Algorithm for Load Curtailment in Aggregated Demand Response Program

Author:

Muhammad Babar

Supervisors:

Dr. Aqueel Shah

Dr. Imthias Ahamed

Prof. Dr. Nazar H.Malik

A thesis submitted in fulfilment of the requirements for the degree of Master in Science (Manufacturing System Design and Management Engineering)

at the

Institute of Manufacturing Engineering and Management

Pakistan Navy Engineering College

National University of Science & Technology

PNS Jauhar–Karachi, Pakistan

February 2013

Declaration of Authorship

I, Muhammad Babar, declare that this thesis titled, 'Algorithm for Load Curtailment in Aggregated Demand Response Program' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date:

List of Publications

Muhammad Babar, Imthias Ahamed, Aqueel Shah and Nazar H. Malik, "*A Dynamic Algorithm for computing Consolidated Demand Reduction Bid under the Constrained Direct Load Control Program*" **IEEE Transaction on SMART GRID**. [Submitted]

Muhammad Babar, Imthias Ahamed, Aqueel Shah and Nazar H. Malik,"*A Novel Algorithm for Aggregated Demand Response Strategy for Smart Distribution Network*",**PES General Meeting 2013**, Vancouver, CA. [Submitted]

Muhammad Babar, Imthias Ahmed, Aqueel Shah, and Nazar H. Malik, "*An Algorithm for Load Curtailment in Aggregated Demand Response Program*",**Second IEEE-PES Conference in Middle East on Innovative Smart Grid Technologies**, 08 - 11 December, Jeddah, 2012 Saudi Arabia.

"The optimization in demand response program should be constrained by a level of customer satisfaction. Otherwise, it might make many customers unhappy and unwilling to continue participating in the program. The concept of aggregated demand response is very interesting and this research caters this problem by considering customer constraints in it's own unique prospective."

Comment by Saudi Arabia Smart Grid Committee on paper 'Algorithm for Load Curtailment in Aggregated Demand Response Program' published in Conference at Jeddah.

Abstract

Advancement in demand side management strategies enables smart grid to cope with the ever increasing energy demand and provide economic benefit to all of it's stakeholders. Moreover, emerging concept of smart pricing and advances in load control can provide new business opportunities for demand side management service provider or aggregator. The aggregator act as a third party between the electricity supply system and the consumers, and facilitate consumers to actively participate in Demand Side Management (DSM) by bidding price against power reduction with some constraints. This work develops a novel algorithm for aggregated demand response for the solution of peak demand problem during peak hours in smart distribution network. In this research, This problem is formulated in its unique prospective such that it catered both "peak demand issue" by load scheduling and controlling and "consumers satisfaction" by enabling them to bid in energy market against their load curtailment. Simulations are carried out over a generalize modeled problem in which consumers identify demand reduction bids and constraints. The simulation results of the proposed algorithm demonstrate the potential impact of an aggregated demand response on the power system.

Acknowledgements

Every time I contacted my advisors Dr. Imthias Ahamed and Dr. Nazar H. Malik , I have learnt some thing new. I express my sincere gratitude to all my guides for keeping their “door open” for me always through out my research.

My due respects to my teachers at this institute for the excellent (formal and informal) courses they offer. I thank the Dean of Institute of Manufacturing Engineering & Management for providing excellent facility and support. I also thank all the staff of the department for their support.

I am grateful for many useful interactions, academic and otherwise, that I have had with my colleagues during this research. In particular, I would like to thank Cdr. Armughan Ahmad, Cpt. Muhammad Imran, Mr. Imran Ijaz, Engr. Qaseem Ali, Engr. Faisal R. Pazheri and Engr. Danish Maqbool. Thank you colleagues for all your help.

I would like to thank all my co-supervisors at Saudi Aramco Chair In Electrical Power, Department of Electrical Enegineering, College of Engineering, King Saud University for their encouragement and support. In particular, I thank Prof. Dr. Abdurrehman Al-Arainy and Prof. Dr. Nazar H. Malik for all their academic and non-academic help.

Contents

List of Figures

List of Tables

Abbreviations

$[\mathcal{N}]$	Set of consumers which are in bilateral contract with aggregator for load curtailment program.
$[N]$	Total number of consumers.
$[n]$	Index for n^{th} consumer.
$[\|T_1 \quad T_2\|]$	Total control period.
$[\mathcal{H}]$	Set of control intervals.
$[\|\mathcal{H}\|]$	Total number of control intervals.
$[h_{step}]$	Duration of a control interval.
$[k]$	Index referred as k^{th} control interval.
$[\mathcal{P}]$	Set of levels of power reduction.
$[P^{max}]$	Maximum power level.
$[\Delta P]$	Step size of power reduction.
$[i]$	Index for i^{th} power level.
$[I]$	Total number of power levels.
$[f_n(P_i)]$	Demand reduction bid by the n^{th} consumer at power level P_i.
$[P_D(k)]$	Power Reduction required by utility at interval k.
$[F(P)]$	Least aggregated reduction bids of all consumers for total reduction of power P.
$[T_{n_{ON}}^{min}]$	Minimum duration for which n^{th} consumer should be continuously ON.
$[T_{n_{OFF}}^{max}]$	Maximum duration for which n^{th} consumer can be continuously OFF.

$[T_n^{max}]$	Total duration for which n^{th} consumer can participate in load reduction. (that is sum of OFF periods should be less than or equal to T_n^{max}.)
$[T_{n_{ON}}(k)]$	Duration for which n^{th} consumer was continuously ON at k^{th} interval.
$[T_{n_{OFF}}(k)]$	Duration for which n^{th} consumer was continuously OFF at k^{th} interval.
$[T(k)]$	Total remaining duration for which n^{th} consumer can participate in load reduction at k^{th} interval.
$[X(k)]$	A column vector with N elements representing the acceptance or refusal of participation of each consumer in direct load control at interval k in term of binary values $\{0,1\}$.
$[\mathcal{D}_n]$	Set of controllable loads of the n^{th} consumer.
$[D_n]$	Total number of controllable loads of the n^{th} consumer.
$[d_n]$	Index for d^{th} controllable load of the n^{th} consumer.
$[q_{d_n}]$	reduction bid of the d^{th} load by the n^{th} consumer at their corresponding power rating.
$[D(k)]$	A column vector of D_n elements representing availability or non-availability of all devices of a consumer that is participating in direct load control at interval k in term of binary values $\{0,1\}$.
$[p_{d_n}]$	Power rating of d^{th} load of n^{th} consumer.
$[T_{dn_{ON}}^{min}]$	Minimum duration for which d^{th} load of n^{th} consumer should be continuously ON.
$[T_{dn_{OFF}}^{max}]$	Maximum duration for which d^{th} load of n^{th} consumer can be continuously OFF.
$[T_{dn_{ON}}(k)]$	Duration for which d^{th} load of n^{th} consumer is continuously ON at k^{th} interval.
$[T_{dn_{OFF}}(k)]$	Duration for which d^{th} load of n^{th} consumer is continuously OFF at k^{th} interval.

$[T_{dn_{ON}}(k+1)]$	Duration for which d^{th} load of n^{th} consumer should be continuously ON at $(k+1)^{th}$ interval. (i.e. if $T_{n_{ON}}(k) \geq T_{dn_{ON}}^{min}$, n^{th} consumer can participate.)
$[T_{dn_{OFF}}(k+1)]$	Duration for which d^{th} load of n^{th} consumer can be continuously OFF at $(k+1)^{th}$ interval. (i.e. if $T_{dn_{OFF}}(k) \leq T_{dn_{OFF}}^{max}$, n^{th} consumer can participate.)

Chapter 1

Introduction

1.1 Introduction

The demand of energy is increasing for industrial development and activity in world. There are many serious challenges faced by energy sector of every country when considering energy use because of inefficient and unclean energy utilization, vulnerability to fuel prices and the sustainable growth of industries[5]. On other hand, sustainable energy technologies are fast advancing in developed countries but developing countries are still far behind due to various barriers. The biggest barrier in developing countries is limited awareness of energy and environmental management for electrical energy[6]. Even in developed nations, billion of common people are unaware to the modern form of energy services[7]. Therefore, strong communication and bonding is required between energy generating utilities, energy service providers and consumers to manage available energy efficiently and effectively[1, 5].

There are two types of Energy Management:

- Supply Side Management (SSM)
- Demand Side Management (DSM)

Supply Side Management generally refers to actions taken to ensure the generation, transmission and distribution of electrical energy are conducted efficiently [8]. In past, SSM is about generation of electricity by fossil fuels but now it is also applied to actions, planning and services concerning the supply of electrical power by other energy resources such as solar, wind, biomass renewable plants [9]. Supply side Management (SSM) makes existing generators able to provide electricity at lower cost, increase economical benefits and reduces environmental emissions [10]. SSM contributes in improving the reliability, attainability and quality of supply system. SSM embarks utility to meet a skyrocketing demand without incurring in unnecessary major capital investment in new generating capacity [11].

Energy Demand Management or Demand Side Management (DSM) is referred as an investigation, analysis and control of energy consumption in a house, industry and other process/ system. The aim of demand side management is to find areas of high usage and electricity waste and determine services and/or systems that will reduce it without fluctuating production [12]. In past literature and studies, DSM is linked only to electrical load management by utilities and governments [13] but emerging concept of demand response (DR) has highlighted the new dimension in demand side management of electrical energy[14]. It provides utility or government a new business approach because in most of the situation the implementation of DSM is more profitable than investing capital in new construction or expansion of generating plants. Utilities and Governments are taking interest in promotion of DSM and energy saving among all [15]. Some countries are also providing financial benefit or other incentives to the customers that are taking part in DR program and curtailing their loads during peak hours [16].

Demand Side Management is one of the most important management strategy that aims to balance electrical supply and demand by reducing the power demand during critical periods instead of increasing the power generation [17]. Efficient demand side management can potentially avoid the construction of an under-utilized electrical infrastructure in terms of generation capacity, transmission lines and distribution networks [18]. Controlling and influencing the energy usage can reduce the overall peak load demand, reshape the demand curve, and increase the

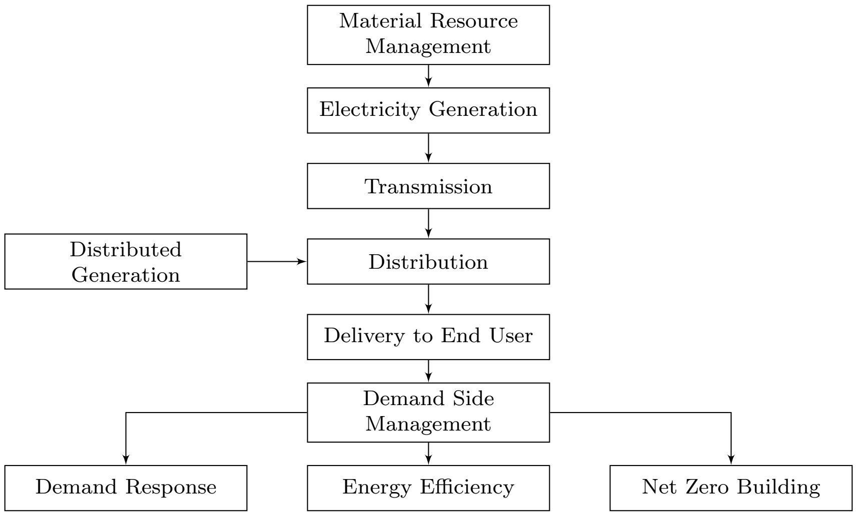

FIGURE 1.1: Vertical Integration of Supply Side Management and Demand Side Management of Electrical Energy.[1]

grid sustainability by reducing the overall cost and carbon emission levels [19]. As shown in Fig. 1.1, DSM is classified into three major categories; Net Zero buildings, Energy Efficiency and Demand Response[5].

One of the most important features of Smart Grid is demand response (DR). DR traditionally refers to the capability to switch off some electrical loads at peak times to lessen the need for peak power generation sources. It focuses on changing the energy consumption behavior of customers on real time basis thereby enabling the utility to modify peak demand. It allows dynamic interaction between energy suppliers and users to flatten the power demand curve[20].

A successful implementation of a DR program can lead to significant financial benefits. From the customer point of view, reduction of total electricity cost is the most important motive for implementing the demand response. But earlier, because of limitation of technology, small household customers have very limited influence on the energy market decisions. Since these customers have very limited or no access to the information regarding the price variation with time, therefore, they do not participate in demand response. Ever increasing advancement in information and communication technology and burgeoning challenges in supply and demand of electrical power engrossed the concept of aggregated demand response program in Smart Grid environment[21]. Since, smart grid has virtually and vertically integrated the supply side and demand side of electrical energy and power systems as shown in Fig. 1.1. Therefore, it allows industrial, domestic and commercial consumers (large and small) to actively participate in aggregated demand response program and will help in improving the efficiency, quality, reliability, economics and sustainability of complete Supply and Demand chain of Electrical Network [22].

1.2 Overview of the Thesis

In this thesis, we propose an Dynamic Programming approach to the design of Aggregated Demand Response Program. First, we argue that Aggregated Demand Response Program can be viewed as a Multistage Decision Problem, and then explain how the Dynamic Programming approach can be used to "solve" this problem. We denote the entity which perform Aggregated Demand Response Program by Aggregator. We propose two algorithm for aggregators in this thesis, and evaluate their performance through simulation. The rest of the thesis is organized as follows.

In Chapter 2, it discusses the significance of demand response in demand side management in light of several work which are presented during last decade. It also presented detail literature review on the emerging concept of aggregator in which it describes the current perception of market and researchers about the aggregator. Finally, it summarizes the concept of aggregator with a discussion over it's implementation, design and business models.

In Chapter 3, it discusses the general Multistage Decision Problem. Then, it discusses the Dynamic Programming approach to solve the Multistage Decision Problem. Two different approaches of dynamic programming is presented namely shortest path approach and allocation approach and solve a general Multistage Decision Problems.

In Chapter 4, it argues how Aggregated Demand Response Program could be viewed as a Multistage Decision Problem. It discusses the Dynamic Programming approach to solve the Aggregated Demand Response Program which requires the analytical model of the system to be scheduled and controlled. Finally, it presents the general Aggregated Demand Response framework for aggregators which is being proposed for optimal algorithm development.

In Chapter 5, it presents a simple Dynamic Programming approach which uses the quantized level of power reduction, demand reduction bid and constraints by consumer and peak demand pattern or value by utility which should be curtailed during peak hours as the input and gives the optimal load schedule and control in demand side management as the output.

In Chapter 6, it study in detail the implications of the design flexibility of the proposed approach to Aggregated Demand Response Program. it also perform simulation of load scheduling and controlling for Aggregated Demand Response Program with an energy bidding and constraints by consumers. In Chapter 7, it summarizes the major contributions of this work.

Chapter 2

Introduction to Demand Response and Aggregators

2.1 Demand Response

With ever increasing demand of energy for a growing population, expanding economies, depleting fossil fuel sources, increasing concerns about green house gases and global warming, there is a strong need to plan wisely to reduce the energy usage and hence demand response is essential[21].

While the public's smart grid attention has focused on smart meters and home energy network, the strategy of curtailing energy use during peak timings at commercial, industrial, institutional and domestic entities as well as electric vehicles on behalf of incentives is referred as Demand Response[23]. Thus, classification of demand response programs are shown in Fig. 2.1.

Moreover, implementation of demand response program can potentially avoid the construction of an under-utilized electrical infrastructure in terms of generation capacity, transmission lines and distribution networks[24].

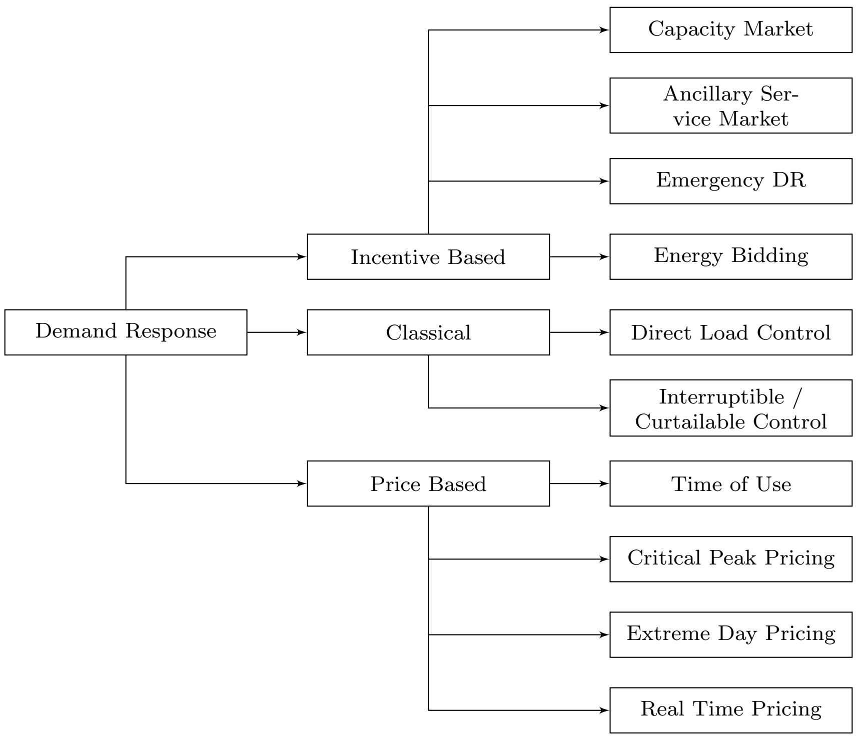

FIGURE 2.1: Classification Demand Response Program.[2]

2.2 Key Responsibilities of Demand Response Program

Demand Response Program is responsible for designing and implementing the DSM program including smart monitoring, load controlling and smart pricing in order to cope with the increasing demand and provide economical benefits to all stakeholders, including[2, 23, 25]:

- Price incentive for the customers who curtails their load during identified hours.
- Overall generation cost reduction because the demand peak will reduce the overall generation peak, which in turn, will result in the less peak generation spinning reserves.
- Reduction of price even for the customers who do not participate because the overall generation cost is reduced.

- Elimination of price spikes because of the elimination of demand spikes.

Thus, it is inferred that demand response program is responsible to provide demand side management services to utility and consumer[14]. So, the responsibilities of demand response could be broadly classified into:

- Load Control and Scheduling,
- Pricing Mechanism.

2.2.1 Load Control and Scheduling

Load management (LM) is a DSM strategy that aims to balance supply and demand by reducing the power use of electrical devices during critical periods instead of increasing the power generation. As smart meters and appliances slowly become mainstream, LM technologies gain strength as an alternative for the electricity market [26, 27].

Load management can generally be classified as [28]

- Indirect control (consumers manually make regulate its consumption in response to incentive programs),
- Automatic Control system (appliance automatically regulates its own power consumption)
- Direct load control (appliances are centrally controlled by the utility or service provider).

Direct Load Control provide utility or service provider to remotely shuts down or cycles a customer's thermally controllable appliance. Controlling and influencing energy demand can reduce the overall peak load demand, reshape the demand profile, and increase the grid sustainability by reducing the overall cost and carbon emission levels.

The first step in the DLC is to perform a study of the loads in order to determine their nature, type and consumption patterns[29]. Then the changes that the different control actions cause in these typical profiles must be analyzed[30]. In this way, the reduction in demand that can be achieved through the application of each control strategy can be determined. This analysis is performed by the utility or aggregator every time if there is alteration in load reduction bid, number of participating consumers, utility requirement, energy price in the electricity market and cost of energy production etc.

Direct Load Control refers to load management strategy which has been used by the utility or system operator since 1980s [31]. Therefore, the objective of optimal DLC scheduling model typically include broad range of goals and could be classified in to:

- Optimal DLC scheduling model before Smart Grid.
- Optimal DLC scheduling model after Smart Grid.

2.2.1.1 Optimal DLC scheduling model before Smart Grid

In 1980, Detroit Edison has accumulated 10 years' operating experience with a large-scale radio controlled electric water heater Load Management system[31]. In this system, direct load controlling of loads were performed by analyzing the load payback patterns with the past and predicted load curve. However, the primitive objective of implementation of DLC technique was minimization of peak load during peak hours. Later on, Carolina Power and Light Company in 1983 [29], Florida Power & Light [32] and Taiwan Power [33] in late 80s accumulated the experiences regarding DLC system of thermally controllable loads i.e. ACs, Electric Water Heater and Chillers [29–31, 34, 35] which were specific to only peak minimization.

With the advancement in computing and control techniques, optimal DLC scheduling models transformed from peak-minimization based analysis to cost-minimization based analysis i.e to minimize operation cost of the power generation[36–40] and maximize utility profit[41]. So , in 1984, Lee and Breiphol used quasistatic system technique to evaluate the viability of this philosophy for a sample system consisting of thermal generation and direct load control[37]. However, in 1986, Bhatnagar and Rehman presented the improved DLC model for fuel cost minimization using quadratic cost curve technique[39]. Later on researchers proposed many DLC scheduling models using Dynamic Programming[33, 36, 39, 40] and Linear Programming[29, 37, 42]. In 1995, Wei and Chen scheduled the control of air conditioners by using Multi-pass Dynamic Programming[34] methods such that the peak load reduction and production cost saving have optimum results. On other hand, in 1995, Laurent and Desaulniers proposed control of electric water heater using Linear Programing for optimal DLC. However, in 1996, Kurucz and Brandt presented the general detailed optimal DLC scheduling model which also considers few system constraints and payback issue for peak and operation cost minimization using Linear programming.

2.2.1.2 Optimal DLC scheduling model after Smart Grid

As discussed earlier, after the advent of smart grid, smart pricing and smart metering become easier for utilities and service providers. In order to achieve the win-win situation that is to provide full benefit to all utility, service provider and consumer, the new DLC Scheduling models introduce the price-based as well as incentive-based direct load controlling. In order to implement this DLC mechanism, many previous techniques like dynamic programming [43] and linear programming [41, 44, 45] are modified. So, the utilities or service providers are capable of offering different incentives[41, 46–49] to respective customers for direct control over selected loads. Enormous literature implement these objectives by using various techniques including heuristic-based Evolutionary Algorithm[19], queuing system model and the Markov birth and death process[50], Particle Swam Optimization[51, 52], Genetic Algorithm[53], Monte Carlo approach[54, 55], Multi

Agent System based algorithm[56], Markov chain models approach[57] and distributed sub-gradient algorithm[58]. Moreever, in the existing literature on aggregated direct load control, Berard and Veillerobe [59] presented discrete time optimal control technique for the payback effect in load pattern during load scheduling.

Currently, DLC is facing the challenge of customer's acceptance and people frowned at the idea of relinquishing control over their own loads. In order to create a balance between the needs and wants of the utility and the customers, load control strategy cannot be implemented without considering the customer's satisfaction [28]. Thus, Bhattacharyya and Crow in [60], Chu and Jong in [61] and Gomes, Antunes and Martins [62, 63] proposed Fuzzy Logic Dynamic Programming, Least Enthalpy Estimator technique and Multi-objective Evolutionary Algorithm respectively for DLC model in which provisions are made for customer preferences in terms of temperature control of thermal appliances.

But, it is still a crucial challenge for any demand side management strategy to guarantee the security of customer's privacy and to provide the customer's satisfaction [64]. So, in order to resolve is issue, DSM should enable consumer to participate in market pricing process.

In 1999, Goran and Kirschen [65] suggested that the concept of consumer participation in market pricing process and stated that it could benefit in minimizing peak demand, maximizing profit of stakeholders and maximizing the social welfare. Laterly, Goel, Aparna and Wang [66] presented the framework for aggregated demand response in which consumers can actively participate in a power reduction program via the market bidding or demand reduction bidding. Thus, currently the researchers are workings on the new framework of DLC Scheduling models which have wide range of objectives including:

- Peak load minimization.
- Operating cost minimization.
- maximization of utility as well as service provider's profit.

- Provide incentive to participating customer.
- maximization of consumer satisfaction.

2.2.2 Pricing Mechanism

Smart Pricing can be used to achieve all social objectives including power reduction, customer satisfaction and securing reserves. Several pricing mechanisms have already been proposed in the literature[2, 14, 67, 68]. However, pricing mechanism in demand response programs can be broadly classified into following two categories as shown in Fig. 2.1.

- Price Based
- Incentive Based

2.2.2.1 Price Based

This type of Pricing Program includes time of use, real time pricing and critical peak time pricing. Since many years time of use pricing based on peak load pricing is implemented in which prices are announced ahead of time at the beginning of the particular operational period [69–71].In order to reflect customer response to TOU, price elasticity of demand can be used [72, 73].

Real time pricing theory was derived from spot price concept given by Schweppe [74]. Many researchers suggests realtime pricing program for optimal implementation load management by aggregators in which reaction of the consumer is kept in special notice for consumer satisfaction and influences on the price of upcoming operational period[75, 76]. However, Critical time pricing is a dynamic prising mechanism, usually hybrid of real time pricing and time of use. Many researchers suggested dynamic pricing model based on CPP considers interest of both consumer as well as aggregator [77–81].

Currently, EnerCON and Comverge are one of the biggest aggregator companies are dynamic price based programs including Time-of-Use(TOU), Critical Peak Pricing(CPP), Real-time Pricing(RTP), and Peak Time Rebate(PTR) [82, 83].

2.2.2.2 Incentive Based

In 1999, Goran and Kirschen [65] proposed the concept of demand side bidding or energy bidding in load management and demand peak minimization. This research also stated the consumer will sign a interruptible contract or other conventional form of load management agreement with service provider which specify the number of load reduction and their respective energy bidding that may be requested. This new smart pricing strategy will enable consumer to actively participate in market pricing process and help in minimizing demand and maximizing social welfare[2, 23]. Lately, Goel, Aparna and Wang [66] presented the framework in which demand side load bidding by the consumer will help contingency management in reliability assessment of restructured power systems and participate in contract market bidding with hybrid market models.

Moreover, one form of energy bidding is demand reduction bidding. In this case, the bidding signals are generated by the customers who are willing to curtail their loads at a certain price [84]. The signal shows the available demand reduction capacity and the price asked for this reduction. So, service provider act as large buyer of energy from utility at a fixed price or bid according to demand side curve. But on other hand, it act as a electricity retailer to small consumers to enroll them in Demand bidding program [85].

Recently, Katherine [86] stated that introduction of secure data networking and communication pushed many utilities and service providing companies to think for providing online demand bidding platform to consumers.

2.3 The Concept of Aggregator

The aggregator is a retailer of electricity that buys electrical energy from utility to supply uninterrupted and high quality power to commercial, industrial, institutional and domestic entities as well as electric vehicles during peak hours and offers ancillary services[87]. Aggregator[1] is also refer as an energy Service Provider, demand response service provider, energy management system, automated demand side management, automated demand response and virtual power plant in many works[64, 76, 88–91]. Till today, the aggregator does not have any empirical definition. So, Following are the three different definitions of Aggregator classified on the basis of it's responsibilities and controls over the consumer which are presented in literature.

2.3.1 Plug-in Electric Vehicles

The aggregator concept was introduced by Kempton[92] in 2001 and further enhanced in many works. In 2010, Sekyung, Soohee and Sezaki extensively discussed the Vehicle-to-Grid regulations from strategic prospective and proposes a pragmatic framework for aggregators which considers the issues that arises due to the integration of Plug-in Electric Vehicles in grid as energy consumers as well as energy suppliers[93]. Bessa and Matos [94] present an overview about the economic potential of electric vehicles and discusses technical details of aggregator in the electricity market. After 2010, literatures [88, 95, 96] refers Aggregator in context of Plug-in Hybrid Electric Vehicles (PHEVs) as a service provider for charging the batteries when the demand of Vehicle to grid supported building is lower than its peak load and discharge the batteries to partially supply the building to reduce the peak demand during a high demand. In [88], Lopes, Soares and Almeida proposed a comprehensive conceptual framework for aggregator which is capable of dealing technical management and market operation with the existing grid to handle EV charging in an effective manner. In [96, 97], a detailed algorithm for

[1]This report will continuously user term "Aggregator" for this business entity.

unidirectional regulation and profit maximization is formulated with system load constraints and energy bidding mechanism for use by an aggregator. However, Wu, Aliprantis and Ying in [95, 98] proposed an operational framework for aggregator in which it uses dynamic algorithm for finding out the optimal minimum-cost load scheduling in the day-aheadmarket and dispatch strategy used for distributing the purchased energy to Plug-In Vehicles (PEVs) on the operating day. Recently, in [89], authors proposed an integrated model for service provider comprising vehicle technology modeling, agent based transportation modeling and power system modeling to analyze the impacts of electric mobility on the domains of power and transportation systems as well as on the environment. Thus, Aggregators are expected to play a significant role in future smart grid because it has to manage PHEV charging so that it does not only occur during peak hours but also does not overload distribution network[99].

Currently,The larger Investor-Owned Utilities (IOUs) in California, that is Southern California Edison (SCE) and Pacific Gas and Electric (PG&E), have shown high concern in integration of electric vehicles to grid and are implementing aggregation programs [100]. "EDISON Project, Electric vehicles in a Distributed and Integrated market using Sustainable energy and Open Networks" in Denmark by Denmark energy Association is developing suitable aggregation technology for low-cost, efficient, plug-and-play integration of Electric Vehicles into the power system [101]. Many Companies like Enervate in UK [102]and Nuvve in USA [103]is providing solutions for Vehicle-to-Grid (V2G).

2.3.2 Virtual Power Plant

In this developing concept of virtual power plant (VPP), some literatures [44, 104], indistinctly use terms "VPP" and "aggregator". However, according to the the recent researchers , define Virtual Power Plant (VPP) as a decentralized energy management system that use to aggregate the capacity of some Distributed Generations (DGs), storage facilities, and dispatchable Loads (DLs) for the purpose of energy trading and providing system support services [90, 105, 106]. In reference [81, 107] , formulated virtual power plants as multiple objective optimization problem with constraints of consumers and indigenous DGs in order to satisfy the market requirements with the least generation cost and increase it's revenue by implementing it's own customized price-based aggregated demand response. However, in [91, 108] researchers combines the concept of microgrid management and virtual power plant as energy management of clusters of DGs, energy storage units, and loads in grid-connected and isolated grid modes.

Southern California Telephone and Energy (SCT&E) is heading towards the implementation of virtual power plant [109], Flexitricity brings VPP business in UK Market [110] and Fenix consortium is contributing in Eurozone through aggregation into Large Scale Virtual Power Plants (LSVPP) and decentralized management [111].

2.3.3 Third Party Entity

In last few years, A large amount of research has been done on aggregated demand and new strategies of direct load control. This emerging concept of aggregated demand response elucidates aggregators as a legal third party entity which has a bilateral contract with a utility as a large energy buyer over negotiated tariff program[84, 112]. On other hand, it contracts large amounts of domestic customers and responsible for designing and implementing their on demand side program including smart monitoring, direct controlling and pricing[57, 58, 76].

In 2010, A Parc Xerox Company USA presented pragmatic solution of augmenting existing grid power distribution with aggregators, providing new services to both utility and customer as middle man or third party [113]. Moreover, Mohagheghi, Stoupis, Wang, Li and Kazemzadeh stated that ADR promotes interaction and responsiveness of the customers and changes the grid from a vertically integrated structure to one that is affected by the need and wants of the consumer[84]. They also presented the aggregated demand response architecture that could be implemented at the distribution level and discussed some practical considerations associated with this approach. In 2011, Ducan S. Callaway summarized Business Models for Demand-side Energy Services: Economics, Challenges, and Opportunities and discussed some of the tradeoffs between price response versus direct load control, grid cyber-infrastructure and control strategies for small versus large loads to deliver aggregated system services[64]. However, reference [75] reported the study of aggregator that synthesizes a daily load profile of Dutch domestic appliances and electric vehicles and simulated them in real-time for economic optimization based on predicted day-ahead prices and the provision of balancing energy.

In short, aggregated demand response can be implemented at the distribution level for the customers via aggregator, a third party entity, under its territory. However, researchers and DR companies are adding value to the aggregated demand response algorithm by incorporating the model of the distribution network, financial aspects, mutual agreement between individual consumer and utility, consumer satisfaction, constraints of load control and pricing mechanism. Currently, EnerNOC and Comverge are most famous third party aggregators which have already implemented the price-based/incentive-based load control mechanism over consumer's thermal appliances after signing bilateral contract or agreement with them[82, 83]. However, EnergyConnect has stepped ahead and recently released GridConnect platform for commercial or large consumers which has enabled them to manage their energy bidding via website[114]. CPower, Energy Curtailment Specialist, EPS Corporation, IQ building, World Energy Solutions and many others has landed in aggregated demand side management as a third party[115].

2.4 Discussion

According to the definitions of the aggregator in the literature, it is an entity which either provides services to the fleet of PEVs for controlled charging and dispatching of energy or a customize aggregated demand response provider to group of consumers (commercial, industrial or domestic) to schedule and control thermal appliances for peak demand shaving during peak hours. Moreover, aggregator is also referred as virtual power plant in several works according to which it is responsible to optimally manage the power flow to and from indigenous DGs, storage facilities and dispatchable loads (thermal appliances, electric vehicles). However, some researchers consider integration and control of indigenous DGs and storage facilities as a economic dispatch and unit commitment problem which comes under the domain of the supply-side management instead of demand-side management[116–118]. Thus, it could be concluded that the VPP combines supply side and demand side management together under one concept and perform virtual vertical integration of electrical network. So, it could be inferred that aggregator might be the part of virtual power plant but could not be referred as VPP in whole.

Hence, in general, aggregator could be define as a third party entity or service provider which responsible to:

- Schedule and control dispatchable loads in order to shave demand peak during peak hours.
- Maximize it's own revenue by finding optimal load control solution in order to fulfill the utility requirement as well as consumer constraints.
- Satisfy consumer and secure it's privacy.
- Develop systematic strategy to achieve win-win condition in supply and demand of electrical network i.e. to provide economical benefit to both utility by minimizing its operational cost and consumers by providing incentives.

Thus, it is evident that a new business opportunity i.e. aggregator is emerged by the proliferation of automatic and direct control of loads and electric vehicles. That is why different business models are being implemented and proposed in works by industrialists and researchers respectively because it depends over number of factors including:

- existing grid network
- existing communication and data network.
- existing business model of electrical network.
- societal norms of inhabitants.
- culture of the people.
- environment of the region.
- economical and financial situation.
- political will.

Moreover, it could be inferred from the existing works that aggregator have contractual relationship with utility as well as consumers. Both of these contracts have two main terms and conditions regarding

- Nature of the Contract.
- Pricing Mechanism.

2.4.1 Contract Between Utility and Aggregator

Contracts may be bilateral or unilateral. If it is a bilateral contract, then it is an agreement in which the utility promises to pay the aggregator, in exchange aggregator promises to curtail the identified power. However, if it is a unilateral contract, then only utility promises to pay the aggregator if it curtails the identified power. It means that aggregator is not under an obligation to curtail the identified power, but utility is under an obligation to pay a reward to aggregator if it does the job.

In any case, Aggregator is a large buyer of electricity from utility or a large consumer that facilitates utility by promising that it could curtail power during peak hours. For this service, it would be rewarded by the utility. Thus, the second term of the agreement is that what would be the pricing mechanism. That is, will the utility pay a fixed reward to aggregator or will the payment of reward is based on either time-of-use, critical peak pricing or others. For instance, PG&E has started Aggregator Managed Portfolio program which is a non-tariff program that consists of bilateral contracts with aggregators with price-responsive pricing mechanism[119].

2.4.2 Contract Between Consumer and Aggregator

Similarly, Contracts between Consumer and Aggregator may be bilateral or unilateral. If it is a bilateral contract, then it is an agreement in which the aggregator promises to pay the incentive to the consumer, in exchange consumer promises to switch off or regulate the specific loads to reduce the required consumption. However, if it is a unilateral contract, then only aggregator promises to pay the incentive to the consumer if it switches off or regulates it's load. It means that the consumer is not under an obligation to control the load, but aggregator is under an obligation to pay a reward to aggregator if it does the job.

Most of the contracts implemented by the aggregators or proposed by the researchers for either European, Scandinavia or North America consumers are bilateral contract because unilateral contract supports on indirect load management strategy which may result in uncertainty, incompleteness and severance during the time of contingency[82, 83, 119]. However, bilateral contracts provide provision all kind of load management strategies i.e. indirect, automatic and direct load control.

As in Section 2.2.2, the two major kinds of pricing mechanism which have already been proposed in the literatures are discussed in detail. It can be inferred that most of the literature developed the business model of aggregator with price-based mechanism because it is more easier to implement for those nations which have already implemented it on domestic level[82, 83]. However, very few researches consider incentive-based i.e. energy bidding as pricing mechanism of aggregator for consumer[84, 86]. Indeed, it is an opportunity for those developing nations which are implementing it because incentive-based pricing mechanism effectively caters the social issues like consumer satisfaction and privacy, as it enables consumers to bid in energy market.

Major Assumptions: The main purpose of this research is to introduce a new strategy of demand side management to the aggregators which are already providing energy services to the consumers in many different region of world. This research proposed demand reduction bid based DLC strategy between the consumer and the aggregator. Following are few major assumptions that are taken during this research:

- The consumer and the aggregator are legally in bilateral contract.
- Aggregator presents retail energy market pricing to consumer before bidding.
- Consumer can change its bidding on the basis of retail energy market and contract policy.
- The third party aggregator and the utility are in bilateral contract.
- Utility offers time-of-use electricity market pricing to the aggregator for business.
- All shareholders especially government, consumers and suppliers are fully committed to SMART GRID.
- Proposed strategy is for already existing aggregators, therefore, it doesnot address the societal issues that may occur during its materialization.
- Similarly, it does not present any study related to economical and financial implication that may be faced during the implementation of smart distribution network.

Chapter 3

Multi-stage Problem Solving Technique

3.1 Multi-stage Problem Solving Technique

Multistage decision problems usually arise when decisions are made in the sequential manner over time where earlier decisions may affect the feasibility and performance of later decisions. The multistage decision making process can be separated into a number of sequential steps, or stages, which is completed in one or more ways. The options for completing stages are known as decisions. The condition of the process at a given stage is known as state at that stage; each decision effects a transition from the current state to a state associated with the next stage.

The multistage decision making process is finite if there are only a finite number of stages in the process and a finite number of states associated with each stage. Many multistage decision processes have returns (cost or benefits) associated with each decision, and these returns may very with both the stage and state of the process. The multistage decision process is deterministic if the outcome of each decision is known exactly.

$$F = \sum_{i=1}^{n} f_i(X_i) \tag{3.1}$$

such that

$$\begin{aligned}
\sum_{i=1}^{n} X_i &\leq b \\
X_i &\geq 0 \\
i &= 1, 2, .., n
\end{aligned}$$

Where, $f_i(X_i)$ are known (non-linear) optimal functions of a single variable and b is a nonnegative integer.

Multi-stage Decision trees are a useful means for representing and analyzing multiple-stage decision tasks as shown in Fig. 3.1, where decision nodes $\square$ indicate decision-maker choices, event nodes $\bigcirc$ represent elements beyond control of the decision-maker, and terminal nodes $\bullet$ represent possible final consequences[120].

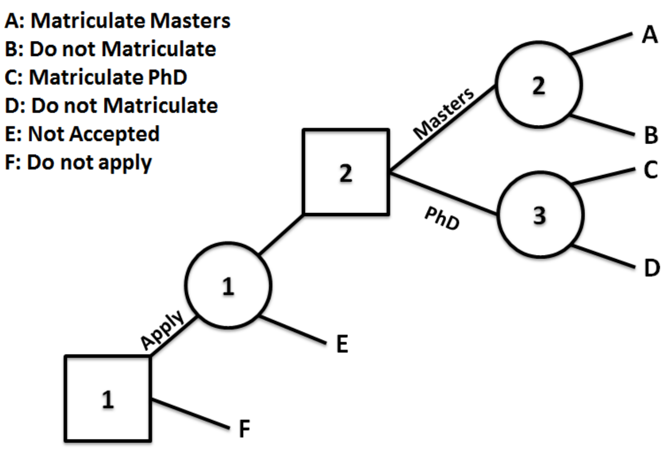

FIGURE 3.1: Example of a real-life situation represented as a decision tree. [3]

For instance The first decision node concerns whether or not to apply to graduate school, which leads to the event node of being accepted. If accepted, a second decision is required concerning which degree to pursue, leading to probabilistic event nodes dictating the decision-makers chances of success for each. While optimal navigation of this rather small decision tree may not seem so overwhelming, one can imagine the difficulty in comprehending the different scenarios involved with larger trees[3].

3.2 Principle of optimality in Dynamic Programming

Dynamic Programming is a mathematical solving methodology for Complex Multi-Stage Decision Making Problem using computer programming. The basic concept of dynamic programming is to transform a complex problem into multiple sub-problems and then to combine solutions of all sub-problems to derive the overall solution. The sub-problems are usually referred to as *stages* and are calculated once during the computation and their results are stored so as to use for future computations. Thus, by this method, the numbers of computations are reduced and consequently an optimized solution is obtained.

In the scheduling of supply and demand side of the electrical power system, DP techniques have been developed for

- Economic dispatch of thermal system.
- Solution of hydrothermal economic-scheduling problems.
- Practical solution of unit commitment problem.
- Demand response.
- Aggregated demand side management.

3.2.1 Shortest path problem

First it will be well to introduce some of the notions of Dynamic Programming (DP) by means of some one-dimensional examples[121]. Special class of dynamic programming is shortest path problem as shown in Fig. 3.2

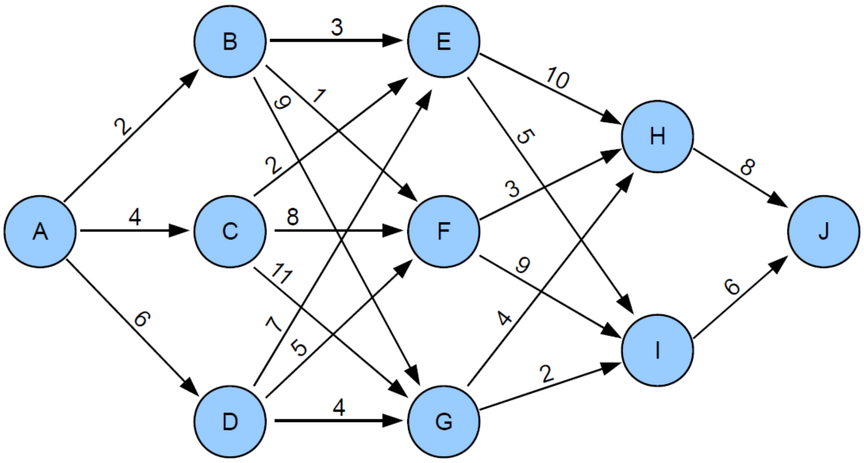

FIGURE 3.2: Shortest path problem. [4]

In this is an example the aim is to calculate the shortest path from node A to node J. Numbers at arrows indicate weights; an arrow shows a possible direction for a move. The network can be divided into five stages, where Stage 1 contains node A, Stage 2 contains nodes B, C and D, Stage 3 contains E, F and G, Stage 4 contains nodes H and I, and Stage 5 contains node J. Let X_n denote nodes in stages n and $n + 1$, with weight $f(X_n)$. For calculating the shortest path, use the recursive function:

$$F_n(X_n) = \min[f(X_n) + F_{n-1}(X_{n-1})] \tag{3.2}$$

Stage	Shortest Distance	Path
1	$F_1(B) = 2$	AB
	$F_1(C) = 4$	AC
	$F_1(D) = 6$	AD
2	$F_2(E) = \min[f(E) + F_1(B), f(E) + F_1(C), f(E) + F_1(D)] = 5$	ABE
	$F_2(F) = \min[f(F) + F_1(B), f(F) + F_1(C), f(F) + F_1(D)] = 3$	ABF
	$F_2(G) = \min[f(G) + F_1(B), f(G) + F_1(C), f(G) + F_1(D)] = 10$	ADG
3	$F_3(H) = \min[f(H) + F_2(E), f(H) + F_2(F), f(H) + F_2(G)] = 6$	ABFH
	$F_3(I) = \min[f(I) + F_2(E), f(I) + F_2(F), f(I) + F_2(G)] = 12$	ADGI
4	$F_4(J) = \min[f(J) + F_3(H), f(J) + F_3(I)] = 14$	ABFHJ

The choice of route is made in sequence. There are very stages transverse. The optimum sequence is called the *optimal policy*. Any subsequence is *sub-policy*. From this it may be seen that the optimal policy i.e. the minimum cost contains only optimal sub-policies. This is the *Theorem of Optimality*.

An optimal policy must contain optimal sub-policies.

3.2.2 An Allocation Problem

Let us solve this an allocation problem example by the help of Dynamic Programming. Firstly, we will decide problem which is spending of money in plants' expansion. Secondly, we need to know our projected GOAL i.e. to obtained maximum revenue by selecting appropriate proposal for each plant. Now, break the problem into three stages: each stage has states that represent the money allocated to a single plant. So stage 1 will have 3 states representing the money allocated to plant 1, stage 2 has 4 states, and stage 3 has 2 states 3.

	Profit from venture		
Investment	Plant 1	Plant 2	Plant 3
0	0	0	0
1	5	-	4
2	6	8	-
3	-	9	-
4	-	12	-
5	-	-	-

Let's try to figure out the revenues associated with each state. So the optimal result after stage 1 would be:

$$[F_{10}\ F_{11}\ F_{12}] = [0\ 5\ 6]$$

Now, for the computations for stage 2, following optimal function is carried. In this case, the best solution will be found for both plants 1 and 2.

$$F_2(X_2) = \min[f(X_2) + F_1(X_1)]$$

such that

Capital	Stage I	Stage II	$F_2(X_2)$	Optimal Investment
0	0	0	0	0,0
1	5	-	5	1,0
2	6	8	6	2,0
3	-	9	13	1,2
4	-	12	14	2,2 or 1,3
5	-	-	17	1,4

We can now go on to stage 3. Once again, we go through all the proposals for this stage, determine the amount of money remaining.

Capital	$F_2(X_2)$		Stage III	$F_3(X_3)$	Optimal Capital Investment
0	0	0,0	0	0	0,0,0
1	5	1,0	4	5	1,0,0
2	6	2,0	-	9	1,0,2
3	13	1,2	-	13	1,2,0
4	14	2,2 or 1,3	-	17	1,2,1
5	17	1,4	-	18	2,2,1 or 1,3,1

Hence, the optimal solution for spending money in these plants is either spend $2 Million to Plant 1 and 2 and $1 million to Plant 3; by this configuration, Proposal 3 will be best fit for Plant 1 and Proposal 2 will be best fit for plant 2 and 3. Or spend $1 Million to Plant 1 and 3 and $3 million to Plant 2; by this configuration, Proposal 3 will be best fit for Plant 2 and Proposal 2 will be best fit for plant 1 and 3.

If you study this procedure, you will find that the calculations are done recursively. Stage 2 calculations are based on stage 1, stage 3 only on stage 2. Indeed, given you are at a state, all future decisions are made independent of how you got to the state. This is the principle of optimality and all of dynamic programming rests on this assumption.

Chapter 4

Aggregator and Electricity Market Framework

4.1 Introduction to Framework

This emerging concept of aggregated demand response elucidates aggregators as a legal third party entity which has a bilateral contract with a utility as a large energy buyer over negotiated tariff program. On other hand, it also bilaterally contracts large amounts of domestic customers and responsible for designing and implementing demand side program including smart monitoring, direct controlling and pricing to satisfy the customers needs and wants.

In this report, a framework for aggregated demand response is proposed for smart grid. The strategy is based on demand reduction bidding[1] and customer satisfaction parameters[2] identified by the customer to the aggregator at the time of contracting. A dynamic programming algorithm is developed for finding the optimal load scheduling and direct controlling of large number of consumers. As shown in Fig. 4.1, aggregator take two decisions; one for optimal load scheduling and

[1]This is an incentive amount or price identified by the consumer on the basis of their satisfaction and domestic use.

[2]Customer Satisfaction parameters are the factors that takecare of consumer satisfaction and ergonomics.

other optimal load controlling. In optimal Load Scheduling, aggregator finds out the optimal level of power reduction during an interval for each consumer. While in optimal load controlling, aggregator finds out the optimal direct load control strategy for controlling of consumers loads.

Section 4.2 and Section 4.3 mathematically formulates the load scheduling and controlling mechanism respectively of aggregator's framework.

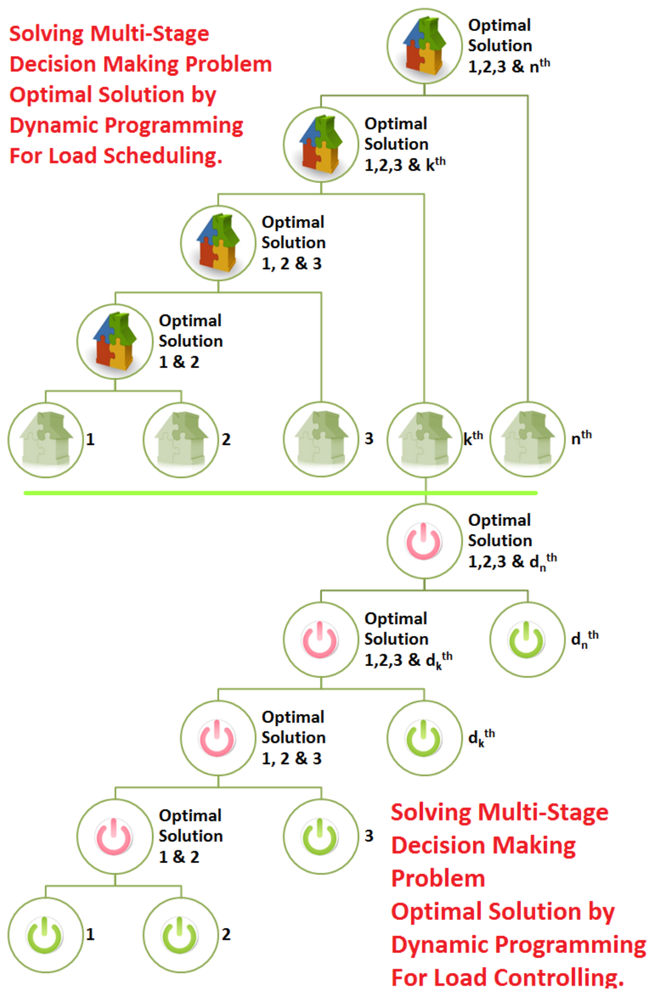

FIGURE 4.1: Aggregator and Electricity Market Framework

4.2 Load Scheduling Mechanism

The purpose of the aggregator is to facilitate the utility in shaving power demand during the peak hours by using aggregated demand response strategy for load scheduling and DLC for load control of consumers in smart distribution network.

If demand reduction bids are given by the consumers as a function of levels of demand reduction required by the aggregator, then, consumers can specify fixed demand reduction bids $f_n(P_i^n)$ for all levels of power reduction $P_i^n \epsilon \{0, \Delta P, 2\Delta P, ..., P_n^{max}\}$, where ΔP is the step size. Thus aggregator can reduce a power P_D ranging from 0 to P^{max}.

$$P^{max} = \sum_{n=1}^{N} P_n^{max}$$

Now the decision making problem for the aggregator is to find the load reduction P^{1*}, P^{2*},..., P^{n*}, ..., $P^{N*}$by individual consumers such that P^1, P^2,..., P^n, ..., P^N= P_D and total incentive given by the consumer $\sum_{n=1}^{N} f_n(P_D)$ is minimal. In summary the optimal problem is

$$\min_{(P^1,P^2,...,P^n)} \sum_{n=1}^{N} f_n(P^n)$$

where;

$$\begin{aligned}
0 &< P^1 < P_1^{max} \\
0 &< P^2 < P_2^{max} \\
&\cdots\cdots\cdot \\
0 &< P^n < P_i^{max} \\
&\cdots\cdots\cdot \\
0 &< P^N < P_n^{max}
\end{aligned}$$

Thus, at a given time interval, if utility calls aggregator to reduce $P_D(k)$ power for N consumers. Then, the prime objective of the aggregator is not only to find the levels of power reduction P^{1*}, P^{2*},..., P^{n*}, ..., $P^{N*}$by all N consumers at the specified time interval, such that P^1, P^2,..., P^n, ..., P^N= P_D. But, it has to find the optimal levels of power reductions by considering the constraints of consumers and calculating least aggregated demand reduction bid by all N consumers in order to maximize its own profit.

For such demand response, the aggregator and the consumers mutually sign the bilateral contracts that facilitate consumers to update their demand reduction bids for a given time period provided some constraints are met. It is assumed that $T_{n_{ON}}^{min}$ is minimum duration for which n^{th} consumer must be continuously ON, $T_{n_{OFF}}^{max}$ is maximum duration for which n^{th} consumer can be continuously OFF and T_n^{max} is total duration for which n^{th} consumer can participate in load reduction program. Thus, $T_{n_{ON}}^{min}$, $T_{n_{OFF}}^{max}$ and T_n^{max} capture constraints of consumers.

Let us assume that $T_{n_{ON}}(k)$ be the duration for which n^{th} consumer is continuously ON during k^{th} interval, $T_{n_{OFF}}(k)$ be the duration for which n^{th} consumer is continuously OFF during k^{th} interval and $T(k)$ be the total duration for which n^{th} consumer is OFF till $(k+1)^{th}$ interval.

Moreover let, $X^n(k)$, denote whether the n^{th} consumer is participating or not in load reduction. $X^n(k)$ is a binary variable and is equal to one if the n^{th} consumer is participating during the k^{th} interval. Thus, the problem could be mathematically expressed as:

$$\min_{P_1^n, P_2^n, \ldots, P_I^n | P^n \epsilon \mathcal{P}} \sum_{n=1}^{N} f_n(P^n(k), X^n(k)) \tag{4.1}$$

s.t.

$$\begin{gathered}
P^{1*}(k),\ P^{2*}(k), \ldots,\ P^{n*}(k),\ \ldots,\ P^{N*}(k) = P_D(k) \qquad \forall\ (k\ \epsilon\ \mathcal{H}) \\
T_{n_{ON}}(k) = 0 \text{ or } T_{n_{ON}}(k) > T_{n_{ON}}^{min} \\
T_{n_{OFF}}(k) < T_{n_{OFF}}^{max} \\
T(k) < T_n^{max}
\end{gathered}$$

The procedure to update $T(k)$, $T_{n_{ON}}(k)$ and $T_{n_{OFF}}(k)$ is explained in the section.

4.3 Load Controlling Mechanism

Assume, aggregator use direct load control for load controlling of consumer's load via OpenADR system in smart grid environment. However, every N consumers do not only identify that it has D_n controllable loads for direct controlling but also update some consumer constraints including $T^{min}_{dn_{ON}}$, $T^{max}_{dn_{OFF}}$, q_{d_n} and p_{d_n} of each d_n load. At this situation, if an aggregator want to reduce power $P_D(k)$ from N consumer in an hour. Thus, the prime objective of the aggregator is to find the optimal load reduction P^{1*}, P^{2*},$\ldots$, P^{n*}, $\ldots$, $P^{N*}$by all N consumers at given time interval, such that

$$P^{1*} + P^{2*} + P^{3*} \ldots + P^{N*} = P_D \tag{4.2}$$

Moreover, aggregator also find the optimal solution in order to maximize it's revenue by paying least aggregated demand reduction bid $F(P)$ to participating consumers. In this way, aggregator is able to find the equilibrium point in the supply and demand curve of the electricity during peak period $[T_1 \;\; T_2]$ without any power generation.

By the advent of OpenADR, aggregator is capable to effectively solve this complex multi-stage decision making problem. The function of OpenADR system is to facilitate sending and receiving control signals from a utility or aggregator to electric devices of consumers. Thus, it enables aggregator shed the power of particular loads out of d_n loads of N consumers respectively. Moreover, OpenADR also sends information of all available and controllable devices of every consumer to aggregator. By this information, aggregator is capable to generate the list of aggregated bids $f_n(P^n_i)$ by participating d_n loads of n^{th} consumer for all level of power reduction $\mathcal{P}$ at given time interval k, such that

$$f_n(P(k)) = \min_{p_1,p_2,\ldots,p_{d_n}} \sum_{d_n=1}^{D_n} q_{d_n}(1 - D_{d_n}(k)) \tag{4.3}$$

Then, aggregator sends the control signals by OpenADR system to n^{th} consumer for switching OFF the particular loads, such that sum of power rating of participating d_n devices must be equal to the level of power reduction P_i reduce by the n^{th} consumer at given time interval. Mathematically,

$$p_1 + p_2 + p_3, \ldots, p_{d_n}, \ldots, p_{D_n} = P^{n*}$$

Chapter 5

Development of Optimization Algorithm

5.1 Dynamic Programming

The basic concept of dynamic programming is to transform a complex problem into multiple sub-problems and then to combine solutions of all sub-problems to derive the overall solution. The sub-problems are usually referred to as *stages* and are calculated once during the computation and their results are stored so as to use for future computations. Thus, by this method, the numbers of computations are reduced and consequently an optimized solution is obtained. The Table below shows the mathematical framework for aggregators as discussed in Chapter 4. It lists the power reduction $P_i(KW)$ by n consumers in an hour as a function of price incentive $f(P)$ given to a particular consumer. Consider, the total amount of power which the utility is required to reduce in an hour is P_D. Then problem is to find the *optimal strategy* by the aggregator so as to pay least incentive payments to the consumers. Aggregator can reduce the maximum power P_{max} which is the integrated sum of maximum power that each consumer can reduce.

Power $P(kW)$	Consumer 1 C_1	Consumer 2 C_2	.	.	Consumer n C_n
P_1	$f_1(P_1)$	$f_2(P_1)$	.	.	$f_n(P_1)$
P_2	$f_1(P_2)$	$f_2(P_2)$	.	.	$f_n(P_2)$
P_3	$f_1(P_3)$	$f_2(P_3)$	.	.	$f_n(P_3)$
.	.	.	.	.	.
.	.	.	.	.	.
P_i	$f_1(P_i^1)$	$f_2(P_i^2)$	.	.	$f_n(P_i^n)$

If aggregator follows policy of step-wise reduction in power, then ΔP would be a step change in power between the two consecutive reductions and i represents the number of steps. i.e.

$$\Delta P = P_2 - P_1 \tag{5.1}$$

and

$$i = \frac{P_D}{\Delta P} \tag{5.2}$$

In order to solve the problem by dynamic programming, it has to be transformed into a multi-stage decision making problem. The objective function of the algorithm is to maximize the total profit of the aggregator by finding least aggregated reduction bids of the consumers. The problem is divided into $N-1$ stages which are discussed as follows.

5.1.1 Stage 1

In stage 1, the problem is to find the optimum reduction by $consumer1$ (P^{1*}) and $consumer2$ (P^{2*}) such that the total incentive to be paid to these two consumer is minimized. If the net incentive paid for reducing (P_T^1) units of power is denoted by $F_1\,(P_T^1)$, then:

$$F_1\left(P_T^1\right) = \min_{\left\{(P^1,P^2)|P^1+P^2=P_T^1\right\}} \left[f_1\left(P^1\right) + f_2\left(P^2\right)\right] ^{1} \tag{5.3}$$

The stage 1 saves value set of P^{1*} and P^{2*} and $F_1\left(P_T^1\right)$ corresponding to every load reduction level P_T for all values of $i = 1 \ldots I$, such that

$$0 < P_T^1 < (P_1^{max} + P_2^{max})$$

5.1.2 Stage 2

In stage 2, *consumer*1 and *consumer*2 are considered as a single composite consumer with composite bid of $F_1\left(P_T^1\right)$ given for $0 < P_T^1 < (P_1^{max} + P_2^{max})$. It may noted that $F_1\left(P_T^1\right)$ is found for all values of P_T^1 in stage 1. In stage 2, the problem is to find the optimal reduction P_T^2 by the composite consumer (P_T^{1*}) and *consumer*3 (P^{3*}), such that:

$$F_2\left(P_T^2\right) = \min_{\left\{\left(P_T^1,P^3\right)|P_T^1+P^3=P_T^2\right\}} \left[F_1\left(P_T^1\right) + f_3\left(P^3\right)\right] ^{2} \tag{5.4}$$

The stage 2 eventually saves value set of P^{1*}, P^{2*}, P^{3*} and $F_2\left(P_T^2\right)$ corresponding to every load reduction level P_T^2 for all values of $i = 1 \ldots I$.

$$0 < P_{T_2} < \left(P_{T_1}^{max} + P_3^{max}\right)$$

5.1.3 Stage K

Similarly in stage K, consumers up to $K-1$ are considered as a single composite consumer with composite bid $F_{K-1}\left(P_T^{K-1}\right)$ given for $0 < P_T^{K-1} < (P_1^{max} + P_2^{max} + ... + P_K^{max})$. It may noted that $F_{K-1}\left(P_T^{K-1}\right)$ is found for all values of P_T^{K-1} in stage K. In this stage, the problem is to find the optimal reduction P_{T_K} by the composite consumer

[1] minimum is calculated over all combination of $\left(P^1, P^2\right)$ such that $\left(P^1 + P^2 = P_T^1\right)$.

[2] minimum is calculated over all combination of $\left(P_T^1, P^3\right)$ such that $\left(P_T^1 + P^3 = P_T^2\right)$ and so on.

($P_T^{(K-1)*}$) and $consumer(K+1)$ ($P_T^{(K+1)*}$), such that:

$$F_K\left(P_T^K\right) = \min\left[F_{K-1}\left(P_T^{K-1}\right) + f_{K+1}\left(P^{K+1}\right)\right] \tag{5.5}$$

The stage K also stores value set of P^{1*}, P^{2*}, P^{3*} up till P^{K*} and $F_K\left(P_T^K\right)$ corresponding to every load reduction level P_T^K for all values of $i = 1 \ldots I$, such that:

$$0 < P_T^K < \left(P_{T_{K-1}}^{max} + P_{K+1}^{max}\right)$$

5.1.4 Stage N-1

So, $F_{N-1}\left(P_T^{N-1}\right)$ is the least aggregated demand reduction bid by all consumers for aggregated load curtailment of P_T^{N-1}, such that:

$$F_{N-1}\left(P_T^{N-1}\right) = \min\left[F_{N-2}\left(P_T^{N-2}\right) + f_N\left(P^N\right)\right] \tag{5.6}$$

The solution of $(N-1)^{th}$ stage which will result in $P_T^{(N-1)*}$ and P^{N*} such that

$$P_T^{(N-2)*} + P^{N*} = P_T^{(N-1)*} = P_D$$

Now, in order to reduce P_D identified by the utility, aggregator could find amount of power to be reduced by every consumer $(P^{1*}, P^{2*}, P^{3*}, ..., P^{N*})$ such that $P^{1*} + P^{2*} + P^{3*} + ... + P^{N*} = P_T^{(N-1)*} = P_D$.

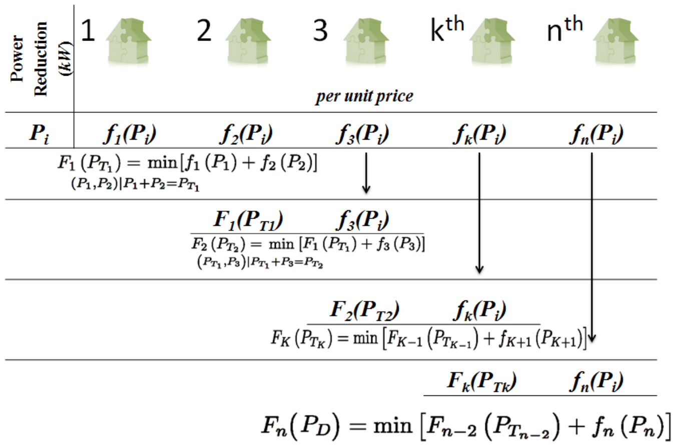

FIGURE 5.1: Dynamic Programming Algorithm

5.1.5 Example

Let us consider an example in which three consumer will be paid for different price incentive over energy reduction of $25KWh$, $50KWh$ and $75KWh$. So, maximum energy $P(max)$ that all consumer can reduce is $150KWh$. If total of $100KWh$ i.e. $P(D)$ is identified by the utility to reduce in any particular hour. Then what would be the optimal policy for aggregator.

TABLE 5.1: Example

Energy Reduction (KWh)	Consumer 1	Consumer 2	Consumer 3
25	20	25	15
50	45	41	25
75	85	75	40

At Stage II, we can compute

TABLE 5.2: Stage II

P	$f_1(P)$	$f_2(P)$	$F_1(P)$	Optimal Policy(O_p)
25	20	25	20	$(25, 0)$
50	45	41	41	$(0, 50)$
75	85	75	65	$(50, 25)$
100	-	-	86	$(50, 50)$

At Stage III, we can compute

Thus, the computation shows that aggregator has to reduce $0KWh$ from *consumer*1, $25KWh$ from *consumer*2 and $75KWh$ from *consumer*3 so as to pay least price

TABLE 5.3: Stage III

P	$F_1(P)$	$f_3(P)$	$F_2(P)$	Optimal Policy(O_p)
25	20	15	15	$(0, 0, 25)$
50	41	25	25	$(0, 0, 50)$
75	65	40	40	$(0, 0, 75)$
100	86	-	60	$(0, 25, 75)$

incentive of $60units$ to itś consumers and as well as satisfy utility requirement of energy reduction.

5.2 Optimal Load Scheduling algorithm

Suppose that the utility supplies the demand for a time period of $[T_1 \quad T_2]$ in a day to the aggregator for peak shaving. Then, first of all, the aggregator divides the identified period $[T_1 \quad T_2]$ in to $|\mathcal{H}|$ intervals. Thus, in order to find out optimal load schedule, the algorithm transforms this problem in to $|\mathcal{H}|$ multi-stage decision problem. Each problem involves two decisions i.e. finding $\mathbf{x}(k) = [X^1(k), X^2(k), \ldots, X^n(k), \ldots, X^N(k)]$ and $P^{1*}(k)$, $P^{2*}(k)$,$\ldots$, $P^{n*}(k)$, $\ldots$, $P^{N*}(k)$. For the first interval (i.e $k = 1$), it is assumed that all consumers are available for load reduction. Thus, $\mathbf{x}(1)$ has ones for all N . To find the $P^{1*}(1)$, $P^{2*}(1)$,$\ldots$, $P^{n*}(1)$, $\ldots$, $P^{N*}(1)$, the problem is divided into $(N-1)$ stage decision making problem and is solved by using dynamic programming.

Next, the problem has to be solved for the remaining intervals i.e. $k = 2, 3, .., |\mathcal{H}|$. The decision variable $X^n(k)$ is determined based on the consumer constraints. During each interval $T_{n_{OFF}}(k)$, $T_{n_{ON}}(k)$ and $T(k)$ are updated as follows:

$$T_{n_{OFF}}(k) = \begin{cases} T_{n_{OFF}}(k-1) + h_{step} & ; \quad \text{if } X^n(k-1)\text{=}1 \\ 0 & ; \quad \text{if } X^n(k-1)\text{=}0 \\ n = 1, 2, 3, ...N & \forall \quad T_{n_{OFF}} \leq T^{max}_{n_{OFF}} \end{cases} \tag{5.7}$$

$$T_{n_{ON}}(k) = \begin{cases} T_{n_{ON}}(k-1) + h_{step} & ; \quad \text{if } X^n(k-1)\text{=}0 \\ 0 & ; \quad \text{if } X^n(k-1)\text{=}1 \\ n = 1, 2, 3, ...N & \forall \quad T_{n_{ON}} \leq T^{min}_{n_{ON}} \end{cases} \tag{5.8}$$

and

$$T_n(k+1) = \begin{cases} T_n(k) + h_{step} & ; \quad \text{if } X^n(k)\text{=1} \\ T_n(k) & ; \quad \text{if } X^n(k)\text{=0} \\ n = 1, 2, 3, ...N & \forall \quad T_n \leq T_n^{max} \end{cases} \tag{5.9}$$

If a particular consumer has been switched OFF for a total duration of T_n^{max} , then that particular consumer can not participate un the load control scheme. That is, if $T(k) \geq T_n^{max}$ then $X^n(k+1)$ =0. If this condition is not satisfied, the algorithm determines $X^n(k+1)$ based on $T_{n_{ON}}(k)$, $T_{n_{OFF}}(k)$ and $X^n(k)$. If $T_{n_{OFF}}(k+1) < T_{n_{OFF}}^{max}$, it means that the participating n^{th} consumer at given interval k could also participate in load curtailment program during the interval $k+1$. If $T_{n_{OFF}}(k+1)$ $> T_{n_{OFF}}^{max}$, it means that the participating n^{th} consumer at given interval k would not participate in load curtailment program during the interval $k+1$. On other hand, if $T_{n_{ON}}(k+1) > T_{n_{ON}}^{min}$, it means that the non-participating n^{th} consumer during a given interval k could participate in the load curtailment program during the interval $k+1$, because n^{th} consumer has remained uncontrolled since $T_{n_{ON}}^{min}$. Conversely, if $T_{n_{ON}}(k+1) < T_{n_{ON}}^{min}$, it means that non-participating n^{th} consumer during the interval k would not participate again in the load curtailment program during the interval $k+1$. That is why, some participating consumer at given interval k might not participate in the next interval $k+1$.

Then, the decision that whether n^{th} consumer participates or not is taken based on the current status of the consumer $X^n(k)$ and values of $T_{n_{ON}}(k)$, $T_{n_{OFF}}(k)$ and $T(k)$ based on the following equation:

$$X^n(k) = \begin{cases} 1 & ; \quad \text{if } X^n(k-1)\text{=1 \& } T_{n_{OFF}}(k) < T_{n_{OFF}}^{max} \\ 1 & ; \quad \text{if } X^n(k-1)\text{=0 \& } T_{n_{ON}}(k) > T_{n_{ON}}^{min} \\ 0 & ; \quad \text{if } X^n(k-1)\text{=1 \& } T_{n_{OFF}}(k) > T_{n_{OFF}}^{max} \\ 0 & ; \quad \text{if } X^n(k-1)\text{=0 \& } T_{n_{ON}}(k) < T_{n_{ON}}^{min} \\ & for\ n = 1, 2, 3, ...N,\ and \\ & k = 1, 2, 3, ...|\mathcal{H}| \end{cases} \tag{5.10}$$

Once $X^n(k+1)$ is decided, $P^n(k+1)$ is obtained by solving eq. 4.1 using dynamic programming [85]. The complete algorithm is explained in Algorithm. 1.

Algorithm 1 Load Scheduling Algorithm

Require: Demand reduction bids and consumer constraints.
Require: Demand reduction pattern from utility for specified time period $[T_1\ \ T_2]$.
Require: Initialize $\mathbf{x}(1)$ with ones for all N .
Require: Initialize $T_{n_{OFF}}(1)$, $T_{n_{ON}}(1)$ and $T_n(1)$ with zeros for all n .
Ensure: Total number of intervals $|\mathcal{H}|$.

```
for k ≤ |H| do
    Find total number of consumers i.e.N .
    for n ≤ N do
        Compute X(k+1) , T_{n_ON}(k+1) and T_{n_OFF}(k+1) for interval k+1.
    end for
    for k ≤ (N−1) do
        Compute optimal solution using eq. 4.1
    end for
    Send list of reduction bid for all levels of power to aggregator.
    Receive direct load control signal.
    Update x(k) , T_{n_ON}(k) and T_{n_OFF}(k) with X(k+1) , T_{n_ON}(k+1) and T_{n_OFF}(k+1) .
end for
```

5.3 Optimal Load Controlling algorithm

Let Suppose, an aggregator decides to curtail power P from any n^{th} consumer at any given time interval k out of $|\mathcal{H}|$ control intervals, where each step h_{step} equals to 10 minutes, during peak time period $[T_1 \;\; T_2]$. So, first of all, aggregator identifies number of controllable loads D_n of that particular consumer by and their respective consumer constraints by using openADR system at any given time step k .

Initially, the load scheduling algorithm compute a column matrix of $\mathbf{d}(k)$ on the basis of information received from openADR. This matrix summarizes the information of all d_n loads of n^{th} consumer regarding their participation in direct load control at time interval k in terms of binary values $\{0, 1\}$, such that:

$$D_{d_n}(k) = \begin{cases} 1 \quad ; & \text{if } {d_n}^{th} \text{ load is participating} \\ 0 \quad ; & \text{if } {d_n}^{th} \text{ load is not participating} \\ & d_n = 1, 2, 3, ...D_n \\ & k = 1, 2, 3, ...|\mathcal{H}| \end{cases} \tag{5.11}$$

Then, algorithm generate list of least reduction bids by participating d_n devices of the n^{th} consumer with optimal load schedule for control at all level of power reduction $\mathcal{P}$. For this algorithm transform this problem into multi-stage decision problem and divide it into $d_n - 1$ stages. algorithm solves this problem by using dynamic programming. Thus, $f_n(P_i^n)$ is the optimal solution by the dynamic programming that is the aggregated reduction bid by d_n controllable load of n^{th} consumer at power reduction level P_i, such that:

$$f_n(P^n) = \min_{\{p_1, p_2, .., p_{d_n} | p_1 + p_2 + .. + p_{d_n} = P^n\}} f_{n(d_n - 2)}(P^n) + q_{d_n}(P^n) \tag{5.12}$$

At this moment, for all N consumer, algorithm can generate the lists of reduction bids $f_n(P_i^n)$ by all participating d_n loads for all level of power reduction $\mathcal{P}$ at given time interval. Now, aggregator can effectively decide the levels of power reduction P^1, P^2,..., P^n, ..., P^Nwhich should be reduced by all N consumer at the given time interval.

Let suppose, If aggregator decide to curtail power P^n or simply P from particular n^{th} consumer at time interval k . Then, it sends control signals for switching OFF the loads corresponding to the power level P in the list and offer $f_n(P)$ as reduction bid.

Finally, algorithm calculates a column matrix of $\mathbf{d}(k+1)$ which contains information of all d_n loads of n^{th} consumer regarding their participation in direct load control at time interval k in terms of binary values $\{0, 1\}$, such that:

$$D_{d_n}(k) = \begin{cases} 1 \;\; ; \;\; \text{if } T_{dn_{OFF}}(k-1) < T_{dn_{OFF}}^{max} \\ \qquad \& \; T_{dn_{ON}}(k-1) > T_{dn_{ON}}^{min} \\ 0 \;\; ; \;\; \text{if } T_{dn_{OFF}}(k-1) > T_{dn_{OFF}}^{max} \\ \qquad \& \; T_{dn_{ON}}(k-1) < T_{dn_{ON}}^{min} \\ \qquad d_n = 1, 2, 3, ...D_n \end{cases} \tag{5.13}$$

If $T_{dn_{OFF}}(k+1) < T_{dn_{OFF}}^{max}$ means that participating d^{th} load of n^{th} consumer at given interval k could also participate in load curtailment program at next interval $k+1$. Conversely, $T_{dn_{OFF}}(k+1) > T_{dn_{OFF}}^{max}$ means that participating d^{th} load of n^{th} consumer at given interval k would not participate in load curtailment program at next time interval $k+1$. On other hand, $T_{dn_{ON}}(k+1) > T_{dn_{ON}}^{min}$ means that non-participating d^{th} load of n^{th} consumer at given interval k could participate in load curtailment program for next interval $k+1$, because d^{th} load is remain uncontrolled since $T_{dn_{ON}}^{min}$. Conversely, $T_{dn_{ON}}(k+1) < T_{dn_{ON}}^{min}$ means that non-participating d^{th} load of n^{th} consumer at given interval k would not participate again in load curtailment program at next time interval $k+1$. That is why, some participating consumer at given interval k might not participate in preceding time interval $k+1$. Thus, when algorithm repeats these steps at next interval but before that it updates the value of $\mathbf{d}(k)$ with $\mathbf{d}(k+1)$.

Algorithm 2 Load Scheduling Algorithm

Require: Power to reduce, consumer constraints.
Require: Initiate $\mathbf{d}(k)$, $T_{dn_{ON}}(k)$ and $T_{dn_{OFF}}(k)$ with ones, $T^{min}_{dn_{ON}}$ and $T^{max}_{dn_{OFF}}$ respectively.
Ensure: Total number of intervals $|\mathcal{H}|$.

for $k \leq |\mathcal{H}|$ **do**
  Find total number of d_n .
  for $d_n \leq D_n$ **do**
    Compute $\mathbf{d}(k+1)$, $T_{dn_{ON}}(k+1)$ and $T_{dn_{OFF}}(k+1)$ for interval $k+1$.
  end for
  for $k \leq (D_n - 1)$ **do**
    Compute optimal solution using eq. 5.12
  end for
  Send list of reduction bid for all levels of power to aggregator.
  Receive direct load control signal.
  Update $\mathbf{d}(k)$, $T_{dn_{ON}}(k)$ and $T_{dn_{OFF}}(k)$ with $\mathbf{d}(k+1)$, $T_{dn_{ON}}(k+1)$ and $T_{dn_{OFF}}(k+1)$.
end for

Chapter 6

Case Studies

The proposed algorithm is investigated considering 15 large consumers who have signed up the bilateral contracts of energy management program using DLC with the aggregator. As per the bilateral contract, every consumer provides demand reduction bids for five large devices which have thermal storage capability such as air-conditioning, electric water heater and electric space-heating system. Thus, aggregated demand response program encourages consumer to provide load reductions at the prices for which they are willing to be curtailed. The aim of this chapter is to test the applicability of the proposed algorithm by considering different case studies.

6.1 Case Study For Optimal Load Scheduling Algorithm

In order to test the efficacy of algorithm 1, it is assumed that utility provide a peak demand curve to the aggregator for a time period of 8 hours ranging from 8:00am to 4:00pm. Thus, the total number of control intervals is equal to $\frac{8\times 60}{10} = 48$. The utility wants that the aggregator should execute it's aggregated demand response program to shave the peak demand. In Fig. 6.1, the solid-line shows the demand curve of 15 consumers before the application of any load control by the aggregator.

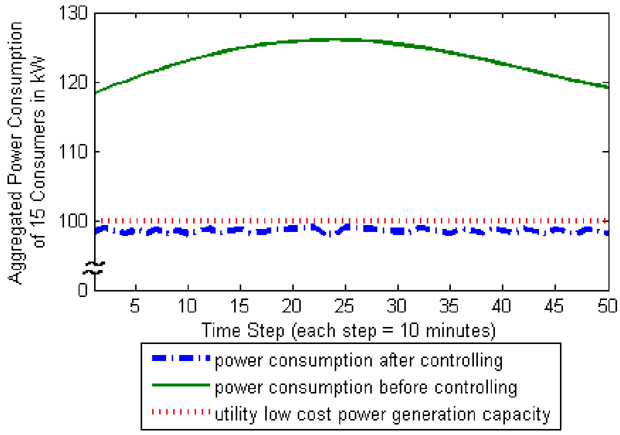

FIGURE 6.1: Power consumed by 15 consumers for a period ranging from 8:00am to 4:00pm

It is observed that collectively all consumers use a maximum power of $127kW$ during the 25^{th} interval. Although, the utility might be capable to provide this much power to these consumers even during the peak hours, usually it may cost more to the utility, because either it buys power from some other providers or runs some inefficient generators. Thus, it is assumed that the utility is capable of providing $100kW$ continuously to the 15 consumers at low cost and high power quality during peak hours, as shown in Fig. 6.1 by dotted-line. So, utility calls the aggregator to shave this peak demand up to it's optimal generation capacity of $100kW$. Then, the aggregator executes this algorithm for the reduction of power and uses predefined demand reduction bids and the consumer constraints by the 15 consumers as shown in Table 6.1 and Table 6.2 respectively.

6.1.1 Simulation Results

As mention earlier, the aggregator has discretized the levels of power reduction by $1kW$. It should be noted that the aggregator runs the load scheduling algorithm at every interval and curtails power of various consumers. Moreover, at a given interval, it also calculates the prospective optimal load control schedule for the next interval. Fig. 6.2 shows power curtailment of each consumer for complete 48 intervals as bar graphs, representing the amount of power curtailed per interval.

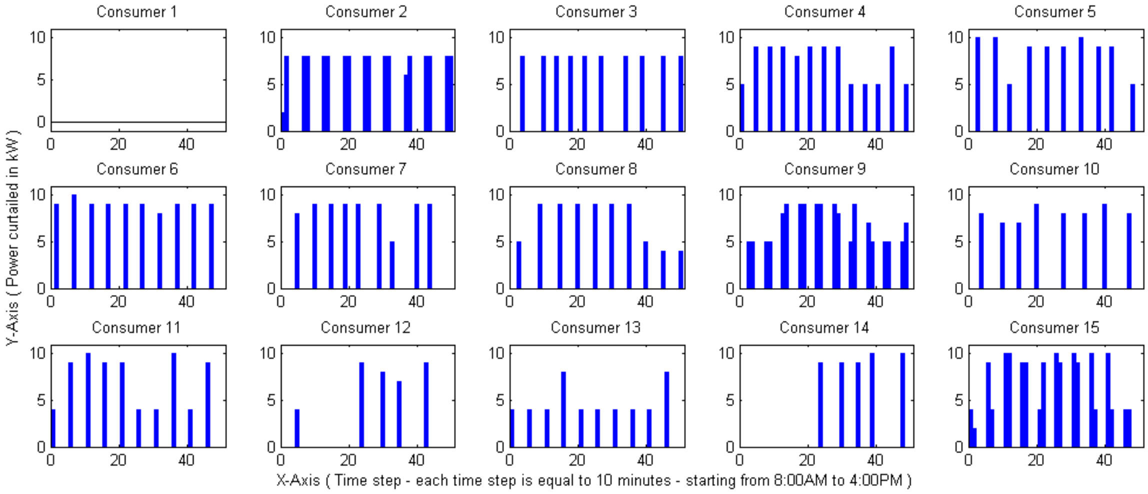

FIGURE 6.2: Power curtailment plots of all consumers for the given 8 hrs

TABLE 6.1: Demand reduction bids proposed by the consumers over corresponding load reduction.

Load Reduction	Consumer 1	Consumer 2	Consumer 3	Consumer 4	Consumer 5	Consumer 6	Consumer 7	Consumer 8	Consumer 9	Consumer 10	Consumer 11	Consumer 12	Consumer 13	Consumer 14	Consumer 15
kW	Power Reduction Bid $/SAR$														
1	0.05	0.01	0.08	0.03	0.07	0.04	0.06	0.05	0.04	0.05	0.03	0.06	0.02	0.10	0.02
2	0.09	0.03	0.12	0.08	0.11	0.07	0.09	0.09	0.07	0.09	0.06	0.10	0.07	0.14	0.04
3	0.17	0.08	0.10	0.09	0.12	0.09	0.11	0.10	0.09	0.10	0.09	0.13	0.10	0.15	0.06
4	0.18	0.08	0.15	0.11	0.13	0.11	0.13	0.12	0.12	0.13	0.10	0.13	0.07	0.13	0.08
5	0.20	0.13	0.16	0.11	0.15	0.14	0.16	0.15	0.13	0.17	0.15	0.19	0.12	0.17	0.12
6	0.24	0.14	0.22	0.19	0.22	0.19	0.20	0.20	0.18	0.21	0.18	0.21	0.18	0.24	0.17
7	0.28	0.20	0.23	0.21	0.23	0.21	0.23	0.22	0.20	0.22	0.21	0.23	0.18	0.26	0.18
8	0.26	0.18	0.24	0.21	0.26	0.22	0.25	0.24	0.23	0.24	0.23	0.25	0.19	0.26	0.24
9	0.33	0.24	0.28	0.23	0.27	0.24	0.27	0.26	0.25	0.27	0.24	0.27	0.24	0.27	0.22
10	0.36	0.28	0.33	0.29	0.30	0.28	0.31	0.30	0.29	0.31	0.28	0.33	0.26	0.30	0.25

In this figure, $y - axis$ shows the levels of power reduction in kW and $x - axis$ shows the interval number.

Table 6.1 shows that each consumer offers demand reduction bidding with different prices. The consumer are shown in Table 6.2. The algorithm has to solve for optimal power reduction using dynamic programming while taking care of the constraints by each consumer during all k intervals. Therefore, it can be observed in Fig. 6.2 that every consumer has different power curtailment pattern for all k intervals. Moreover, it can also be observed that the aggregator does not curtail the load of 1^{st} consumer because it is among the highest bidding consumers as shown in Table 6.1 as well as it is also among the consumers with tight constraints i.e. $T^{min}_{n_{ON}}$ =40 minutes and $T^{max}_{n_{OFF}}$ =10 minutes as shown in Table 6.2. On other hand, the aggregator curtails most of the power of 2^{nd}, 9^{th} and 15^{th} consumer because they are among the consumers with least reduction bids as well as they offer $T^{max}_{n_{OFF}}$ =20 minutes and $T^{min}_{n_{ON}}$ =30 minutes as shown in Table 6.2.

It can also be observed from Fig. 6.2 that aggregator did not curtail power of consumers continuously through out the control intervals because of their identified consumer constraints. For instance, aggregator controls load of consumer 13 for $T^{MAX}_{13_{OFF}} = 10$ minutes at 1^{st} interval of a peak hours and should resume it for $T^{MAX}_{13_{ON}}$ $= 40$ minutes (i.e. for next 4 intervals). Now, if aggregator need to curtail more power for 13^{th} consumer, then it has to wait for atleast 4 intervals before the commencement of the next curtailment. So, at 6^{th} interval, the aggregator again curtails the power of the 13^{th} consumer. Although, 13^{th} consumer has identified that the aggregator can curtail it's power for total of 240 minutes per day (i.e. 24 intervals per day) as shown in Table 6.2, but even then aggregator can not continuously curtail power of this consumer because of the constraints. Thus, this trend of power reduction during the intervals is observed in Fig. 6.2 for all consumers because of the predefined constraints.

Table 6.2: Consumer constraints by 15 consumers

Consumer	T^{MAX}	T^{MIN}_{ON}	T^{MAX}_{OFF}
	minutes	*minutes*	*minutes*
1	360	40	10
2	360	40	20
3	240	30	10
4	360	30	10
5	300	30	10
6	360	40	10
7	360	30	10
8	240	40	10
9	360	30	20
10	300	40	10
11	360	40	10
12	360	30	10
13	240	40	10
14	290	30	20
15	200	30	20

It is also observed from Fig. 6.2 that during the load control of any consumer, the aggregator can change it's level of curtailment in next interval. For instance, 15^{th} consumer reduces power of 4kW for 10 minutes at 1^{st} interval. Since, it has identified $T_{15_{OFF}}^{MAX} = 20$ minutes, so, aggregator curtails 3kW power of this consumer during the next interval. Similarly, aggregator curtails 2kW power of 2^{nd} consumer at 1^{st} interval, while during 2^{nd} interval, aggregator increased the power curtailment up to 8kW. However, aggregator always take care of $T_{n_{OFF}}^{max}$ of all N consumers during the change in the level of curtailment at any interval.

Semi-dotted-line in Fig. 6.1 shows the aggregated consumption of 15 consumers after the optimal load control by aggregator is applied. Moreover, it can be observed from Fig. 6.1 that the aggregated power after application of load control is lower than the utility's identified efficient generation capacity. Thus, it is evident from the simulation results that the proposed algorithm successfully achieve the prime objectives of the aggregator i.e. to maximize it's profit by paying minimal aggregated demand reduction bid to consumers and to shave the peak demand as per utility requirement thereby providing full satisfaction to consumers by considering consumer constraints in demand side management program.

6.2 Case Study For Optimal Load Control Algorithm

The proposed algorithm was analyzed by considering a particular consumer characterized as having five large devices which have thermal storage capability such as air-conditioning, electric water heater and electric space-heating system. The aim of this case study is to test the applicability of the proposed algorithm. It is considered that the consumer initially send consumer constraints to the aggregator regarding their controllable devices as shown in Table 6.3. Thus, this program encourages consumer to provide load reductions at the prices for which they are willing to be curtailed.

Table 6.3: Consumer constraints of 5 large devices by consumer

Devices	T_{ON}^{MIN}	T_{OFF}^{MAX}	Power Rating	Demand Reduction Bidding
	minutes	*minutes*	*kW*	*SAR*
1	40	10	0.5	0.05
2	40	10	0.5	0.60
3	30	10	1.0	0.12
4	30	10	2.5	0.11
5	30	10	1.5	0.12

For simulation aggregator executes the algorithm for any the n^{th} consumer using consumer constraints in Table 6.3 over corresponding loads at a control period of one hour. Thus, firstly aggregator divides control period of one hour into $|\mathcal{H}|$ = 6 intervals with h_{step} = 10 minutes. During the first interval i.e. k = 0, all loads of consumer are ready to participate in load reduction program. However, aggregator proposes aggregated power which should be reduce by this particular consumer on the basis of list of reduction bids, corresponding to different levels of power at interval k = 0, produced by the algorithm. Then, on the basis of consumer constraints, algorithm updates the list of participating loads for preceding interval and prepares itself to provide new list of reduction bids to aggregator at the preceding interval. This process continues till the end of control period as shown in algorithm 2.

6.2.1 Simulation Results

Table 6.4 and Table 6.5 shows different actions taken by aggregator at control periods of two consecutive day. It also shows the effect of a particular action at any interval over the decision for preceding interval of control period of a day.

6.2.1.1 Day First

In the control period of first day, aggregator decide to curtail power of 2.5kW out of maximum deducible power of 6.0kW from consumer during first interval as shown in Table 6.4. So, it switches OFF the load 4 for a bid price of 0.11SAR. Then, algorithm updates the list of reduction bid for preceding interval on the

Table 6.4: Simulation results of day first during control period

Power(kW)	at $k=0$		at $k=1$		at $k=2$		at $k=3$		at $k=4$		at $k=5$	
	Devices	Price(/SAR)	Devices	Price(/SAR)	Devices	Price(/SAR)	Devices	Price(/SAR)	Devices	Price(/SAR)	Devices	Price(/SAR)
First Day												
0.5	1	0.05	1	0.05	1	0.05	2	0.6	–	–	–	–
1.0	3	0.12	3	0.12	1,2	0.65	–	–	–	–	3	0.12
1.5	5	0.12	5	0.12	–	–	–	–	–	–	5	0.12
2.0	1,5	0.17	1,5	0.17	–	–	–	–	–	–	–	–
2.5	4	0.11	3,5	0.24	–	–	–	–	4	0.11	3,5	0.24
3.0	1,4	0.16	1,3,5	0.29	–	–	–	–	–	–	–	–
3.5	3,4	0.23	1,2,3,5	0.89	–	–	–	–	–	–	–	–
4.0	4,5	0.23	–	–	–	–	–	–	–	–	–	–
4.5	1,4,5	0.28	–	–	–	–	–	–	–	–	–	–
5.0	3,4,5	0.35	–	–	–	–	–	–	–	–	–	–
5.5	1,3,4,5	0.4	–	–	–	–	–	–	–	–	–	–
6.0	1,2,3,4,5	0.1	–	–	–	–	–	–	–	–	–	–

Table 6.5: Simulation results of day second during control period

Power(kW)	at $k=0$		at $k=1$		at $k=2$		at $k=3$		at $k=4$		at $k=5$	
	Devices	Price(/SAR)	Devices	Price(/SAR)	Devices	Price(/SAR)	Devices	Price(/SAR)	Devices	Price(/SAR)	Devices	Price(/SAR)
Second Day												
0.5	1	0.05	2	0.6	3	0.12	2	0.6	–	–	1	0.05
1.0	3	0.12	3	0.12	2,3	0.72	–	–	–	–	–	–
1.5	5	0.12	2,3	0.72	–	–	–	–	5	0.12	–	–
2.0	1,5	0.17	2	–	–	–	–	–	–	–	–	–
2.5	4	0.11	4	0.11	–	–	–	–	–	–	4	0.11
3.0	1,4	0.16	2,4	0.71	–	–	–	–	–	–	1,4	0.16
3.5	3,4	0.23	3,4	0.23	–	–	–	–	–	–	–	–
4.0	4,5	0.23	2,3,4	0.83	–	–	–	–	–	–	–	–
4.5	1,4,5	0.28	–	–	–	–	–	–	–	–	–	–
5.0	3,4,5	0.35	–	–	–	–	–	–	–	–	–	–
5.5	1,3,4,5	0.4	–	–	–	–	–	–	–	–	–	–
6.0	1,2,3,4,5	1	–	–	–	–	–	–	–	–	–	–

basis of current decision. It can be observed from Table 6.4 that at $k=1$, load 4 is not participating as it has participated at $k=0$. Because, of this maximum power which can be reduced by the consumer at k = 1 has reduced to 3.5kW. Moreover, according to the consumer constraints load 4 will not participate in load curtailment for preceding 30 minutes. So, it is also observed from Table 6.4 that load 4 is again able to participate in interval k = 4. At k = 3 and k =4, aggregator has only one choice i.e. 0.5kW and 2.5kW respective because of consumer constraints.

6.2.1.2 Day Second

In the control period of first day, aggregator decide to curtail power of 2.0kW out of maximum deducible power of 6.0kW from consumer during first interval as shown in Table 6.5. So, it switches OFF the load 1 as well as load 5 for a bid price of 0.17SAR. Then, algorithm updates the list of reduction bid for preceding interval on the basis of current decision. It can be observed from Table 6.5 that at k = 1, load 1 and load 5 are not participating as they have participated at k = 0. Because, of this maximum power which can be reduced by the consumer at k = 1 has reduced to 4.0kW. Moreover, according to the consumer constraints load 1 and load 5 will not participate in load curtailment for preceding 40 minutes and 30 minutes respectively. So, it is also observed from Table 6.4 that load 5 is again able to participate in interval k = 4. However, load 1 is again able to participate in interval k = 5. At k = 3 and k = 4, aggregator has only one choice i.e. 0.5kW and 1.5kW respective because of these consumer constraints.

Thus, Table 6.4 and Table 6.5 also elucidates that on availability of controllable load, consumer constraints and decision at previous intervals, aggregator always has different list of reduction bids at upcoming interval.

Chapter 7

Conclusion

The advancements in information and communication technology and burgeoning challenges in supply and demand of electrical power have led to the concept of Smart Grid. Smart Grid is expected to improve the efficiency, quality, reliability, economics and sustainability of complete Supply and Demand chain of the Electricity. In brief, Smart Grid is an energy management system of electrical power grid using advance data communication and networking in order to cope with skyrocketing demand and provide economical benefit to all stakeholders.

Aggregated Demand Side Management or Aggregated Demand Response is one of the most important management strategy that aims to balance electrical supply and demand by reducing the power demand during critical periods instead of increasing the power generation. Efficient demand side management can potentially avoid the construction of an under-utilized electrical infrastructure in terms of generation capacity, transmission lines and distribution networks. Controlling and influencing the energy usage can reduce the overall peak load demand, reshape the demand curve, and increase the grid sustainability by reducing the overall cost and carbon emission levels.

The skyrocketing advancement in smart pricing in demand response, communication and data networking and embedded systems evolve the concept of Open Automated Demand Response (OpenADR) system for commercial and domestic buildings. This system provides incentives to customers for investing in DMS technologies that also enable them to perform demand response and encourages them to participate aggregated demand response programs via direct load controlling. Consumers who sign up the contract with aggregator are allowed to participate in aggregated demand side management using OpenADR. In this program, consumer transceive control signals regarding their pre-define loads using OpenADR, and then aggregator shed consumer's load by using optimal load scheduling strategy.

As, Direct Load Control (DLC) provide utility or service provider (aggregator) to remotely shuts down customer's thermally controllable appliance. So, by controlling the large number of electrical devices, they can reduce the overall peak demand, reshape the demand profile, and increase the grid sustainability by reducing the overall cost and carbon emission levels. DLC as energy management strategy has been a focus of research since last thirty decades. Conventionally, objective of the direct load control was either cost minimization of the peak load or minimization of production cost. Even till today many researchers are studying several direct load control techniques and algorithms for demand side management because DLC had faced the challenge of customer acceptance i.e security of consumer's privacy and satisfaction.

This report proposes an algorithm for load curtailment in aggregated demand response program. The research provides the optimized policies that an aggregator should execute load controlling algorithm along with optimal load scheduling in order to economically benefit itself as well as the customers and manage peak demand during peak hours as per utility requirements.

In this report, a direct load scheduling algorithm is developed for aggregator who can use OpenADR standard for transceiving information from consumer regarding it's participating loads and consumer constraints. The proposed load controlling algorithm will enables aggregator to develop direct load control program using OpenADR system for efficient controlling in smart grid environment. The research mathematically formulates the generalize algorithm based on dynamic programming as discussed in Section 4.3. Moreover, Algorithm consider consumer constraints and also allow every consumer to bid price for it's participating devices on the basis of it's utilization and importance. The simulation results in Section 6.2 shows that this algorithm is able to effectively schedule the participating devices even with tight constraints and generate list of reduction bids and available devices for all possible levels of power reduction for aggregator.

Furthermore, report also presented an algorithm for load scheduling based on dynamic programming in an aggregated demand response program. Algorithm provides an optimal solution by using the proposed mathematical framework for aggregated load scheduling discussed in Section 4.2. This algorithm takes into account the bilateral contract between the aggregator and end-user for curtailment of load over their energy bidding. This proposed algorithm fulfils objectives of utility by minimizing demand during the peak hours. It also helps the aggregator in maximizing it's profit. Moreover, it satisfies the consumer by providing high quality and low-cost power and incentives for load reductions with mutual agreements. The simulation results shown in Section 6.1 proves that the algorithm is able to achieve all the objectives effectively for a large number of consumers.

In Short, these algorithms collectively allow aggregator to achieve prime objectives of demand side management that includes revenue maximization of aggregator, minimization of peak demand during peak, minimization of operational cost of utility, and provide personal security and satisfaction to consumer.

Recommendations: Since, Pakistan Electrical Industry reviving their electrical power grid. So, it would be recommended that they should:

- Deploy smart meters at houses that contain flexible communication modules and advance home-controlling system.
- Introduce price-responsive tariffs in wholesale energy market.
- Motivate entrepreneurs for installation of distributed generators.
- Instead of load shedding, deploy direct load control in offices, malls, shopping centers, markets and other large consumers.
- Make retail energy market transparent to consumers.

- Ensure sincerity and commitment towards implementation of Smart Grid among all stakeholders.
- Introduce Aggregators to provide demand response program to their consumers.

If Pakistani power industry try to implement these recommendations, then it surely make Pakistani grid sustainable, reliable and provide high quality power to their consumers. This seems to be large capital investment in Electrical Power Industry. But, this investment will benefit the nation for long run and will help in over coming the current energy crises.

Future Work: Following are few major areas of future research in aggregated demand response:

- Suitable state estimation method by incorporating a large amount of data from modern measurement devices.
- Investigating and determining customer flexibility.
- Reduce the consequences of uncertainty from both stochastic power production and consumption.
- The wide area situational awareness and societal acceptance.
- Fast fault location identification.
- Investigating and determining network margins under stochastic power production and consumption.
- Enhance network-monitoring capability.
- The evaluation of the impact and of the future control actions.
- Predict limitations of control actions taken in the distribution network.
- Defined and investigated control actions (availability and its time dependency).
- The evolution of the impact of communication architecture and data transmission protocols on the dynamics of control loops.
- Development of simulation platform.
- Development of dynamics of models of microgrids and/or DG units,
- Methods of compensations of delayed or lost data from instrumentation.

Bibliography

[1] Sustainable energy regulation and policymaking for africa. URL http://www.unido.org/fileadmin/user_media/Publications/Pub_free/training_manual_on_sustainable_energy_regulation_and_policymaking_for_Africa.pdf.

[2] M.H. Albadi and EF El-Saadany. A summary of demand response in electricity markets. *Electric Power Systems Research*, 78(11):1989–1996, 2008.

[3] J.G. Johnson and J.R. Busemeyer. Multiple-stage decision-making: the effect of planning horizon length on dynamic consistency. *Theory and Decision*, 51(2):217–246, 2001.

[4] A.J. Wood and B. Wollenberg. *POWER GENERATION OPERATION & CONTROL, (With CD)*. John Wiley & Sons, 2006.

[5] Sustainable energy - united nations development programme. URL http://www.undp.org/energy/.

[6] A.M. Omer. Energy, environment and sustainable development. *Renewable and Sustainable Energy Reviews*, 12(9):2265–2300, 2008.

[7] SA Al-Ajlan, AM Al-Ibrahim, M. Abdulkhaleq, and F. Alghamdi. Developing sustainable energy policies for electrical energy conservation in saudi arabia. *Energy policy*, 34(13):1556–1565, 2006.

[8] REEEP and UNIDO. Energy efficiency technologies and benefits, . URL http://africa-toolkit.reeep.org/modules/Module12.pdf.

[9] S. Arora and P. Kumar. Infrastructural development of energy planning and energy management for smart grid implementation. *International Organization of Scientific Reseearch Journal*.

[10] REEEP and UNIDO. Regulation and sustainable energy. . URL http://www.reeep.org/830/sern.htm.

[11] M.W. Kirby. Supply-side management. *The British economy since 1945*, pages 236–60, 1945.

[12] C. Beggs. *Energy: management, supply and conservation*. Butterworth-Heinemann, 2009.

[13] S. Talukdar and C.W. Gellings. *Load management*. IEEE, 1987.

[14] S.D. Maqbool, T.P.I. Ahamed, E. Al-Ammar, and NH Malik. Demand response in saudi arabia. In *2nd International Conference on Electric Power and Energy Conversion Systems (EPECS), 2011*, pages 1–6. IEEE, 2011.

[15] M.F. Fels and K.M. Keating. Savings from demand-side management programs in us electric utilities. *Annual review of energy and the environment*, 18(1):57–88, 1993.

[16] G. Strbac. Demand side management: Benefits and challenges. *Energy Policy*, 36(12):4419–4426, 2008.

[17] S.M. Amin. For the good of the grid. *IEEE Power and Energy Magazine*, 6 (6):48–59, 2008.

[18] Assessment of demand response and advanced metering. *Federal Energy Regulatory Commission,*, 2008.

[19] T. Logenthiran, D. Srinivasan, and T.Z. Shun. Demand side management in smart grid using heuristic optimization. *IEEE Transactions on Smart Grid*, 3(3):1244–1252, 2012.

[20] M.H. Albadi and EF El-Saadany. Demand response in electricity markets: An overview. In *IEEE Power Engineering Society General Meeting, 2007.*, pages 1–5. IEEE, 2007.

[21] A. Brooks, E. Lu, D. Reicher, C. Spirakis, and B. Weihl. Demand dispatch. *IEEE Power and Energy Magazine,*, 8(3):20–29, 2010.

[22] Us department of energy - smart grid. URL http://energy.gov/oe/technology-development/smart-grid.

[23] S. Borenstein, M. Jaske, and A. Rosenfeld. Dynamic pricing, advanced metering, and demand response in electricity markets. 2002.

[24] C.W. Gellings. *The smart grid: enabling energy efficiency and demand response*. Fairmont Press, 2009.

[25] K. Spees and L.B. Lave. Demand response and electricity market efficiency. *The Electricity Journal*, 20(3):69–85, 2007.

[26] B.J. Kirby. *Spinning reserve from responsive loads*. Department of Energy-United States., 2003.

[27] D.S. Callaway and I.A. Hiskens. Achieving controllability of electric loads. *Proceedings of the IEEE*, 99(1):184–199, 2011.

[28] C. Diduch, M. Shaad, R. Errouissi, ME Kaye, J. Meng, and L. Chang. Aggregated domestic electric water heater control-building on smart grid infrastructure. In *7th International Power Electronics and Motion Control Conference (IPEMC), 2012*, volume 1, pages 128–135. IEEE, 2012.

[29] SH Lee and CL Wilkins. A practical approach to appliance load control analysis: a water heater case study. *IEEE Transactions on power apparatus and systems*, (4):1007–1013, 1983.

[30] A.I. Cohen, J.W. Patmore, D.H. Oglevee, R.W. Berman, L.H. Ayers, and J.F. Howard. An integrated system for residential load control. *IEEE Transactions on Power Systems*, 2(3):645–651, 1987.

[31] BF Hastings. Ten years of operating experience with a remote controlled water heater load management system at detroit edison. *IEEE Transactions on Power Apparatus and Systems*, (4):1437–1441, 1980.

[32] R. Bhatnagar, J. Latimer, L. J. Hamant, A. A. Garcia, G. Gregg, and E. Chan. On-line load control dispatch at florida power & light. *IEEE Transactions on Power Systems*, 3(3):1237–1243, 1988.

[33] W.C. Chu, B.K. Chen, and C.K. Fu. Scheduling of direct load control to minimize load reduction for a utility suffering from generation shortage. *IEEE Transactions on Power Systems*, 8(4):1525–1530, 1993.

[34] D. Wei and N. Chen. Air conditioner direct load control by multi-pass dynamic programming. *IEEE Transactions on Power Systems*, 10(1):307–313, 1995.

[35] J.C. Laurent, G. Desaulniers, R.P. Malhame, and F. Soumis. A column generation method for optimal load management via control of electric water heaters. *IEEE Transactions on Power Systems*, 10(3):1389–1400, 1995.

[36] A.I. Cohen and C.C. Wang. An optimization method for load management scheduling. *IEEE Transactions on Power Systems,*, 3(2):612–618, 1988.

[37] FN Lee and AM Breipohl. Operational cost savings of direct load control. Technical report, Department of Electrical Engineering, The Univ. of Kansas, Lawrence, KS, 1984.

[38] KD Le, RF Boyle, MD Hunter, and KD Jones. A procedure for coordinating direct-load-control strategies to minimize system production costs. *IEEE Transactions on Power Apparatus and Systems*, (6):1843–1849, 1983.

[39] R. Bhatnagar and S. Rahman. Dispatch of direct load control for fuel cost minimization. *IEEE Transactions on Power Systems*, 1(4):96–102, 1986.

[40] Y.Y. Hsu and C.C. Su. Dispatch of direct load control using dynamic programming. *IEEE Transactions on Power Systems*, 6(3):1056–1061, 1991.

[41] K.H. Ng and G.B. Sheble. Direct load control-a profit-based load management using linear programming. *IEEE Transactions on Power Systems*, 13 (2):688–694, 1998.

[42] CN Kurucz, D. Brandt, and S. Sim. A linear programming model for reducing system peak through customer load control programs. *IEEE Transactions on Power Systems*, 11(4):1817–1824, 1996.

[43] Y.C. Chang. An outstanding method for saving energy-optimal chiller operation. *IEEE Transactions on Energy Conversion*, 21(2):527–532, 2006.

[44] N. Ruiz, I. Cobelo, and J. Oyarzabal. A direct load control model for virtual power plant management. *IEEE Transactions on Power Systems*, 24(2): 959–966, 2009.

[45] L. Yao and H.R. Lu. A two-way direct control of central air-conditioning load via the internet. *IEEE Transactions onPower Delivery*, 24(1):240–248, 2009.

[46] H.T. Yang and K.Y. Huang. Direct load control using fuzzy dynamic programming. In *IEE Proceedings-Generation, Transmission and Distribution,*, volume 146, pages 294–300. IET, 1999.

[47] K.Y. Huang and Y.C. Huang. Integrating direct load control with interruptible load management to provide instantaneous reserves for ancillary services. *IEEE Transactions on Power Systems*, 19(3):1626–1634, 2004.

[48] H. Salehfar, PJ Noll, BJ LaMeres, MH Nehrir, and V. Gerez. Fuzzy logic-based direct load control of residential electric water heaters and air conditioners recognizing customer preferences in a deregulated environment. In *IEEE Power Engineering Society Summer Meeting, 1999.*, volume 2, pages 1055–1060. IEEE, 1999.

[49] H. Jorge, C.H. Antunes, and A.G. Martins. A multiple objective decision support model for the selection of remote load control strategies. *IEEE Transactions on Power Systems*, 15(2):865–872, 2000.

[50] SC Lee, SJ Kim, and SH Kim. Demand side management with air conditioner loads based on the queuing system model. *IEEE Transactions on Power Systems*, 26(2):661–668, 2011.

[51] A. Sepulveda, L. Paull, W.G. Morsi, H. Li, CP Diduch, and L. Chang. A novel demand side management program using water heaters and particle swarm optimization. In *IEEE Electric Power and Energy Conference (EPEC), 2010*, pages 1–5. IEEE, 2010.

[52] M. Pedrasa, T.D. Spooner, and I.F. MacGill. Scheduling of demand side resources using binary particle swarm optimization. *IEEE Transactions on Power Systems*, 24(3):1173–1181, 2009.

[53] L. Yao, W.C. Chang, and R.L. Yen. An iterative deepening genetic algorithm for scheduling of direct load control. *IEEE Transactions on Power Systems*, 20(3):1414–1421, 2005.

[54] Saeid Bashash and Hosam K. Fathy. Modeling and control of aggregate air conditioning loads for robust renewable power management. *IEEE Transactions on CONTROL SYSTEMS TECHNOLOGY*, 2012.

[55] A. Molina-García, M. Kessler, J.A. Fuentes, and E. Gómez-Lázaro. Probabilistic characterization of thermostatically controlled loads to model the impact of demand response programs. *IEEE Transactions on Power Systems*, 26(1):241–251, 2011.

[56] M. Biabani, M.A. Golkar, and A. Sajadi. Operation of a multi-agent system for load management in smart power distribution system. In *11th International Conference on Environment and Electrical Engineering (EEEIC), 2012*, pages 525–530. IEEE, 2012.

[57] J.L. Mathieu, S. Koch, and D.S. Callaway. State estimation and control of electric loads to manage real-time energy imbalance. *IEEE Transactions on Power Systems*, 2012.

[58] N. Gatsis and G.B. Giannakis. Residential load control: Distributed scheduling and convergence with lost ami messages. *IEEE Transactions on Smart Grid*, 3(2):770–786, 2012.

[59] A. Berard, N. Veillerobe, M. Hennebel, and Y. Phulpin. Strategies for demand load control to reduce balancing costs. In *7th International Conference on the European Energy Market (EEM), 2010*, pages 1–6. IEEE, 2010.

[60] K. Bhattacharyya and ML Crow. A fuzzy logic based approach to direct load control. *IEEE Transactions on Power Systems*, 11(2):708–714, 1996.

[61] C.M. Chu, T.L. Jong, and Y.W. Huang. Mitigating dlc constraints of air-conditioning loads using a group-dlc method. In *IEEE Power Engineering Society General Meeting, 2007.*, pages 1–6. IEEE, 2007.

[62] A. Gomes, C.H. Antunes, and A.G. Martins. A multiple objective evolutionary approach for the design and selection of load control strategies. *IEEE Transactions on Power Systems*, 19(2):1173–1180, 2004.

[63] A. Gomes, CH Antunes, and AG Martins. A multiple objective approach to direct load control using an interactive evolutionary algorithm. *IEEE Transactions on Power Systems*, 22(3):1004–1011, 2007.

[64] D.S. Callaway. Can smaller loads be profitably engaged in power system services? *IEEE Power and Energy Society General Meeting, 2011*, pages 1–3, 2011.

[65] G. Strbac and D. Kirschen. Assessing the competitiveness of demand-side bidding. *IEEE Transactions on Power Systems*, 14(1):120–125, 1999.

[66] L. Goel, V.P. Aparna, and P. Wang. A framework to implement supply and demand side contingency management in reliability assessment of restructured power systems. *IEEE Transactions on Power Systems*, 22(1):205–212, 2007.

[67] S. Borenstein, M. Jaske, and A. Rosenfeld. Dynamic pricing, advanced metering, and demand response in electricity markets. 2002.

[68] J. Wang, S. Kennedy, and J. Kirtley. A new wholesale bidding mechanism for enhanced demand response in smart grids. In *Innovative Smart Grid Technologies (ISGT), 2010*, pages 1–8. IEEE, 2010.

[69] J.T. Wenders. Peak load pricing in the electric utility industry. *The Bell Journal of Economics*, pages 232–241, 1976.

[70] M.A. Crew, C.S. Fernando, and P.R. Kleindorfer. The theory of peak-load pricing: a survey. *Journal of regulatory economics*, 8(3):215–248, 1995.

[71] Y. Tang, H. Song, F. Hu, and Y. Zou. Investigation on tou pricing principles. In *Transmission and Distribution Conference and Exhibition: Asia and Pacific, 2005 IEEE/PES*, pages 1–9. IEEE, 2005.

[72] AK David and YZ Li. Effect of inter-temporal factors on the real time pricing of electricity. *IEEE Transactions on Power Systems*, 8(1):44–52, 1993.

[73] D.S. Kirschen, G. Strbac, P. Cumperayot, and D. de Paiva Mendes. Factoring the elasticity of demand in electricity prices. *IEEE Transactions on Power Systems*, 15(2):612–617, 2000.

[74] F.C. Schweppe, R.D. Tabors, MC Caraminis, and R.E. Bohn. Spot pricing of electricity. 1988.

[75] A. Abdisalaam, I. Lampropoulos, J. Frunt, GPJ Verbong, and WL Kling. Assessing the economic benefits of flexible residential load participation in the dutch day-ahead auction and balancing market. In *9th International Conference on the European Energy Market (EEM), 2012*, pages 1–8. IEEE, 2012.

[76] Y. Li and M. Trayer. Automated residential demand response: Algorithmic implications of pricing models. In *IEEE International Conference on Consumer Electronics (ICCE), 2012*, pages 626–629. IEEE, 2012.

[77] R. Yu, W. Yang, and S. Rahardja. Optimal real-time price based on a statistical demand elasticity model of electricity. In *First International Workshop*

on Smart Grid Modeling and Simulation (SGMS), 2011 IEEE, pages 90–95. IEEE, 2011.

[78] J.Y. Joo, S.H. Ahn, and Y.T. Yoon. Enhancing price-responsiveness of end-use customers' loads: dynamically administered critical peak pricing. *European Transactions on Electrical Power*, 19(1):113–126, 2009.

[79] K. Herter. Residential implementation of critical-peak pricing of electricity. *Energy Policy*, 35(4):2121–2130, 2007.

[80] P. Samadi, H. Mohsenian-Rad, R. Schober, and V.W.S. Wong. Advanced demand side management for the future smart grid using mechanism design. *IEEE Transactions on Smart Grid*, 3(3):1170–1180, 2012.

[81] H.G. Kwag, Y.H. Kim, and J.O. Kim. Virtual peak plant concepts of demand response. In *International Conference on Systems and Informatics (ICSAI), 2012*, pages 614–618. IEEE, 2012.

[82] The comverge smartprice intelligent dynamic pricing solution. URL http://www.comverge.com/DynamicPricing-1.

[83] Enernoc - get more from energy, . URL http://www.enernoc.com/our-resources/138-resources/white-papers/566-the-demand-response-baseline.

[84] S. Mohagheghi, J. Stoupis, Z. Wang, Z. Li, and H. Kazemzadeh. Demand response architecture: Integration into the distribution management system. In *First IEEE International Conference on Smart Grid Communications (SmartGridComm), 2010*, pages 501–506. IEEE, 2010.

[85] M. Babar, I. Ahmed, A. Shah, S.H. Al Ghannam, E.A. Al-Ammar, N.H. Malik, and F.R. Pazehri. An algorithm for load curtailment in aggregated demand response program. In *2012 IEEE PES Conference on Innovative Smart Grid Technologies-Middle East (ISGT Middle East)*. IEEE, 2012.

[86] Katherine Tweed. Demand response companies meet customer engagement, 2010. URL http://seekingalpha.com/article/219713-demand-response-companies-meet-customer-engagement.

[87] C.M.D. Puckette, G.J. Saulnier, R.A. Korkosz, and J.E. Hershey. Ghm aggregator, February 12 2002. US Patent 6,346,875.

[88] J.A.P. Lopes, F.J. Soares, and P.M.R. Almeida. Integration of electric vehicles in the electric power system. *Proceedings of the IEEE - Inst. de Eng. de Sist. e Comput. do Porto-INESC Porto, Porto,*, 99(1):168–183, 2011.

[89] M.D. Galus, R.A. Waraich, F. Noembrini, K. Steurs, G. Georges, K. Boulouchos, K.W. Axhausen, and G. Andersson. Integrating power systems, transport systems and vehicle technology for electric mobility impact assessment and efficient control. *IEEE Transactions on Smart Grid*, 3(2):934–949, 2012.

[90] S. Carr. Virtual power plants. *International Journal of Scientific & Engineering Research (ISSN 2229-5518)*, 2011.

[91] S.A. Arefifar, Y.A.R.I. Mohamed, and T.H.M. El-Fouly. Supply-adequacy-based optimal construction of microgrids in smart distribution systems. *IEEE Transactions on Smart Grid*, 3(3):1491–1502, 2012.

[92] W. Kempton, J. Tomic, S. Letendre, A. Brooks, and T. Lipman. Vehicle-to-grid power: battery, hybrid, and fuel cell vehicles as resources for distributed electric power in california. 2001.

[93] S. Han, S. Han, and K. Sezaki. Development of an optimal vehicle-to-grid aggregator for frequency regulation. *IEEE Transactions on Smart Grid*, 1 (1):65–72, 2010.

[94] R.J. Bessa and M.A. Matos. Economic and technical management of an aggregation agent for electric vehicles: a literature survey. *European Transactions on Electrical Power, 2011*, 2011.

[95] D. Wu, D.C. Aliprantis, and L. Ying. On the choice between uncontrolled and controlled charging by owners of phevs. *IEEE Transactions on Power Delivery*, 26(4):2882–2884, 2011.

[96] E. Sortomme and M.A. El-Sharkawi. Optimal charging strategies for unidirectional vehicle-to-grid. *IEEE Transactions on Smart Grid*, 2(1):131–138, 2011.

[97] E. Sortomme and M.A. El-Sharkawi. Optimal scheduling of vehicle-to-grid energy and ancillary services. *IEEE Transactions on Smart Grid*, 3(1):351–359, 2012.

[98] D. Wu, D.C. Aliprantis, and L. Ying. Load scheduling and dispatch for aggregators of plug-in electric vehicles. *IEEE Transactions on Smart Grid*, 3(1):368–376, 2012.

[99] H.A. Sher and K.E. Addoweesh. Power storage options for hybrid electric vehicles- a survey. *Journal of Renewable and Sustainable Energy*, 4:052701, 2012.

[100] C. Tudor, E. Sprung, L. Nguyen, and R. Tatro. Plug-in & hybrid electric vehicle charging impacts: A survey of california's utility companies. In *IEEE 13th International Conference on Information Reuse and Integration (IRI), 2012*, pages 513–518. IEEE, 2012.

[101] Edison project electric vehicles in a distributed and integrated market using sustainable energy and open networks, 2012. URL http://www.dtu.dk/centre/cet/English/research/projects/22_TheEDISON_project.aspx.

[102] Enervate - uk, accelarating e-mobility, electric vehicle technology, . URL http://www.enevate.eu/Workpackage1?Edition=en.

[103] Nuvve - usa, smart grid powered by v2g. URL http://www.nuvve.com/Home_Page.html.

[104] T. Sousa, H. Morais, Z. Vale, P. Faria, and J. Soares. Intelligent energy resource management considering vehicle-to-grid: A simulated annealing approach. *IEEE Transactions on Smart Grid*, 3(1):535–542, 2012.

[105] P. Lombardi, M. Powalko, and K. Rudion. Optimal operation of a virtual power plant. In *IEEE Power & Energy Society General Meeting, 2009. PES'09.*, pages 1–6. IEEE, 2009.

[106] M. Peik-Herfeh, H. Seifi, and MK Sheikh-El-Eslami. Decision making of a virtual power plant under uncertainties for bidding in a day-ahead market using point estimate method. *International Journal of Electrical Power & Energy Systems*, 44(1):88–98, 2013.

[107] J. Gong, D. Xie, C. Jiang, and Y. Zhang. Multiple objective compromised method for power management in virtual power plants. *Energies*, 4(4):700–716, 2011.

[108] D. Pudjianto, C. Ramsay, and G. Strbac. Virtual power plant and system integration of distributed energy resources. *Renewable Power Generation, IET*, 1(1):10–16, 2007.

[109] Virtual power plant - southern california telephone and energy. URL http://www.socaltelephone.com/energy.cfm.

[110] flexitricity. URL http://www.flexitricity.com/.

[111] Fenix. URL http://www.fenix-project.org/.

[112] S. Dave, M. Sooriyabandara, and L. Zhang. Application of a game-theoretic energy management algorithm in a hybrid predictive-adaptive scenario. In *2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies (ISGT Europe), 2011*, pages 1–6. IEEE, 2011.

[113] Fast demand response. *PARC, A Xerox Company*, 2010.

[114] Energy connect incorporation - integrated demand response, . URL http://www.energyconnectinc.com.

[115] Katherine Tweed. The top five players in demand response, 2010. URL http://www.greentechmedia.com/articles/read/top-5-demand-response/N2/.

[116] FR Pazheri, MF Othman, NH Malik, and OK Safoora. Economic and environmental dispatch at highly potential renewable area with renewable storage. *Int J Environ Sci Dev*, 3(2):177–182, 2012.

[117] S. Brini, H.H. Abdallah, and A. OUALI. Economic dispatch for power system included wind and solar thermal energy. *Leonardo Journal of Sciences*, 14:204–220, 2009.

[118] N.S. Rau and W.D. Short. Opportunities for the integration of intermittent renewable resources into networks using existing storage. *IEEE Transactions on Energy Conversion*, 11(1):181–187, 1996.

[119] Aggregator managed portfolio (amp) program, pacific gas and electric company. URL http://www.pge.com/mybusiness/energysavingsrebates/demandresponse/amp/.

[120] S.I. Gass. Decision making, models and algorithms. chapter 23. *JOHN WILEY & SONS, INC., ONE WILEY DRIVE, SOMERSET, NJ 08873(USA), 1985, 410*, 1985.

[121] A. Kaufmann and H.C. Sneyd. *Graphs, dynamic programming, and finite games*, volume 36. Academic Press New York, 1967.