(n) \leq z^*\} \tag{5.10}$$

where z^* is the unique solution of

$$E[z - p(j)]^+ = \frac{c}{l_i(j)}, \tag{5.11}$$

where $E[]^+$ stands for the value is larger than zero.

The proof of Theorem 1 is given by the theory of optimal stopping rule in the Chapter 4 of book [58], by transforming (5.2) into their Theorem of Optimal Solution to Housing Selling problem (without recall).

Note that by using this optimal method, the problem of (5.9) is transformed into a price threshold problem. By stopping here it means when the real-time pricing is lower than a threshold price value, the load demand will be consumed at the timeslot.

Even though the power price is not a pre-known but mathematically, the statistic distribution of the power price should be pre-known, in order to solve the threshold in (5.11).

If $P(n)$ is uniformly distributed on $[p_a, p_b]$, then the solution of z^* can be calculated by plug into the solution in [17] as

$$z^* = \sqrt{\frac{2(p_b - p_a)c}{l_i(j)}} + p_a \,. \tag{5.12}$$

Remark I: If the real-time power price of each timeslot is following other distributions, such as Gaussian distribution, it can also using (5.11) to calculate the threshold to make the stopping decision.

5.4 Customer Cost Minimization Problem Using Optimal Stopping Rule Within Comfortable Level

Since the optimal stopping rule model gives a solution to find the optimal timeslot for scheduling each single load demand to minimize its total cost, it can also be designed to solve the problem of multiple load demands throughout a day or several days. To achieve this, we can put multiple load demands into the delaying status, and check the price threshold for each load demand at each timeslot. Assume that there is no instantaneous load cap for each customer. If the RTP price is lower than the price thresholds of several load demands, then these load demands can stop delaying and start to consume.

However, the problem is that theoretically it is possible that some of the load demands will be kept delaying for a long time so that the customer will not be satisfied with optimal stopping rule scheduling results. But in practice the customer cannot let the load demands delay unlimitedly to later timeslots. Therefore, in order for customer i to have a comfortable level of power consumption, it needs to satisfy an accepted energy consumption level for the customer to be tolerant about the energy consumption delay.

Let ΔO_i denote the predefined acceptable comfort level of energy consumption of customer i for a day. This is the minimum total load demand that customer i can be tolerant with the delay of load consumption. Assume that each customer is honest about its load demands.

Let K be number of timeslots for a day. Then the current timeslot j can be expressed as

$$j = Kv + u\,, \tag{5.13a}$$

where

$$\begin{aligned} u &= 0,1,...,K-1 \\ v &= 0,1,... \end{aligned} \tag{5.13b}$$

Let $o_i(j)$ denote the actually consumed power load for customer i during the timeslot j.

Cost Minimization Problem within Comfortable Level

Then the problem can be formulated as,

Objective:

$$\min_{n=j,j+1,...} E[\sum_{j=Kv+u}^{[K(v+1)+u]-1} Y_{i,j}(n)\cdot\lambda_i(j)] \tag{5.14a}$$

subject to:

$$Y_{i,j}(n) = -[X_{i,j}(n) + (n-j)c] \tag{5.14b}$$

$$X_{i,j}(n) = l_i(j)P(n) \tag{5.14c}$$

$$\lambda_i(j) = \begin{cases} 0\ , & if\ \ l_i(j) = 0; \\ 1\ , & if\ \ l_i(j) \neq 0. \end{cases} \tag{5.14d}$$

$$\Delta O_i \leq \sum_{j=Kv+u}^{[K(v+1)+u]-1} o_i(j)\,. \tag{5.14e}$$

Assume that each two load demands during the day are independent to each other. That is, for $\forall j_1, j_2 \in \{j, j+1, ..., j+K-1\}$, $l_i(j_1)$ and $l_i(j_2)$ are independent to each other. Since last subsection we introduced how to solve single load cost minimization problem using optimal stopping rule model. Therefore, for all load demand that is generated by the customer during the day, they are put into the delay status and using the optimal stopping rule model to calculate its

price thresholds. If the real-time price is higher than their price thresholds, they are kept delaying for the lower price to minimize the total cost until they are at $n_i(j_1)^{th}$ and $n_i(j_2)^{th}$ timeslot.

Let $S_i(j)$ denote the set of all the load demands that are scheduled to the timeslot j. It can be expressed as,

$$S_i(j) = \{l_i(k) \mid k \in \{1,...,j-1\} \\ and\ n_i(k) = j\} \quad . \tag{5.15}$$

Let $o_i(j)$ denote *the actually consumed power load* for customer i during the timeslot j. Here we assume that there is no maximum constraint of the instantaneous load consumption at each timeslot, that is, if multiple load demands are scheduled to consume at current timeslot j, then the customer will consume all of them. Thus, $o_i(j)$ can be calculated as,

$$o_i(j) = \begin{cases} \sum_{k \in S_i(j)} l_i(k), & if\ n_i(j) \neq j; \\ \sum_{k \in S_i(j)} l_i(k) + l_i(j), & if\ n_i(j) = j \end{cases} \quad . \tag{5.16}$$

Another challenge of this problem is that if the customer keeps delaying its load consumption, it may miss the acceptable comfortable level of energy consumption constraint. Therefore, the need for customer to be aware of the how far it is away from missing the acceptable comfortable level of energy consumption.

Let $c_{i,j}$ denote the *comfortable cost per timeslot* before the ΔO_i is consumed for every individual load demand $l_i(j)$ after it is generated and it can be defined as

$$c_{i,j} = \frac{\Delta O_i - \sum_{k=Kv+u}^{j} o_i(k)}{K - [j - (Kv+u)]} \, . \tag{5.17}$$

In order to improve the chance of guaranteeing the comfort level of consumption of the load demands while the optimal stopping rule scheduling keeps delaying the load demands to minimize the total cost. The solution is to integrate this $l_i(j)$ unit comfortable cost into the optimal stopping rules model, it means if the customer chooses to delay load demand $l_i(j)$ for one timeslot, it not only pays the fixed delay cost each timeslot, but also pays a corresponding comfortable cost for the load demand per timeslot. It means that if the customer keeps delay that load demand, then there are two costs that each load would pay for.

By using the model from last subsection. Let $X_{i,j}(n) = l_i(j)P(n)$, and let $c_{i,j}^{total}$ denote the total cost per timeslot that the customer pays for the load demand $l_i(j)$ each timeslot. Then it can be defined as,

$$c_{i,j}^{total} = c + c_{i,j}. \tag{5.18}$$

Then we can derive to Theorem 2.

Theorem 2: if $\{P(n)\}$ is an i.i.d. process, then the optimal stopping rule which solves the single time-slot bill payment minimization problem in (5.9), exists, and is calculated as

$$n_i(j) = \min\{n \geq j : p(j) \leq z^*\}. \tag{5.19}$$

where z^* is the unique solution of

$$E[z - p(j)]^+ = \frac{c + c_{i,j}}{l_i(j)}. \tag{5.20}$$

If $P(n)$ is uniformly distributed on $[p_a, p_b]$, then the solution of z^* can be calculated as

$$z^* = \sqrt{\frac{2(p_b - p_a)(c + c_{i,j})}{l_i(j)}} + p_a. \tag{5.21}$$

Remark II: each customer can apply this modified optimal stopping rule model with comfortable delay cost con using solution (5.21) as the threshold for each load demand. If the RTP power price is lower than the threshold in (5.21), the customer decision to run the load consumption for demand $l_i(j)$. This method is expected to minimize the cost for customer with an acceptable level comfort constraint.

Energy Consumption Scheduling Algorithm Using Optimal Stopping Rule: Executed by Each Customer i

// busy-waiting for the real-time price $p(j)$

1: wait for $p(j)$ from the power provider until receiving it;

2: **if** $\Delta O_i - \sum_{k=Kv+u}^{j} o_i(k) \geq 0$

3: update the threshold using (5.21)

4: make the decision of (5.16) based on (5.21)

5: **if** $\Delta O_i - \sum_{k=Kv+u}^{j} o_i(k) < 0$

6: update the threshold using (5.12)

7: make the decision of (5.16) based on (5.12)

5.5 Simulation

5.5.1 Simulation Design

Assume that at every timeslot each customer generates a load request, but the request could be zero. Assume every timeslot there is a load request, but the request could be zero. Also assume that the amount of each customer's load demand follows the same normal distribution.

Table 5.1 Stream Table

Stream	**Purpose**
1	load requests time is constant and requests at each timeslot
2	load request of a customer follow the above normal distribution
3	Power price follows the uniform distribution over timeslots

Note that all the time in the simulation is integer, marked as timeslots such as 1,2,3, …. Here time of 1 means that it's the 1st timeslot. Initially, every customer schedules its first load request at the beginning of the 1st timeslot and sends the request to the power provider. Assume the communication overhead and delay between all the customers and the power provider are

ignored. Then the power provider updates the real-time power price for the current timeslot after receiving the load requests. Finally, each customer makes its own energy consumption decision on how much load to consume and how much load to delay at current j^{th} timeslot.

Table 5.2 Simulation Parameters

Experiment Parameters	**Values**
Load Peak	1000kWh
N	100
K	1000
p_a	0
p_b	0.1
ΔO_i	50% of Load Peak
μ	1000kWh
c	0.2

Assume all the customers have the same level of comfortable requirements, which means that ΔO_i is all equal where $i = 1,2,...,N$. Let every customer generate a load request $l_i(j)$ following the normal distribution $N(\mu / N, (\mu / 3N)^2)$ at each timeslot, where μ is equal to Load Peak as seen in Table 5.1. Load Peak is the predefined grid's load handling status, which is constant set by the power provider. Because the timeslot here is considered to be a very small unit time, it is safe assumed that the Load Peak is 1000kWh by the power provider. Also assume

that the total simulation running time of a day is K=1000 timeslots. Assume that there are 100 customers within the power provider's distribution network. Price random variable $P(j)$ follows the uniform distribution $P(j) \sim U(p_a, p_b)$. The full set of simulation parameters are shown in Table 5.1.

With the above simulation design and set of parameters, in order to compare the performance of two algorithms, we introduce a normalized metric. Let $c_i^{total}(j)$ denote the normalized total cost for customer i at timeslot j. It is calculated as

$$c_i^{total}(j) = \frac{\sum_{k=1, m \in S_i(k)}^{k=j} [o_i(k)p(k) + c(k-m)]}{j}, \tag{5.22}$$

where $S_i(k)$ is defined in (5.15).

5.5.2 Total Cost Comparison with Greedy Algorithm

For the greedy algorithm, intuitively, it consumes the load requests whenever the real-time power price is lower than the average RTP power price.

From Fig. 5.1, it is seen that the total cost using the Optimal Stop Rules is much lower than of the Greedy algorithm after the 100th timeslot.

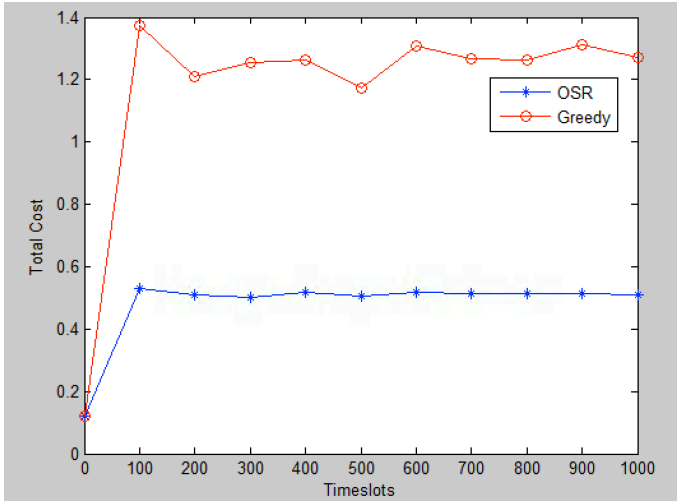

Fig. 5.1 Total Cost Of Optimal Stop Rules Algorithm And Greedy Energy Scheduling Algorithm Throughout

5.5.3 Performance Comparison Based on Different Waiting Costs

The simulation's setup is seen in Table 5.3. The real-time power price still follows the uniform distribution $P(j) \sim U(p_a, p_b)$. The comfortable level is 70% of the Load Peak level. Load request's normal distribution μ=70%*Load Peak. Therefore, the goal of this simulation setup is analyze the performance of total cost (5.22) by varying the parameter of waiting cost per timeslot c.

From Fig. 5.2, it can be seen that the total cost of energy scheduling doesn't vary much with the increasing of waiting cost changing when using the optimal stopping rules algorithm. Especially when the waiting cost $c \geq 0.7$, the total cost of the optimal stopping rules algorithm is almost convergent to 0.5. However, the total cost of energy scheduling increases linearly with the growing of the waiting cost when using greedy algorithm.

Table 5.3 Simulation Parameters

Experiment Parameters	**Values**
Load Peak	1000kWh
N	100
K	1000
p_a	0
p_b	0.1
ΔO_i	70% of Load Peak*j/ N
μ	1000kWh

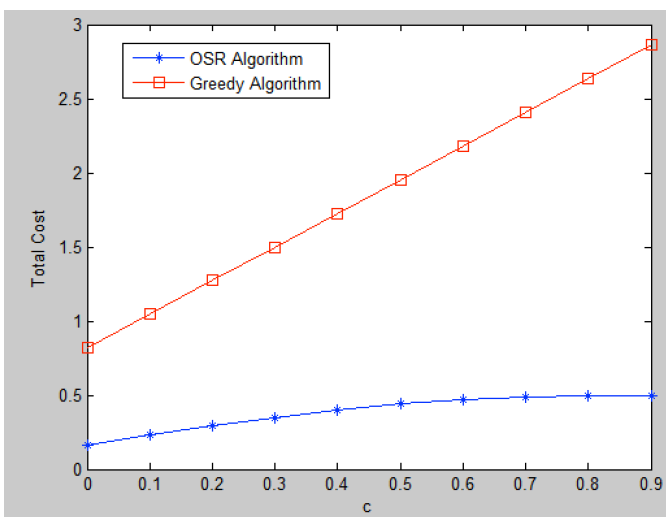

Fig. 5.2 Total Cost Of Optimal Stopping Rule Algorithm And Greedy Energy Consumption Scheduling Algorithm With Different Waiting Cost

5.5.4 Performance Comparison Based on Different Load Requests

The simulation's setup is seen in Table 5.4. The real-time power price still follows the uniform distribution $P(j) \sim U(p_a, p_b)$. The comfortable level is 70% of the Load Peak level. Let the waiting cost per timeslot c=0.2. Therefore, the goal of this simulation setup is analyze the performance of total cost (5.22) by varying the parameter of Load request's normal distribution μ.

Table 5.4 Simulation Parameters

Experiment Parameters	**Values**
Load Peak	1000kWh
N	100
K	1000
p_a	0
p_b	0.1
ΔO_i	70% of Load Peak*j/ N
c	0.2

As seen in Fig. 5.3, the total cost of energy scheduling increases linearly with the growing of the load request's parameter μ when using greedy algorithm. But the total cost of using optimal stopping rule is growing non-linearly. After the $\mu \geq 0.9$ *Peak Load, the total cost of using the optimal stop rules algorithm is even slightly smaller than the $\mu = 0.8$ *Peak Load.

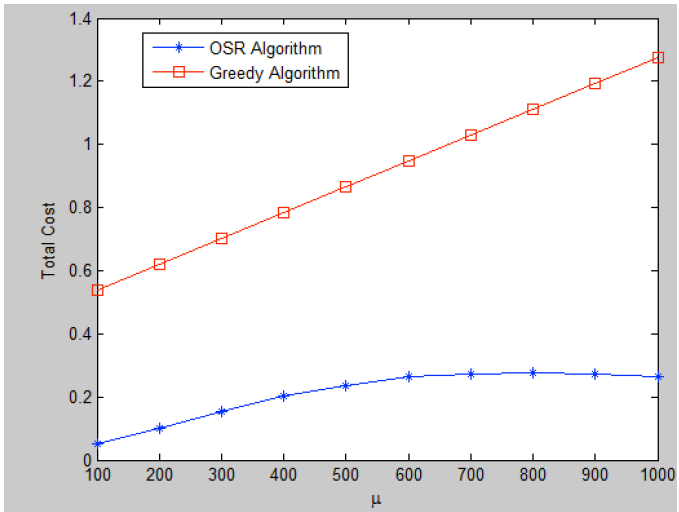

Fig. 5.3 Total Cost Of Optimal Stopping Rule Algorithm And Greedy Energy Consumption Scheduling Algorithm With Different Load Request's Parameter μ

5.5.5 Performance Comparison Based on Different Comfortable Levels

Table 5.5 Simulation Parameters

Experiment Parameters	**Values**
Load Peak	1000kWh
N	100
K	1000
p_a	0
p_b	0.1
c	0.2
μ	1000kWh

The simulation's setup is seen in Table 5.5. The real-time power price still follows the uniform distribution $P(j) \sim U(p_a, p_b)$. Let the waiting cost per timeslot c=0.2. Let the parameter of Load request's normal distribution μ =Peak Load. Therefore, the goal of this simulation setup is analyze the performance of total cost (5.22) by varying the comfortable level.

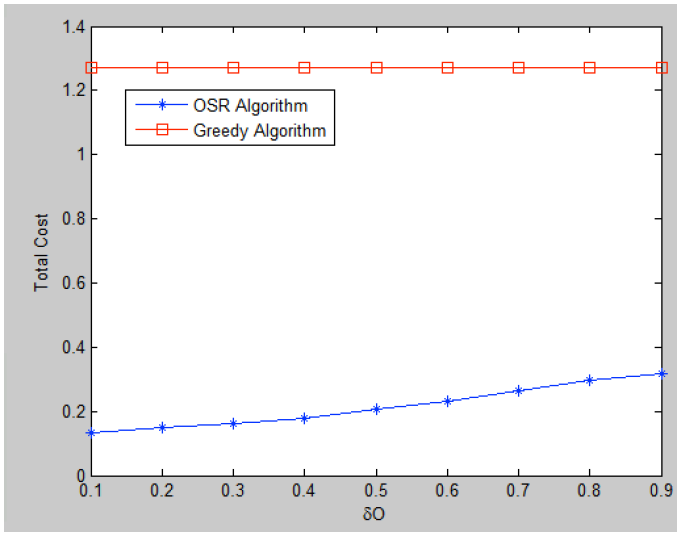

Fig. 5.4 Total Cost Of The Optimal Stopping Rule Algorithm And Greedy Energy Consumption Scheduling Algorithm With Different Comfortable Level

As seen in Fig. 5.4, the total cost of greedy energy scheduling algorithm does not vary with the growing of the comfortable level ΔO_i. But the total cost of using optimal stopping rule has a non-linear growth from 10% of Load Peak*j/N to 90% of Load Peak*j/N. Therefore, in terms of the total cost, the optimal stopping rules energy scheduling has much better performance comparing to the greedy algorithm.

However, it is vital to point out that the optimal stopping rule algorithm has a limitation, which is it not always satisfy the comfortable level constraint when ΔO_i is too large. As

$\Delta O_i = 70\% *$ Load Peak*j/N, the actual total consumed energy for a customer at the end of the day $\sum_{j=1}^{K} l_i(j)$ is 71%* Load Peak*j/N, which meet the comfortable level constraint. But when $\Delta O_i = 80\% *$ Load Peak*j/N and $\Delta O_i = 90\% *$ Load Peak*j/N, the actual total consumed energy loads for a customer for a day are 76.1%* Load Peak*j/N and 78.8%* Load Peak*j/N. Whereas, the greedy algorithm still meets the comfortable level, when $\Delta O_i = 80\% *$ Load Peak*j/N and $\Delta O_i = 90\% *$ Load Peak*j/N.

5.6 Conclusion

This paper studies the cost minimization problem for all customers within a neighborhood area network. First, it models the single load request cost minimization problem with the Optimal Stopping Rule method. Thus, a mathematical solution of the optimal result is given by optimal stopping rule deduction. Second, we define the cost minimization problem with a comfortable level constraint. An optimal stopping rule based energy consumption scheduling algorithm is proposed. Finally, the simulation results show that the proposed algorithm has much better performance in terms of the total cost comparing with a greedy based energy scheduling algorithm.

Because of the length restriction of this paper, some future work could not be included. For example, two other possible comparison could be as following. Strategy I: use greedy strategy to satisfy the ΔO_i since the beginning of the time until and then using regular optimal stopping rule in (5.12) to schedule the load demand. Strategy II: use greedy strategy to satisfy the ΔO_i soon after the day starts until the ΔO_i constraint is satisfied, the rest of the time use regular optimal stopping rule in (5.12) to schedule the load demand.

6 CONCLUSION & FUTURE WORK

How to consume energy in a more efficient manner has never been studied more vigorously by the researchers. In smart grid, successful demand response has a large impact on the success of smart grid. As a result, the importance of customer participation has been raised to a whole new level. No one would question the fact that customers would always respond to a smaller energy bill. Therefore, if a program can minimize the energy cost for customers, then it will ultimately benefit the whole smart grid and every user that is connected to it.

This dissertation studies three problems: real-time demand response in smart grid distribution using energy consumption scheduling, fair delay in energy consumption scheduling demand response problem in relation to cost minimization, and customer cost minimization problem using energy consumption scheduling with Optimal Stopping Rules in RTP demand response program. All of these problems are yet to be studied in the academia. Chapter 3 proposes a real-time demand response system with its energy consumption scheduling algorithm that intends to solve RTP's total cost minimization problem. This problem has yet to be discussed especially in a neighborhood area network level. The simulation results confirm that the solution offered achieved total cost minimization while considering the customers as an entity in the neighborhood area network. In Chapter 4, fairness is discussed and explored in terms of fair delay, instead of the existing fair bill approach. The algorithm proposed focuses on how to make the waiting time fair so that all customers can have their energy load requests met in a relatively reasonable time frame while minimizing the cost for their energy consumption. Chapter 5 aims at solving the cost minimization problem through the optimal stopping rule

approach. The discussion takes into consideration of the character of neighborhood area network, which is one energy provider to multiple customers. Simulation results demonstrate the advantages of the proposed energy consumption scheduling algorithm with optimal stopping rule.

The algorithm solutions proposed can effectively solve the discussed problems as shown through the success of computer simulations in Chapters 3, 4 and 5. The proposed solutions, when applied to the industry, will bring in more customers to participate in demand response programs and smart grid. The flourish of smart grid participation will for sure push smart grid forward and bring forth more technological advancements to make the grid more effective.

It is also important to be aware of the fact that the proposed solutions were successful when tested by simulations because they were constrained by a number of assumptions. However, in the everyday production at the power plant, constrains must be overcome for it to become compatible with the current systems. For example, both Chapters 3 and 4 model the energy consumption scheduling problem with a mathematical approach, and then adopt simulation as a method to reach the optimal result. In practice application, different sets of parameters should be implemented to reach the best results. Similarly, in Chapter 5, optimal stopping rule brings its own limitation to the dissertation for it assumes that RTP price is following some statistical distribution, otherwise the mathematical solution would not be solvable in deduction. Regardless of the mentioned limitations, the solutions provided in this dissertation still have their own advantages and benefits.

In addition, while we value the customers, the benefits of power provider's should not be neglected as well for it is also an important participant of smart grid and demand response. Future work could look at the possible programs that aim at maximizing the power provider's profit or minimizing the operational cost while using the same energy consumption scheduling

model and simulation study. Both of the above-mentioned problems may take fair delay into consideration, as well. Moreover, it is plausible to use the optimal stopping rule model as another approach to offer a mathematical solution.

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