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Modeling and Analysis of Residential Demand Response Programs With Real Time Pricing

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Submitted By:

Shalini Pal

(2013REE9545)

Supervisor:

Dr. Rajesh Kumar

MALAVIYA NATIONAL INSTITUTE OF TECHNOLOGY

JAIPUR, RAJASTHAN

DECLARATION

I, Shalini Pal, declare that this Dissertation titled, "Modeling and Analysis of Residential Demand Response Programs with Real Time Pricing" and the work presented in it are my own. I confirm that:

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(Dr. Rajesh Kumar)

Professor

Department of Electrical Engineering

MNIT, Jaipur

Place: Jaipur

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ABSTRACT

The smart grid is a self-employed future generation electricity grid. As per the conventional power system with thermal generation, it is not able to meet the future growing energy demand which leads the application of demand response (DR). As smart grid enablers, demand response programs have been a major attraction for reducing the peak demand in the electrical power system. The uncertain nature of residential loads makes it more valuable in the execution of DR. The household user can contribute a significant potential for reduction in energy demand during peak hours. In this work, the focus is oriented to execute DR for residential customers. Firstly, the automatic load scheduling with real-time pricing environment for the residential load is proposed. The bi-directional communication between energy customer and load-serving entity runs with the help of automatic load control unit (ALCU), which consists of a built-in smart meter. While executing DR with real-time pricing, the price prediction is a requirement to know future prices. For price forecasting, it needs a call from optimization techniques. The revolutionary advancement in the automotive field has given electric vehicle (EV) load as new transportation. Next, the problem of load scheduling is obtained by including new EV load with bidirectional communication of power between user and grid. A concept of neighborhood power-sharing is proposed in the presence of EV. Finally, the renewable sources are also integrated with the proposed load scheduling in the presence of EV and battery energy storage. With the inclusion of renewable sources a problem of carbon mitigation is also proposed. The existing load scheduling can result in forming new off-peak loads, to avoid the generation of new off-peak load, the load scheduling incorporating demand fluctuations is developed.

To deal with the competitive environment among users and utility, various decision-making approaches are combined as a part of this work. A game theoretic based model by incorporating consumer preference is proposed, this initiates an energy consumption scheduling using correlated equilibrium. The proposed model assures fairness of Nash Equilibrium among the user, in the long run, to serve as a benchmark for performance evaluation. DR problem in centralized framework involves several issues such as privacy, compatibility, and scalability for the user. Therefore a distributed algorithm for load scheduling is proposed by using an alternating direction method of multipliers (ADMM). The proposed ADMM algorithm executed in the parallel form and guaranteed the fast convergence for the problem. The motivation behind this work is to develop a framework that takes advantage of DR as a reliable source in the electricity infrastructure.

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List of Abbreviations

ADMM	Alternating method of multiplier
AI	Artificial intelligence
ALCU	Automatic load controller unit
AMI	Advanced metering infrastructure
ANN	Artificial neural network
BESS	Battery energy storage system
BC	British Columbia
CCU	Centralized control unit
CPP	Critical peak pricing
DAP	Day-ahead price
DLC	Direct load control
DR	Demand response
DSM	Demand side management
EVs	Electric vehicles
FC	Fuel cell
GA	Genetic algorithm
GMM	Gaussian mixture model
HA	Home agent
HAN	Home area network
HC	High consumption
HEM	Home energy management
IBR	Inclining block rate
LAN	Local area network
LC	Low consumption
LF	Load factor
LPM	Linear prediction model
LSE	Load-serving entity
Max	Maximum
MBLP	Mixed binary linear programming

MC	Mid consumption
MILP	Mixed integer linear programming
Min	Minimum
OP	Optimization problem
PAR	Peak to average ratio
PHEV	Plug-in electric vehicle
PSO	Particle swarm optimization
PV	Photovoltaic
RA	Retailer agent
RTP	Real time pricing
TCF	Total cost function
TOU	Time of use
V2G	Vehicle-to-grid
V2H	Vehicle-to-home
V2N	Vehicle-to-neighbor
VHC	Very high consumption
WAN	Wide area network

Chapter 1

Introduction

Today's electricity grid is designed in such a way that it can improve the operation of generation, transmission, and distribution of conventional electricity grid with advanced control systems and devices. However as the new generation of electricity paradigm evolves with renewable energy sources penetration, it changes the whole game for the system operators, electricity market players, and the end-customers. The other challenge is to manage the communication requirements to achieve reliable and automatic operation of the electricity grid. The next generation grid called a smart grid is equipped with information and communication technology (ICT) and real-time analysis to enhance the flexibility and forecasting to build protection from internal and external hazards [1]. The smart grid can handle the uncertain power transfer, utilizing renewable sources, evaluating the unpredictable islanding and planning operations in the system. The smart grid utilizes the information and communication technology (ICT) to automate the operations on a smart meter as to achieve security, efficiency and reliability [2]- [3]. The development of smart grid depends on system operators, utilities, policy makers, stakeholders, technology providers, researchers, and end-customers. The implementation of the smart grid is not possible without buy-in or stakeholders involvement. Policy-makers are corporate and state regulators to design policies according to all parties. The installation and implementation of power grid technologies are managed by utilities. The technology providers are responsible for the development of smart grid technologies for grid enhancements. Researchers develop the tools and techniques for the smart grid. The end-customers participates and gives their input to regulate the smart grid. For the deployment of the smart grid the demand side management programs are developed to provide the control on growing power demand.

1.1 Demand Side Management

Demand side management (DSM) is developed to modify the end-customer load demand for reducing the monetary cost for expensive generators and additional power generation in the long run. DSM programs are commonly referred by utility companies to handle the demand of customers by utilizing smart meters. DSM programs have the opportunity to provide the benefits to both utility and the customer which helps the electricity market to operate efficiently by reducing peak to average ratio of supply and real-time power transactions [4].

DSM contributes to emission reduction from conventional plants, customer cost reductions, and generation reliability. These factors affect utility load-curve. The DSM is implemented via techniques such as peak clipping, valley filling, load shifting, load building, energy conservation and flexible load [5]. The graphical representation of these DSM techniques is shown in Fig. 1.1.

- *Peak clipping:* It refers to the reduction of demand during peak periods. It can reduce the need for additional generation capacity. The net result is a reduction in both peak demand and total power consumption. Peak clipping may be achieved using direct control of customer appliances.
- *Valley filling:* The load demand during off-peak hours is increased to achieve flatten load profile. The load increment is done by encouraging the user to increase their energy demands.
- *Load shifting:* It involves shifting loads from on-peak to off-peak periods. The net result is a decrease in demand for peak periods, without changing total power consumption.
- *Load building:* It is utilized when load demand is increased due to excess energy production.
- *Energy conservation:* It refers to reduce the load consumption by consumers. There is a decrease in both demand and total power consumption. Strategic conservation can be achieved by motivating customers to use more energy-efficient appliances.

Among all the techniques listed above, load shifting is the most intellectual choice because it shifts the load according to consumer preference ensuring their satisfaction.

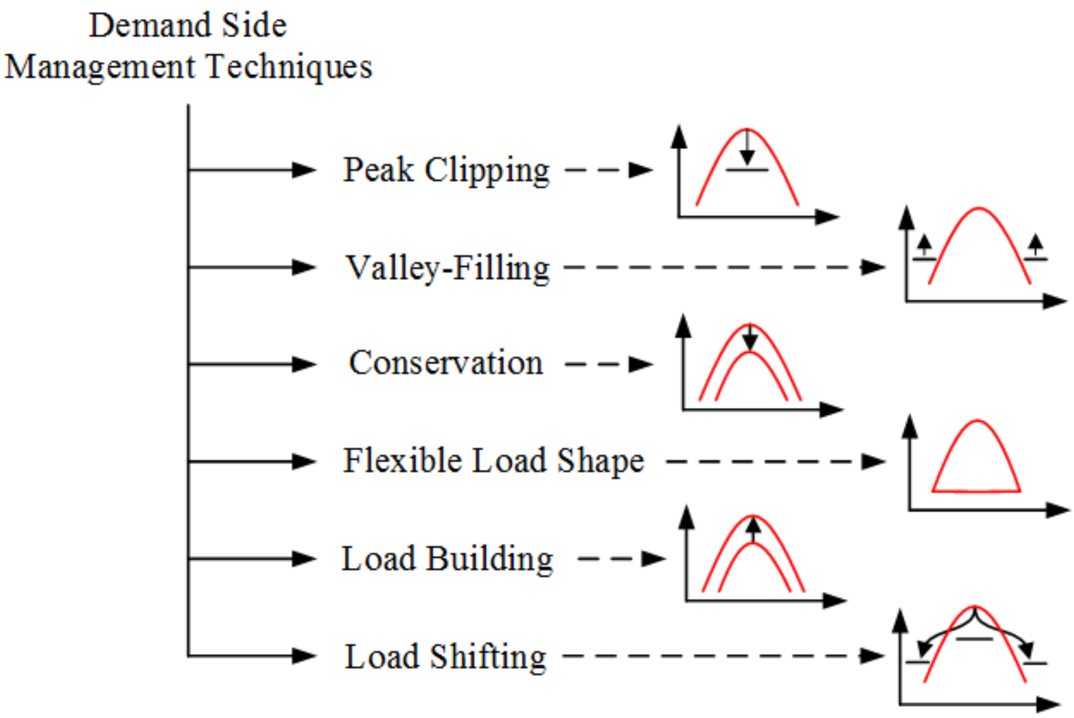


Figure 1.1: DSM techniques

There are two terms which is widely used to maintain the supply-demand ratio i.e. demand side management and demand response programs. The DSM programs are used at end-user level but their primary goal is energy efficiency. DSM actions provides change in energy use for given energy service, by reducing long-term energy requirements. On the other hand Demand response (DR) programs are used for short-term reductions in the energy demand. DR programs have two main goals i.e. 1) economic benefits for the utility and end-consumer and 2) customer satisfaction and improved power system reliability [6].

1.2 Demand Response Programs

The standard definition of demand response is provided by U.S. Department of Energy Information as, "*Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized* [7]." DR is also defined as the term used for programs to encourage the end-customers to make short-term reductions in their power demand in exchange of price information from the electricity grid or hourly energy market [8]. The DR actions are only associated with the distribution or demand-side network of electricity grid infrastructure. Generally, the range of DR actions lies between 1 to 4 hour of period and includes turning off of certain lighting banks or shutting down a manufacturer load side.

The DR actions are also beneficial as they offer the customers to shed loads during peak hours of demand for the whole electric system. The main reason for DR benefits is that the demand-supply under tight constraints can help in reducing peak hour electricity prices and total price volatility for all end-customers. Another benefit is by reducing peaks in system load curve it can reduce the need for installing new expensive generation, transmission, and distribution equipment to meet the peak demand. The DR programs are also proven more attractive than energy efficiency programs as it requires little capital expenses comparatively as they are operating in short cycle. On the other hand, energy efficiency programs have expensive capital expenditure and a long-term payback cycle. The risk offered by DR programs are also minimal as when prices are low, the customer can even get benefit by achieving lesser electricity bill without any DR opportunity. In this sense, DSM programs are likely proven riskier if the price expectation does not occur the economic saving get reduced, and payback cycle becomes lengthy.

1.3 DR Challenges and Opportunities

The DR programs consist two main entities to execute their actions i.e. the end-customer and utility company or energy provider entity according to the National Institutes of Standards and Technology [9]. The execution of DR programs have several challenges and opportunities associated with load handling, variety of customers, price information handling and communication requirements at the end-customer's location.

1.3.1 Customer Classification

The interaction between end-customer and utility companies plays an important role for executing DR programs. The customers consumes energy provided by the electricity grid and the participation in DR is voluntary or compulsory according to policies offered by utility companies. According to the U.S. Department of Energy, the energy customer can be classified on the basis of their energy usage [10] as follows,

- Commercial

- Industrial
- Residential
- Transportation

The energy consumption by different sectors accounts for total electricity usage in a nation's electricity requirement. Each type of end-user is able to reduce their usage through DR programs. The commercial sector comprises the service and equipment provider entities, government authorities and private entities. On an average scale, the commercial sector is responsible for more than one-third of electricity consumption [11]. The commercial sector loads are mainly due to heating and lighting devices, air-conditioning and ventilation. The commercial load demand is mostly high due to large working hours for business operations, but their demand decreases during nights hours and weekends.

The industrial sector consists the manufacturing, mining, agricultural and construction industries. They are also equipped with food and equipment processing, producing or assembling. This sector is occupied less than one-third of electricity consumption. Most of the demand is due to the manufacturing companies for acquiring various machinery equipment. Another demand occurs due to electrochemical processes which are used for energy transformation purpose. In this sector, the demand pattern does not have much uncertainty; even the demand pattern is similar throughout the year.

The residential sector comprises the single-member family houses and multi-occupancy homes. This sector claims to occupy with more than one-third of total electricity consumption. Even this sector occupies maximum consumption among all energy sectors. Residential houses consume for different critical and non-critical appliances such as lighting devices, heating and cooling equipment, food making appliances, air-conditioners, and other daily utility appliances. In this sector, electricity demand is highly correlated to the different season of the year. The residential demand does also depend on individual user behavior.

The transportation sector consists of the automobiles used in daily life transport. The transport vehicles are running on fossil fuels such as natural gas, diesel, and petrol. But nowadays due to the emerging technology, electric vehicles (EVs) have gained attention. EVs are also used as a mode of transportation. EVs can be of a type as pure battery-powered cars, hybrid vehicles, and plug-in vehicles which has battery storage facility from the electricity grid and use the power for other purposes. The different automobiles such as electric vans, trucks, and buses are available in the market. This sector consumes less than 1 percent of total electricity consumption. This type of vehicles is also utilized for fed back power to the grid during peak hours. This sector also contributes to storage asset for the household users.

As the DR programs are associated with the customer interest for participation, this certainly depends on the type of customer. As in the case of the commercial and industrial user, it captures high consumption, the potential of utilizing DR in these categories are very high because of high individual demands. But most of the application associated with commercial and industrial users are critical in usage, so it is not much benefit to getting a demand reduction via these customers. Whereas residential customers occupy most of the energy usage in total, but individual demand is comparatively low. Therefore in the residential sector, DR programs are proven a more powerful approach to enhance the reduction in the peak demand of the total system.

1.3.1.1 Load Handling

The load demand and electricity price are the two main parameters for building DR actions. For DR execution, the customer is required to communicate their aggregated load demand to the utility company. This load information can be utilized to define the peak and off-peak demands periods. The utility can store the load information given by users and can convert it into historical load data. This historical data is useful for future load scheduling of customers. The future load of a customer can be forecasted by analyzing the customer behavior data and through advanced forecasting techniques. The accurate estimation techniques [12] are need to be established for customer load prediction. Estimation techniques can also predict customer usage behavior.

1.3.1.2 Electricity Price Information

In DR programs, the customer gets price information from a utility in exchange for their load in real-time or day-ahead basis. An efficient DR depends on the ability of price forecasting at the end of customers and market side as well. Conventional forecasting techniques are mature enough to deal with the situation, but the involvement of real-time pricing (RTP) make it challenging. The forecasting for RTP should be done in short intervals such as one hour or half an hour or even a few minutes before. In this context, the smart meters are required to face this challenge. Effective price prediction techniques should be developed and embedded in the smart meter structure to handle the increased uncertainties in the system.

The common behavior of electricity prices mainly depends on certain features [13] given as follows,

- Seasonal electricity prices
- Price dependency on past similar days
- Electricity price and load correlation

1.3.2 Communication Infrastructure

The communication infrastructure is an essential requirement for implementing DR to enable two-way information communication between utility and customers. With the advancement of advanced metering infrastructure (AMI) and its bi-directional communication capabilities, the vision of the future smart grid is achievable. The AMI technology comprises different components such as smart meters, different levels of communication with hierarchy architecture, meter data management systems (MDMS), data collection in software platform and its interfacing [14].

The two-way communication techniques are most attractive due to its feature of allowing monitors the DR event and identify the load distinction. By using such infrastructure, it is possible that the utility can also directly communicate and measure the requirement of the individual customer. The customer load reduction involvement can also be monitored during DR real-time actions. The two-way communication also allows the utility to control the intermittent nature of renewable generation combined with DR to drive services such as frequency control and voltage support. The communication infrastructure of the smart grid exhibits central controllers with the hierarchical structures as shown in Fig. 1.2. It also includes home area network (HAN) which consists the home appliances and devices connected to the smart meters with the gateway. The different HANs are then connected to the neighborhood area networks (NANs) and communicating the information to the utility or energy management system.

The wireless networks are top rated in recent times due to their economic cost charges, but congestion problem is the main obstacle for the wireless communication network. The utilization of power line communication (PLC) technology has gained attention due to low-cost employment and network latency. A review in [15] shows the application of PLC which is utilized for a smart grid from high-voltage lines to smart meter inside the home. The implementation of signal processing algorithm is essential to make

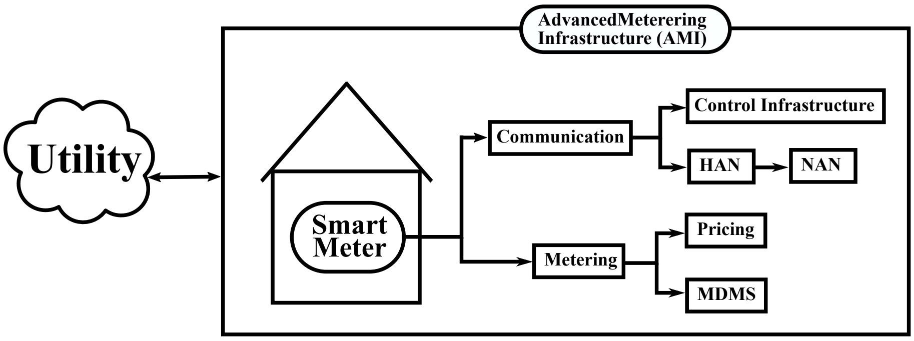


Figure 1.2: AMI hierarchical structure

decisions in short time intervals for getting a large amount of information to be transmitted through the network and to provide better control on appliances action for DR customers.

1.3.3 Electric Vehicles Integration

Recent trends have led the emergence of a concept of EVs in the world of automotive industry. The environmental benefits of electric vehicles and impact on the carbon emission level have taken it into the limelight [16]. The integration of EVs to the electricity system is associated with certain challenges such as the optimal time slots of charging and discharging of EVs and uncertainties related to EVs availability. To analyze the potential of electric vehicles usage in the power system, it is important to know when to charge and when to discharge them. It leads to their application in demand response programs where the solution for the scheduling.

1.3.4 Renewable Sources Deployment

The DR economic benefits to the customer and utility are highly encouraging for users to utilize it, but the need to reduce carbon footprints for global environment is also a matter of concern, which is influenced by electricity generation and consumption. This issue can be resolved by utilizing renewable energy sources (RES) and by maintaining the electricity consumption at the end-customer side. The carbon capture technologies in electricity generation will be deployed time by time. The available renewable sources such as hydro, wind, natural gas, solar, nuclear and geothermal energies offer lesser carbon impacts, where solar and wind generations are available for deployment purpose and produce clean energy. A high number of wind farms are available at the potential location worldwide, where wind impacts are high. Rooftop solar panels have also gained much attention due to available solar capacities. But unlikely conventional generations, the solar and wind generation are highly uncertain and uncontrolled. The integration of renewable sources to the electricity grid requires advanced technology and efficient control system to operate reliably [17]- [18]. The renewable sources deployment in the DR programs can make it more feasible to reduce carbon impact and reduction in peak demand due to surplus generation available at the customer side.

1.4 Research Goals

In this thesis, the problem of residential DR is attempted to solve by using different approaches with the incorporation of the electric vehicle and renewable generation. The presented work is applicable for different options to determine the challenges associated with residential DR. In this thesis; the following primary goals are considered to implement appropriate and practical DR approach for residential customers,

- Residential customers are equipped with distinct appliances at homes. The appliances have specific characteristics in individual houses, and it is necessary to model the appliances in an appropriate way that user should not comprise their comfort while executing DR. For this purpose, various type of appliances with their priority operating time is considered in this research.
- The user willingness in participating DR programs is a point of consideration. Individual users should gain economic benefits while participating in proposed DR approaches. However, the approach should be user-friendly to make user operation easier.
- The DR approach should be expandable to execute it over a large number of houses. The proposed approach is developed by considering this option of expanding them into a large pool of residential customers.
- From energy provider or the electricity grid point of view, lowering the peak to average ratio (PAR) is an important objective to achieve. But in the era of renewable generation and EVs deployment, the objective of only minimizing PAR is not suitable. From the customer's point of view, their economic benefits should be present in the process DR executions while executing future DR approaches.
- The involvement of a large number of end-customers in the DR execution can make the environment competitive from the point of energy consumption schedul-

ing and economic benefits as well as. It is required to develop a healthy environment for the execution of a DR where a separate user should be operated in a fair competitive environment.

- The influence of carbon footprints in the environment is rapidly increasing. There is an alarming situation which should be taken in care. With this perspective, the utilization of clean energy sources will be advantageous. The integration of carbon-less electric vehicle and renewable sources to the DR problem is made useful in this research.

1.5 Research Contribution

The main objective of DR programs is to maintain the demand-supply ratio to achieve a desired load demand curve. This thesis mainly covers the various aspect of the DR approach combines with the electric vehicle and renewable generation. The main contributions of the work as mentioned in the above goals are explained as follows,

1. The proposed DR approach exhibits the smart charging technology for EV scheduling in the residential sector. The operation and analysis of power transaction incorporation are done between the user and the electricity grid in the presence of power-sharing concept among neighbors in the residential DR framework.

2. The proposed dynamic DR model introduces a correlated equilibrium approach in a game theoretic scenario for the residential consumer. The proposed methodology reveals a scheduling sequence based on the users priority order which leads to high economic benefit for a particular user as well as for society. The proposed model also assures the fairness of Nash Equilibrium among the user, in the long run, to serve as a benchmark for performance evaluation.

3. The proposed DR approach is evaluated in the distributed framework which avoids the limitation of the centralized manner for load scheduling optimization. In this context, an alternating direction method of multiplier (ADMM) is used to solve the optimization problem which works in parallel form. This approach exhibits the customer's privacy measure in the DR load scheduling. It makes this system reliable and controlled to ensure user privacy. The ADMM algorithm guaranteed the fast convergence of the optimization problem.

4. A structure of a smart household with distinct appliances is considered in this DR approach. The utilization of renewable sources, electric vehicle and battery

energy storage system are assembled to achieve the reduction in peak demand and optimizing the user electricity bill. Here a customer's satisfaction parameter is also included in DR.

5. The smart appliance load scheduling of residential user mainly depends on the uncertain behavior of user for utilizing their appliances. Here the consumer preferences inclusion in the DR problem is incorporated to analyze user behavior. In this approach, a household user is participating in the dual problem of minimizing their electricity bill and reducing carbon emission with the inclusion of renewable energy sources.

6. The DR applications are full of benefits, but there is a disadvantage of implementing DR programs. The DR approach encourages the participants to shift their load demand from peak hours to off-peak hours. It can lead to a situation where off-peak times can be converted into peak demand hours, As to cope with this problem an extra term for deviation cost is added to user problem which can prevent the formation of new peaks during off-peak hours.

1.6 Thesis Organization

The brief thesis organization is shown in Fig. 1.3. Chapter 2 illustrates the literature review based on DR classified associated programs, DR issues. Chapter 3 provides detail about the modeling of appliances in DR programs. The exploration of different DR pricing scheme is executed in this chapter. The DR problem is also explored with the potential of price prediction techniques in this chapter. Chapter 4 describes the integration of electric vehicle in DR problem presented in several scenarios such as the deployment of vehicle to grid, vehicle to home and vehicle to neighbor technologies. Chapter 5 explains the utilization of renewable energy source in DR context to electricity bill minimization and reduction in carbon footprints. Chapter 6 describes a game theory based model to solve energy consumption scheduling problem in a distributed manner. In Chapter 7, DR problem is solved in a distributed manner to overcome the privacy concern for household customers. Chapter 8 concludes with the explanation of DR approach benefits and future scope.

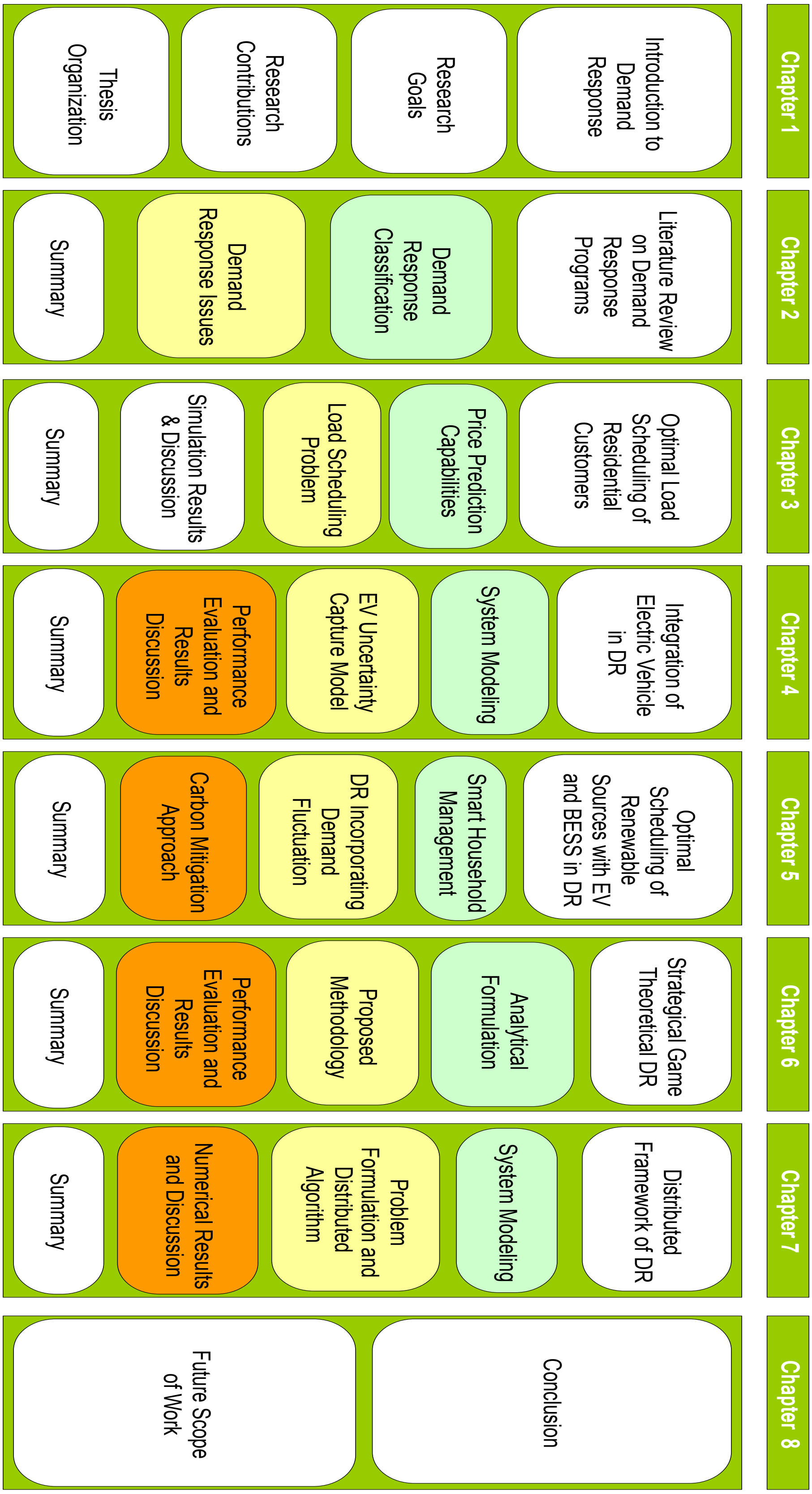


Figure 1.3: Thesis Structure

Chapter 2

Demand Response: Literature Review

2.1 Introduction

The DR programs have initiated in early 1980s when spot pricing has came into limelight [19] as the development of the new electricity price in market. Here spot pricing is referred as demand charges and determined fro buying and selling electricity by the analyzing the demand and supply condition at the the spot. In the same DR context, a theory of utility-consumer interaction based on dynamic tariffs is developed in [20]. This work has extended the concept of spot pricing in dynamic tariff in terms of utility-consumer interaction for large industrial consumers. The theory of user interaction models and price forecasting under dynamic conditions is examined and observed that the model can get benefits for both the user and utility in the electricity market. A summary of demand response in the electricity market is discussed in [21]. The DR standard definitions and classification is examined to analyze the potential economic benefits and reliability of system. The experience of different utilities for DR programs is also described.

The ability to shape the load-demand curve DR has become essential approach to make future smart grid employable. In the present work, the focus is oriented on residential DR. The abstract picture of DR is shown in Fig. 2.1. In the DR, a residential household is available at demand side. The residential household is equipped with different shiftable and non-shiftable type of electric appliances. These electric appliances includes lighting, air-conditioner, washing machine, ironing appliances, refrigerator and others. At the supply side utility companies or load serving entities are available to provide the electricity to household user from bulk generation. For communication purpose between the utility and customer, a automatic load control unit (ALCU) is installed in

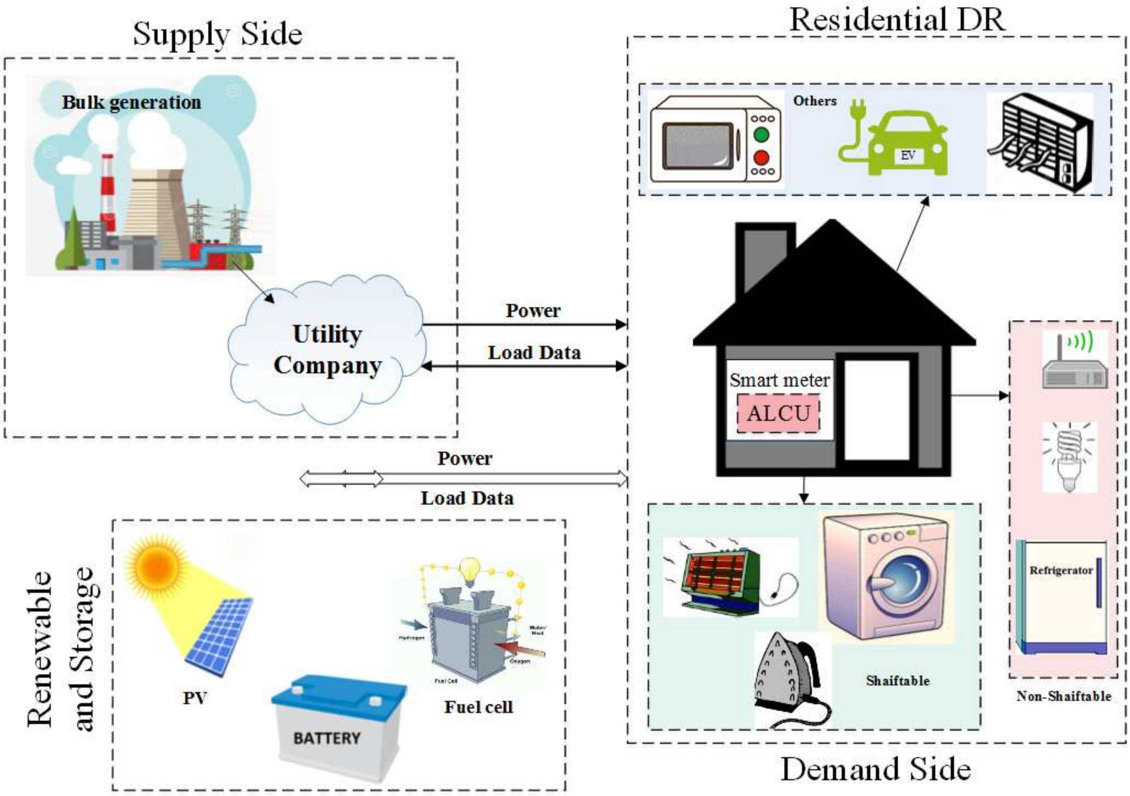


Figure 2.1: Residential DR abstract picture

each customer houses. This ALCU has a built-in smart meter to enable the communication. The ALCU is a component by through a user can run the energy consumption scheduling. Presently many customers have prefer to install some renewable generations such as wind, solar and fuel-cell at their ends. The customer is required to give their load information data to the utility in exchange of day-ahead electricity prices.

DR employs by the means of tariffs or incentives provided by utility to encourage the user for participating in load-shifting programs [21]. The literature DR programs can be divided into three segments as by the classification, DR issues and the computational techniques applications.

2.2 Demand Response Classification

The DR programs can be classified in two categories i.e. the incentive based DR and price-based DR programs as shown in Fig. 2.2.

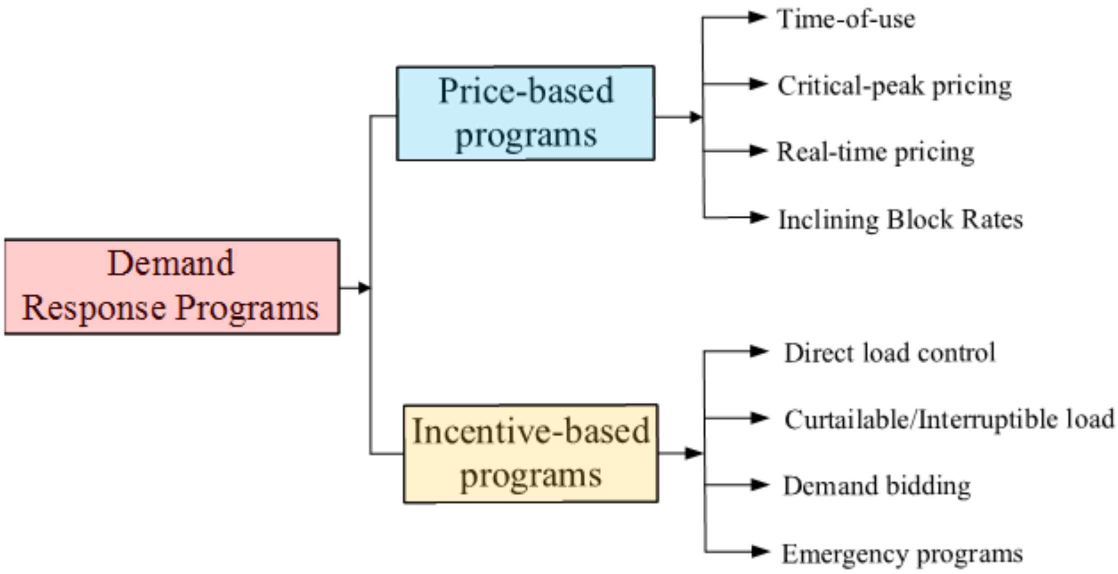


Figure 2.2: DR Clssification

2.2.0.1 Incentive based DR

The incentive-based programs provides facilities to the participant user for the load-reduction during peak demand hours or system failure. By participating in such programs customers are offered certain incentives or reduction on their electricity bills.

(i) *Direct load control:* The direct load control (DLC) programs are fully governed by power utility company. The utility controls the certain equipment of participant customer and govern the power to make it shut down remotely on a short notice. Generally the equipment like air-conditioner and heaters are employed in this program. Such programs are mainly employed for residential and small commercial consumers.

The DLC problem for air-conditioner is examined in [22], where a fuzzy dynamic programming is attempted to solve the DLC problem. The DLC factors are modeled in fuzzy set representation and built in a unit commitment problem. The solution is tested on Taiwan power 38 unit system. A residential air-conditioner DLC management is proposed in [23], which physically modeled the air-conditioner (AC) by employing state variables. The DLC algorithm is based on maximum likelihood operation is built using a hardware. An interruptible load management technique is proposed in [24] for integrating DLC to provide reserve for ancillary services. This work outcomes shows that customer can avail exact amount in real time by reducing forecasting errors and handling uncertainties. A DLC for water heaters and storage is developed in [25] to minimize the power losses in the distribution system. In this wok a Lagrange multiplier method is attempetd to solve the DLC problem. When DLC is employed all the water heaters are disconnected and when switched on all affected heaters must be recovering but this can cause new peaks in the system. As a solution to this, a DLC problem for residential water heaters is developed in [26]. This work incorporates the factor affecting DLC and analyzed them. The disconnection of heaters also gives rise in payback.

(ii) *Curtailable/Interruptible load:* Similar to DLC programs, in Curtailable/Interruptible programs customer receives rat discounts or incentive payments. In these programs consumer are asked to reduce their load-demand to certain predecided values. The customers who do not accept the demanded reduction have to face penalties on the basis of utility conditions. There is a defined range for the customer who can participate, their demand must be 200 kW for base loads can extend upto 3 MW [27]. These type of customer are agree to shut down a specific block load or curtail according to consumption as to pre-specified levels. A practical study of Curtailable/Interruptible load for industrial and residential customer is developed in [28]. Initially the load measurement and forecasting is done with practical data of ten utilities.

(iii) *Demand bidding:* In demand bidding programs customer is required to bid for specific load reductions in the electricity market. In this process a bid can be accepted only when is less than market price. The customer should reduce their load by as by specification in the bid or face some penalties [29]- [30]. This type of programs are offered to large consumption users. A robust optimization technique is proposed in [31] for obtaining optimal bidding strategy of microgrid under demand management. A demand side bidding strategy is developed in [32] for residential energy management. In this work, the customers willingly to reduce their flexible load demands by their own bidding strategy in the demand outstrip event.

(iv) *Emergency Programs:* Emergency DR programs are employed when electricity grid is subjected to sudden failure or out of reserve. I these programs customer are paid incentives for according their load reductions on short notice [33]. The work in [34] proposes an emergency DR program with incentive based rewards design to maximize the DR benefits with reserve capacity constraints.

2.2.0.2 Price-based DR

The price-based DR programs are most attractive programs. The price based programs encourages customer to schedule their load-demand by providing future price information. The price-based tariffs are dynamic varying electricity prices, it does not include fixed prices. The main objective is to achieve flatten load demand curve by reducing consumption in peak hours via offering low prices during off-peak hours. This type of programs offers benefits and opportunities for both customer and utility. In these programs customers have chance to become a part of electricity infrastructure, which makes the system operation reliable. The various type of tariffs are subjected to this category i.e. time-of-use (TOU), real time pricing (RTP), critical peak pricing and inclining block rates (IBR). The different pricing models and their assessment to the DR programs is described in [35].

(i) *Time-of-Use:* In time-of-use (TOU) tariffs, the day is divided into various segments based on the utilization or demand. Each time segment slots are utilize with different electricity prices [36]. These time segments can be termed as on-peak, mid-peak and off-peak time slots. The TOU tariffs can be different at the time or season of the year. The on-peak hours represent the peak times of demand-load curve, in this time duration the electricity prices are mostly high. The mid peak hours are referred as the medium time of demand-load curve, it offers the prices less than on-peak times. The off-peak hours represent the off-time when electricity consumption is low and charges lower prices [37]. For residential load control TOU prices are very useful and implemented by many researcher [38–40]. In a study the TOU prices are proven beneficial for industrial consumers as well.

(ii) *Critical peak pricing:* The critical peak pricing (CPP) follows a structure with constant rate during system stress periods. The basic structure of rate is TOU but when system reliability under stress, a high price value than a normal peak price is employed [41]. The participating users are informed about this type of dispatchable high prices in advance or provide some automatic control technology for disturbances. This type of pricing is not economical for users as it charges critical peak prices [42]. The work in [43] have examined the CPP as for controlling residential demand ate critical times. The CPP is implemented for residential user as to measure the impact of electric vehicles load [44].

(iii) *Real time pricing :* Real time pricing (RTP) is a dynamic tariff where different electricity prices are offered during each hour or in each 15 minutes [45]. RTP is generally operated on hour-ahead basis or day-ahead basis. A day-ahead RTP is employed in Illinois, USA by Ameren Illinois corporation [46]. The RTP rates are widely used and considered most efficient and reliable DR programs. The RTP tariffs benefits are likely to outweigh for large customers. The RTP also regulates in the long run efficiency in a competitive electricity market [47]. The customer response to dynamic prices is very important to employ the RTP. Many customers face RTP need some way to manage their exposure to varying price [48]. The greenness environment related to RTP is investigated in [49], which shows that RTP also contributes for significant reduction on SO_2, NOx, and CO_2 emissions.

(iv) *Inclining Block Rate:* The inclining block rate (IBR) is defined as two-rate structure. The two-rate structure implies a higher and lower rate for different levels of consumption. Lower level rate is employed upto certain limit of consumption to the customer whereas a higher rate is employed for a consumption level above to the threshold value. This type of tariff is widely employed in British Columbia Hydro in Canada, Pacific Gas and Electric, Southern California Edison in USA [50]. The BC Hydro company charged their customers under residential conservation scheme, which is a rate divided into two parts. They determined the lower level threshold as step 1 is 0.0858 per kWh for first 1,350 kWh in an average two month billing period. The higher step 2 rate is 0.1287 per kWh over the 1,350 kWh of consumption.

This means customers are charged one rate of electricity up to a certain point in each billing period and a higher rate for any electricity used beyond that point. The point where the customer is paying a higher rate is called step 2 threshold and is based 205 on 90 % of the average household consumption in all household.

2.3 Demand Response Issues

Demand Response acts to make consumer demand independent to the grid. In the past years, a lot of literature work has been done for DR in smart grid [51]- [52]. Residential load management programs are developed to executed DR on a residential level. In [53], the author presented a self-governing and distributed energy management system among consumers that incorporates benefits of a two-sided good communication infrastructure that is envisioned in the future smart grid. A fully automated DR is the modern automation type smart household energy management (HEM) System [54]. For monitoring of home appliances and managing their operation, HEM system has taken responsibility for their actions. A modified approach for residential load scheduling is explained in [55]. Where the author revisited the energy management problem and formed it using incentive-based approach by taking consideration of user satisfaction and benefits for consumer and utility. An optimal power scheduling method has explained in [56]. The author has introduced the generic scenario of HEM system in a home area network (HAN) and how the EMS works in the home. In [57], the author investigated the consumption scheduling problem for residential consumer, which is framed as a coupled-bound game by taking the interaction among users and the temporally-coupled constraint into consideration.

The demand response is mostly executed on the residential sector platform as compared to commercial and industrial. The residential customers are more sensitive to varying price because of uncertain behavior of distinct appliances. The two way communication by advanced metering infrastructure (AMI) provides a convenient environment to exchange price and load information between user and energy providers. On this platform, the home energy management system (HEMS) makes it feasible by exchanging user information to energy providers [58]- [59]. The demand response scheduling can be executed via appliance-based and data-based.

2.3.1 Appliance-based Scheduling

In appliance based scheduling, there is an energy consumption scheduling device installed at each household, which controls the ON/OFF switch. The electricity price information is given by utility and demand of user is exchanged by home area network (HAN). The scheduling load controller co-ordinates each appliance as per user's requirement. After applying DR, the controller sends ON/OFF control commands to the users via HAN and then it results to energy consumption scheduling. In this context, an appliance based scheduling is attempted in [60] for HEMS. Here, each user tries to find the starting time of the appliances and their operating mode for schedulable and base load appliances. A customer reward based demand response for residential appliances is executed in [61]. This study examined the non-controllable and controllable appliances with appliance flexibility index and data is obtained from customer survey data.

2.3.2 Data-based Scheduling

In this kind of scheduling, the scheduling is based on historic aggregated hourly data provided by users to utility. A household energy consumption segmentation is presented in [62] by using hourly load data. Here, author examined five different segmentation schemes for load curve. A data based demand response for residential building is presented in [63], where author has implemented a detailed single family home model with OpenStudio with considering geographical environment. A price-responsive DR strategy is executed in [64], which offers a regression technique to model home energy consumption based on data available from software. A tool for assessing the demand profile flexibility is explained in [65] by forming aggregated load for customer behavior. An architecture for load management in smart buildings is developed in [66], where tool has designed for the DR scheduling.

2.4 Summary

Demand response arises as a promising platform to develop technology for energy customers and energy providers. On first hand it encourages user to involve with price-based DR by facilitating dynamic pricing for energy usage. Secondly it is beneficial for energy provides as well by reducing peak demand during peak hours. The bi-directional communication between user and electricity grid make the electricity system more interactive.

Chapter 3

Optimal Load Scheduling of Residential Consumers

3.1 Introduction

As discussed in chapter 1 Demand Response (DR) programs are required as the need of hour. DR plays a significant role in maintaining supply and demand ratio in the future. Real time pricing (RTP) models are widely accepted for application of DR. RTP is associated with pricing models, where the energy price generally varies at particular time-periods of a day [45]. RTP is normally released before an hour from their actual time or before day-ahead price (DAP) basis. For RTP environment, it is necessary for DR model to have prediction capabilities. It is particularly true if the utility companies give price information only one or two hours ahead of time. DR programs depend severely on the capability of price prediction at the utility company as well as on the customer's side. Price prediction can be done on the basis of different time intervals as a day-ahead, an hour ahead, half an hour, or minutes earlier. Therefore, there is a requirement of accurate and efficient price prediction techniques.

In the literature, several price prediction techniques are developed for the electricity market. A neural network approach is proposed in [67] for load and price forecasting on hours ahead basis. A hybrid algorithm based on the combination of the wavelet transform, Firefly algorithm, and fuzzy techniques is proposed to predict day-ahead electricity prices [68]. In [69], computationally intensive methods is implemented using artificial agents based simulations. A day ahead price prediction technique is proposed using robust recursive functional principal component analysis (RFPCA) and auto-regressive model [12]. The ability of support vector machine (SVM) methods to solve nonlinear regression estimation problem makes SVM successful in prediction [70]. For comparative analysis, the application of artificial neural network (ANN) technology [71] is also adopted. A linear prediction model is also developed to test the capability of linear prediction analysis among different methods [72]. The motive of this chapter is to investigate the application of price prediction techniques.

This chapter presents a load scheduling problem for residential consumers. Here, the smart grid is considered with communication facilities and selection information to make a more efficient and reliable operation for residential customers and utilities. By implementing the two-way communication technologies of the smart meter, it becomes possible to achieve interactions between consumer and utility [73]. RTP is considered as DR policy so it can disclose the electricity prices and offers the most accurate approach to among consumers to schedule their load. Here, the residential load model, price prediction techniques and load control problem are developed. The primary purpose is to deploy a day ahead RTP with the help of prediction techniques. The second purpose is to develop an automatic load control algorithm to achieve optimal scheduling of residential consumers and to improve energy efficiency. The RTP pricing models with price prediction are combined to design a price-based demand response model. The ability of various prediction techniques such as linear prediction model, artificial neural network (ANN) and support vector regression (SVR) are deployed with load management problem.

This chapter is organized as follows. Section 3.2 explores the electricity price prediction capabilities. System modeling is illustrated in section 3.3. The load scheduling problem is formulated in Section 3.4. The simulation results and discussion is shown in Section 3.5. The summary is represented in Section 3.6.

3.2 Price Prediction Capabilities

3.2.1 Dynamic Pricing Model

In the past, various dynamic pricing models have been developed for residential customers. For example, BC Hydro applied inclining block rates (IBR) [74]. The rates of electricity is decided from 7.52 cents/kWh to 11.27 cents/kWh as per the energy consumption of consumer. The rates are based on the following rule i.e. if the energy consumption for 2 month period is less than 1350 kWh, consumer will pay first slot price (7.52 cents/kWh); otherwise have to pay second slot price 11.27 cents/kWh.

In the power system, energy demand is extremely variable quantity, and economic storage of electricity cannot be served. Hence, the different power generation plants/units are mixed to achieve the increased the load demand. To reduce peak demand, the real-time pricing models have been initiated. The real-time pricing (RTP) is proved an effective factor for residential DR programs. The RTP data is taken from Ameren Illinois Corporation [46]. The sample electricity prices for BC Hydro and RTP is shown in Fig. 3.1 and Fig. 3.2, respectively.

To change the flat rate tariffs, RTP with IBR is a appropriate dynamic pricing models for residential consumers. This section presents mathematical modeling for pricing model RTP combined with IBR. It is assumed that the forthcoming price values are known to consumers before the time. Total hourly energy consumption of consumer is denoted by l_t at each approaching hour. The $C_t(l_t)$ denotes electricity price for l_t load demand in t^{th} time slot and represented as,

$$C_t(l_t) = \begin{cases} x_t, & \text{if } 0 \leq l_t \leq \delta_t. \\ y_t, & \text{if } l_t > \delta_t. \end{cases} \tag{3.1}$$

$x_t, y_t, \delta_t \geq 0$

Where x_t, y_t denotes the step 1 and step 2 price value. δ_t is the price threshold limit.

RTP model used by Ameren Illinois Corporation,

$$x_t = y_t, \forall t \in T$$

Inclining block rates used by British Columbia Hydro Company,

$$x_1 = x_2 = ... = x_{T-1} = x_T \; y_1 = y_2 = ... = y_{T-1} = y_T$$

$$\delta_1 = \delta_2 = ... = \delta_{T-1} = \delta_T \tag{3.2}$$

BC Hydro prices are independent of time, they change over consumption level as shown in Fig. 3.1. By combining RTP with IBR, both wholesale prices and consumption level are considered into account.

In general, price function parameter depends on season price-dependent volatilities and correlation between electricity price and load [75]. The price variation also depends on weekdays and on weekends. This information can also be helpful for price prediction

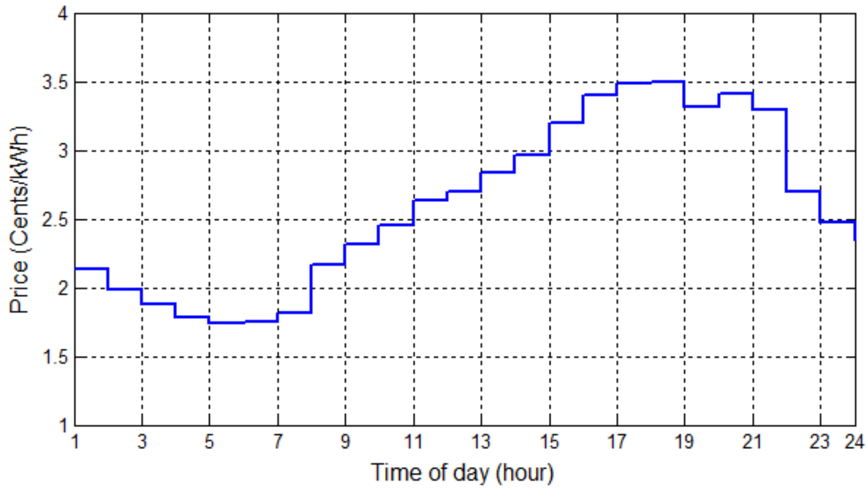


Figure 3.1: Two-level inclining block rates set by BC Hydro

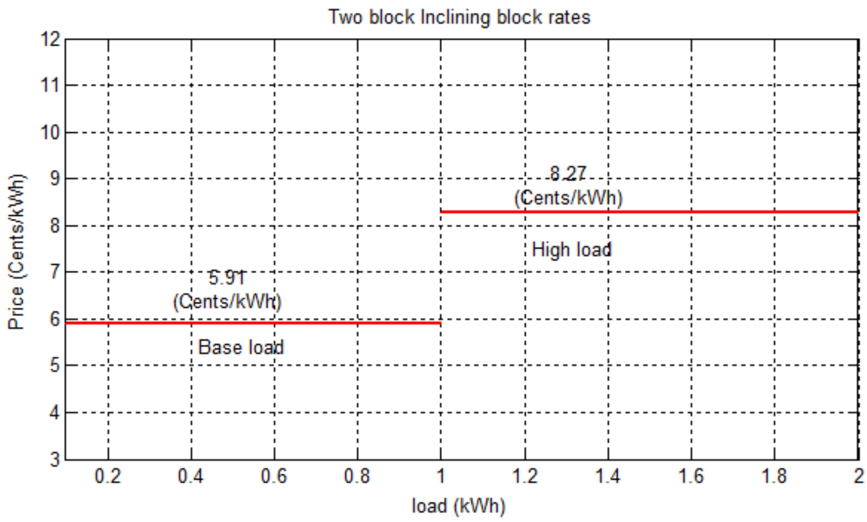


Figure 3.2: Real-time prices set by Power Smart Pricing Company

in RTP environment. Here for accurate predictions, focus is oriented on low computational complexity price predictors. Therefore, the predictors can be easily deploy for residential smart meters for customers load scheduling.

3.2.2 Statistical Analysis of Data

The hourly price data is taken from the Ameren Illinois Power Corporation for the year 2013 to 2015 [46]. To detect the factors affecting price parameter, initially the average price over the different years is plotted in Fig. 3.3. From the average prices for years, it is interpreted that the variation in prices are very less, although they look partially similar. There is a requirement to perform statistical analysis of data to develop an enhanced prediction model for the different time scale. The average prices over month and week are shown in Fig. 3.4 and Fig. 3.5, respectively. The monthly average shows a significant change in prices. But average prices in summer should be higher, so monthly basis, the prediction does not seem feasible. Average price for the week is partially similar in weekdays, but the change in prices for weekends are significant. The prices are lower on Saturday and Sunday. Therefore, the relationship is developed between weekday and weekend.

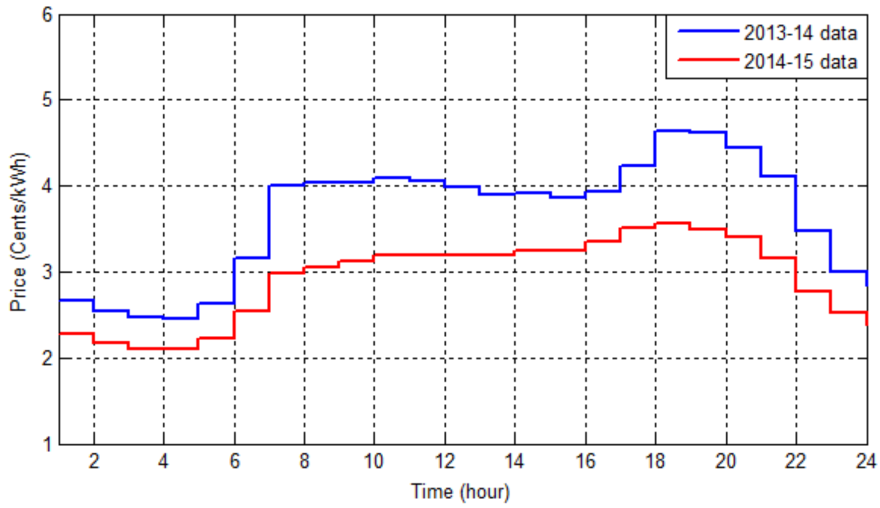


Figure 3.3: Analysis of price data on the basis of years

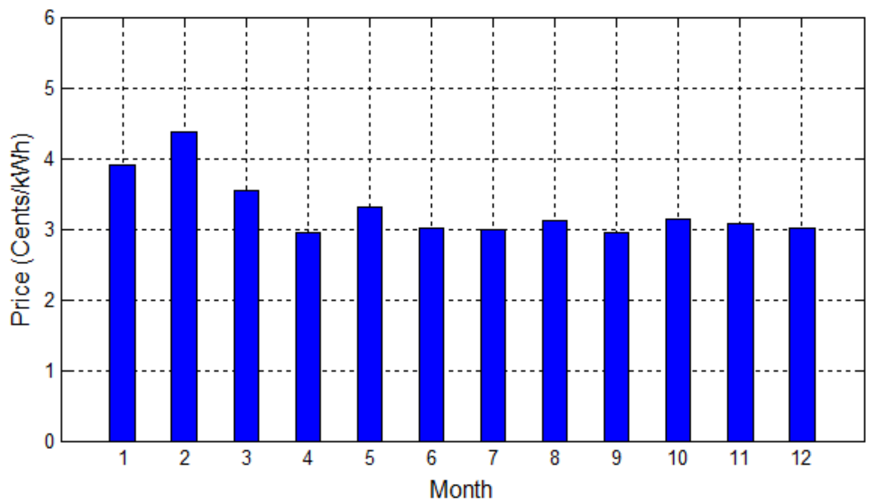


Figure 3.4: Analysis of price data on the basis of months

3.2.3 Correlation in Historic Data

The correlation of price data is made for average prices over the week. The correlation plot is shown in Fig. 3.6, from plot it is shown that the correlation between the present

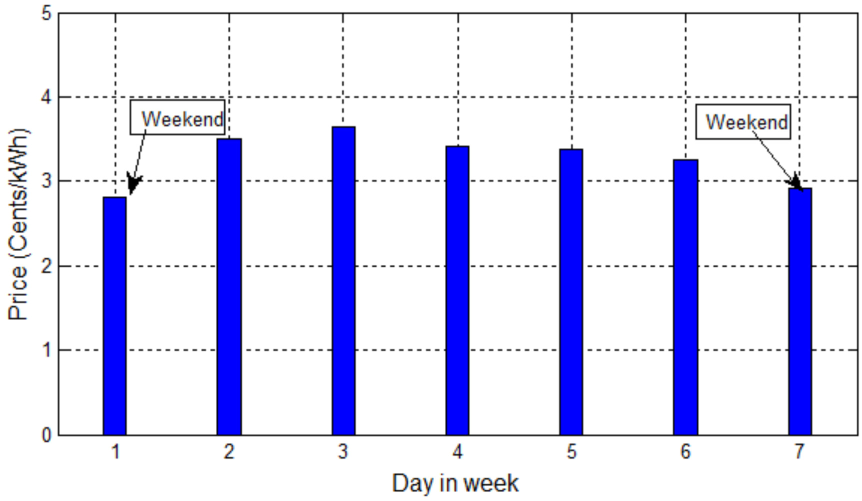


Figure 3.5: Analysis of price data on the basis of days of week

day and yesterday is very high (0.9986). Therefore, yesterday is considered as one of the prediction features. However, a high correlation is measured for a day before yesterday and the same day in last week as shown in Fig. 3.6.

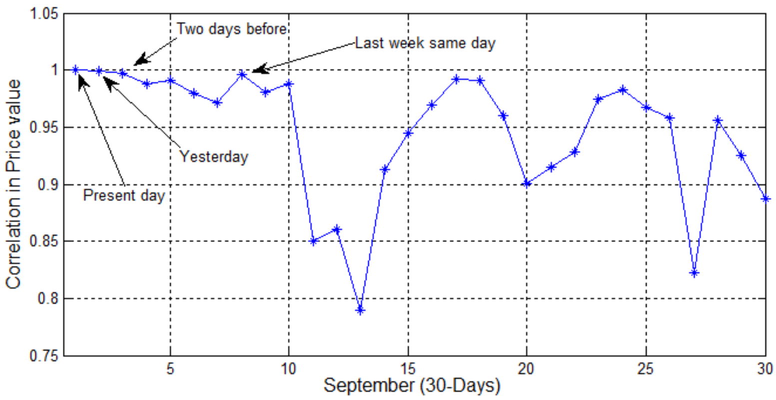


Figure 3.6: Correlation in Prices

3.2.4 Linear Prediction Model

Linear prediction model (LPM) is a discrete time signals based model, it produces linear function which is able to predict future data based on past data samples. For a day ahead price prediction, as per correlation shown in Fig. 3.6 three days are measured as high correlated with the present data. First is the yesterday data highly correlated; second is the day before yesterday and third, the same day in previous week. In LPM the output and input are mathematically related by using filter coefficient. The filter coefficient is determined by using linear prediction theory.

The mathematical model is represented as in (3.3)

$$\widehat{y_t}[d] = k_1 y_t[d-1] + k_2 y_t[d-2] + k_7 y_t[d-7] \tag{3.3}$$

Where, $y_t[d-1], y_t[d-2]$ and $y_t[d-7]$ denotes the price values for y_t on yesterday , the day before yesterday and same day in last week respectively. k_1, k_2 and k_7 are the filter coefficients of model. The prediction output is denoted by $\widehat{y_t}$.

3.2.5 Artificial Neural Network (ANN)

Artificial neural networks (ANN) are most popular artificial intelligence (AI) technique. ANN is highly applicable in pattern recognition and predictions [75] among other techniques. Here, the feed forward ANN is developed to predict the day-ahead electricity prices. These networks are called feed forward because there is no loops, information travels in forward from input nodes to output nodes through hidden nodes. Feed-forward with single-layer perceptron is considered which contains no hidden layer and similar to linear regression, where perceptron learning rule is a method for finding the weights in a network. The perceptron has one input and one output layer. The output are calculated simply from the sum of the product of weights with similar input.

The ANN model requires decision parameters, input variables, model structure and training algorithm. The back propagation algorithm is used for the training purpose for day ahead price forecasting. The details of ANN are as follows,

***Input layer*:**
$u_j = x_j (j = 1, 2...n)$

Where x_j is the input variables for the model and n is the number of decision variables. Here $n = 3$ is taken by analysis past input data sets. Three input variables are the prices on the previous day, prices two days before and prices on the same day in last week. Each input consists 20 neurons.

***Hidden layer*:**
The output terminal of input layer is defined as hidden layer. Transfer function trans-sigmoidal is used for hidden layer.

***Output layer*:**
The outputs of hidden layer are considered as inputs for output layer. The single output

layer consists one neuron in the network. The output obtained are the predicted hourly prices for next day.

Fig. 3.7 shows the ANN architecture. For the ANN implementation total one year data is used. Where total 8760 number of samples are found, from which 60% is used for training purpose, 20% is used for testing and 20% is used for validation.

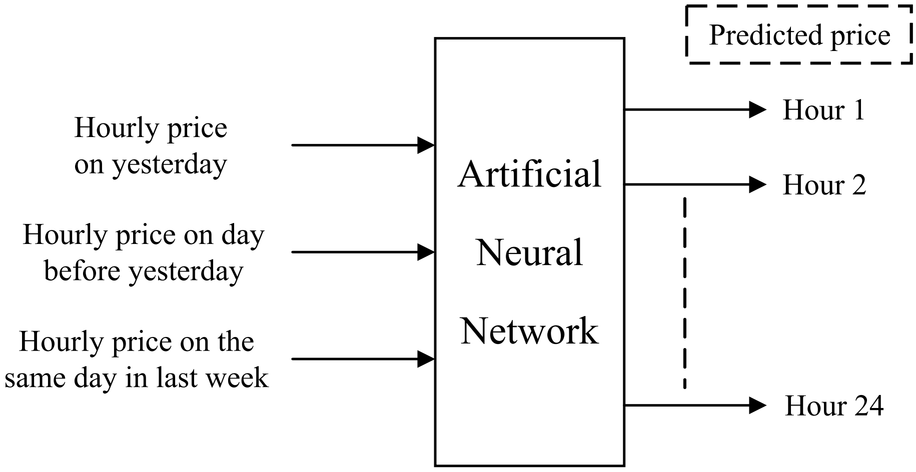


Figure 3.7: Artificial neural network architecture

3.2.6 Support Vector Regression Models

3.2.6.1 Support Vector Regression (SVR)

Initially, the idea for SVM is given by Vapnik in 1995 [76]. The SVM basic concept comes to map original nonlinear data x into higher dimensional space. A set of data $G = \{(x_t, a_t)\}_{t=1}^{N}$ is given for SVR. Where x_t represent the input vector, a_t is the actual value and total numbers of data patterns represented by N. Therefore SVR function can be defined as,

$$y = f(x) = w\varphi(x) + b \tag{3.4}$$

Where, $\varphi(x)$ is defined as the nonlinear feature which is mapped from input space x. The w and b are the coefficients which can be determined by minimization of risk function $R(C)$.

$$R(C) = (C/N)\sum_{t=1}^{N} L_{\epsilon}(a_t, y_t) + \parallel w \parallel^2 /2 \tag{3.5}$$

Where L_{ϵ} known as ϵ- insensitive loss function and defined as,

$$L_\epsilon(a,y)=\begin{cases}0 & |\, a-y\,| \leq \epsilon \\ |\, a-y\,|-\epsilon & \text{otherwise,}\end{cases} \tag{3.6}$$

Where, $\epsilon > 0$ is a predefined constant which controls the noise tolerance. The constant $C > 0$ determines the trade-off between the flatness of model and the amount up to which deviations larger than ϵ are tolerated. The flatness of function measured by $\| w \|^2 /2$. Two positive slack variables γ and γ^* have introduced, which represent the distance from actual values to the corresponding boundary values of ϵ-tube. Therefore equation (3.5) can be transformed in given form.

$$\text{Minimize} \quad R(w,\gamma,\gamma^*) = \| w \|^2 /2 + C\Big(\sum_{t=1}^{N}(\gamma+\gamma^*)\Big) \tag{3.7}$$

Subjected to the constraints,

$$\begin{aligned} w\varphi(x_t)+b_t-a_t &\leq \epsilon+\gamma^*, \quad t=1,2......N \\ a_t-w\varphi(x_t)-b_t &\leq \epsilon+\gamma, \quad t=1,2......N \\ \gamma,\gamma^* &\geq 0, \quad t=1,2......N \end{aligned} \tag{3.8}$$

To solve this constrained optimization problem, the Lagrangian multiplier approach has been used, which is shown in following equation,

$$\begin{aligned} L\big(w,b,\gamma_t,\gamma_t^*,\alpha_t,\alpha_t^*,\beta_t,\beta_t^*\big) = \Big(&\| w \|^2 /2 + C\Big(\sum_{t=1}^{N}(\gamma_t+\gamma_t^*)\Big) \\ &- \sum_{t=1}^{N}\beta_t\big[w\varphi(x_t)+b_t-a_t+\epsilon+\gamma_t\big] \\ &- \sum_{t=1}^{N}\beta_t^*\big[a_t-w\varphi(x_t)-b_t+\epsilon+\gamma_t^*\big] \\ &- \sum_{t=1}^{N}(\alpha_t\gamma_t+\alpha_t^*\gamma_t^*)\Big) \end{aligned} \tag{3.9}$$

The equation (3.7) is maximized with respect to non-negative Lagrangian multiplier $\alpha_t,\alpha_t^*,\beta_t,\beta_t^*$ and minimized with respect to primal variables w,b,γ_t,γ_t^*, that gives the following equation.

$$\begin{aligned}\frac{\partial L}{\partial w} &= w - \sum_{t=1}^{N}(\beta_t - \beta_t^*)\varphi(x_t) = 0\\ \frac{\partial L}{\partial b} &= \sum_{t=1}^{N}(\beta_t^* - \beta_t) = 0\\ \frac{\partial L}{\partial \gamma} &= C - \beta_t - \alpha_t = 0\\ \frac{\partial L}{\partial \gamma^*} &= C - \beta_t^* - \alpha_t^* = 0\end{aligned} \tag{3.10}$$

The Karush-Khun-Tucker (KKT) conditions have applied to the regression problem and dual problem is built by substituting equations (3.10) into (3.9),When K is a kernel function define as $K(x_t, x_j) = \varphi(x_t)\varphi(x_j)$.

$$\begin{aligned}v(\beta_t,\beta_t^*) = &\sum_{t=1}^{N} d_t(\beta_t - \beta_t^*) - \epsilon\sum_{t=1}^{N}(\beta_t + \beta_t^*)\\ &-\frac{1}{2}\sum_{t=1}^{N}(\beta_t - \beta_t^*)(\beta_j - \beta_j^*)K(x_t, x_j)\end{aligned} \tag{3.11}$$

Subjected to,

$$\begin{aligned}&\sum_{t=1}^{N}(\beta_t - \beta_t^*) = 0\\ &0 \le \beta_t \le C, \quad t = 1, 2.....N\\ &0 \le \beta_t^* \le C, \quad t = 1, 2.....N\end{aligned} \tag{3.12}$$

The Lagrange multipliers β_t and β_t^*, are calculated and an optimal desired weight vector of the regression hyper plane is,

$$W^* = \sum_{t=1}^{N}(\beta_t - \beta_t^*)\varphi(x) \tag{3.13}$$

Hence, the regression function cab be represented as,

$$f(x,\beta_t,\beta_t^*) = \sum_{t=1}^{N}(\beta_t - \beta_t^*)K(x, x_t) + b \tag{3.14}$$

Here, $K(x, x_t)$ is a kernel function, which is equal to the inner product of two vectors x and x_t in the feature space $\varphi(t)$ and $\varphi(x_t)$ respectively i.e. $K(x, x_t) = \varphi(x)\varphi(x_t)$. Commonly, there are different type of kernel function exist, i.e. polynomial kernel, the multi-layer perceptron kernel function, and the Gaussian RBF kernel function etc. The Gaussian RBF kernel function is used for SVR [76]. The Gaussian RBF kernel function is defined in following expression,

$$K(x_t, x_j) = e^{-(x_t - x_j)^2/\sigma^2} \tag{3.15}$$

3.2.6.2 Parameter Optimization using Genetic Algorithm

To achieve high accuracy of prediction, the parameters of SVR can be optimized. For optimizing the parameters C , ϵ and σ genetic algorithm (GA) is used. For the purpose of initially developing the SVR model parameters are chosen on the basis of hit and trial approach based on past data. The parameter C, ϵ and σ values are considered initially as 0.05, $5 * 10^{-4}$ and $5 * 10^{-5}$ respectively. GA methodology is inspired from [71]. For the optimization, the mean absolute percentage error (MAPE) is considered as objective function. In order to minimize the MAPE, iterative procedure for parameter optimization is solved by GA. The methodology for genetic algorithm is described in Algorithm 3.1.

Algorithm 3.1 Genetic Algorithm

```
procedure
Input the data
MAPE as objective function
Start
    Encode the solution into chromosomes (binary strings)
    Define fitness F(e.g., F ∝ f(x)for minimization)
    Generate the initial population
    Generate new solution by crossover and mutation
    Accept the new solution if their fitness decreases
    Select the current best for new generation
    Decode the parameters new values
End
end procedure
```

3.2.7 Performance Evaluation

For simulation two-year RTP data has been taken from the Ameren Illinois Power Corporation from 2013 to 2015. Three consecutive days such as 6th, 7th and 8th December 2015 is selected for validation purpose. For performance assessment of prediction techniques, mean absolute percentage error (MAPE) and mean absolute error (MAE) indices are considered. The error E is defined as the difference between original prices and predicted prices.

$$E_t = a_t - y_t \tag{3.16}$$

Where, a_t is original value of price and y_t is the hourly predicted price in t^{th} hour. MAE is calculated by taking mean of error.

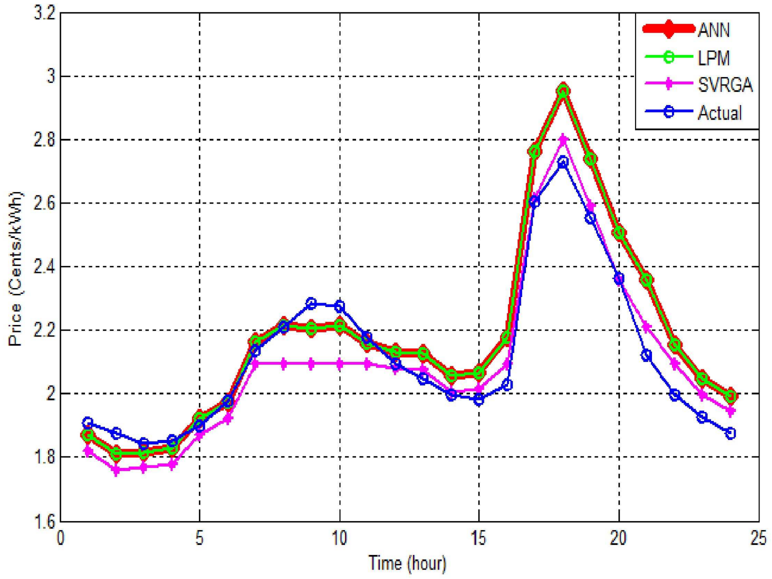


Figure 3.8: Price prediction for 5th December 2015

MAPE is defined as mean absolute percentage error.

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{a_i - y_i}{a_i} * 100\% \tag{3.17}$$

The price prediction for 5th December 2015 by using LPM, ANN, and SVRGA techniques is shown in Fig. 3.8. The predicted price for 5th Dec. is determined by using past days 4th, 3rd Dec. and 28th Nov. 2015. The price prediction from SVRGA is very close to actual price pattern. From Table 3.1, it is shown that the MAPE and MAE of SVRGA are 3.84 % and 9.16 % respectively. While MAPE and MAE determined for LPM are 7.06 % and 16.082 % which is higher in comparison with SVRGA. It is reported that SVR parameter tuned with GA gives a better result as compared to LPM and ANN. The MAPE by using ANN method is 6.4 % which is comparatively lower than error obtained with LPM i.e. 7.06 %.

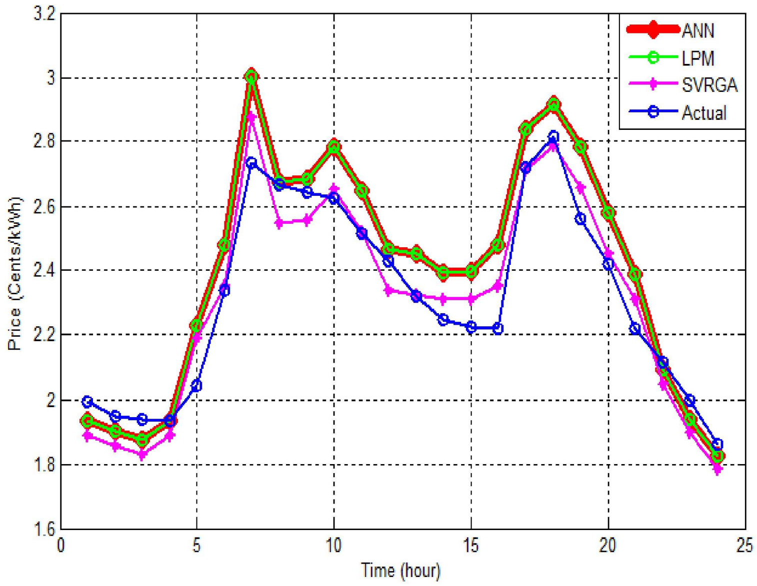


Figure 3.9: Price prediction for 6th December 2015

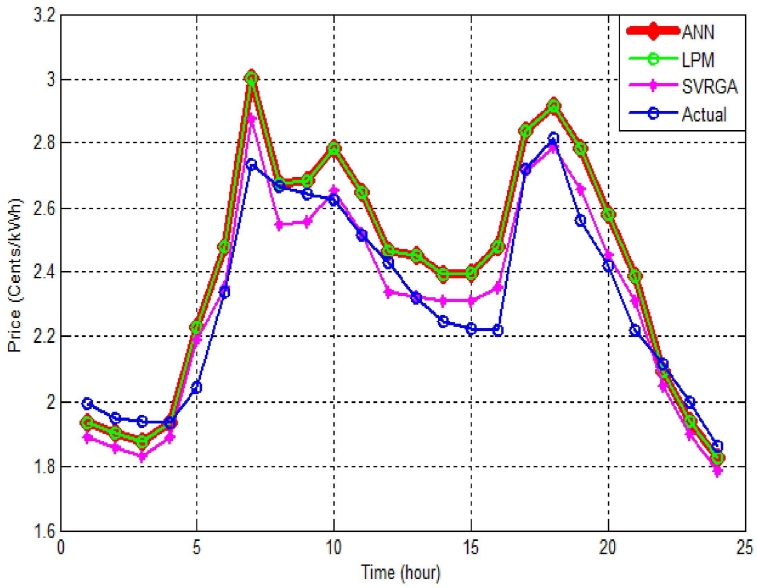


Figure 3.10: Price prediction for 8th December 2015

Fig. 3.9 shows the price prediction for 6th Dec by using past price data of 5th, 4th Dec. and 29th Nov. 2015. Price for 7th Dec. is obtained using past data from 6th, 5th Dec. and 30th Nov. 2015 is shown in 3.10.

From the comparative analysis SVRGA performed better than LPM and ANN techniques in terms of performance parameters such as MAPE and MAE. The patterns for ANN and LPM are almost similar, but overall the closeness to the actual prices are

Table 3.1: Performance parameters of prediction techniques

Date	Technique	MAPE (%)	MAE (%)
5th Dec 2015	ANN	6.40	14.67
	LPM	7.06	16.1842
	SVRGA	3.8413	9.16
6th Dec 2015	ANN	8.678	17.87
	LPM	4.07	8.86
	SVRGA	3.64	8.234
7th Dec 2015	ANN	8.46	20.35
	LPM	4.75	11.42
	SVRGA	3.78	9.46

effective in the case of LPM.

3.3 Household Model

A smart power system with a single energy provider, various residential customers, and a regulatory entity is considered. An automatic load controller unit (ALCU) is installed with each residential consumer and it has a built-in smart meter. The purpose of ALCU is to maintain and control the consumer's energy consumption and to interact with energy provider when required. The ALCUs of the different customers are connected to each other and energy provider via a communication network such as home area network (HAN).

In household model, three types of appliances such as non-shiftable, shiftable ans shiftable continuous run appliances are considered. The non-shiftable appliances can not be shifted to another time, but energy consumption of appliance can be the changed as per appliance usage requirement. TV and lighting devices come in this category. So, consumer can have an opportunity to switch on or off the TV at any time he needs without the intervention of the ALCU. The shiftable appliances can be shifted one time to another time as long as the specified amount of total consumed energy is used, and ALCU may only delay its operation. It includes pool pumps and electric vehicles (EVs) charging. The shiftable continuous run should run without interruption. Washing machines or dishwasher are the sample examples in residential setting as well as in the industrial context.

3.3.1 Appliances Classification

Household appliances are categories into various classes respective to the appliance type and the customer requirement.
1. Non-shiftable appliances: It include all appliances those can not be interrupted and they have to run continuously. In this study, the daily energy consumption for all non-shiftable appliances aggregated and modeled from historical data. For example, refrigerator and lighting appliances etc.
2. Time-shiftable appliances: It includes shiftable appliances those consumption is manageable during their operation, by intervention or repressing its usage. For these type of appliances the ALCU has to achieve the required energy usage E_a for a particular time Δt_a. For example, pool pump usage time can be flexibly controlled.
3. Time-shiftable continuous run appliances: In this type, all the appliances should have to pursue a known usage profile for operation cycle and should run continuously. This type of appliances can be shifted from one time other time but cannot be interrupted once the operation begin. For example, clothe dryer cannot be interrupted once started and have to run for certain time.
4. Power-shiftable appliances: It includes shiftable appliances have flexible power consumption with a minimum standby power and a maximum operating power. This type of appliance can also be shifted from one time other time. For example, water heater power range can be varied.
The appliances data with their priority operating time is shown in Table 3.2.

3.4 Load Scheduling Problem Formulation

This section presents problem of automatic load scheduling to minimize the total electricity bill of residential consumers. Here, an assumption is made that futuristic statistical load information is known. Various type of appliances is used for the residential load model. For each consumer $k \in K$, let AP_k denote the set of appliances for k^{th} consumer and for each appliance $a \in AP_k$. The time horizon is denoted by T, where for each forthcoming hour represented by $t \in T$. For each consumer k with appliance a, the energy consumption is defined as $w^t_{k,a}$ in t time slot. The time horizon is for 24 hours. The hourly consumption of each consumer is defined as,

$$\sum_{a \in AP_k} w^t_{k,a} \cong l^t_k, \quad \forall t \in T \tag{3.18}$$

For each appliance the total daily consumption is fixed,

$$\sum_{t=1}^{24} w_{k,a}^{t} = E_a, \quad \forall k \in K, a \in AP_k \tag{3.19}$$

The information regarding consumer operation is known to ALCU. To minimize the electricity cost of consumers with real time pricing is formulated as,

$$Minimize \sum_{,t=1}^{24} C_t\Big(\sum_{a\in AP_k} w_{k,a}^{t}\Big)\Big(\sum_{k\in K}\sum_{a\in AP_k} w_{k,a}^{t}\Big) \tag{3.20}$$

Subject to constraints,

$$\sum_{t=t_a^0}^{t_a^f} w_{k,a}^{t} = E_a, \quad \forall k \in K \tag{3.21}$$

$$\alpha_a \leq w_{k,a}^{t} \leq \beta_a, \quad \forall t \in T_a \tag{3.22}$$

$$w_{k,a}^{t} = 0, \quad \forall t \in T/T_a \tag{3.23}$$

$$T_a = [t_a^0..........t_a^f] \tag{3.24}$$

The objective function in (3.20) represents the total daily payment for consumers while cost function is the expected cost of energy for the upcoming hours. The first constraint represent time-flexible shiftable appliances. Where t_a^0 and t_a^f are the starting and finishing time of for the appliance. The second constraint is for power shiftable appliances, where α_a and β_a are the minimum and maximum power limits respectively.

The power shiftable appliances can be easily scheduled but time shiftable appliances have fixed power consumption. For example daily requirement of the washing machine is 1.5 kWh. According to constraint (3.21) the washing machine can consume 0.25 kWh for six hours and zero for remaining time. Besides washing machine can not be used as per this schedule because it requires some fixed amount of power to be run. The power consumption of washing machine can be scheduled, for 1st hour operation it might consume 1.0 kWh and for 2nd hour 0.5 kWh. Such kind of appliances require switch control operation. Therefore, the optimization problem is solved using mixed binary linear programming.

The executed algorithm is explained in Algorithm 3.2, initially appliances are defined with their power requirement. The appliances with binary variables is classified. With the help of ALCU the predicted prices is included in the algorithm and synchronized with problem. Then next step is to define the constraints for all the appliances. The optimization problem is modeled as mixed integer linear programming (MILP) and solved using convex optimization tool CVX [77] on MATLAB platform.

Algorithm 3.2 MBLP optimization formulation

```
1: procedure MBLP(optimization)
2: With the help of appliance data calculate total energy consumption
   (Ea) (Including all users)
3: Calculate unscheduled load profile and total cost of energy with load profile
   Start
4:        Define types of appliances
5:        Define binary variable to on-off household appliances (As per the type of
   appliance)
6:        For the fixed energy consumption with the help of ALCU optimize total load
7:        Define constraints for upper and lower threshold value
8:        Calculate total cost for optimized load profile

9: end procedureEnd
```

3.5 Simulation Results & Discussion

100 number of residential household is considered for simulation. Each user is equipped with 10 to 20 shiftable and non-shiftable appliances. It is assumed that with the help of ALCU day ahead RTP predicted prices is communicated and informed to each consumer. The data for different type of appliances is given in Table 3.2. The running time slots of each appliance is determined by using probability based on historical data.

The Fig. 3.11 shows the real time prices with IBR. The threshold load value is determined from peak load and average load. For simulation purpose, it is considered $y^t = 1.5x^t$.

The load profile without suing automatic load control is shown in Fig. 3.12. The load profile after automatic load scheduling is presented in Fig. 3.13. In automatic load scheduling, the RTP prices encourage users to shift their load from peak hours to off peak hours. Fig. 3.13 clearly depicts that all user tries to shift their load from high price period to low price periods.

The total cost incurred to the consumers is shown in Table 3.3. From numerical results it is analyzed that without load control to load control figure acquires significant change. Here the used RTP price is predicted from three different techniques. In Table 3.3,

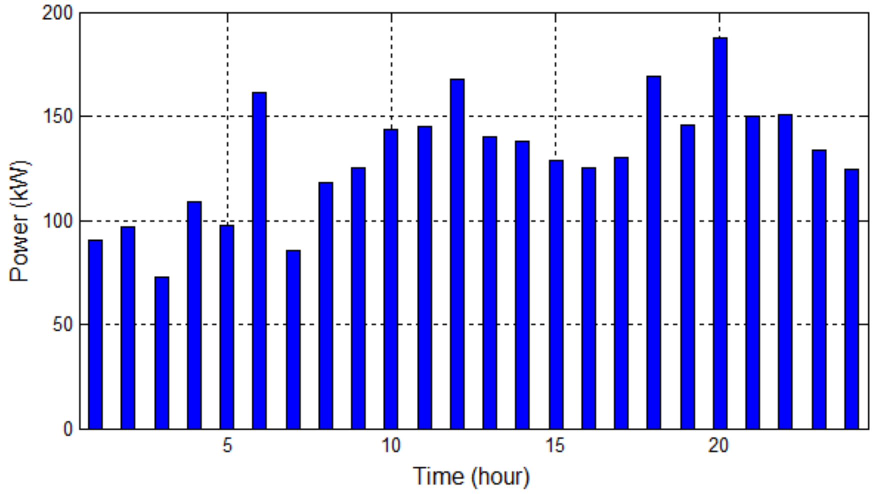


Figure 3.11: Price function for RTP with IBR

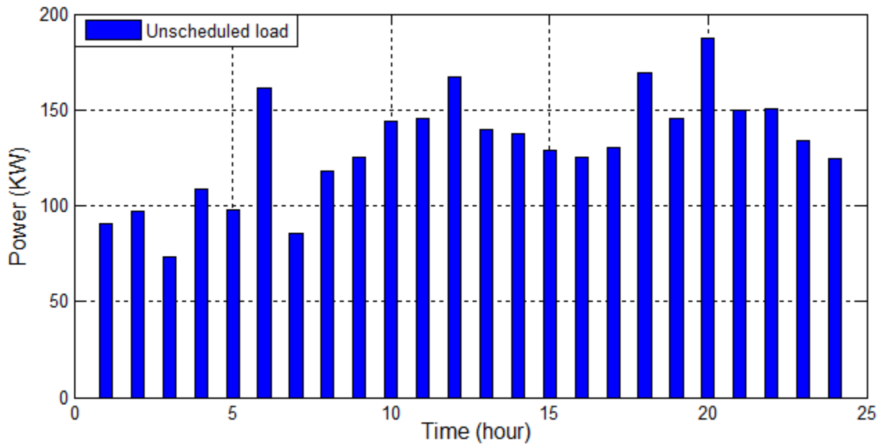


Figure 3.12: Load Profiles without automatic load control

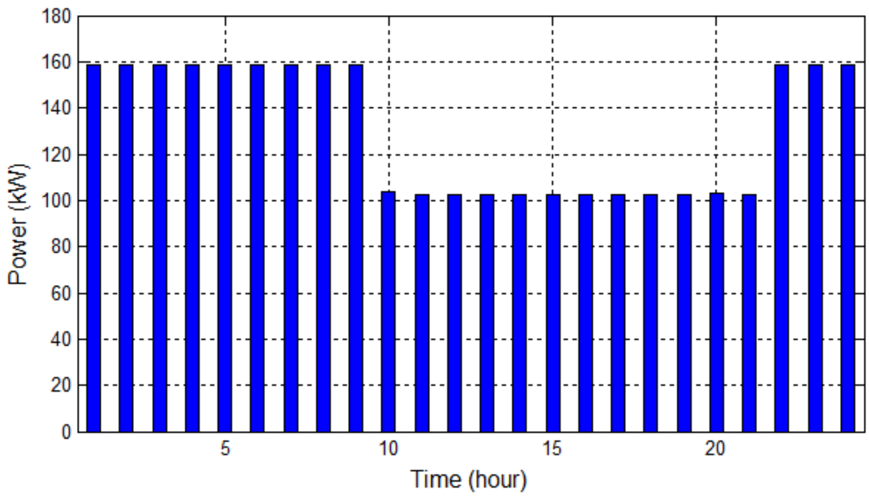


Figure 3.13: Load Profile with automatic load control

Table 3.2: Appliances Data

Appliance	**Power rating (kW)**	**Duration for probable operation**	**Type**
light	0.5	[18:00, 24:00]	Non-shiftable appliances
refrigerator & freezer	0.125	[01:00, 24:00]	
electric stove	1.5	[06:00, 14:00]	
heater	1	[18:00, 06:00]	
TV	0.25	[16:00, 24:00]	
PC	0.25	[08:00, 18:00]	
Hair dryer	1	[06:00, 10:00]	
Others	1.5	[01:00, 24:00]	
Dish washer	1	[10:00, 21:00]	Time-shiftable continuous run appliances
clothe dryer	0.5	[06:00, 22:00]	
vaccum cleaner	1.5	[08:00, 18:00]	
ironing applinaces	1	[06:00, 18:00]	
air conditioner	1.5	[08:00, 18:00]	
Pool pump	2	[04:00, 22:00]	Time-shiftable appliances
Others	1	[01:00, 24:00]	
water heater	1	[05:00, 20:00]	Power-shiftable appliances
others	1	[01:00, 24:00]	

it is shown that when different techniques price are employed in load scheduling the significant variations is found in cost with and without control. Where with RTP load scheduling acquires \$ 6 cost benefit, RTP with IBR is captured cost benefit of \$ 15.80, price with ANN and SVR occupies cost benefits of \$ 5, 29 and \$ 2.12 respectively.

The peak to average ratio for unscheduled is 1.433 and for scheduled load is 1.215. The change in PAR from unscheduled to scheduled consumption is 18 %.

Table 3.3: User Daily payment

Pricing model	Cost without control (in \$)	Cost with control (in \$)	Total benefit (in \$)
RTP	83.80	77.80	6.01
RTP with IBR	93.70	77.80	15.80
Predicted price by LPM	75.30	69.00	6.27
Predicted price by ANN	86.00	80.70	5.29
Predicted price by SVR	71.53	69.40	2.12

3.6 Summary

DR programs with dynamic pricing have significant potential to optimize a load of a consumer with their payments in smart grid environment. Even though the implementation of DR requires an advanced metering infrastructure, this chapter presented an automatic load control scheme with price-prediction capabilities. Some households are examined to test the capability of the proposed model. The application of prediction techniques played an important role to obtain the cost in a real environment. The performance of load control algorithm is validated from the results. The residential consumer acquired cost benefit by using this approach. Here in this chapter, no power limits are imposed on the load curve. Due to this, a consumer has only option to shift their load to low prices hour which can lead to the formation of unwanted peaks in the system.

Chapter 4

Integration of Electric Vehicle to Demand Response

4.1 Introduction

The presence of EVs have induced diversity in both the reserve and electricity market. In the energy market, EVs are considered as shiftable type load. The scheduling of shiftable load is primary course of action for the application of effective demand response. The bigger share of shiftable load means more prominent benefits. Since EVs usage is growing day by day and its high energy consumption can affect the electric bill. Thus inclusion of EV in DR increases the share of shiftable load by a larger means. The proposed household model comprises several assets including non-shiftable appliances, shiftable appliances, and EVs. By simply analyzing the consumer behavior, EV availability and real time price fluctuation, the smart charging of EV is done by performing peak clipping, valley filling, load shifting or load building. Since EVs popularity increasing among electricity user, So avoiding higher electricity rate for EV battery charging becomes the main objective of demand response (DR). Optimizing EV charging time by analyzing consumer behavior, with constraint of vehicle availability and avoiding demand in peak hours with high electricity charges is solution for utilizing EV.

To determine the real-world randomness to the EVs availability for household user, a demand shaping problem is proposed in [78], which incorporates the vehicle to grid (V2G) technology in the game environment. It incorporates arrival time, departure time and charging demand to models the DR problem. A peak demand reduction of up to 20 % is found by executing the V2G mode of vehicles in the game environment.

The inclusion of an energy storage system (ESS) with EV, which can further reduce the electricity cost by imposing hard and soft peak power limiting DR strategies is discussed in [79]. A multi-agent based decentralized method is proposed to aim energy sharing among smart homes [80], where utilization of renewable sources with storage unit and energy sharing are done via home batteries, it can provide energy for neighbors. While in [80], it doesn't consider the electric vehicle as the home asset and home to grid technology is not available during energy schedule. The self-generation of household is managed by solar radiation which is not available in the winters; this can affect the energy sharing algorithm. In [81], the problem have described a coordination operation of household consisting EV, storage, and renewable generation. Where the vehicle to home and vehicle to grid modes among three number of users. The study provides the insight of energy sharing among household, however, the numerical aspect does not reveal the benefits gained by the home user for different energy transaction. All the above mentioned studies are limited to operation of small number of users and fails to attempt the smart charging for EVs among a large number of households in DR programs.

Nowadays due to emerging EVs, the fast charging stations have become a point of the competitive environment in the market. The supercharging of an electric car is almost equivalent to 120 houses coming online for half an hour, where the average energy consumption of a household in the US is around 19 kWh per day, according to US energy information association [82]. A supercharging process does not take more energy to charge; it just makes charging faster, but when it comes to the electricity grid, it can become a severe issue. Therefore, this kind of problem can be solved with the application of smart charging for EV, so the grid burden issue can be resolved.

This chapter investigates the operation of the distinct type of residential electricity consumer system in demand response architecture. Each household user is equipped with the shiftable and non-shiftable type of appliances whereas some user is also installed with electric vehicle (EV) which contributes to vehicle to grid (V2G) and vehicle to home (V2H) modes with power sharing concept. The system operates under the bidirectional information communication between the user and load-serving entity (LSE) by utilizing AMI. The EV arrival time and departure time uncertainty is captured by the application of Gaussian distribution method. The neighborhood connection named as vehicle to neighbor (V2N) is also enabled for a large group of customers with the different types of EVs installed. The contributions of this chapter is summarized as follows:

- Here, an energy consumption scheduling with different types of load for several residential homes is proposed. The proposed algorithm solves an electricity payment optimization problem with bi-directional information communication between the electricity grid and residential homes. By execution of a centralized algorithm, the running scheduled of each appliance is determined. The EV smart charging is considered as the main goal of an energy consumption scheduling problem.

- The introduction of operations with the bi-directional power transaction between user and the electricity grid in the demand response framework. With the help of ALCU, the information communication is enabled at both ends.

- Each household is connected via a centralized control unit (CCU). Which works as a power exchange medium between one user to another user. The power-sharing concept among neighbors has proposed incorporation with energy consumption scheduling.

Organization of the rest chapter is as follows. Section 4.2 explains the system modeling. EV uncertainty capture model is presented in Section 4.3. In Section 4.4 performance evaluation and result explanation is discussed. The chapter summary is presented in Section 4.5.

4.2 System Modeling

4.2.1 Overview of System

The proposed system consist a group of household customers operating under a smart grid which entails a load serving entity (LSE), and an automatic load control unit (ALCU). Each home is installed with ALCU with a built-in smart meter. A group of different types of the customer based on usage is considered. The customers are classified into four categories based on their energy consumption in a day.

1. In the first group, household consumes less energy and it occupies two members. This kind of houses is equipped with few appliances.

2. The second group is inhabited by a five-member family in the house. This group consumes comparative more energy than the low consumption house of group 1.

Table 4.1: List of variables used in this chapter

$k(K)$	Index (set) of household user
$t(T)$	Index (set) of time periods
$C_{t,buy}$	Electricity price for purchasing energy from grid
$C_{t,sell}$	Electricity price for selling energy to grid
$E_{k,t}^{grid}$	Energy consumed by kth user from grid in t time slot
$E_{k,t}^{NS}$	Energy consumed by non-shiftable appliance of user k in t time slot
$E_{k,t}^{S}$	Energy consumed by shiftable appliance of user k in t hour
$E_{k,t}^{ev,C}$	Energy consumed by EV for charging of user k in t hour
$E_{k,t}^{ev,D}$	Energy consumed by EV for discharging of user k in t hour
$\widehat{E}_{k,t}^{ev}$	Energy rating of EV of user k in t hour
η_{ev}^{D}	Discharging efficiency of EV
η_{ev}^{C}	Charging efficiency of EV
T_a	Arrival time of EV
T_d	Departure time of EV
E_{trip}	Energy consumed in a trip
$E_{k,max}^{ev}$	Maximum energy required by EV for user k
$E_{k,min}^{ev}$	Minimum energy required by EV for user k
$EL_{k,t}^{ev}$	Energy level required for EV of user k in t hour
$EL_{k,min}^{ev}$	Minimum energy level required for EV of user k
$EL^{initial}$	Initial energy level required for EV
E_{charge}	State of Charge for EV
B	Binary variable for EV charging & discharging
$E_{k,t}^{load}$	Energy consumption for shiftable and non-shiftable appliances
α	Service charge for using grid infrastructure
$E_{k,t}^{ev,onr}$	Energy requirement of owner EV
$E_{k,t}^{nbr}$	Energy requirement of neighbor seeking energy purchase
$E_{k,t}^{l,nbr}$	Individual energy requirement of owner seeking to sell energy
L_{peak}^{U}	Peak load of unscheduled consumption
L_{peak}^{S}	Peak load of scheduled consumption
L_{valley}^{S}	Valley load of scheduled consumption
L_{mean}	Mean value of load
L_{total}^{S}	Total scheduled load
L_{total}^{U}	Total unscheduled load
γ	Coefficient for allowed margin

3. Any home in group 3 is a high consumption household which are having 7-8 eight members in the house. It is classified as high consumption house.

4. The fourth group is classified as very high consumption home.

It is assumed that each household is registered for the net metering system in coordination with LSE to communicate the demand load information and to get day-ahead electricity prices in reverse. The electricity prices considered are not real prices, although it can give close information to the actual charges. Few households are equipped with EV at their premises. The EV customers are registered for the V2G, V2H and V2N type of modes. ALCU of each household handles the bidirectional information for the energy and price communication.

For the applicability of V2N connection, each household is connected to the centralized control unit (CCU). The transmission of bi-directional power flow and energy information is updated via CCU. When there is a surplus energy available to a customer, stored in the storage asset, the power flow is enabled to transfer the electricity to the neighborhood through CCU. Afterwards, the CCU can utilize the surplus energy via power transaction to another customer having energy requirement. This type of problem arises in peak hours when LSE is not able to fulfill the demand. As a solution, the concept of selling power from one end-consumer to another can enhance the flexibility. This idea can also be applicable in times when LSE is serving load at high charges during peak hours; Therefore a customer can get power from a neighbor at comparatively lower prices. The prices for buying and selling the energy should be same for customers participating in such event.

The degradation of EV battery during charging and discharging is a major concern. Here it is assumed that depreciation of EV battery is taken care of by EV manufacturer company in battery rental business [83]. The charging of EV can be of two types. First is dumb charging; it is applicable when EVs begin charging immediately after returning from their last journey of the day. Another is smart charging; in this EVs are charged at low electricity prices during off-peak hours and discharge when electricity prices are high.

4.2.2 Mathematical Modeling

This section presents mathematical model for the proposed system. The operation of a household is analyzed for a single day. The day is split into equal time divisions and the time horizon for the day is denoted as T and indexed as t.

4.2.2.1 Smart Charging Mode of Operation

The objective function of the proposed smart charging is to minimize the total daily cost for energy usage of each household. The cost function described in (4.1) is the total cost function (TCF) calculated for a for household customers shown as,

$$\text{Minimize TCF} = \sum_{k=1}^{K} \sum_{t=1}^{24} C_{t,buy}\, E_{k,t}^{grid} \tag{4.1}$$

The objective function describes the total cost for procuring energy transaction between the user and the grid. The energy purchased from grid by user is utilized for appliance usage and charging of EV. The cost for EV maintenance and other appliances is neglected here. The minimization of total cost function of energy demand is subjected to various constraints described as follows,

a) Power Balance Constraints:

The power balance at each time step within a household is described as:

$$P_{k,t}^{grid} = P_{k,t}^{NS} + P_{k,t}^{S} + P_{k,t}^{ev,C} \tag{4.2}$$

Where $P_{k,t}^{grid}$ is the power supplied by grid. $P_{k,t}^{NS}$, $P_{k,t}^{S}$, $P_{k,t}^{ev,C}$ are the power for non-shiftable, shiftable and EV load respectively.

$$E_{k,t}^{grid} = P_{k,t}^{grid} * t \tag{4.3}$$

The time sampling is considered as one hour. Equation (4.2) represents the power balance equation for smart charging optimization framework. In this scenario, the total energy brought from grid $E_{k,t}^{grid}$ is consumed for the purpose of non-shiftable, shiftable appliance and EV load demand, which is $E_{k,t}^{NS}$, $E_{k,t}^{S}$ and $E_{k,t}^{ev}$ respectively.

$$\text{Minimize } \sum_{k=1}^{K} \sum_{t=1}^{24} C_{t,buy} \left(\underbrace{(E_{k,t}^{NS})}_{\text{I}} + \underbrace{(E_{k,t}^{S} + E_{k,t}^{ev,C})}_{\text{II}} \right) \tag{4.4}$$

The objective function is split into two parts as in (4.4). The first term represents the non-shiftable type of appliances, it results no shifting in load. The second part comprises the cost for the shiftable type of appliances and EV which varies. Hence the total cost is optimized.

b) Electric Vehicle Constraints: In smart charging, EV is considered only for charging purpose. The charging schedule of EV is determined by optimizing the total cost function. The charging and discharging equation of EV is represented in (4.5-4.6), where η_{ev}^{C} and η_{ev}^{D} are the charging and discharging efficiency of EV, respectively.

$$E_{k,t}^{ev,C} = \frac{\widehat{E}_{k,t}^{ev}}{\eta_{ev}^{C}} \tag{4.5}$$

$$E_{k,t}^{ev,D} = \widehat{E}_{k,t}^{ev} * \eta_{ev}^{D} \tag{4.6}$$

$$EL_{k,t}^{ev} \leq E_{k,max}^{ev} \quad \forall t \in [T_a, T_d] \tag{4.7}$$

$$EL_{k,t}^{ev} \geq E_{k,min}^{ev} \quad \forall t \in [T_a, T_d] \tag{4.8}$$

The maximum and minimum limits imposed on state of energy level of EV is represented in (4.7-4.8). The charging of EV can only be done when vehicle is at home i.e. between the arrival time T_a and departure time T_d.

$$E_{t}^{trip} \leq E_{k,max}^{ev} \quad \nexists\, t \in [T_a, T_d] \tag{4.9}$$

$$EL^{initial} + E_{charge} \geq E_{trip} \tag{4.10}$$

For the purpose of going on a trip the EV can use maximum energy i.e. $E_{k,max}^{ev}$. The energy required for a trip should always be less than the sum of initial battery level and state of charge as shown in (4.10).

b) Power Transaction Constraints: The power transaction limits are imposed on each type of connection. The upper and lower limit of peak load is defined in (4.11)-(4.12).

$$\begin{aligned} L_{peak}^{S} &\leq L_{mean} + Margin \\ L_{valley}^{S} &\geq L_{mean} - Margin \end{aligned} \tag{4.11}$$

$$L_{total}^{U} = L_{total}^{S} \tag{4.12}$$

$$Margin = \frac{L_{peak}^{U} - L_{mean}}{\gamma} \tag{4.13}$$

Where, γ is the coefficient of allowed margin which can be interpreted as,

If $\gamma = 2$, allowed margin is 25 % of previous peak

1. Lower the margin better the PAR but lower the consumer benefits.
2. Higher margin means better consumer benefit but less improved PAR.
3. Therefore, a balanced γ should be chosen, so there could be balance restored in PAR and consumer benefit.

4.2.2.2 Vehicle to home (V2H) Modeling

The household energy is supplied by EV during peak periods in V2H mode. The function in (4.14) represents final objective for V2H mode. The negative sign represents that the energy is supplying from vehicle to home.

$$\text{Minimize } \sum_{k=1}^{K} \sum_{t=1}^{24} C_{t,buy} \left(E_{k,t\ fixed}^{NS} + E_{k,t}^{S} + E_{k,t}^{ev,C} - E_{k,t}^{ev,D} \right) \tag{4.14}$$

The energy balance constraints for this mode of operation are described as follows ,

$$E_{k,t}^{grid} = E_{k,t}^{NS} + E_{k,t}^{S} + BE_{k,t}^{ev,C} - (1 - B)E_{k,t}^{ev,D} \tag{4.15}$$

$$E_{k,t}^{ev,D} = \left\{ \begin{array}{ll} E_{k,t}^{ev,D}, & \text{if } E_{k,t}^{ev,D} \leq E_{k,t}^{load} \\ E_{k,t}^{load}, & \text{if } E_{k,t}^{ev,D} \geq E_{k,t}^{load} \end{array} \right\} \tag{4.16}$$

$$E_{k,t}^{load} = E_{k,t}^{NS} + E_{k,t}^{S} \tag{4.17}$$

The energy supplied by grid is consumed by household appliances and EV as shown in equation (4.15). The binary variable B is interpreted 1 if EV is in charging mode and 0 if it is in discharging mode. The charging and discharging equation of EV is given by (4.5) and (4.16).

4.2.2.3 Vehicle to grid (V2G) Modeling

In V2G mode, the energy can be fed back to the grid when household acquires surplus energy at home. The objective function for this mode is represented in (4.18). The objective function is split into two parts. The first part is to minimize the total cost of purchasing energy from the grid. The second part comprises the maximization of total revenue obtained by selling energy back to the grid.

$$\begin{aligned} \text{Minimize} \sum_{k=1}^{K}\sum_{t=1}^{24}\Bigg\{ & \underbrace{C_{t,buy}\,(E_{k,t}^{NS} + E_{k,t}^{S} + E_{k,t}^{ev})}_{I} \\ & - \underbrace{(1-\alpha)C_{t,sell}\,E_{k,t}^{ev,D}}_{II}\Bigg\} \end{aligned} \tag{4.18}$$

Where, α is the service charge for using grid infrastructure i.e. usually 5% to 15% of selling price of electricity at that time. The service charge depends on the location and the electricity grid. The energy balance constraint in (4.19) shows that B is a binary variable for EV charging and discharging which can be assigned a value as 1 and 0 respectively.

$$E_{k,t}^{grid} = E_{k,t}^{NS} + E_{k,t}^{S} + BE_{k,t}^{ev,C} - (1-B)E_{k,t}^{ev,D} \tag{4.19}$$

4.2.2.4 Vehicle to neighbor (V2N) Modeling

In V2N mode, the power sharing is enabled from vehicle to a neighbor. The surplus energy available for vehicle is shared to a neighbor during peak price hours. The objective function for this mode is represented in (4.20). Where first part denotes the energy brought from grid and second part denotes the energy sold among neighbors.

$$\begin{aligned} \text{Minimize} \sum_{k=1}^{K}\sum_{t=1}^{24}\Bigg\{ & \underbrace{C_{t,buy}\left(E_{k,t}^{NS} + E_{k,t}^{S} + E_{k,t}^{ev,C} - E_{k,t}^{ev,onr}\right)}_{I} \\ & - \underbrace{C_{t,sell}E_{k,t}^{nbr}}_{II}\Bigg\} \end{aligned} \tag{4.20}$$

The energy balance constraint is represented by (4.21), whereas equation (4.22)-(4.24) gives the information about the energy required for a neighbor which is transferred by the owner of an EV.

$$E^{grid}_{k,t} = E^{NS}_{k,t} + E^{S}_{k,t} + BE^{ev,C}_{k,t} - (1 - B)E^{ev,D}_{k,t} \tag{4.21}$$

$$E^{ev,D}_{k,t} = E^{ev,onr}_{k,t} + E^{nbr}_{k,t} \tag{4.22}$$

$$E^{ev,onr}_{k,t} = \left\{ \begin{array}{ll} E^{ev,D}_{k,t}, & \text{if } E^{ev,D}_{k,t} \leq E^{l,onr}_{k,t} \\ E^{load}_{k,t}, & \text{if } E^{ev,D}_{k,t} \geq E^{l,onr}_{k,t} \end{array} \right\} \tag{4.23}$$

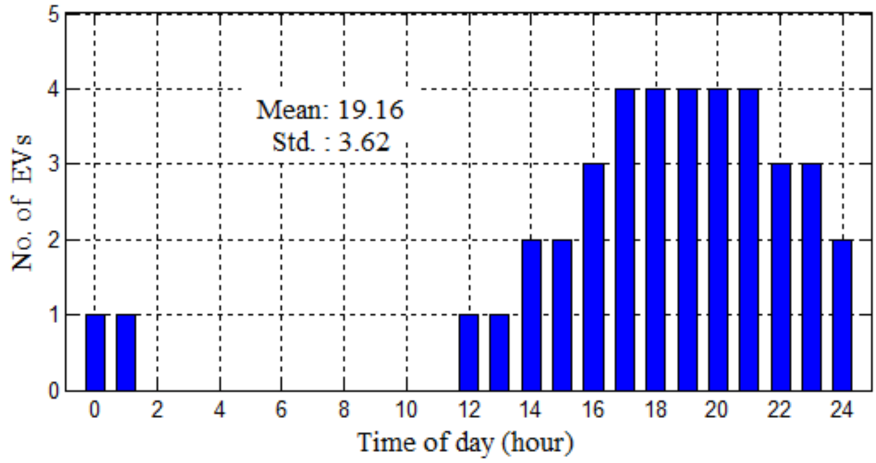
$$E^{nbr}_{k,t} = \left\{ \begin{array}{ll} E^{ev,D}_{k,t} - E^{l,onr}_{k,t}, & \text{if } E^{ev,D}_{k,t} \leq E^{load}_{k,t} \\ 0, & \text{if} E^{ev,D}_{k,t} \geq E^{load}_{k,t} \end{array} \right\} \tag{4.24}$$

In V2N mode, it is considered that a vehicle owner is sharing their surplus power to a certain neighbor. But there is a constraint that neighbor will only consume power from vehicle owner when the offering electricity prices are less than the grid electricity prices in the particular time period. $C_{t,buy}$ denotes the electricity buying price which is a real-time price offered by load-serving entity (LSE) on a day-ahead basis. Whereas $C_{t,sell}$ denotes the energy selling price to a neighborhood consumer. Here for a particular scenario this $C_{t,sell}$ is fixed. The concept can be simplified as the neighbor consumer seeking for energy demand will only purchase energy from another consumer if the offering prices are less than the grid prices for a particular hour. This concept will be proven beneficial when the grid energy prices are very high during peak-hours. In the peak hours, a neighbor can purchase the energy from another consumer, particularly vehicle owner. The selling price can be decided on the basis of peak demand and peak energy prices at different times.

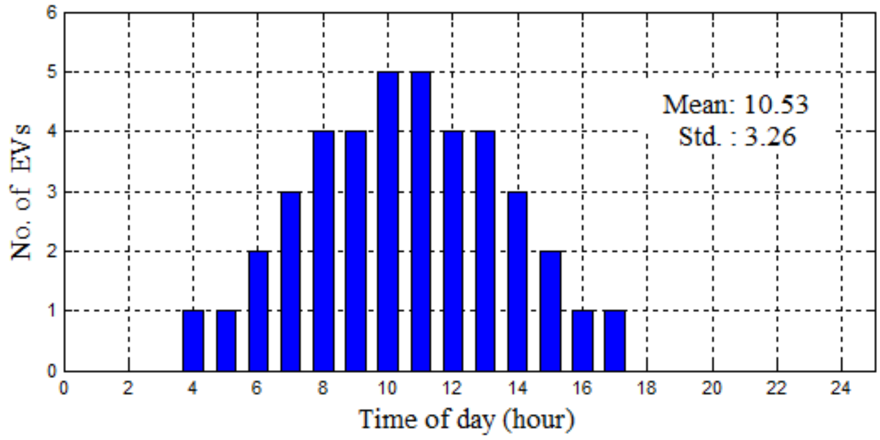
4.3 EV uncertainty capture model

The EV uncertainties are accounted to generate the appropriate input scenarios for EV arrival and departure time. The realization of the uncertain variables is modeled through Gaussian distribution method. This distribution is widely used for arrival and departure time [84].

The data for EV arrival and departure time have taken from [84]. The arrival and departure time is plotted in Fig. 4.1. The Gaussian distribution considered here as arrival time with the mean of 19.62 and standard deviation of 3.62. The departure time is considered



(a) Arrival time



(b) Departure time

Figure 4.1: Daily driving statistics

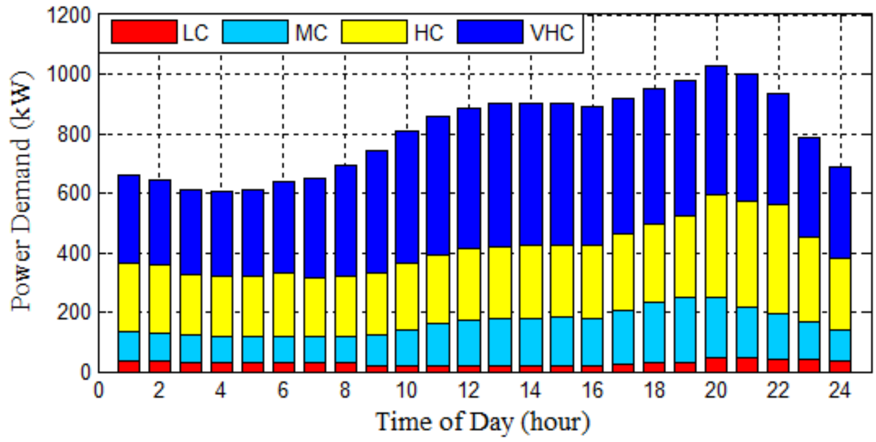


Figure 4.2: Residential power demand profile.

with 10.53 mean and 3.26 standard deviation. The range should be maintained that the departure time must be greater than or equal to the sum of arrival time and the required

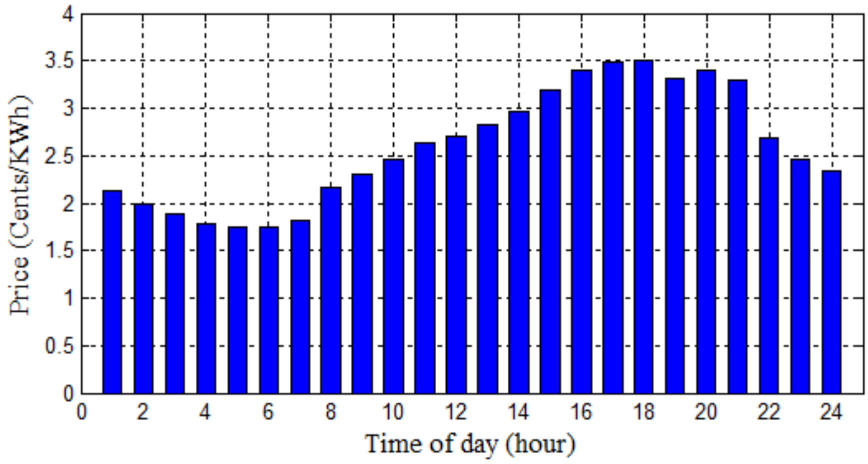


Figure 4.3: Dynamic price signals.

charging time.

4.4 Performance Evaluation & Results Discussion

The simulation results are presented and analyzed to justify the performance of proposed approach.

4.4.1 Input Data

In the simulation, 100 household consumers of different type is considered. The houses are divided into four groups. In the first class, 40 houses are considered as low consumption (LC) users. In the second class 40, households are taken as mid-consumption (MC). The third class as high consumption (HC) users having 15 homes. The fourth class of very high consumption (VHC) consists of five homes. The total load data is taken from BGE suppliers [85]. For user preference appliance data is shown in Table 3.2. Total demand for the different type of users based on their consumption is shown in Fig. 4.2.

The household is assumed to be contracted for the day ahead pricing from LSE via AMI technology. For day ahead pricing scheme the load demand of consumers is updated to LSE, and in return, the price signals are informed to the user for next day. Price information is highly volatile, and to get future price information; the prediction techniques are needed. The future price can be predicted by applying prediction techniques. The price signal used for the day ahead pricing is taken from Ameren Illinois Power [46] as shown in Fig. 4.3.

In the system, each house is not equipped with EV. The capacity of EV in the system is considered based on the practical scene. In a society, the different class of customers exists, it is not possible for everyone to purchase an EV. Therefore only a few houses are considered to be installed with EV. In total four type of 40, EVs are equipped with the system. The number of EVs installed is 10, 16, 10 and 4 for LC, MC, HC and VHC user, respectively. The electric cars data and ratings are represented in Table 4.2 have been taken from [83].

The optimization problem for total cost minimization is formulated as MILP aimed to reduce the daily bill of the user. Each household user is operating with their individual ALCU and controlling their energy expenses and load. Although, there is one centralized unit is operating for every user and managing the operations in a centralized fashion. The MILP optimization problem is solved using CVX version 2.0 beta [77] on the MATLAB platform.

4.4.2 Assumptions

The few assumptions have been taken for the implementation purpose of the proposed system and briefly explained as,

1. The ratio of shiftable loads is considered from 30-40 % of total amount (randomly selected for users).
2. For the V2H mode, the power required for the house is supplied by vehicle (either load or rated discharge value).
3. For V2N mode, energy to a neighbor, is supplied only when owner meets demand (only surplus energy is applicable send to the neighbor).
4. For V2G mode, energy fed back to the grid is applicable for peak price times since frequent charging and discharging of the battery also cause the decrease in life span of battery).
5. The charging and discharging of the EV can not take place simultaneously.

Algorithm 4.3 Smart charging

procedure
Organize consumer load data on consumption base (equation 4.2)
Prepare EV consumption data with associated user
Consider EV uncertainty model for real-world randomness
Calculate day-ahead dynamic prices (RTP) using prediction technique
Note: All the MILP optimization problem is solved using CVX version 2.0 beta on the MATLAB platform
Based on shiftable appliances, prepare shiftable-load in variable form ((equation 4.2) where shiftable and EV with binary variable)(using binary variable)
Based on EV's availability and charging constraint build EV load in binary variable form
Run (MILP objective function for smart charging mode (equation 4.4))
  Constrains:
    Fixed total power consumption $L^{S}_{total} = L^{U}_{total}$
    Power transaction limits (upper and lower limit) (equations 4.11-4.13)
    EV charging constrains (equations 4.5,4.7-4.10)
  End constrains
Verify (Verify results obtained from solver)
end procedure

Note: Gurobi package is mandatory in CVX version for MILP solution.

4.4.3 Results and Discussion

The simulation is done for different mode of operations to evaluate the EV capabilities applicable for smart charging, V2H, V2G and V2N modes. In smart charging, the day ahead load scheduling with dynamic prices is executed. The energy scheduling under varying price encourages the user to shift their energy demand to low price hours. The methodology of smart charging is discussed in Algorithm 4.3.

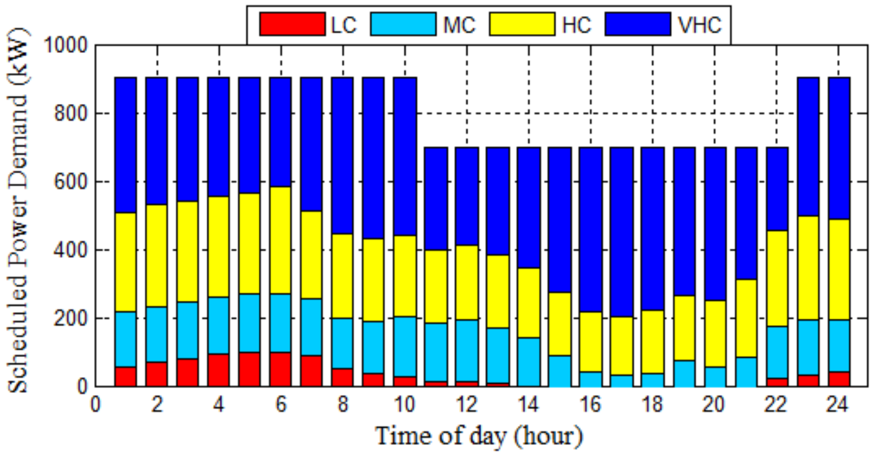


Figure 4.4: Residential power demand for shiftable appliance.

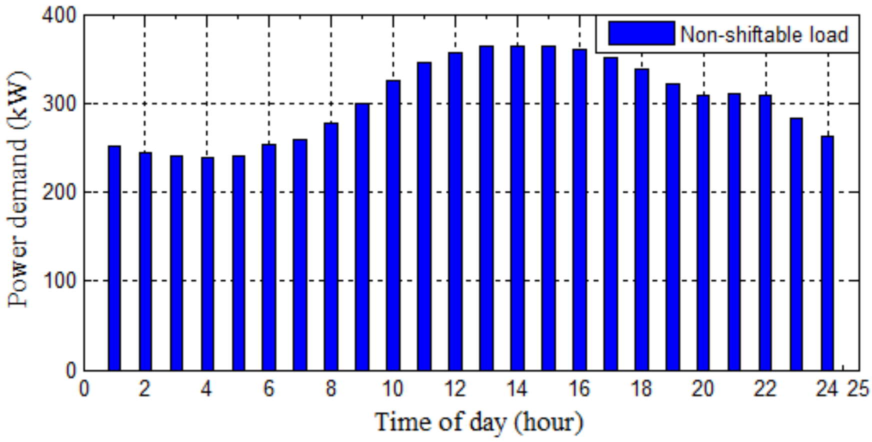


Figure 4.5: Residential power demand profile for non-shiftable appliance.

If all user tries to deviate their load to low price hours, the grid may suffer due to accumulated load. For this purpose, the peak power limiting strategy is applied for scheduling user's load. Total load demand comprises non-shiftable and shiftable type of load as shown in Fig. 4.4 and Fig. 4.5. The non-shiftable appliance load can not be shifted even with time-varying prices whereas shiftable appliance load is schedulable.

Algorithm 4.4 Vehicle to home (V2H)

procedure
Organize consumer load data including EV's similarly as earlier (4.15)
Similarly calculate day-ahead prices Based on EV's availability and charging/discharging constraint build EV load in binary variable form
Run (MILP objective function for V2H (4.14)
  Constraints:
    Fixed total power consumption $L^S_{total} = L^U_{total}$
    Similarly power transaction constraints (4.11-4.13)
    EV charging/discharging constraints (4.5-4.10)
    EV V2H discharging constraints (4.16)
  End constraints
Verify (Verify results obtained from solver)
end procedure

Here, two type of EV charging is employed i.e. dumb charging scenario and smart charging. The dumb charging allows the user to charge their EVs at any times when they return at home. But in smart charging user is participating in optimization process to determine the optimal charging time allocation. It enables the economic benefits to the users in term of reducing their daily energy bill.

The algorithm executed for V2H and V2G connection is shown in Algorithm 4.4 and Algorithm 4.5, respectively. For the operation of V2G and V2N modes, the scheduled

Algorithm 4.5 Vehicle to grid (V2G)

procedure
Prepare predicted RTP and consumer load data including EVs similarly as earlier (4.19)
Define EV consumer to grid energy selling price
Based on EVs availability and charging/discharging constraint build EV load in binary variable form
Run (MILP objective function for V2G (4.18)
    Constraints:
        Similarly total power consumption $L^S_{total} = L^U_{total}$
        Power transaction constraints(4.11-4.13)
        EV charging/discharging constraints (4.5-4.10)
        Only difference will be in (4.16), where EV discharge upper limit is not bonded by EV consumer household consumption
    End constraints
Verify (Verify results obtained from solver)
end procedure

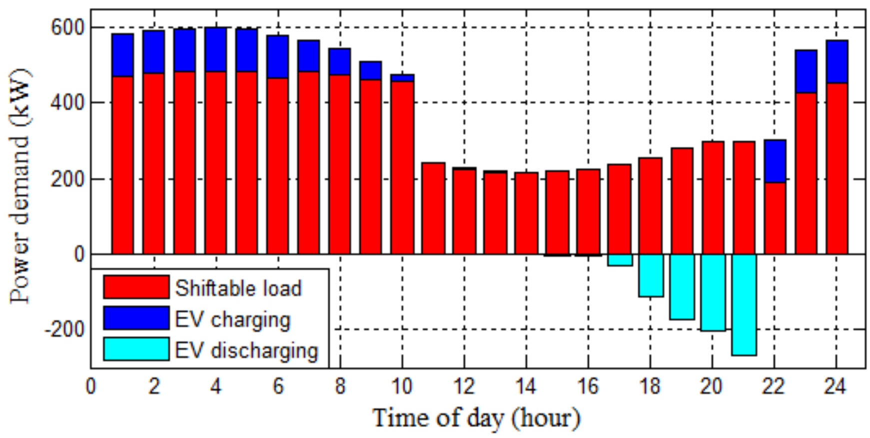
load is shown in Fig. 4.6b. The vehicle is charging in off-peak hours and supplying a load of the consumer in high price region when owner vehicle is available that time only. However, there are some limitations in V2H connection i.e. EV will supply only when the discharge rate of EV is greater than the household requirement.

In the simulation results, due to various assumptions, it is observed that the scheduled load look almost similar when the vehicle is supplying to home either to grid but the effect of operation can be seen in the daily energy payment shown in Table 4.3. In V2G operation, the household who is supplying power to the grid has to bear the charge for using grid infrastructure.

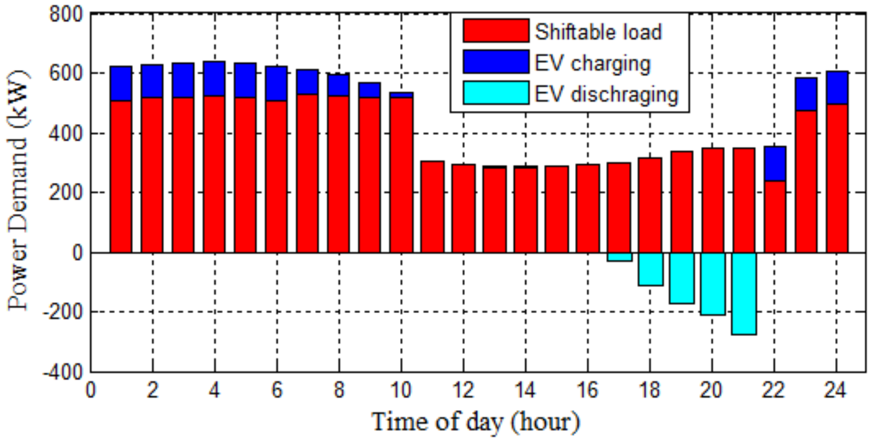
Algorithm 4.6 Vehicle to neighbor (V2N)

procedure
Prepare consumer load data including EV's similarly as earlier (4.19)
Prepare predicted RTP and define neighbor energy selling price **Run** (MILP objective function for V2G (4.20)
    Constraints:
        Power balance constraint (4.21-4.22)
        Power transaction limits (4.11-4.13)
        EV to owner power supply constraint (4.23)
        EV to neighbor power supply constraint (4.24)
    End constrains
Verify (Verify results obtained from solver)
end procedure

In the operation of V2N mode, the power transactions are done between the vehicle owner who is having excess energy that can be transferred to a neighbor facing difficulty



(a)



(b)

Figure 4.6: Load scheduling for proposed system with a) V2G connection and b) V2N connection.

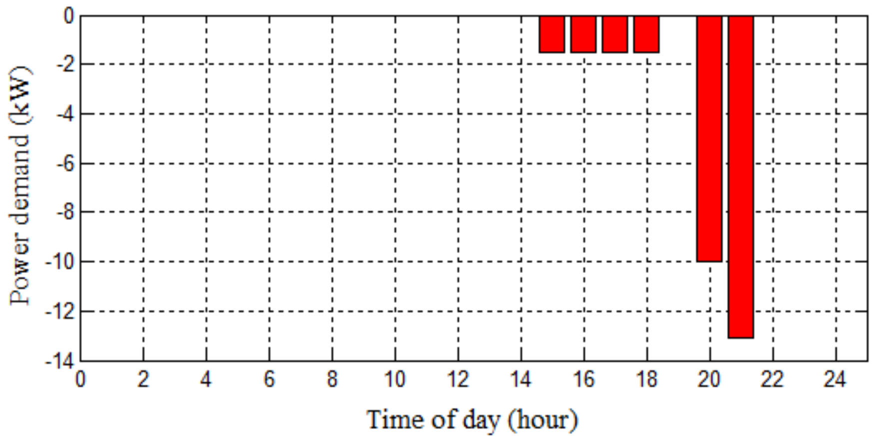


Figure 4.7: Power shared to neighbor.

in scheduling the load at the peak hours when the grid is offering power at high prices. During the V2N operations, some limits have been imposed on energy transaction i.e.,

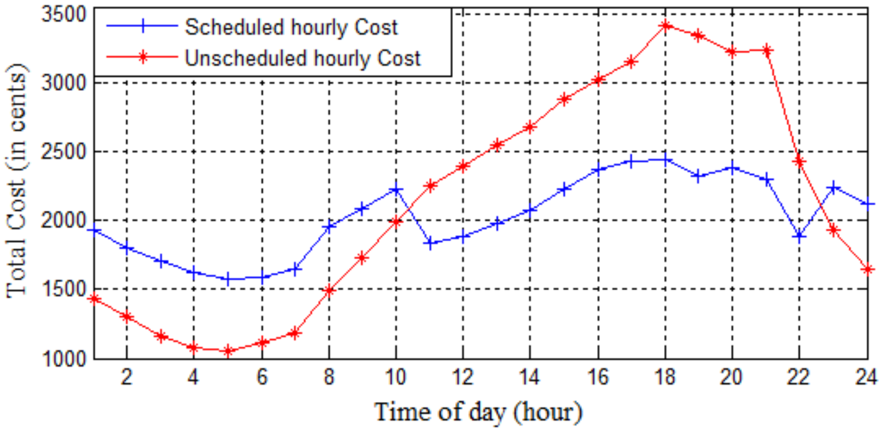


Figure 4.8: Hourly cost benefit for the proposed system with smart charging.

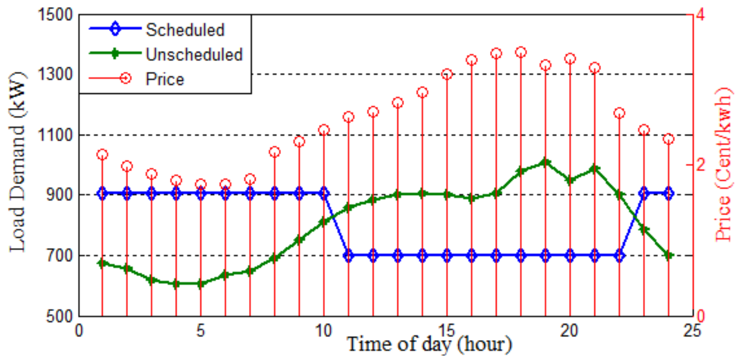


Figure 4.9: Load demand on hourly basis for the proposed system with smart charging.

the neighbor will get additional power available only when the EV discharge rate is higher than total owner house load and neighbor load. The power shared to a neighbor in V2N connection is shown in Fig. 4.7.

It is shown in Fig. 4.6a that the discharging of EV is occurring during evening 5 to 10, this is the period when vehicle with surplus storage can supply to the neighbor. The total cost appeared during unscheduled and scheduled is shown in Fig. 4.8. It can be analyzed that the hourly cost is reduced during peak hours. The impact of smart charging is also analyzed in term of cost. The scheduled load shown in Fig. 4.9 can result in a flattened load curve. In this context, the benefits to the user on a daily basis is represented in Fig. 4.10. Here it is shown that the economic benefit is high for the EV owners as compared to other. The large consumption users are getting large benefits as compared to low consumption users because of their capacity and EVs. The selling electricity price from vehicle to a neighbor is considered fixed as 3 Cents/kWh.

The influence of using EVs is very high for users in their cost benefits. The results in Fig. 4.11 can prove the benefits of using EVs as the compare to those who do not

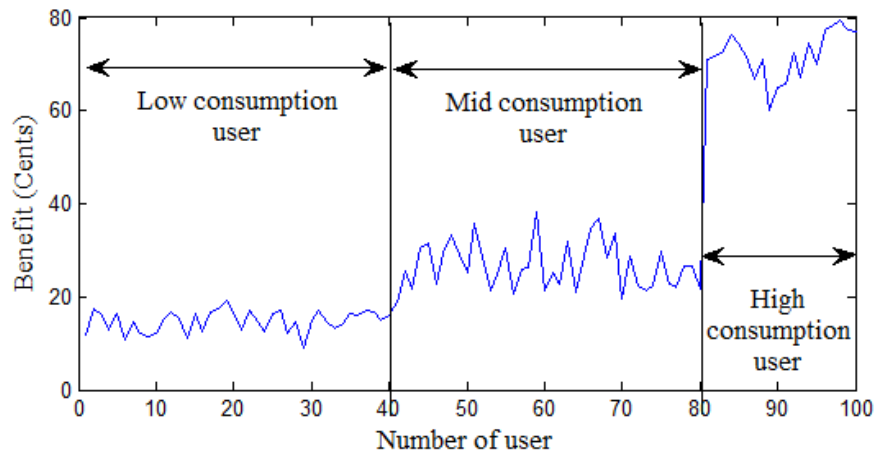


Figure 4.10: Total benefits of different class users.

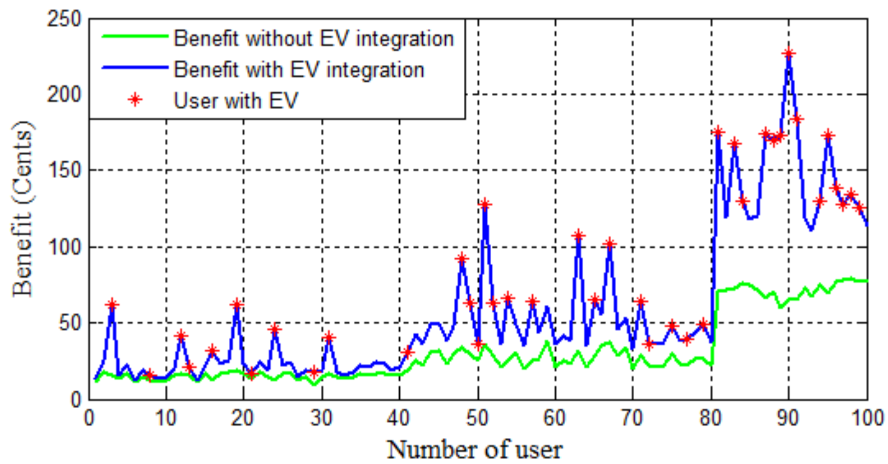


Figure 4.11: Benefits of EV integration.

have EVs. The benefits are also compared for proposed system with and without EV integration, and it can be seen that impact of using EVs is very high on system benefits for each user.

The numerical analysis of results for different operating modes is shown in Table 4.3. It can be seen that a significant reductions is observed in PAR. The total benefits for bill payment is proved effective for the proposed strategy. The cost benefit is analyzed with respect to base scenario i.e without application of optimization or unscheduled load. The cost benefit for smart charging is 31 $ whereas the operating modes V2H, V2G and V2N is 59.6 $, 60.29 $ and 60.29 $. The cots benefits for V2G and V2N modes are similar because only one mode can operate at a time. The choice of using EVs can affect the user load as well as total electricity bills.

Table 4.2: Electric Vehicle Data

Parameter	Tesla roadster	BMW mini E	Think city	Chevy volt
Capacity [kWh]	53	35	28.3	16
Maximum usable capacity [kWh]	47.7	31.5	25.5	14.4
Min capacity [kWh]	5.3	3.5	2.83	1.6
Charging & discharging efficiency [%]	0.93	0.93	0.93	0.95
Full charging time [hour]	3.5	3	13	5.1
V2G Discharging time [hour]	3.5	3	13	5.1

Table 4.3: Daily Cost Benefits.

Operation	Cost Benefit (in Cents)	PAR reduction (%)
Smart Charging	3100.1	10.2232
V2H mode	5964.1	6.0675
V2G mode	6029.6	5.9673
V2N mode	6029.6	5.9673

4.5 Summary

The operation of residential energy customers equipped with an ALCU was studied. Under a centralized system, a controller is aimed to minimize the total energy procuring cost with dynamics pricing environment. Furthermore, various operating modes have been analyzed to prove the benefits of the proposed methodology. The bi-direction flow of power was considered between each house and load-serving entity which also contributes to neighborhood communication. The application of the proposed methodology encourages the household user to shift their energy consumption in order to achieve lower daily energy bills. The simulations confirmed that by using proposed approach, in addition to maximizing the user benefit, the energy provider can benefit as well by reduced PAR. Further integration of vehicles in the transportation environment has introduced the new kind of load in the residential sector, whereas the proposed strategy can develop smooth operations in the scenario.

Chapter 5

Optimal Scheduling of Renewable Sources with EV and BESS in DR

5.1 Introduction

Price-based DR programs can eventually determine the actual energy prices such that energy user is encouraged to change their consumption patterns and shifts demand from peak hours to off-peak hours [4]. With the help of technological advancement of advanced metering infrastructure (AMI), the bidirectional communication of information between electricity user and a load-serving entity can be achieved [14]. The smart metering technology has removed the barrier for two-way information communication. The household user can contribute a significant potential for reduction in energy demand during peak hours. With the rapid growth of electric vehicles (EVs), residential users are encouraged to utilize electric vehicle [86]. The EV load is treated as a shiftable load, so it can make a voluntary impact on the demand of the residential consumer, which improve the efficiency of DR programs.

Renewable energy integration to the electricity grid is a fundamental, solid integration approach to maximize the cost-effectiveness of incorporating renewable sources in the power system and ensuring that the system stability and reliability is imperative. According to the US Energy Department report, the renewable sources sustain the potential to fulfill the energy needs in society [87]. In the context, the combination of EVs and renewable sources based DR is proposed in [88], the approach contributes towards the fluctuation cost term regarding uncertain appliance load and EV load in user electricity bill. A day-ahead renewable power accumulation based DR is proposed in [89], a two-stage stochastic mixed-integer programming problem is modeled.

The inclusion of renewable sources in the DR programs makes it more convenient to the user to manage household load when user can have private source for energy producing. The use of renewable sources can reduce the burden of the electricity grid atleast in peak demand hours. A day-ahead load scheduling for home management with PV system is proposed in [90], which executed a robust algorithm for incorporating the uncertainty related to household PV system. The high penetration of plug-in electric vehicle (PHEV) and photovoltaic (PV) is found in [91], followed by analysis of demand response programs for residential customer's aspect. A household simulation model is presented in [92], which proposes a technique to stabilize the charging issues of plug-in electric vehicles. Where, a vehicle-to-grid energy transaction is made possible with the help of bidirectional communication between household and energy user.

The inclusion of renewable energy sources is a highly beneficial to avoid the coal-based plant for energy generation which contributes toward less carbon environment [93]. The carbon emission free nature of electric vehicle enables the opportunity to introduce it in the application of multiple energy systems for the residential user. Integration of carbon emission reduction approach with the home energy scheduling makes DR actions much adaptable for the customers [94]. The advent of carbon-free technologies have led to the application of electric vehicles in the power industry. The electric vehicle provides the facility such that it can be used as load as well as a source. This can reduce the burden on conventional energy sources. The renewable energy sources with DR framework is enabled to facilitate carbon footprints reduction approaches. In this context, a residential automated system with a hybrid fuel cell (FC) and solar PV system modeled is explored in [95]. Similarly, a residential hybrid thermal/electrical grid-connected home management system is analyzed in [96], this home system includes a fuel cell with combined heat and power (CHP) and a battery system as storage. The author examines the battery and renewable sources capacity for the electrical and thermal generation by using a lookup table.

This chapter is focused on the energy management of household with several assets including home appliances, renewable sources, electric vehicle (EV) and battery energy storage system (BESS). The optimization problem of smart home energy management is developed as a mixed integer linear programming (MILP). Smart home energy is driven via the acquisition of residential customer's preference in an automated system participating in DR programs. The main contributions of this chapter is summarized as follows,

- The smart home energy management comprises two main parts: home automation and energy management of different combination of appliances present in homes.

The user behavior is accounted in the form of their daily energy need based on the appliance operation.

- The smart household management problem is investigated under the presence of dissatisfaction factor and by incorporating demand fluctuation.
- The bidirectional transaction of energy between customers and LSE is managed with the help of EVs and BESS.
- The DR load scheduling mechanism with utilization of renewable sources as carbon mitigating approach is also proposed in this chapter. The proposed mechanism also offers the dual approach where a user can minimize their electricity bill and carbon emission simultaneously without interfering their comfort.

The rest of chapter is organized as follows. The smart household management is described in Section 5.2. Residential DR model in the presence of demand fluctuation is described in Section 5.3. Carbon mitigation mechanism is presented in Section 5.4. The summary of chapter is given in 5.5.

5.2 Smart Household Management

The primary objective of the home energy management (HEM) system is to conserve energy, reduce cost & improve comfort. After the smart grid has come into an act, now it is viable to serve DR for having a better control of power consumption at residential places. A home energy management system has been proposed using mixed-integer linear programming (MILP) approach that processes a task-based energy consumption scheduling of a household [97]. The operation of distinct appliances such as thermal and critical appliance is investigated in [98]- [99]. The electricity consumer is assumed to be registered for real time prices based demand response programs by the load serving entity (LSE). A day ahead load scheduling is done to allow the smart charging of energy storage and scheduling of smart appliances in order to reduce carbon emission and consumer daily bill benefits by indulging in the programs by the load-serving entity. A energy management system for residential and communities of home user has been proposed by [59]. It has also included linear regression model to predict solar panel potential home appliances usage. A hardware model of home energy management has also implemented in [100]. It employs a experimental smart metering system with semantically enabled user interfaces.

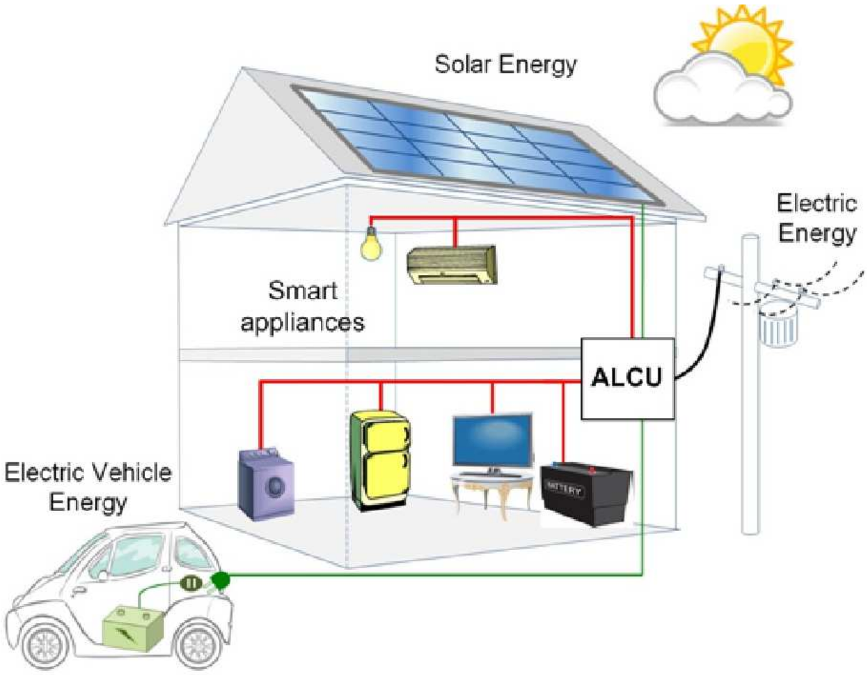


Figure 5.1: Smart household architecture

5.2.1 System Overview

A detailed structure of a smart household consisting of distinct appliances is considered here. The small scale solar photovoltaic system is available as a self-generation for the home user. The electric vehicle (EV) and battery energy storage system (BESS) are also present in the household system. The MILP model is formulated for implementation. The user equipped with automatic load controller (ALCU) has the capability to enable the bi-directional communication of load to the load serving entity (LSE). The information of real time prices is conveyed by LSE on day ahead basis. The smart household architecture is shown in Fig. 5.1.

5.2.1.1 Home Appliances

DR is applied on a single household user operating under program. The user is installed with different AC appliance in home. AC appliances have specific characteristic according to applications. On the basis of characteristics, appliance are classified as follows,
1. Non-shiftable appliance: This type of appliance is considered as critical load of user. It can not be shiftable to some other time slot. The power consumed due to this type of appliance is denoted by P_t^{NS} in t^{th} hour.
2. Time-shiftable appliances: These appliances can be shifted from one time slot to

other. But it has some fixed minimum and maximum operating power limits. Its operating power is signified by $P_t^{TS(int)}$.

3. Time-shiftable continuous run appliances: Some appliance are time shiftable in nature but once started operating can not be interrupted. It makes them continuous run appliances. Its power rating denoted by $P_t^{TS(cont\_run)}$

4. Power-shiftable appliances: These appliances have flexible power limit but can not be shifted to some other schedule time. P_t^{PS} denotes the power rating of these type of appliance.

The total load consumed by household user can be given as follows,

$$P_t^{a,load} = P_t^{NS} + P_t^{TS} + P_t^{PS} \tag{5.1}$$

$$P_t^{TS} = P_t^{TS(cont\_run)} + P_t^{TS(int)} \tag{5.2}$$

Where, $P_t^{a,load}$ defines the total load by home appliances.

5.2.1.2 Mathematical Modeling

The mathematical modeling of different asset installed in smart household is modeled here. The operation of household appliances are considered for total T hours, the individual hour is denoted by t.

Electric vehicle (EV) modeling : EV system is included for charging and discharging purpose. The charging of EV is done by taking power from electricity grid. The discharging is happen when vehicle is not available at home. The mathematical interpretation of EV can be modeled by employing equations (5.3)-(5.7).

$$P_t^{ev,C} = \frac{\widehat{P}_{ev}}{\eta_{ev}^C} \qquad \forall t \in [T_a, T_d] \tag{5.3}$$

$$P_t^{ev,D} = \widehat{P}_{ev} * \eta_{ev}^D \qquad \forall t \in [T_a, T_d] \tag{5.4}$$

Where, $P_t^{ev,C}$ and $P_t^{ev,D}$ denotes the charging and discharging capacity of EV battery for t time slot, respectively. $\widehat{P}_{ev}$ is the rated power of EV battery. η_{ev}^C and η_{ev}^D are efficiency of EV charging and discharging. respectively. T_a and T_d are the arrival and departure time of vehicle.

$$E_t^{ev,soe} + E_t^{ev,C} \leq E_{max}^{ev} \qquad \forall t \in [T_a, T_d] \tag{5.5}$$

$$E_t^{ev,soe} - E_t^{ev,D} \geq E_{min}^{ev} \qquad \forall t \in [T_a, T_d] \tag{5.6}$$

$$E_{min}^{ev} \leq E_t^{ev,soe} \leq E_{max}^{ev} \qquad \forall t \in [T_a, T_d] \tag{5.7}$$

$E_t^{ev,soe}$ is the initial state of energy for EV battery. The maximum and minimum allowable energy limits of EV battery is denoted by E_{max}^{ev} and E_{min}^{ev}. $E_t^{ev,C}$ and $E_t^{ev,D}$ is the energy consumed by EV for the charging and discharging time, respectively.

Solar photo voltaic (PV) modeling: The small scale solar rooftop PV generation is installed in smart household. The utilization of PV power is included for appliance usage and BESS charging purpose and after this if available can be fed back to grid. The PV power production can be modeled by,

$$P_t^{pv,used} = P_t^{pv,pro} \tag{5.8}$$

Equation (5.8) states that the power produced by PV in each hour is utilized by home appliances and asset.

Battery energy storage system (BESS) modeling: The employment of BESS is done for both charging and discharging purpose. The mathematical representation of battery modeling can be analyzed from equation (5.9)-(5.13).

$$P_t^{bess,C} = \eta_{bess} * \widehat{P}_{bess} \tag{5.9}$$

$$P_t^{bess,D} = \frac{\widehat{P}_{bess}}{\eta_{bess}} \tag{5.10}$$

The equation (5.9) and (5.10) describes the charging and discharging power capacity of BESS, respectively. $\widehat{P}_{bess}$ and η_{bess} represents the rated power and efficiency of battery, respectively. The charging and discharging efficiency of battery are same.

$$E_t^{bess,ini} + E_t^{bess,C} \leq E_{max}^{bess} \qquad \forall t \in T \tag{5.11}$$

$$E_t^{bess,ini} - E_t^{bess,D} \geq E_{min}^{bess} \qquad \forall t \in T \tag{5.12}$$

$$E_{min}^{bess} \leq E_t^{bess,ini} \leq E_{max}^{bess} \qquad \forall t \in T \tag{5.13}$$

Where, $E_t^{bess,ini}$ denotes the initial state of energy for BESS. E_{min}^{bess} and E_{max}^{bess} are minimum and maximum energy that can be consumed from BESS. $E_t^{bess,C}$ and $E_t^{bess,D}$ specifies the energy consumed by BESS for charging and discharging purpose.

5.2.2 Problem Formulation

The problem of day-ahead load scheduling for a smart household is formulated as minimization of user's daily electricity bill. The appliance load of smart household is generated with the help of historic data informed. The scheduling is done with the varying price information based on real-time pricing (RTP) data. The proposed objective function is the combination of the total cost of purchasing electricity from grid and dissatisfaction factor of user. If there is a situation when user denies to schedule their appliances as proposed by controller. In this case, a certain amount of penalty is applied to the user. Each appliance of user is denoted by a and set of appliance is A, $\forall a \in A$. The total developed revenue as objective function is as follows,

$$\begin{aligned} \text{Minimize} \quad & \sum_{t=1}^{24} \left(C_{t,buy} * E_t^{grid} - (1-\alpha) C_{t,sell} \, E_t^{sold} \right) \\ & + \sum_{t=1}^{24} \sum_{a=1}^{A} \left(\delta_a \, \omega_{ap} * P_t^a \right) \end{aligned} \tag{5.14}$$

Where, E_t^{grid} denotes the energy consumption by availing P_t^{grid} power from electricity grid. $C_{t,buy}$ is the hourly RTP prices for purchasing energy from grid. E_t^{sold} is the corresponding energy consumption by selling P_t^{sold} power to the grid. $C_{t,sell}$ denotes the prices for selling electricity back to grid. Here α is the service charge for using grid infrastructure i.e. usually 5% to 15% of selling price of electricity at that time. The service charge depends on the location and grid.

The second term in revenue represents the penalty caused by waiting of any appliance. δ_a represents the dissatisfaction factor defined for an appliance. Here dissatisfaction factor such as penalty is considered 20 % of hourly prices in Cents/kWh. The waiting period for an appliance is denoted by ω_a. P_t^a is the power corresponding to an individual appliance a.

Power balance constraints:

$$P_t^{grid} = P_t^{a,load} + P_t^{ev,C} + P_t^{bess,C} \tag{5.15}$$

$$P_t^{PG} = P_t^{pv,used} + P_t^{ev,D} + P_t^{bess,D} \tag{5.16}$$

$$P_t^{sold} = \left\{ \begin{array}{ll} P_t^{PG} - P_t^{grid}, & \text{if } P_t^{grid} < P_t^{PG} \\ 0, & \text{otherwise} \end{array} \right\} \tag{5.17}$$

Equation (5.14) represents the power balance equation for the household energy system. It justifies that the sum of power consumed by home appliance load $P_t^{a,load}$, EV charging load $P_t^{ev,C}$ and BESS charging load demand $P_t^{bess,C}$ should be equal to power demanded from grid. P_t^{PG} denotes the surplus power available at home by generation or discharging of assets. The power sold to grid is applicable only when surplus power is available at home. Equation (5.17) refers that sold power P_t^{sold} is available when the surplus power is greater than household usage power.

Power transaction limit constraints : The total load on the system for unscheduled consumption is denoted by L_{unsh} and modeled as,

$$L_{unsh} = \sum_{t=1}^{24} P_t^{a,load} + P_t^{ev,C} - P_t^{pv,used} \tag{5.18}$$

The total load after energy consumption scheduling is represented by L_{sch} and defined as,

$$L_{sch} = \sum_{t=1}^{24} P_t^{grid,sch} \tag{5.19}$$

$$L_t^{unsh} = L_t^{sch} \tag{5.20}$$

$$\begin{aligned} L_{sch} &\leq mean(L_{unsh}) + \mu_1 \\ L_{sch} &\geq mean(L_{unsh}) - \mu_2 \end{aligned} \tag{5.21}$$

$$\mu_1 = \frac{max(L_{unsh}) - mean(L_{unsh})}{\gamma_1} \tag{5.22}$$

$$\mu_2 = \frac{mean(L_{unsh}) - min(L_{unsh})}{\gamma_2} \tag{5.23}$$

In the system, sum of total load in a day before and after scheduling will remain same. From (5.21)- (5.23) shows the power transaction limit imposed on the system for load scheduling. Where L_{sch} denotes the load after scheduling. μ_1 and μ_2 are the margin parameters. γ_1 and γ_2 are the coefficient of allowed margin which helps to decide peak and valley load. The coefficient of allowed margin can be interpreted as,

If $\gamma_1 = \gamma_2 = 2$, allowed margin is 25 % of previous peak i.e.

- Lower the margin better the peak to average ratio (PAR) but lower the consumer cost benefits.
- Higher margin means better consumer benefit but less improved PAR.

The coefficient of allowed margin worked as trade-off between PAR and consumer benefit. Therefore, it should be chosen to restore the balance.

5.2.3 Case Studies for load scheduling

To examine the capabilities of proposed approach different scenario has been included. The mathematical explanation for scenarios is presented below.

5.2.3.1 Scenario 1: Scheduling without assets

In this case, the household with PV power production and EV smart charging is enabled. No power is fed back to the grid, only appliance usage and EV charging is considered. For the purpose, above equation presents additional constraints.

$$
\begin{aligned}
P_t^{grid} = P_t^{a,load} + P_t^{ev,C} - P_t^{pv,used} \\
P_t^{sold} = 0
\end{aligned}
\tag{5.24}
$$

For execution of equation (5.24) it is assumed that $P_t^{pv,used} < (P_t^{a,load} + P_t^{ev,C})$.

5.2.3.2 Scenario 2: Scheduling with assets

This scenario consists PV power injection, EV smart charging, and BESS charging/discharging both. Surplus power remaining after usage of appliance and EV, can be fed back to grid. The power constraint can be modified as follows.

$$
P_t^{grid} = P_t^{a,load} + P_t^{ev,C} + P_t^{bess,C} - P_t^{pv,used} \tag{5.25}
$$

$$
P_t^{sold} = \left\{ \begin{array}{ll} 0, & \text{if } P_t^{bess,D} < P_t^{grid} \\ P_t^{bess,D} - P_t^{grid}, & \text{otherwise} \end{array} \right\} \tag{5.26}
$$

While discharging, $P_t^{bess,C} = 0$. Charging and discharging cannot place at the same time. Therefore, if house power consumption is less than battery power discharge, then extra power will be fed back to grid.

5.2.3.3 Scenario 3: Scheduling with bidirectional energy transaction

This scenario evaluates with PV power production, EV charging/discharging and BESS charging/discharging. So the power constraint is modified as follows.

$$
P_t^{grid} = P_t^{a,load} + P_t^{ev,C} + P_t^{bess,C} - P_t^{pv,used} \tag{5.27}
$$

$$
P_t^{sold} = \left\{ \begin{array}{ll} 0, & \text{if } (P_t^{bess,D} + P_t^{ev,D}) < P_t^{grid} \\ (P_t^{bess,D} + P_t^{ev,D} - P_t^{grid}), & \text{otherwise} \end{array} \right\} \tag{5.28}
$$

5.2.4 Performance Evaluation and Results Discussion

For the simulation purpose, a single smart household system with 21 appliances is developed. To analyze consumer behavior, the practical data of appliances is considered.

The appliance load modeling is done on the basis of historic data shown in Table 3.2. On the basis of stored past data, user appliance load data is generated as shown in Fig. 5.2. The household user is equipped with assets i.e. electric vehicle, battery system as shown in Table 5.1. The user is allowed to deny the requested scheduling given by ALCU, but penalty will be imposed. The optimization problem in (5.14) is formulated as mixed integer linear programming (MILP). The MILP optimization problem for load scheduling is solved using CVX version 2.0 beta [77] on the platform of MATLAB software.

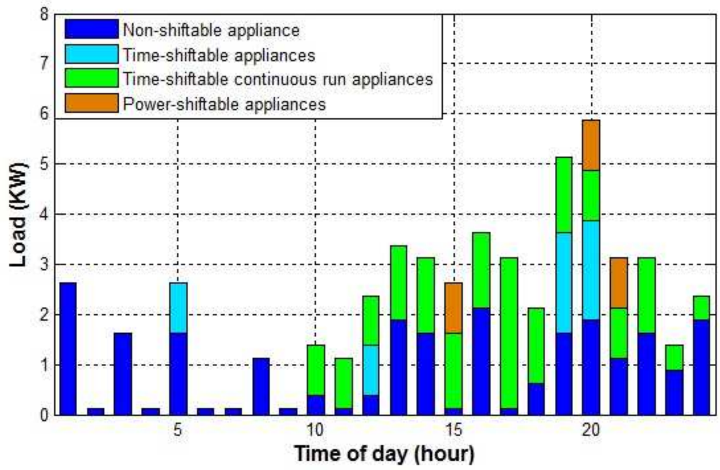


Figure 5.2: Smart household appliance unshceduled load

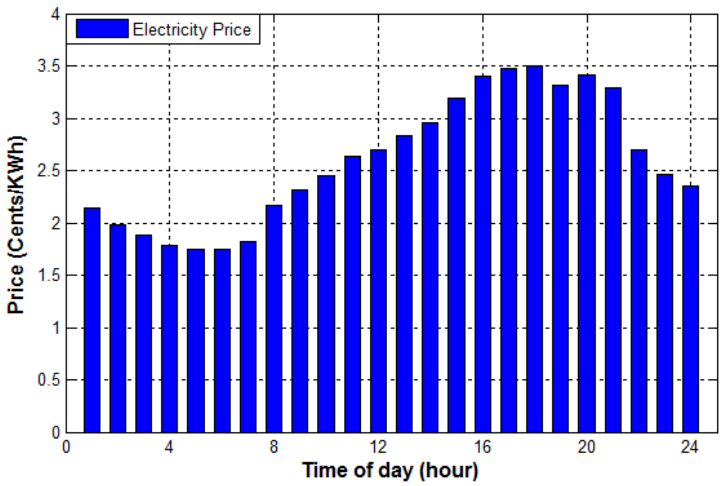


Figure 5.3: RTP price data

The household user is contracted for day-ahead RTP price from LSE and price is communicated to user via the ALCU. In day ahead pricing, the load demand of consumers is updated to LSE and in return, the price signals are informed to the user for next day. Price information is highly volatile and for the purpose of getting future price information, the prediction techniques are needed. Future Price can be predicted by applying

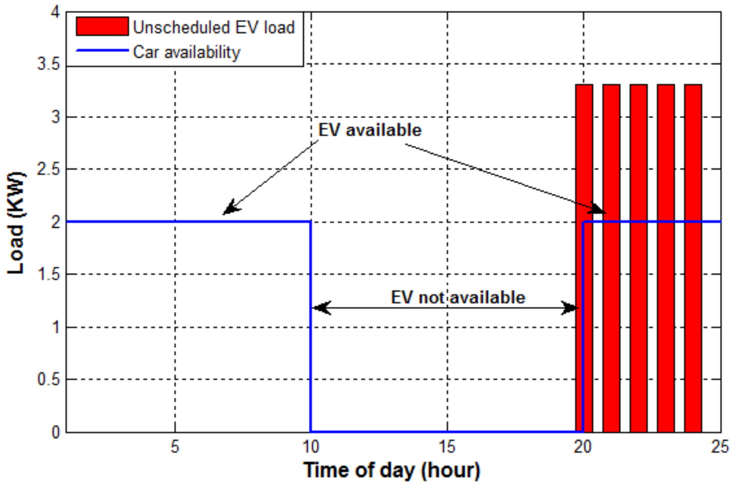


Figure 5.4: EV car availability

prediction techniques. The real time price data is taken from Illinois Power Corporation [46] as shown in Fig. 5.3. The small scale PV of 2 kW power production for the home is considered. For an initial operation of EV, the vehicle arrival time and departure is shown in Fig. 5.4. It is also assumed that when vehicle is returned to home 60% discharging of EV battery is already consumed.

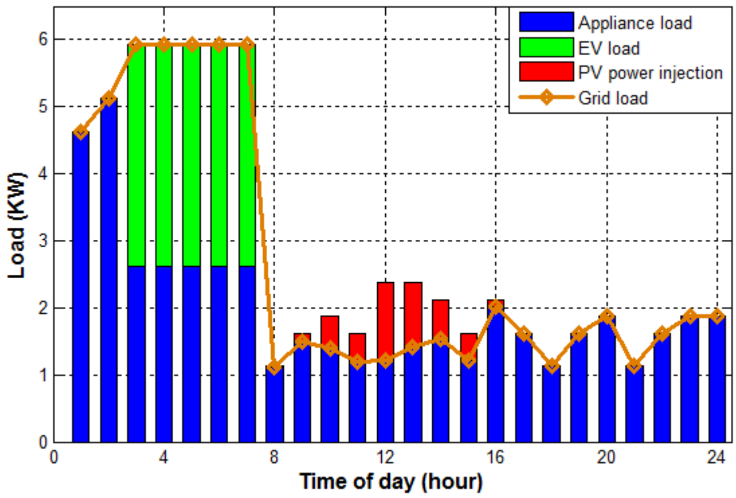


Figure 5.5: Load scheduling for scenario 1

Results discussion : The simulation has been done to utilize the capability home assets. The EV is a high consumption load present in present power system. It is required to operate with this load smartly otherwise it can damage the electricity grid. The smart charging operation of EV has the capability to provide the optimal time slot for charging activity. In the smart charging operation, the charging of EV is done in off-peak hours which is also acknowledge as low-price hours. The smart charging of EV offers

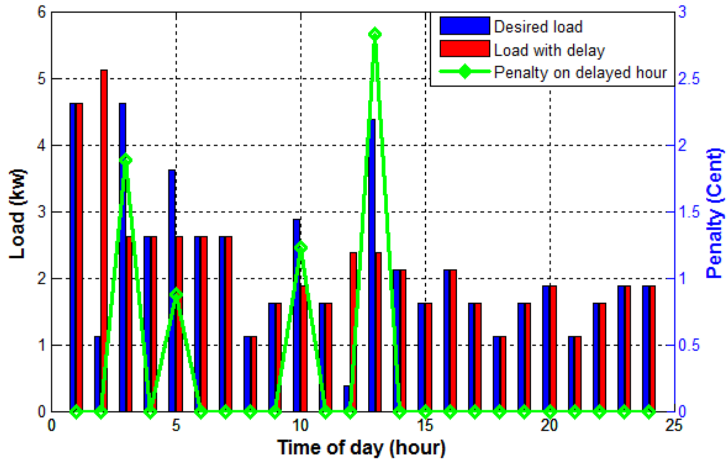


Figure 5.6: Penalty result for scenario 1

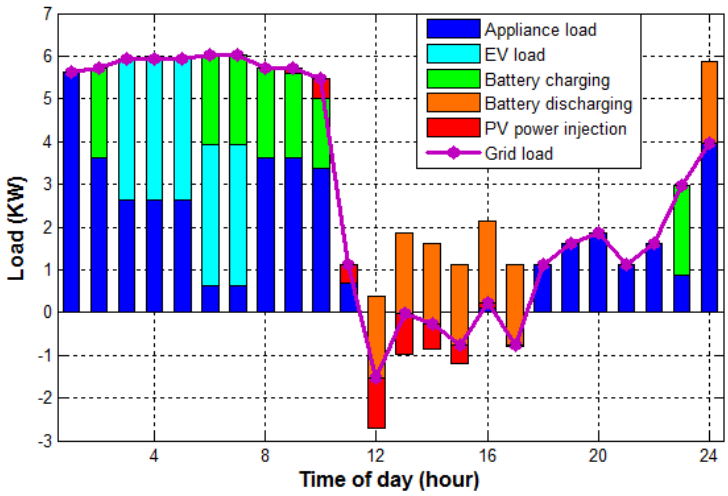


Figure 5.7: Load scheduling for scenario 2

grid to security benefit and user also gets reduction on their energy bill by using EV for charging purpose in low-peak hours. The proposed scheduling also provides reduction in peak to average ratio (PAR) of total demand which is highly desirable to maintain the power demand and supply ratio. The numerical results are shown in Table 5.3.

Table 5.1: System Components

Resource	Capacity (kWh)	Full charging time (hr)	Max/Min SOE (kWh)	Charging/Discharging efficiency (%)
EV (Chevy Volt)	16	5.1	14.4/1.6	0.95
BESS	2	-	1.95/0.05	0.95

In scenario 1, the household user is enabled with load scheduling of home appliances in the presence of smart charging of EV and solar PV generation. The load scheduling results are shown in Fig. 5.5. It depicts that the appliance load of user is supplied by grid and self PV generation. The PV generation is only available in day hours, so it should be consumed in day hours. The effect of smart charging of EV can be analyzed by that the EV load is scheduled in night hours which offers high cost benefits to user. In Fig 5.6 the effect of penalty applied on user for refusing the offered scheduling can be seen, which shows the desired load offered by controller and load after refusing the controller offer. The cost of purchasing energy from the grid before application of scheduling is 203.78 Cents, whereas the cost obtained in this scenario is 146.64. The user gets benefits of 57.13 Cents by application of smart charging operation. The peak to average is reduced from 3.14 to 2.19 by application of the smart charging. The user has to pay 6.8 Cents penalty because of refusing controller schedule.

Scenario 2 comprises the home assets such as EV, PV generation, and BESS. The operation of EV is enabled for smart charging option and BESS is utilized for charging and discharging both. Basically in this case, BESS charging and discharging is added to the scenario 1. The charging of EV and BESS is employed in low price hours. The simulation results of proposed load scheduling are shown in Fig. 5.7. It can be analyzed by Fig. 5.7 that the EV and BESS charging is done in off-peak hours between 11 pm to 10 am. The positive part of BESS discharging is used for the home appliance usage. When the load supplied by grid for EV and home appliance is less than the total power available at home, the surplus power can be fed back to the grid. EV is applicable only for smart charging purpose. The load scheduling measured cost is 127.36 i.e. occurred to user for usage. The total benefit gained by user is 76.41 by employment of BESS charging/discharging. This scenario results in PAR reduction upto 2.22.

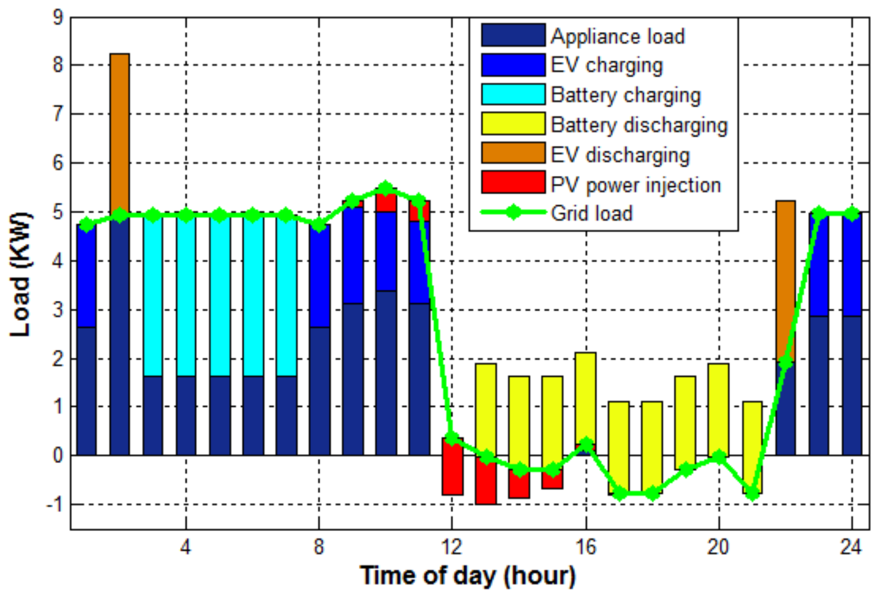


Figure 5.8: Load scheduling for scenario 3

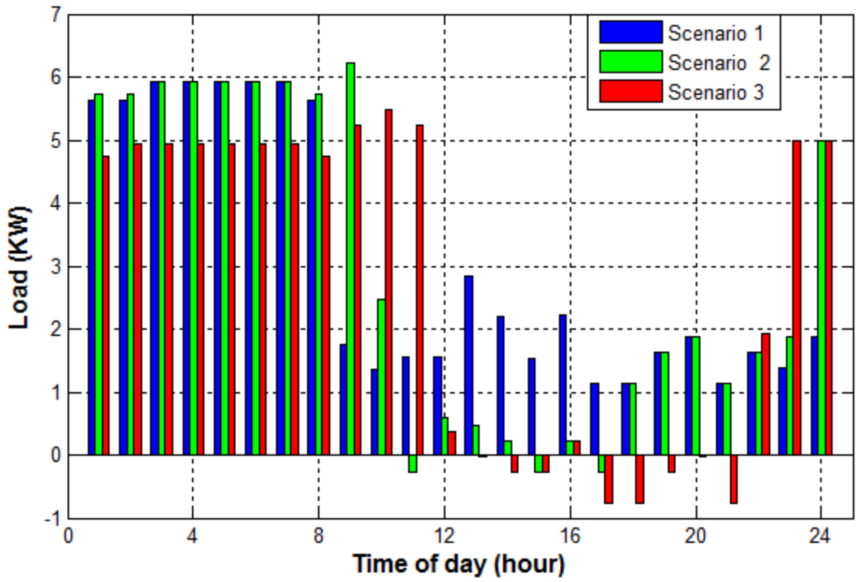


Figure 5.9: Comparison of scenarios

In scenario 3, the discharging of EV is also enabled. The EV can be discharged in peak hours to supply the load of user. Fig. 5.8 shows the results of load scheduling by execution of EV and BESS both charging/discharging. In this case, EV can supply approx 3.3 kW load to appliance and battery at 2 am. The battery is having 2 kW power requirement, so 2 kW can be given to BESS and remaining can utilize for appliance consumption. BESS discharging is employed from 1 pm to 9 pm for supplying the appliances load and surplus load can be fed back to grid. The surplus power available at home due to PV production is also fed back to grid. By employing this approach user achieved cost of 116.72 Cents and total benefit gain is 87.06 Cents. The peak to average ratio is reduced upto 2.05.

Table 5.2: Numerical Results

	Total cost (Cents)	User benefits (Cents)	PAR	PAR reduction (%)	Penalty (Cents)
Unscheduled	203.78	-	3.14	-	-
Scenario 1	146.64	57.13	2.19	29.99	6.81
Scenario 2	127.36	76.41	2.22	29.29	6.65
Scenario 3	116.72	87.06	2.05	34.40	8.60

The comparison of load scheduling for all proposed scenario is shown in Fig. 5.9. It depicts that the most of the energy fed back is found in scenario 3 because of EV and BESS discharging. But in scenario 3 power fed back to grid is because of BESS discharging and PV surplus. The comparative analysis of numerical results is shown in Table 5.3. It can be analyzed that the scenario 1 cost is more as compare to scenario 2 and scenario 3. The scenario 3 offers the highest reduction in electricity bill i.e. 87.06

Cents. The peak to average ratio reduction is found by 29.99 %, 29.29 % and 34.40 % for scenario 1, 2 and 3 respectively. The employment of PV, EV and BESS offers benefit of 87.06 Cents to the user and 34.4 % a significant reduction in PAR to the grid. The penalty involved is the measure of loss acclaimed to user by deviating the appliances from a prescribed schedule. The proposed load scheduling is accounted beneficial for user as well as for energy providers.

5.3 DR Incorporating Demand Fluctuation

A price aware residential DR by incorporating demand fluctuation and renewable source is also proposed in this chapter. The user load model is considered with the non-shiftable and shiftable type of appliances load. The EV car is also considered for certain residential premises. The pricing policy is considered as real-time pricing obtained from LSE. Generally, price-based DR execution results into formation of new peaks because each user tries to shift their load to low price hours. Therefore to avoid the formation of new peaks in DR scheduling, one extra term regarding uncertain events in DR is included as a part of user electricity bill to contribute to flattening demand curve.

5.3.1 Mathematical Modeling

The system investigated here contains a LSE as a source of electricity supply, and the residential consumer is utilizing the energy provided by LSE.

The K number of home users are present in the system, where $k \in K$. A day is divided into total T time slots which is denoted by t. Base load of user due to non-shiftable appliance in t^{th} time slot is denoted by $P_{k,t}^{NS}$. The power corresponding to the shiftable appliance load, EV load and renewable source for individual user in t^{th} time slot is denoted by $P_{k,t}^{S}$, $P_{k,t}^{ev}$ and $P_{k,t}^{R}$, respectively. The total load of the system is indicated by $P_{k,t}^{load}$ for each user,

$$P_{k,t}^{load} = P_{k,t}^{NS} + P_{k,t}^{S} + P_{k,t}^{ev} + P_{k,t}^{R} \tag{5.29}$$

Here, $P_{k,t}^{R}$ is power generation in each hour from the solar rooftop which is a self-generation of the home user. It is a negative value as this would reduce the burden of grid in terms of energy needs. The total shiftable load of user is denoted by l_n^S as per daily needs,

$$\sum_{t\in T} P^S_{k,t} = l^S_n \qquad\qquad 0 \leq P^S_{k,t} \leq P^{max}_k \tag{5.30}$$

Where P^{max}_k is the maximum load demand of individual user on daily basis. The EV load consumption is represented as follows,

$$P^{load}_{k,t} = \frac{P^{ev,C}_{k,t}}{\eta_C} + \eta_D P^{ev,D}_{k,t} \tag{5.31}$$

$$P^{ev,C}_{k,t} = \left\{ \begin{array}{ll} \Delta P^{ev}_{k,t}, & \text{if } \Delta P^{ev}_{k,t} \geq 0 \\ 0, & \text{otherwise} \end{array} \right\} \tag{5.32}$$

$$P^{ev,D}_{k,t} = \left\{ \begin{array}{ll} \Delta P^{ev}_{k,t}, & \text{if } \Delta P^{ev}_{k,t} \leq 0 \\ 0, & \text{otherwise} \end{array} \right\} \tag{5.33}$$

Where $P^{ev,C}_{k,t}$ and $P^{ev,D}_{k,t}$ represents the charging and discharging power for EV operation. The EV charging and discharging equations are shown in (5.32) and (5.33), respectively. The charging of EV is done only when the vehicle is available at residential premises. EV discharging is considered only when user is not available at home. The energy change in the EV battery from time of arrival to the time of departure is denoted by $\Delta P^{ev}_{k,t}$. The user EV battery size is denoted by E_k for particular k^{th} user. The mathematical change in energy of EV battery from arrival time to departure time is described as follows,

$$\sum_{t=t^a_k}^{t^d_k-1} \Delta P^{ev}_{k,t} = S^Q_k - S^P_k \qquad\qquad r^{min}_t \geq \Delta P^{ev}_{k,t} \geq r^{max}_t \tag{5.34}$$

Where S^P_k represents left energy in EV battery when arrives home and S^Q_k represents energy requirement for next trip. The t^a_k and t^d_k denotes the arrival and departure of EV. The r^{max}_t and r^{min}_t denotes the maximum charging and min discharging rate of EV battery respectively. The EV battery is charged between arrival and departure time only for the next trip. The sum of battery, left energy in EV battery and energy change should always be less than the size of EV battery of particular user.

$$0 \le \left(S_k^P + \sum_{t=t_k^a}^{t_0} \Delta P_{k,t}^{ev}\right) \le E_k \qquad t_0 = t_k^a, (t_k^a + 1) \ldots \ldots (t_k^d - 1) \tag{5.35}$$

5.3.2 Load Scheduling Problem Formulation

A residential DR load scheduling problem is formulated to achieve an objective of minimization of total electricity bill of each user without interfering their usage requirement. The user gets the real-time energy prices on the day-ahead basis from the LSE company in advance. It can encourage users to shift the energy demand from peak hours to off-peak hours. From user perspective, the minimization of electricity bill for the day ahead load scheduling can provide high monetary benefits. But at the same time, each user tries to minimize energy cost by shifting demand to low price periods which can lead the formation of new peaks in load curve. To overcome this situation, an extra term for deviation cost is added to user cost minimization problem which can prevent the formation of new peaks during off-peak hours. The user electricity bill function is formulated as follows,

$$f(1) = \sum_{t=1}^{T} C_{t,buy} * \left(\sum_{k \in K} P_{k,t}^{load}\right) \tag{5.36}$$

Where the $C_{t,buy}$ is the real time price (RTP) cost in each hour. The deviation cost function can be made as follows,

$$f(2) = \sum_{t=1}^{T} C_{t,buy} * \left(\sum_{t \in T} \left|P_{k,t}^{load} - m\right|\right) \tag{5.37}$$

The absolute value of the difference of a load of each user and mean usage plays a role to prevent the formation of new peaks. The m denotes the mean usage can be defined as,

$$m = \frac{1}{T} \sum_{t=1}^{T} \left(\sum_{k \in K} P_{k,t}^{load}\right) \tag{5.38}$$

The household user load scheduling problem can be formulated by combining equation (5.36) and (5.37) and represented as follows,

$$\text{Minimize}\Big[f(1) + \alpha f(2)\Big] \tag{5.39}$$

The above formulation can be simplified as follows,

$$\text{Minimize} \sum_{t=1}^{T} C_{t,buy} * \Big[\Big(\sum_{k\in K} P_{k,t}^{load}\Big) + \alpha\Big(\sum_{k\in K} \big|P_{k,t}^{load} - m\big|\Big)\Big] \tag{5.40}$$

Where α is the weighting factor for deviation cost function. It shows the amount of priority given to demand fluctuation curve in numerical analysis of the system. With this deviation cost function, the user will collaborate to reduce the variance of the demand curve, and also leads to minimize the generation cost for utility company and electricity bill. This also helps to improve the utilization of resources available in the system.

5.3.3 Simulation Results and Discussion

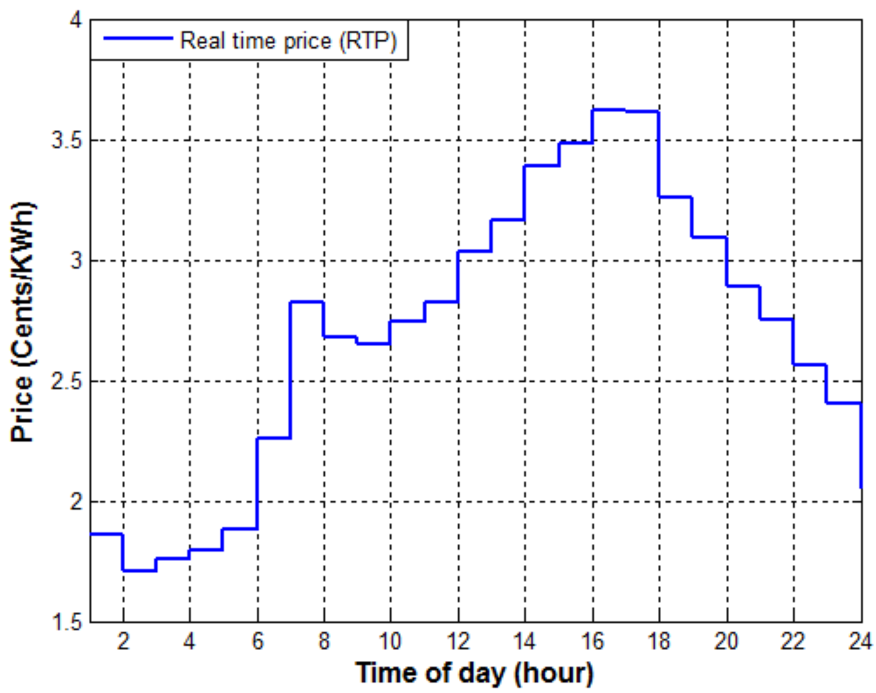


Figure 5.10: Real time pricing

Input data : In this simulation, the total $K = 50$ household user is considered for the operation of the system. The household users are equipped with different base load appliance and shiftable appliances. The 10 number of users are also installed with

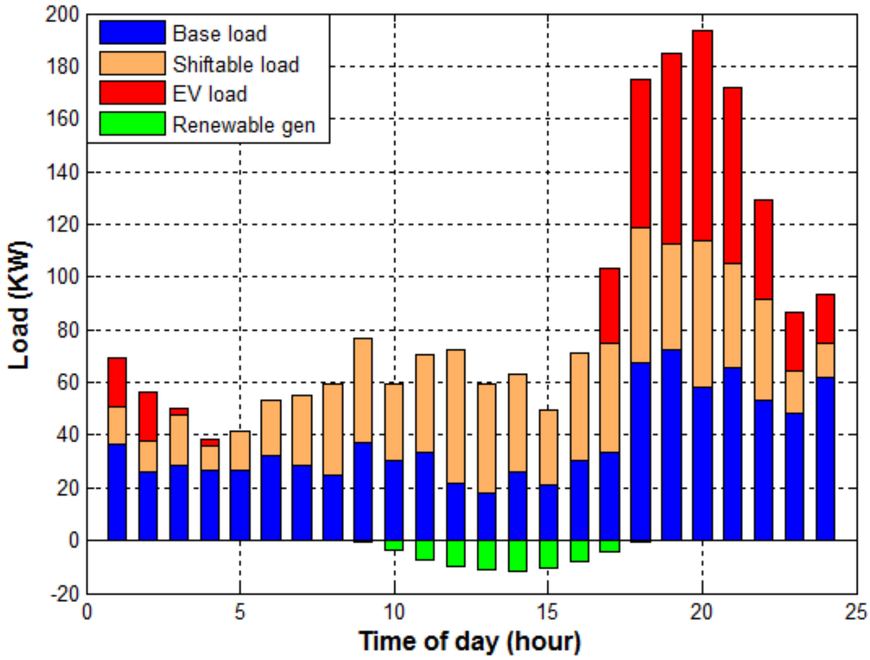


Figure 5.11: Total household user load in the system

electric vehicle at their premises. The 10 number of solar photo-voltaic installed on rooftop with a capacity of 1 kW to 4 kW. To build the load model of a user on preference basis appliances data is shown in the Table 3.2. The different electric cars are utilized for user and EV car data is shown in Table 4.2. The price signal used for the day ahead pricing is taken from Ameren Illinois Power [46] as shown in Fig 5.10. The optimization problem for total cost minimization as a convex problem in (5.39) is formulated as MILP aimed to reduce the daily energy bill of the user. The optimization problem is convex in nature and solved using CVX version 2.0 beta [77] on the MATLAB platform.

Result discussion : A day-ahead load scheduling is executed to reduce the energy bill of a household user in the presence of renewable energy sources. A day is divided into 24 slot, $T = 24$. The load data generated on the preference basis is plotted in Fig. 5.11. The system load in Fig. 5.11 shows the peak hours are present in the system between 5 pm to 10 pm. With the application of price-based DR, each user tries to shift their load during lower energy prices periods. The comparison of unscheduled and scheduled load is shown in Fig. 5.12. It can be analyzed that each user tries to optimize the energy bill but due to the effect of deviation cost the formation of new peaks is avoided in the scheduled consumption.

The execution of proposed approach not only beneficial to user but also improves the system peak to average ratio (PAR) from utility perspective. The numerical results

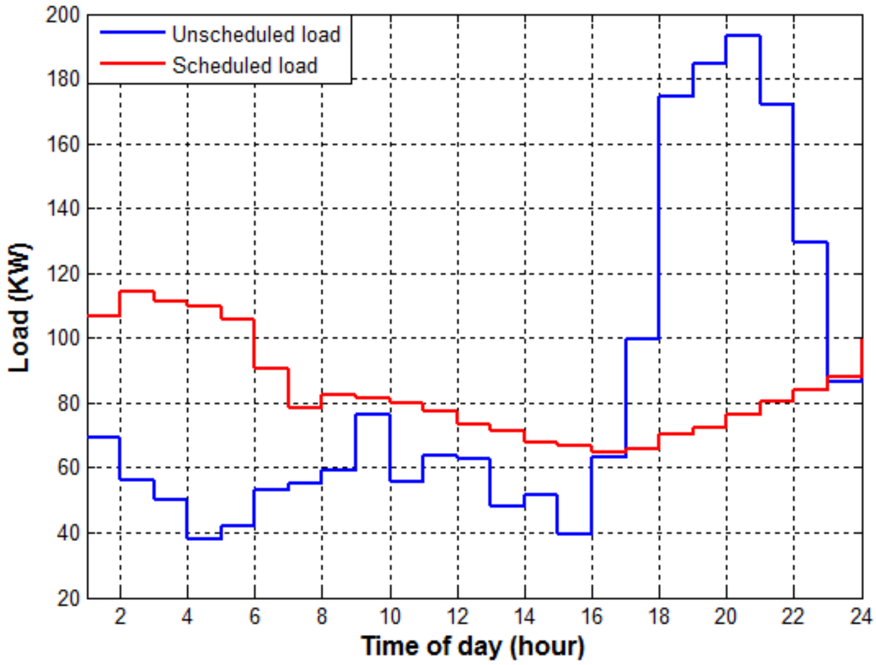


Figure 5.12: Scheduled and Unscheduled load

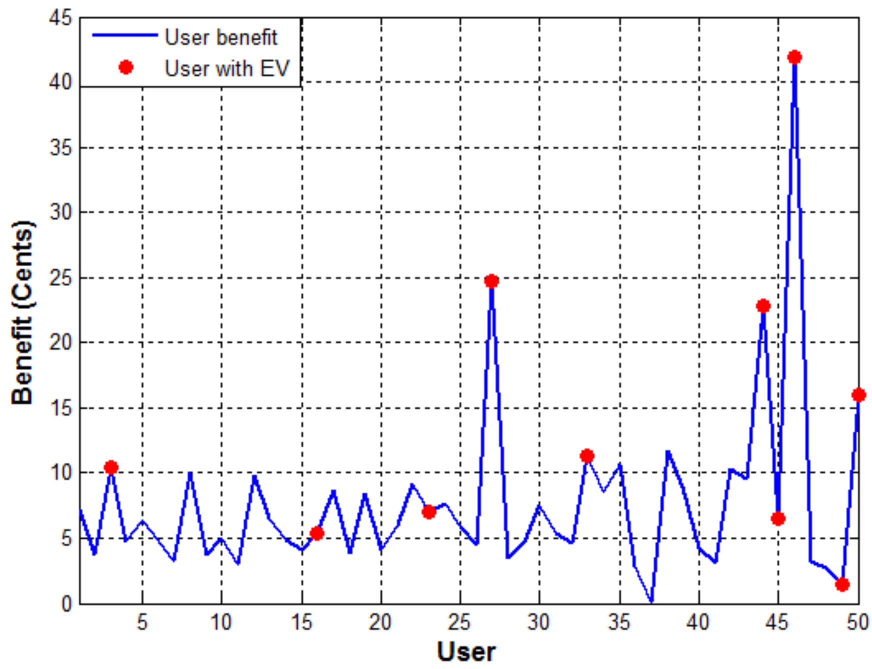


Figure 5.13: User benefit via load scheduling

shown in Table 5.3 validates the effectiveness of the proposed approach, where the total benefits reaped by a user is 2.17 $ from unscheduled to unscheduled with generation. Whereas, the benefit of scheduling occurs in term of cost benefit of 6.01 $. The load curve peak to average ratio is reduced from 2.23 to 1.35.

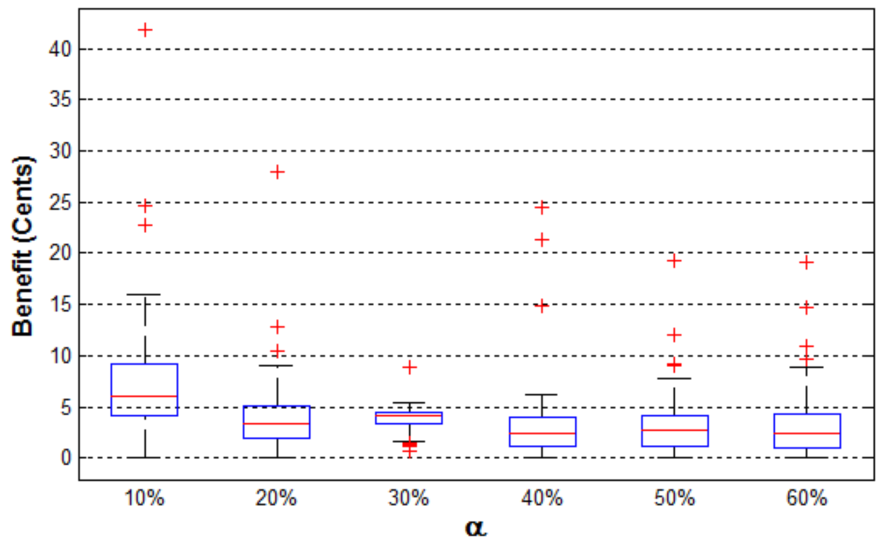


Figure 5.14: Monetary benefit with α variation

The user benefits in term of EV utilization is shown in Fig 5.13. It is analyzed that user with EV gained high economic benefits as compare to user without EV. It is also analyzed that the user which operate EVs with high capacity are entitled to high monetary benefits. The α plays an important role to enhance the flatten load curve quality from the utility perspective. The plot in Fig. 5.14 shows the capability of α in improving peak to average ratio of the system. With the increasing value of α it results into lower consumer benefits and at the same time improving load curve. While the lower value of α results in high monetary benefits for user.

Table 5.3: Numerical Results

Operation	Daily Cost (Cents)	PAR
Unscheduled consumption	5789.16	2.2265
Unscheduled consumption with renewable	5572.63	2.3001
Scheduled consumption	5188.24	1.3598

5.4 Carbon Mitigation Approach

The carbon mitigation mechanism is proposed in the background of DR. This approach is focused on reducing the carbon emission while executing the DR load scheduling. A demand response problem with a multi-energy user framework is considered. The distinct type of smart appliances, EVs, battery storage and renewable generations are installed in the homes. The proposed DR load scheduling mechanism describes the role and utilization of renewable sources for carbon mitigation. The mechanism also offers the dual approach where a user can minimize their electricity bill and carbon emission, simultaneously.

5.4.1 Mathematical Model

The electric vehicle, battery energy storage system, fuel cell, and solar PV are key features of the appliance base system model. The home appliance load is denoted by $P_t^{a,load}$ and represented as in (5.1).

5.4.1.1 Electric vehicle (EV)

Here, EV is considered as a load of household user. The application of EV is used here for smart charging purpose. A total load of user is build with appliance load and EV load. The EV battery discharging is enabled only when a vehicle is not present at home. The mathematical modeling of EV operation is given from (4.5)-(4.10).

5.4.1.2 Battery energy storage system (BESS)

The BESS charging is completed when electricity prices are low. BESS discharging can be done at times when user requires load in peak hours i.e. high price periods. The modeling of BESS is as follows.

$$P_{k,t}^{BESS,C} = \eta_{BESS}^{C} * \widehat{P}_{k,t}^{BESSS} \tag{5.41}$$

$$P_{k,t}^{BESS,D} = \widehat{P}_{k,t}^{ev,rated} / \eta_{BESS}^{D} \tag{5.42}$$

$$E_{k,t}^{BESS,soe} + E_{k,t}^{BESS,C} \leq E_{BESS}^{k,max} \tag{5.43}$$

$$E_{k,t}^{BESS,soe} - E_{k,t}^{BESS,D} \geq E_{BESS}^{k,min} \tag{5.44}$$

$$E_{BESS}^{k,min} \leq E_{k,t}^{BESS,soe} \leq E_{BESS}^{k,max} \tag{5.45}$$

Where, $P_{k,t}^{BESS,C}$ and $P_{k,t}^{BESS,D}$ are charging and discharging power of BESS for k^{th} user in t time slot. η_{BESS}^{C} and $\widehat{P}_{k,t}^{ev}$ denotes the efficiency and rated power of battery of BESS system, respectively. $E_{k,t}^{BESS,soe}$ stand for initial state of energy of BESS. $E_{BESS}^{k,max}$ and $E_{BESS}^{k,min}$ are upper and lower energy limits for BESS.

5.4.1.3 Solar photovoltaic (PV)

The rooftop solar PV equipped in the house can be used for supplying power to the home appliance load and BES system. The power balance equation can be represented as follows,

$$P_{k,t}^{pv} = \left\{ \begin{array}{ll} P_{k,t}^{pv}, & \text{if } P_{k,t}^{pv} \leq P_{k,t}^{a,load} \\ P_{k,t}^{a,load} + P_{k,t}^{BESS,C/D}, & \text{if } P_{k,t}^{pv} \geq P_{k,t}^{a,load} \end{array} \right\} \tag{5.46}$$

Where, $P_{k,t}^{pv}$ denotes the power generated from solar PV setup for each home in distinct time slots. Power generated from PV can be directly fed to home/BES.

5.4.2 Problem Formulation

The problem of energy consumption scheduling incorporation with CO_2 emission reduction is proposed. The proposed objective function comprises electricity bill minimization with carbon emission reduction. The load pattern of user appliances is known by analyzing the historic data from their usage. The data analyzed from behavior is considered as unscheduled consumption of user. The energy consumption scheduling is done for day-ahead basis. PV and fuel cell are taken as self-generation of the user. The proposed energy consumption scheduling is executed with two different objectives. Objective 1 proposes an energy scheduling aimed at reducing carbon reduction CO_2 emission and objective 2 targets on the trade-off built between CO_2 emission and daily electricity bill of the user.

5.4.2.1 Objective 1: Carbon mitigation approach

Objective 1 is formulated for energy consumption scheduling as minimization of total CO_2 emission (TCE),

$$\text{Minimize} \sum_{k=1}^{K} \sum_{t=1}^{T} \left(C_t^{em} * P_{k,t}^{grid} \right) \tag{5.47}$$

The power balance equation for scheduled load is represented in (5.48).

$$P_{k,t}^{grid} = \Big(\beta_{k,t}^{a} * P_{k,t}^{a,load} + \beta_{k,t}^{ev} * P_{k,t}^{ev,C} + \gamma * \beta_{k,t}^{BESS} * P_{k,t}^{BESS,C} + \beta_{k,t}^{BESS} * P_{k,t}^{BESS,D} - P_{k,t}^{pv} - P_{k,t}^{FC} \Big) \quad \forall t \in T, k \in K \tag{5.48}$$

Where, C_t^{em} is the CO_2 emission coefficient in (lbs/kWh) for energy consumption load $P_{k,t}^{grid}$ of individual household user in h hour. γ is known as a binary variable to represent the on/off operational situation of BESS. The value of γ can be -1, 0 and 1 for discharging, no operation and charging, respectively. Here, the energy is taken as equivalent to power, via considering one hour time stamping. $\beta_{k,t}^{a}$, $\beta_{k,t}^{ev}$ and $\beta_{k,t}^{BESS}$ are the binary scheduling variable corresponding to appliances, EV and BESS system, respectively. $P_{k,t}^{pv}$ and $P_{k,t}^{FC}$ denotes the power generated by solar PV and Fuel cell, respectively. The objective function presented in (5.47) is enabled with following constraints,

$$\sum_{t=1}^{T} \beta_{k,t}^{a} = Duration^{a} \qquad \forall\, a \in A, k \in K \tag{5.49}$$

$$\sum_{t=1}^{T} \beta_{k,t}^{ev} = Charging\_time^{ev} \qquad \forall\, k \in K \tag{5.50}$$

$$\sum_{t=1}^{T} \beta_{k,t}^{BESS} \geq 0 \qquad \forall\, k \in K \tag{5.51}$$

Where $Duration^{a}$ denotes the daily time duration for a certain appliance run. The set of appliances is denoted by A. $Charging\_time^{ev}$ represents the total time required for EV charging. Power balance constraint for load before scheduling is represented as,

$$P_{k,t}^{grid,unsch} = \Big(P_{k,t}^{a,load} + P_{k,t}^{ev,C} + \gamma * P_{k,t}^{BESS,C} - P_{k,t}^{pv} - P_{k,t}^{FC} \Big) \quad \forall t \in T, k \in K \tag{5.52}$$

$$L_{unsh} = \sum_{k=1}^{K} P_{k,t}^{grid,unsch} \qquad \forall t \in T \tag{5.53}$$

The load shifting technique with real-time pricing scheme is employed. The time varying tariff employment can convert off-peak load into accumulated peak load. Therefore, power transaction constraints are imposed on the system.

$$\begin{aligned} L_{sch}^{peak} &\leq L_{mean} + \mu_1 \\ L_{sch}^{valley} &\geq L_{mean} - \mu_2 \end{aligned} \tag{5.54}$$

$$\mu_1 = \frac{max(L_{unsh}) - mean(L_{unsh})}{\gamma_1} \tag{5.55}$$

$$\mu_2 = \frac{mean(L_{unsh}) - min(L_{unsh})}{\gamma_2} \tag{5.56}$$

Equation from (5.54)- (5.56) are the power transaction limit constraints for energy consumption scheduling. Where L_{sch}^{peak} and L_{sch}^{valley} are the peak load and valley load for scheduled consumption respectively. μ_1 and μ_2 are the margin parameters. γ_1 and γ_2 are the coefficient of allowed margin which helps deciding peak and valley load. If $\gamma_1 = \gamma_2 = 2$, it means allowed margin is 25 % of previous peak. Lower the margin better the peak to average ratio (PAR) but lower the consumer cost benefits. Higher margin means better consumer benefit but less improved PAR. Therefore, a balanced coefficient should be chosen which maintains the balance restored in PAR and consumer benefit.

5.4.2.2 Objective 2: Dual objective approach

The objective in (5.47) leads the energy consumption scheduling for minimizing the carbon emission. But it doesn't offer any benefits to the user in term of reducing their energy bill. Therefore for optimizing the carbon emission and electricity bill of user, a dual objective is framed as follows.

$$\sum_{k=1}^{K}\sum_{t=1}^{T}\Big[(\alpha \underbrace{\widehat{C_t^{em}} * P_{k,t}^{grid,sch}}_{\text{CO}_2\text{ emission}}) + (1-\alpha)(\underbrace{\widehat{C_t} * P_{k,t}^{grid,sch}}_{\text{Energy cost}})\Big] \tag{5.57}$$

The objective in (5.57) is a dual objective function with a trade-off factor α. Where $P_{k,t}^{grid,sch}$ is defined as in (5.48). $\widehat{C_t^{em}}$ is the normalized CO_2 emission coefficient and $\widehat{C_t}$ is the normalized price term for purchasing electricity from the grid. These normalized parameters is defined as follows.

$$\widehat{C}_t^{em} = \frac{C_t^{em} - min(C_t^{em})}{max(C_t^{em}) - min(C_t^{em})} \qquad \forall t \in T \tag{5.58}$$

$$\widehat{C}_t = \frac{C_t - min(C_t)}{max(C_t) - min(C_t)} \qquad \forall t \in T \tag{5.59}$$

The objective function presented in (5.57) is executed with constraints from (5.49)-(5.56). The CO_2 emission and electricity price is normalized between 0 to 1. The α represent the trade-off factor between electricity bill and CO_2 emission. By using optimization problem in (5.57), consumer gets opportunity to schedule their appliances with lower electricity bill as well as reduced carbon footprints.

5.4.3 Simulation Results & Discussion

5.4.3.1 Input Data

In the simulation setup, 50 residential users are considered. Each user is equipped with 12 appliances. 10 user has allocated electric vehicle. EV is applicable for charging purpose only. The 10 number of each fuel cell, solar PV, and BESS is granted in the total system. The four distinct type of vehicle is used and details are shown in Table 4.2. The appliance data is given in Table 3.2. The fuel cell of 0.7 kW capacity is considered as fixed generation available at household. 1 kW PVs are installed at rooftops. BESS with 4.8 kWh capacity is considered.

The solar radiation is considered for Illinois city. The hourly carbon emission. The energy scheduling problem is formulated as mixed integer linear programming (MILP) and solve using CVX version 2.0 beta [77] on the MATLAB platform.

5.4.3.2 Result Discussion

The simulation is done for various scenarios to test the capability of EV and renewable sources for carbon emission reduction. The DR energy consumption scheduling encourages users to schedule the load and get economic benefits in return. But the proposed algorithm executes an energy consumption scheduling with minimizing carbon attributes produced via electricity consumption reduction.

Before application of scheduling algorithm, the household load is shown in Fig. 5.15. The power consumed by appliances represents the variability of a load. The system is

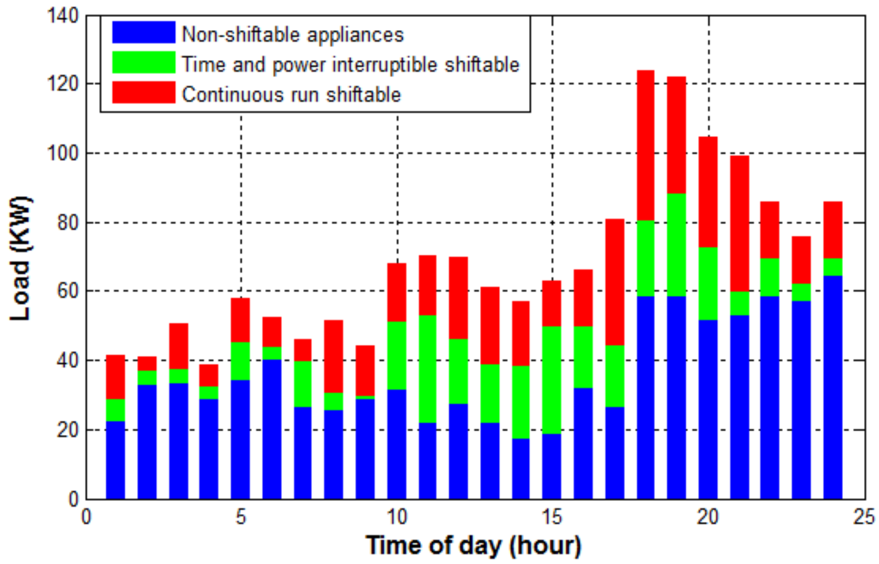


Figure 5.15: Appliance load data

operating under the household appliance load, EV load. But due to sources like PV and fuel cell, power injection is also present in the system which can significantly reduce the dependency on grid generation. Fig. 5.16 shows the load consumption from grid and power injection from sources. The hourly RTP and CO_2 emission is displayed in Fig. 5.17. To investigate the potential of proposed DR algorithm, two case studies are developed as follows,

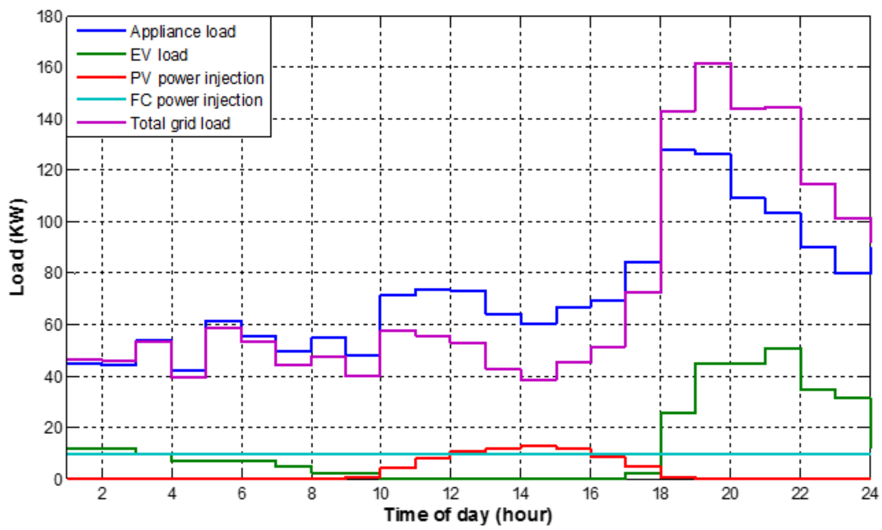


Figure 5.16: System load

Without renewable and BESS: In this case, the total energy supplied by electricity grid is available only. Renewable sources and BESS system are not considered, and EV is taken as a load. It is considered as a base case for energy consumption scheduling.

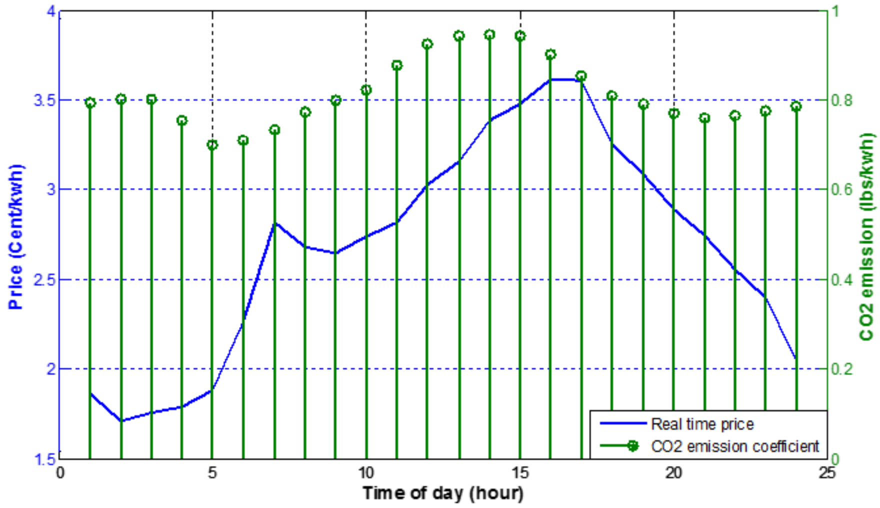


Figure 5.17: RTP price and CO_2 emission

The electricity tariff is considered as RTP prices. The optimization problem with two different objectives is recognized. The CO_2 emission reduction and consumer cost-benefit both are optimized. This case is represented as without generation and BESS.

Table 5.4: Numerical Results

		Total CO_2 emission (lbs)	CO_2 reduction (Ibs)	PAR	Cost reduction (Cents)
Unscheduled	-	1660.1	-	2.0012	-
Objective 1	Case 1 Case 2	1621.2 1413.3	38.8939 246.8	1.8340	288.4552 1154.1
Objective 2	Case 1 Case 2	1645.2 1437.4	14.8121 222.6920	1.8343	469.3045 1334.9

With renewable and BESS: In this case, users are equipped with individual energy generation sources such as fuel cell and PV. EV is used for charging purpose only. The RTP prices are considered as purchasing electricity from the grid. Objective functions are analyzed to test the potential of renewable sources. It can be displayed as with generation and BESS.

Fig. 5.18 shows the energy consumption scheduling result by solving optimization problem (OP) of objective 1 in (5.47). In Fig. 5.19, the comparison of unscheduled load and scheduling without and with generation is analyzed. This OP is focused on carbon emission reduction. Therefore the load is shifted to the night hours which results into significant carbon reduction. Table 5.4 shows the numerical results via energy consumption scheduling. It can be seen that the 38.89 lbs and 246.8 lbs CO_2 emission is achieved without and with generation, respectively. The cost reduction of 288.45 Cents

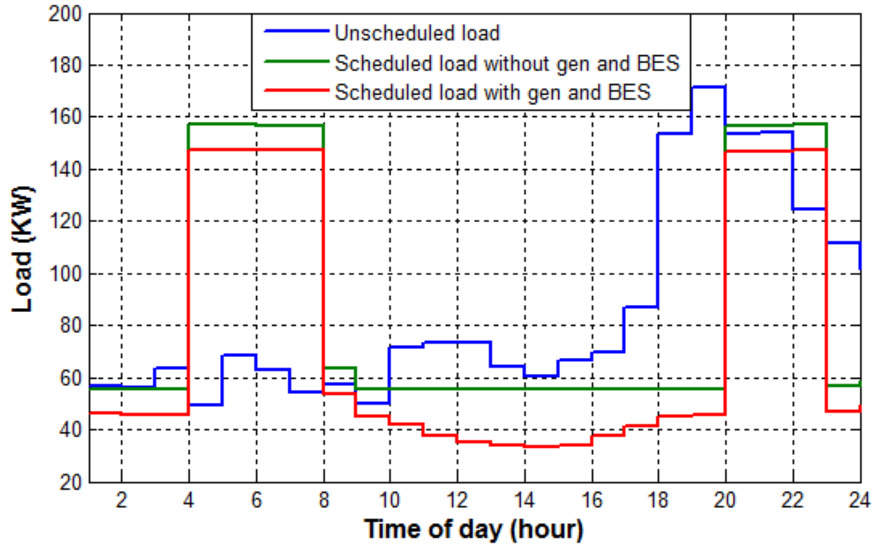


Figure 5.18: Load scheduling with objective 1

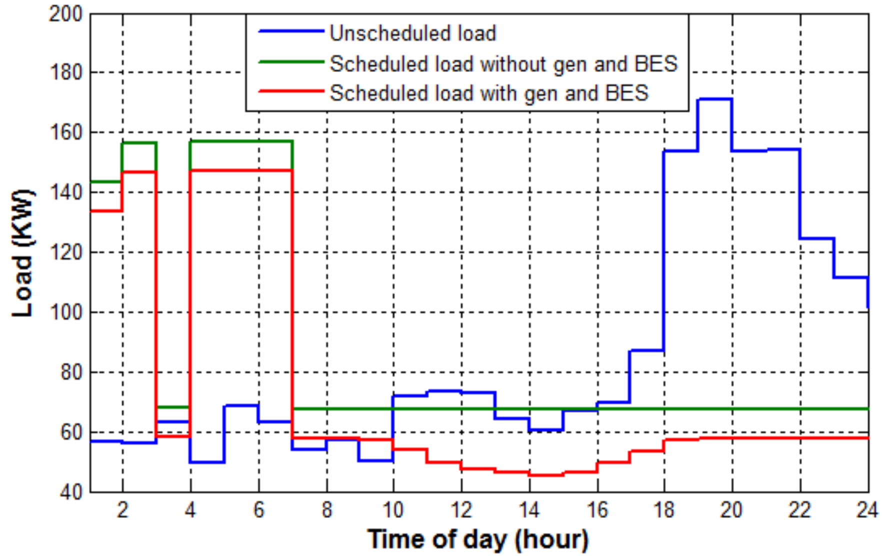


Figure 5.19: Load scheduling with objective 2

and 1154.1 Cents is obtained without and with generation. By numerical results, it can be analyzed that by using generation and BESS the consumer cost and CO_2 both are considerably reduced. The peak to average ratio (PAR) from unscheduled to scheduled consumption is reduced by 8.35 %.

The Fig. 5.19 denotes the comparison of load obtained after scheduling by execution of objective 2 in (5.57). In this OP, both CO_2 emission and user bill both are optimized as a dual objective. Carbon emission reduction values are 14.8121 lbs and 222.7 lbs without and with generation, respectively. The consumer benefit on their bill is 469.3045 Cents and 1334.9 Cents without and with generation, respectively. The PAR in this case is

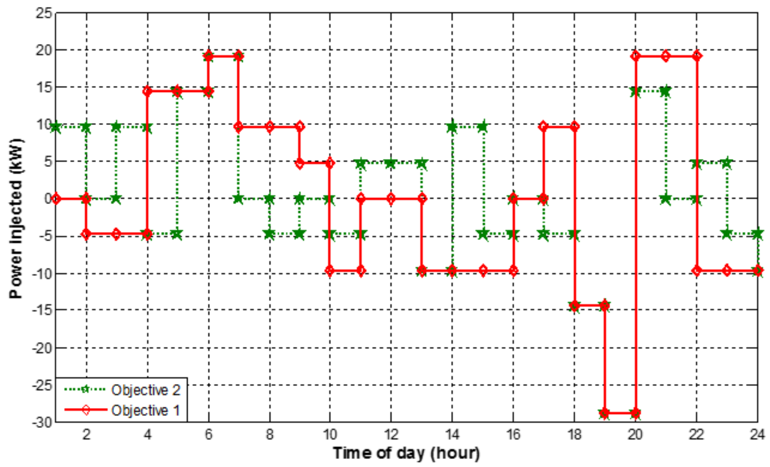


Figure 5.20: BESS charging/discharging

reduced by 8.34 %. α is considered as 0.5 for this scenario and if it is increased the high benefits can be gained by user but reduce the carbon impact.

The operation of battery for different objectives are shown in Fig. 5.20. It can be analyzed that battery is charged during off -peak hours and can be used for discharging purpose when prices are high. By comparing the numerical results of energy consumption scheduling, it can be interpreted that those user employing renewable sources and BESS gets high economic benefits. The practice of renewable generation affect the carbon footprint, the motivational reduction is found. Overall the every objective analyzed have exhibited some significant points. The highest carbon reduction is found with analyzing objective 1 i.e. 246.8 lbs. Whereas the objective 2 offers the maximum cost benefits of 1334.9 Cents.

Objective 1 gives best CO_2 emission reduction, but give increased PAR ratio. By controlling the margin parameters μ_1 and μ_2 desired PAR can be achieved. The coefficient of allowed margin γ_1 and γ_2 should be chosen in appropriate manner to balance both PAR and CO_2 emission. Objective 2 results reduction in both CO_2 emission and cost optimization. The value of α decides the weight of cost benefits in energy scheduling. For objective 2 emission reduction and consumer benefit are balanced but consumer benefit can be improved by changing variable α. The application of the proposed DR algorithm in can leads the way to valuable carbon reduction approach.

5.5 Summary

This chapter presented the load scheduling of smart household in the presence of home assets such as electric vehicle, battery system, and small-scale PV generation. The main motive is to analyze the application of technologies such as EV and BESS for the operation of home and grid. The proposed optimization problem is developed as MILP formulation. The EV and BESS played a role in enabling technologies to reduce the energy bill of a household user and to maintain comfort. The user comfort is modeled through waiting parameter of operation of any appliance. The surplus power available at home can be fed back to the grid, and more savings are achieved. Execution of the proposed approach increases the reliability of the HEM system in terms of utilization. The simulation results can prove the importance of proposed scheduling regarding reduced consumer bill payment and reduced peak demand. The practical implementation of such home energy scheduling can increase the flexibility in the electrical power system.

The operation of residential energy customers equipped with various appliances and asset is examined. Under this system, a controller is aimed to minimize the total energy procuring cost with dynamics pricing environment in the presence of renewable sources. Furthermore, an extra term is added to improve the demand curve which enhances the capability of the system. The application of the proposed methodology encourages the household user to shift their energy consumption to achieve lower daily energy bills. Further integration of vehicles in the transportation environment has introduced the new kind of load in the residential sector, whereas the proposed strategy can develop smooth operations in the scenario. The proposed case study can be extended to the practical scene of several household users aiming to utilize the resources.

The utilization of renewable sources and battery system for carbon emission reduction along with residential demand response is also investigated. The operation of a household is evaluated for cases such as without and with renewable generation. The encouragement of carbon emission reduction technique is the key feature of the work. The simulation results also demonstrate that the proposed system is effective in reducing the carbon footprints, consumer payments, and peak load while maintaining the comfort and convenience of the user.

Chapter 6

Strategical Game Theoretical DR

6.1 Introduction

The advent of future electricity paradigm in the form of smart grid encourages the participation of electricity customers in the operational and market policies of power system via DR programs. The operation of DR programs enables the interaction among electricity end consumers and utility for empowering the smart grid. DR programs are encouraging the user to become part of electricity infrastructure and being informed of energy management decisions. The huge data communication and interaction from one end to another end in DR programs made the implementation more challenging. With the help of optimization and decision making techniques electricity customer will be able to mange interaction between customers and energy providers.

Game theory is a computational model of interaction and competition among energy user and utility company is extensively used to DR programs. The study in [101] presents a non-cooperative demand mechanism game to minimize user expenses by producing or storing the battery energy instead just buying from the grid. Two design is developed such as to optimize separate user by formulating the grid optimization problem as a non-cooperative game other as joint optimization of the whole system allowing some cooperation among the users. A smart power system with distributed consumers seeking their power requirement to the utility company is proposed in [102]. In this model, user tries to minimize for their batteries during off-peak hours and discharging the energy at peak hours. A Stackelberg game is presented in [103] between utility companies, and end-consumers to maximize the economic benefit of the utility company and user payoff. The game theory applications for DR in [53] used the players in the games that can be naturally modeled by autonomous agents. An autonomous DR model is developed in [104] that can achieve both optimality and fairness. The work on achieving fairness in DR framework is limited, perhaps fairness point of view is included in [104]. A repeated game is presented in [105] which shows the inefficiency of the Nash Equilibrium as a one-shot game, hence represented as repeated game. To incorporate the fairness among users, they are divided into groups and only one group is allowed to participate in a DR program at a time. An online long-term scheduling algorithm is developed in [106] to model the uncertain behavior of price and load demand as a Markov decision process. To make the problem tractable, each user is required to execute an algorithm to approximate the state of users.

Load shifting and load curtailment are the two mechanisms to implement DR programs. Reduction in the power consumption is obtained by motivating the consumers to adopt energy enlightened pattern [107]. On the other hand, load shifting takes advantage of time independence of loads, and shifts loads from peak time to off-peak time in order to avoid accumulated load at peak hours. Some users have their usage timings of individual appliances, which can not be shifted. Even though shifting can provide benefit in terms of cost but comfort can not be compromised. A human expert based load curtailment approach is investigated in [108] to model a complex decision-making process. In this approach, a load curtailment allocation is implemented by prioritizing the importance of customers and type of loads. A direct load control technique is proposed in [109] to implement a semi-automated demand response with Gaussian mixture model (GMM) for estimation purpose of load demand.

The literature reveals that use of game theory in demand response problem is a fascinating approach to deal within an interactive environment. Most of the research work in the past has dealt with the problem of interaction between user and utility but the accountancy of fairness of Nash Equilibrium is limited throughout the literature. This chapter presents a game theory based DR model using correlated equilibrium. Some residential user equipped with a set of appliances is considered. The optimization problem is formulated as the minimization of the cost levied on the user for usage of appliances in the system. The energy consumption scheduling is determined in chronological sequence, which is obtained as a solution of an optimization problem. The schedule time period for an appliance is obtained so that as an effect on future allocated times, the optimization offers cost benefit to each user within a community in the long run. The unique features of the chapter are stated as follows,

- The proposed dynamic demand response model introduces correlated equilibrium approach in a game theoretic scenario for the residential consumer.

- The proposed methodology reveals a scheduling sequence based on the user priority order which leads to high economic benefit for a particular user as well as for society.
- The proposed model assure fairness of Nash Equilibrium among the user, in the long run, to serve as a benchmark for performance evaluation.

The structure of the chapter is represented as follows. The architecture of the proposed system and pricing scheme is introduced in Section 6.2. The mathematical modeling of the proposed system is demonstrated in Section 6.3. Methodology of correlated equilibrium approach is explained in Section 6.4. Performance evaluation and result discussion is given in Section 6.5. Finally, conclusion is presented in Section 6.6.

Table 6.1: List of variables used in this chapter

$k(K)$	Index (set) of users in the system.
$a(A)$	Index (set) of appliances.
$t(T)$	Index (set) of time periods.
u	Individual user.
$d(D)$	Index (set) of days.
W_t	Base load at t^{th} hour.
$\widehat{\mathbb{P}}_{a,k}$	Power rating of a^{th} appliance of $k^{th} user$.
$\Delta t_{a,k}$	Running duration for a^{th} appliance of k^{th} user.
$C(W_t + \widehat{\mathbb{P}}_{a,k})$	Cost of using appliance a of k^{th} user at t^{th} hour.
$C(W_t' + \widehat{\mathbb{P}}_{a,k})$	Cost of using appliance a of k^{th} user if scheduling has occurred prior to it actually occurs.
$x_{a,k,d}$	Energy consumption scheduling vector of a^{th} appliance of appliance of k^{th} user for d^{th} day.
$x^t_{a,k,d}$	Energy consumption scheduling vector of a^{th} appliance of k^{th} user on d^{th} day at t time slot.
tos_k	Time of scheduling of user k.
$W_t^{tos_k}$	Base load of t^{th} hour at time of scheduling of user k .
$bfd_{a,k,d}$	Balance factor of k^{th} user for a^{th} appliance on d day.
$bf_{k,d}$	Balance factor of k^{th} user on d day.
$P_{k,d}$	Payoff of k^{th} user on d day.
$\mathbf{X}_{(k,d)}$	Set of scheduling vector of appliances of k^{th} user for a day d.
$\mathbf{X}_{-(k,d)}$	Set of scheduling vector of appliances of other user than k^{th} for a day d.

6.2 System Model

6.2.1 Overview of System

K number of users are considered in the system represented by k, $k \in [1, K]$. Each user is having A set of appliances indexed as a, $a \in [1, A]$. The energy consumption of each appliance is represented by $E_{a,k}$ and power rating as $\widehat{\mathbb{P}}_{a,k}$. For a specific appliance daily running duration if fixed. The presented model encompasses user preference as one of its highlighting features. Users can set preferences for the start and end of the time to schedule their appliances. The consumer preference based running duration of a^{th} appliance of k^{th} user can be denoted by $\Delta t_{a,k}$.

Each home is installed with ALCU which has a built-in smart meter. ALCU enables controlling load and communicating load information to the centralized controller unit. The centralized unit communicates with LSE to exchange the price and load information. All the information that pertains to appliances of the end user is stored in ALCU. The ALCU then communicates the information to the centralized controller in such a way that peak to average (PAR) ratio of load on the whole system is reduced, energy bill of user is minimized, and the overall cost of the system is reduced, without infringing the users' preferences. After completing such scheduling, ALCU recommends users to run their appliances at the available time slot which is optimally selected.

To bridge the communication among residential users and utility and to avoid latency issue related to information delay many approaches have been developed in the literature [3]. A two-layer communication base architecture is considered as per demonstrated in [110]. A simple structure of communication network is shown in Fig. 6.1. It is assumed that each appliance has a wireless communication module which is required for sending/receiving information. All the appliances are equipped with smart plugs which a ZigBee electricity meter to be connected with ALCU via the wireless link with Zigbee technology [111]. The communication is named as home area network (HAN) where all users get connect to wide area network (WAN). Smart meters has ability to connect the HAN, and this can further facilitate awareness to the users for energy usage cost and control the appliance's consumption. Zigbee technology is widely popular for wireless communication, it has the ability to operate in mesh network which is advantageous for household appliances such as appliance can remain in sleep mode when they are not operating. It is also assumed that the energy provider protects the security of user load information, i.e., the centralized controller has in-built privacy control mechanism.

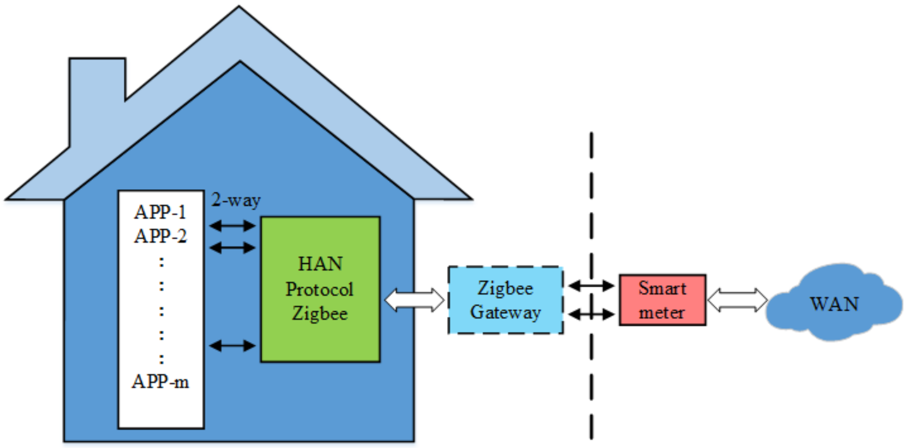


Figure 6.1: Communication Network Architecture

6.2.2 Load Based Pricing Mechanism

The inclusion of dynamic pricing is proved as an encouraging factor for the users to shift their appliances based loads accordingly to reduce the system PAR performance.

Here, $C(W_t + \widehat{\mathbb{P}}_{a,k})$ represents the cost incurred by an arbitrary user k by running a^{th} appliance, in Cents for the time between t and $(t+1)$, where W_t is the expected base load on the system before scheduling the a^{th} appliance of user k. W_t is not considered as the part of scheduling process because it is fixed but it needs to be encapsulated in the cost function. W_t is the base load consumed by user in t^{th} time slot. To develop a cost function as required by the system particular assumption should be taken care as,

Assumption 1: Cost function is assumed to be increasing with total per hour load. For each time duration $t \in T$, the following inequality holds,

$$C(W_1 + \widehat{\mathbb{P}}_{a,k}) < C(W_2 + \widehat{\mathbb{P}}_{a,k}), \quad \forall W_1 < W_2 \tag{6.1}$$

Assumption 2: A cost function is assumed to be strictly convex in nature [112]. A function C_t is said to be convex for any arbitrary W_1 and W_2, for any θ with $0 \leq \theta \leq 1$, when

$$C\Big(\theta(W_1 + \widehat{\mathbb{P}}_{a,k}) + (1-\theta)(W_2 + \widehat{\mathbb{P}}_{a,k})\Big) \leq \theta C\Big((W_1 + \widehat{\mathbb{P}}_{a,k}) + (1-\theta)C(W_2 + \widehat{\mathbb{P}}_{a,k}) \tag{6.2}$$

Therefore, it is necessary that the cost function should be a convex function. Mathematically the quadratic function is a suitable convex function [112]. Hence, a quadratic

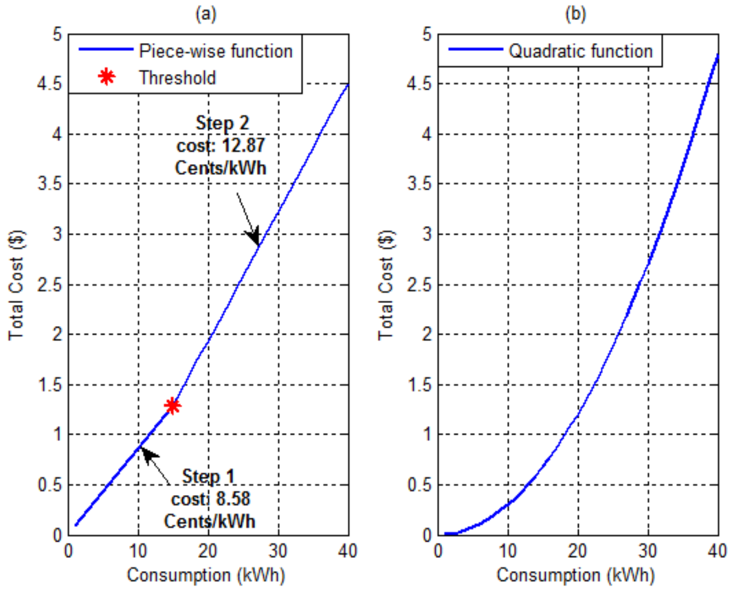


Figure 6.2: Sample convex functions: (a) 2 step piece-wise and (b) Quadratic cost function

function is used as cost function. The cost functions used is per hour based cost functions $C(W_t + \widehat{\mathbb{P}}_{a,k})$ that is proportional to the total energy usage during the same time window denoted by $(W_1 + \widehat{\mathbb{P}}_{a,k})$. Therefore, $C(W_1 + \widehat{\mathbb{P}}_{a,k})$ can be explained as follows,

$$C(W_t + \widehat{\mathbb{P}}_{a,k}) = a_t(W_t + \widehat{\mathbb{P}}_{a,k})^2 + b_t(W_t + \widehat{\mathbb{P}}_{a,k}) + c_t \tag{6.3}$$

where $a_t > 0$ and $b_t, c_t \geq 0$ are pre-determined parameters.

Generally, two cost functions are considered in the electrical power system, i.e. piece-wise linear cost function and quadratic cost function [113]. The piece-wise linear cost functions used in industry are typical to adopt for modeling of the proposed system. For example, a 2-step piece-wise linear cost function in convex price model form is adopted by BC Hydro. The BC Hydro company charged customers under residential conservation scheme, which is a rate divided into two parts. This means customers are charged one rate of electricity up to a certain point in each billing period and a higher rate for any electricity used beyond that point. The point where the customer is paying a higher rate is called step 2 threshold and is based on 90% of the average household consumption in all household. A sample 2 step piece-wise linear function utilized by BC Hydro is shown in Fig. 6.2a, where step 1 rate is 8.58 Cents/kWh and step 2 rate is 12.87 Cents/kWh. A quadratic cost function as in equation (6.3) is a simple load-based quadratic function. The piece-wise linear function is difficult to track for optimization purpose. Whereas a sample quadratic cost functions as shown in Fig. 6.2b provides smooth operation in the optimization process and it is easily tractable.

6.3 Analytical Formulation

6.3.1 Problem Formulation

The proposed problem accounts for the social fairness point of view for users in such a way that available energy capacity is utilized to minimize their energy bill expenses. The cost incurred on an arbitrary appliance a of user k on a day d is expressed in (6.2).

$$\sum_{t=0}^{T} \left[C(W_t + \widehat{\mathbb{P}}_{a,k})\ (x^t_{a,k,d}) \right] \tag{6.4}$$

Here $x^t_{a,k,d}$ is a energy consumption scheduling variable for a^{th} appliance of k^{th} user in a day. From [112], [114] it can be inferred that since (6.4) is the sum of convex functions, it is a convex function as well. The cost incurred by a user k, is the sum of the cost incurred on individual appliances and can be formulated as optimization problem,

$$\text{Minimize} \quad \sum_{a=1}^{A} \left[\sum_{t=0}^{T} C(W_t + \widehat{\mathbb{P}}_{a,k})\ (x^t_{a,k,d}) \right] \tag{6.5}$$

Each and every user intends to minimize the energy consumption bill. But in general way, minimum cost is incurred by a user when the cost with respect to its appliances are minimum. This situation leads to the problem that which can be addressed through the proposed model. Thus, the scheduling should done be in such a way that the users have to pay to the minimum bill feasible to attain, that inspires to solve the following problem in (6.5). However, the solution can lead to an arbitrary distribution of cost benefits to the users.

6.3.2 Fairness Evaluation

The proposed model assures the fairness in the long run for scheduling purpose among users. Let $C(W_t^{tos_1} + \widehat{\mathbb{P}}_{a_1,1})$ and $C(W_t^{tos_2} + \widehat{\mathbb{P}}_{a_2,2})$ be the cost of using appliances at t^{th} hour by two random user. Where tos_1 and tos_2 are times at which the process of computation of costs at various hour for user 1 and user 2 took place respectively. Let an arbitrary appliance of user 1 and user 2 be a_1 and a_2 respectively. If $tos_1 < tos_2$ i.e. user 1 gets scheduling before user 2, then

$$\forall t \in T, \quad C(W_t^{tos_1} + \widehat{\mathbb{P}}_{a_1,1}) \leq C(W_t^{tos_2} + \widehat{\mathbb{P}}_{a_2,2}) \tag{6.6}$$

and

$$\exists t \in T, \quad C(W_t^{tos_1} + \widehat{\mathbb{P}}_{a_1,1}) < C(W_t^{tos_2} + \widehat{\mathbb{P}}_{a_2,2}) \tag{6.7}$$

Conversely, if $tos_1 > tos_2$, i.e.

$$\forall t \in T, \quad C(W_t^{tos_1} + \widehat{\mathbb{P}}_{a_1,1}) \geq C(W_t^{tos_2} + \widehat{\mathbb{P}}_{a_2,2}) \tag{6.8}$$

and

$$\exists t \in T, \quad C(W_t^{tos_1} + \widehat{\mathbb{P}}_{a_1,1}) > C(W_t^{tos_2} + \widehat{\mathbb{P}}_{a_2,2}) \tag{6.9}$$

Proof of Theorem 2 and Theorem 3 are given in the Appendix B and Appendix C, respectively. As described in Theorem 2 and Theorem 3 it is interpreted that a user who gets a chance to schedule first has lower cost expenses than on someone who got scheduling chance later. Since all users have some appliances, and most of their appliances are similar, their power ratings are ought to be similar. The appliance which is not being used frequently by a user doesn't make much difference to the behavior of the system model.

However, the above inference could be seen as true for almost all the time, which is also found right during simulations. Because each user has some appliances, and given that the time of scheduling tos_k for appliances of a user 1 takes place earlier than that of all appliances of user 2, there needs to be a disparity in the benefits reaped by the user. Unless there is a change in scheduling sequence, the disparity will keep on increasing every day. Theorem 3 also states that the measured cost of user 2 is more than user 1. Generally, user 1 denotes the user which request execute the scheduling before the other users in the system. Therefore it seeks to minimize cost charged on each user as well as ensuring fairness in distributing profit among all users. It is done by finding the solution from (6.5) for each appliance of every user with changing the chronology of tos_k of a user for separate days.

To encapsulate such disparity, the following terms are introduced i.e. Balance factor of appliance represented as $bfd_{a,k,d}$, which denotes balance factor of a^{th} appliance of k^{th} user till day d, where$d \in D$. Balance factor of user u as $bf_{k,d}$ till day d and fair term.

6.3.2.1 Balance factor for appliances

The balance factor $bfd_{a,k,d}$ of appliance a of user k on a day $d \in D$ is defined as the difference between the cost that would have incurred by a if scheduling of k would have taken place the earliest and cost that has incurred by the appliance a by the scheduling when it actually occurred, per kWh of energy usage by a over days upto D, i.e. $d_1, d_2, ...d \in D$.

$$bfd_{a,k,d} = \sum_{d=1}^{D} \Big[\sum_{t=0}^{T} x^t_{a,k,d} \Big\{ C(W_t + \widehat{\mathbb{P}}_{a,k}) - C(W_t^{'} + \widehat{\mathbb{P}}_{a,k}) \Big\} \Big] \tag{6.10}$$

6.3.2.2 User balance factor

Balance factor $bf_{k,d}$ of user k on day $d \in D$ is the sum of $bfd_{a,k,d}$ of all appliances of k.

$$bf_{k,d} = \sum_{a=1}^{A} bfd_{a,k,d} \tag{6.11}$$

It follows that later the scheduling, higher would be the cost incurred and lesser would be balance factor.

6.3.2.3 Fairness

The 'fair' term is defined as scheduling of a given user 1 over finite d number of days would be considered fair if for every pair of user 1 & user 2 for two days preceding to each other, within every finite day window interval for which the balance factor for different user on same day is related as follows.

$$bf_{1,1} > bf_{2,1} \text{ and } bf_{1,2} > bf_{2,2}$$

6.4 Proposed Methodology

The objective of minimizing the cost of energy usage along with ascertaining fairness among all users in the long run without forgoing the preferences of users is represented as the scheduling game. Such a game theoretic model uses correlated equilibrium to determine the scheduling sequence in which user cost minimization is done.

6.4.1 Game Theoretic Formulation

- **Players**: Total number of users where each user is denoted by k and indexed from 1 to K.
- **Strategies**: Energy consumption scheduling vector $\mathbf{X}_{k,d}$, for each user k.
- **Payoffs**: $P_{k,d}(\mathbf{X}_{(k,d)}, \mathbf{X}_{-(k,d)})$ define payoff for each user on particular day d.

The payoff is defined as the negative of the cost that should be incurred on a user k on using total appliances on any given day d.

$$P_{k,d}(\mathbf{X}_{(k,d)}, \mathbf{X}_{-(k,d)}) = -\sum_{a=1}^{A}\sum_{t=0}^{T}\left[C(W_t + \widehat{\mathbb{P}}_{a,k})\,(x^t_{a,k,d})\right] \tag{6.12}$$

Since (6.12) is the negative of a convex function, it is a concave function. Therefore, a unique and Nash Equilibrium (NE) theorem in [115] is applied to the proposed scheduling game. Theorem 1 given in Appendix A proves that the optimization problem in (6.5) is the Nash Equilibrium of the game.

In order to maximize the profit of user, the payoff function should also be optimized. For the above problem objective function can be formulated as,

$$\begin{aligned} &\text{Maximize} \quad P_{k,d}(\mathbf{X}_{(k,d)}, \mathbf{X}_{-(k,d)}) \\ &\text{Such that,} \quad \sum_{t=0}^{T} x^t_{a,k,d} = \Delta t_{a,k} \end{aligned} \tag{6.13}$$

The (6.13) represents the payoff function of a given user k when the corresponding scheduling vector is $X_{(k,d)}$ while another player (user) schedule vector is denoted by $X_{-(k,d)}$.

6.4.2 Chronological Optimization Process

The $bf_{k,d}$ is used in increasing order to determine the sequence of users for the optimized scheduling process. Such a mechanism can be viewed as a coordination game where players are coordinated to choose an equilibrium which is not only favorable to each player but also an equitable solution to the problem. The ALCU is the fair ordering medium here. For each and every user it determines the time at which the process of finding out the optimal timing of running their appliances should execute, i.e. tos_k. One of the essential features of using correlated equilibrium is that no user can benefit more by deviating from the strategy prescribed by their ALCU, given that all other users keep up to the prescribed plan given by ALCU. Theorem 4 in Appendix D also proves that no user has any incentive to deviate from the specified ordering. It validates the operation of the system in fair environment.

Despite the chronological order of the tos_k of user k, (6.5) always give NE of the scheduling game. Under the hood, the shuffling of the chronology of tos_k actually shuffles the NEs of the users. It is a fact that any randomization over NEs is correlated equilibria as well [115], [116]. Hence, this is another way that proves that the approach qualifies for using correlated equilibrium and the solution achieved are valid and consistent for all purpose.

Another benefit of using the chronological ordering for determining the tos_k of users is that it reduces the overall cost of using electricity on the system. Hence, the use of ordering improves the total monetary charge levied on the system. Additionally, the proposed correlated equilibrium strategy is egalitarian in nature and even-handily reduces the cost of each user. The optimization problem in (6.13) is solved by using coordinate ascent method [117] in distributed fashion to find out the optimal scheduling sequence. Algorithm 6.7 expose the procedure of scheduling game algorithm executed in the proposed approach.

The tos_k should not be mixed with the time at which appliances are going to run. It is the time slot at which an appliance a of user k on d^{th} day is encapsulated in $x_{a,k,d}$. Each $x_{a,k,d}$ has 24 elements represents 24 hours of the day in such a way that,

$x^t_{a,k,d}$ = 1, if the corresponding appliance is scheduled to run between t and (t+1) hour.

$x^t_{a,k,d}$ = 0, if the corresponding appliance is not going to run between t and (t+1) hour.

6.5 Performance Evaluation and Result Discussion

6.5.1 Input Data

For the simulation purpose 20 users are considered in the system. Each user is having appliances randomly between 12 to 17. The appliances are both shiftable and non-shiftable in nature. The appliances data is given in Table 3.2. The duration for which the appliances have to run, the time window (includes the start time allowed and end time)

Algorithm 6.7 Algorithm executed on centralized controller unit

procedure
Initialization of predefined parameters;
Repeat once everyday ();
for collect base load data of next day;
  for user k sequentially from K;
    for each appliance a sequentially from A;
      Calculate cost for all appliances (6.4);
      Increase base load at scheduled hours through $\widehat{\mathbb{P}}_{a,k}$;
      Calculate $bf_{a,k,d}$(6.11) ;
    end for
    Calculate $bf_{k,d}$ (6.12);
  end for
Rearrange all user according to $bf_{k,d}$;
end for
d = d.nextDay();
end procedure

in which the appliances are allowed to run and the type of appliance are known before the start of the simulation. The expected dynamic load data before scheduling of any appliance under simulation has been taken from New Hampshire electric cooperative [118]. Once the appliances scheduling of a user is done, the dynamic load for the next appliance or the next user to be scheduled changes. The energy consumed by the previously scheduled appliance is added to the new dynamic load. It is assumed that value of predetermined parameters in cost function is fixed for each period. The wholesale price of the electricity (a_t) is taken as 3 cents/kWh. For the sake of simplicity the b_t and c_t are assumed to be 0. The simulation has been run for 10 days in a stretch for the purpose of day-ahead energy consumption scheduling. Each day is split into 24 time periods representing the 24 hours of the day. The Java platform with IntelliJ IDEA software has been used to run the simulations.

Few assumptions have been taken for implementation purpose. It is assumed that load data of next day can be known in prior by using prediction techniques from past load data. In the literature many methods have been developed for load prediction [71]. It is also assumed that ALCU is installed with built in smart meter which connected to centralize controller unit which will take decision for day ahead scheduling.

The appliances are randomly distributed over all users. The working methodology of proposed approach is shown in Fig. 6.3. The optimal sequence for various appliances can be found by solving the chronological optimization using correlated equilibrium. So initially, users have scheduled on the basis of their balance factor. The user with highest balance factor is allowed to scheduled first in starting. But after starting the day

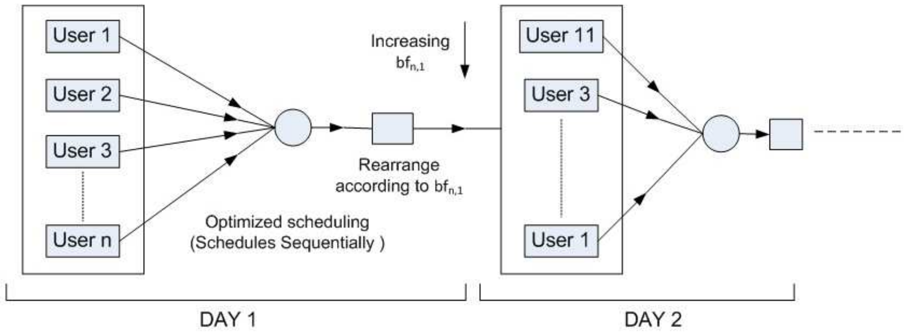


Figure 6.3: Working methodology

it is not necessary that the same user is allowed to schedule the load in the same slot. So the scheduling sequence is changed for future times. The optimal sequence is varied for each day and solution is considered in the fair environment.

6.5.2 Scenarios and Evaluated Factors

For evaluating the performance, two different scenarios are compared.

6.5.2.1 Non-optimized

There is no degree of optimization regarding any parameters. The trend in consumption seems random at times. It can be viewed as a mode of using appliances where a user directly turns his appliance on/off as per requirement. This scenario ignores encompassing the concept of cost optimization.

6.5.2.2 Optimized under non-correlation

The ALCU leverages the schedule returned by NEs of (6.13) to schedule the appliances. Similar to the proposed technique, the tos of different users do not overlap. However, the order of tos isn't reshuffled at all. This scenario follows the steps to minimize the cost as described in section 6.3 but ignores the fairness aspect which has been outlined in proposed approach.

The proposed model was simulated the scenarios with respect to the following factors,

- *PAR of the system:* The peak to average ratio of the system under all three scenario is evaluated.

- *Average benefit from optimized over non-optimized scheduling:* The benefit can be defined as the reduction in the cost incurred on the user if he schedules his appliances optimally over non-optimally. For the sake of representing ability, the benefit gained by users is averaged on a given day under different scenarios.
- *Fairness:* The fairness is defined as equitable distribution of balance factor for each user in the long run. Its performance is evaluated in scenario 2 and the proposed.
- *Total cost on the system:* It is defined as the sum of cost on each user for using their appliances.

The benefit is derived by subtracting the cost of running appliances during the time returned by correlation from the cost of running appliances in a non-optimized way. The cost is calculated using the base load at the point of time decided by the ALCU for scheduling a particular appliance.

6.5.3 Results and Discussion

The simulation results are described here for performance assessment of the proposed model. The system PAR is shown in Fig. 6.4. It is shown that the PAR is reduced considerably on using optimization through correlation over non-optimization. The average change in PAR by using proposed correlated optimization over non-optimized is 31.54 %. The PAR of optimization using NEs without correlation has been found very similar to the proposed method.

Fig. 6.5 and Fig. 6.6 shows that the variance and standard deviation of balance factor $bf_{k,d}$ does not change much in proposed approach, but it does in non-correlated approach.

Hence, it is apparent that the problem of disparity does not aggravate in the proposed technique. The balance factor for different users under non-correlation (Scenario 2) and optimized with correlation is shown in Fig. 6.7 and Fig. 6.8 respectively. From balance factor for various users, it can be clearly seen under non-correlation that if the balance factor is increasing for any particular user, it is going on increasing, but in the case of under correlation, the balance factor is symmetrically distributed over all users. So under the proposed scenario, the balance factor of the users is distributed in order to maintain fairness among all users.

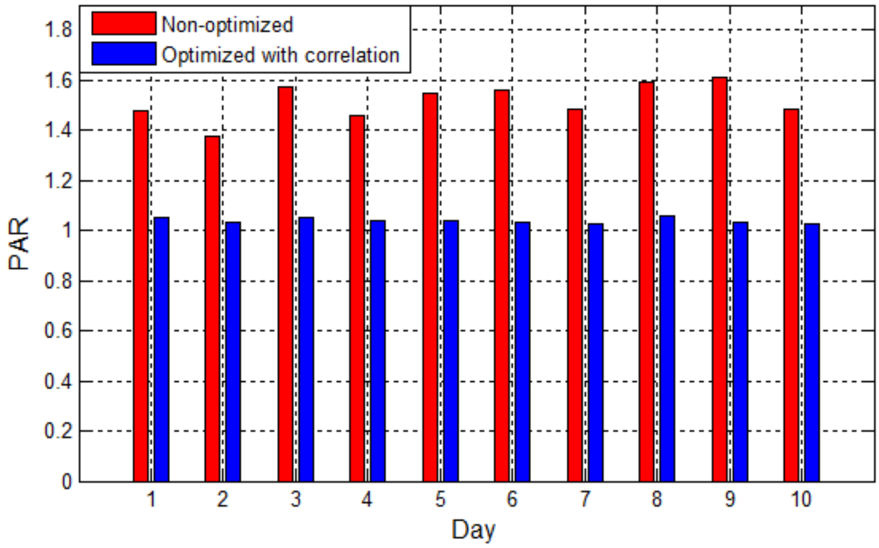


Figure 6.4: System Peak to average ratio (PAR)

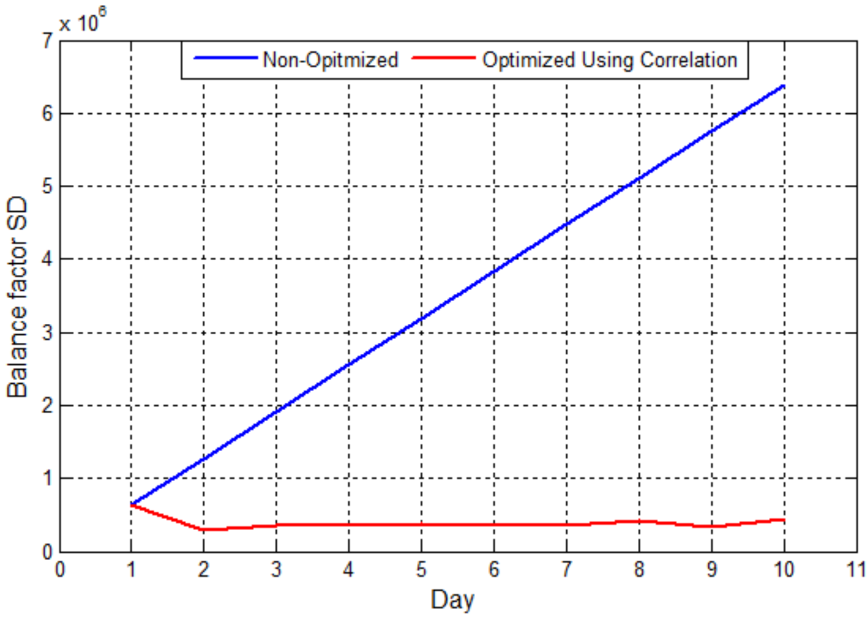


Figure 6.5: Standard deviation of balance factor

The comparison of features in the proposed model for different scenarios is shown in Table 6.2. The values in the cell represent relative ranking to each other. The lower ranking of a scenario shows better performance with respect to other. By this, it is shown that the non-optimized scheduling which is scenario 1 has been ranked 2 for every feature, however the scheduling is done with game theoretic with and without correlated has performed better in terms of evaluated parameter. While comparing the fairness feature in non-correlated and proposed scenario, the proposed correlated optimization has shown better performance.

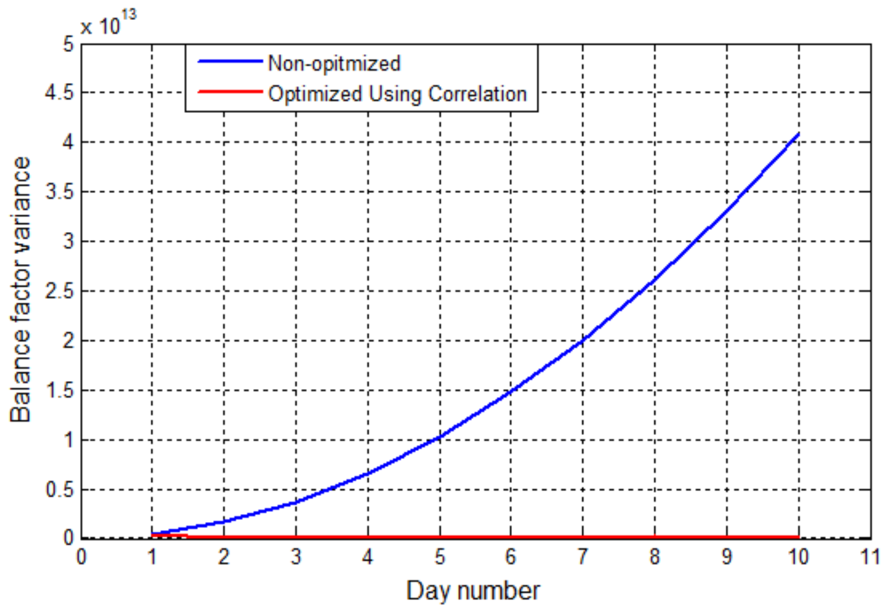


Figure 6.6: Variance of balance factor

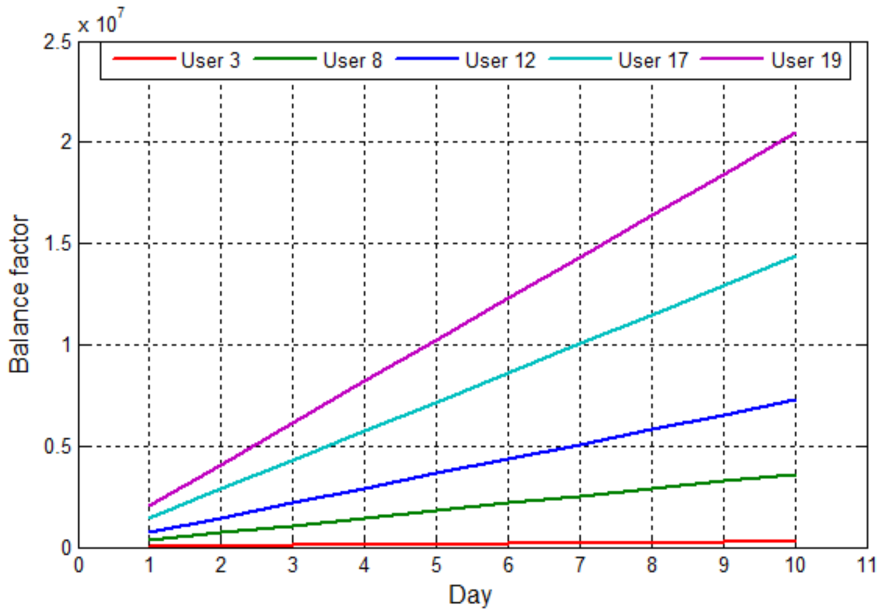


Figure 6.7: Balance factor for different users under non correlation

Table 6.2: Performace Index

Scenario	PAR	Benefit of user over non optimized scheduling	Fairness in the long run
Proposed	1	1	1
Scenario 1	2	2	NA
Scenario 2	1	1	2

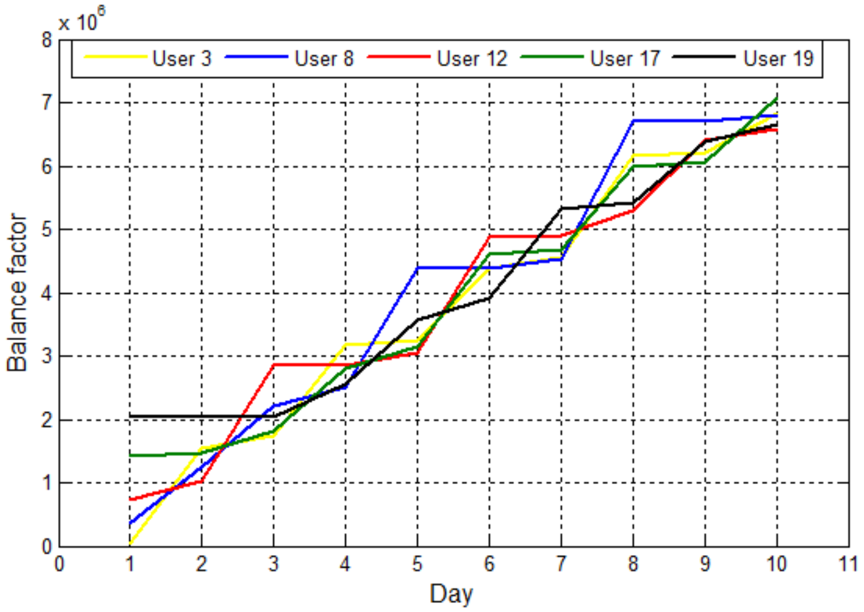


Figure 6.8: Balance factor for different users under correlation

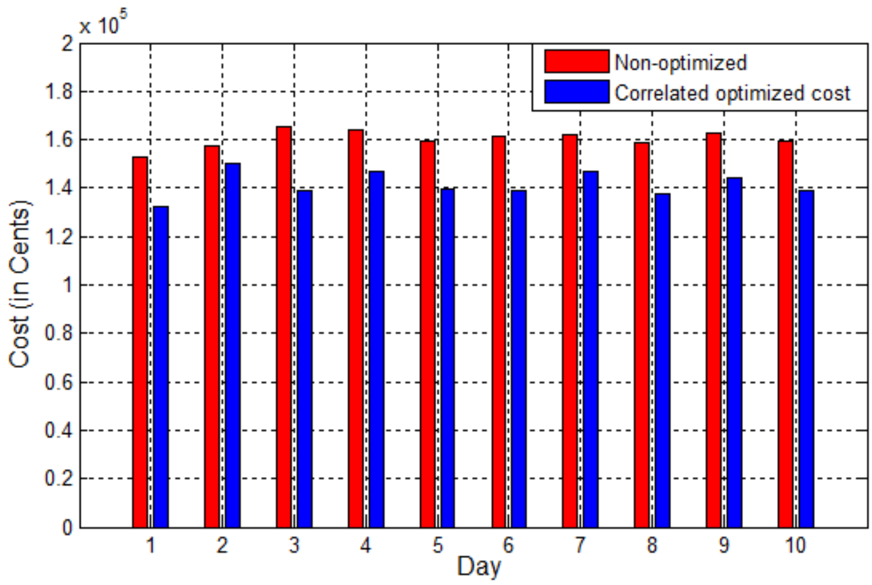


Figure 6.9: Total cost on the system

Fig. 6.9 show that correlated processing for scheduling yields lower total cost than non-optimized. It can be measured that the average of total cost of the system over 10 days is \$160.33 for non-optimized scheduling, whereas the optimized cost with proposed is \$141.48. The significant change in cost minimization of \$18 is found in proposed approach over non-optimized scenario on an average basis.

The monetary benefit gained by users for a given day is shown in Fig. 6.10. The simulation results clearly show that in the benefit term the proposed technique outperforms

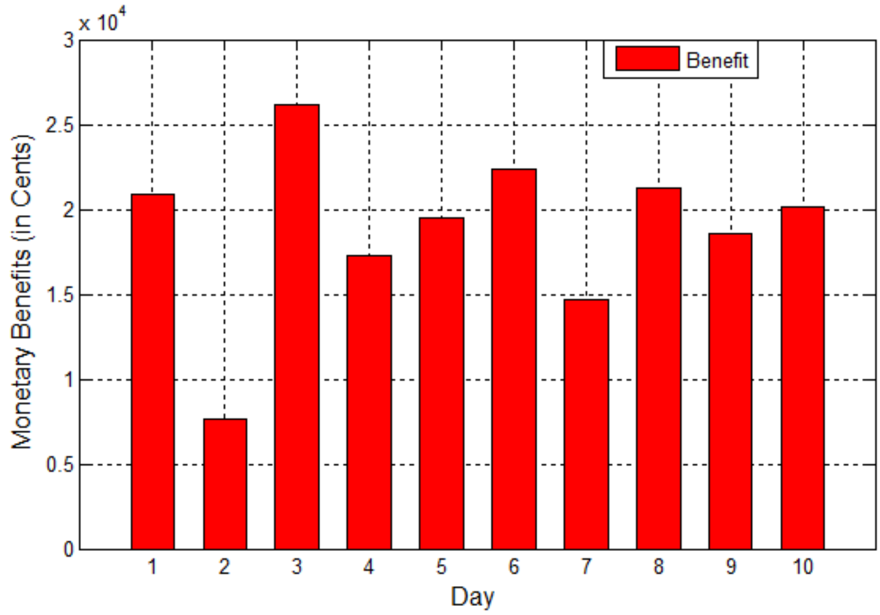


Figure 6.10: Monetarty benefit for the system

the non-optimized scheduling as in Scenario 1, by at least \$7.26 and utmost by \$26.16. From the benefit, it can be seen that for various days the benefit does not show much difference. So it can be interpreted that in a long run every user gets benefit which is a fair environment.

6.6 Summary

This chapter proposed a DR model which encapsulates the day ahead optimal scheduling with fairness among users. The concept of “Fairness” in this model has been inculcated to have equitable benefit distribution among all users over a long run. The performance index comparison for different scenarios has shown validation for proposed mechanism of scheduling in a fair environment. So it has been shown that no user can gain more by deviating from the prescribed strategic order. Such deviations would increase the cost imposed on all users. The proposed model is using an alternative billing model to improve fairness while maintaining a close to optimal overall system performance. It has been confirmed that the proposed design is advantageous by analytical case studies and simulations. The proposed model can be efficiently implemented for residential users in practical scenario. The usage of model can ensure the effectiveness of DR programs in the real world applications.

Chapter 7

Distributed Framework of DR

7.1 Introduction

Most of existing DR approaches are executed in centralized frame. Moreover, they are not tailored to address the challenges of privacy in emerging DR problems. In centralized frame, the user is not allowed to take their decision by own. Centralized controller or utility will take the decision on behalf of user. Whereas in the distributed optimization consumer is offered to take their decision for load scheduling. In this context, the author in [119] is proposed a multi agent framework to solve the DR problem for heterogeneous homes. The different agents are considered such as home agents (HAs) and retailer agent (RA) to evaluate distributed control algorithm for scheduling of heterogeneous household electricity usage to improve energy efficiency. A distributed algorithm to solve the DR problem proposed in [120] using Newton's method. A distributed algorithm to minimize the electricity bill of user with electric vehicle load scheduling in smart grid is developed in [88]. Where, the optimization is done using alternating direction method of multipliers which results into fast convergence and optimal solution to the problem.

A home to grid algorithm is introduced to cut the peak energy usage of a household user [121], Baye's theorem is used to determine the probability of each appliance energy consumption on the basis of historical usage data. The algorithm result is leading to cost reduction in domestic energy and reduce or even eliminate peak-hour energy consumption. In [122], the DR problem is solved using convex programming with home appliances load management. The problem is solved in terms of L_1 regularization technique for shiftable load of appliances in the form of binary decision variable. L_1 regularization technique is also known as least absolute deviations (LAD), least absolute errors (LAE). It is minimizing the sum of the absolute differences between the target value and the estimated values of key variables. The home energy management problem with solar PV generation, energy storage devices, mixed type of home appliances AC and DC load is formulated in [58]. To investigate the behavior of battery and characteristics of AC and DC conversion the different comparison has been made which result into the increment in saving.

In this chapter, DR participant household users are registered for the price-based demand response program in the framework of the smart grid. LSE supplies multiple energy users power. A home area connection is made through the technology of advanced metering infrastructure. The connection between LSE and user is made via home automation wireless network based on Bluetooth devices [123]. A load of user is considered from historical load data. To avoid the limitation of centralized manner for load scheduling optimization, the distributed algorithm is implemented for the minimization of user daily cost occurred. The alternating direction method of multiplier (ADMM) is used to solve the optimization problem. ADMM algorithm works in parallel form. This method is profoundly advantageous to the user, because user don't need to share their information with LSE. Which makes this system reliable and controlled to ensure user privacy. The ADMM guaranteed the fast convergence of the problem, and it can be easily implemented in practical cases.

The chapter is organized as follows. Section 7.2 presents the system model of energy multi-user with the characteristic load. Section 7.3 discusses the problem description and proposed distributed algorithm. The simulation result of analyzing the given system model is present in Section 7.4. Finally, the conclusion with future aspect is presented in Section 7.5.

7.2 System Model

In this architecture, a LSE is supplying electricity to multiple users as shown in Fig. 7.1. Each user is installed with automatic load control unit (ALCU). It is assumed that the built-in smart meter is composed in ALCU. This unit can be used as a medium of communication between LSE and energy user. Each user is participating in the price-based DR program offered by the LSE. The system exhibits a distributed model in which user doesn't need to share their load information to LSE so that privacy of the user can be maintained. The user is allowed to take the scheduling their decision by their ALCU system in which their preferences can also be sent. The different options are available for the user to participate in the DR programs. The different objective has been built

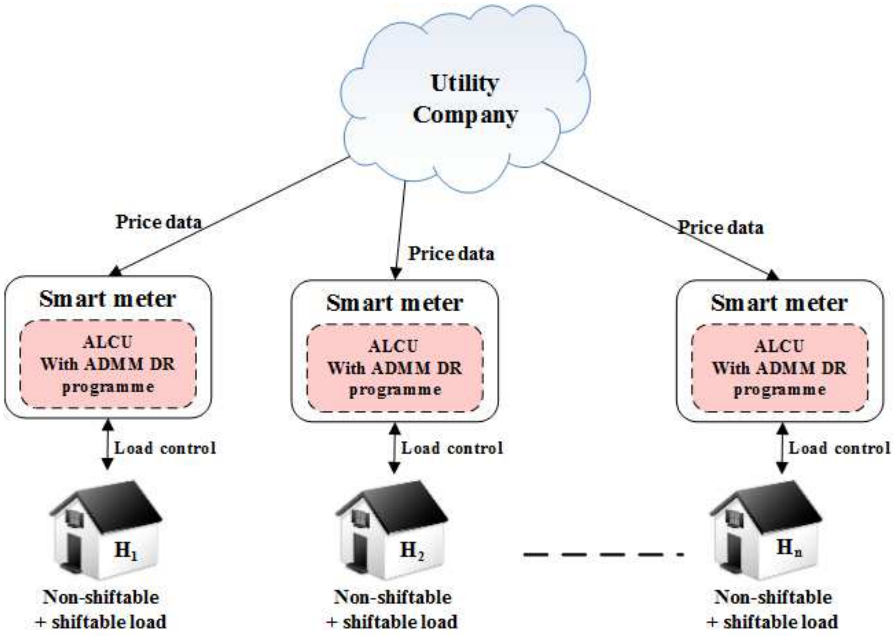


Figure 7.1: DR system architecture

in ALCU for the sake of users. The ALCU receives the real time prices data from the gateway built for the residential by the LSE and applies the DR algorithm to find out when and how to operate home appliances.

The aim of proposed algorithm is to automatically control the load of home appliances and optimize the benefit for users. A load of user and cost occurred by energy usage is optimized using distributed DR algorithm. The objectives can be composed as follows,

- The reduction in peak demand of the objective load curve.
- Reduce the energy cost occurred on users as energy bills.
- The regulation of energy efficiency in a household.
- Utilization of energy when electricity prices are low.

7.2.1 Appliance load

The household user consists distinct characteristic appliances. Two type of home appliance such as non-shiftable and shiftable are considered. The non-shiftable appliances are base load of a house and it is necessary to fulfill the energy requirement as they can't be shifted to any other time slot. The shiftable appliances can be shifted from one to another time slot. shiftable appliances can be a time-flexible and power-flexible appliance. In time-flexible their energy demand cannot be compromised but possible to shift from one slot to another as offered by load scheduling mechanism. Power-flexible appliances cannot be interrupted once started running, but their energy can be varied within a limit.

7.3 Problem Formulation

7.3.1 Electricity usage model for user

The problem of automatic load scheduling is executed in a various manners. Although the main objective is to maximize the saving on daily electricity bill occurred on a user that minimizes the total electricity cost of the system. The total consumption of user $E_{k,t}$ is modeled as follows,

$$E_{k,t} = E_{k,t}^{shiftable} + E_{k,t}^{non-shiftable} \tag{7.1}$$

Where $E_{k,t}^{non-shiftable}$ and $E_{k,t}^{shiftable}$ are non-shiftable and shiftable appliance consumption for user k during t time slot, respectively. The number of non-shiftable and shiftable appliance varies for each user in the system.

The concept of load shifting technique is described in Fig. 7.2. The load shifting is done by transferring the load from high price hour to low price hour. The $x_{k,t}$ is the load shifting variable of k^{th} user in hour t. The electric price in each hour is denoted by P_t. The objective function which depicts the load scheduling of energy user can be discussed via following cases.

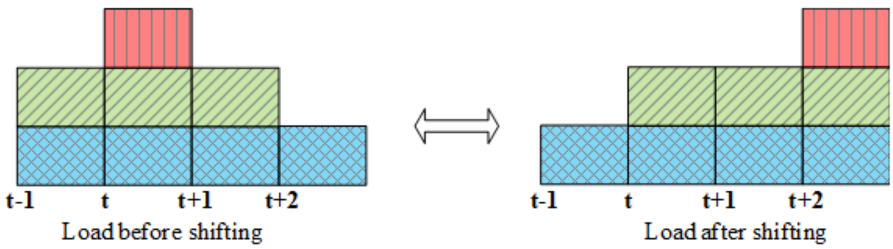


Figure 7.2: Load shifting technique

7.3.1.1 Case 1: load minimization

In this case, the objective function for optimizing user energy bill can be formulated in term of a total load of the user. The non-shiftable load of the user is fixed during optimal load scheduling. Therefore only shiftable load can only be used for load shifting purpose. The objective function $f_1(x)$ can be represented as follows,

$$\text{Minimize } \; f_1(x) = \sum_{t=1}^{24} \Big(E_{k,t} + x_{k,t} \Big)^2 \qquad \forall k \in K \tag{7.2}$$

$$\text{Subject to } \; -E_{k,t}^{shiftable} \leq x_{k,t} \leq E_{k,t}^{shiftable} \qquad \forall k \in K \tag{7.3}$$

The load shifting variable of each user is different, and it is calculated in a parallel iterative procedure. In this case, the aim of optimization is to shift a total load of the user. The total cost occur on each user C_k can be calculated as,

$$\mathrm{C}_k = \sum_{t=1}^{24} \Big(P_t * (E_{k,t}^{non-shiftable} + x_{k,t}) \Big) \tag{7.4}$$

7.3.1.2 Case 2: shiftable load minimization

In this case, the objective function is made with only shiftable load. This objective can have more impact on the saving of user because only shiftable load regulates the load shifting process. The similar objective function $f_2(x)$ can be made as follows,

$$\text{Minimize } \; f_2(x) = \sum_{t=1}^{24} \Big(E_{k,t}^{shiftable} + x_{k,t} \Big)^2 \qquad \forall k \in K \tag{7.5}$$

$$\begin{aligned} \text{Subject to } \; A_k * x_{k,t} &= B_k \qquad \forall k \in K \\ \sum_{t=1}^{24} x_{k,t} &= 0 \qquad \forall k \in K \end{aligned} \tag{7.6}$$

Where A_k is the coefficients of shiftable load and $B_k = 0$.

The total cost of each user can be defined as,

$$C_k = \sum_{t=1}^{24} \Big(P_t * (E_{k,t}^{non-shiftable} + E_{k,t}^{shiftable} + x_{k,t}) \Big) \tag{7.7}$$

7.3.1.3 Case 3: load minimization with real time price coefficient

This case represents the optimization of total load for each user concerning real time price coefficients. The optimization problem with $f_3(x)$ objective function is formulated such as,

$$\text{Minimize } f_3(x) = \sum_{t=1}^{24} \Big(P_t * (E_{k,t}^{non-shiftable} + x_{k,t})^2 \Big) \qquad \forall k \in K \tag{7.8}$$

$$\begin{aligned} \text{Subject to } A_k * x_{k,t} &= B_k & \forall k \in K \\ \sum_{t=1}^{24} x_{k,t} &= \sum_{t=1}^{24} E_{k,t}^{shiftable} & \forall k \in K \\ -E_{k,t}^{shiftable} \le x_{k,t} &\le E_{k,t}^{shiftable} & \forall k \in K \end{aligned} \tag{7.9}$$

Where A_k is the coefficients of sum of total load and $B_k = E_{k,t}^{shiftable}$. The energy cost of each user is formulated as,

$$C_k = \sum_{t=1}^{24} \Big(P_t * (E_{k,t}^{non-shiftable} + x_{k,t}) \Big) \tag{7.10}$$

7.3.1.4 Case 4: cost minimization

This case evaluates the performance of optimization for the cost saving formulation. Here the aim of optimization is centered around cost optimization of energy user which can be proven highly effective for bill saving of user.

$$\text{Minimize } f_4(x) = \sum_{t=1}^{24} \Big(P_t * (E_{k,t}^{non-shiftable} + x_{k,t}) \Big)^2 \qquad \forall k \in K \tag{7.11}$$

$$\begin{aligned} \text{Subject to } A_k * x_{k,t} &= B_k & \forall k \in K \\ -E_{k,t}^{shiftable} \le x_{k,t} &\le E_{k,t}^{shiftable} & \forall k \in K \end{aligned} \tag{7.12}$$

Where A_k is the coefficients of total load $B_k = E_{k,t}^{shiftable}$. The energy cost of each user is formulated as,

$$\mathrm{C}_k = \sum_{t=1}^{24} \Big(P_t * (E_{k,t}^{non-shiftable} + x_{k,t})\Big) \tag{7.13}$$

7.3.1.5 Case 5: dual objective

In this case, a dual objective approach is analyzed. This function comprises the load and cost. This approach can be proven highly effective because of the summing the two main aim of the system. It can be formulated as follows,

$$\begin{aligned} \text{Minimize } \; f_5(x) = \sum_{t=1}^{24} \Big((E_{k,t} + x_{k,t})^2 + \alpha * P_t * (E_{k,t}^{non-shiftable} + x_{k,t})^2\Big) \\ \forall k \in K \end{aligned} \tag{7.14}$$

$$\begin{aligned} \text{Subject to } \; A_k * x_{k,t} = B_k \qquad & \forall k \in K \\ -E_{k,t}^{shiftable} \leq x_{k,t} \leq E_{k,t}^{shiftable} \qquad & \forall k \in K \end{aligned} \tag{7.15}$$

Where A_k is the coefficients of constraint, which is sum of total load and $B_k = E_{k,t}^{shiftable}$. Here α is defined as a constant parameter which can affect the performance of optimization process. The significance of this parameter is defined in the result section. The energy cost of each user is formulated as,

$$\mathrm{C}_k = \sum_{t=1}^{24} \Big(P_t * (E_{k,t}^{non-shiftable} + x_{k,t})\Big) \tag{7.16}$$

7.3.2 Distributed Optimization using alternating method of multiplier (ADMM)

The optimization of convex problem set in equation (7.2), (7.6), (7.8), (7.11) and (7.14) is solved by iterative procedure in distributed manner. The distributed optimization framework overcome the disadvantage occurred in a centralized manner. Distributed optimization offers energy user to optimize their saving in a separate manner. In this framework, the user needs not to expose their information to the LSE. Therefore optimization is done using an alternating method of multiplier (ADMM) in distributed manner [124].

7.3.2.1 ADMM Method

ADMM is a well-recognized technique to distributed convex optimization. Consider a constrained convex optimization problem for function $f(x)$,

$$\begin{aligned} \text{Minimize } & f(x) \\ \text{Subject to } & Ax = B \end{aligned} \tag{7.17}$$

Where $x \in R^q$, $A \in R^{p \times q}$ and $f : R^k \to R$ is convex.

By using Lagrangian the problem can be expressed as,

$$L(x, y) = f(x) + y^T (Ax - B) \tag{7.18}$$

Where y is the Lagrange multiplier. For solving the problem using Lagrangian method the dual iterative procedure can be made as,

$$\begin{aligned} x^{n+1} &= argminL(x, y^n) \\ y^{n+1} &= y^n + \alpha^n (Ax^{n+1} - B) \end{aligned} \tag{7.19}$$

Where α^n is a step size.The dual method can be extended to Augmented Lagrangian methods. The augmented methods are introduced to increase the robustness of dual methods. The augmented Lagrangian of problem (7.14) is,

$$L_\rho(x, y) = f(x) + y^T (Ax - B) + (\rho/2)||Ax - B||_2^2 \tag{7.20}$$

Where $\rho > 0$ is penalty parameter. With association of augmented Lagrangian the optimization problem can be formed as,

$$\begin{aligned} \text{Minimize } & f(x) + \rho/2)||Ax - B||_2^2 \\ \text{Subject to } & Ax = B \end{aligned} \tag{7.21}$$

The dual update can be made as,

$$\begin{aligned} x^{n+1} &= argminL_\rho(x, y^n) \\ y^{n+1} &= y^n + \alpha^n (Ax^{n+1} - B) \end{aligned} \tag{7.22}$$

The augmented Lagrangian method is called alternating direct method of multipliers [125].

7.3.2.2 DR distributed algorithm

The distributed ADMM method is applied to the DR problem stated in Section 7.3.1. The individual user problem can be easily solved by the distributed algorithm. The problem in (7.14) can be extended in Lagrangian form as,

$$\begin{aligned} L_\rho(x_{k,t}, y) = \sum_{t=1}^{24} \Big((E_{k,t} + x_{k,t})^2 + \alpha * P_t * (E_{k,t}^{non-shiftable} + x_{k,t})^2 \Big) \\ + y^T (A_k x_{k,t} - B_k) + (\rho/2) \| A_k x_{k,t} - B_k \|_2^2 \qquad \forall k \in K \end{aligned} \tag{7.23}$$

where ρ is a predefined penalty parameter. Basically ADMM cycles through the following update until its convergence is reached.

$$x_{k,t}^{n+1} = argminL_\rho(x_{k,t}, y^n) \tag{7.24}$$

$$y^{n+1} = y^n + \alpha^n (A_k x^{n+1} - B_k) \tag{7.25}$$

To solve the equation (7.24) and (7.25), iterative procedure is continuing up to convergence is reached. The iteration of a procedure is denoted by n. The $x_{k,t}^{n+1}$ is updated by solving convex optimization problem. The problem in (7.24) and (7.25) can also be solved in parallel. In the remaining section, this iterative procedure is referred as ADMM scheduling method.

7.4 Numerical Results and Discussion

7.4.1 Numerical Setup

In this setup, $K = 10$ number of the residential user is considered for distributed ADMM scheduling. Each customer is considered with 15 to 20 home appliance. The appliance load of user is non-shiftable and shiftable in nature. The sum of shiftable and non-shiftable load is taken from BGE suppliers [85]. The total load of the system can be

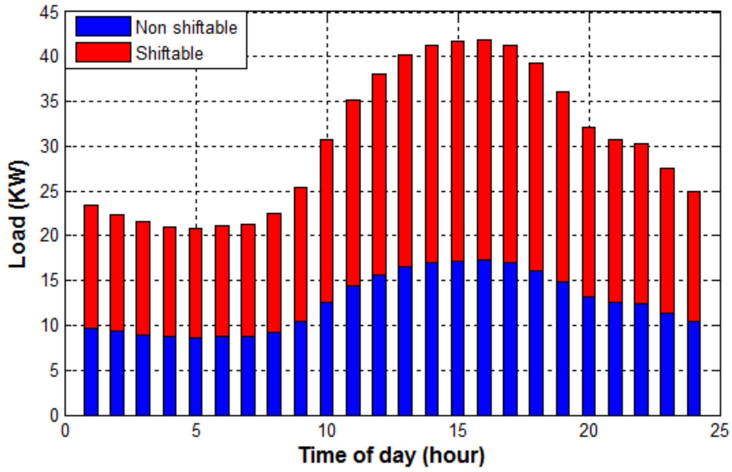


Figure 7.3: Total load of the system

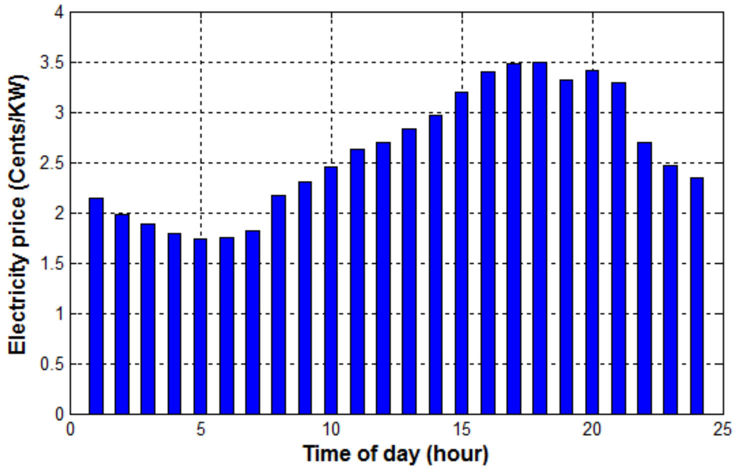
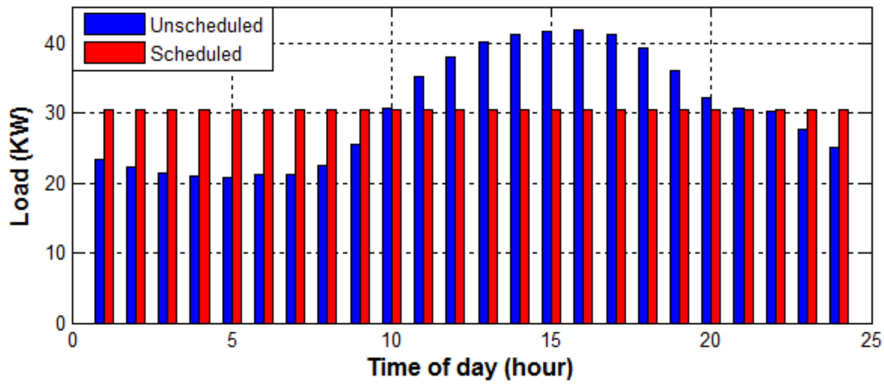


Figure 7.4: RTP price data

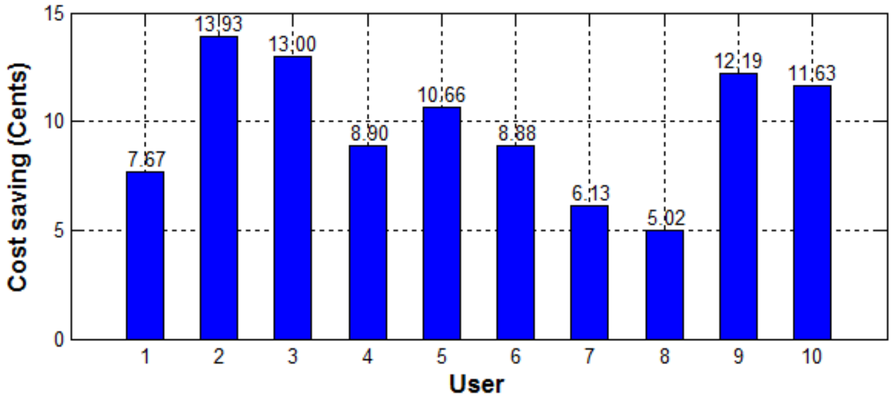
shown in Fig. 7.3. The customers are contracted for the RTP data information. The RTP data has been taken from Ameren Illinois Power corporation [46]. The RTP price data is shown in Fig. 7.4. The implementation of proposed algorithm is executed on the platform of MATLAB software on Core i3 processor.

7.4.2 Results and discussion

In this chapter, different objectives are executed via distributed optimization to analyze the customer saving. From the point of LSE, the flatten objective load curve is highly desirable. But from the point of a customer, focus is oriented on their energy bill saving. The customer energy bill is optimized with consideration of objective load curve. Therefore LSE and customer both will get benefits from the proposed algorithm. In the proposed distributed algorithm each user is optimizing their objectives in parallel form.



(a) Load scheduling

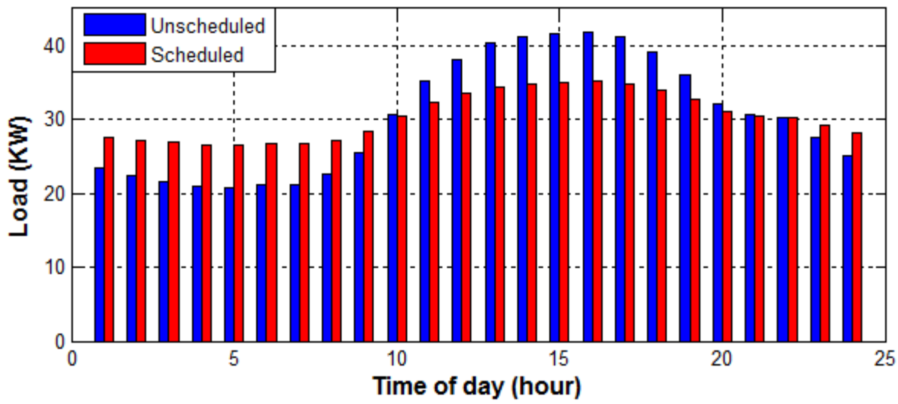


(b) Monetary benefits

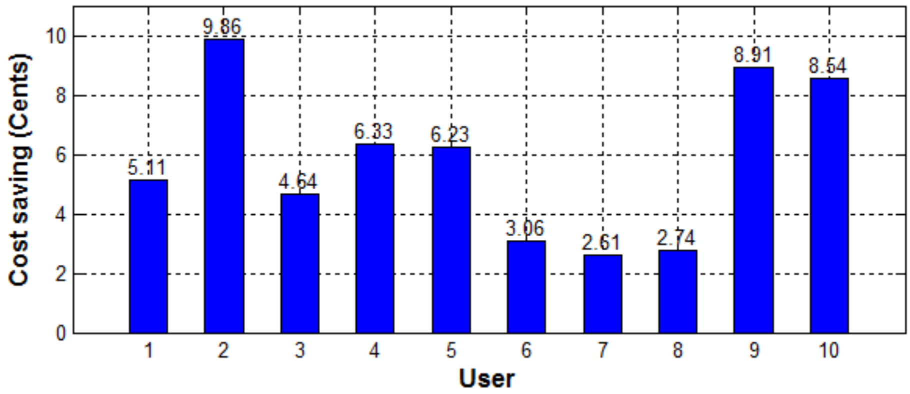
Figure 7.5: Simulation results for Case 1

The Case 1 evaluates the minimization the total load on the system by load shifting technique. Here the price is not having any role in an optimization process. The unscheduled and scheduled load for case 1 is shown in Fig. 7.4.2. The scheduled load curve is almost flattening which shows the best possible peak to average ratio. If we see the practically the flat load curve is not easily available because of consumer preferences and lack of shiftable appliances availability. In this case, the PAR is minimized by 27.16%. After applying load scheduling algorithm, the user has gained considerable cost saving on their bill which can be interpreted from Fig. 7.4.2. The total bill saving of each user is determined by the difference with and without scheduling cost. Here it can be analyzed the user who has participated in shifting with more amount of load have gained more saving on the bill as compared to others. For this case, the user 2 has gained 13.93 Cents, which is highest saving among all user. The total energy bill saving for the system is obtained 4.9 %.

In the Case 2, the user is allowed to optimize only shiftable appliance load. The result in Fig. 7.6 shows the load before and after scheduling. The peak to average ratio in this case is minimized by 16 %. The cost saving for an individual user is shown in Fig. 7.6.



(a) Load scheduling



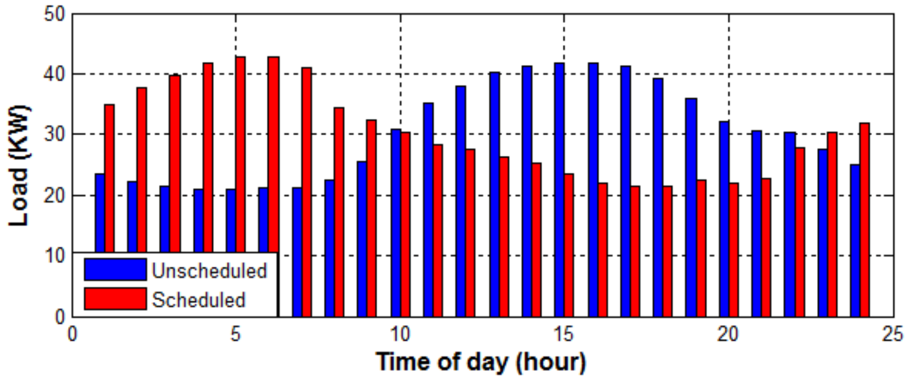
(b) Monetary benefits

Figure 7.6: Simulation results for Case 2

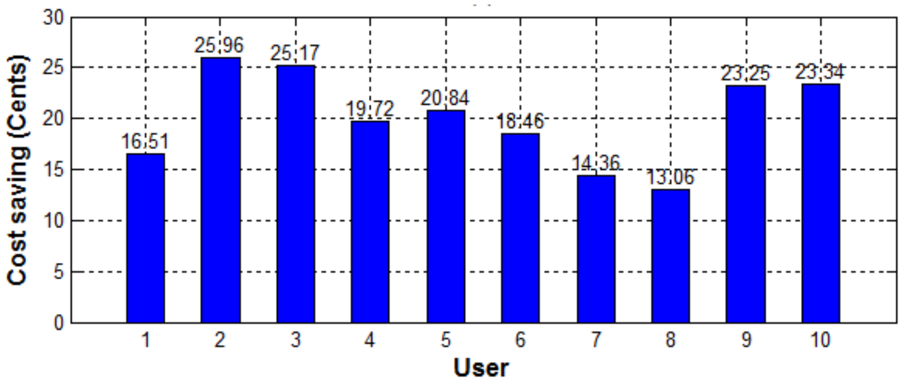
The total cost saving for the system is maximized by 2.9 %.

In the Case 3, total load minimization with RTP price coefficients is served as a goal of the optimization. The Fig. 7.7 represents the load with and without scheduling. The cost saving for each user can be represented in Fig. 7.7. In this case, the cost saving has more impact as compared to PAR. The involvement of price coefficients is proven to be effective for cost saving purpose. The total 200.68 Cents cost saving is achieved for the system. Whereas individually say user no. 2 and user no. 3 has gained highest saving i.e. 25.96 and 25.17 Cents cost saving.

The Case 4 introduces the objective as cost minimization of the individual user. The results in Fig. 7.8 shows the impact of load scheduling on the total load of the system. The proposed distributed algorithm solved each optimization problem to achieve the highest benefit for the user which lack behind the objective load curve responsibility. Therefore PAR of the system is increased for the particular case. The cost benefits redeem by an individual user can be critically examined in Fig. 7.8. The total 296.4 Cents cost saving is obtained in this setup which is considerably large.



(a) Load scheduling

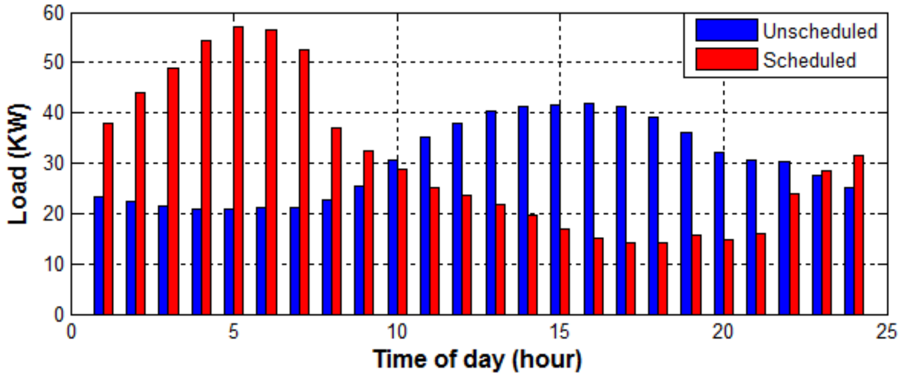


(b) Monetary benefits

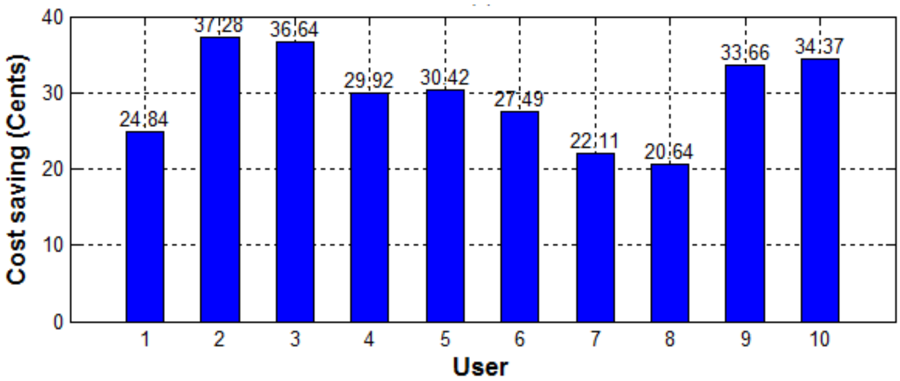
Figure 7.7: Simulation results for Case 3

The Case 5 implements the optimization of function made from cost and load minimization. From the Fig. 7.9, it can be analyzed that obtained load curve is highly desirable for any LSE. The scheduled load curve almost looks like flattening curve with consumer preferences. In this case both objective such as PAR minimization and cost saving both achieved in a balanced manner. The total cost saving from this case is 132.4277 Cents as shown in Table 7.1. The constant α can affect the convergence rate of the algorithm, here it is considered as 0.1.

Fig. 5.9 shows the scheduled load comparison for each case with the unscheduled load. From Fig. 5.9, it can be seen that the best load curve is achieved in Case 1 but with less amount of savings. Whereas the Case 5 offers appropriate load curve as desired for practical scenarios. For Case 5 it also gives the sufficient amount of cost saving to the users. Also from Table 7.1, it is seen that Case 5 can be proven most suitable objective for LSE as well as for the user. The convergence plot for objective function of a single user is shown in Fig. 7.11. It can be seen that user is able to optimize their objective after completing 20 iterations of the process. The error deviation is shown in Fig. 7.12, it is taking 20 iterations for settling .



(a) Load scheduling

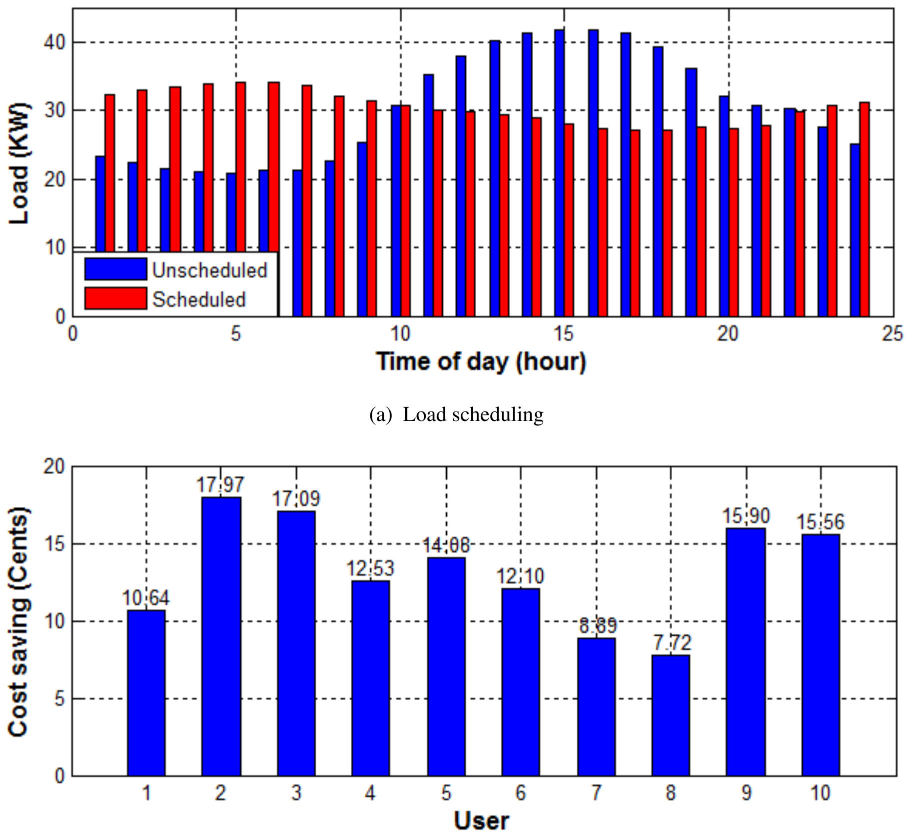


(b) Monetary benefits

Figure 7.8: Simulation results for Case 4

As per computational aspect, it is not necessary to increase the value of ρ to infinity to induce the convergence in a method of multiplier. This is an advantage, which results in the elimination ill conditioning (non-convergence) problem. An another advantage of this method is that its convergence range is better than penalty method. The variation of penalty parameter ρ has an effective impact on the algorithm. As per computational aspect, the initial value of ρ should not be too large so that it will not lead to ill-condition result in first iteration. The value of parameter ρ should increase with iteration so that it can utilize the positive feature of multiplier iteration. Parameter ρ is not increasing fast enough to the threshold point than too much ill condition is forced upon function constraint minimization. If parameter ρ increasing very slow to the threshold, it will lead to the poor convergence rate. For the algorithm, the initial value of ρ_0 has been taken 0.01. The updated value of ρ with iteration has considered as $\rho = \rho_0 * 2^{iteration}$.

The proposed automatic load scheduling of household users in demand response framework offers their energy cost minimization to the users. From the Table 7.1, it can be analyzed that how a user can get the significant amount of cost saving by implementing proposed methods of automatic load scheduling. Here with the help of DR distributed optimization algorithm user gets a chance to develop their role in the elec-



(a) Load scheduling

(b) Monetary benefits

Figure 7.9: Simulation results for Case 5

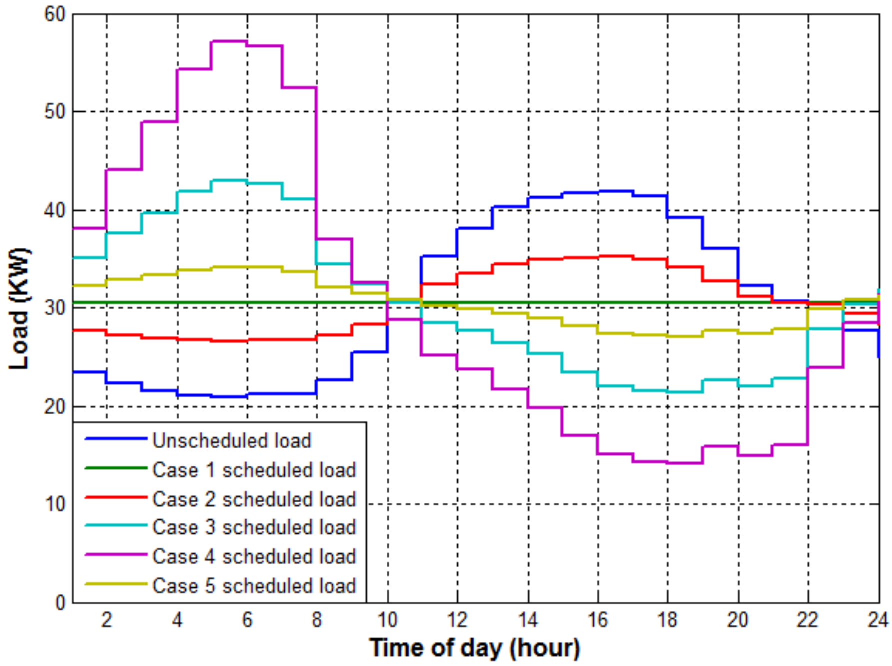


Figure 7.10: Scheduled load

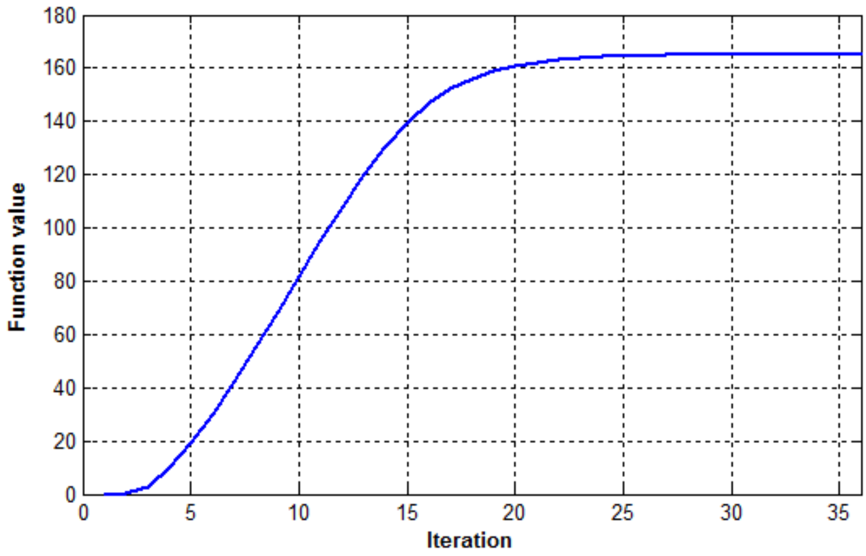


Figure 7.11: Function convergence Plot

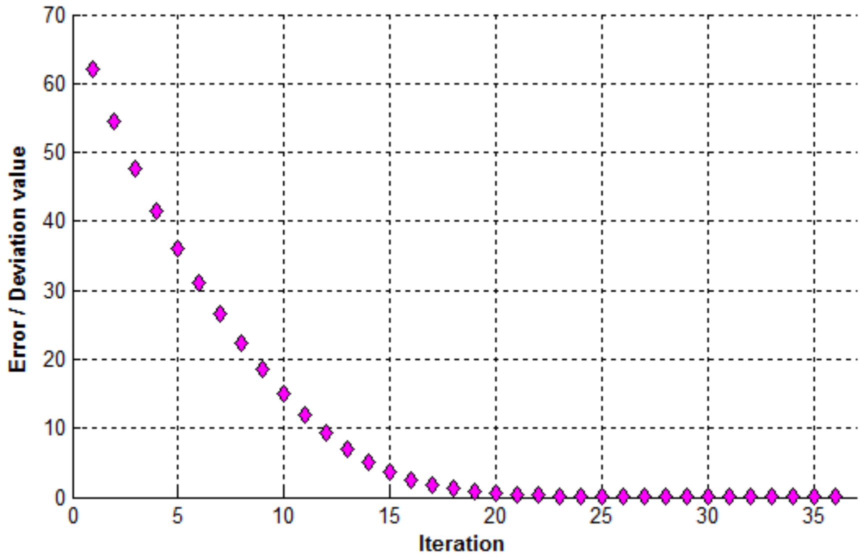


Figure 7.12: Error convergence plot

tricity paradigm. After processing optimization algorithm, user gets scheduled load as the result of automatic load scheduling. Here, the real time prices taken from retail market provides the information of real time tariff via ALCU. The proposed technique does not collaborate with the energy market. Only energy tariff is required from the LSE.

Table 7.1: Numerical Results

	Unscheduled PAR	Scheduled PAR	Total scheduled Cost (Cents)	Cost Saving (Cents)	Computation time (sec)
Case 1	1.3743	1.00	1894.9	98.0082	162.647
Case 2	1.3743	1.1543	1934.9	58.0335	108.40
Case 3	1.3743	1.4083	1792.2	200.6830	131.973
Case 4	1.3743	1.8761	1695.6	296.400	129.312
Case 5	1.3743	1.1193	1860.400	132.477	131.281

7.5 Summary

A multi user electricity usage model is developed for the shiftable and non-shiftable appliance load. The real-time pricing information is transferred to the user by utilizing the smart metering infrastructure. The load and cost optimization problem of the user in centralized form is converted to distributed parallel algorithm. The optimization of an individual user is implementing in parallel iteration procedure. The optimization problem is solved by using an alternating direction method of multiplier in distributed manner. The different case study is proposed to evaluate the performance of optimization process. The results in terms of user bills and PAR have shown the effectiveness of the proposed algorithm. The specific user saving for each case study has proven the capability of the proposed algorithm.

Chapter 8

Conclusion and Future Work

8.1 Conclusion

Demand response emerges as a highly constructive solution to reduce peak energy demand in the electricity network infrastructure. DR has shown potential to increase the interaction between energy customers and electricity grid. The aim of DR is not only reducing customer's electricity bill or saving energy, but also advantageous for system operation, grid flexibility, system expansion, energy efficiency. The smart meters played a significant role to enable bi-directional communication between customer and utility. To achieve interactive environment, the computational techniques such as game theory proven beneficial for the system operations. By adopting of EV and renewable sources in the DR, makes it more convenient for energy users. DR programs need to be installed to encourage customer participation in electricity infrastructure. The significant findings for this work are summarized below:

- In Chapter 3, residential users are equipped with distinct type of appliances at their homes. The appliances have distinct characteristics in individual houses, and it is necessary to model the appliances in an appropriate way that user should not comprise their comfort while executing DR. For this purpose different appliances with their priority operating time is considered in this research.
- In Chapter 4, the large number of EVs are executed for DR. When number of EVs emerges at same time, the grid overloading can not be avoided. Therefore the application of smart charging is proven beneficial for reducing peak demand and grid overloading can be avoided. The bi-directional power transaction among users and grid are beneficial as the point of economics.

- In Chapter 5, the home energy management with EV and renewable provides flexible operation with grid transaction. Incorporating dissatisfaction factor in DR problem is proven more realistic due to uncertain behavior of users. The penalty with dissatisfaction can make system reasonable. The EV and BESS played a role of enabling technologies to reduce the energy bill of household user and to maintain the comfort. The incorporation fluctuation term in DR problem avoid the formation of unwanted peak in desired load curve. The application of renewable sources is beneficial to reduce carbon impacts in society.
- In Chapter 6, dynamic demand response model introduces correlated equilibrium approach in a game theoretic scenario for the residential consumer. This approach provides a suitable platform to execute DR in residential frame and to achieve economic benefits, comfort reliability and most important fair environment.
- In Chapter 7, the distributed framework offers a secure operation of user in DR. To preserve the privacy of user single objective for each user is executed in parallel simulation. While parallel operations can save operating time.

8.2 Future Scope of Work

The future utilization of presented work is summarized a follows,

- With regard to user load model throughout this work, it is assumed that consumer previous day load is known to user . For future work, the application of load prediction techniques can be integrated to user load model. The user behavior on the basis of preferences and conditions can be considered in the load model as future work.
- In power systems, ancillary services are important for the well-being of the system. However, such services have usually been provided from the supply side as opposed to the demand side. In the power system, ancillary services are required for the well-operation of the system. These services are produced from supply side network. So, the integration of supply side can be done in future. At present the operation of DR is considered from demand side consumer only. The future problem can be extended to the operation of DR in the presence of electricity distribution system.

- Mostly the energy consumption scheduling done on day-ahead basis is implemented here. With the development of fast forecasting techniques it is possible to perform the energy consumption scheduling on hour-ahead basis or real-time.

- EV uncertainty is employed but the renewable sources are assumed to supply constantly on the basis of given data. The uncertainty can also be employed for renewable sources in future work.

- The modeling and analysis for residential sector only is presented in this work which can be further extended to the combination of residential, industrial and commercial sectors.

Appendix A

Proof of Theorem 1

The optimization problem is the Nash Equilibrium of the game. Let X_k^* is the strategy at which the corresponding cost C^* is minimum. Hence,

$$C^* \leq \sum_{t=0}^{T} C(W_t + \widehat{\mathbb{P}}_{a,k}) \tag{A.1}$$

Multiplying by $(-)$ on both sides

$$-C^* \geq \sum_{t=t_{a,u}^{start}}^{t_{a,k}^{end}} C(W_t + \widehat{\mathbb{P}}_{a,k}) \tag{A.2}$$

$$P_k(X_k^*, X_{-k}) \geq P_k(X_k, X_{-k}) \tag{A.3}$$

The optimal solution of problem in 6.13 assures the existence of a Nash equilibrium The proposed optimization problem is Nash equilibrium [[115], Theorem 1]. Moreover, the Nash equilibrium is unique due to [[115], Theorem 3].

Appendix B

Proof of Theorem 2

Let there be two users u_1 and u_2 with appliances a_1 and a_2, respectively.

B.1 Case I

When there is no ordering and all users try to schedule optimally at the same time, i.e. $tos_1 = tos_2$. In such a case due to the fact that cost functions are convex all user will find the same time t to schedule their appliances.

Hence, cost levied on each user,

$$C(W_t + \widehat{\mathbb{P}}_{a_1,u_1} + \widehat{\mathbb{P}}_{a_2,u_2}) \tag{B.1}$$

Cost levied on system = 2 * cost levied on each user

$$2 * C(W_t + \widehat{\mathbb{P}}_{a_1,u_1} + \widehat{\mathbb{P}}_{a_2,u_2}) \tag{B.2}$$

B.2 Case II

When there is ordering. Let $tos_1 < tos_2$.

Let time at which appliances are scheduled to run be t_1 and t_2 respectively.
Cost levied on user 1,

$$C(W_1 + \widehat{\mathbb{P}}_{a_1,u_1}) \tag{B.3}$$

Cost levied on user 2,

$$C(W_1 + \widehat{\mathbb{P}}_{a_2,u_2}) \tag{B.4}$$

$$\text{Where,} \quad \begin{aligned} W_2 &= W_1 + \widehat{\mathbb{P}}_{a_1,u_2} \quad \text{if } t_1 = t_2 \\ W_2 &< W_1 + \widehat{\mathbb{P}}_{a_1,u_1} \quad \text{if } t_1 \neq t_2 \end{aligned}$$

Total cost on system is expressed by combining (B.3) and (B.4),

$$C(W_1 + \widehat{\mathbb{P}}_{a_1,u_1}) + C(W_1 + \widehat{\mathbb{P}}_{a_2,u_2}) \tag{B.5}$$

By comparing case I and case II, since cost functions are quadratic.

$$2 * C(W_t + \widehat{\mathbb{P}}_{a_1,u_1} + \widehat{\mathbb{P}}_{a_2,u_2}) > \left[C(W_1 + \widehat{\mathbb{P}}_{a_1,u_1}) + C(W_1 + \widehat{\mathbb{P}}_{a_2,u_2})\right]$$

Hence, in case of ordering in *tos* cost levied on system on a whole is lesser when there is no ordering in *tos*.

Appendix C

Proof of Theorem 3

Let $C(W_t^{tos_1})$ and $C_2(W_t^{tos_2})$ be the cost of using appliances at hour t on load $W_t^{tos_1}$ and $W_t^{tos_2}$ by two random users, where tos_1 and tos_2 are time at which the process of computation of costs at various hour for user 1 and user 2 took place.

C.1 Case I

Both appliance scheduled at hour t.

$$W_t^{tos_2} = W_t^{tos_1} + \widehat{\mathbb{P}}_{a_1,u_1}$$

$$\text{Therefore,} \quad W_t^{tos_2} > W_t^{tos_1}$$

Since, cost function is quadratic. Therefore,

$$C(W_t^{tos_1}) < C(W_t^{tos_2}) \tag{C.1}$$

C.2 Case II

a_1 is scheduled at hour t but a_2 is not. So,

$$W_t^{tos_2} = W_t^{tos_1}$$

$$\text{Therefore,} \quad C(W_t^{tos_1})_{u_1} = C(W_t^{tos_2})_{u_2} \tag{C.2}$$

So, it can be inferred from (C.1) and (C.2).

If $tos_1 < tos_2$, measuring cost of using appliance at various hours and for scheduling for user 1 is earlier than that of user 2.

$$C(W_t^{tos_1})_{u_1} \leq C(W_t^{tos_2})_{u_2} \tag{C.3}$$

Therefore, it can be stated that the user who has scheduled their appliances before another (i.e. $tos_1 < tos_2$) will get less energy cost and gain more benefit on daily electricity bill.

Appendix D

Proof of Theorem 4

Let u_1 and u_2 be two different users, a_1 and a_2 be their respective appliances, tos_1 and tos_2 be their respective time at which the process of finding their optimal running time is run. Let $tos_1 < tos_2$,

D.1 Case I

When prescribed chronology by ALCU is adhered. Let t_1 and t_2 time at which they are scheduled to run. W_{t_1} & W_{t_2} be the respective base loads.
Cost to be incurred on user 1,

$$C(W_{t_1} + \widehat{\mathbb{P}}_{a_1,u_1}) \tag{D.1}$$

Cost to be incurred on user 2,

$$C(W_{t_2} + \widehat{\mathbb{P}}_{a_2,u_2}) \tag{D.2}$$

$$\begin{aligned} \text{Where,} \quad W_{t_2} &= W_{t_1} + \widehat{\mathbb{P}}_{a_1,u_1}, &\quad \text{if } \; t_1 = t_2 \\ W_{t_2} &< W_{t_1} + \widehat{\mathbb{P}}_{a_1,u_1}, &\quad \text{if } \; t_1 \neq t_2 \end{aligned}$$

D.2 Case II

When u_2 deviates from prescribed chronology prescribed by ALCU and run process of finding the optimal time of along with u_2, i.e. $tos_1 = tos_2$

In such a case the minimum cost incurring scheduled time would be same for both u_1 & u_2, Therefore $t_2 = t_1 = t$, due to the reason that the cost functions are convex in nature. Hence, cost incurred on both u_1 & u_2,

$$C(W_{t_1} + \widehat{\mathbb{P}}_{a_1,u_1} + \widehat{\mathbb{P}}_{a_2,u_2}) \tag{D.3}$$

By comparing both the cases.
For user 1: Since cost functions are quadratic then from (D.1) and (D.3) it can be justified that,

$$C(W_{t_1} + \widehat{\mathbb{P}}_{a_1,u_1} + \widehat{\mathbb{P}}_{a_2,u_2}) > C(W_{t_1} + \widehat{\mathbb{P}}_{a_1,u_1})$$

For user 2: Again, cost function are quadratic, from (D.2) and (D.3) it can be proved that,

$$C(W_{t_1} + \widehat{\mathbb{P}}_{a_1,u_1} + \widehat{\mathbb{P}}_{a_2,u_2}) > C(W_{t_1} + \widehat{\mathbb{P}}_{a_2,u_2})$$

Hence, It can be seen that no user can gain more by unilaterally deviating from the prescribed chronological order. Such deviations would increase the cost levied on all users. Through the validation of Theorem 4, it is analyzed that all the users in the system is operating under a fair environment so no user can gain benefit with deviating by prescribed strategy offered through coordination game.

Appendix E

Mixed Integer Linear Programming (MILP)

Mixed integer linear programming (MILP) refers to optimization problems with continuous and integer variables and linear functions in the objective function and/or the constraints. Mixed-integer linear programming theory provides a mechanism for optimizing decisions of mathematical programming. Where, mathematical programming formulations include a set of variables, which represent actions that can be taken in the system being modeled. Then attempts to optimize (either in the minimization or maximization sense) a function of these variables, which maps each possible set of decisions into a single score that assesses the quality of the solution that take place in complex systems.

A standard mixed integer linear program has the formulation:

$$\begin{aligned} \text{Min} \quad & c^T x \\ \text{subjected to} \quad & Ax\{\geq, =, \leq\}b \\ & l \leq x \leq u \\ & x_i \in Z \quad \forall \in S \end{aligned}$$

where

$x \in R^n$	is the vector of structural variables
$A \in R^{m \times n}$	is the matrix of technological coefficients
$c \in R^n$	is the vector of objective function coefficients
$b \in R^m$	is the vector of constraints right-hand sides
$l \in R^n$	is the vector of lower bounds on variables
$u \in R^n$	is the vector of upper bounds on variables
S	is a nonempty subset of the set {1.......,n} of indices

In this model, some or all of x must take integer values, which may be in the form of binary {0,1}. A typical MILP problem can have several equality and inequality constraints to model real-life applications.

List of Publications

Journal Publications

1. **Shalini Pal**, Sanjay Thakur, Rajesh Kumar, B.K. Panigrahi, "A Strategical Game Theoretic Based DR model For Residential Consumers in a Fair Environment," *International Journal of Electrical Power and Energy Systems*, vol. 97, pp. 201-210, April 2018.

2. **Shalini Pal**, Rajesh Kumar, "Electric Vehicle Scheduling Strategy in Residential Demand Response Programs with Neighbor Connection," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 3, pp. 980-988, Mar. 2018.

3. **Shalini Pal**, Rajesh Kumar, "Effective Load Scheduling in Distributed Demand Response Framework using ADMM," *International Journal of Emerging Electric Power Systems*. (Under Review)

International Conference Publications

1. **Shalini Pal**, Rajesh Kumar, "Smart Household Energy Management by Employing EV and BESS as Enabling Technologies," IEEE India International Conference on Power Electronics (IICPE-2018), Jaipur, India, 13-15th December, 2018.

2. **Shalini Pal**, Rishabh Verma, Rajesh Kumar, "Residential Demand Response Framework by Incorporating Renewable Energy Sources to Reduce Carbon Footprints," 10th International Conference on Information Technology and Electrical Engineering (ICITEE), Bali, Indonesia, pp. 553-558, 24-26th July, 2018.

3. **Shalini Pal**, Mukesh Kumar, Rajesh Kumar, "Price Aware Residential Demand Response with Renewable Sources and Electric Vehicle," IEEE International Women

in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE 2017), Dehradun, India, pp. 11-114, 18-19th December, 2017.

4. **Shalini Pal**, Rajesh Kumar, "Price Prediction Techniques For Residential Demand Response Using Support Vector Regression," IEEE 7th POWER INDIA International Conference (PIICON), Bikaner, India pp. 1-6, 25-27th November, 2016.

5. **Shalini Pal**, Rajesh Kumar, "Effective Load Scheduling of Residential Consumers Based on Dynamic Pricing with Price Prediction Capabilities," 1st IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES-2016), Delhi, India, pp. 1701-1707, 4-6th July 2016.

6. **Shalini Pal**, Rajesh Kumar, "DSM Scheduling Mechanism With Pricing Schemes Using Integer Linear Programming," 39th National Systems Conference (NSC), Ghaziabad, India, pp. 1-6, Dec. 2015.

7. **Shalini Pal**, B.P. Singh, R. Kumar , B.K. Panigrahi, "Consumer End Load Scheduling in DSM Using Multi-objective Genetic Algorithm Approach," IEEE Int. Conf. on Computational Intelligence Communication Technology (CICT), Ghaziabad, India, pp. 518-523, Feb 2015.

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