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DEMAND RESPONSE FOR RESIDENTIAL APPLIANCES IN A SMART ELECTRICITY DISTRIBUTION NETWORK: UTILITY AND CUSTOMER PERSPECTIVES

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KEYWORDS

Action space, Adjustability of appliances, Advanced metering infrastructure, Ancillary services, Appliance flexibility, Appliance priority, attributes of appliances, Customer discomfort, Customer Reward, Customer satisfaction, day-ahead bid, Decision making, Demand Response, Direct load control, Dispatch signal, Distributed generation, Electricity price, Forecast, Frequency, Grey variable, In-home display unit, Load adjustments, Market operator, Markov process, Optimal policy, Overload, Pairwise probabilistic comparison, Peak load, Power consumption, Preferred order of appliances, Ramp rate, Real-time price, Real-time, Rebate, Regulation services, Renewable generation, Retailer, Seasonal flat pricing, Smart grid, Smart meter, State space, Stochastic ranking, Stochastic scheduler, Tariff, Transition Probability, Uncertainty, Utility, Voltage violation, Wholesale electricity price, Zigbee interface

ABSTRACT

Recent advancements in Advanced Metering Infrastructure (AMI) enable optimum utilization of existing electricity network via Demand Response (DR). A flexible and reliable electricity network can be created by allowing open access information sharing and independent decentralized decision-making for unbundled market participants including utility and end-users. The massive rollout of AMI (such as smart meters) alone, however, may not be sufficient and there is a need for well thought algorithms to achieve desired benefits. This research work introduces efficient algorithms for residential appliances to achieve economic as well as network benefits for all participants.

Firstly, a new technique based on a customer reward mechanism is proposed, where the network provider controls residential appliances to achieve peak shaving and improve voltage profile. Then, an improved Real-Time Pricing (RTP) scheme for residential customers is introduced. Home energy management systems are proposed to account for the uncertainties in RTP and appliance power consumption. Finally, a control method to provide regulation services in the market via DR is proposed. These methods are tested using mathematical simulation models representing a cluster of demand responsive proactive customers.

Initial study focuses on load control method via a customer reward scheme. The network peak shaving and improvement in the voltage profile while maintaining customer satisfaction is achieved. Customer survey information of appliance characteristics and real-time appliance operation data are used to calculate indices. These indices combined with the sensitivity based house ranking are used for load selection in a network feeder. As customers participate in the direct load control, rebates are awarded in return. A network level economic analysis is proposed for the calculation of rebates.

Secondly, a new price based DR technique to handle peak demand and voltage violations. In contrast to first phase, customers have their own choice of controlling their loads based on time varying price signals. An improved RTP scheme for residential customers with three components based on power consumption, adverse wholesale price variation and feeder voltage violation is

proposed. Using broadcasted price information, Smart meters and in-home display units provide appropriate load adjustment signals, which give customers an opportunity to respond to price signals.

Uncertainties in RTP variation and power consumption pattern of appliances have a significant implication on decision making during DR. Hence, a stochastic Home Energy Management (HEM) system is proposed next, which facilitates customers to adjust their loads while considering uncertainties in RTP and appliance power status. The proposed HEM scheduler aims to reduce the cost of energy consumption in a house while maintaining customer satisfaction. It works in three subsequent steps namely real-time monitoring, stochastic scheduling and real-time control of appliances. In the first step of real-time monitoring, characteristics of available controllable appliances are monitored in real-time and stored in HEM scheduler. In second step, HEM scheduler computes an optimal policy using stochastic dynamic programming to select a set of appliances to be controlled with an objective of minimizing customer discomfort as well as the total cost of energy consumption in a house. In third step, HEM scheduler initiates the control of the selected appliances ultimately providing an efficient house based energy management by appropriate load adjustments utilizing stochastic information.

Finally, the control method for appliances to provide regulation services is proposed. Registered retailers schedule their loads to match a dispatch regulation signal offered by the wholesale electricity market operator. Stochastic DR method using a pool of thermostatically controllable appliances is proposed, where the selection of appliances is based on a probabilistic ranking technique.

Various findings from this research work have multi-faceted benefit and are helpful for (1) policy makers to develop proper power pricing scheme; (2) distribution network providers to utilize AMI effectively and (3) end-users by making them aware of the associated financial benefits.

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LIST OF ABBREVIATIONS

AC	Air Conditioner
AEMO	Australian Energy Market Operator
AFI	Appliance Flexibility Index
AMI	Advanced Metering Infrastructure
API	Appliance Priority Index
ASI	Appliance Satisfaction Index
AU	Appliance Unit
BESS	Battery Energy Storage System
CDF	Cumulative Distribution Function
CoEC	Cost of Energy Consumption
CPP	Critical Peak Price
CR	Customer Reward
DLC	Direct Load Control
DR	Demand Response
FCAS	Frequency Control Ancillary Services
HEM	Home Energy Management
HEMS	Home Energy Management Scheduler
HPSI	High Power Consumption Index
LV	Lower Voltage
MDP	Markov Decision Process
NERC	North American Reliability Corporation
PEV	Plug- in Electric Vehicle
PMF	Probability Mass Function
PMU	Phasor Measurement Unit

PRD	Price Response Demand
PSI	Power Similarity Index
PV	Photovoltaic cells
RRP	Regional Reference price
RTC	Real-Time Control
RTM	Real-Time Monitoring
RTP	Real-Time Price
SDP	Stochastic Dynamic Programming
SOC	State of Charge
SR	Stochastic Ranking
STS	STochastic Scheduling
TCA	Thermostatically Controllable Appliances
TOU	Time Of Use
WH	Water Heater

VARIABLES AND NOTATIONS

Variable	Meaning
$C(i,j,k)$	k^{th} criteria of i^{th} house and the j^{th} controllable load
API_{ij}	API for i^{th} house and j^{th} appliance
Pr_{ij}	priority value for i^{th} house and j^{th} appliance
T_{wh}	Water heater, hot water temperature
T_r	Room temperature
T_{wh}^{set} and T_{wh}^{db}	Temperature set point and dead-band of water heater
T_{ac}^{set} and T_{ac}^{db}	Temperature set point and dead-band of AC
PSI_{ij}	PSI for i^{th} house and j^{th} appliance
$HPCI_{ij}$	HPCI for i^{th} house and j^{th} appliance
ρ_i^p	Voltage sensitivity of i^{th} house in p^{th} phase
r_{ij}^p	Rank of i^{th} house and j^{th} appliance in p^{th} phase
e_{ij}	Status (On/Off) signal of j^{th} appliance in i^{th} house
G	Conductance of feeder
B	Susceptance of feeder
θ	Bus angle
P	Real power
Q	Reactive power
V	Voltage
Dec_{ij}	Decision for i^{th} house and j^{th} controllable load
$Rebate_i$	Rebate in $/day for i^{th} house
E_i^l	Shifted energy for i^{th} house at the l^{th} load adjustment
Π_{avg}	constant tariff or flat rate price of electricity
Π_i^t	Real-time price for i^{th} house at t^{th} time

$L_{capacity}$	Network capacity
Π_{BL}	baseline of wholesale electricity price
$\Pi^{t}_{wholesale}$	Wholesale electricity price at t^{th} time
N	Number of houses in the network
X_{kij}	k^{th} criteria for i^{th} house, j^{th} appliance for PRD scheme
D_j	j^{th} appliance
$INTRP_{Dj}$	Interrupt signal of Appliance D_j
ζ_{max}^{intrp}	maximum number of interruptions for an appliance
W_{Dj}^{max}	Maximum allowable waiting time of appliance D_j
$t_{Dj}^{connect}$	Time when appliance D_j in plugged into HEMS
C_n^{total}	CoEC of a house at n^{th} time step
S_k	k^{th} state of CoEC
A_n^q	q^{th} action (sets of appliances) at n^{th} time step
TR	Transition probability of state changes
R	A state (S) dependent reward function
$\mathbf{P}$	Probability
β_n^{Dj}	Operating status of appliance D_j at n^{th} time step
Reg^n	dispatch instructions at n^{th} time step
AT_{ki}^n	k^{th} attribute for i^{th} appliance at n^{th} time step
AT_{Gki}^n	k^{th} grey attribute for i^{th} appliance at n^{th} time step
$g_i^n(AT_k)$	PMF for i^{th} appliance at n^{th} time, k^{th} (k=1,2) attribute
$f_{ij}^n(AT_{Gk})$	PMF of (AT_{Gki}^n-AT_{Gkj}^n) representing comparison of i^{th} and j^{th} appliances with respect to k^{th} attribute
N_{app}	Number of total available appliances in the network
$\mathbf{P}_D^n$	decision probability matrix at n^{th} time step
$\mathbf{P}_{rank}^n$	Probability for appliance ranking at n^{th} time step

CONTRIBUTIONS

1) Demand Response (DR) Scheme via Customer Reward Scheme for residential customers

- Defined appliance characteristics based on appliance priority, flexibility, satisfaction and power consumption and represented as indices
- Defined house ranking based on voltage sensitivity
- Utilized appliance indices and house ranking for appliance selection
- Developed an algorithm for appliance control based on appliance selection and ensured elimination of overload and adverse voltage conditions
- Established a customer reward scheme considering both appliance load adjustment and voltage support

2) Improved Real-Time Pricing (RTP) Scheme for residential customers

- Developed RTP components considering energy consumption, network overload conditions, adverse feeder voltage conditions and wholesale price spikes
- Appliance choice values based on appliance adjustability, preferred order, and operation status of appliances are found
- Algorithm for appliance indication, utilizing appliance choice values is developed

3) Real-time Stochastic Home Energy Management Scheduler

- An algorithm for scheduling appliances in a house to minimize the cost of energy consumption is developed (comprising of three subsequent phases) based on RTP
- Real-Time Monitoring (Phase 1)- Appliance operating statuses are defined in real-time based on their characteristics
- Stochastic Scheduling (Phase 2)- Appliances are stochastically selected in real-time considering uncertainties in appliance power consumption and RTP variation
- Real-Time Control (Phase 3)- Selected appliances in phase 2 are controlled

4) Stochastic Ranking Method for thermostatically controllable appliances to provide regulation services

- Developed a stochastic ranking algorithm based on pairwise probabilistic comparison of appliances
- Probabilistic decision based on appliance attributes such as temperature variation, switching status and power rating are considered.
- Average possible regulation services for a network with 30, 120 and 960 houses are computed

LIST OF PUBLICATIONS

(Related to research work presented in this thesis)

Publications:

1. C. Vivekananthan, Y. Mishra, et al., “Demand Response for Residential Appliances via Customer Reward Scheme”, *IEEE Transactions on Smart Grid,* vol. 5, no. 2, Mar. 2014.
2. C. Vivekananthan, Y. Mishra, et al., “Aggregated Control of Thermostatically Controllable Appliances for regulation purposes utilizing Home Energy Management Systems,” *accepted for IEEE Transactions on Power Systems*, 2014.
3. C. Vivekananthan, Y. Mishra, et al., “Real-Time Price Based Home Energy Management Scheduler,” *currently under review of IEEE Transactions on Power Systems*, 2014.
4. C. Vivekananthan, Y. Mishra, et al., “Real-Time Stochastic Coordination of Home Energy Management Schedulers to alleviate Network Peaks,” *Abstract currently under review of IEEE Transactions on Smart Grid*, 2014.

Conferences:

1. C. Vivekananthan, Y. Mishra, et al., “A Novel Real-Time Pricing Scheme for Demand Response in Residential Distribution Systems,” *39th International Conference on Industrial Electronics (IECON)*, Vienna, Austria, Nov. 2013.
2. C. Vivekananthan, Y. Mishra, et al., “Using multi objective genetic algorithm for the optimal arrangement and size of a feeder level battery energy storage in the distribution system for voltage improvement,” *4th International Conference on Computational Methods*, Gold Coast, Australia, Nov. 2012.
3. C. Vivekananthan, Y. Mishra, et al., “Energy Efficient Home with price sensitive stochastically programmable TCAs,” *accepted for 40th International Conference on Industrial Electronics (IECON)*, Dallas, TX, USA, Oct. 2014.

STATEMENT OF ORIGINAL AUTHORSHIP

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

QUT Verified Signature

Signature: _

Cynthujah Vivekananthan

Date: 04.09.2014.

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Chapter 1

Introduction

This chapter outlines the background in section 1.1 and research problem in section 1.2. Research methodology and significance is explained in sections 1.3 and 1.4 respectively. Finally, section 1.5 includes an outline of the remaining chapters of the thesis.

1.1. Background

The traditional electricity network is being transformed to a smart grid environment characterized by the utilization of advanced metering, sensing frameworks and wireless two-way communication facilities in electricity generation, transmission and distribution infrastructure. Smart grid enables to deal with the complex nature of the present electricity network, with a goal to achieve stability, reliability and security. A smart electricity network can self-repair during adverse network conditions, prevent power leakages and allow flexible market augmentation. Decentralized power generation and Demand Response (DR) are the key features of the smart distribution grid.

Decentralized generation can be any source of power generation connected in a distribution network such as roof top PV cells micro wind turbines. DR refers to a temporary load curtailment scheme to minimize energy consumption during adverse network conditions. It is a promising scheme in future smart grid environment due to the benefits it offers. The DR scheme is made possible by the massive rollout of advanced metering infrastructure. The present research focuses on DR schemes in a residential distribution system and its benefits for both electricity customers and electric utilities.

DR is primarily used to reduce network peaks. An increasing trend of peak electricity demand is observed in present residential distribution systems. Therefore, DR is utilized to handle network peaks by time-shifting residential loads. This provides benefits to an electric utility by deferring the investment cost of network upgrades and the usage of expensive generation plants to cater to peak demand. Customers who participate in a DR scheme through load curtailments receive benefits through incentives.

Furthermore, DR is capable of responding to uncertainties in electricity consumption and supply, thus preventing unexpected system instability. The unpredictable nature of electricity demand is detected on a daily and seasonal basis. The integration of renewable energy generation and distributed generation also increases system uncertainty to a further extent. DR easily handles uncertainties and prevents the use of expensive generators to maintain the capacity margin during uncertainties. In addition, DR can considerably reduce the wholesale price spikes. Fluctuations in fuel price and the uncertain nature of electricity demand and supply are the main causes for wholesale price spikes. A real-time curtailment of loads in the residential distribution system consistently reduces the possibility of wholesale price spikes and provides immense cost benefits to an electric utility. A Real-Time Pricing (RTP) scheme for residential customers reflecting the wholesale price variation is used for this purpose. Here, customers tend to reduce their electricity bills by scheduling their loads through Home Energy Management (HEM) units when the electricity price becomes high. Therefore, it provides benefits to customers who incur a reduced cost for energy consumption when they create an energy efficient home.

DR has an added advantage of providing regulation services in the ancillary services market in order to maintain the supply and demand balance. Electricity retailers get benefit through this scheme by obtaining profit from the ancillary services market and customers are given rebates for load curtailment.

1.2. Research Problem

DR is becoming increasingly important in the current electricity grid as it is the key to unlocking market flexibility and empowering electricity customer choices. Moreover, it is a very cost effective technique. An immense amount of research has been carried out on DR in recent years but the implementation of DR schemes is still in the preliminary stage and needs to be explored further. Among the ongoing research problems related to DR, the present study focuses on the following four areas: incentive based DR; the Real-Time Pricing (RTP) method (price based DR); Home Energy Management (HEM) schedulers; and DR for regulation services.

- Incentive based DR

Studies related to DR in residential distribution systems are mostly conducted with the aim to reduce network peaks and adverse feeder voltage conditions by time-shifting residential appliances. Such efforts are based on optimization techniques to maximize electric utility benefits or customer satisfaction. However, optimization techniques may be time consuming and it may be difficult to simulate load curtailments within a short timeframe. Therefore, an efficient load selection method is required considering both electric utility and customer benefits. Furthermore, most of the techniques consider particular appliances such as water-heaters, air-conditioners and plug-in electric vehicles in the DR process. However, the engagement of most residential appliances is possible. A detailed model of appliance engagement is essential to validate this statement. Moreover, a comprehensive customer reward scheme for load curtailment based on both overload prevention and voltage support has not yet been studied. Therefore, the first phase of this research focuses on an effective real-time DR method considering a detailed residential load model. It considers both electric utility and customer benefits during load selection for curtailment. A guaranteed rebate scheme is also developed for participating customers to provide incentives.

- RTP Methods

A number of price-responsive demand techniques have been proposed in the past, including time of use pricing, critical peak pricing and real-time pricing. RTP is a promising option as it reflects the wholesale price variation within short timeframes, creating a bridge between the wholesale and retail electricity market. Recently, RTP has been applied in the residential distribution sector with the deployment of smart meters and in-home display units. Most of the available RTP schemes reflect the average wholesale price. This may adversely affect customers when there are unacceptably high wholesale price spikes. Therefore, a rational price component for RTP is essential. In the majority of available RTP schemes, the prices are broadcast on an hourly basis. This may not reflect the actual network conditions and hence the RTP scheme may not be able to achieve the required demand shift. This gives rise to the need to increase the frequency of RTP broadcasting. Moreover, the RTP concept can be applied to prevent overload and improve voltage conditions in the electricity network. Therefore, an improved RTP scheme is developed in the second phase of this research based on a consideration of wholesale price variations, network peaks and adverse voltage conditions.

- HEM Scheduler

A HEM system helps customers to react to RTP variations efficiently by scheduling residential appliances to reduce the cost of energy consumption. Recent studies in HEM systems were based on real-time techniques and did not consider the uncertain nature of appliance usage or RTP variation during appliance scheduling. Some of the available HEM systems use predictive techniques for appliance scheduling, which may deviate from the real system. Therefore, a fully-fledged HEM scheduling algorithm which handles the uncertainty in both appliance power consumption and RTP variation is developed in the third phase of this research.

- DR for regulation services

The DR technique can also be used to provide regulation services. Studies in the literature indicate the utilization of thermostatically controllable loads for appliances such as water-heaters and air-conditioners. The selection of these loads is based on real-time temperature ranking methods. This technique is only valid with short time step controls such as one minute. However, in the Australian ancillary services market, regulation services are scheduled to a five minute dispatch framework. This gives rise to the need for an accurate stochastic appliance ranking scheme to predict the appliance status in the five minute timeframe. Therefore, a stochastic appliance ranking algorithm is developed in the fourth phase of this research to enable a retailer to provide effective regulation services.

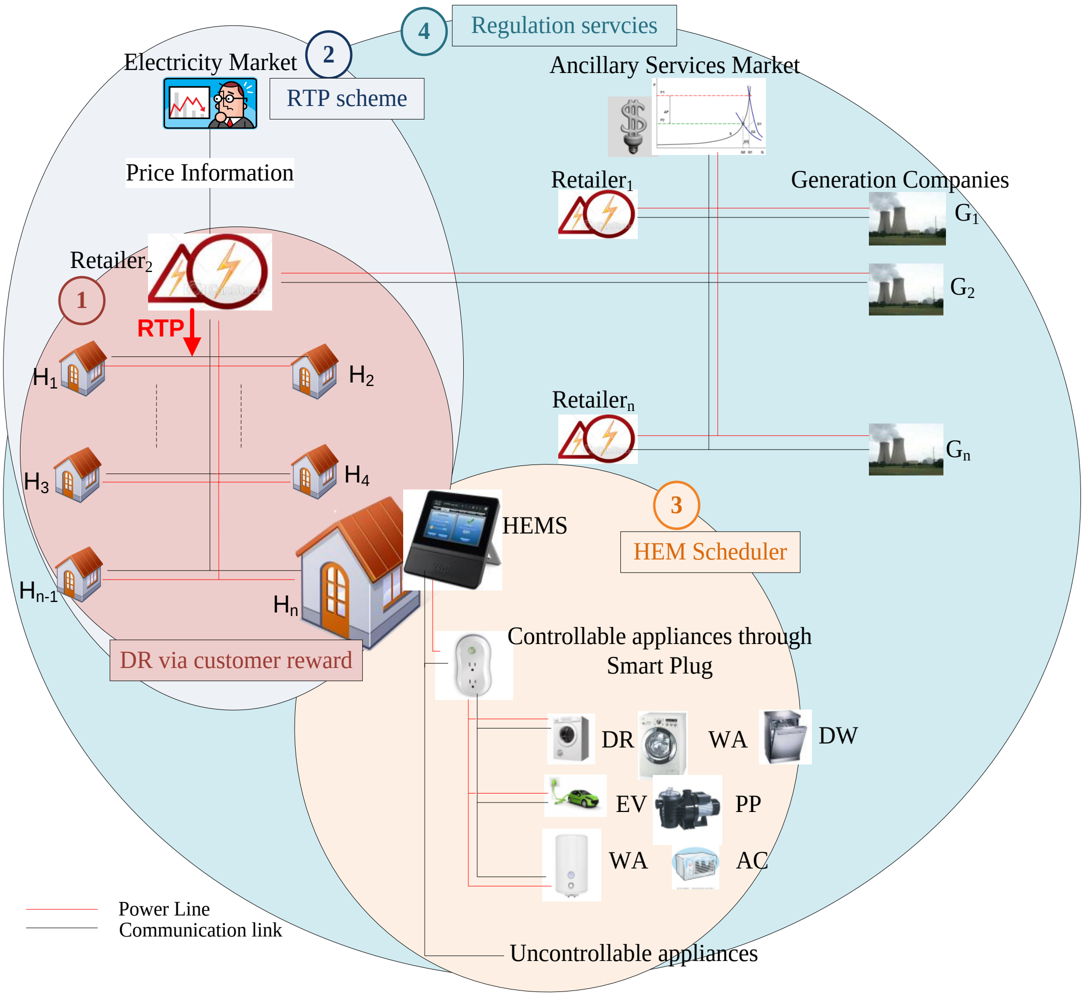

Fig. 1.1 Illustration of research with four phases

The present research focuses on the above four issues in order to enhance the implementation of DR in real-world applications as in Fig. 1.1. The methods applied to achieve the proposed improvements and applications of DR are discussed in the following section.

1.3. Research Method

This research primarily aims to establish new efficient algorithms for DR to comply with different applications in the electricity network and provide benefits to network participants. The main purpose of this research is to propose innovative and resourceful DR schemes to achieve a more reliable and economical distribution system. The research is conducted in four consecutive phases. The first two phases of this research are based on the DR techniques used for peak shaving and eradicating adverse voltage conditions. A new direct load control technique based on a customer reward mechanism is introduced in the first phase of the research. Here, the electric utility can have complete control of residential appliances in the network. The second phase of the research proposes a price-responsive technique providing greater customer choices in comparison with the first phase. It also introduces an improved RTP scheme for residential customers. The third phase mainly focuses on house-level stochastic energy management systems. It deals with the uncertainties in RTP and appliance power consumption. Unlike the first three phases, the fourth phase proposes a new application of DR in the ancillary services market for providing frequency regulation considering load uncertainty. A brief conceptual outline of the above four phases is discussed next.

The initial study focuses on a direct load control method for DR via a customer reward scheme for peak shaving and the mitigation of adverse voltage conditions in the network while also maintaining customer satisfaction within allowable limits. Information from a customer survey on appliance characteristics and real-time appliance operation data are used to calculate indices reflecting appliance priority, flexibility, customer satisfaction and power statuses. These indices and the sensitivity-based house ranking are used for appropriate load selection in a network feeder for DR. As customers are forced to accept direct load control, they are given a reward in the form of a rebate. A network-level economic analysis is used for rebate formulation and it is found that rebates can be paid based on the load shift and voltage improvement due to load adjustments.

The second phase of the research focuses on a new detailed price-based DR technique to handle peak demand and adverse voltage conditions. In contrast to the first phase, customers have their own choice in controlling their loads based on time-varying price signals. An improved RTP scheme for residential customers with three components based on power consumption, adverse wholesale price variation and feeder voltage violation is proposed. Smart meters and in-home display units can be used to broadcast price information and appropriate load adjustment signals so that customers have an opportunity to respond to price signals optimally by choosing the appropriate load adjustments broadcast by the electric utility.

Uncertainties in RTP variation and the power consumption patterns of appliances have a significant impact on decision-making during DR. Hence, a stochastic HEM system is proposed in the third phase which enables customers to adjust their loads based on RTP while also considering uncertainties in RTP and appliance power status. The proposed real-time HEM scheduler aims to reduce the cost of energy consumption in a house while maintaining customer satisfaction. It works in three steps, namely, real-time monitoring, stochastic scheduling and the real-time control of appliances. In the first step of real-time monitoring, the characteristics of the available controllable appliances are monitored in real-time and stored in the HEM scheduler. In the second step, the HEM scheduler computes an optimal policy using stochastic dynamic programming to select a set of appliances to be controlled with the objective of minimizing customer discomfort as well as the total cost of energy consumption in a house. In the third step, the HEM scheduler initiates the control of the selected appliances, ultimately providing efficient house-based energy management by appropriate load adjustments utilizing stochastic information.

The fourth phase of this research focuses on a different dimension of DR used in the ancillary services market to provide fast frequency regulation services. Registered retailers are urged to stochastically schedule their loads to match a time step-ahead of the dispatch regulation signal offered by the ancillary services market. Hence, a new stochastic DR methodology applied on a pool of thermostatically controllable appliances is proposed. It considers water-heaters and air-conditioners as they are in operation most of the time during a day and are available for control. The selection of appliances is based on a probabilistic ranking technique whereby three attributes of appliances related to temperature variation, appliance power status and appliance power rating are analyzed for decision-making. The first two attributes are stochastically forecasted for the next time step and follow a Markov process.

The performance of the proposed methods is clarified by applying them in a real-time simulation environment representing a cluster of demand-responsive proactive customers. Realistic mathematical residential load models are utilized for this purpose.

1.4. Research Significance

This research provides significant benefits and outcomes in four different phases of this study.

The algorithm developed for DR in first phase of this research can be implemented efficiently in real-time environment within short time frame. In comparison with past studies, it considers both customer and utility perspectives during decision making for appliance curtailment. It provides benefit to customers by maintaining appliance satisfaction, flexibility and priority within allowable limits. The utility benefits by eliminating overload and adverse voltage conditions in the network. A fully guaranteed customer reward scheme, considering both load adjustment and voltage support is established which makes this DR scheme economically feasible.

The RTP method developed in second phase of this research is significant from existing methods as it considers power consumption, overloading conditions, voltage violations along with wholesale price spike in RTP. Active participation in this RTP guarantees elimination of overload, adverse voltage conditions and wholesale price spikes. Customers benefit from reduction in cost of energy consumption. The appliance indication developed for load curtailment is unique from existing methods which ease the appliance control process for customers via in-home energy management units.

A novel stochastic HEM scheduling algorithm developed in third phase of this research provides significant benefit to customers by appropriately acting according to proposed RTP variation. It is unique from the existing methods as it considers uncertainties in appliance power consumption and RTP variation effectively. It ensures reduced cost of energy consumption in a house.

The algorithm developed for providing regulation services via DR is distinctive as it uses stochastic appliance ranking method to predict appliance controls for regulation. It is very useful in ancillary services market which broadcasts offers every five minutes, necessitating the prediction of appliance status for next five minutes.

1.5. Thesis outline

The remaining chapters of this thesis are organised as follows. Chapter 2 is a comprehensive literature review which leads to the development of the research hypotheses presented in this thesis. This is followed by the original work in Chapters 3, 4, 5 and 6. The thesis concludes with a summary of the research work and findings in Chapter 7.

1.5.1. **Outline of Chapter 2**

Chapter 2 presents a detailed study of existing electricity infrastructure which provides the motivation for this research. Recent developments in the electricity sector such as market liberalization, the smart grid concept and DR schemes are discussed in detail. An in-depth study on DR in residential distribution systems is carried out, as it is the main focus of this thesis. The benefits and applications of DR in a smart grid environment are identified. A comprehensive literature review is conducted on existing and proposed DR options in the electricity market. The drawbacks in present DR schemes are highlighted and the need for an improved DR technique is elaborated upon, which leads to the generation of the hypotheses to be tested in the subsequent research work in Chapters 3, 4, 5 and 6.

1.5.2. **Outline of Chapter 3**

Chapter 3 proposes a novel customer reward-based DR technique which can be easily implemented in a residential distribution system to prevent overload and adverse voltage conditions in the feeder. Customer preferences are considered during the selection of appliances for curtailment. For this purpose, customer survey information and real-time power consumption data are used to calculate appliance-based indices such as appliance flexibility, satisfaction and priority. This ensures that customer comfort is maintained within acceptable limits. A voltage sensitivity-based ranking is used along with the indices to improve voltage in the residential feeder. A novel reward scheme for customer load adjustments is also proposed, with rewards paid in the form of rebates based on voltage improvement and power curtailment. The analysis and results to validate the efficacy of the proposed technique are also presented in this chapter.

1.5.3. **Outline of Chapter 4**

Chapter 4 proposes a new “price response demand” technique which can be applied in a residential distribution system with the purpose of preventing overload and adverse voltage conditions. It is achieved by introducing a novel real-time pricing scheme, reflecting the actual power consumption, feeder voltage deviation and wholesale electricity price. Customers are given the opportunity to react to the real-time price signals broadcast through in-home display units. This scheme offers more benefits than the direct load control technique in Chapter 3, as it provides flexibility for customers during load adjustments.

1.5.4. **Outline of Chapter 5**

There is a necessity for an efficient HEM system for residential customers, in order to react efficiently to the real-time pricing scheme proposed in Chapter 2. Hence, Chapter 5 proposes a real-time HEM scheduler with the aim to reduce the cost of consumption in a house while at the same time maintaining customer satisfaction. This technique considers the stochastic behavior of appliance usage and real-time pricing during appliance selection. Stochastic dynamic programming is used to incorporate uncertainties in pricing and appliance usage. Real-time appliance monitoring, stochastic appliance scheduling and real-time appliance control are the main steps used in the proposed HEM scheduler. It ensures the reduced cost of consumption and minimal customer discomfort.

1.5.5. **Outline of Chapter 6**

Chapter 6 utilizes the residential DR option as an operating reserve in the ancillary services market for the purpose of providing regulation services. Retailers can bid in the day-ahead market and respond to the real-time regulation offered by appropriate load control. This part of the study proposes a method for the stochastic ranking of appliances in a retail network in order to select appropriate appliances for regulation purposes. A pool of thermostatically controllable loads such as air-conditioners and water-heaters are used for load adjustments. The ranking method is based on the pairwise probabilistic comparison of appliances. The attributes of appliances such as comfort, switching state and power rating are used for decision-making. System performance is verified for a given regulation signal. The network capability for regulation is also analyzed during various seasons to show the robustness of the system for regulation.

1.5.6. **Outline of Chapter 7**

Chapter 7 summarises the original research work presented in Chapters 3, 4, 5 and 6. The techniques and algorithms proposed to achieve the objectives of the study are briefly reviewed. The significant research findings and analysis are specified. The benefits and importance of the proposed techniques are summarised, demonstrating the relevance of the research findings to the present electricity industry. Suggestions for implementing the proposed methods in the real world are also made. Finally, future directions in research that can be carried out to extend and improve the present study are suggested.

Chapter 2

Literature Review for Demand Response

This chapter delineates the historical background and recent developments in the electricity industry as a motivation for the research work presented in this thesis. Initially, a brief overview of past and present trends in the electric power system is presented. Recent developments in the electricity network such as market liberalization, the introduction of renewable energy and the development of the smart grid concept are discussed in detail. A comprehensive study of the DR mechanism in the smart grid environment is conducted as it is the main target of this research work. Problems and constraints associated with the recent developments in the electricity market are analyzed and the DR solutions proposed in the literature are extensively analyzed. This theoretical outline of DR helps to develop a conceptual framework for the generation of the hypotheses in this study and helps to define the research structure of this thesis as well as setting the scene for the following chapters.

This chapter begins with the historical background and recent developments in the electric power system in Section 2.1, followed by a review of the literature in section 2.2. Concluding this chapter, Section 2.3 highlights the implications of the findings in the literature and develops the conceptual framework of the study.

2.1. Historical Background and Recent Developments in Electricity System

Electricity is increasingly important in the modern globalized economy and serves as an essential resource in the day-to-day life of every individual. Hence, electricity supply is expected to be reliable and affordable with a minimum impact on the environment. As electricity is a non-storable commodity, a comprehensive and careful focus on policy actions is vital in order to have an accurate balance between electricity supply and demand. This is made possible by the liberalization of the electricity sector [1].

2.1.1. **Liberalization of Electricity Sector**

In the early 1990s, many power systems were characterized by a vertically integrated structure, whereby electricity generation, transmission and distribution belonged to one electric utility. Electricity prices for these three sectors were bundled together, reflecting the cost of the provided services [2].

However, in most countries, this monopolistic market structure has been replaced by a deregulated and competitive market arrangement. This involved the act of breaking the electricity market into components, based on each component's functionality or physical structure. Ownership of these unbundled market components is provided to authorized and independent operators. This liberalization of the market structure provides flexibility to end-users to choose their provider. Trading between market components is well organized. Market based competition are created such that electricity can be bought or sold, similar to other commodities. It leads to efficient operations of the electricity system with more effective investment decisions in terms of timing, sizing and technological improvements. Furthermore, the transparency created by the competitive environment addresses critical policy challenges related to environmental issues and network reliability. Liberalization of the electricity market has been successfully practiced in the real-world and is being augmented by more appropriate policy prescriptions [3], [4].

However, the present electricity network has drawbacks. Increased carbon emission leads to global warming and there is a need to introduce renewable energy sources to the electricity grid. The integration of renewable energy sources and the increasing demand for electricity due to the fast growing world population make the present electricity system more vulnerable. Hence, the reestablishment of the power grid with increased flexibility and efficiency via the smart grid concept is essential to provide intelligent services to end-users [5].

2.1.2. **Smart Grid Concept**

The smart grid concept is made possible by the vast improvements in information and communication technology. An electric utility is capable of providing electricity to meet increasing demand, with better reliability and quality of power supply via the smart grid concept. It leads to increased energy efficiency. The integration of low carbon energy sources effectively mitigates the consequences of climate change. DR and advanced metering infrastructure (AMI) are the essential requirements for a smart grid [5]-[8].

AMI creates a two-way communication network between smart meters and the electric utility through advanced sensors, monitoring systems and data management systems. The real-time consumption and price information of electricity can be easily transferred due to AMI. As power consumption information is remotely monitored, errors and costs due to manual reading are prevented. Multiple vendors can change their services to customers in real-time. Ultimately, the electricity grid can be supported by AMI through low latency and high bandwidth communication services to achieve these services and much more [7].

Moreover, the smart grid enables efficient utilization of renewable generation resources and helps in reducing carbon emissions. The intermittent and unpredictable nature of renewable energy generation can be handled using smart grid technology.

DR can contribute to the integration of renewable energy resources in order to achieve system stability. DR primarily controls energy demand during critical situations to create a balance between electricity supply and demand. Therefore, the improved utilization of available energy and existing infrastructure enables the power network to be operated reliably and cheaply. This dissertation is mainly focused on the contribution of DR; hence, DR is discussed in more detail in this section. As illustrated in the conceptual design of the smart grid environment in Fig. 2.1, DR is made possible through AMI and the home area network [9].

During DR, the AMI serves to provide the customers' energy consumption information to the electric utility and the real-time price information from the electric utility to the customers through two-way communication capabilities. The home area network is the heart of DR whereby appliances in a house are remotely monitored and controlled during adverse situations [10].

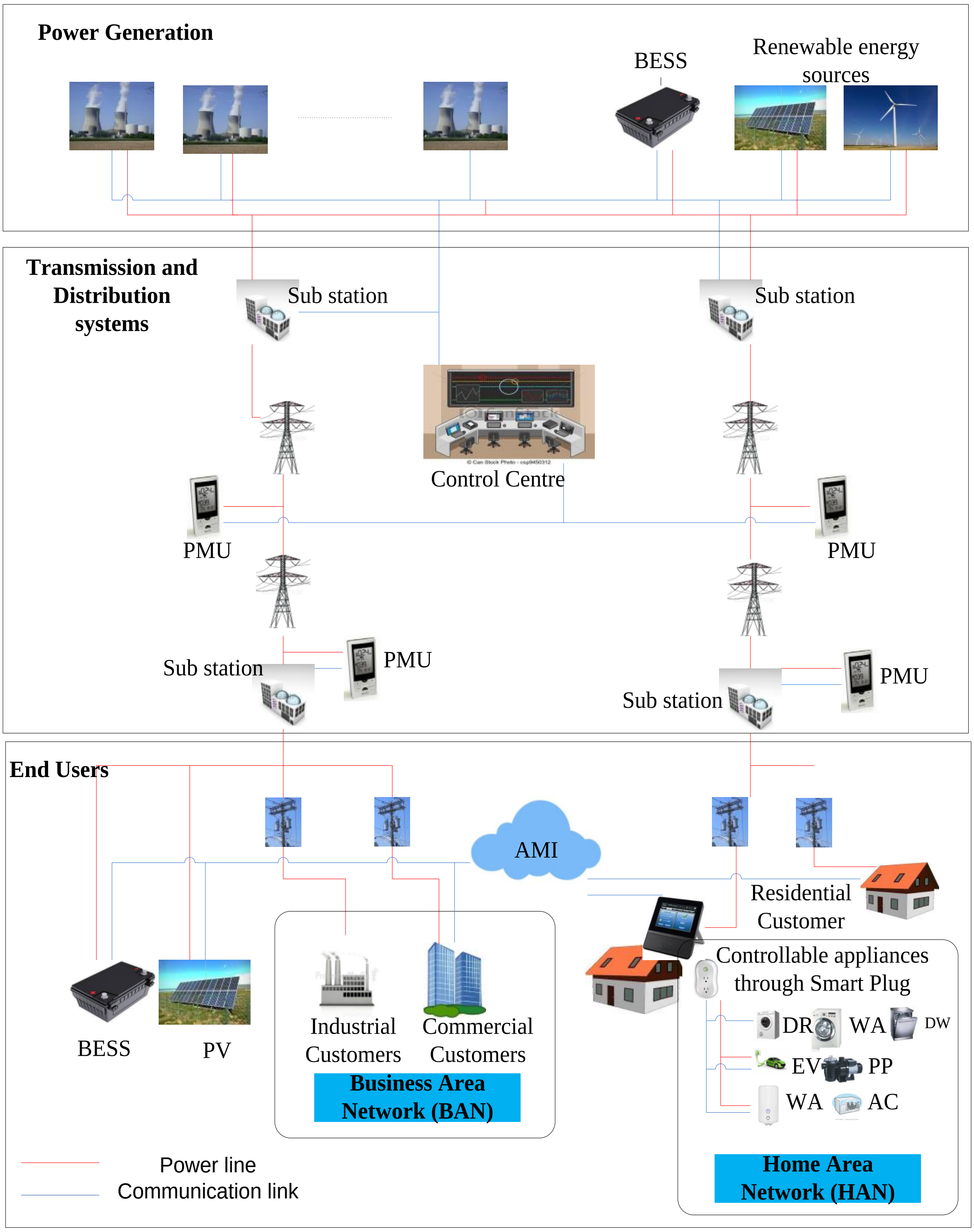

Fig. 2.1 Conceptual design of a smart grid environment

2.2. DR Approach

DR is an integral component of the envisioned smart grid infrastructure. It primarily refers to activities related to active load control during high market price or when grid reliability and stability are jeopardized.

DR provides a number of key benefits for both the electric utility and customers. For the electric utility, DR maintains electricity system reliability by lowering the likelihood of consequences arising from unexpected outages which create financial losses and inconvenience to customers. For example, DR compensates for the uncertainty brought by intermittent renewable energy sources. It can also react to problems caused by distributed generation instantaneously. Network overloads and adverse feeder voltage conditions can also be mitigated. Furthermore, financial benefits are obtained by lowering wholesale market prices by preventing the use of costly generation [11].

Customers also benefit from DR schemes in many ways. Careful attention to home energy consumption leads to energy efficient buildings. Participating customers can save considerable amounts of money due to load adjustments by means of reduced electricity prices or incentive payments.

Currently, electric utilities have focused most of their DR efforts on industrial or commercial buildings based on the reasonable argument that large customers can provide more savings with fewer numbers of load adjustments [12], [13]. However, residential customers can be incorporated into DR schemes for equally valid reasons. Residential customers make the large contribution to peak load in the network. Hence, overload prevention can be performed by DR in the residential electricity network [14]. Adverse voltage conditions in residential feeders can also be mitigated by residential DR. Flexible house appliances such as plug-in electric vehicles, air-conditioners and water-heaters are easy to incorporate in residential DR schemes. Hence, residential DR can play an important role in the smart grid environment. The next sub-section provides a brief description of DR in the smart electricity distribution network.

2.2.1. DR in the Smart Electricity Distribution Network

A smart distribution network is an important part of the smart grid which connects the main network with the user-oriented supply. With emerging technological improvements, the smart distribution system is made possible by the large-scale deployment of smart meters and HEM units, intelligent assets for condition monitoring, distributed generation and DR. Data acquisition and real-time monitoring and analysis make it a reality [15], [16].

The smart distribution network should be able to handle variation in electricity demand which is changing instantaneously due to changes in electricity-driven activities at different times. There is a major peak demand for electricity between 1800 to 2100 hrs. Further, daily variations throughout the year occur due to seasonal factors (such as the temperature and rainfall), the level of industrial and agricultural activities and other causes such as holidays and festivals. [17].

Furthermore, plug-in electric vehicles could have a significant impact on the smart distribution grid by adding a new load on the existing primary and secondary distribution networks, many of which do not have any spare capacity. The additional charging load of plug-in electric vehicles is typically behind either an existing secondary distribution transformer in a residential neighbourhood or a transformer connected to a distribution feeder. The vehicles range in battery capacity from 16 kWh to 53 kWh. They require a full charge within a reasonable time which is usually 3 to 4 hours plugged in with 6.6 kW or 16 kW capacities [18]. The use of a plug-in electric vehicle more than doubles the average household load during charging, as found in [18].

Hence, handling the peaking scenario will be a principal concern in electricity systems in the future due to the expected rapid penetration of plug-in electric vehicles. In the worst case, it will lead to the overloading of transformers at the distribution level, potentially causing outages and could even lead to voltage collapse. The smart distribution grid is capable of handling such adverse conditions by creating a self-healing environment [19]. The DR techniques that are available to be implemented in the residential electricity system are discussed next.

2.2.2. **DR Options**

Two main categories of DR options are possible in the real-world electricity environment based on the way in which the load adjustments are made. They are the price response demand options and the incentive-based options, as illustrated in Fig. 2.2.

An incentive-based DR is established by electric utilities when the utility has the direct control of residential loads. Customers are provided with an incentive separately or as a reduced rate in their electricity bill. This group of options functions when adverse network conditions exist or when a high wholesale price spike occurs. In contrast, price response demand options refer to the changes in usage of electricity in response to the electricity price variation. Customers tend to reduce their consumption in order to reduce the cost of their consumption during times of high electricity prices [11]. Here, the customer response is entirely voluntary. Details of both techniques are discussed next.

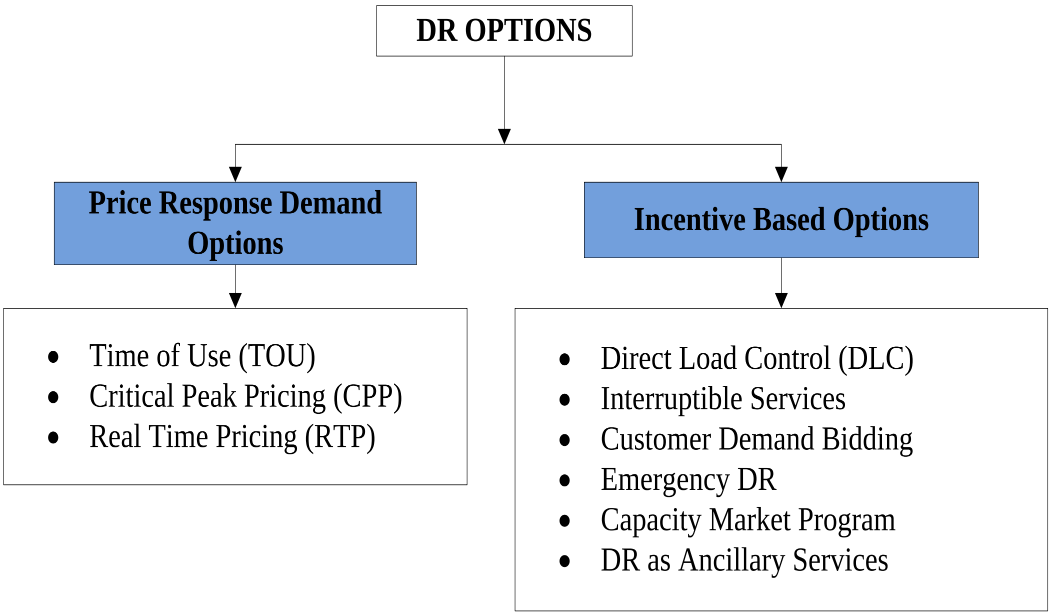

Fig. 2.2. Available DR Options

2.2.2.1. ***Incentive-Based Options***

Incentive-based programs are market based and give the electric utility the authority for appliance control. Participating customers are provided with a reward [11]. Examples of incentive-based programs include:

- **Direct load control**

  In a direct load control scheme, the electric utility remotely shuts down or adjusts residential appliances on short notice. Customers are provided with rebates or reduced bills for the forced load adjustments.

- **Interruptible services**

  In the interruptible services approach, the electric utility provides flexibility to customers to adjust their loads during critical conditions. Curtailment options are broadcast to the customers in advance with appropriate retail tariffs and discounts or rebates. Customers automate their loads for control according to curtailment options. If the customers fail to curtail their loads, penalties are applied to the customers.

- **Customer demand bidding**

  In customer demand bidding, an opportunity is given to residential customers to offer bids based on the wholesale price or an equivalent price signal. The electric utility selects loads based on the bids and remotely controls the loads of selected customers.

- **Emergency DR**

  In an emergency DR scheme, customer load adjustments are conducted during a power shortfall and incentives are provided for affected customers.

- **Capacity market program**

  In a capacity market program, customers offer bids according to possible load curtailments in the capacity market as a replacement for expensive generators. The electric utility selects the customers based on the bids and sends prior notice of curtailment. Customers automate their loads for control in order to match with the prior notice for curtailment. Penalties may apply if the customers fail to curtail their loads during the given time.

- **DR for ancillary services**

  Unlike the capacity market program, customers in a DR for ancillary services scheme bid for load curtailment as operating reserves. Upon the acceptance of bids by the ancillary services market, offers are provided to customers during selected dispatch time steps. Finally, loads are subjected to control based on the offers.

2.2.2.2. ***Price Response Demand Options***

Price response demand options include:

- **Time of Use (TOU) Pricing**

  In the time of use pricing approach, different blocks of prices are broadcast for different timeframes within a day. The prices reflect the average cost of generation and power delivery during each timeframe.

- **RTP**

  RTP is a tariff scheme for customers reflecting real-time variations in wholesale price. The real-time price is broadcast on a day-ahead or hour-ahead basis which helps the customers to take decisions for their optimal power consumption.

- **Critical peak pricing**

  Critical peak pricing is a pricing scheme that combines the time of use and RTP techniques. During a normal day, customers are provided with a time of use pricing scheme. However, during a critical peak day, the customer tariff is switched to the RTP scheme. This reduces the likelihood of adverse network conditions.

2.2.3. **Analysis of DR techniques for residential distribution system - Direct Load Control, RTP, HEM system and DR for ancillary services**

Among the incentive-based DR techniques, the interruptible services, emergency DR, customer demand bidding and capacity market programs are found to be the most suitable for large-scale industrial or commercial customers. These may not be appropriate for residential customers due to the lack of customer flexibility, complex bidding mechanism and unacceptable penalties. Hence, the direct load control is best suited for a residential distribution system. The direct load control technique is discussed in more detail in the next Section 2.2.3.1

Among the price response demand options, the RTP scheme is also a promising mechanism for residential customers. A more detailed discussion of RTP is also presented in the next Section 2.2.3.2. HEM system and DR for ancillary services are discussed in Section 2.2.3.3 and 2.2.3.4 respectively.

2.2.3.1. *Analysis and Argument in Recent Studies on Direct Load Control (DLC)*

To date, a considerable amount of research has been carried out on direct load control, with a major focus on optimizing appliance scheduling for DR. Most of the studies aim to eliminate system peaks, minimize system operating costs and maximize profit for electric utilities [20], [21]. Some of the DLC techniques are discussed here.

A DLC scheme to manage a virtual power plant was proposed in [22] which also aimed to find the optimal control schedules of thermostatically controllable appliances. Residential heating/cooling is one of the major constituents of electricity demand from residences. Efficient thermal management of home heating applications with peak load shifting and consumption during low wholesale prices can be achieved with maximum consumer satisfaction. This scheme can also provide energy efficiency gains and could possibly result in energy cost savings [23].

Savings in electricity bills can be achieved by the installation of a storage tank, since the air-conditioning load is shifted from the daytime to the evening discount period [24]. A new control structure called the group-direct load control (g-DLC) method was proposed to achieve minimum discomfort while implementing load control. The g-DLC method arranges the schedule of the air-conditioner loads being controlled in such a way as to maintain thermal comfort at a rational level [25].

A vehicle-to-grid control of grid-connected plug-in electric vehicles as a direct load control method in the ubiquitous power grid was proposed in [26]. It is based on simple droop characteristics against the power system frequency at the plug-in terminal, considering the risks in the use of the vehicle and battery condition. This approach flattens the natural variability, ensuring grid-wide frequency stability, and suppressing the rise in voltage caused by reverse power flow [27]. These studies only considered particular selected appliances such as air-conditioners and electric vehicles. However, most house appliances have the capacity for load adjustments.

Hence, a detailed study which considers most residential controllable appliances is essential.

Various algorithms have been proposed in formulating direct load control methods with the objectives of finding a dynamic programming-based solution [28] and a fuzzy logic-based solution [29]. In some solutions, the direct load control problem has also been integrated with other traditional electric utility objectives. For instance, direct load control is combined with unit commitment and the integrated problem is solved through dynamic programming [30]. Furthermore, a load control problem was modelled from an electric utility perspective as a profit maximization problem and linear programming was applied to solve it [31]. Optimization programs are used for the load selection process in most studies in the literature. It may be cumbersome to implement these schemes in real-world environments with short timeframes, as it may be time consuming.

In order to solve that issue, an intelligent direct DR technique was developed with the primary objective of limiting peak load on the network below the rated value. This intelligent control system uses the instantaneous load level and not price as the control signal to initiate load management. It assumes that consumers are given an incentive to participate in the scheme. Here, plug-in electric vehicles are considered as just another component of the system. This holistic approach recognizes the potential of complex interactions to solve overload problems. The system employs low-cost intelligent controllers in each house as well as at the supply transformer [32]. The authors of [32] used a realistic system with time-varying appliance models and proposed a direct DR technique for peak shaving. This approach mitigates the overloading problem of the transformer but the voltage violations remain towards the end of the feeder.

All of the above approaches considered only the prevention of overloading of the transformers as the main objective. However, it is observed that the voltage violations still exist towards the end of the feeder. Therefore, Masoum carried out an extensive study on DR for overload prevention and loss minimisation to achieve voltage control but with only the coordination of plug-in electric vehicle charging patterns [33]. Power quality issues for a distribution system with high penetration of plug-in electric vehicles during DR are also considered in [34] as an extended research of [33]. Lopes proposed some strategies for load shedding for coordinated voltage support which is achieved through an optimisation program [35]. In both cases, a realistic system involving other appliances was not considered during the analysis.

Hence, the present study proposes a full investigation that includes most of the controllable appliances in residences. An easy computation method for appliance selection based on benefits for both the electric utility and the customer is used with the primary objective of peak shaving and voltage support. In addition, a customer rebate scheme is also studied in detail.

2.2.3.2. ***Analysis and Arguments in recent studies on RTP***

RTP is a dynamic pricing scheme which directly reflects the marginal cost variation of electricity production at each dispatch time interval. It efficiently bridges the link between the wholesale and retail electricity market by updating price signals every hour or less. The RTP concept was introduced by Schweppe [36]. Although RTP was introduced in the 1980s, implementing this concept took time due to the lack of building automation.

Some pilot studies or permanent programs on RTP have been applied on large customers in commercial and industrial applications [37], [38]. These have not yet been applied on residential customers as there are some implications related to ensuring customers get sufficient time to respond to price changes. However, due to improvements in the communication infrastructure, researchers have begun to focus their attention on residential customers as well. Initially, a two-part RTP scheme was designed including a flat rate or time of use price, layered with the wholesale price when the consumption rises above a predefined baseline value. It allows customers to hedge a part of their loads above the baseline [39].

Another study in [40], proposed an RTP scheme with inclined block rates in order to have balanced residential loads with a lower peak to average ratio. In that scheme, a price prediction filter is also used for scheduling loads on an hourly basis. However, the price prediction may create errors compared to real-time results. The authors of [41], proposed a method which provides prices not only on the power consumption but also changes in consumption. This helps to resolve market clearance issues.

Updating the “cycle of price” is an important aspect in defining an RTP scheme for electricity. The shorter the updating cycle, the more efficient are the required load control outcomes. However, the studies in [39]- [41] used an hourly cycle of price and hence the schemes proposed in those studies may not respond accurately to achieve the required demand reduction.

In contrast, a pilot study by the US Department of Energy, teamed with an electricity service provider, tested an RTP scheme on a residential distribution system by providing smart equipment for each residence [42]. They succeeded in maintaining a cycle of price of five minutes. In another recent study, the real-time price was published every 15 minutes and air-conditioners were automatically controlled in response to price changes [43]. Research findings in [42], [43] showed the efficacy of the system with a shorter cycle of price.

However, these past studies have proposed the real-time price as a representation of the average change in the wholesale electricity price. The direct application of the average wholesale price may have some adverse effects on residential customers. For example, wholesale price spikes may lead to unacceptable increases in the real-time price.

Hence, an efficient RTP scheme is proposed in the present study to price the excess load consumption, voltage violation in the feeder and also a sensible representation of the wholesale price spike. The proposed method also has a short cycle of price (five minutes). It is made possible by a short simulation time for price and simulation for appropriate load adjustments in a house.

2.2.3.3. ***Home Energy Management (HEM) Units***

A significant amount of studies have been conducted to reduce cost of energy consumption in a house by appropriate scheduling of appliances. They show that HEM unit is essential for appliance scheduling to handle the uncertain nature in RTP variation and appliance power consumption.

A real-time HEM system is proposed using ‘particle swarm optimization’ and ‘genetic algorithm’ in [44], [45]. However, authors did not consider the uncertain behavior of RTP or power consumption of appliance in their algorithm. A decision support tool using linear programming technique is developed in [46]. An hour-ahead price predictor to plan the energy consumption is used but it is not included in the appliance scheduling process. This issue is resolved by [47], [48] by using a predictive tool in real-time appliance scheduling process. However, a predictive method for HEM system may lead to erroneous results when the predicted outcomes do not match with the actual network conditions.

As a solution to the above issue, a stochastic optimization to minimize the expected electricity payment is proposed in [49], [50] incorporating uncertainty in RTP via expected downside risk and price prediction noise respectively. Nevertheless, uncertainties in appliance power consumption pattern are not incorporated. Therefore, the authors of [51] develop an algorithm as a bottom up approach considering both uncertainties in appliance power consumption and RTP variation. This method considerably increases number of controls due to its individual appliance based control scheme and affects customer satisfaction. Therefore, it necessitates the need of an efficient HEM scheduler incorporating both uncertainties in RTP variation and appliance power consumption. An algorithm based on minimizing total cost of energy consumption in a house rather than individual appliance based optimization may effectively optimize the number of controls. Hence, this research focuses on a house based stochastic optimization scheme to achieve energy management effectively.

2.2.3.4. ***DR for providing regulation services***

DR can be effectively used for regulation services as it has the capability of responding faster than conventional generators. Some of the studies for DR utilized for regulation purposes are explained here. Aggregated water heaters used to provide regulation services is proposed in [52] using a day-ahead forecasted model. Here, selection of loads is based on predicted outcomes. A detection mismatch rate of 33.3% is observed due to its forecasted model and it may fail to provide accurate regulation services.

The authors of [53] develop a deterministic minute to minute regulation service utilizing water heaters. Here, loads are ranked based on water heater tank temperature. Coordination of expected control signals are based on thermostat status of previous and next time step. The authors of [53] uses appliance ON/OFF switching to accomplish control, whereas the authors of [54] consider temperature set point adjustments. However, these processes fails to predict appliance status on the next time step which is vital as the appliance consumption pattern and temperature variation are highly uncertain. In order to resolve this issue, a probability function for water consumption rate is taken in [55]. However, appliance selection method is still deterministic based on a power tracking method and did not consider the uncertainties in appliance power consumption.

Hence, this research proposes a probabilistic pairwise appliance ranking method for selecting appliance for regulation purposes. It incorporated uncertainties in appliance power consumption and temperature variation.

2.3. Summary and Implications

The available techniques for DR in the current electricity market are applied for the purpose of handling network peaks and adverse feeder voltage issues. Most of the existing studies are based on optimization techniques to maximize electric utility benefits or customer satisfaction. However, optimization techniques may be time consuming and it may be difficult to simulate load controls within a short timeframe. Hence, a simplified method that considers the benefits for both the electric utility and the customer is required. Furthermore, most of the existing techniques consider particular appliances such as water-heaters, air conditioners and plug-in electric vehicles in the DR process. Hence, a study is required to ensure the participation of most of the controllable appliances in a house. Moreover, a comprehensive customer reward scheme for load curtailment, based on both overload prevention and voltage support, has not yet been studied.

RTP is a promising option as it reflects the wholesale price variation within short timeframes. In most of the available RTP schemes, the real-time price reflects the average wholesale price. This may adversely affect the customers when there are unacceptable wholesale price spikes. Hence, a rational price component for RTP should be studied. Furthermore, in most of the available RTP schemes, the real-time prices are broadcast on an hourly basis. This may not reflect the actual network conditions and hence the scheme may not be able to achieve the required demand shift. This gives rise to the need to increase the time steps of RTP broadcasting. Moreover, the RTP concept can be applied to prevent overload and improve voltage conditions in the electricity network. Therefore, an improved RTP scheme can be developed by considering the wholesale price variation, network peak and adverse voltage conditions. Such a scheme can be extended with the addition of an electric vehicle charging rate and feed-in tariff for PV cells.

A HEM system helps customers to react to RTP variations efficiently. Recent studies on HEM systems are based on real-time techniques and do not consider the uncertain nature of appliance usage or RTP variation during appliance scheduling. Some of the available HEM systems use predictive techniques for appliance scheduling, which may cause errors. Hence, a fully-fledged HEM system which handles the uncertainty in both appliance power consumption and RTP variation should be studied.

The DR technique can also be used for the provision of regulation services. Studies in the literature indicate the utilization of thermostatically controllable loads in appliances such as water-heaters and air-conditioners. The selection of these loads is based on real-time temperature ranking methods. This technique is only valid with short time step controls such as one minute. However, in the Australian ancillary services market, regulation services are scheduled to a five minute dispatch framework. Hence, there is a need for an accurate stochastic appliance ranking scheme to predict the appliance status in the next five minute timeframe.

Chapter 3

Demand Response for Residential Appliances via Customer Reward Scheme

This chapter illustrates a reward based demand response algorithm for residential customers to shave network peaks. Customer survey information is used to calculate various criteria indices reflecting their priority and flexibility. Criteria indices and sensitivity based house ranking is used for appropriate load selection in the feeder for demand response. Customer Rewards (CR) are paid based on load shift and voltage improvement due to load adjustment. The proposed algorithm can be deployed in residential distribution networks using a two-level hierarchical control scheme. Realistic residential load model consisting of non-controllable and controllable appliances is considered in this study. The effectiveness of the proposed demand response scheme on the annual load growth of the feeder is also investigated. Simulation results show that reduced peak demand, improved network voltage performance, and customer satisfaction can be achieved.

3.1. Introduction and Related Work

Concerns regarding the stability and reliability of an electricity network arise due to the adverse effect of peak power demand. Demand response is one way to deal with peak events and prevent network overloading because it provides the flexibility required to time shift loads [56]-[57]. It is a cost effective technique and can be achieved by either price based (indirect load control) or incentive based (direct load control) demand response programs.

Indirect load control or price based demand response can be achieved through electricity price changes which encourage customers to regulate their consumption patterns [58]. Real time pricing, Time Of Use (TOU) tariffs, and critical peak pricing can be categorized under, price based demand response where the fluctuations and risks in wholesale electricity prices are imposed on the end consumers [59]. The non-residential critical peak pricing scheme is shown to reduce peak demand [60]. The real time pricing scheme has equity problems due to highly varying day-time and night-time prices [11]. Moreover, it was also found that consumers are less likely to make active decisions about their load on an hourly basis under the real time pricing scheme [61].

Direct Load Control (DLC) or incentive based demand response can be used by utilities to adjust and time shift customer load directly during network peak events [62]-[64]. Although incentives are provided to consumers for their participation in the DLC program, recent field experiences showed some resentment due to mandatory interruption of electricity services [65]. Few pilot studies involving peak time rebates were conducted in the past where a priori fixed rebate structure is used which neglects the actual supply-demand status [66]. A variable rebate based demand response was proposed recently in [67], which took into account the variability of customer participation and offered coupons and incentives to achieve peak shaving.

None of the models considered above investigated the detailed appliance modeling and customer satisfaction, which is necessary for residential demand response. Air conditioners (ACs) were modeled and proposed to adjust the temperature for demand response in [68]. Similarly, the charging profile of electric vehicles as a load in distribution networks was considered in [69]-[71]. A real-time appliance scheduling scheme using time sensitivities and duty cycles of appliances was considered in [72]. These previous studies considered only a few selected appliances in the network. However, a holistic study, incorporating all major appliances has yet to be investigated.

Moreover, approaches in the literature aimed at network peak shaving via overload reduction completely neglected feeder voltage issues. In another study, Peças Lopes proposed a strategy for load shedding with coordinated voltage support using an optimization program [73], which was limited to a small system with few appliances. Optimizing the decision vector handling multi-layers of the demand response using customer priority criteria and satisfying both utility and consumer was proposed in [74]. ACs, water heaters and clothes dryers were the only controllable appliances considered in this study. Another attempt to bring the actual load consumption curve closer to the desired load consumption curve through an optimization process was proposed in [75], but it neglected the effect on customer satisfaction.

This chapter proposes a new incentive based residential demand response using a Customer Rewards (CR) scheme, which not only achieves peak shaving but also improves the feeder voltage profile under different spatial distributions of residential loads. The proposed load control strategy does not depend on the cost of electricity consumption. Various indices reflecting customer priority, satisfaction, and flexibility are included in this research. Houses are ranked with a factor reflecting their impact on voltage due to their load. A low voltage distribution network, subject to real-time load adjustment, is considered in this chapter. Rewards for each customer are based on their willingness to participate in the scheme and are calculated dynamically every day.

The chapter is organized as follows. The detailed description of demand response for residential appliances is proposed in Section 3.2. Specifically, the concept of a customer reward (CR) scheme is explained in Section 3.2.4. A critical assessment on the CR scheme is discussed in Section 0. The realistic residential load model including the distribution feeder and the corresponding results are presented in Section 3.4 and Section 3.5 concludes the chapter.

3.2. CR based Demand Response for Residential Appliances

Customer participation is usually encouraged through a detailed survey at the beginning of the demand response program. The information obtained is then used to calculate various indices to incorporate customer preferences and hence satisfaction during load adjustment. These indices, including network topology, are used to define an appropriate load adjustment. Customer rewards are calculated every 24 hours based on their participation. The details are discussed below.

3.2.1. **Seeking customer preferences for demand response**

A customer survey is proposed which can be conducted in a real network while implementing the demand response scheme. It is expected to be conducted for all residential customers to obtain their inputs and preferences regarding their participation in the demand response programs. A sample survey or questionnaire is shown in Table 3.1.

Table 3.1 Sample customer survey questionnaire

Appliance	Availability/ Priority order		Desired Operation Region		
			F_1	F_2	F_3
Water Heater (WH)	✓		×	✓	✓
Desired Tank Temperature	62 °C	1			
Pool Pump (PP)	✓		✓	✓	×
Average Total operating time	8 hrs	7			
AC- hysteresis (ACH)	×				
set point of AC	-	0			
AC- inverter (ACI)	✓		×	✓	✓
set point of AC	24 °C	2			
Electric Vehicle (PEV)	✓		✓	×	✓
battery capacity	2 kW	4			
Dish Washer (DW)	✓		×	✓	✓
Average total operating time	60 min	3			
Clothes Washer (WA)	✓		×	✓	✓
Average total operating time	55 min	5			
Dryer (DR)	✓		×	✓	✓
Average total operating time	70 min	6			
F_1= off peak (2200hrs:0700hrs) , F_2= shoulder peak (0700hrs:1600hrs, 2000hrs:2200hrs); F_3= peak hours(1600hrs:2000hrs)					

Utilities are interested to know appliance preferences of various customers and their time of operation. For simplicity, the survey may divide a day into three separate operation regions namely F_1, F_2, and F_3 representing off peak, shoulder peak, and peak hours respectively. The survey should be designed to collect important information such as the items listed in Table 3.2. In order to verify the collected data from customers, past and current appliance usage patterns can be carefully studied for each house. Customer priority and the flexible range of usage time for appliances can be extracted from the above data. Details in the customer questionnaire can be verified with the extracted values. Moreover, these extracted values can be used when the information provided is inconsistent and/or ambiguous.

Table 3.2 Required data from customers

Data in Customer Survey	Required Instance
Total operating time of pool pump	For appliance satisfaction calculations
Set point of AC and water heater	
Battery capacity of electric vehicle	
Average total operating time of dishwasher, clothes washer and dryer	
Ordered list of appliances that the customer likes to connect between 16:00-22:00 hrs (peak and shoulder peak time)	For appliance priority calculations
Adjustable range of time for each appliance within a day	For flexibility calculations

Customer preferences are taken into account before designing the load control algorithm. It is assumed in this study that each house has ten non-controllable loads (lighting, fridge, freezer, cooker, electric oven, microwave, television, computer, stand-by appliance, and miscellaneous appliance) and seven controllable loads (swimming pool pump, PEV, electric water heater, dish washer, clothes washer, dryer, and AC). They are modeled according to residential load modeling data provided in [76]-[77], [32]. Appliance modelling is discussed in detail in Appendix A.

3.2.2. **Calculation of various criteria indices from customer survey**

Information from customers is used to define various indices for appropriate load selection. Therefore, five criteria indices ($C(i,j,k)$ for the k^{th} criteria index of the

i^{th} house and the j^{th} controllable load, $C(i,j,k) \in [0,1]$) are proposed in this research work to reflect the customer's satisfaction, flexibility, and willingness to participate in demand response. They are explained next.

3.2.2.1. ***Appliance Priority Index (API)***

API is a user-defined value where the user (i.e., the customer) has the authority to order/arrange loads that should be operated per the priority of the duties. This is also obtained from the customer survey considering the 8-hour time span from 16:00 to 00:00. API_{ij} for the i^{th} house and for the j^{th} appliance can be calculated using the priority value (Pr_{ij}) in the ordered list. This is shown in (3.1). The maximum of Pr_{ij} represents the total available controllable appliances within that house.

$$API_{ij} = \begin{cases} \dfrac{1}{\mathrm{Pr}_{ij}} & override = 1 \\ \dfrac{\mathrm{Pr}_{ij}}{\max(\mathrm{Pr}_{ij})} & override = 0 \end{cases} \tag{3.1}$$

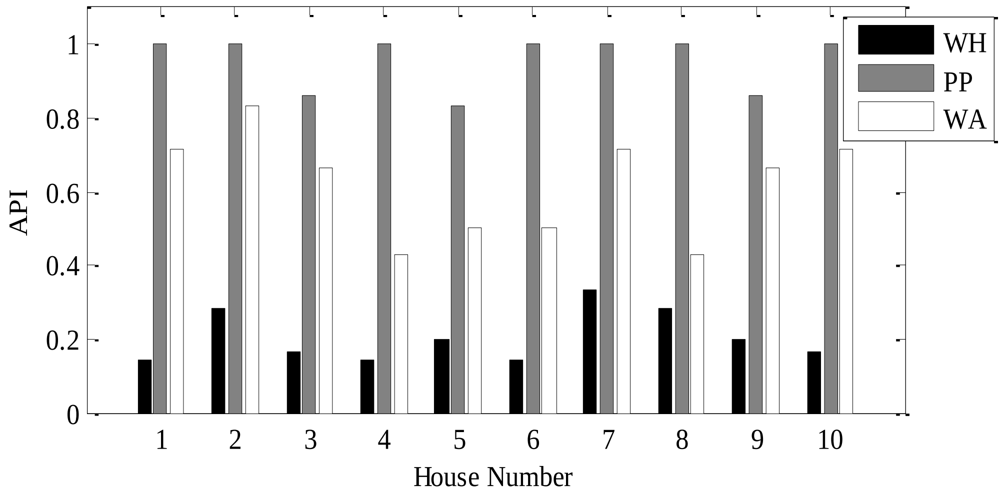

Fig. 3.1 API of houses in phase-A of feeder 1

Table 3.3 Priority of Appliances in House 1

Appliance	WH	PP	ACI	PEV	DW	WA	DR
Priority(Pr_1)	1	7	2	4	3	5	6
API_1	0.143	1	0.286	0.571	0.429	0.714	0.857

Table 3.3 gives the order of appliances in house 1 which has 7 controllable appliances. It is obtained from the customer survey as in the second column of Table 3.1. It shows that lower priority appliances, like the swimming pool have higher

possibility for load adjustment. Further, Fig. 3.1 shows the priority of selected appliances such as the washing machine, swimming pool, and water heater for houses in phase-A of a selected feeder. If the customer chooses to turn on the appliance more than once, it can be considered as an “Over-ride”. This “Over-ride” will change the API for that appliance to 1.

3.2.2.2. ***Appliance Flexibility Index (AFI)***

AFI is a measure of the adjustable range of time of appliances and it depends totally on their characteristics and necessity. For example, a swimming pool pump can be operated at any time during a day and therefore has the maximum flexibility. Washer and dryer have the lowest flexibility because they can only be operated in-between 6 p.m. to 11 p.m. This desired appliance operation time range is obtained from customer survey data. Each customer will specify the flexible range of time of his appliances in advance, according to the TOU tariff of that particular season [78]. Off peak (9 hrs), shoulder peak (11 hrs), or peak region (4 hrs) is selected by a customer for a desired operation as shown in Table 3.1. Hence, he/she determines his/her appliance usage pattern within a day according to a time schedule to reduce the cost. Here, the total available time is one day or 24 hours.

Finally, the utility calculates the appliance flexibility index for load adjustment using equation (3.2). Here, the user defined data (adjustable range of time) is divided by the total available time within 24 hours. Table 3.4 provides the sample values of flexibility for each controllable appliance when customers are at home.

$$AFI_{ij} = \frac{adjustable\ range\ of\ time}{total\ available\ time\,(24\,hrs)} = C(i,j,2) \tag{3.2}$$

Table 3.4 Flexibility of appliances

Appliances	WH	PP	ACI	PEV	DW	WA	DR
Adjustable time range (hrs)	13	18	6	11	2	2	2
AFI	0.542	0.75	0.25	0.458	0.083	0.083	0.083

3.2.2.3. ***Appliance Satisfaction Index (ASI)***

ASI is calculated every four minutes and indicates how close the appliance operating state is to its limiting state of operation. ASIs of different appliances are calculated as shown in Table 3.5 and used as the criteria index *C(i,j,3)*. The current power level and time of operation state of each controllable appliance is used to calculate this index. The desired values and the set points are randomly defined within the program. For example, a mean value of 67°C and 25°C are chosen for set point of the water heater and AC, respectively, for random data generation. ASI is maintained close to unity. Here, T_{wh} and T_r are water heater tank and room temperature respectively. Further, T_{wh}^{set} and T_{wh}^{db} are temperature set point and dead-band of water heater respectively. Similarly, T_{ac}^{set} and T_{ac}^{db} are temperature set point and dead-band of AC respectively.

Table 3.5 Calculation of ASI for different appliances

Appliances		Satisfaction
Water Heater	$T_{wh}^{actual} < T_{wh}^{set} - T_{wh}^{db}$	0
	$T_{wh}^{set} - T_{wh}^{db} \leq T_{wh}^{actual} \leq T_{wh}^{set} + T_{wh}^{db}$	$\frac{(T_{wh}^{actual} - T_{wh}^{set})}{(2.T_{wh}^{db})}$
	$T_{wh}^{actual} > T_{wh}^{set} + T_{wh}^{db}$	1
AC	$T_{r}^{actual} < T_{ac}^{set} - T_{ac}^{db}$	0
	$T_{ac}^{set} - T_{ac}^{db} \leq T_{r}^{actual} \leq T_{ac}^{set} + T_{ac}^{db}$	$\frac{(\mathrm{T}_{r}^{actual} - \mathrm{T}_{ac}^{set})}{(2.\mathrm{T}_{ac}^{db})}$
	$T_{r}^{actual} > T_{ac}^{set} + T_{ac}^{db}$	1
Swimming Pool		$\frac{\text{time taken for the operation}}{\text{desired total operating time}}$
PEVs		$\frac{\text{available charge of PEV}}{\text{capacity of the battery of PEV}}$
Dish Washer, Clothes Wash and Dryer		$\frac{\text{time remaining to complete that cycle}}{\text{Appliance operating cycle time}}$

For dish washer, clothes washer, and dryer the cycle has to be completed once started by the customer. If this load is delayed by utility, then it will reset and start again at a later time. These loads are given low AFIs and hence the least priority for adjustment. ASI will help to maintain a high probability that the dish washer, clothes washer, and dryer will not be interrupted in the middle of a cycle via decision matrix values as (3.9).

3.2.2.4. ***Power Similarity Index (PSI)***

PSI represents how close a load is to the required amount of total load adjustment and it is used as the criteria index *C(i,j,4)*. This is calculated using (3) for each appliance at each instant.

$$PSI_{ij} = 1 - \left| \frac{\text{ApplianceLoad - Required Average Load Adjustment}}{\text{Applianceload}} \right| \tag{3.3}$$

For example, in a peak day, if a transformer is overloaded by 120 kVA, then on an average 1 kVA is to be adjusted in each house with the assumption of 120 houses. This required load adjustment is compared with the rating of each appliance to calculate PSI_{ij}. For each house, the appliance with the highest PSI is the most appropriate for the adjustment. Table 3.6 illustrates how PSI is used to select a particular load for adjustment. If 1 kVA load were to be adjusted, then the washer load, which has a highest PSI of 0.9091 compared to all other loads in that house, should be adjusted. Whereas, if 2 kVA load were to be adjusted, then AC load (PSI is 0.8696) should be chosen. Selection of AC for the necessary 2kVA adjustment is much better than the selection of any other combination of appliances which add approximately 2kVA power level (e.g., washer 1.1 kW and dryer 1.3 kW). Here, 2 control commands are reduced into 1, which means the control algorithm chooses only one load at a step. Hence the 2 kVA load is chosen for load adjustment instead of two loads with 1.1 kW and 1.3 kW. This explains the effectiveness of PSI. Highest PSI values for each average load adjustment per house are shown as bold numbers in Table 3.6.

Table 3.6 PSI calculation of house- 1 for a particular instant

Average Load Adjustment per House	Power Similarity Index (PSI)		
	AC (2.3 kW)	Water Heater (3.6 kW)	Washer (1.1 kW)
1kVA	0.4348	0.2778	**0.9091**
2kVA	**0.8696**	0.5556	0.1818

PSI is required to select the closest and most appropriate load to be adjusted to eliminate overload. Use of PSI will minimize overall control commands in the network.

3.2.2.5. ***High Power Consumption Index (HPCI)***

HPCI aims at identifying the house which is consuming the highest power at a time when load adjustment is required. $HPCI_{ij}$ for i^{th} house and j^{th} appliance is calculated as in (3.4) and is used as the criteria index $C(i,j,5)$. For example, if a house has 5 kVA of connected load and the load consumption is 5 kVA at that time, then HPCI is 1 at that time. At other time instants, if load consumption is 3 kVA, HPCI is 0.6 (=3/5). HPCI is one way to socialize the load adjustment such that network overload is effectively mitigated.

$$HPCI_{ij} = \frac{Total\ load\ of\ i^{th}\ house}{House\ load\ with\ \max\ consumption\ in\ the\ network} \tag{3.4}$$

3.2.3. **Using house ranking and criteria indices for load adjustment**

Houses are ranked with a factor to replicate the impact of load on voltage violation. The random selection of house loads will result in a number of unnecessary load adjustments when voltage violation exists. Hence, this ranking mechanism is introduced for each house to avoid unnecessary load adjustment during voltage problems. Traditionally, the sensitivity method [79], [80] has been used for load ranking and can be used here to choose the most suitable house for required load adjustment.

The rank for each house at each instant is calculated using the voltage magnitude and angle of each house from a three-phase unbalance load flow program. Voltage sensitivity is considered as an appropriate voltage measure in this process. Voltage sensitivity parameter (ρ) is the average change in the voltages of all houses in a feeder due to load adjustment at that house. Inverse Jacobian matrix parameters [81] are used to calculate the voltage sensitivity at each house. The parameter ρ of the i^{th} house in the p^{th} phase for a three-phase unbalanced system is derived using (3.5).

$$\rho_i^p = \frac{\sum_{h=1}^{n}\sum_{m=1}^{3}\left(\frac{\partial \Delta V_h^m}{\partial \Delta P_i^p}\Delta P_i^p + \frac{\partial \Delta V_h^m}{\partial \Delta Q_i^p}\Delta Q_i^p\right)}{3n_p} \tag{3.5}$$

Where, n_p is the total of number of houses in one phase. Maximum and minimum values of the sensitivity parameter in each phase is calculated and used in (3.6) to define rank, r_{ij}^p, for the i^{th} house and the j^{th} appliance in the p^{th} phase.

$$r_{ij}^p = \left(\frac{\rho_i^p - \min_i(\rho_i^p)}{\max_i(\rho_i^p) - \min_i(\rho_i^p)}\right) * e_{ij} \tag{3.6}$$

Where, e_{ij} is the appliance status (On/Off) signal at a particular time for the i^{th} house and the j^{th} appliance and can be obtained from smart meters. P and Q are real and reactive power, respectively. Value of e_{ij} is 1 if the appliance is on at a particular time and 0 otherwise.

The overall control process maintains voltage and network power levels within limits. Here, 0.94 p.u. and 1.06 p.u. are the minimum and maximum voltage levels, respectively, because +/- 6% are the Australian standards [82]. Also, network power limits are taken as the capacity of the transformer (chosen here as 500 kVA). Power flow equations used during the three-phase unbalanced load flow program is provided here. The derived mismatch equations for the load buses are (3.7)-(3.8).

$$\Delta P_i^p = P_i^p + \sum_{h=1}^{n}\sum_{m=1}^{3}\left|V_i^p\right|\left|V_h^m\right|\left\{G_{ih}^{pm}\cos(\theta_i^p - \theta_h^m) + B_{ih}^{pm}\sin(\theta_i^p - \theta_h^m)\right\} \tag{3.7}$$

$$\Delta Q_i^p = Q_i^p + \sum_{h=1}^{n}\sum_{m=1}^{3}\left|V_i^p\right|\left|V_h^m\right|\left\{G_{ih}^{pm}\sin(\theta_i^p - \theta_h^m) - B_{ih}^{pm}\cos(\theta_i^p - \theta_h^m)\right\} \tag{3.8}$$

Here, G_{ih}^{pm} and B_{ih}^{pm} are conductance and susceptance of the feeder connecting the i^{th} and the h^{th} house in phase p due to the effect of phase m, respectively; θ_i^p is the bus angle at the i^{th} house in phase p; and V is the bus voltage. The rank of each house is then multiplied with the decision value for the appropriate selection of load.

Overall, the above parameters provide the decision for load adjustment. These indices (as discussed in Section 3.2.2) along with the appropriate rank (as discussed in this Section) for each house are used in decision matrix calculation. Dec_{ij}, the decision for the i^{th} house and the j^{th} controllable load, is defined as in (3.9).

$$Dec_{ij} = r_{ij}^{p} \sum_{k=1}^{5} C(i,j,k) \tag{3.9}$$

Where, $C(i,j,k)$ is the criteria raking matrix for the k^{th} criteria index of the i^{th} house and the j^{th} controllable load ($C(i,j,k) \in [0,1]$). An efficient solution can be achieved with the combination of multiple criteria indices into a single criterion by multiplying each criterion with a positive weight and summing the weighted criteria [83]. For simplicity, this research considers unity weights for all five criteria.

For the i_0^{th} house in the p_0^{th} phase, if $\rho_{i_0}^{\ p_0}$ is the minimum ρ in that phase, then r_{ij}^{p}=0 and hence Dec_{ij}=0. This means that the corresponding appliance will not be selected for load adjustment at that time instant. This is reasonable because at that time instant, the i_0^{th} house is the least sensitive to the voltage violation in the feeder. Since the voltage sensitivity depends on house locations as well as load consumption, at other time instants the same house may not have the minimum sensitivity and hence the corresponding load can be selected for adjustment at that time.

3.2.4. **Customer reward (CR) Scheme**

CR scheme provides rebates to residential customers for their participation in the demand response. The proposed rebate is a function of both shifted energy and voltage improvement due to load adjustments as shown in (3.10). The shifted energy of the house is the sum of the product of all load adjustments and the respective waiting times. Here, waiting time is the time that is delayed by the controller to re-connect the appliance to the system. The effective change in voltage within the network due to a particular load adjustment is taken as the ratio of voltage deviation of the i^{th} house to the voltage improvement from the lower limit.

$$\begin{aligned} \text{Rebate}_i &= f(\text{shifted energy}, \text{voltage improvement}) \\ &= \alpha * \left(\exp\left(\sum_{l=1}^{Nadj} \frac{E_i^l}{E_{\lim}} \right) - 1 \right) + \beta * \sum_{l=1}^{Nadj} \left(\frac{\Delta V_i^{\ l}}{\Delta V_{i,\lim}^{\ l}} + \sum_{\substack{m=1 \\ \neq i}}^{Nv} \frac{\Delta V_m^{\ l}}{\Delta V_{m,\lim}^{\ l}} \right) \end{aligned} \tag{3.10}$$

Here, $Rebate_i$ is the rebate in \$ for a given day of i^{th} house; E_i^l is the shifted energy for the i^{th} house measured at the l^{th} load adjustment; E_{lim} is the limit of maximum shifted energy (chosen to be 12kWhr in this case); ΔV_i^l is the voltage deviation in p.u. and $\Delta V_{i,lim}^{\ l}$ is the voltage improvement (from lower limit of 0.94) in p.u of the i^{th} house measured at the l^{th} load adjustment; N_{adj} is the total number of load adjustments per day for the i^{th} house; N_v is the number of houses with voltage violations in the same feeder as the i^{th} house; α and β are cost coefficients for shifted energy and voltage improvement chosen here as 20 and 1, respectively. Evaluation of cost coefficient α and β is shown in Section 3.3.2.

An exponential function for shifted energy is chosen to provide increased benefit to customers who are willing to participate in load adjustments for a longer time. The rebate for voltage improvement due to load adjustment of a house has two components, i.e., one resulting in the voltage improvement of that particular house whose load is adjusted and the second being the improvement in voltage profile in all other houses down the feeder. This is important since load adjustment in the house which happens to be at the beginning of the feeder would inadvertently improve the voltage of other houses down the feeder and therefore should be rewarded accordingly. In particular, each house will be benefitted by the load adjustment at the end of the day with rebates.

3.2.5. **Implementation and operation of load control algorithm**

The sample load control process of CR scheme is shown in Fig. 3.2 and Fig. 3.3. As shown in Fig. 3.2, the signal from the smart meters is received every four minutes. Data processing and identification of load adjustments are achieved offline in 2 minutes and then signals are sent for load adjustment.

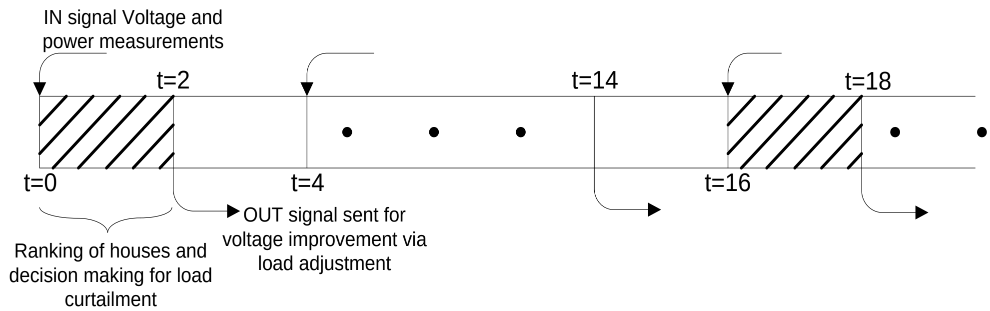

Fig. 3.2 Time schematic of the load control process

Communication network like WiMAX has a bit rate in between 5-25 Mbps where it has a tendency to vary with distance [84]. Also, 900 MHz system and ZigBee network have a bit rate of 20 and 250 kbps, respectively. Hence, it takes less than a second for signal transfer. Further, the data process time calculated in our program is roughly 10-15 seconds for 120 customers. Here, a two minutes time frame is selected as a reasonable time for data collection and processing and another 2 minutes for sending back data and load curtailment. Hence, load curtailment happens every 4 minutes. The 4-minute time window is chosen in this research to make it roughly aligned with the DMS updates, which usually occur every tens of seconds to a few minutes.

From time $t=0$ minute, at each instant $t=t_1$, signals from the primary controllers (smart meters) are received by a secondary controller. Received appliance state and power data are used in the load flow program to calculate voltage at each house. Total network power and voltage at each house are checked to insure that they are kept within standard limits. The above measurement and data processing occurs every 2 minutes.

Offline load flow studies are performed to obtain the appropriate load adjustments in the case that the power level and/or voltage at each house are violated.

The offline load flow block is an iterative process that selects multiple sets of loads for adjustment in that time step as summarized in Fig. 3.3. The criteria indices and rankings and hence decision value (Dec_{ij}) are calculated for each iteration. The maximum value of Dec_{ij} is used to find the corresponding j_0 th load of the i_0^{th} house for load adjustment. The power and voltages are recalculated after this load is adjusted in the offline load flow program. If violations exist, another load is selected for adjustment by recalculating the updated criteria indices and decision values. This process is repeated until violations are removed. At the end of the “offline selection of load” block, multiple sets of appliances that need to be adjusted are identified to keep the voltage and power within limits.

All the selected appliances for adjustments are saved and signals are sent at $t=t+2$ minutes to relevant smart meters. If loads are adjustable (such as AC and water heater loads), then the AC set point is increased by 1 °C and the water heater set point is decreased by 1 °C for 15 minutes. Whereas, the non-adjustable loads are switched off for 4 minutes. The process is repeated for the whole day and after 24 hours. Rebates to the customer are calculated as per (3.10). Set point adjustments would result in the reduction of power consumption, which will be used along with associated waiting time to calculate the shifted power. Fig. 3.3 summarizes the load control process with CR scheme for a particular day.

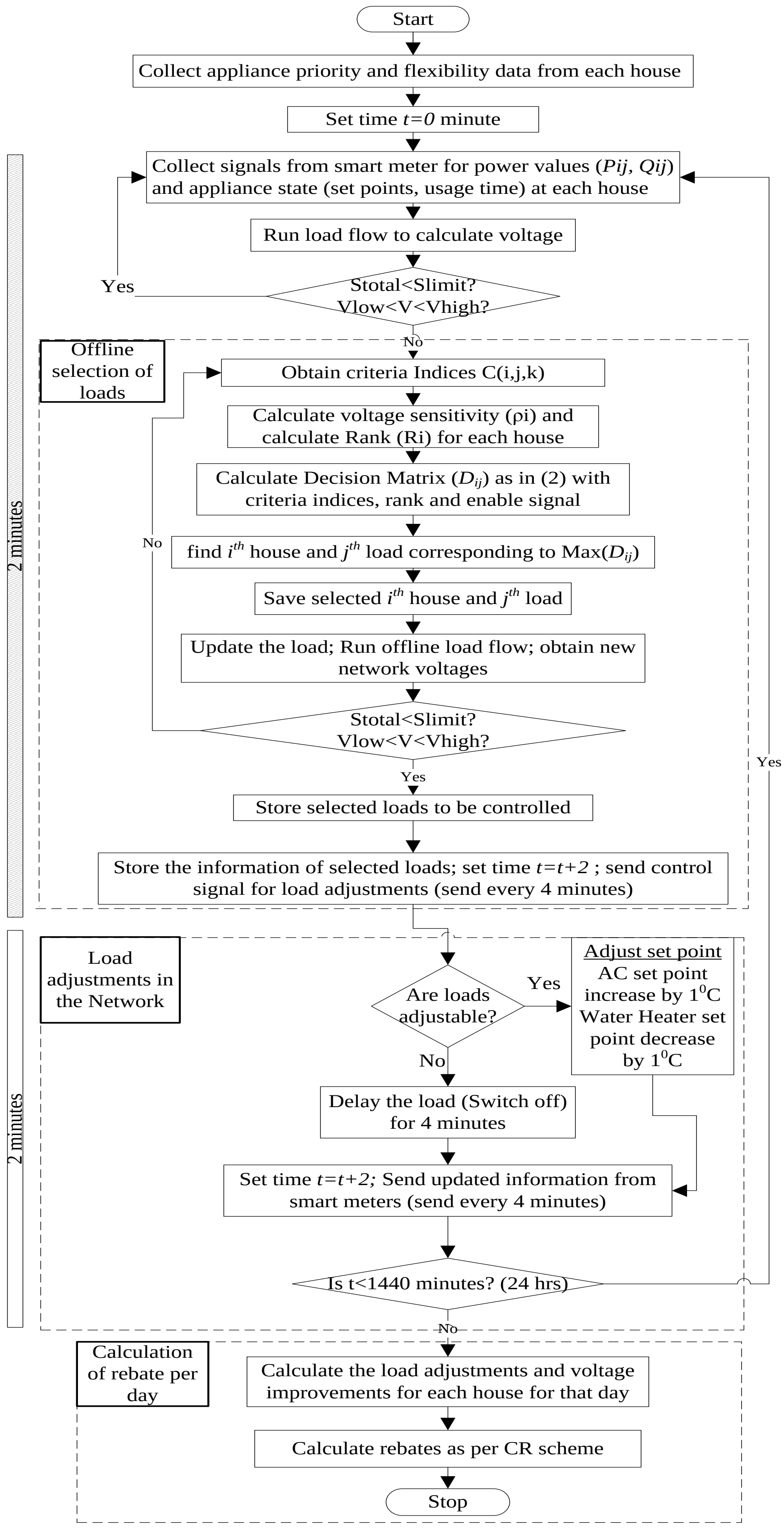

Fig. 3.3 Load control process with CR scheme for a particular day

Most of the appliances that do turn ON, run for a certain time as a constant power load and then turn OFF. This defines a discrete event. Once the control signal for adjustment is sent for certain loads, such as hysteresis type ACs, inverter type ACs, and water heaters, another signal is not sent for the next 15 minutes. For example, at time instant $t=2$, the control signal is sent for adjusting the water heater of House#4 (say). Once the measurements are obtained at $t=4$, the decision matrix is calculated as per (3.9), and the control signals are sent again at $t=6$ for another set of load adjustment. This signal would not adjust the water heater of House#4 until after $t=16$, where the measurements are taken again. The decision matrix is again calculated at $t=16$ and if the water heater is required to be adjusted, then the signal would contain a message to adjust the water heater of House#4 at $t=18$ (as illustrated in Fig. 3.2).

3.3. Critical Assessment of CR Scheme

This section critically assesses various aspects of the demand response and evaluates the necessity of indices, CR, and challenges in the implementation of the proposed scheme.

3.3.1. **Significance of indices in control scheme**

As discussed in the previous section, customer information is used to define five indices for effective load control. Here, each index is critically evaluated to justify its necessity in the load adjustment algorithm.

A single-phase five-house radial network is considered for this purpose. Impedance of a single phase line is considered as the data presented in Appendix B Table B.1, where the similar value is maintained in each line [85]. All houses are assumed to have seven similar controllable appliances. Initially, two different decision processes are analyzed; one with API and the other without API. As shown in Fig. 3.4, customer priority deviates more if API is not considered during decision making. That is, appliances with higher customer priority are also selected for adjustment.

Further, the average selection of loads for 30 random days is observed. The selection of loads deviates from the reference API values as in Fig. 3.5 (a), violating customer preferences. A similar study is done using AFI and results are shown in

Fig. 3.5 (b). Hence, these indices are important in maintaining customer preferences. Here, all houses are assumed to have the same reference values for API and AFI. Also, ranks of houses are kept constant. Actual API and AFI are calculated based on the number of controls within the day without API and AFI in decision process. Appliance selection deviates from the customer specified value if these indices are removed from the decision process.

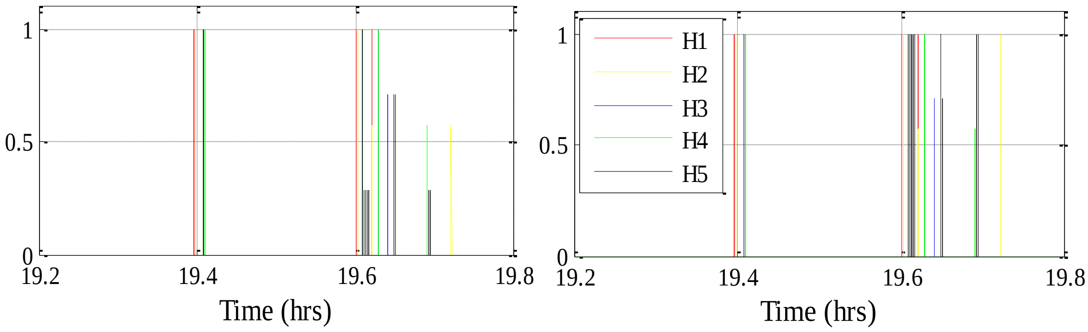

Fig. 3.4 API during each control (a) without (b) with API in decision process

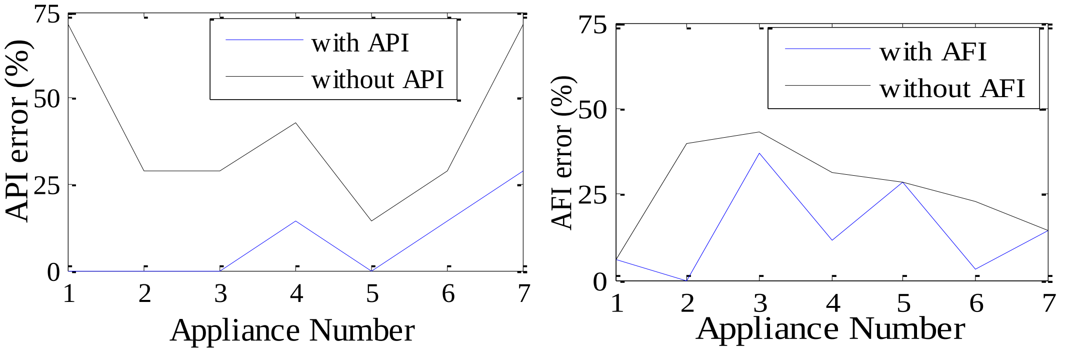

Fig. 3.5 Error in (a) API (b) AFI when API (or AFI) is considered or not

Moreover, ASI is significant because it reduces the selection of appliances which are in the middle of operation. An experiment with and without ASI during decision process is conducted for 30 days and results are compared. The percentage of appliances such as washing machines, dish washers, and dryers interrupted in the middle of operation is 2-5% whereas it is 12.5% without ASI. Hence, it prevents these appliances from being interrupted in the middle of their operation cycle.

The significance of PSI is analyzed in a case study with and without PSI. It is observed that controls reduce from 39 to 32 in a significant day. On an average 15-25% of controls are reduced by the use of PSI. Hence PSI is an effective factor in the decision process. HPCI is important in selecting house with maximum consumption that lead to network problems. It provides benefits to the customers who have an average consumption schedule and do not considerably violate the network. If HPCI is not included in decision process, a house with maximum consumption is likely to be selected only 20-30% of the time. This shows that each criteria index is complementary and necessary for effective load adjustment.

3.3.2. **Evaluation of cost coefficients for CR**

Annual supply and demand curves are used to find cost coefficients of the rebate function in (3.10). The supply curve is dependent on the marginal operating costs of various generators in the electricity market. The demand curve changes according to the consumption pattern of customers. These curves can be obtained from utilities and market operators and have daily (peak and off peak) as well as seasonal (summer and winter) variations [86]. For simplicity, the monotonically decreasing demand curve and monotonically increasing supply curve, as shown in Fig. 3.6, are considered for the calculation of α and β.

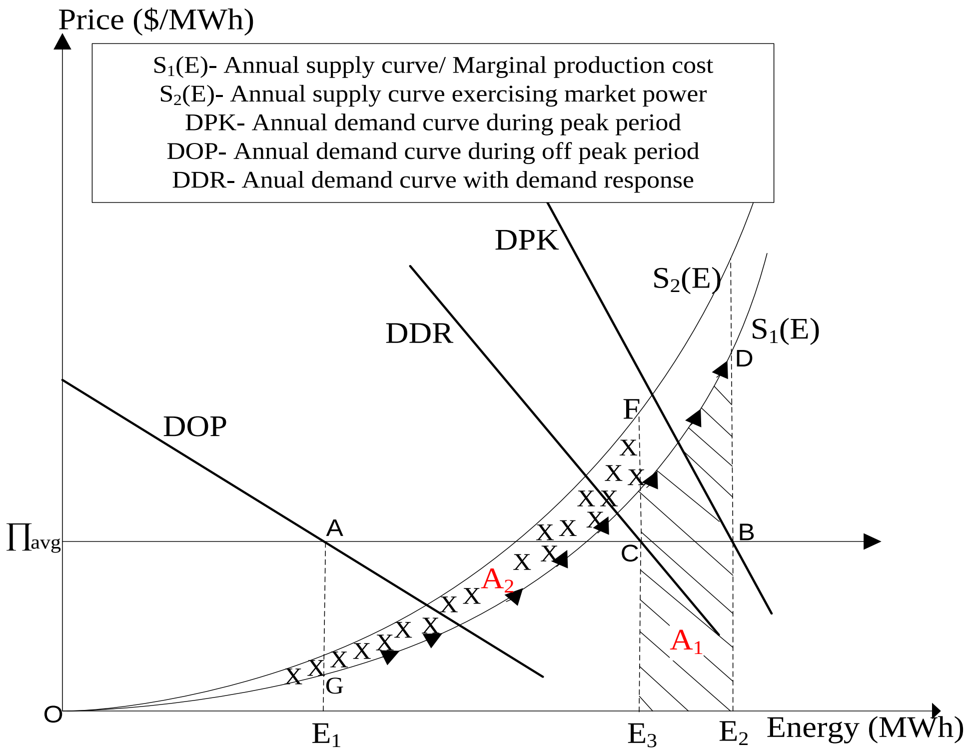

Fig. 3.6 Supply and demand curve with and without CR scheme

During off-peak time, demand is lower and is represented by the curve DOP, whereas the increase in demand at peak time can be shown by curve DPK. For a constant tariff (flat rate), the price is fixed at Π_{avg} and therefore the market during off-peak time operates at point A for quantity demanded E_1. The increase in demand causes a shortage of supply, which leads to an increase in price. Due to the increased price, the utility will increase the quantity of supply from point G to point D, as shown in Fig. 3.6, to cater to the increase in quantity demanded from E_1 to E_2. However, due to flat rate, the market operates at point B. The demand response will reduce the demand and shift the demand curve to the left, which can be represented as DDR [87]. At the same time, the supply price increases and shifts the supply curve to S_2. This is because the suppliers are provided with reduced incentives to exercise market power [88]. Finally, the market operates at point C after demand response achieves the reduction from E_2 to E_3.

The cost of supply due to demand response is reduced and it is the difference between ODE_2 (area under the supply curve S_1) and OFE_3 (area under supply curve S_2). For simplicity, it can be represented as (A_1-A_2) as shown in Fig. 3.6.

Energy values E_1, E_2, and E_3 are found using annual supply curves mapped to the intersection of demand curves with a fixed price. A_1 and A_2 are found after the computation of E_2 and E_3, respectively.

The total rebate in the network for a day should be less than the reduction in cost of supply due to demand response. Hence, the total rebate for the network, $Rebate_{total}$, that can be offered by the utilities to their customers should be less than the cost savings because of demand response. That is, (A_1-A_2) should satisfy (3.11).

$$\left\{Rebate_{total} = N * \left(\alpha . E_{shift}^{avg} + \beta . \Delta V_{imp}^{avg}\right) \text{ and } Rebate_{total} < \left(A_1 - A_2\right)\right\} \tag{3.11}$$

Here, N is the number of houses in the network. E_{shift}^{avg} and ΔV_{imp}^{avg} are components related to the average shift in energy and voltage improvement that is calculated from offline load flow studies using the annual demand and supply curves.

For example, if a 500kVA network is overloaded by 150 kVA, then E_2 and E_3 are 650 kVA and 500 kVA, respectively. The reduction in cost, i.e., (A_1-A_2), is \$100 using a sample supply curves from [89]. E_{shift}^{avg} and ΔV_{imp}^{avg} are found to be 0.041 and 2.0, respectively, for an average house using offline load flow studies. If β is kept at 1.0, the value of α is found to be 20 to satisfy (3.11). Note that the utility can choose appropriate values of α and β to incentivize the increase of customer participation. This depends on the network layout, the number of customers, and the existing tariff. The rebate pattern can be changed by the utility for every quarter of the year to accommodate seasonal load changes.

3.3.3. **Customer rewards**

A single-phase five-house model is considered to evaluate rebate calculations. For simplicity, houses are assumed to have similar appliances of 1 kVA each. The power consumption profile in each house is assumed to be the same. API and AFI are fixed in every house as in Table 3.3 and Table 3.4.

A rebate for each house is calculated every 24 hours by the utility to provide benefit to the customers as discussed in Section 3.2.4. The results obtained for 5 houses are tabulated in Table 3.7. H2 pool pump (#2) and electric vehicle (#5) are adjusted for 12 minutes and for 4 minutes with 1 kW of shifted power, respectively. Hence, the rebate for the total shifted energy and the voltage improvement is $0.45 and $0.51, respectively. So, H2 will get a total rebate of $0.96 ($0.45+$0.51). It shows an increased rebate towards the end of the feeder in case 1. Customers towards the end of the feeder will be benefitted with an increased rebate due to more load adjustments. Here, the total rebate paid by the utility to all five houses is $9.99. It is interesting to note that H1, at the beginning of the feeder, has fewer rebates for voltage improvement than H5 at the end of the feeder. H5 will have significant effect on the feeder voltage due to load adjustment and, hence, will have a higher rebate component for voltage improvement than the corresponding energy component.

Scenarios with traditional demand response (no rebates) and CR scheme are compared for Australian residential tariff 11, which is 0.25 $/kWhr [90]. The cost of consumption is calculated based on the price of electricity and energy consumed every hour. Table 3.8 shows the cost of electricity for a few selected customers for a peak day. For instance, with constant tariff, the consumption cost of H1 is $10.45.

If H1 participates in the traditional demand response, the cost is reduced to $9.85, due to reduced or delayed load consumption on that peak day. In the absence of any rebates the customer is not rewarded for their participation in load adjustment. With the proposed CR scheme, the rebate obtained due to load adjustment of H1 is $0.52 ($9.85 -$9.33=$0.52). Hence, H1 will pay only $9.33. Note that the rebate increases towards the end of the feeder due to significant voltage improvement component.

3.3.4. **Implementation and operations of CR scheme**

A two-level hierarchical control scheme is proposed for demand response in the residential distribution feeder. The primary control level is used to regulate the feeder voltage within an acceptable range and the secondary control level is conceived to prevent respective transformer overload. The primary controllers (smart meters) are installed at each house to collect power consumption data and communicate with the secondary controllers installed at the transformer.

Each appliance in the house has appliance units (AU) and communicates usage characteristic data at each time interval. AUs collect data from other AUs and then transmit and receive data from central smart meter via WiFi or ZigBee. It has a customer override button in case of any emergency operations. A simple block diagram shows a smart meter as in Fig. 3.7. This system will allow customers to have an efficient and economical electric system. Signals obtained from smart meters include ON/OFF time, power rating, and the power level of the appliances. This is feasible for houses equipped with smart meters. The role of the secondary controller is to maintain all the transformer loads below their rated values, while minimizing the negative impacts on the customer side. All controllers have low bandwidth and two way communication capabilities.

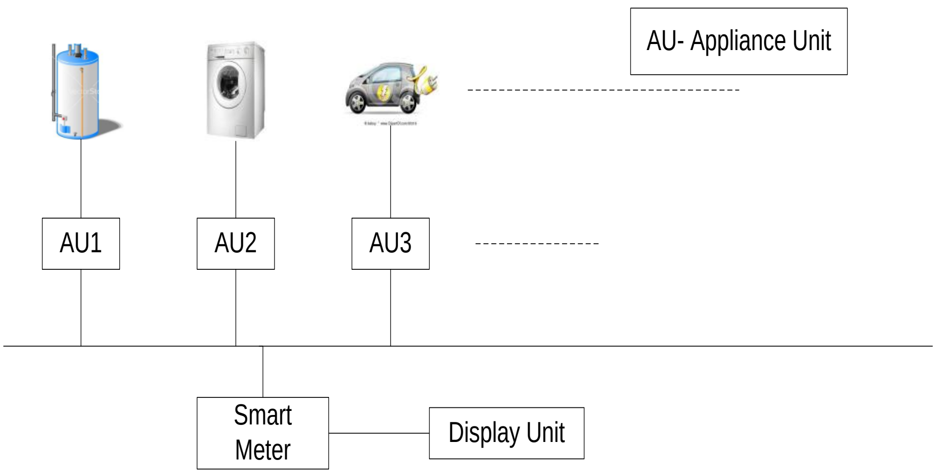

Fig. 3.7 A smart meter at each house connected with appliances

Table 3.7 Detailed Calculation of Rebate for 5 Houses in one feeder

House No#	Appliance No #* (Power(kW),Time(min))	Energy Shift, E_i (kWhr)	Rebate for shifted Energy ($) $\alpha * \left(\exp\left(\sum_{l=1}^{Nadj} \frac{E_i^l}{E_{\lim}} \right) - 1 \right)$	Component of Voltage improvement of that house (p.u.) $\sum_{l=1}^{Nadj} \frac{\Delta V_i^{\,l}}{\Delta V_{i,\lim}^{\,l}}$	Component of Voltage improvement of other houses(p.u.) $\sum_{l=1}^{Nadj} \sum_{\substack{m=1 \\ \neq i}}^{Nv} \frac{\Delta V_m^{\,l}}{\Delta V_{m,\lim}^{\,l}}$	Rebate for voltage improvement ($)	Total Rebate $Rebate_i$ ($)
1	2(1,12)	0.2	0.34	0	0.18	0.18	0.52
2	2(1,12),5(1,4)	0.27	0.45	0	0.51	0.51	0.96
3	2(1,20),5(1,12),7(1,4)	0.47	0.79	0	0.82	0.82	1.61
4	2(1,20),5(1,12),7(1,4)	0.60	1.03	0.71	1.41	2.12	3.15
5	2(1,8),4(1,28),5(1,8)	0.73	1.26	0.82	1.67	2.49	3.73

*Appliance No #1-Water heater; #2-swimming pool pump, #3-hysteresis type AC, #4-inverter type AC, #5-Electric Vehicle, #6-Dish Washer, #7-Clothes Washer, #8- Dryer .

Table 3.8 Cost of electricity consumption in a peak day for few houses

House No#	Without Demand Response ($)	With Traditional Demand Response (no rebates) ($)	With CR Scheme ($)
H1	10.45	9.85	9.33
H2	10.45	9.64	8.68
H3	10.45	9.04	7.43
H4	10.45	8.65	5.5
H5	10.45	8.26	4.51

Programmable Logic Controllers (PLC) can be used for this purpose which has the many more advantages. PLC is cost effective for complex control systems and flexible which can be reapplied to control other parameters in future. Further, it has computation ability to allow more sophisticated control. Trouble shooting aids with reliable components in PLC helps it for long lasting applications. It can mainly contain inbuilt Ethernet cards, RS232 ports for hardware links, good memory and I/O (analogue and digital) cards for complex programming.

Although the transient effect can be important during the demand response, voltages and currents transients caused by load change may last for no more than 50 and 20 milliseconds, respectively. In the 4 minute timeframe for load adjustment, this effect is not considered at this stage.

The step by step load control process, as discussed in the load control section above, is more efficient because it removes the rebound effect from the decision of which loads are to be curtailed. It also provides an appropriate control of power and voltage as it constantly checks for violation during the offline process.

3.3.5. **Scalability**

This decision process can be separated for subsystems (For example, each 500 kVA network). Load curtailment can be made separately for each subsystem when it is subject to overloads or voltage violations. This is made possible by having a main controller at each transformer level which has access to relevant smart meters in the houses. Hence, it can be deployed at a range of scales in small and large configurations easily. Data processing can be done in parallel for each system and therefore the time consumed in processing data is minimal.

3.3.6. **Prevention from customers misusing this scheme**

Possible gaming can be avoided by restricting customer load switching by introducing an override command. This will dynamically change the API to 1 for that load and therefore it will not be selected for adjustment for the rest of the day. If a customer chooses to operate a particular load more than two times in the peak period, then the information is send back to the utility as an override and rebate would not be paid for that load shift.

3.4. Case Study

Implementation of this control scheme for DLC for residential customers is shown in Fig. 3.8. The 11kV/415V, 500 kVA transformers have four feeders. Each feeder contains 30 houses evenly divided per phase. There are eight 11kV/ 415V transformers with controllers further controlled by the controller of a 33kV/ 11kV, 4 MVA transformers. Again, there will be six 33kV/11kV transformers which will be controlled by the controller of a 132kV/ 33kV, 24 MVA transformer at sub-transmission level.

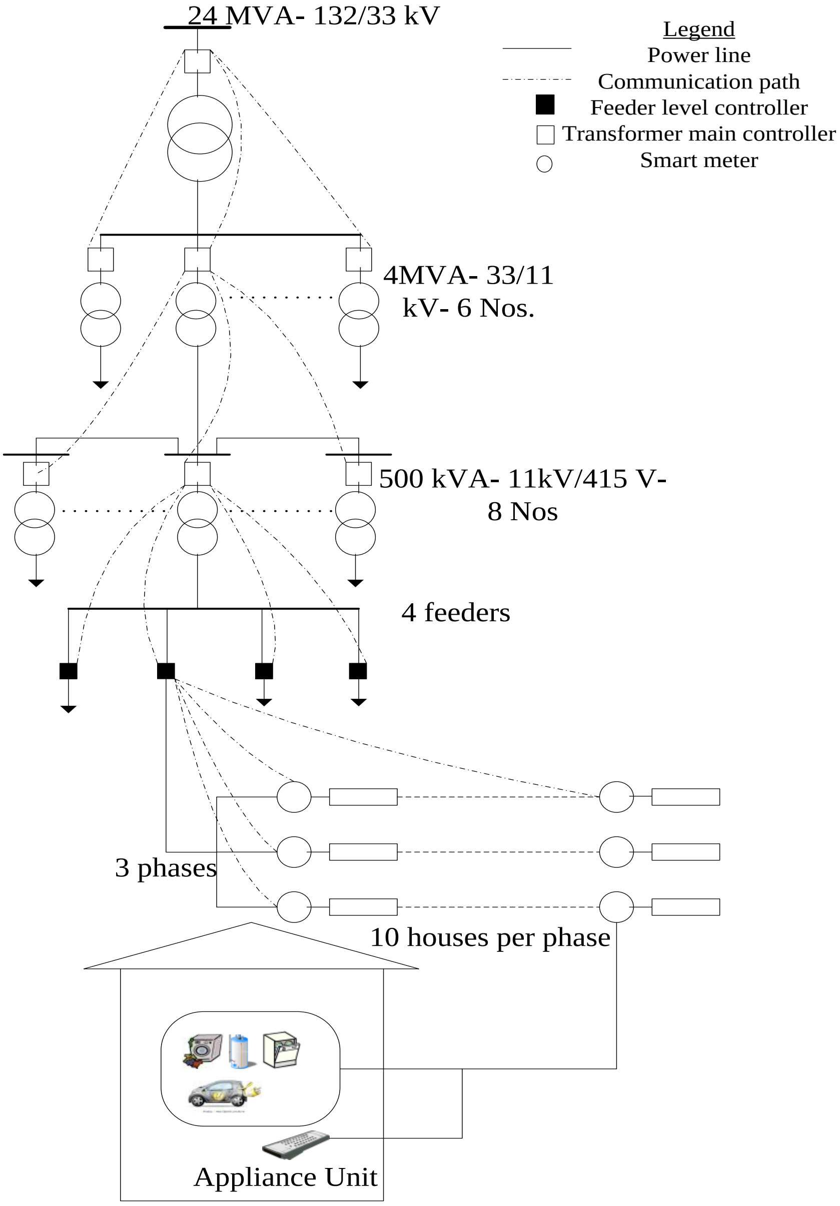

Fig. 3.8 Hierarchical control scheme for CR based Demand response

An indoor thermal model for a house is used which affects the power consumed by ACs, ambient temperature [91], and the floor area of each house. Each appliance contains a mean power rating and a time usage pattern which closely suits the real system.

A climate model is used to vary the temperature and it is linked with the time usage pattern of individual appliances. Transformer and other switch gear ratings are chosen to meet the aforementioned requirement. Further, every house is assigned with a floor area corresponding to the Australian 2008 new house data [92] which is used for the calculation of appliance loads. In order to create a realistic system, 90% of the houses are considered as unoccupied during week days (8am to 5pm) where most of the appliances will be unused as people are assumed to be at work. Simulations in all models maintain a fixed time step of 2 minutes of a user-defined interval to generate regular events. Network and transformer loads are calculated based on the algebraic sum of active and reactive loads.

3.4.1. **Impact on feeder voltage and transformer overload**

The voltage profile of a selected three-phase feeder with and without the proposed control scheme is shown in Fig. 3.9. Improvement in voltage profile is apparent, especially towards the end of the line at each phase. Similar improvement is observed in other feeders as well.

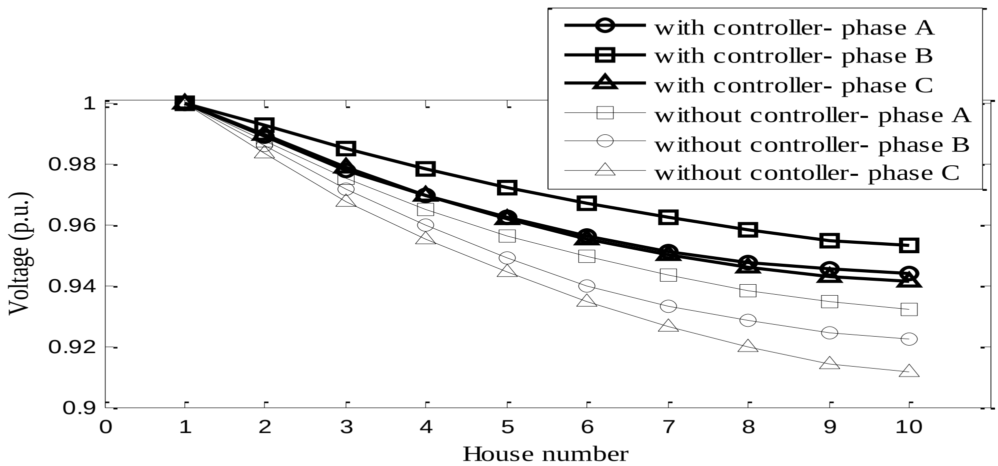

Fig. 3.9 The voltage profile of the residential feeder at peak time (1940 hrs)

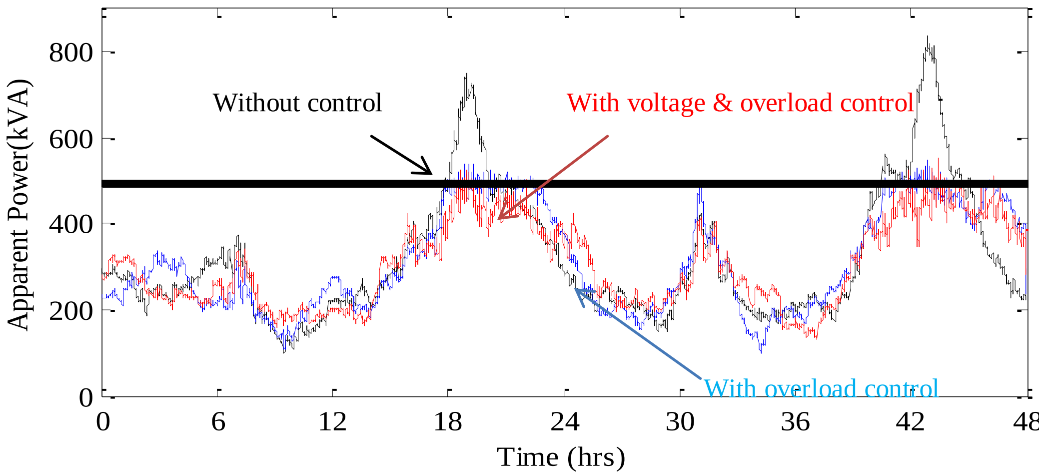

Fig. 3.10 Loading of 500kVA transformer without and with controller

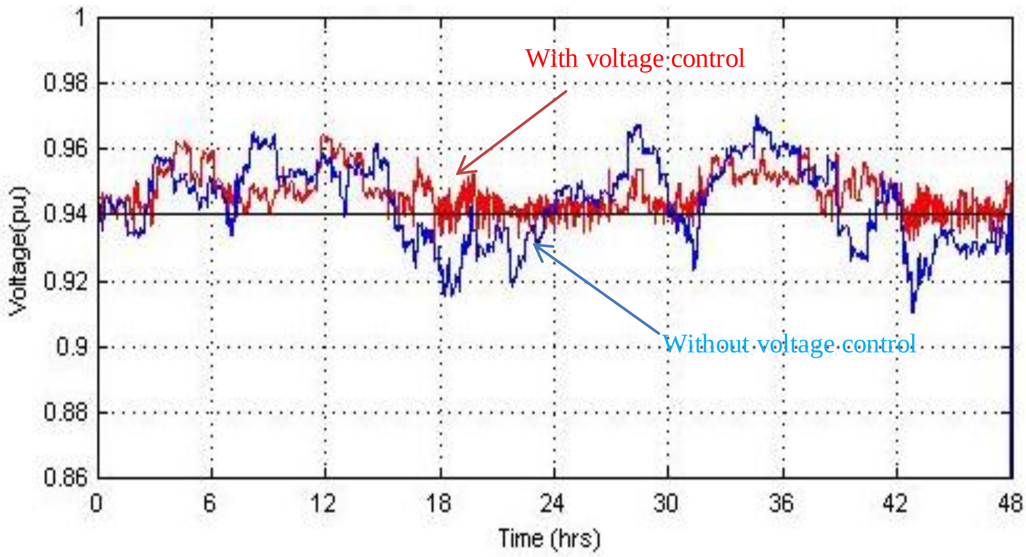

Fig. 3.11 Voltage profile at the end bus of feeder- 1 without and with control

Furthermore, the network loading level is observed via the 500 kVA transformer for a 48-hour period and is shown in Fig. 3.10. The transformer is overloaded by approximately 50% for a 2-hour period without any control scheme. The proposed voltage controller is able to relieve the transformer overloading. Transformer overloading can still be avoided with the implementation of a simple overload (power) controller, as shown in Fig. 3.10.

A simple overload (power) controller uses the same load control process (as in Fig. 3.2 and Fig. 3.3) except for the limitations in voltage. Therefore, voltages in the network are not monitored and/or controlled. Fig. 3.11 reveals the effect of the proposed voltage controller over the simple overload (power) controller. When the voltage profile towards the feeder end is analyzed, the proposed voltage controller performance can be appreciated during peak hours, i.e., hours 18 and 42, as shown in Fig. 3.11. Thus, this illustrates the importance of the proposed control scheme in eliminating voltage violations.

3.4.2. **Power loss reduction in the network**

This control scheme automatically results in loss. As an added advantage, network loss calculations were done along with the load flow study and the loss is again added instantaneously with the total load during the control action. The observed losses during the peak hour were 26.8 kW and 14.8 kW with and without the controller. Hence it considerably reduces the losses and creates an efficient system. The losses with and without the control scheme is depicted in Fig. 3.12.

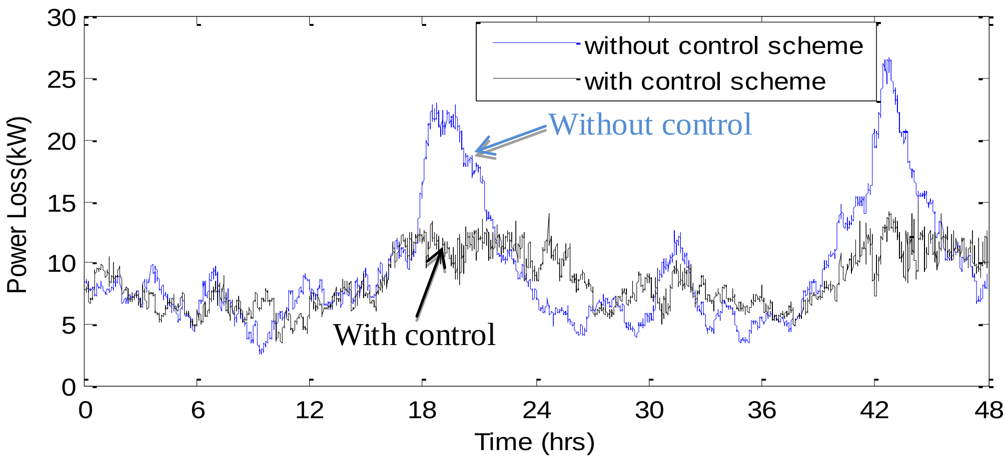

Fig. 3.12 The active power loss of the network with and without control

3.4.3. **Effect on customer loads and its impact on ASI**

The performance of this control scheme on the customer side is investigated by observing the effect on the operation of a few critical controllable loads. Fig. 3.13 shows the waveform of the charging states, reflected by ASI, of three selected PEVs in the network. It shows that the PEVs are being charged after arriving home (hour 18) and it achieves 100% charging by midnight. Small flat line segments in the graph shows that the PEVs are disconnected due to the control action and then reconnected after 4 minutes.

Inverter-based ACs and water heaters are large adjustable loads where the set points of room temperature and the water tank temperature can be adjusted during the control action. ASI values of three selected ACs are shown in Fig. 3.14. The controller increases the temperature by 1ºC during each control action and is re-adjusted (if required) after 15 minutes. The sudden variation of the temperature set point of a selected inverter type AC in phase- A during the control action is shown in Fig. 3.15.

Considerable satisfaction, in terms of ASI for AC loads, is achieved. ASI of water heater and the tank temperature set point variation are shown in Fig. 3.16 and Fig. 3.17, respectively. Similar behavior is observed for all controllable loads in the network which confirms that the control scheme does not affect ASI adversely.

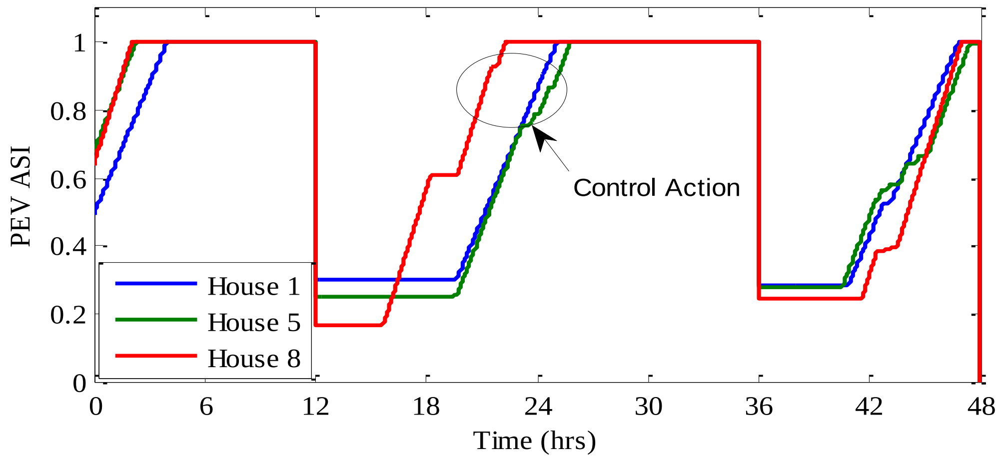

Fig. 3.13 ASI of 3 selected PEVs in phase- A of feeder 1

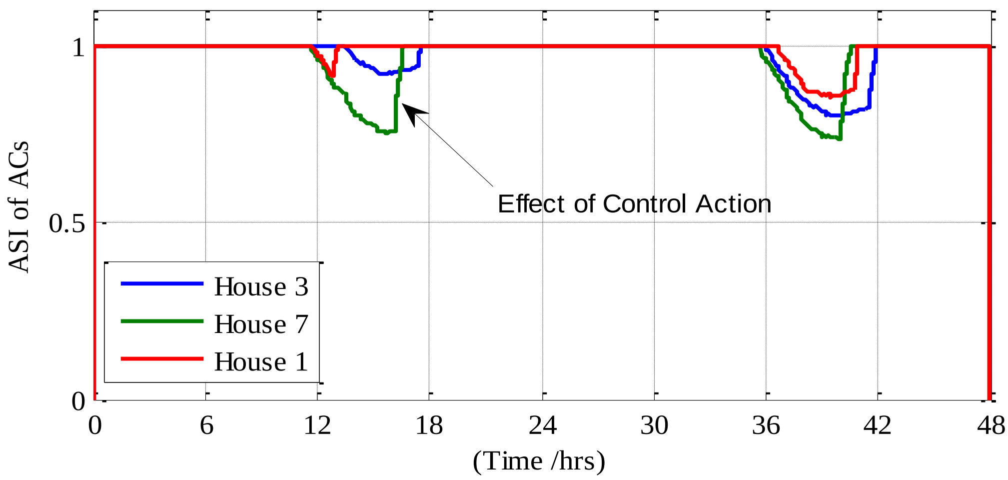

Fig. 3.14 ASI of Inverter type Air Conditioners in phase- A of feeder 1

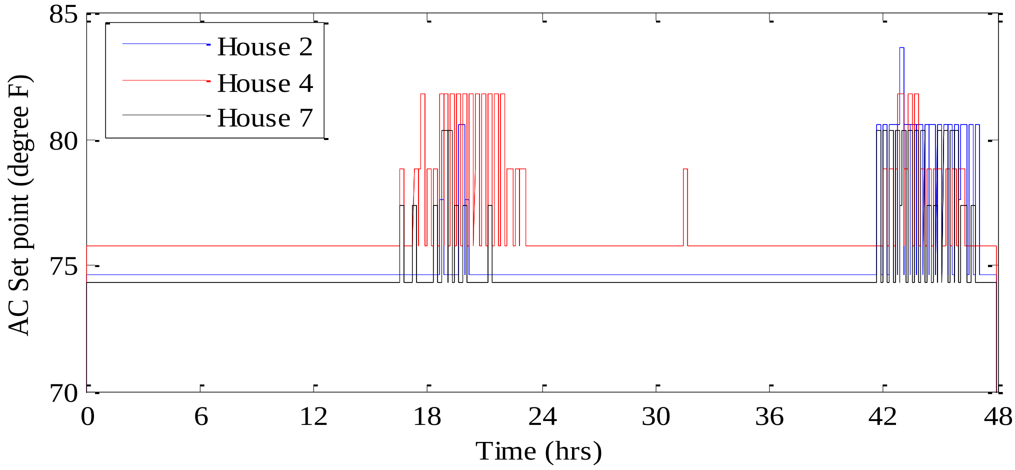

Fig. 3.15 Set point variation of inverter type AC in house 2, 4,7 (phase A)

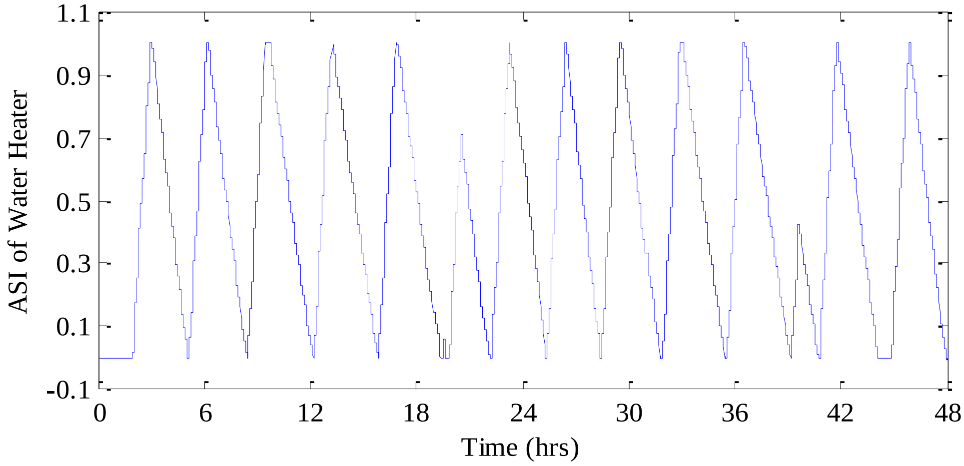

Fig. 3.16 ASI of a water heater in House 7 of Phase- A of feeder 1

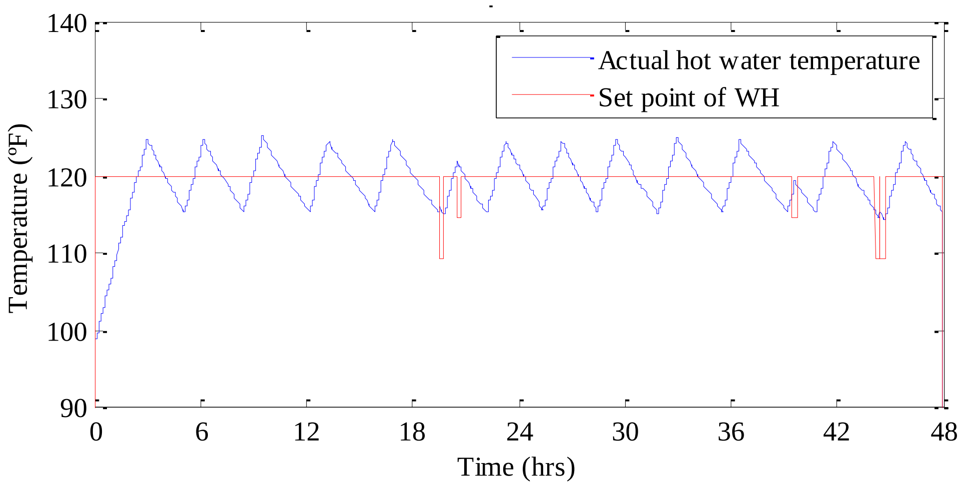

Fig. 3.17 Set point and actual tank temperature variation of a WH in House 7

3.4.4. **Robustness of CR scheme under increasing PEV penetration**

The robustness of this control scheme is tested by increasing the penetration of PEVs in the distribution feeder. System with low (25%), medium (40%) and high (75%) penetration of PEVs is simulated in the LV network. The results are shown in Fig. 3.18. Voltage dip is very high without control. Using control scheme, the voltage profile is drastically improved.

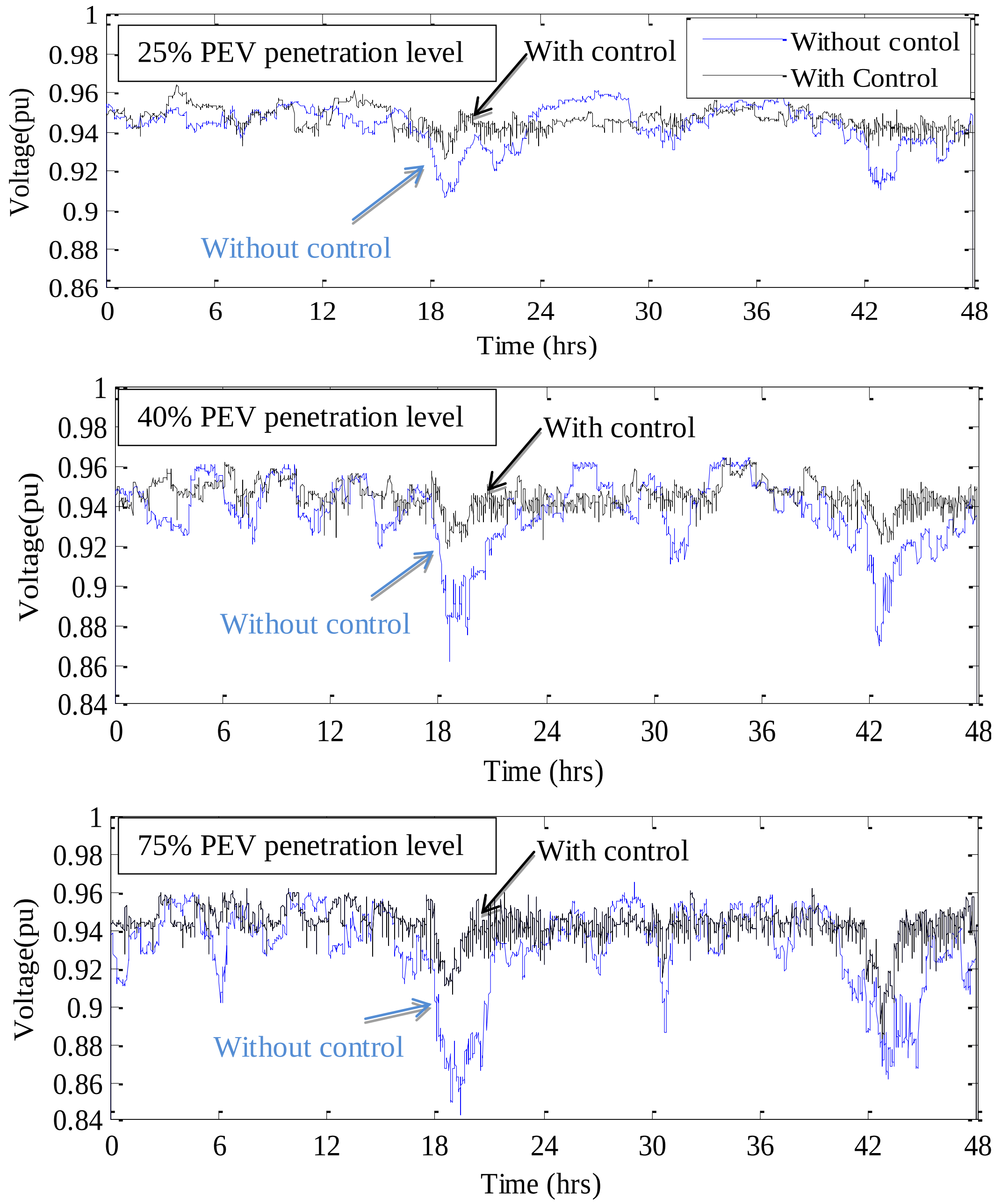

Fig. 3.18 Voltage profile at the end- bus at phase- C with and without control

3.4.5. **Effectiveness of this scheme on overloading due to load growth**

An annual peak demand growth of 4.36% [93] is assumed and CR scheme is tested on the 500 kVA network. The system loading level and ASI of appliances are observed for the next 15 years. Simulation results can be summarized using Fig. 3.19. ASI of two selected appliances drops below the acceptable limit of 0.9, when the increase in peak demand reaches 299 kVA. Later, the system overloads and then diverges (i.e. divergence of power flow solver) when peak power increase beyond 300 kVA. Therefore, the proposed demand response scheme can effectively shave the network peak for almost eleven years ($500\times1.0436^{11}\approx500+299$), before the transformer needs to be upgraded. The proposed control scheme allows a peak increase of 299 kVA, without worsening ASI and protecting the network from overload and voltage violations.

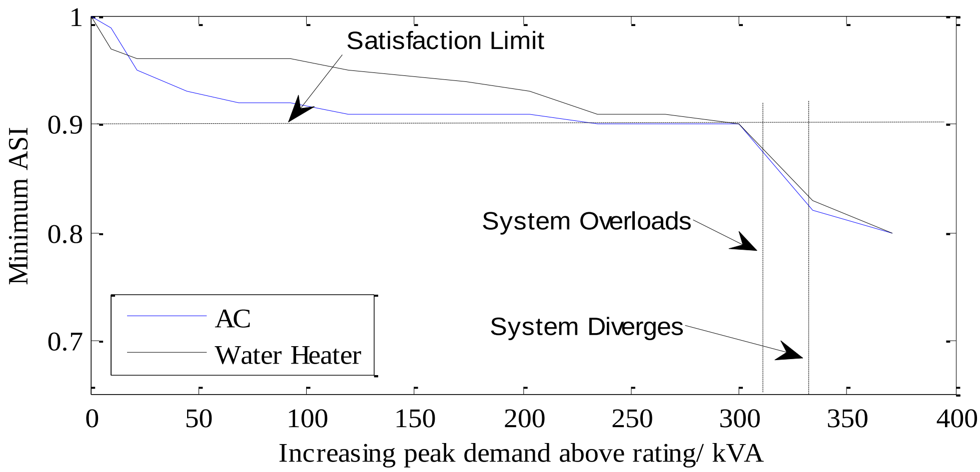

Fig. 3.19 Appliance Satisfaction Index verses increased peak demand

3.5. Summary and Conclusion

Demand response for a residential distribution system using a Customer Reward (CR) scheme is proposed in this research work. CR deploys two-level hierarchical control schemes consisting of the primary controller (smart meters) to regulate the feeder voltage within an acceptable range and the secondary controller to prevent transformer overload. Various indices reflecting a customer's flexibility and satisfaction for controllable loads are modeled to obtain decision matrix for load adjustment. Customer engagement is encouraged through the reward mechanism. The impact of CR on network voltages, customer satisfaction indices, and appliance usage patterns are investigated. Customers are rewarded based on their participation for load shifting and associated voltage improvement in the feeder. The proposed demand response via CR scheme can effectively shave the network peak for several years, before the feeder transformer needs to be upgraded.

Chapter 4

A Novel Real-Time Pricing Scheme for Demand Response in Residential Distribution Systems

Price based technique is one way to handle increase in peak demand and deal with voltage violations in residential distribution systems. This chapter proposes an improved real-time pricing scheme for residential customers with demand response option. Smart meters and in-home display units are used to broadcast the price and appropriate load adjustment signals. Customers are given an opportunity to respond to the signals and adjust the loads. This scheme helps distribution companies to deal with overloading problems and voltage issues in a more efficient way. Also, variations in wholesale electricity prices are passed on to electricity customers to take collective measure to reduce network peak demand. It provides customers to make their own choices during appliance adjustments comparing to Direct Load Control (DLC) technique in Chapter 3. It is ensures that customers and utility benefit by this scheme.

4.1. Introduction and Related Work

Increase in network peak demand, leading to overloading and poor voltage profile is one of the major problems faced by the present electricity distribution system operators. Direct Load Control (DLC) approach has been used to curtail the customer loads and avoid network overload [94]-[97]. Another option is the Price Response Demand (PRD) scheme, where the customers will be adversely affected by high price signals during peak hours due to high power consumption. PRD allows customers to participate in this scheme by shedding their loads to reduce the energy consumption cost [98].

Several cost functions are introduced to support PRD including hourly pricing, daily pricing, fixed Time Of Use (TOU) pricing [99] and seasonal flat pricing. Special provisions for electric vehicle charging rate and rates related to distributed generation are also introduced [100]. Fig. 4.1 summarizes the various schemes available under PRD.

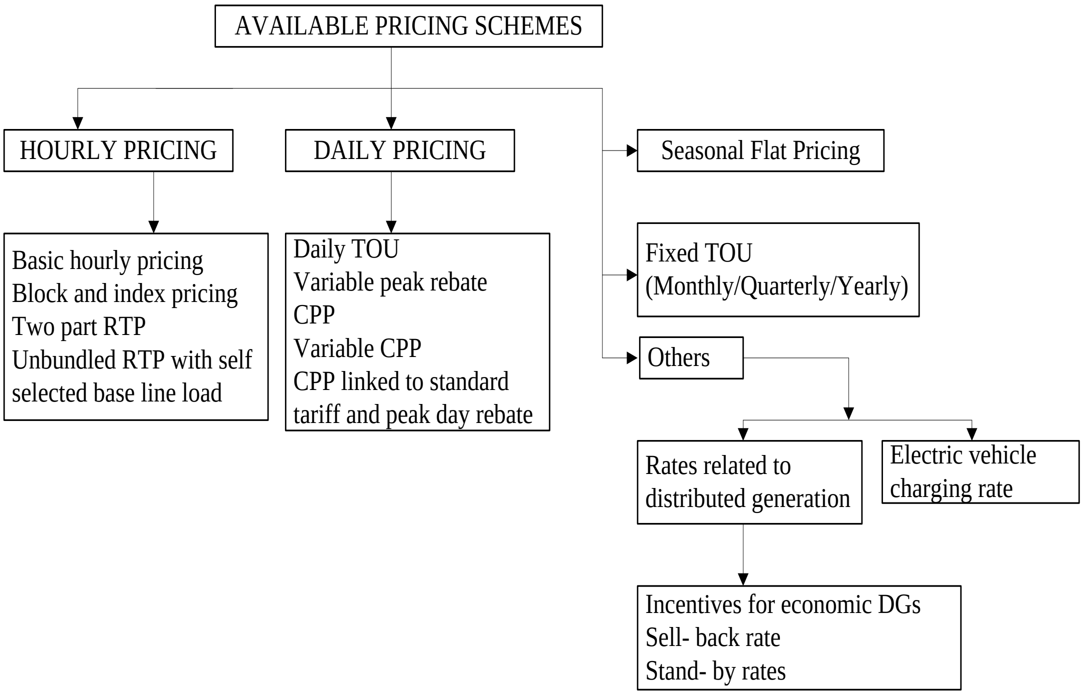

Fig. 4.1 The Available retail pricing scheme

Hourly pricing scheme defines retail energy prices reflecting the variation in the wholesale market every hour and is applied mostly on large customers. In contrast to the hourly pricing, daily pricing has various fixed blocks of prices while keeping at least one block price variable within a day. The variation in price is announced on day-ahead or hour-ahead basis [101]. Further, pricing periods are defined according to time of day, day of week or season and they are fixed and announced monthly in advance in TOU tariff. However, the defined prices are inflexible [102]. The seasonal flat pricing has a fixed value for a season and varies for different seasons. The price represents the average difference between the power costs in relevant season and is announced one month in advance [103]. In addition, Critical Peak Price (CPP) and peak day rebate programs provide price signals to consumers reflecting wholesale prices only on critical peak day and the fixed standard tariff is used in the rest of the days [104].

The above methods have their own pros and cons. For instance the hourly pricing scheme has fixed blocks of prices which are inflexible and does not reflect the actual demand. TOU price does not provide incentives for critical days with actual power system conditions and unusual wholesale prices. Flat seasonal rates are the average of low and high cost of energy within a season and hence do not reflect the actual demand variation. CPP and peak day rebate rates have some implications on energy providers and customers. Customers have less risk on peak day rebate than facing unpredictable high price during CPP. But billing under CPP is much easier than peak day rebate for the energy providers [100].

A Real-Time Pricing (RTP) is introduced in [105] where price is calculated based on previous demand and then any deviation from actual consumption after a time step is reimbursed. Due to predicted price components, this pricing scheme may not be suitable for a system with more uncertainties and information asymmetry. However, RTP proposed in our research work has price components with instantaneous data analysis and hence accurately provide price information. The authors of [106] propose a new RTP to reduce peak to average load ratio. It is based on a two stage optimization technique, considering both customers to maximize payoff and retailers to maximize their profit. Another study proposes an optimal and automatic energy consumption scheduling of residences to minimize both electricity price and waiting time of appliances. Here, the RTP with inclined block rates are used [107]. However instantaneous optimization may consume more simulation time for decision making. However, method proposed in our research work has comparatively less data processing time due to simple calculations. It also considers not only excess load consumption but also voltage violations and wholesale price spikes while defining price unlike in other studies mentioned above.

Overall, this part of the research work proposes a new pricing scheme reflecting the actual load consumption of a residential customer, the wholesale price of the network and voltage violations in the network. Section 4.2 describes the new pricing scheme and Section 4.3 proposes the actual implementation of it. Section 4.4

describes the algorithm proposed for in-home display of customer's loads that would be beneficial to reduce the electricity consumption cost. Finally, Section 4.5 shows the results of a sample system due to the proposed scheme and illustrates the impact of this scheme to the customers, followed by conclusions.

4.2. The Novel Real-Time Pricing Scheme

The proposed price function for a house has three components reflecting actual load consumption, transformer overloading, voltage violations created in the network and wholesale electricity price of the retailer as in (4.1) and shown in Fig. 4.2. The price value (Π_i^t) is updated every five minutes and is available through smart meters.

$$\Pi_i^t = \Pi_{1i}^t + \Pi_{2i}^t + \Pi_{3i}^t \tag{4.1}$$

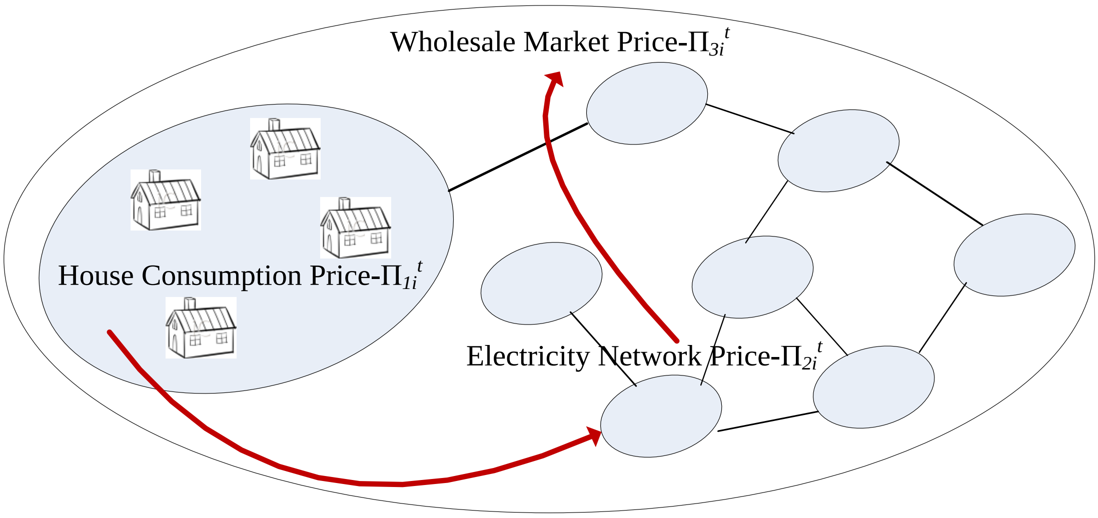

Fig. 4.2 Three price components of proposed pricing scheme

4.2.1. **Price component for actual load consumption (Π_{1i}^t)**

This price component has a factor of energy consumed when the network is not overloaded (This component is similar to stand alone electricity charge [109]) and has an added exponential component during overload situation. This first price component can be written as in (4.2) for i^{th} house at t^{th} time.

$$\Pi_{1i}^t = \begin{cases} \alpha_1 . E_i^t , \quad if \ L < L_{capacity} \\ \alpha_1 . E_{i\lim} + \alpha_2 . e^{\frac{(E_i^t - E_{i\lim})}{E_{i\lim}}} , if \ (L \geq L_{capapcity}) \text{ and } (E_i^t \geq E_{i\lim}) \end{cases} \tag{4.2}$$

where E_i^t is the energy consumption of i^{th} house during t^{th} time (5 minute interval); $E_{i\ lim}$ is the energy limit for i^{th} house and is taken as 0.3472 kWh (4.166x 5/60); L and $L_{capacity}$ is the kVA loading and capacity of the network respectively; α_1 and α_2 are cost coefficients, which can be decided by retailers and are taken as 5 and 1 respectively.

For example, for an overloaded network having a capacity of 500 kVA ($L_{capacity}$) and 120 houses, customers who consume more than the average maximum house limit of 4.166 kVA (i.e. 500 kVA/120) should be penalized. Therefore, this price scheme helps utility to penalize customers who consume above the threshold of 4.166 kVA, when the network is overloaded above the limit of 500 kVA using an exponential function for the price component.

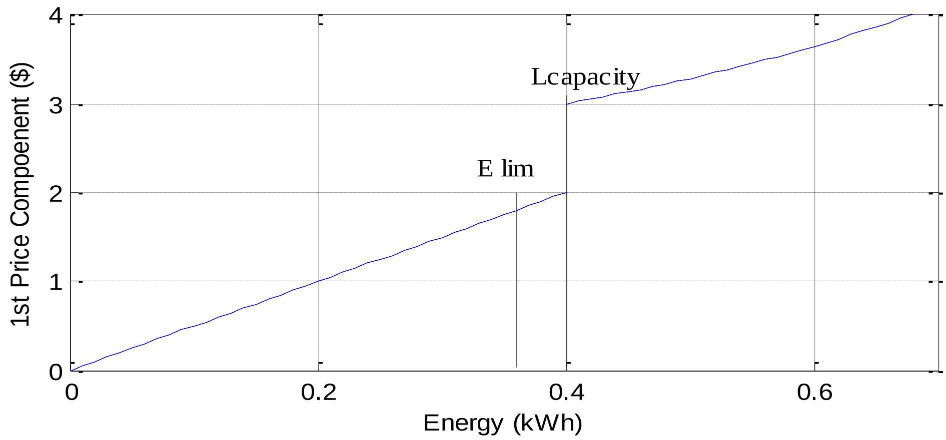

Fig. 4.3 First price components verses energy consumption

Fig. 4.3 shows the variation of proposed first price component Π_{1i}^t , with the increase in energy consumption. It shows that a linear cost profile is maintained until the network capacity ($L_{capacity}$) is not exceeded. Once, the network capacity ($L_{capacity}$) exceeds the limit, the exponential cost is added along with the linear cost profile which is subjected to the extra energy that is consumed above the energy consumption limit ($E_{i\ lim}$) of i^{th} house.

4.2.2. **Price component for Voltage Violation (Π_{2i}^t)**

The houses towards the end of the feeder experience voltage violations even when their loading is within limits. Hence, this pricing component is added for those houses that create voltage violations in the feeder. Voltage Sensitivity (ρ) parameter is used, which eliminates the risk of compensating the houses towards the end of the feeder by correctly choosing a pricing scheme. ρ is a sum of voltage deviations in all houses within one phase due to a particular load adjustment for i^{th} house. This is more realistic than the measure of voltage violation, because it exactly identifies the impact of load change on voltage. This price measure can be written as in (4.3).

$$\Pi_{2i}^{t} = \gamma . \frac{\rho_i^t}{\sum_{j=1}^{N_p} \rho_j^t} \quad V_j^t < 0.94\, p.u. \tag{4.3}$$

where N_p is the number of houses in a phase of particular feeder; γ is a cost coefficient (chosen as 10 in this study); V_j is the voltage of j^{th} house having voltage violation in the same phase.

4.2.3. **Price component for reflection of wholesale price (Π_{3i}^{t})**

Wholesale price depends on the electricity market competition and congestion in the transmission network and is decided by transmission grid operators. Retailers observe the variations in the wholesale price and can choose to pass on this to the residential customers. For a peak day, increase in the wholesale prices from the baseline price (Π_{BL}) can be passed on to the customers as per (4.4). It is noteworthy that this price is only applicable during critical peak days. The day-ahead or hour-ahead dispatch forecast ($\Pi^{t}_{wholesale}$) is used to calculate this price component.

$$\Pi_{3i}^{t} = \beta . e^{\frac{\Pi^{t}_{wholesale} * E_i^t - \Pi_{BL} * E_{i\,avg}}{\Pi_{BL} * E_{i\,avg}}} \quad , if \quad (\Pi^{t}_{wholesale} > \Pi_{BL}) \text{ and } (E_i^t > E_{i\,avg}) \tag{4.4}$$

where β is cost coefficient and is taken as 0.001; E_{iavg} is average house hold consumption chosen to be 1.5 kVA times five minute for all houses. When the wholesale price goes above Π_{BL}, the customers who consume more than the average value $E_{i\,avg}$ will be affected by the increase in price. In this study, Π_{BL} is chosen as 100 $/MWh.

Fig. 4.4 shows the variation of proposed third price component with the increase in energy consumption. Energy cost variation with four different electricity wholesale prices of 100, 110, 120 and 130 $/MWh is analysed. i^{th} house consuming more than the average consumption ($E_{i\,avg}$) is given with the third price value when the wholesale price ($\Pi^{t}_{wholesale}$) exceeds above the baseline value (Π_{BL}).

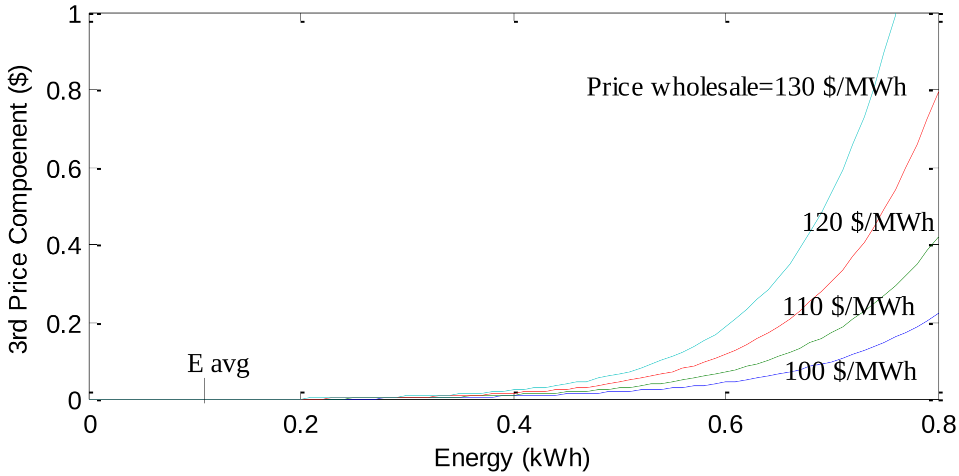

Fig. 4.4 Third price components verses energy consumption

Overall, the utility benefits when the customers willingly participate in this scheme by preventing overloads and voltage violations and also the risk due to critical day wholesale prices. Risk in the network is avoided so that a reduced price will be provided to the customers. The customers who are not willing to take part in this program considerably violate the network conditions and hence should pay a higher price due to the risk in the network. Therefore, this pricing scheme doesn't need another risk premium on pricing and it is advantageous for both customers and utility.

4.3. Practical Implementation of this Scheme

Advanced metering infrastructure having two ways communication capabilities can be used to implement the algorithm presented in Section 4.4. The voltage and power data from smart meters is sent in five minute intervals to the main controller and the calculated price signals and appliance indication details are sent back to smart meters located at each house. The communication capability of the network can be shown as in Fig. 4.5.

Collective points with low cost air interface (ZigBee) are much more feasible because it reduces the expensive modules of broadband wireless interfaces. The in-home display units have the capability of showing the details of current electricity cost and indicate the appropriate lamps when the price goes high to identify the appropriate appliance which can be switched off by the customers [109].

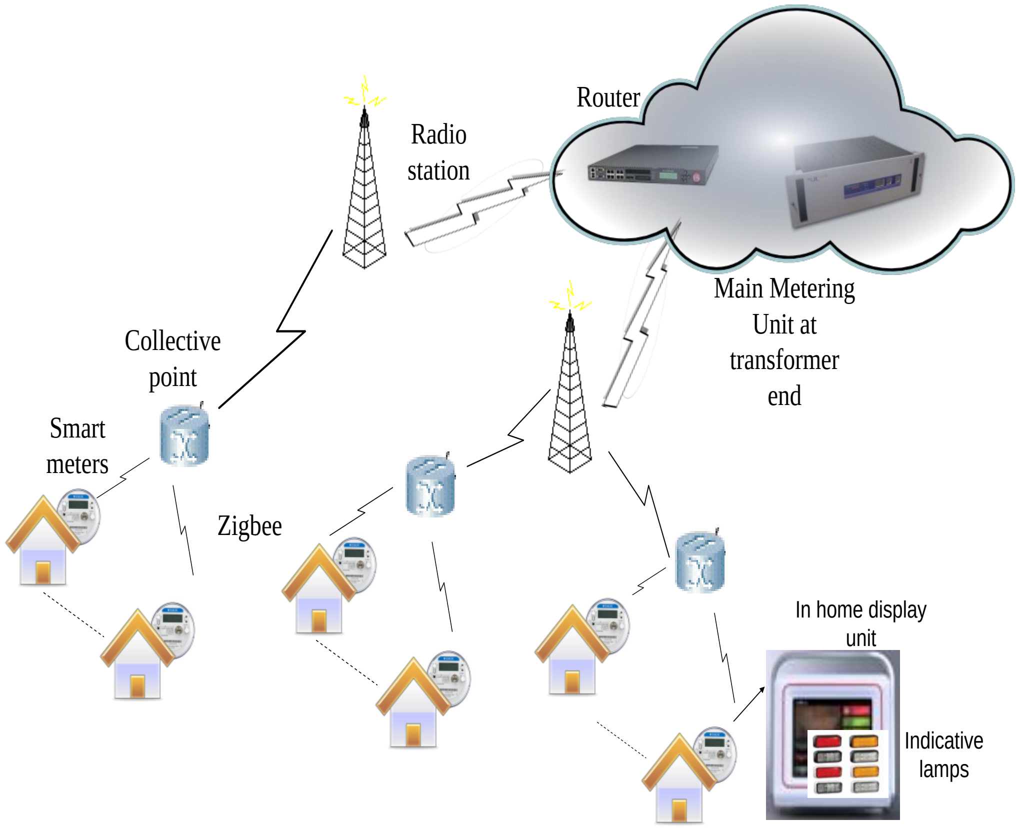

Fig. 4.5 Communication Capability of the network

4.4. Identification of Critical House Loads for Possible Adjustment

Smart Meters and in-home display units are used to identify the critical house loads for possible adjustments. It helps customers to easily identify the loads and take actions to minimize their electricity cost and help retailers to protect the network from overload and voltage violations. The in-home display unit will have a panel of eight indicative lamps representing selected eight controllable appliances such as water heaters (WH), Air Conditioners (AC), swimming pool pump (PP), electric vehicles (PEV), dish washers (DW), clothes washers (WA), and dryers (DR). The detailed appliances model used during the simulations are in Appendix A. The loads which can be adjusted will be indicated when the price goes higher than the normal consumption level. So, customers can easily spot the loads to be disconnected.The appliance selection procedure for indication is shown in the algorithm as in Fig. 4.7 which is discussed in detail at the end of this section. It is easier for the customers to manually control their appliances based on the indication. Initially the three parameters such as adjustability, operational characteristics and preferred order of the controllable appliances are calculated for five minute time interval. Then the appliances are arranged in ascending order according to the choice list and then the algorithm will indicate the appropriate appliances for possible load adjustments.

4.4.1. **Adjustability (*X_{1ij}*)**

The parameter adjustability for each appliance in a house will depend on their characteristics. Some appliances can be shifted any time during the day and it has the highest adjustability. A normalized value is obtained for the adjustability of j^{th} appliance in i^{th} house as in (4.5). The dish- washer, clothes washer and dryer have a very low adjustability because they cannot be stopped during operation and if it is stopped, it should start again from the beginning to complete the cycle. The calculation of adjustability is in Table 4.1.

$$Adjustability = \frac{adjustable\ range\ of\ time}{total\ available\ time\,(24\,hrs)} = X_{1ij} \tag{4.5}$$

4.4.2. **Customer preferred order of appliances (*$X_{2\,ij}^{t}$*)**

Customer preferred order ($X_{2\,ij}^{t}$) specifies the need of appliance at a particular time *t* according to the priority of appliance usage. A normalized value is obtained by using the total number of loads.

Table 4.1 Adjustability and Preferred Order of Appliances

Appliances	SW	PEV	AC	WH	DW	WA	DR
Adjustable range (hrs)	21	17	17	12	5	5	5
Adjustability	0.9	0.7	0.7	0.5	0.2	0.2	0.2
Priority order	7	3	6	1	2	4	5
Preferred Order	0	0.57	0.1	0.85	0.71	0.43	0.29

For example, water heater has the highest priority in i^{th} house at t^{th} time. So, 0.85(=1-1/7) is the preferred order of the water heater as shown in Table 4.1. Desired values of adjustable range of time and preferred order of appliances (as in Table 4.1) can be obtained from a customer survey and values are fixed for each peak day. The authors of [110] show that electricity consumption exhibits strong cyclic patterns over time. Hence, customer given data can be used for deciding load curtailment for a specific season. Further, customer data can be validated by observing power consumption profile of each customer appliance before implementing this scheme. The power consumption profile of each appliance in a house exhibits priority of them during peak hours. It also shows time range of appliance usage. Fig. 4.6 illustrates the preferred order of three selected houses for all appliances.

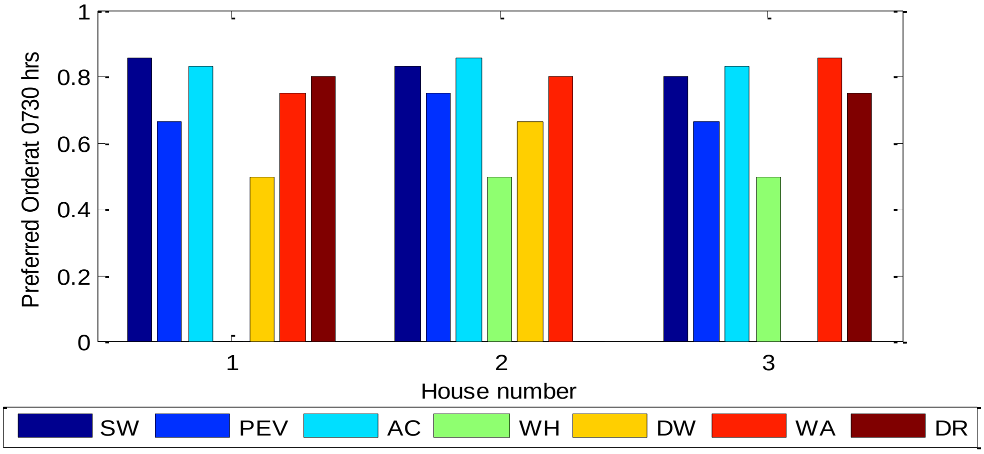

Fig. 4.6 Appliance Preferred order House 1, phase A, feeder 1 at 1900hrs

4.4.3. **The operational state of appliances ($X_{3\ ij}^{t}$)**

Operational state of appliances depicts actual state of appliance compared to desired state of it at a certain time instance. It is different for each appliance and changes with time. Operating statuses of each appliance are calculated based on Table 3.5 in Chapter 3.

The price signals are sent to the houses every five minutes. Selection of appliance for indication should depend on the above three parameters. A customer choice value is calculated as in (4.6) for this purpose. (i.e. the selection should happen with maximum adjustability, minimum preferred order and minimum operational state. Details of appliance selection algorithm are shown in Fig. 4.7.

$$Choice_{ij}^{t} = \text{average}\left(x_{1ij},\ (1-x_{2ij}^{t}),\ (1-x_{3ij}^{t})\right) \tag{4.6}$$

The choice value is used in the algorithm for appropriate load indication. The load indication in each house in the network can happen as shown in the algorithm in Fig. 4.7. Initially, the appliance list is prepared automatically according to the choice value at each house and at each time interval, when the price goes above the limit. If the first price signal goes high due to excess power consumption, the loads in the choice list is selected to match the excess power in that house (i.e. the appliances resulting excess power in a house will be indicated in the order of choice list). When the wholesale price increases, the total excess load in the network is recognized and divided among those houses which are consuming above the average of 1.5kVA. Furthermore loads relevant to voltage violations are identified using (4.7) as an offline process.

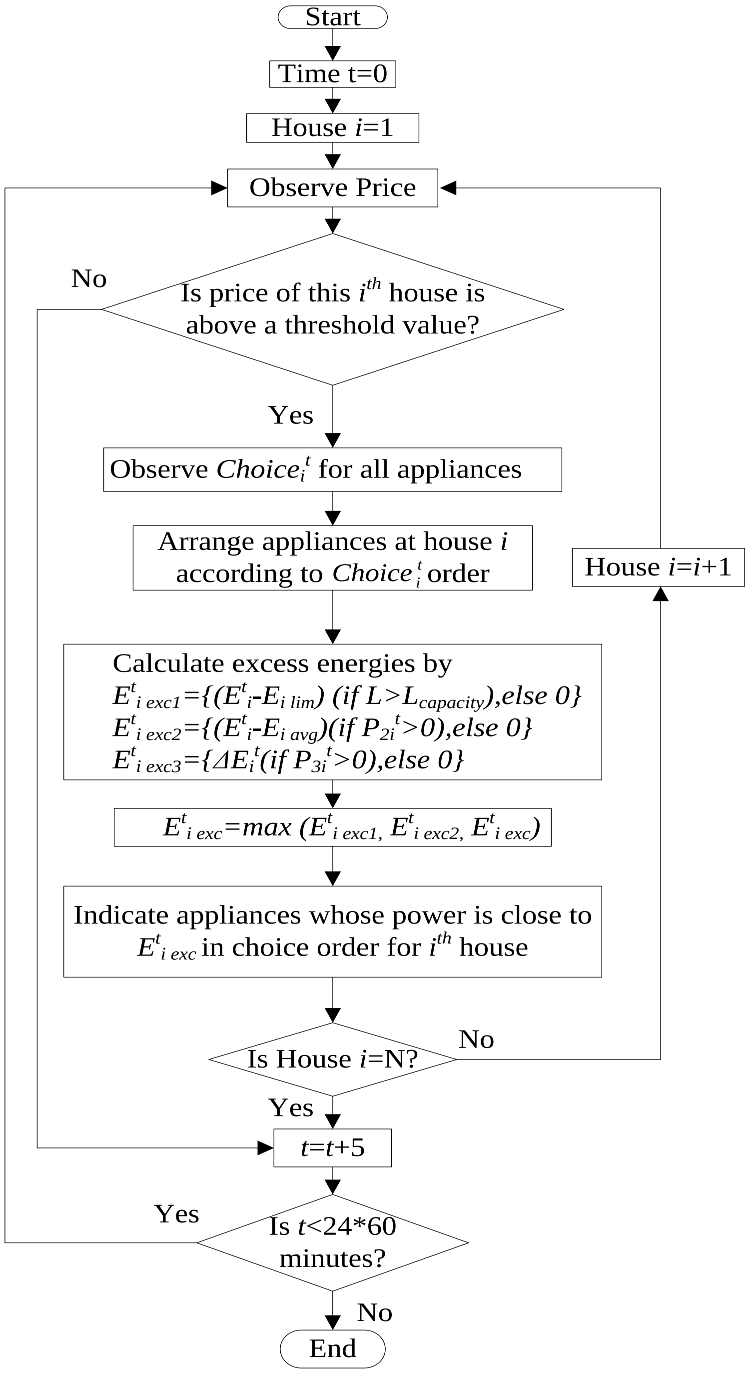

Fig. 4.7 Algorithm for appropriate indication of appliances in each house

$$\Delta P_i^t = \sum_{k=1}^{N_v} \frac{\partial P_i}{\partial V_k}^t \cdot \Delta V_k^t \qquad (4.7)$$

Where, N_v is the number of houses with voltage violations; ΔV_k is the voltage violation below the limit of 0.94 *p.u.* in k^{th} house. ΔP_i^t is the excess power in i^{th} house at t^{th} time.

4.5. Simulation Results

A simple distribution system with 30 houses connected to a 500 kVA transformer built by the authors of [32] is chosen for this study, to verify the efficacy of proposed pricing scheme for demand response. MATLAB is used to perform the simulations.

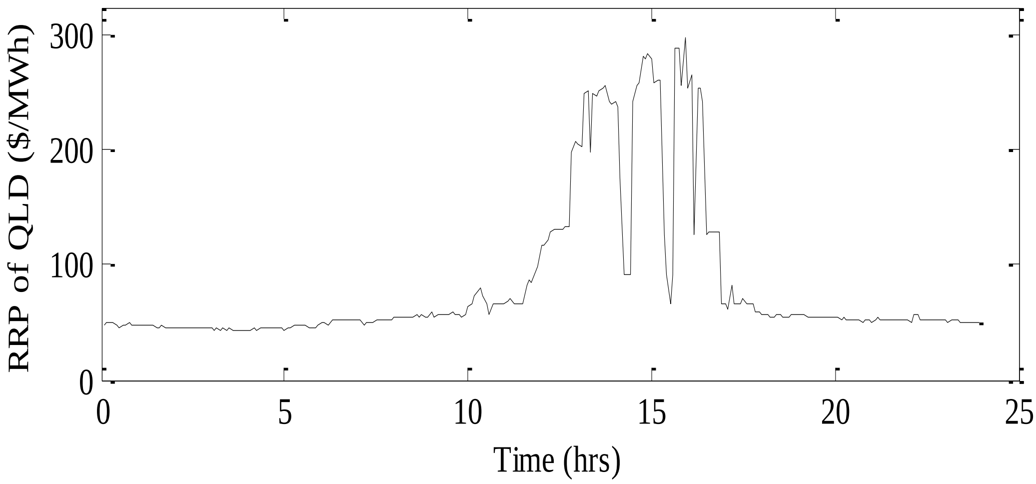

Fig. 4.8 RRP of QLD on 29th November 2012

The third price component (Π_{3i}^t) related to wholesale price variation during a peak day is observed. AEMO data for wholesale price for Queensland region is selected for this study with 5 minutes dispatch time [111]. Dispatch details are obtained from 28/11/2012 16:50 to 29/11/2012 16:45 with Regional Reference Price (RRP) in $/MWh which is the dispatch forecast of QLD as in Fig. 4.8. Main controller uses RRP in (4.4) to broadcast a third price signal (Π_{3i}^t) for every i^{th} house.

The fifth house (H5) in phase A of feeder 1 is chosen to analyze the price and the load variation for two consequent days is shown in Fig. 4.9. It is assumed that H5 does not take any action for load adjustment. Load consumption of H5 is shown in

Fig. 4.9 (a). In-home display unit is used to indicate the price signal for next five minutes and is refreshed in five minute interval.

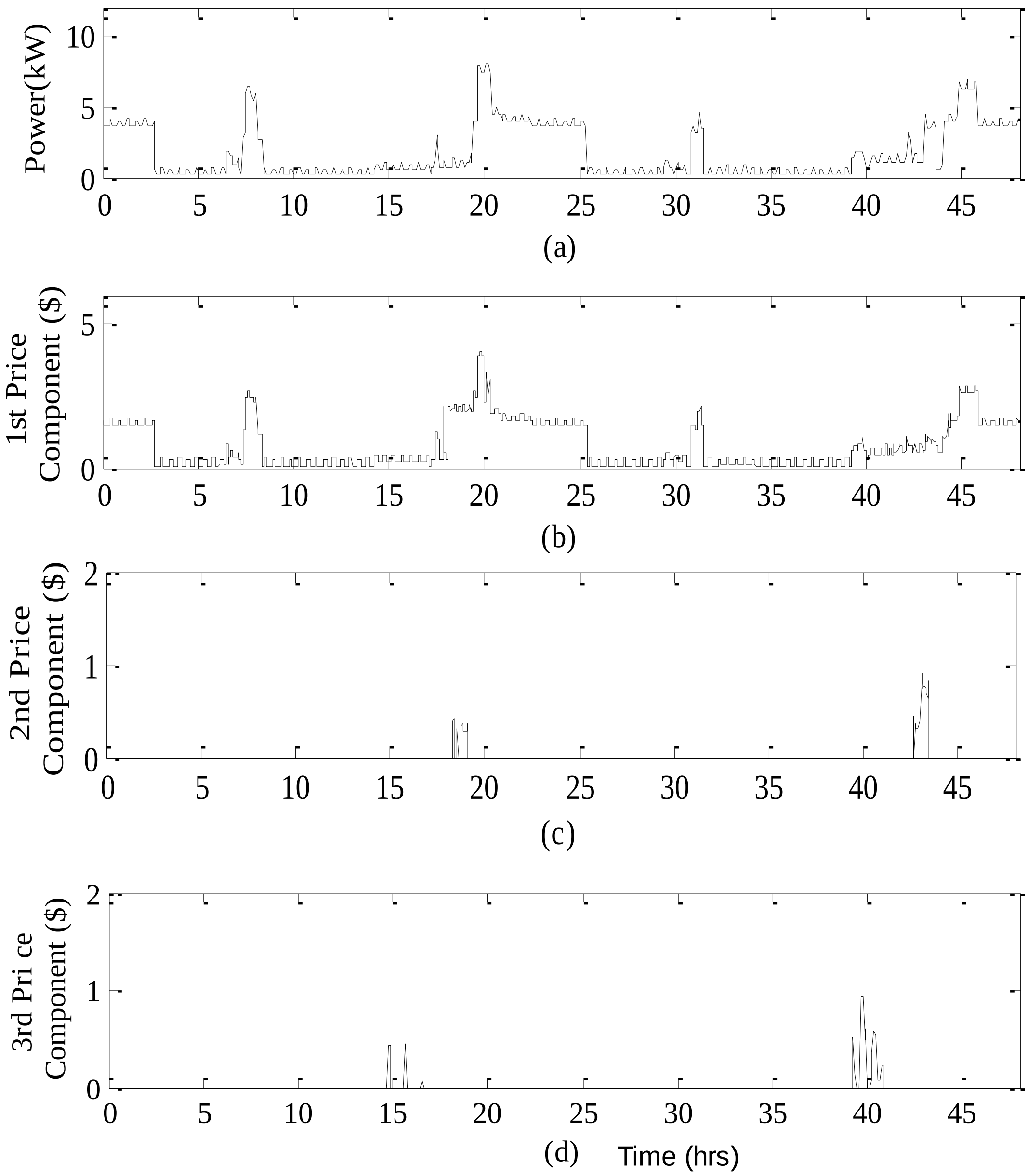

Fig. 4.9 (a) Power (b) 1st (c) 2nd (d) 3rd price component of house 5- feeder 1

At 18:00, Π_{15} (Fig. 4.9 (b)) and Π_{25} (Fig. 4.9 (c)) i.e. first and second price component of H5 increases due to increase in the load consumption of H5 and voltage violation in the network due to the loads in H5 respectively. As H5 does not adjust the loads, Π_{25} price remains high until the network peak disappears at 20:00. Similarly, Π_{15} remains high until 23:00 when H5 load consumption plummets.

Therefore, H5 observes a high price during peak hours. Π_{35} price component for H5 is in Fig. 4.9 (d).

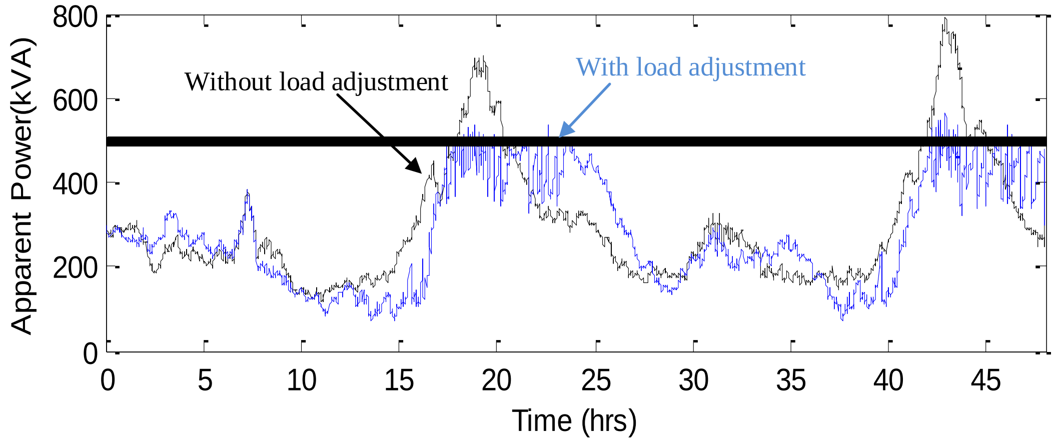

Fig. 4.10 Loading level of the 500kVA distribution transformer

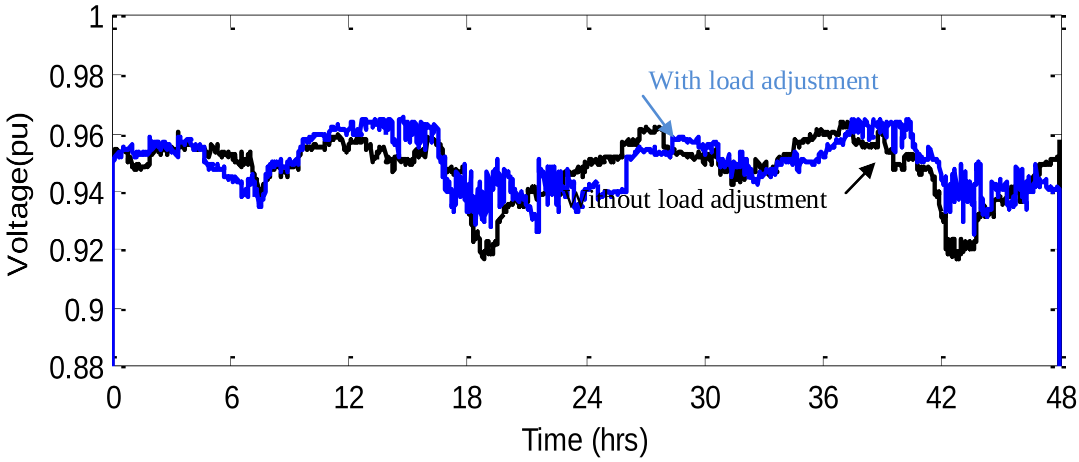

Fig. 4.11 Voltage profile at the end bus of feeder 1

Later, the price scheme is applied on the 500 kVA network and assuming that 100% of customers take action due to the price signal broadcasts. It is observed that the overload problem is eliminated as shown in Fig. 4.10. The voltage within the feeder is also improved above the allowable limit of 0.94 *p.u.*, and it is checked by plotting the end bus voltage profile of feeder 1 as in Fig. 4.11.

Furthermore, the prices for first five selected houses in feeder 1 are compared with and without the new pricing scheme and load adjustment as in Table 4.2. The prices are analyzed for a peak day with high wholesale price and peak demand. For example, H5 have to pay \$ 7.89 if H5 responds to the increase in price and adjust the loads. However, if H5 chooses not to respond to the proposed scheme, H5 will be penalized from all the three types of pricing and will have to pay $ 25.97. Therefore, customers benefit by this scheme by reduced price of electricity.

Table 4.2 Variation of Price of selected houses per day

House No#	Electricity cost with load adjustment ($)	Electricity cost without load adjustment ($)			
		1st Price ($),$L>L_{capacity}$	*2nd Price ($)*	*3rd Price ($)*	*Total cost ($)*
H1	8.70	6.87	2.25	0.58	16.8
H2	6.34	5.50	2.87	1.87	15.77
H3	7.68	4.45	3.10	1.59	15.61
H4	8.40	6.48	2.78	2.79	19.35
H5	7.89	10.93	3.32	4.80	25.97

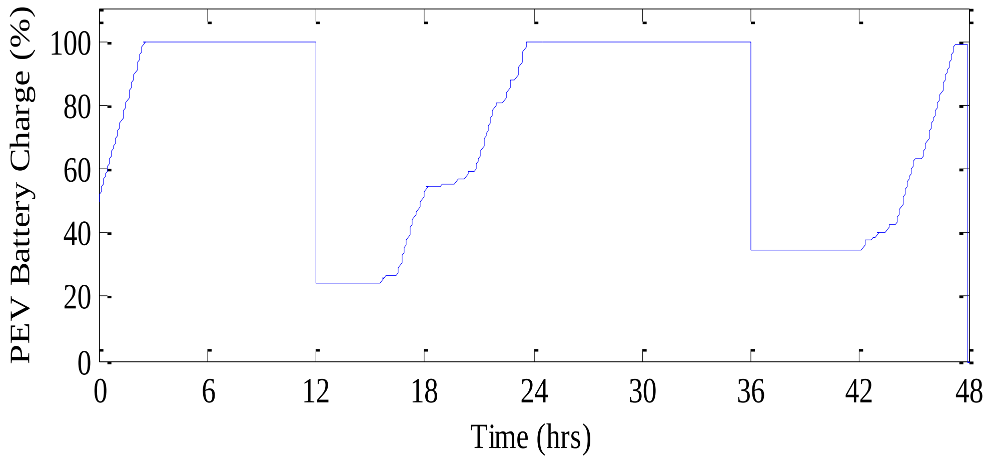

Fig. 4.12 selected PEV battery charge in phase- A of feeder 1

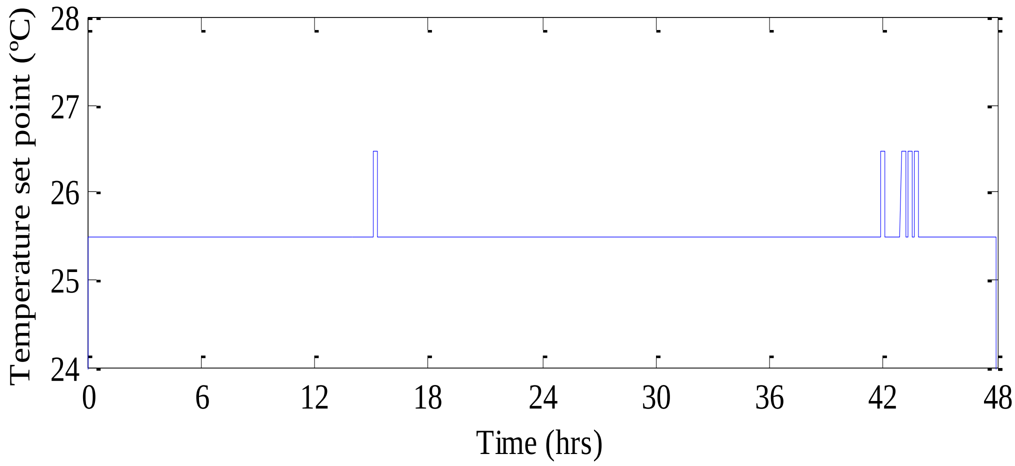

Fig. 4.13 Temperature set point adjustment of selected AC

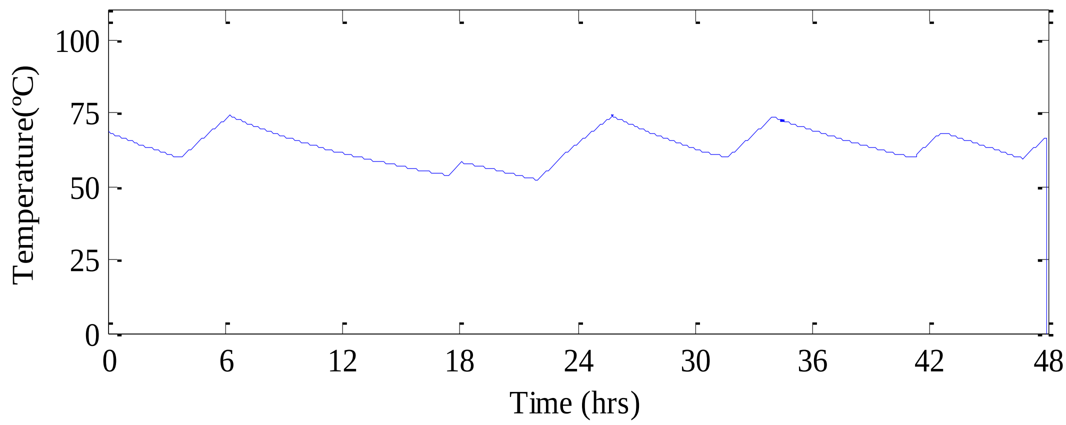

Fig. 4.14 Water Heater tank temperature change of a selected house

Moreover, effect on customers due to the load adjustments in accordance to price variation is also studied. It is ensured that the effect on customers due to load curtailment is minimal. The characteristics of major residential appliances such as PEVs, ACs and WHs are closely observed. The state of charge of PEV in a selected house is observed as in Fig. 4.12. The temperature set point adjustment of a selected AC for two consecutive days is also monitored as in Fig. 4.13. Further, the water heater tank temperature change of a selected house is reflected as in Fig. 4.14. Hence, Fig. 4.12, Fig. 4.13 and Fig. 4.14 show that the effect on appliance usage pattern is minimal comparing to the cost benefits received by the customer on a critical day with high electricity prices. Price is not alone the factor on decision making. Appropriate selection of loads for curtailment leads to allowable customer satisfaction. Here, operational state of appliances during demand response is maintained from 80- 95%. Violations from desired customer adjustability and priority is minimal (10- 20 %). Hence, this process considers financial benefits, customer preferences and provides benefits for both customers and utility.

4.6. Summary and Conclusion

An improved real-time pricing scheme for customers is proposed to alleviate voltage violations and peak load problem. It would help is reducing the unexpected increase in wholesale price of electricity. Customers are benefitted by reduced price due to load adjustments. An algorithm for appropriate indication of loads to be adjusted according to price variations is proposed. The proposed scheme can be implemented using smart meters and in-home display units. The results are validated in a sample distribution system. The impact on customer side due to the proposed real-time pricing scheme does not hamper the appliance usage patterns of customers.

Chapter 5

Real-Time Home Energy Management Scheduler Using Stochastic Dynamic Programming

With the recent development of advanced metering infrastructure, Real-Time Pricing (RTP) scheme is anticipated to be introduced in future retail electricity market. Home Energy Management (HEM) facilitates customers to adjust their loads based on RTP. This research work proposes a real-time Home Energy Management Scheduler (HEMS) aiming to reduce the cost of energy consumption in a house while maintaining customer satisfaction. The proposed HEMS works in three subsequent phases namely real-time monitoring (RTM), stochastic scheduling (STS) and real-time control (RTC) of appliances. In RTM phase, characteristics of available controllable appliances are monitored in real-time and stored in HEMS. In STS phase, HEMS computes an optimal policy using stochastic dynamic programming (SDP) to select a set of appliances to be controlled with an objective of minimizing customer discomfort as well as the total cost of energy consumption in a house. Finally, in RTC phase, HEMS initiates the control of the selected appliances. The proposed real-time HEMS is unique as it intrinsically considers uncertainties in RTP and power consumption pattern of various appliances. In RTM phase, appliances are categorized according to their characteristics to ease the control process, thereby minimizing the number of control commands issued by HEMS. Simulation results validate the proposed method for HEMS.

5.1. Introduction and Related Work

Retailers in most electricity markets, provide a fixed electricity tariff scheme for customers, independent of the cost of electricity generation during the time of consumption. However, the true opportunity cost of electricity consumption varies with the marginal cost of electricity production. This causes inelastic behavior in customer electricity demand within short time frames which may ultimately lead to losses for both retailers and customers during adverse conditions such as price spikes/falls [112].

Introducing a time varying electricity retail price, known as Real-Time Pricing (RTP) is one of the solution. The concept of RTP was introduced long ago, but it has been only recently possible for practical implementation due to vast technological improvements in advance metering infrastructure [113], [114]. RTP provides benefit to retailers by reflecting marginal cost of production and encourages customers to control their electricity consumption [115]. Smart meters and in- home display units aim to help customers in reducing their Cost of Energy Consumption (CoEC) and control their appliances on a regular basis [116]. However, due to uncertainty in price variation and electricity demand, appropriate control of appliances is cumbersome.

A Home Energy Management (HEM) system helps residential customers to respond to RTP by reducing CoEC [117]. The authors of [44] and [45] have proposed a real-time HEM system with a complex scheduler, using ‘particle swarm optimization’ and ‘genetic algorithm’. However, the uncertainties in RTP of electricity or the power consumption of appliances are not considered during their appliance scheduling processes. The authors of [46], however, propose a decision support tool using linear programming optimization and a price predictor to get hour-ahead price information and plan the upcoming energy consumption. However, the predicted price is not included in the optimal scheduling of appliances. This problem is mitigated by [47] and [48], where a predictive tool along with real-time optimization is proposed. Nevertheless, the real-time optimization and control along with predictive techniques is cumbersome and may lead to less accurate results.

In another study, stochastic optimization with an objective of minimizing expected electricity payment using Monte Carlo simulations [49] and Markov

Decision Process (MDP) [50] is proposed. The uncertainty in RTP is incorporated via expected downside risk [49] and price prediction noise [50]. However, the uncertainty in appliance power usage is not considered. Taking a step further, the authors of [51] propose a bottom up approach to represent several house appliances in a network incorporating uncertainties in both appliance power consumption and RTP. This model nonetheless increases the number of control commands issued for adjusting appliance thereby affecting customer comfort.

Contributions: The objective of this part of research, therefore, is to find a desired tradeoff between incurred cost of energy consumption and customer comfort level. This chapter proposes a real-time Home Energy Management Scheduler (HEMS), which aims to reduce the cost of energy consumption in a house while maintaining customer satisfaction. This research work is different from [44]-[50], as it considers the uncertainties in both RTP and residential appliance power consumption pattern during appliance scheduling. Unlike [51], a top down approach from house to appliance level is taken. I. e. a set of appliances is selected optimally for control based on their stochastic behavior, with an overall objective of reducing the total cost of energy consumption in a house. Similar to [49], [50], appliances are categorized to ease the process of control in this part of research.

Another contribution of this work is that the dimensionality of stochastic scheduling is reduced. Real-time monitoring is used and that leads to an efficient control system. The proposed real-time HEMS works in three subsequent phases i.e. real-time monitoring (RTM), stochastic scheduling (STC) and real-time control (RTC). Similar to [50]- [51], MDP is used for stochastic optimization.

In section 5.2, the proposed real-time HEMS is described. The operation of HEMS with these three subsequent phases is summarized in Section 5.3. A test system description and simulation results are presented in Section 5.4 followed by conclusions in Section 5.5.

5.2. Proposed Real-Time HEMS using SDP

This section introduced a new real-time HEMS using SDP and can be deployed in houses. Retailers bid in the wholesale electricity market on a day-ahead/real-time basis to cater their load demand. The customers/end-users, whereas, have a choice to either take fixed price or RTP based tariff from demand aggregator or retailer. In some cases, the demand aggregator uses RTP signal from retailers and provide demand-response/load-reduction by adjusting customers' load and provide coupons/incentives in return. Although promising, this method may not be attractive to the customers who want to have the flexibility to modulate their loads themselves and be rewarded accordingly.

This chapter, therefore, proposes RTP signals (from either demand aggregators or retailers) to be send directly to customers/end-users to adjust the loads themselves, giving them flexibility to choose the level of load adjustments and achieve the reduced cost of energy consumption. The optimal decision to control the appliance is taken by HEMS in order to reduce the cost of energy consumption. As the control of appliances is dependent of individual HEMS, the network scalability is not an issue and it is easy to implement regardless of the size of the distribution network. This process is made possible with the advanced metering infrastructure and there are no additional communication requirements for the proposed algorithm. HEMS collect the relevant information about the appliances at regular intervals using home area networks such as Zigbee, HomePlug Wifi, Z-wave etc. The demand aggregator/retailers broadcast the RTP signal to respective customers, who use HEMS to adjust the loads using the proposed algorithm. As HEMS only communicate to demand aggregators/retailers, the current low power radiofrequency transmitters working in the 900MHz-2.4 GHz band is sufficient.

Appliance control process is performed by HEMS at house level where every HEMS in a network are remotely connected to the utility to obtain RTP information. Thereby, a large network with utility connected HEMS at each residence is possible due to the independent operation of HEMS. It has better performance than a centrally controlled algorithm for residential appliances in a large network which may raise scalability issue.

The functionality of HEMS and retailer/utility interference can be summarized using Fig. 5.1. Retailer/utility receives price information from wholesale electricity market and demand information from the respective houses on a continuous basis. The local retailer checks system constraints so as to command appropriate RTP to HEMS. The optimal decision to control the appliance is taken by real-time HEMS in order to reduce the cost of energy consumption.

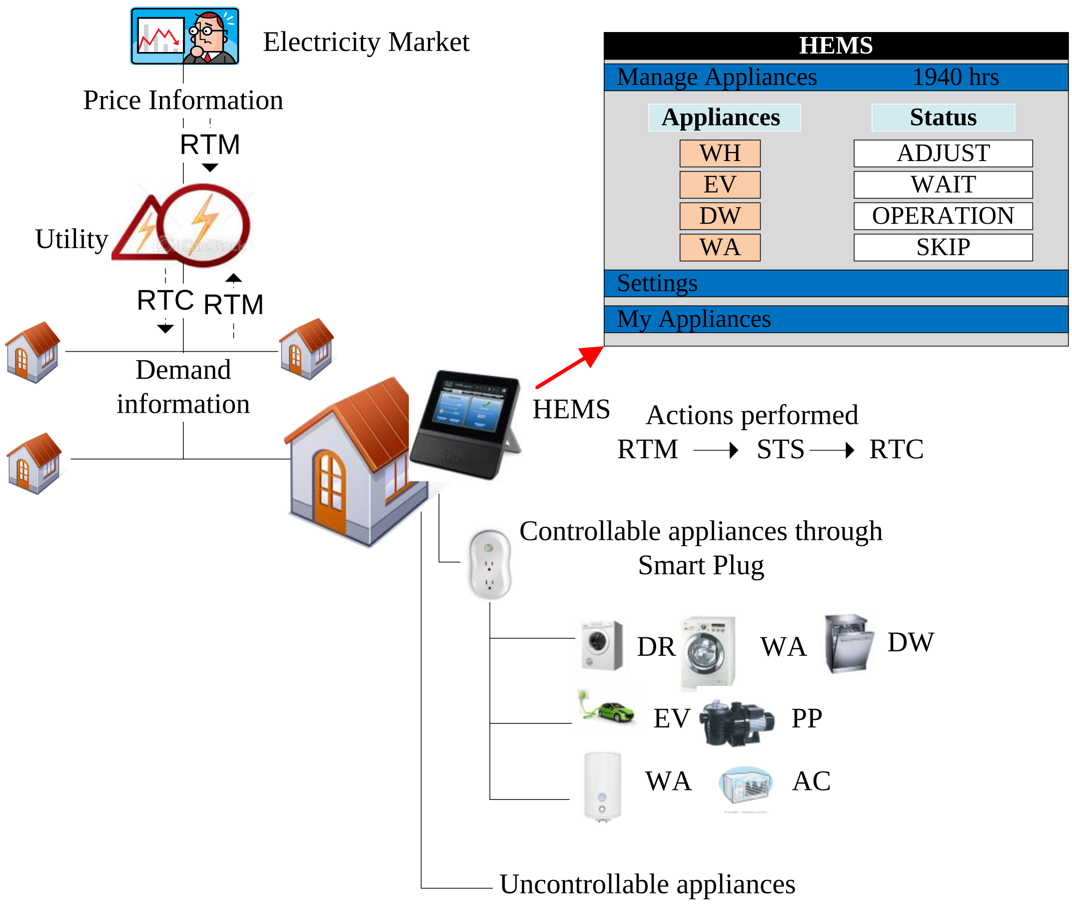

Fig. 5.1 Descriptive diagram of HEMS and utility interference

In this research work, seven controllable appliances including water heater (WH), air conditioner (AC), electric vehicle (EV), dish washer (DW), clothes washer (WA), clothes dryer (DR) and swimming pool pump (PP) are connected through HEMS and the uncontrollable appliances are directly connected to the utility.

The proposed real-time HEMS works in three subsequent phases i.e. RTM, STS and RTC and can be summarized in Fig. 5.2. In RTM phase, HEMS monitors appliance characteristics and data is processed to make it ready for the STS phase, where SDP is used for scheduling appropriate appliances. In RTC phase, HEMS takes appropriate actions on the selected loads. This process is repeated every four minutes. The three phases are described below in detail:

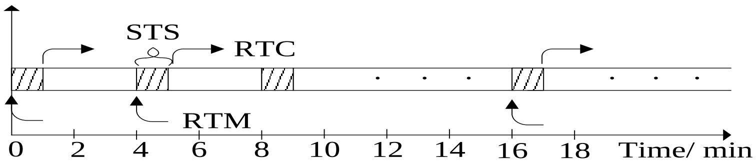

Fig. 5.2 Timing diagram of control process

5.2.1. **Real-Time Monitoring (RTM) Phase**

In RTM phase, the data is collected from all the customers and processes it, so that it can be used for STS phase. Appliances can be classified into three categories namely *Cat1*, *Cat2* and *Cat3* as per their characteristics:

- *Cat1*: Appliances that can be delayed for a certain time such as DW, WA, DR and PP.
- *Cat2*: Appliances whose operation schedule depends on its charging characteristics such as EV.
- *Cat3*: Appliances that can be adjusted with the change in the temperature set point such as WH and AC.

Customers have flexibility to specify whether an appliance can be interrupted or not i.e. Appliance D_j with signal $INTRP_{Dj}$= '*True*' or '*False*'. Furthermore, maximum number of interruptions (ζ_{max}^{intrp}) of a particular appliance is maintained below 'two' to prevent adverse effect on life span of the appliance. Depending on the appliance category (*Cat1/Cat2/Cat3*), utility will decide the operating status of appliances (*WAIT/OPERATION/SKIP /ADJUST*). Descriptions of various statuses are as below:

- Appliances which are connected to HEMS but not in operation are in status '*WAIT*'
- Appliances which are already in operation are in status '*OPERATION*'
- Appliances which should not be controlled at a particular time due to constraints are in status '*SKIP*'
- Appliance which can be adjusted with its set point is in status '*ADJUST*'

Utility gives less possibility of interruption to the appliances which are in '*OPERATION*' and '*ADJUST*' status during STS whereas appliances in '*WAIT*' status have higher possibility to be controlled. Appliances' lifespan is reduced and customers' comfort is affected when operating appliance are interrupted. Therefore, the rationale is to avoid interrupting those appliances which are in operation. Appliances that are waiting to be connected, whereas, can be delayed up to maximum allowable time and hence are suitable for control. The three categories (*Cat1/Cat2/Cat3*) of appliances and the decision for corresponding operating status (*WAIT*/*OPERATION*/*SKIP* /*ADJUST*) need further explanations.

***Cat1* and *Cat2* appliances:** Maximum allowable waiting time or delay (W_{Dj}^{max}) of a corresponding appliance D_j under *Cat1* is specified by the customer. Customer also specifies departing time (t_{dept}) and charging status of electric vehicle (*Cat2*) which helps to calculate maximum possible delay of electric vehicle. Slow (CH_1) and normal charging (CH_2) are the two possible charging statuses. The maximum allowable delay for electric vehicle can be calculated using (5.1)-(5.3) as below.

$$\Gamma_{total}^{CH_k} = \frac{E_{nominal}}{P_{charging}^{CH_k}} \tag{5.1}$$

$$\tau_{remaining}^{CH_k} = (1 - SOC_{initial}).\Gamma_{total}^{CH_k} \tag{5.2}$$

$$W_{D_j}^{\max} = t_{dept} + \left(24 - t_{D_j}^{connect}\right) - \tau_{remaining}^{CH_k} \tag{5.3}$$

Charging cycle duration (Γ_{total}^{CHk}) of a battery can be obtained by dividing the nominal capacity ($E_{nominal}$) of the battery by charging power ($P_{charging}^{CHk}$) for k^{th} charging status as in (5.1). Remaining charging time ($\tau_{remaining}^{CHk}$) can be calculated as in (5.2). Here, $SOC_{initial}$ is the initial state of charge (SOC) of the battery when electric vehicle is plugged in to HEMS. Here, evolution of SOC of the battery is considered to have linear relationship with time while charging [118]. Maximum allowable waiting time of electric vehicle is calculated as in (5.3). Here, $t_{Dj}^{connect}$ is the time when electric vehicle is plugged in to HEMS. Status of appliances in *Cat1* and *Cat2* are determined using Algorithm 1 as summarized below.

When appliance, D_j, is plugged in to HEMS at time $t_{Dj}^{connect}$ ($t_{n-1} < t_{Dj}^{connect} < t_n$), it should wait until the next time step t_n. The initial waiting time before connecting the appliance is denoted as $W_{Dj}^{initial}$. If an appliance is still waiting to be connected at time t_n, it should be assigned '*WAIT'* status. This is valid irrespective of customer input, $INTRP_{Dj}$. If plug in time, $t_{Dj}^{connect}$, of an uninterruptible appliance is before t_{n-1}, it means that the appliance is already in operation which should not be interrupted and hence is assigned '*SKIP*' status.

Whereas, if $t_{Dj}^{connect}$ is less than earlier time step t_{n-1} and if total waiting time (W_{Dj}) and number of interruptions (ζ_{Dj}^{intrp}) are within limits, then appliance D_j can remain in the previous status (i.e. it can be delayed further until limits are not exceeded). When limits for W_{Dj} and ζ_{Dj}^{intrp} are exceeded, appliance is considered in '*SKIP*' status.

***Cat3* appliances:** Thermostatically controllable appliances such as WH and AC are considered in this category. Variation of water temperature is modeled using (5.4) as in [119].

$$\frac{dT_{wh}^{n}}{dt_n} = \left(\frac{G+B}{\psi_w}\right).T_{wh}^{n} + \frac{1}{\psi_w}\begin{bmatrix} G & B & Q_{wh} \end{bmatrix} \times \begin{bmatrix} T_a^n \\ T_{in} \\ K_{wh}^n \end{bmatrix} \tag{5.4}$$

Where T_{wh}^{n} is water temperature at time t_n, T_a is ambient temperature, T_{in} is inlet cold water temperature, Q_{wh} is energy input rate of WH, K_{wh} is binary signal for thermostat settings, G- standby heat loss of the tank, B- heat consumption rate of water and ψ_w- thermal capacity of water in the tank.

$$\frac{dT_{r}^{n}}{dt_n} = -\left(\frac{U_a+H_m}{\psi_{ac}}\right)T_{r}^{n} + \frac{1}{\psi_{ac}}\begin{bmatrix} U_a & H_m & Q_{ac} \end{bmatrix} \times \begin{bmatrix} T_a^n \\ T_m^n \\ K_{ac}^n \end{bmatrix} \tag{5.5}$$

Furthermore, thermodynamic equation for AC is shown in (5.5). Here, T_r^n is the room temperature at time t_n, Q_{ac} is energy input rate of AC, K_{ac} is binary signal for thermostat settings, T_a- ambient temperature, T_m- mass temperature of the house, ψ_{ac}- thermal mass capacity of interior air, U_a- heat loss coefficient and H_m- interior mass conductance of the house [54]. Detailed model of ACs and WHs are discussed in Appendix B.

For *Cat3* appliances, if customer input, $INTRP_{Dj}$, is false, then the set point is adjusted to reduce for power consumption of the appliance and is assigned

'*ADJUST*' status. Otherwise, appliance is assigned '*SKIP*' status. This is summarized in Algorithm 2.

Algorithm 1 (Cat1 & 2) - Determine status $M^{n}_{D_j}$ of appliance D_j at time t_n

input $W^{\max}_{Dj}, INTRP_{D_j}, t^{connect}_{D_j}$

if $INTRP_{D_j} = False$

if $t_{n-1} < t^{connect}_{D_j} < t_n$

$M^{n}_{D_j} = WAIT, W^{initial}_{D_j} = t_2 - t^{connect}_{D_j}$

elseif $t^{connect}_{D_j} < t_{n-1}$

$M^{n}_{D_j} = SKIP$

elseif $INTRP_{D_j} = True$

if $t_{n-1} < t^{connect}_{D_j} < t_n$

$M^{n}_{D_j} = WAIT, W_{initial} = t_2 - t^{connect}_{D_j}$

elseif $t^{connect}_{D_j} < t_{n-1}$ & $0 \le W_{Dj} < W^{\max}_{A_j}$ & $\zeta^{\text{int}rp}_{D_j} \le \zeta^{\text{int}rp}_{\max}$

if $M^{n-1}_{D_j} = WAIT$ then $M^{n}_{D_j} = WAIT$

if $M^{n-1}_{D_j} = OPERATION$ then $M^{n}_{D_j} = OPERATION$

elseif $t^{connect}_{D_j} < t_{n-1}$ & $\left(W_{Dj} > W^{\max}_{D_j} \quad or \quad \zeta^{\text{int}rp}_{D_j} > \zeta^{\text{int}rp}_{\max}\right)$

$M^{n}_{D_j} = SKIP$

end

Algorithm 2 (Cat3) - Determine status $M^{n}_{D_j}$ of appliance M_j at time t_n

if $P^{n}_{D_j} > 0 \;\&\; INTRP_{D_j} = True$

$M^{n}_{D_j} = SKIP$

elseif $P^{n}_{D_j} > 0 \;\&\; INTRP_{D_j} = False$

$M^{n}_{D_j} = ADJUST$

5.2.2. **Stochastic Scheduling (STS) phase**

Although, real-time monitoring of appliances' usage and price information gives the details of current status of various appliances, it is not sufficient to make a decision for appropriate selection. It is due to various uncertainties in electricity price variation, appliance operation, user behavior and preferences. Hence, SDP is proposed to include the uncertainties in decision making. This phase helps in identifying the appropriate appliances to be controlled.

5.2.2.1. ***Analyzing stochastic behavior of RTP and demand of Electricity:***

An infinite horizon discrete time dynamic model is formulated for the stochastic control process where time steps are indexed by {n=0, 1, 2, ……..}. This scheduling problem focuses on CoEC at each time step. The total CoEC (C_n^{total}) of a house at n^{th} time step from t_{n-1} to t_n is the product of RTP of electricity, π_n, total power consumption, P_n^{total} , and the time step, dt, i.e. (t_n - t_{n-1}) as shown in (5.6).

$$C_n^{total} = \pi_n . P_n^{total} .dt \tag{5.6}$$

$$P_n^{total} = \sum_{j=1}^{N} P_n^{D_j} + P_n^{other} \tag{5.7}$$

Here, total power consumption, P_n^{total} at n^{th} time step is calculated as in (5.7**)**. It is the sum of power of adjustable and non-adjustable appliances. Power consumption of an adjustable appliance D_j connected to HEMS at time t_n is given as P_n^{Dj}. P_n^{other} is the total power consumption of non-adjustable appliances of that house at time t_n.

CoEC is considered as a time varying stochastic variable and its behavior is analyzed in this study. Initially, a discrete time stochastic process for C_n^{total} is created as C^{total} = {C_n^{total}, n = 0, 1, 2, . . .} where $C_n^{total} \in S$. Here, S represents a set of states such as S = {S_k, k = 1, 2, …. k_{max}} defined for the above stochastic process. k^{th} state S_k, (for all k) is defined by a range of predefined CoEC in a house so that C_n^{total} lies within a range of a particular state S_k. Let us consider discrete cost variables {C_0^{total} , C_1^{total} , C_2^{total}, …} to occupy a value in a set of states (S). The sequence of C^{total} = {C_n^{total}, n = 0, 1, 2, . . .}, is considered as a Markov chain as the future CoEC is independent of the past CoEC, conditioned on the present value. It can be further elaborated by a transition probability, i.e., if the chain is in state S_i, the transition probability, $\mathbf{P}_{xy}(n+1)$, says how the chain chooses to jump to next state, S_y , at the time step (n+1) as in (5.8).

$$\mathbf{P}_{xy}(n+1) = \mathbf{P}\,(C_{n+1}^{total} \to S_y \mid C_n^{total} \to S_x) \tag{5.8}$$

As CoEC satisfies dynamics of Markov dependent structure, Markov Decision Process (MDP) is a suitable method for optimal scheduling of appliances within a house [120]. MDP can be defined as five tuples <l,S,A,TR,R>, where, l represents length of planning horizon, S is a finite state space of discrete states reflecting CoEC, A is for a finite action space and $TR{:}\to\mathbf{P}(S)$, is a transition function describing probability of distribution of next states as in (5.8). Further, $C^{total}:SxA\rightarrow R$ is cost of executing an action in a state and it represents R, which is a state dependent reward function.

5.2.2.2. ***Problem Formulation***

Markov Decision Process (MDP) is used to minimize CoEC via optimal scheduling of appliances. Expected outcome of this process is optimal STS of appliances.

Time Horizon: An infinitely repeated 24 hour cycles are considered and is discretized into intervals of four minutes (i.e. CoEC of a house is monitored and expected to be controlled on daily basis). Time cycles are incorporated into state space thus the decision making time horizon is n={1,2,3,…..}.

State Space: State space is defined to replicate a range of CoEC. For this purpose, CoEC of a house is observed at every time step for an entire season. A probability density function for C^{total} is formed to define boundaries of CoEC for states from the data obtained. B_k and B_{k+1} are boundaries for CoEC for k^{th} state, S_k as defined in (5.9). B_k and B_{k+1} can be found by predefining $\mathbf{P}(B_k \leq C^{total} < B_{k+1})$ as in (5.10).

$$S_k = [B_k, B_{k+1}) = \{C^{total} \mid B_k \leq C^{total} < B_{k+1}\} \tag{5.9}$$

$$\mathbf{P}\left(B_k \leq C^{total} < B_{k+1}\right) = \int_{B_k}^{B_{k+1}} C^{total}(x).dx \tag{5.10}$$

In this research work, $\mathbf{P}(B_k \leq C^{total} < B_{k+1})$ is considered as 50%, 10% for k=1 and k={2,3,4,5,6} respectively. Overall state space is defined as $S=\{S_k, k=1,2, \dots, 6\}$.

Action Space: An action space A_n, contains a set of actions $A_n^q:S\rightarrow\sigma(A_n)$. $A_n^q(S_k)\subseteq A_n$ denotes q^{th} set of actions that can be applied in k^{th} state, S_k , at n^{th} time instant. $\sigma(A_n)$ is power set of the action space A_n. An action is considered as a set of appliances that can be curtailed at a given time step.

Consider a set D, consisting of N number of controllable appliances in a house as in (5.11). A subset D_n^{av} can be defined as the available appliances connected to HEMS at n^{th} time instant. Then, an action, $A_n^q(S_k)$, (i.e. a set of possible curtailment of appliances) is defined as a subset of D_n^{av} as in (5.12). The power set, $\sigma(A_n)$, denotes number of all possible subsets of D_n^{av} or number of actions as in (5.13).

$$D = \{D_1, D_2, ...D_N\}; \quad D_n^{av} \subseteq D \tag{5.11}$$

$$A_n^q(S_k) \subseteq D_n^{av} \tag{5.12}$$

$$\sigma(A_n) = 2^{\eta\left(D_n^{av}\right)} \tag{5.13}$$

In this study, seven (N=7) controllable appliances are considered in a house. For instance, if two appliances D_4 and D_6 are connected to HEMS at n^{th} time step, then $D_{av}{}^n=\{D_4,D_6\}$, $\eta(D_n^{av})=2$ and $\sigma(A_n)=2^2$. Hence, four actions are possible which are {}, $\{D_4\}$, $\{D_6\}$ and $\{D_4, D_6\}$. Empty set {} represents action of no curtailment. $\{D_4\}$ and $\{D_6\}$ represents when only one appliance, either D_4 or D_6, is selected for curtailment respectively. When both appliances are selected, action $\{D_4, D_6\}$ is possible.

Transition Probability: Transition function is a function of probability that CoEC jumps from state S_x to S_y at $(n+1)^{th}$ time step during q^{th} action and is defined as $Tr{:}SxAxS \rightarrow \mathbf{P}_{n+1}(S_y|S_x,A_n^q) \in [0,1]$. As the probability depends on states and actions, an action and state dependent transition probability block is defined. Initially, daily power consumption profile of each appliance in a house is observed for a particular season. Daily variation of RTP is also observed for the given time frame. Then, Algorithm 3 is repeated for each action to calculate transition probabilities as summarized below. Algorithm 3 starts with the calculation of CoEC (C_n^{Aq}) at n^{th} time step for q^{th} action as defined in (5.14).

$$C_n^{A_q} = \pi_n \left\{ \left(P_n^{total} - \sum_{j=1}^{N_{A_q}} P_n^{Dj} \right) . dt \right\} \tag{5.14}$$

Here, sum of power of appliances that can be curtailed during q^{th} action is subtracted from total power consumed (P_n^{total}) to find total power consumption during q^{th} action. This value is multiplied by π_n and dt, the RTP and length of time interval respectively to obtain C_n^{Aq}.

Algorithm 3 - *C*omputation of transition probability block

for time $t_n = 0$ to $24\,hrs\,(4\min \text{increment})$

initialize count $N_{ij}^{A_q} = 0$

  for day $d = 1$ to 90

  Calculate CoEC $C_n^{A_q}(d)$ as in (18)

    for state $i = 1$ to 6

      for state $j = 1$ to 6

        if $C_n^{A_q}(d) \in S_i \cap C_{n+1}^{A_q}(d) \in S_j$

        $N_{ij}^{A_q} = N_{ij}^{A_q} + 1$

        end if

      end for loop of state j

      $\mathbf{P}_{n+1}(S_j \mid S_i, A_p) = N_{ij}^{A_q} \Big/ (\sum_{k=1}^{6} N_{ik}^{A_q})$

    end for loop of state i

  end for loop of day d

end for loop of time t_n

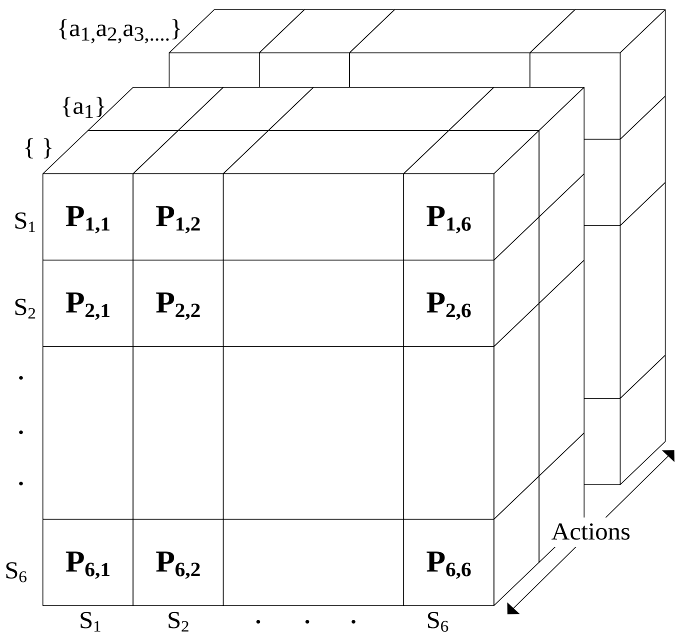

Fig. 5.3 Block of transition probability (*Tr*)

Here, N_{Aq} is the number of appliances in q^{th} action. State change of C_n^{Aq} at q^{th} action from S_x to S_y from subsequent time steps n and $n+1$ are observed on daily basis. Number of days is counted for this specific jump (N_{ij}^{Aq}). It is divided by the total number of days where states changes from S_x to the other states S_k from 1 to 6.

($\sum N_{ik}^{Aq}$) to obtain the transition probability $\mathbf{P}_{n+1}(S_y|S_x,A_n^q)$. This process is repeated at each time step. Further, Algorithm 3 is repeated for each action to obtain the transition probabilities of all possible state changes or jumps for the whole action space and is shown in Fig. 5.3.

Reward Function: Accurate definition of reward function ($reward_{xy}^{Aq} \in R$) is vital in MDP due to its importance in decision making. It helps to choose best possible action, A_n^q, for appropriate selection of appliances. A reward value is defined as in (5.15), which is four tuples,$<S_i/S_j, \beta_k, P_k, W_k>$.

$$reward_{xy}^{A_q}(n) = \begin{cases} \alpha \dfrac{S_x}{S_y} \displaystyle\sum_{j=1}^{N_{A_q}} \beta_n^{D_j} . P_{D_j}^{rating} . \left(1 - \dfrac{W_{D_j}^{n}}{W_{D_j}^{\max}}\right) & (\forall A_n \text{ and} \{\} \notin A_n) \\ \alpha \dfrac{S_x}{S_y} & A_n^q = \{\} \end{cases} \tag{5.15}$$

(i) Reward component 1(S_i/S_j) - Ratio of state change from S_x to S_y as an effect on jumps from one state to another. Purpose of this component is to provide less reward for a state changing from low to high value (for $i<j$) and to provide more reward for a state changing from high to low value (for $i>j$). As an effect of this reward component, an action which causes furthest state change from high to low value will be chosen. (ii) Reward component 2 (β_n^{Dj}) - Status of appliances which are '*WAIT*' / '*OPERATION*' / '*ADJUST*'. Appliance in *'WAIT'* status is given with a higher reward value comparing to the other statuses '*ADJUST*' and *'OPERATION'*. In our study, values for β_n^{Dj} for *WAIT*, *OPERATION* and *ADJUST* are considered as 1, 0.5 and 0.75 respectively. Purpose of appliance status β_n^{Dj} in reward function is to prioritize appliances which are in '*WAIT*' status and still not in operation rather than appliances which are in operation. It allows in maintaining appliance comfort and reduces the possibility of appliances being interrupted in the middle of their operation. (iii) Reward component 3 ($\sum P_{Dj}^{rating}$) - Summation of power ratings of appliances, involved in a particular action. Reward depends on the availability of power curtailment in a particular action. Purpose of this component is to provide higher reward for an action with more curtailment of loads comparing to actions with less curtailment of loads. Therefore, an action with highest available power for curtailment will be prioritized for control. (iv) Reward component 4 ($1-W_{Dj}^{n}/W_{Dj}^{max}$) – A function of waiting time of an appliance. Appliance which is delayed more is considered to have less reward comparing to appliance which is delayed less. Time varying term ($1-W_{Dj}^{n}/W_{Dj}^{max}$) provides this function. Here, W_{Dj}^{max} is the maximum allowable waiting time of appliance D_j. Purpose of this component is to prioritize appliance which is delayed less comparing to other appliances which are delayed more. As an effect, appliance that can be sufficiently delayed is chosen to be controlled.

Coefficient α is chosen by utility according to their requirement. Overall, reward function is designed so that it provides benefit to customer by satisfying their need and by reducing cost.

Markov Decision Process (MDP): Objective of MDP in this study is to maximize the reward function, so that customer indirectly minimizes CoEC while satisfying their needs. Reward of execution (R) is the sum of all rewards along the path from $S_{initial}$ (initial state) to the first goal state. $S^G \subseteq S$ is the set of goal states (i.e. $S_g^G \subseteq S^G$ which terminates an execution) [121]. Here, transitions are managed stochastically by transition block, TR. A policy λ_n:$S \rightarrow A_n$ is defined as a mapping from state space S to action space A_n and at n^{th} time step, an optimal action is mapped to all possible states. An optimal policy (λ_n^*:$S \rightarrow A$) is obtained from MDP. A value iteration algorithm is used to evaluate optimal policy to satisfy the objective. Algorithm 4 explains the value iteration and is summarized below.

Algorithm 4 - Value Iteration

Input a MDP $= < S, A_n, Tr, R >, \delta$ threshold value

Initialize V

$0 \leftarrow \textit{Bellman error}$

While $\textit{Bellman error} > \delta$

for each state $S_y \in S$

$V_{prev} \leftarrow V(S_y)$

$V(S_y) = \max_{a \in A_q(S_y)} \left[R(S_y, A_q) + \sum TR_{A_q}(S_y \mid S_x) V^*(S_x) \right]$

$\textit{Bellman residual}(S_y) = \left| V(S_y) - V_{prev} \right|$

$\textit{Bellman error} \leftarrow \max(\textit{Bellman error}, \textit{Bellman residual}(S_y))$

end while

return V

The value function is initialized based on dynamic programming. A value function is defined as a mapping from state S (V_λ:$S\rightarrow R$) as in (5.16). Bellman operator is used to update the values iteratively for having successive approximation at each state per iteration. A Bellman equation related to value functions with an objective function is created as in (5.17) using reward and transition blocks. Dynamic-programming algorithm is used to search the solution space by using the recursive structure of the Bellman equation which is more efficient than exhaustive-search algorithms.

Here, a Bellman residual of a state is defined as the absolute difference of a state value before and after Bellman operation. Value iteration stops after convergence. The largest Bellman residual of all states becomes less than a pre-defined threshold δ. Finally, optimal policy is obtained from value function is as in (5.18).

$$V^{\pi}(S_y) = R(S_y, \lambda(S_y)) + \sum_{S_y \in S} TR_{\lambda(S_y)}(S_y \mid S_x) V^{\pi}(S_x) \tag{5.16}$$

$$V^{*}(S_y) = \begin{cases} 0 & \text{if } S_y \in S^G \\ \max\limits_{a \in A_q(S_y)} \left[R(S_y, A_q) + \sum TR_{A_q}(S_y \mid S_x) V^{*}(S_x) \right] & \text{else} \end{cases} \tag{5.17}$$

$$\lambda^{*}(S_y) = \arg\max_{a \in A_q(S_y)} \left[R(S_y, A_q) + \sum TR_{A_q}(S_y \mid S_x) V^{*}(S_x) \right] \quad \forall S_y \in S - S^G \tag{5.18}$$

In real-time, if CoEC lies in state S_y, the optimal action mapped in the proposed policy will be chosen for control. Ultimately, optimal policy gives the optimal curtailment schedule of appliances.

5.2.3. **Real-Time Control (RTC) Phase**

In RTM phase, the status of appliances are determined which helps to find the optimal policy or the optimal action with a set of selected appliances in STS phase. Then in RTC phase, HEMS send signals to adjust selected set of appliances.

5.2.3.1. ***RTC of Cat1 and Cat2 appliances***

Fig. 5.4 illustrates the change in operating statuses of *Cat1* and *Cat2* appliances. Appliances can be in any of the five conditions as shown in Fig. 5.4

(conditions represent '*if*'' clauses in algorithm 1). **Condition 1** shows an appliance connected to HEMS within time t_{n-1} to t_n and identified to be in '*WAIT*' status during RTM. It has an initial waiting time of $W_{initial}$. If this appliance is selected for control during RTC, it will be delayed for another four minutes. Hence, operating status of this appliance again becomes '*WAIT*'. This is true irrespective of customer input '*INTRP*'. Then, at next time step, t_{n+1}, utility connects this appliance in offline STS program to check whether reconnection is possible. If reconnection is possible at t_{n+1}, appliance is connected, otherwise, it is delayed until next time step.

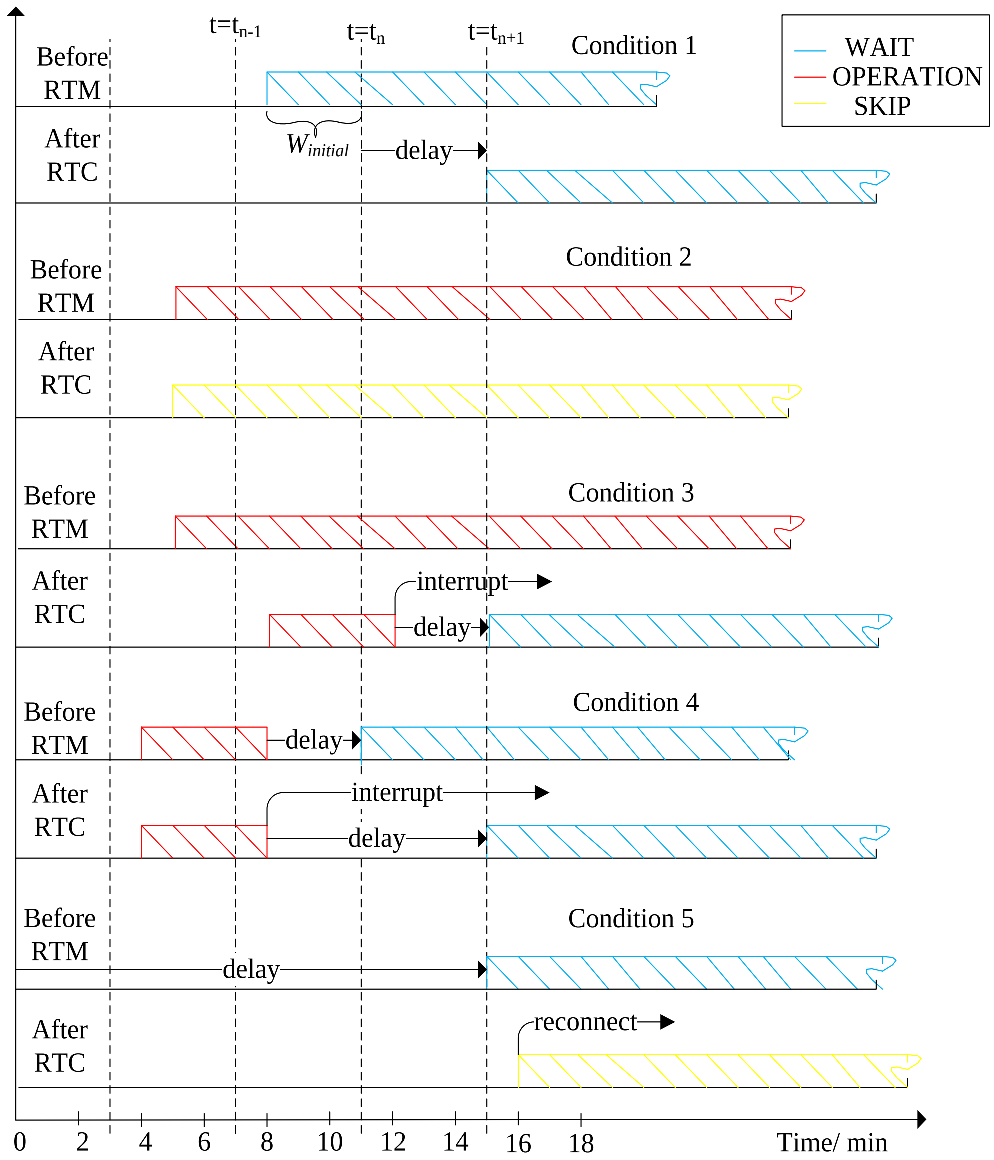

Fig. 5.4 Operating statuses of appliances before RTM and after RTC phase

Condition 2 shows appliances which cannot be interrupted in the middle and are already in operation during RTM. Then, it is considered to be in '*SKIP*' status and continuously connected to utility without subjecting to RTC. **Condition 3** shows appliance in '*OPERATION*' status during RTM. If this appliance is chosen to be controlled, it is interrupted after one minute from a time step for next three minutes and goes to '*WAIT*' status after RTC. **Condition 4** illustrates an appliance which is already delayed in time step t_{n-1} and is in '*WAIT*' status. If the maximum waiting time and maximum number of interruptions are not exceeded, it can be further delayed at t_n and again stays in '*WAIT*' status. **Condition 5** shows an appliance already in '*WAIT*' status during RTM. It will be reconnected during RTC and will go into '*SKIP*' status if and only if the maximum limits for waiting time and interruptions are exceeded.

A notification signal can be sent to the customers four minutes in advance to show that if the appliance is to be started near an expected peak in cost of energy consumption. Hence, a customer can make a decision to increase the waiting time of respective appliance.

5.2.3.2. ***RTC of Cat3 appliances***

RTC of *Cat3* appliance, however, is different. If a *Cat3* appliance is identified to be in ADJUST status during RTM, then the set point of the appliance is adjusted during RTC. Set points of ACs and WHs can be adjusted in three different ways. I.e. set point is increased or decreased for cooling or heating load respectively.

- Stepwise set point adjustment

Here, for each control action, set point (T_{set}^{Dj}) is adjusted step by step by a constant temperature value. In this study, set point of a cooling and heating load is increased or decreased by 1°F at each control step respectively. However, set point adjustments are maintained within 5°F.

- Set point adjustment using linear droop curve of CoEC

Stepwise set point adjustment does not reflect the effect of CoEC increase in an efficient manner. Hence, a set point (T_{set}^{Dj}) is adjustment subjected to linear variation is CoEC in introduced here. If CoEC during RTC is above the limit (C^{total}_{lim}), T_{set}^{Dj} for a cooling load D_j, is increased linearly as in Fig. 5.5.

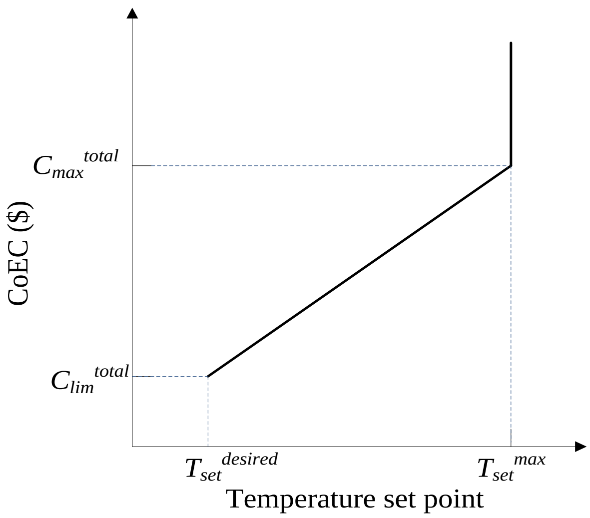

Fig. 5.5. Linear droop curve for set point adjustment of a cooling load

Similarly, if CoEC during RTC is above C^{total}_{lim}, then T_{set}^{Dj} for a heating load is decreased linearly using droop curve in Fig. 5.6. In this study, T_{set}^{max} and T_{set}^{min} in cooling and heating load are chosen as 5°F above and below the desired set point ($T_{set}^{desired}$) respectively.

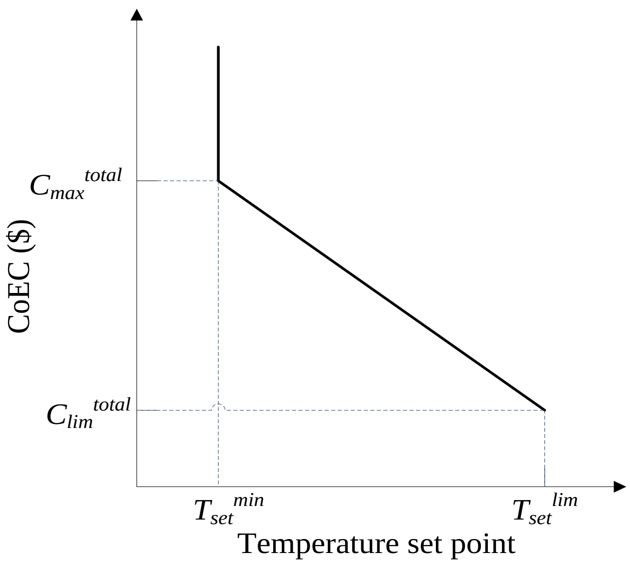

Fig. 5.6. Linear droop curve for set point adjustment of a heating load

- Set point adjustment using exponential droop curve of CoEC

Linear droop curve may not change set points sufficiently in response with the increase in CoEC. Hence, an exponential droop is introduced which provides significant set point adjustment with the variation in CoEC. T_{set}^{Dj} for a cooling load

D_j, is increased exponentially as in Fig. 5.7. Similarly, T_{set}^{Dj} for a heating load is decreased exponentially as in Fig. 5.8, when CoEC during RTC is above C^{total}_{lim}. Set point adjustments are maintained within 5°F.

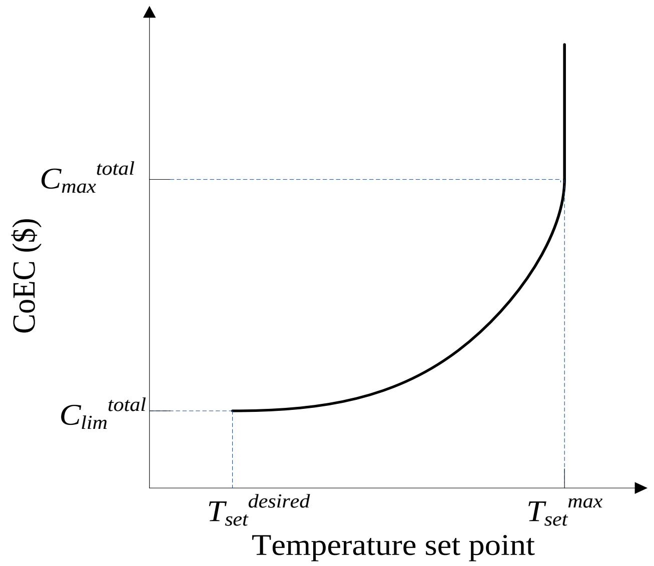

Fig. 5.7. Exponential droop curve for set point adjustment of a cooling load

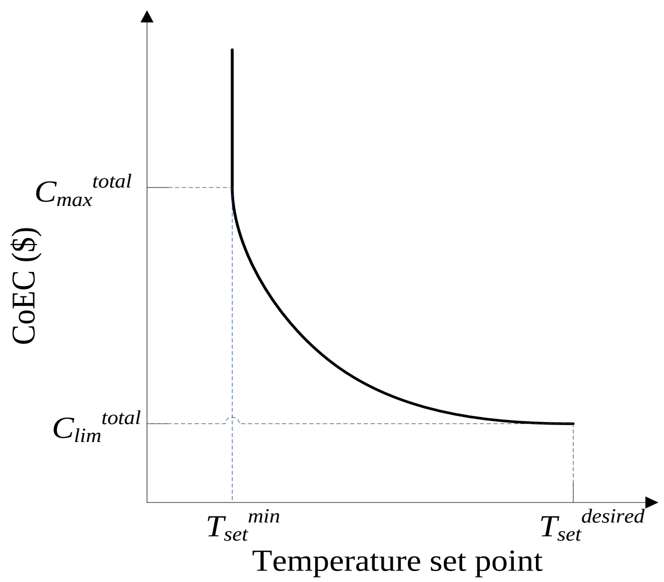

Fig. 5.8. Exponential droop curve for set point adjustment of a heating load

Droop curves are obtained from historical data for each season for a particular house prior to control. Seasonal variations are considered due to operability of ACs and WHs according to seasonal temperature variations.

A HEMS in a utility should have the capability to switch on, switch off or delay appliances connected to relevant HEMS in order to reduce overall energy consumption cost of a house. Discussion on control algorithm is as follows.

5.3. Description of Overall Control Process

Flow chart of the overall control process is summarized in Fig. 5.9. At each time step, real-time price and the total energy consumption of a house is observed to compute the cost of energy consumption. If the cost of energy consumption exceeds a predetermined limit, RTM, STS and RTC phases are triggered subsequently. (The limit of CoEC is predetermined as the average of maximum CoEC of a house).

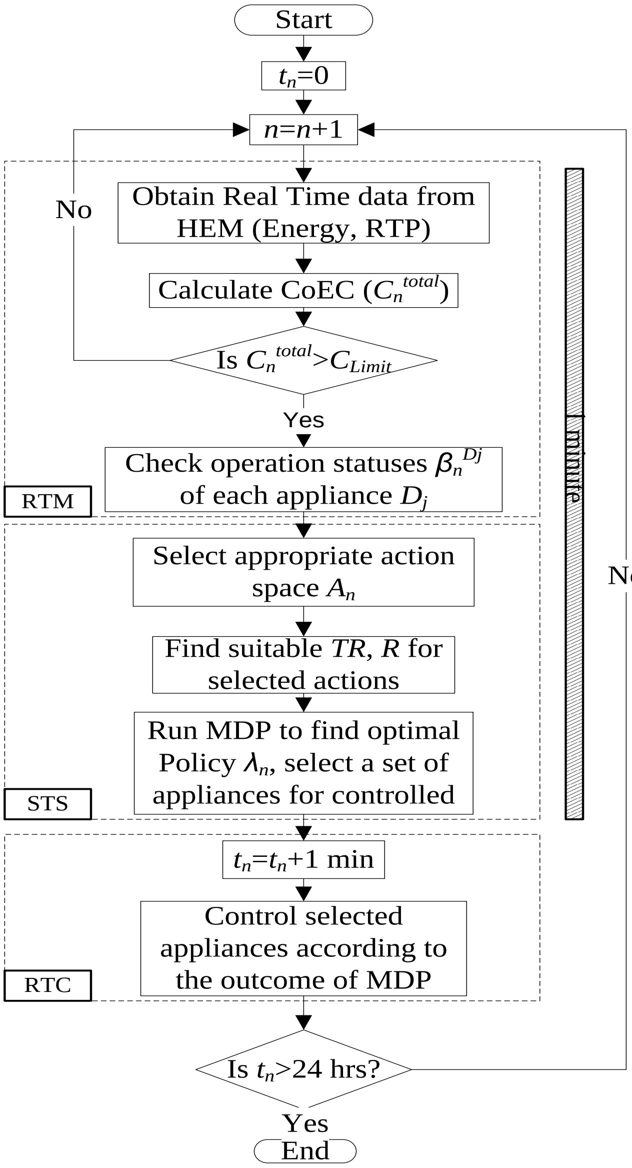

Fig. 5.9 Operation of HEM Scheduler with RTM, STC and RTC phases

During RTM phase, available appliances at that particular time are checked. Actions are selected during STS phase using the data collected in RTM phase. MDP helps to select the optimal set of appliances to be controlled by obtaining policy values.

The current state of CoEC is mapped with the policy values to obtain optimal action or schedule of curtailment. Transition and reward blocks help to run MDP for the above computation. After one minute, the selected appliances are controlled or switched off. This process is repeated every four minutes to have an optimal control of appliances to reduce the cost of consumption.

5.4. Test System and Simulation Results

5.4.1. **Results related to HEMS**

A single house with seven controlled appliances connected to HEMS is taken as test system (as shown in Fig. 5.1). RTP of electricity is considered as the reflection of electricity spot price in electricity market during simulation. Electricity market spot price for a typical summer period (i.e. 3 months) in Australia is taken for this study, which is used for the calculation of state space and transition block.

As discussed in section 5.2.2.2, state space $S=\{S_k, k=1,2,3,4,5,6\}$ represents a range of CoEC. Its boundaries are defined by finding cumulative distribution function (CDF) of CoEC data as in (5.9)-(5.10). It is observed that the CoEC of a house lies in the range of 0- 300 cents and it is the cost of energy within four minutes. In this study, boundaries of states B1-B7 are 0.00, 1.00, 1.50, 2.00, 3.50, 20 and 300.00 cents respectively as shown in Fig. 5.10. Then, the CoEC is categorized into unequal ranges of costs defined as states as shown in Fig. 5.11. The transition probability block is calculated using algorithm 3 for the given states. When there is no curtailment ($A_n^q=\{\}$), the variation of state transitions of a typical house for three typical summer days is illustrated in Fig. 5.12. It shows that day 2 has more state changes due to higher volatility in the electricity price.

A transition probability block at 2000 hrs of day 1 is illustrated in Fig. 5.13 then there is no curtailment (i.e. $A_n^q=\{\}$). It shows the probability values of CoEC state changes. For example, probability of CoEC remaining in 4^{th} state ($TR(4,4)$) is 0.7500. Then, a state dependent reward function is defined for each time step as in

(5.15). Change in reward is observed when there is no curtailment (i.e. A_n^q={}) and when all seven appliances are controlled and is shown in Fig. 5.14. (Here, α is taken as 1 and component of waiting time (W_n^{Dj}) is omitted). Reward gets a higher value when the state changes from 6 to 1 in the next time step and it has the least value when there is a jump from state 1 to 6. This ensures that there is higher reward for larger curtailment.

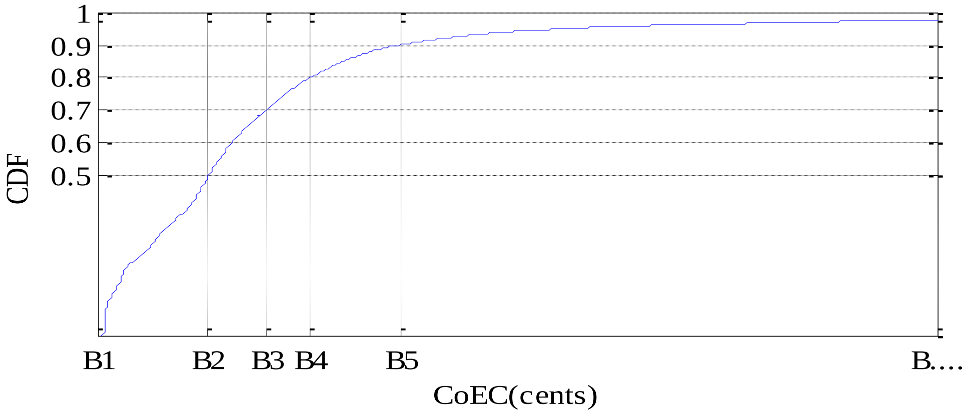

Fig. 5.10 Defining boundaries of states

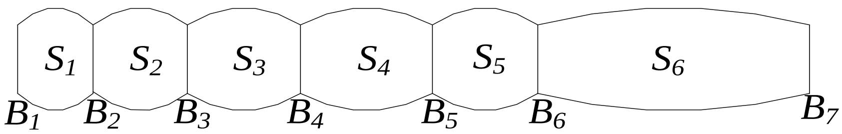

Fig. 5.11 Definition of states for CoEC

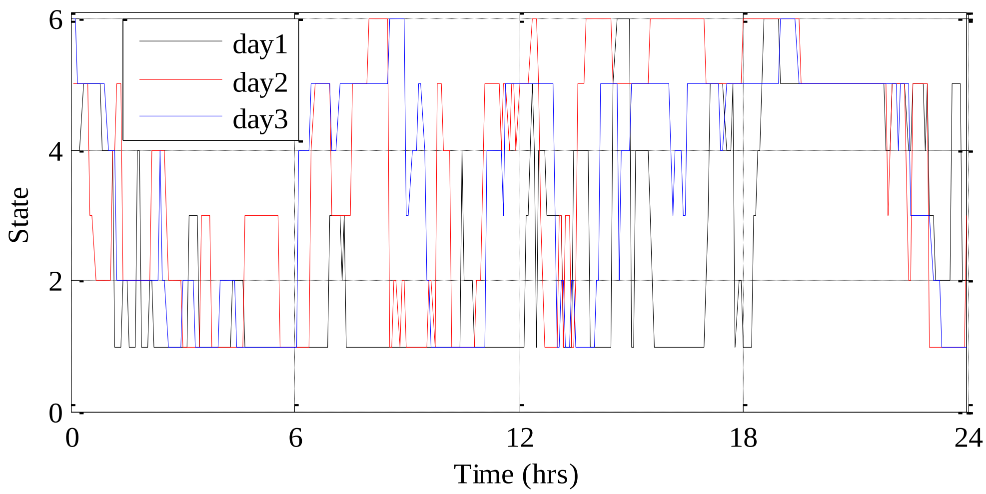

Fig. 5.12 State changes in three typical days of a house in summer

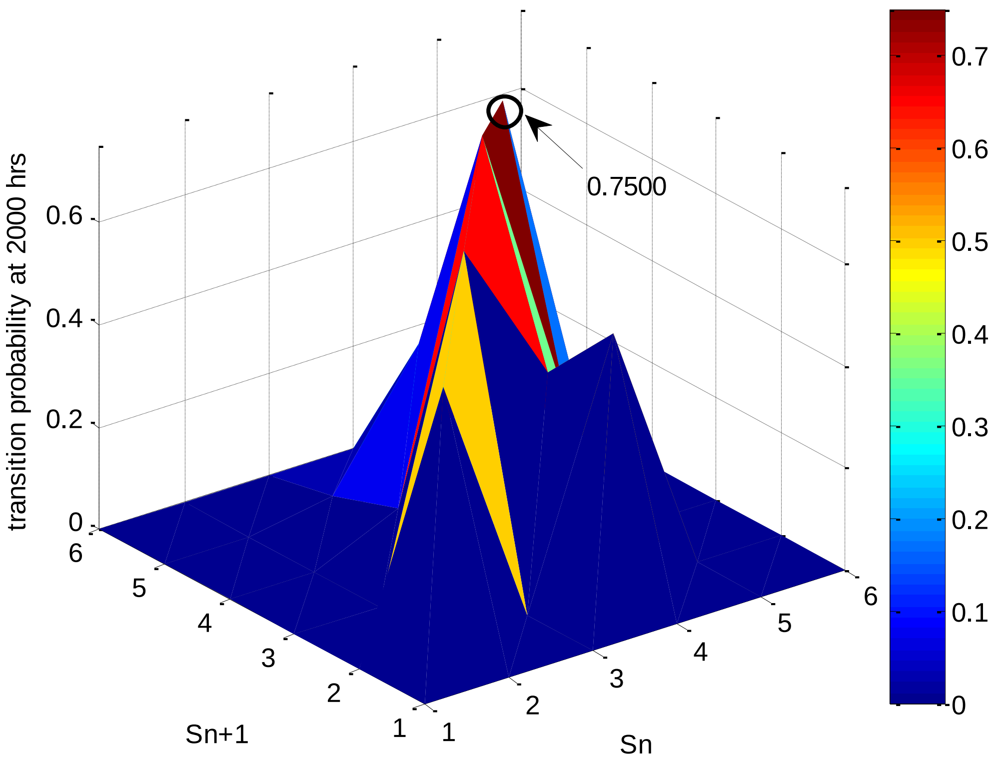

Fig. 5.13. Transition probability of CoEC states at 2000 hrs in winter day

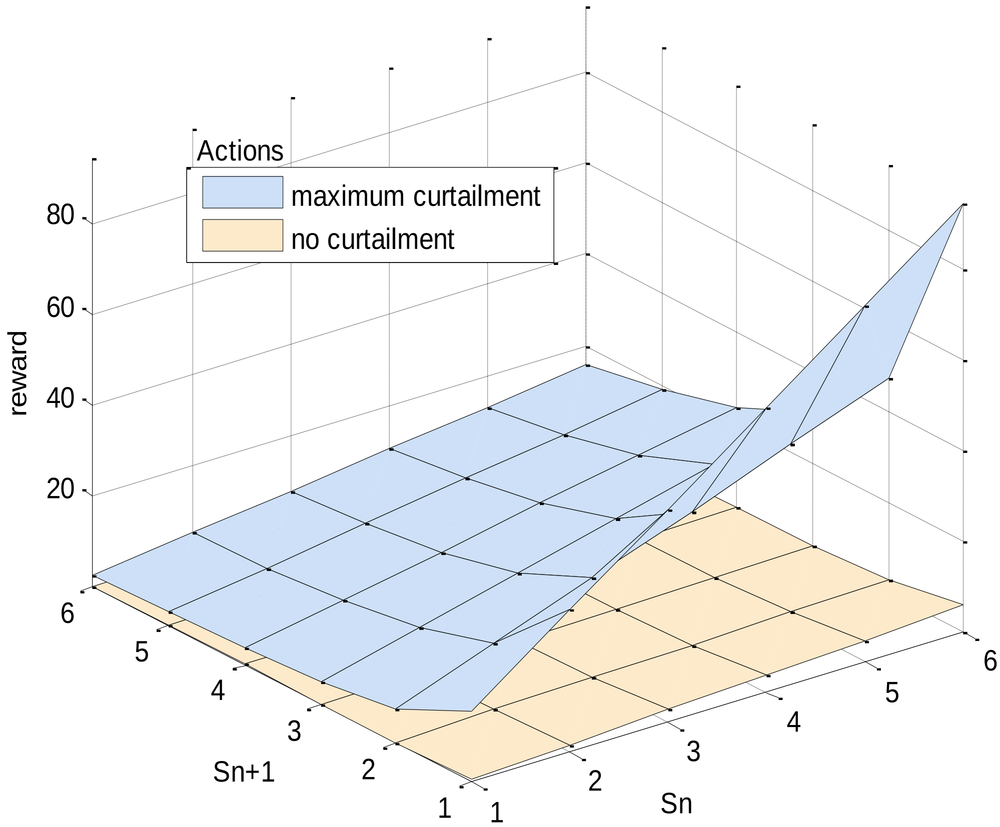

Fig. 5.14 Reward when there is no curtailment and maximum curtailment

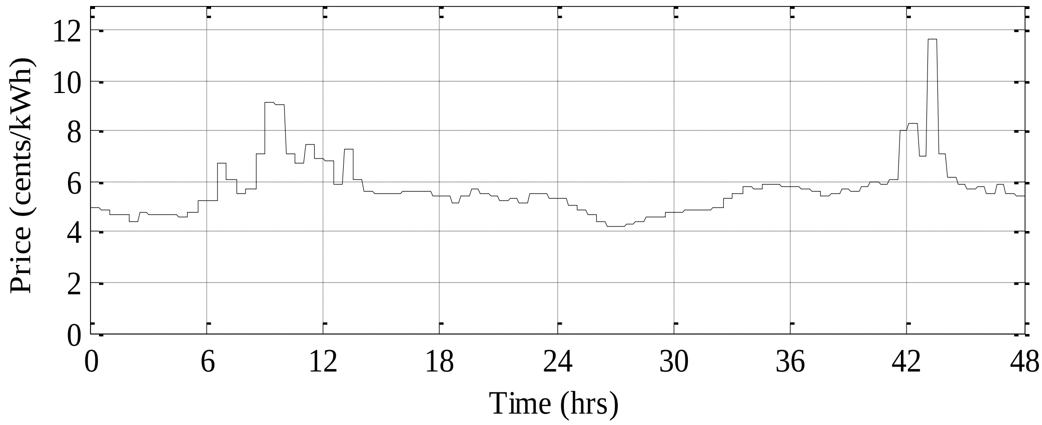

Fig. 5.15. The Real-Time Price considered for real-time model

The retailers will use the information from the wholesale electricity market price to calculate the RTP for individual feeders [111]. Therefore, wholesale price is taken to simulate the R TP variations that are used to broadcast to individual HEMSs and is illustrated in Fig. 5.15. A house with seven controllable appliances are considered and RTM occurs every four minutes. A two day simulation is done and the results are obtained for the optimal policy.

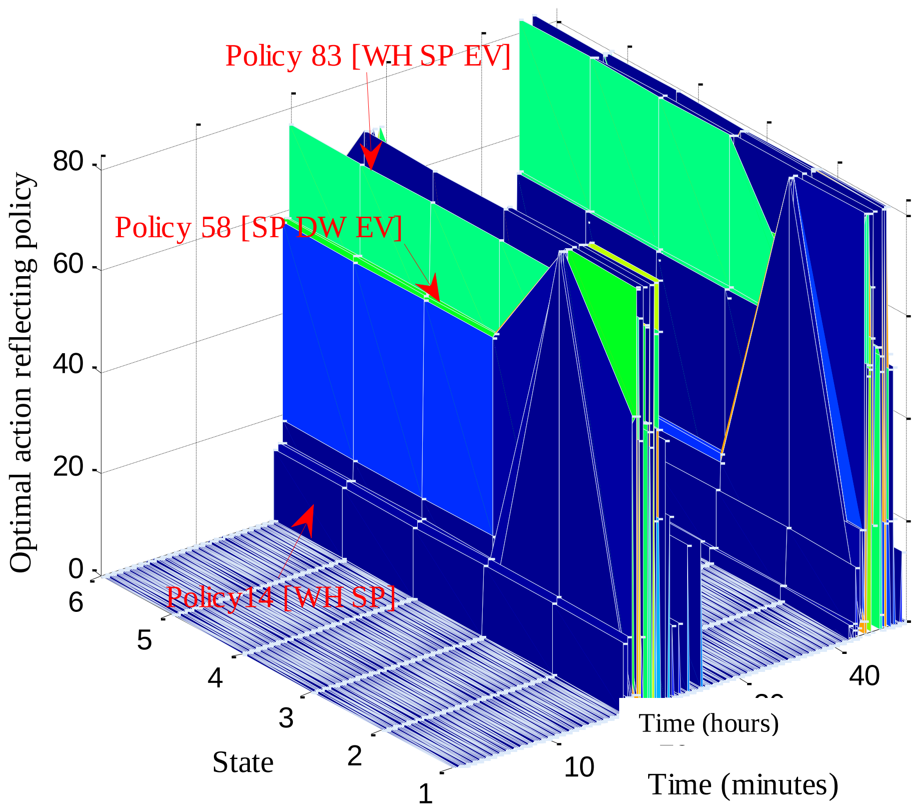

Fig. 5.16. Optimal policy values for two consecutive days

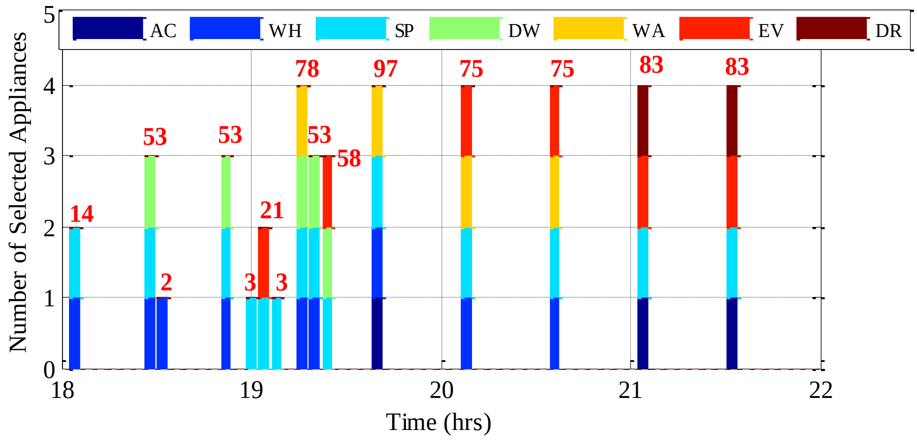

Fig. 5.17. Optimal policy values for a time frame withing a day

The optimal action is plotted as in Fig. 5.16. At time 6.00-8.00 pm, policy values goes high allowing more curtailment. If policy reaches 14, the 14th set of action or the appropriate combination of available appliances is subjected to control to reduce CoEC (i.e. WH and SP). Similarly policy value 58 and 83 represent a combination of [SP, DW, EV] and [WH, SP, EV] respectively. Each policy value represents a set of appliances that can be curtailed at that time step.

The details of selected appliances during 1800 to 2200 hours are shown in Fig. 5.17. Before each control action, HEMS evaluates the current state of CoEC and matches with the corresponding policy value to select appliances appropriately. WH and SP are selected at 1804 hours and the respective policy value is 14. 14th action represents the availability of only WH and SP (i.e. [0 1 1 0 0 0 0] is the binary representation of second (WH) and third (SP) appliance) representing policy value.

Simulation data for winter season is analysed. The overall power profile of the house is shown in Fig. 5.18 with and without HEMS. It shows a shift is power consumption profile due to the load adjustments during increase in CoEC. CoEC of the house in two subsequent day with and without HEMS is shown as in Fig. 5.19. A reduction in CoEC is shown when there is an increase in CoEC.

The change in appliances statuses, when they are subjected to control, is summarized in Table 5.1. If a *Cat* 1 or 2 appliances is subjected to control which was initially under '*WAIT*' or '*OPERATION*' status, it is again kept at '*WAIT*' status confirming that the waiting time and the maximum number of interruptions are not exceeded. Similarly, if a Cat 3 appliance is subjected to control, which was initially under '*ADJUST*' status, it is again kept at '*ADJUST*' status confirming that the set point limit and the maximum number of interruptions are not exceeded.

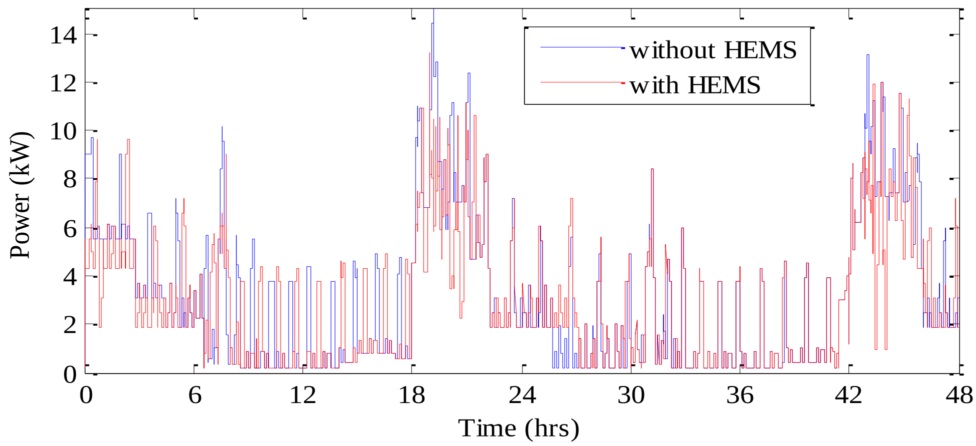

Fig. 5.18. Power profile of the house without and with HEMS

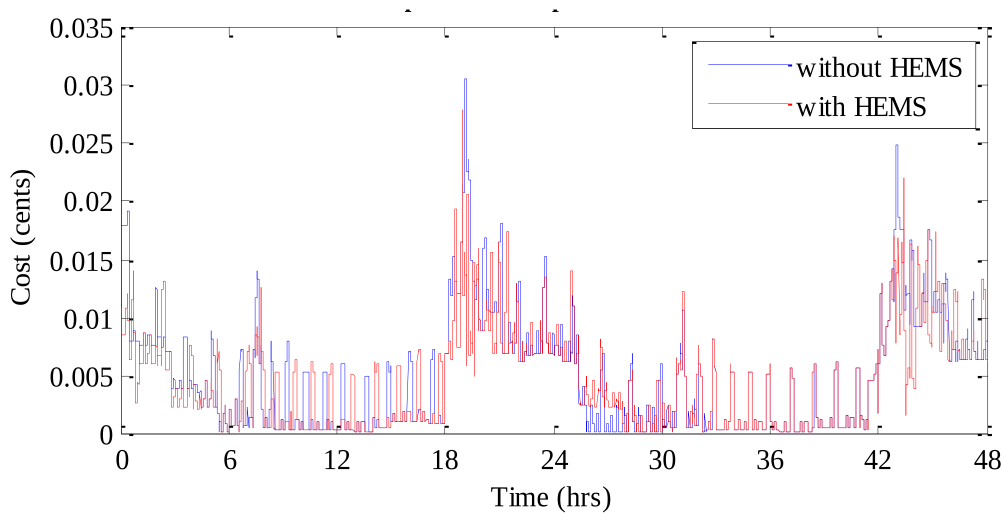

Fig. 5.19 CoEC of the house without and with control

Table 5.1 Changes in appliance statuses when they are subjected to control

Appliance	Conditions	Initial status	Status after control
Cat 1 and Cat 2	$W_{Dj} < W_{Dj}^{max}$ and	*WAIT*	*WAIT*
	$INTRP_{Dj} = true$	*OPERATION*	*WAIT*
Cat 3	$P_{Dj}^{n} > 0$ and $INTRP_{Dj} = true$	*ADJUST*	*ADJUST*

Table 5.2 Appliance status changes at 1940 hours

Appliances	Availability	Selected for control	Status at 1940 hrs	Status at 1944 hrs
AC	Yes	Yes	*ADJUST*	*ADJUST*
WH	Yes	Yes	*ADJUST*	*ADJUST*
SP	Yes	Yes	*WAIT*	*WAIT*
DW	No	-	-	-
WA	Yes	Yes	*OPERATION*	*WAIT*
EV	Yes	No	*WAIT*	*OPERATION*
DR	No	-	-	-

Table 5.2 shows the changes in statuses of appliance at 1940 hours in a particular day. Here, AC, WH, SP, WA and EV were available for control during this time and AC, WH, SP and WA are selected for control in STS phase. Their respective status changes are shown in Table 5.2. For example, WH which was already in '*OPERATION*' is switched off and kept in '*WAIT*' status. Operation of *Cat 1* appliance happens by switching ON and OFF during the control process. As an example, a dishwasher operation with and without HEMS is illustrated in Fig. 5.20. Here, a constant power consumption is assumed during different functions of a dishwasher such as washing, drying and disinfection. The power profile and the temperature variation of water heater is shown in Fig. 5.21. Here, the set point adjustments are shown when there is an increase in CoEC.

Computation time for STS phase of HEMS is approximately 7.5 seconds for a house with seven controllable appliances. Simulations were performed using MATLAB software platform in a 64 bits operating system with 2.10 GHz processor. Thus it makes this algorithm suitable for practical implementation.

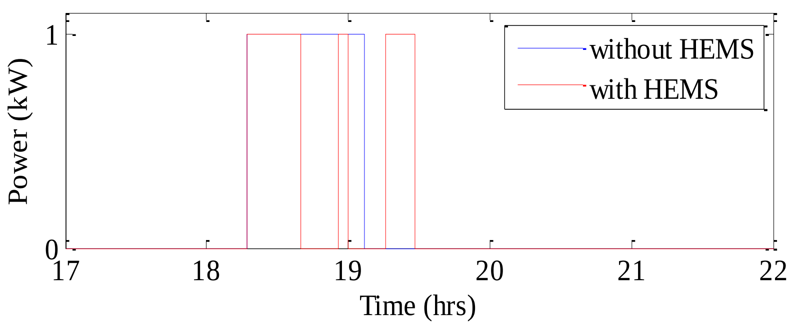

Fig. 5.20 Dish Washer Power Profile of the house with HEMS (*Cat* 1)

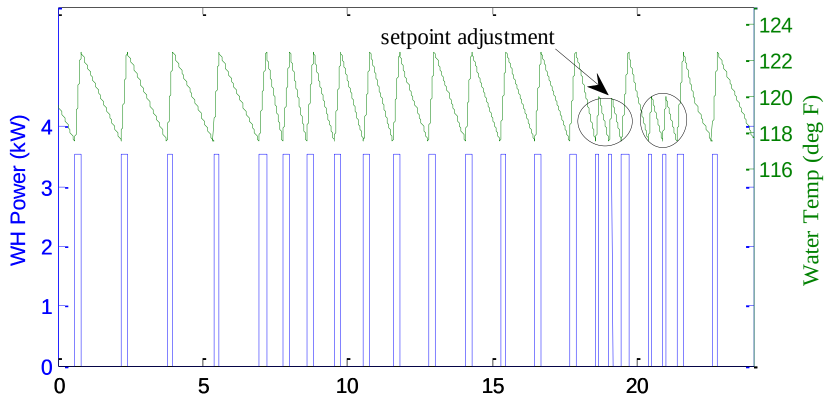

Fig. 5.21 Water Heater Power Profile of the house with HEMS (*Cat* 3)

Table 5.3 Energy and CoEC savings with HEMS

Seasons	Energy Savings due to HEMS (kWh)		CoEC savings ($)	
	One day	3 months	One day	3 months
Winter	2.10	364.4	0.85	77.8
Autumn	0.70	98.6	0.32	31.32
Summer	0.79	99.8	0.59	41.39
Spring	1.76	22.4	0.38	36.53
Annual	--	791.2	--	187.03

Table 5.4 Effect of HEMS on COEC due to uncertainty (A winter day)

Effect of Uncertainty in RTP			Effect of Uncertainty in Appliance power consumption			Effect of Uncertainty in both RTP and Appliance power consumption		
Mean of RTP (μ_{RTP})	CoEC (cents) in a day		Mean of power consumption ($\mu_{ApplPower}$)	CoEC (cents) in a day		Mean of RTP and Appliance power consumption (μ_{RTP}, $\mu_{ApplPower}$)	CoEC (cents) in a day	
	Without HEMS	With HEMS		Without HEMS	With HEMS		Without HEMS	With HEMS
0.8	349.13	334.51	0.5	362.96	351.91	(0.8,0.5)	357.96	348.31
0.9	352.13	335.63	0.75	363.85	352.08	(0.9,0.75)	359.85	348.53
1.0	353.87	335.73	1.0	366.41	352.13	(1.0,1.0)	360.41	348.83
1.1	364.51	336.14	1.5	368.07	352.51	(1.1,1.5)	364.07	349.15
1.2	368.16	336.71	2.0	371.12	352.85	(1.2,2.0)	369.12	349.25

The effect of HEMS on the seasonal variation is summarised in Table 5.3. Although on a daily basis, there is no significant energy reduction as the appliances are shifted rather than curtailed, a considerable reduction in energy consumption (791.2 kWh) and CoEC ($ 187.03) on an annual basis using HEMS (11% reduction in annual CoEC).

The efficacy of HEMS on the electricity cost in a day due to uncertainties in RTP or power consumption is summarised in Table 5.4. It also shows the electrocity cost when uncertainties in both RTP and power consumption exist. Firstly, the mean value of RTP is varied during 1800-2000 hrs (with a variance of 0.1) while keeping a constant power consumption profile. With HEMS, the variations in RTP does not affect the cost of energy consumption in a day (maintained at 335 cents). Similarly, HEMS effect due to uncertainties in power consumption profile is observed. The RTP profile is fixed and the uncertainty in power consumption is modeled by varying the mean while keeping the variance constant at 0.1. Again, the variation in electricity cost is suppressed and is maintained at fixed cost of 352 cents in a day with HEMS. Furthermore, the uncertainties in both RTP and appliance power consumption are considered using variable mean and constant standard deviation of 0.1 and electricity cost is maintained at 348 cents. It can be concluded that that HEMS achieves the aim of maintaining the reduced daily electricity cost of consumption.

5.4.2. **Results related to appliances connected to HEMS**

Characteristics and operation of Cat3 appliances are discussed in this section. Droop curve for set point adjustment as in 5.2.3.2 is created and fixed for a particular season by HEMS of a house. Value of CoEC limit (C^{total}_{lim}) and maximum possible value of CoEC (C^{total}_{max}) are found by plotting 90% and 99.9% of Cumulative Distribution Function (CDF) of CoEC respectively, for each season. Calculation of C^{total}_{lim} and C^{total}_{max} is described in detail below. Data dispersions are removed by choosing 99.9% limitation for C^{total}_{max}.

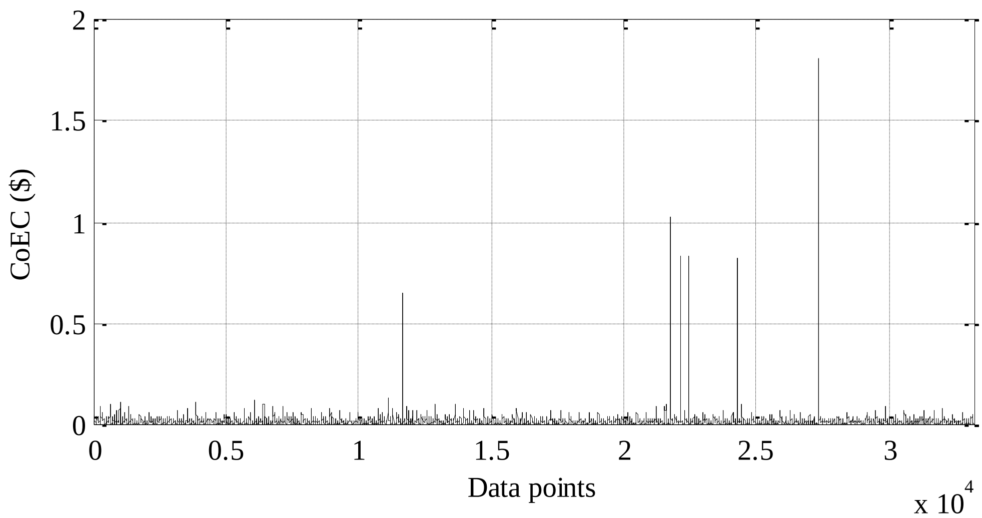

Fig. 5.22 CoEC data of a house in winter season

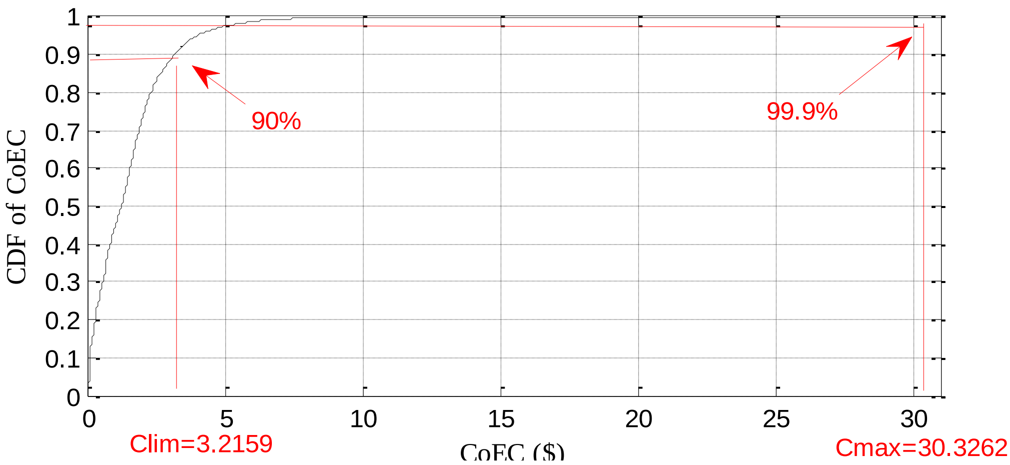

Fig. 5.23 CDF of CoEC of a house during winter

Table 5.5 Calculation of C^{total}_{lim} and C^{total}_{max} of each season for HEMS

Season	C^{total}_{lim} 90% CDF of CoEC ($)	C^{total}_{max} 99.9% CDF of CoEC ($)
Winter	3.2159	30.3262
Autumn (Fall)	3.1266	15.1876
Summer	3.5577	115.2029
Spring	2.7673	13.3685

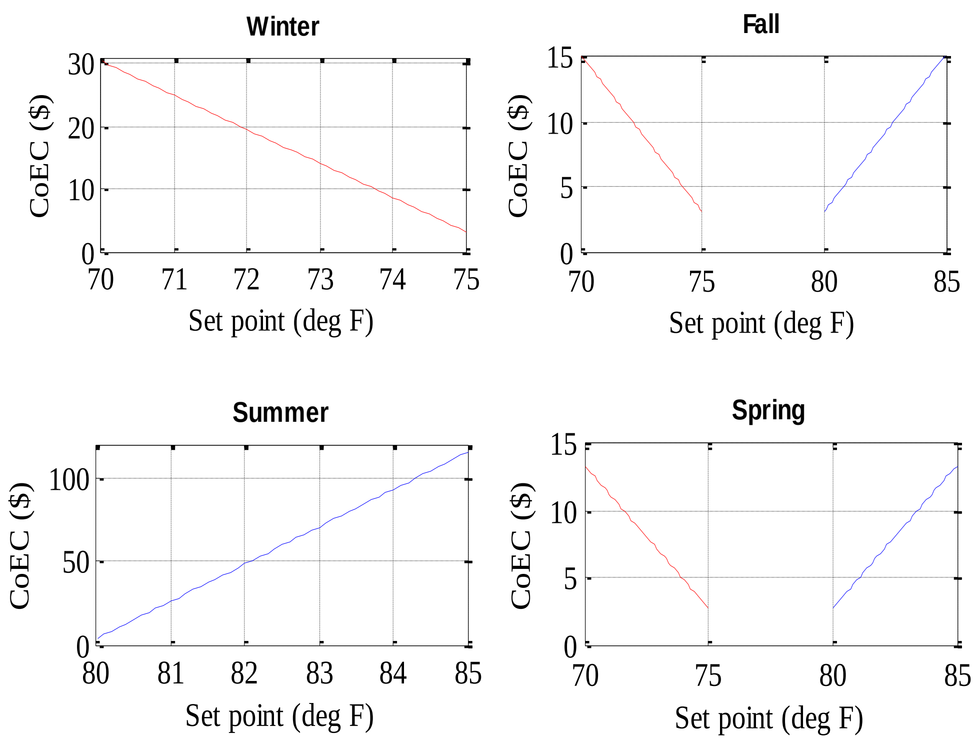

Fig. 5.24. Linear droop curve obtained for each season for HEMS

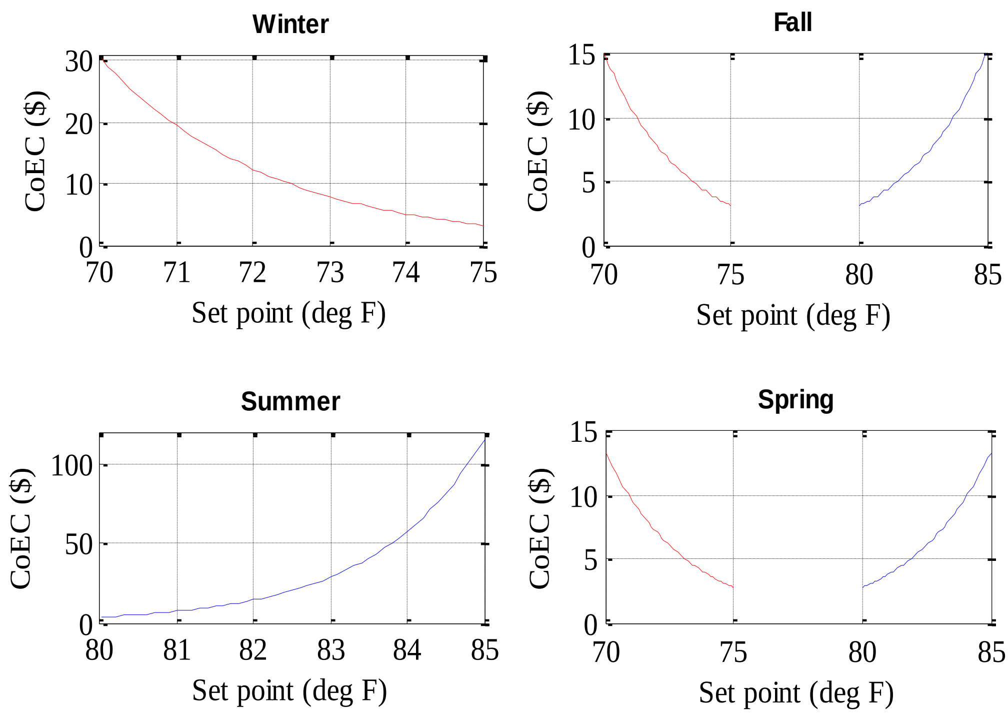

Fig. 5.25 . Exponential droop curve obtained for each season for HEMS

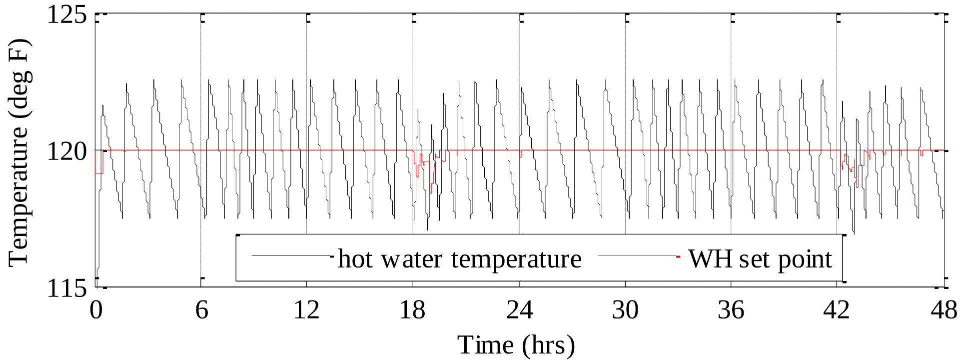

Fig. 5.26 Hot water temperature variation with exponential droop control

Initially, CoEC data is collected for a year and 91 days are considered to represent each season. For example, winter data for CoEC is collected from 21st of June to 22nd of September 2013 as per seasons in Brisbane, Australia. Data dispersion of winter season is shown in Fig. 5.22. It represents the variation of a data set with four minute time steps of each selected day. This data is used for the calculation of CDF as shown in Fig. 5.23. It helps for determining C^{total}_{lim} and C^{total}_{max} during winter, which are \$3.2159 and \$ 30.3262 respectively. Similarly, values of C^{total}_{lim} and C^{total}_{max} are determined for other seasons which are tabulated in Table 5.5.

Linear droop curves obtained for HEMS for a particular house in each season is shown in Fig. 5.24. Values of CoEC such as $C^{total}{}_{lim}$ and $C^{total}{}_{max}$ in Table 5.5 are used for defining these curves. During winter, only the droop curves of heating loads are considered and during summer, only the droop curves of cooling loads are considered. However, during autumn and spring, droop curves of both heating and cooling loads are considered. Curves are selected based on customer requirement for cooling or heating purposes. Similarly, exponential droops for each season for a particular house are obtained as in Fig. 5.25. Temperature ranges are chosen for a particular house as in Fig. 5.24 and Fig. 5.25. However, the droop curves will change according to the temperature set-point preferences in each house.

Furthermore, hot water temperature variation with exponential droop control for a particular house, during RTC is shown in Fig. 5.26. Similarly, room temperature variation is also plotted with the exponential droop control as in Fig. 5.27. It shows that significant set point adjustment is performed during RTC by the use of exponential droop.

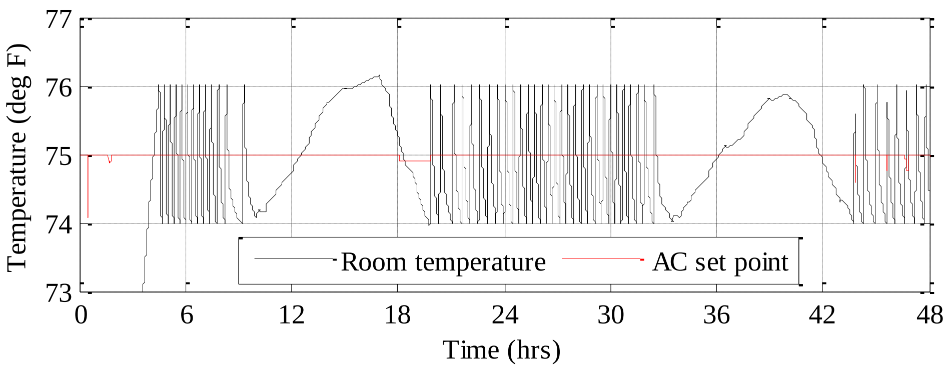

Fig. 5.27 Room temperature variation with exponential droop control

5.5. Summary and Conclusion

This part of research work, mainly focuses on a simple algorithm for a real-time home energy management unit for reducing the cost of energy consumption in a house. It is possible with the introduction of advanced metering infrastructure including smart meters and home energy management systems. The overall control process is composed of three subsequent phases namely Real-Time Monitoring (RTM), Stochastic Scheduling (STS) and Real-Time Control (RTC). During RTM phase, utility remotely monitors the appliances connected to Home Energy

Management Unit (HEMS) of a house at every time step. It also obtains price information from electricity market. When there is an increase in cost of energy consumption, utility defines the operating status of each controllable appliances according to its operating characteristics and customer input. Although RTM provides information of current status of appliances, it may not be sufficient for making appropriate control decisions. It is due to the uncertainties in electricity price variation, appliance operation, user behavior and preferences. Hence, a STS process is performed next utilizing the information of operating status of appliances. Markov Decision Process is used to minimize cost of energy consumption by predicting the appropriate curtailment of appliances based on the stochastic behavior of cost of consumption. Customer priorities are also intrinsically considered during the control process by adding constraints. Furthermore, interrupting an appliance while it is in operation reduces its life span and customer comfort. Constraints for appliance interruption are also included in STS phase. Subsequently, selected appliances are controlled at the third phase of RTC. Outcomes show that a significant reduction in cost of energy consumption is achieved also maintaining customer comfort.

Chapter 6

Stochastic Ranking Method for Thermostatically Controllable Appliances to Provide Regulation Services

Demand Response (DR) is preliminarily used for peak load shaving and alleviating voltage issues in an electricity feeder. However, DR can also be used for providing regulation services in the electricity markets. The retailers can bid in day-ahead market and respond to real-time regulation signal by load control. This part of research work, proposes a new stochastic ranking method to provide regulation services via demand response. A pool of Thermostatically Controllable Appliances (TCAs) such as air-conditioners and water-heaters are adjusted using the direct load control method. The selection of appliances is based on a probabilistic ranking technique utilizing attributes such as temperature variation and statuses of TCAs. These attributes are stochastically forecasted for the next time step using day-ahead information. System performance is analyzed with a given regulation signal. Network capability to provide regulation services under various seasons is analyzed. The effect of network size on the regulation services is also investigated. Customer comfort is maintained by keeping the temperature within allowable limits.

6.1. Introduction and Related Work

Demand Response is introduced in the electricity market to achieve peak load reduction, [67], [122] and eliminate adverse network voltage conditions [123] as in Chapter 3 and Chapter 4. It is accomplished with the participation of end users in electricity market by means of direct load control (Chapter 3) or indirect price responsive load adjustments (Chapter 4). The immediate need of network upgrade cost is deferred and the end users are offered either a reduced price for consumption [124] or rebate for load curtailments [125]. Recent studies [53]-[127] indicate that DR in distribution network can also be used for regulation purposes.

The integration of intermittent renewable energy sources such as wind and solar requires additional generation or load devices capable of providing regulation services to maintain reliable and safe operation. Conventional generators may not be capable to provide regulation services due to practical constraints such as low ramp rate. Moreover, repeated exposure to system fluctuations will reduce the life span of conventional generators [53]. DR, whereas, is one of the promising option for providing short term regulation services to the network.

Availability and flexibility to adjust Thermostatically Controllable Appliances (TCAs) especially Water Heaters (WH) and Air Conditioners (AC) make them ideal for providing regulation services via DR [126]. With the introduction of smart meters and in-home energy management units, it is possible to manage these appliances without jeopardizing customer comfort.

The authors of [52] have proposed a method of using aggregated WHs with the aim of providing ancillary services. Here, a day-ahead forecasted model is used and control commands are broadcasted based on the predicted outcomes. Due to forecasted control model, there is a detection mismatch rate of 33.3%, which limits its usefulness to provide accurate regulation services.

A deterministic minute to minute regulation services is proposed in [53], [127] utilizing aggregated loads of WHs and ACs respectively. Here, loads are prioritized based on temperature (i.e. if regulation raise or lower service is required, appliances are selected by sorting temperature values in ascending or descending order respectively). It coordinates expected control signals based on thermostat status of previous and next time instant. However, this technique fails to focus on prediction of appliance status on the next time step. Prediction of appliances is extremely important as the appliance consumption patterns and temperature variations are highly uncertain.

Regulation technique in [53], [127] is accomplished by switching selected appliances ON and OFF at each control step. The authors of [54] propose temperature set point adjustments to reduce switching actions and uses day-ahead load profile of appliances in the network, while neglecting the uncertainty in appliance consumption. A probability function for water consumption rate is taken in [55], but the appliance selection procedure is based on a power tracking method, which does not consider uncertainties in appliance power consumption.

Contribution: Hence, research work in presented in this chapter proposes a new stochastic ranking method based on pairwise probabilistic comparison of TCAs with respect to different appliance attributes during decision making. The two attributes i.e. temperature variation and appliance switching status, are time varying and hence, their expected values are stochastically determined for next time step. As these attributes closely follow Markov process, the values for next time step depends only on the values of current time step. The probabilistic comparison of appliances based on various attributes is used to compute appliance ranking for a given regulation requirement. Customer comfort is maintained by keeping the temperature within allowable limits. Similar to the proposed method in [53]- [127], this research also considers the direct load control via instantaneous switching actions, but uses probabilistic measure to predict the status of attributes. Hence, this scheme incorporates uncertainty and hence provides better regulation services.

The detailed background of the regulation services as well as the proposed stochastic ranking method is discussed in section 6.2. The mathematical models used for simulation and results are analyzed in section 6.3 followed by conclusions in section 6.4.

6.2. Stochastic Ranking Method for TCAs to Provide Regulation Services

6.2.1. **Background on Regulation Services**

Traditionally, the ancillary services market is responsible for providing services to manage power system reliability and security. In Australian context, the Australian Energy Market Operators (AEMO) offers Frequency Control (FCAS), Network Control and System Restart Ancillary Services. This study specifically focuses on FCAS regulation market, which is responsible for maintaining frequency within upper and lower limits (Allowable limit of 0.2 % frequency deviation i.e. between 49.9 and 50.1 Hz) by balancing generation and demand. AEMO offers regulation services using day-ahead market for all registered retailers, who submit a bid a day prior to the trading day for demand response.

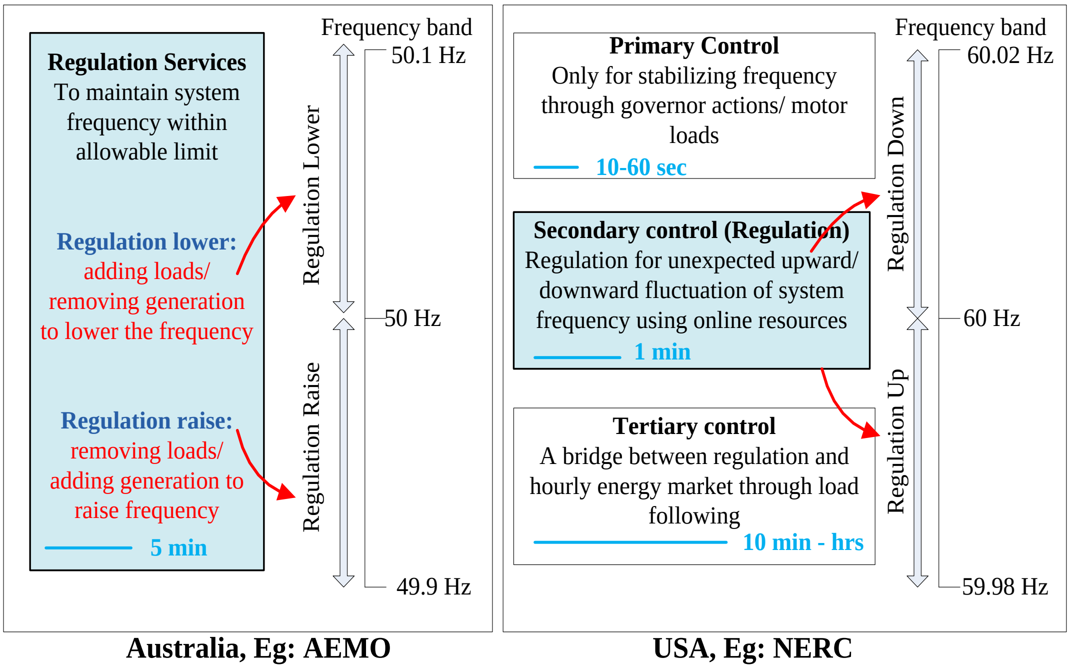

Fig. 6.1. Comparison of AEMO and North American markets

If a retailer submits a bid for regulation raise, it represents the amount of power that retailers can curtail from the system in a given time frame to raise frequency whereas, a bid for regulation lower represent the amount of power that can be added to the system in a given time frame to lower the frequency. FCAS sends offers of dispatch instructions to retailers at five minute dispatch interval in a trading day

[128]. Similarity of FCAS regulation at AEMO and North American Reliability Corporation (NERC) regulations can be summarized by Fig. 6.1. As per NERC standards, system operators offer frequency control services in three steps i.e. Primary control (10 -60 sec), Secondary control (1 -10 min) and Tertiary control (10 min- 1 hr). The secondary control is achieved by regulation services on a minute to minute basis [129], similar to FCAS regulation services. The algorithm developed here, however, is generalized and applicable in any market around the world.

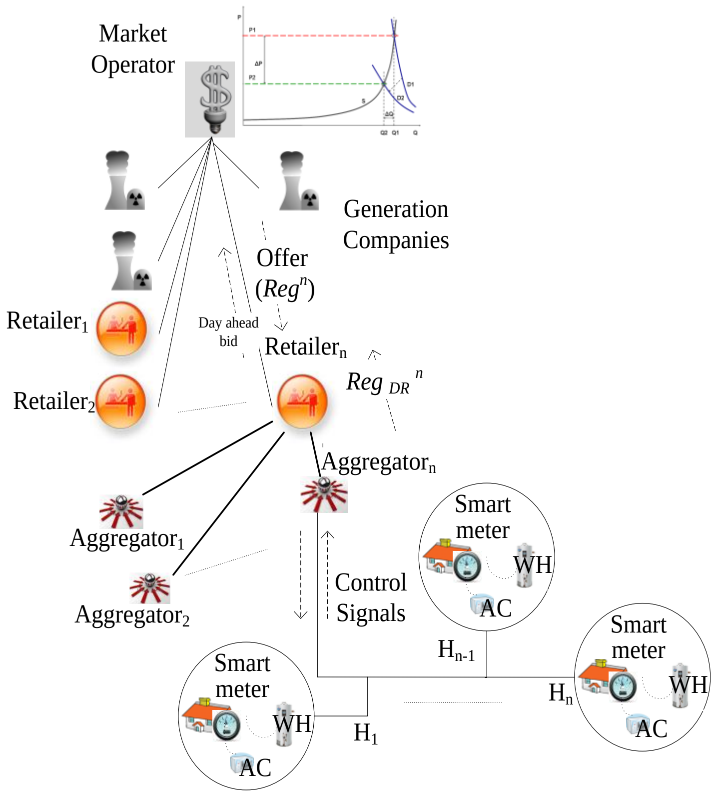

Fig. 6.2. Providing regulation services via DR

Conventionally, generation companies register in ancillary services market to provide regulation services. Recent advancements in metering and communication infrastructures has enabled load serving entities (retailers) to participate via DR scheme.

Initially, retailers, who are providing regulation services to the grid, submit a day-ahead bid based on expected load availability (computed using historical load pattern) to the market operator for the next day. On a trading day, system operator offers dispatch instructions (Reg^n at n^{th} time step) to participating retailers at regular time intervals. Retailers, upon receiving this signal, send instructions to different aggregators (representing a cluster of energy users and capable of taking control actions for a pool of appliances) to perform load adjustments. The aggregators, after receiving the information from retailers, perform Stochastic Ranking (SR) algorithm and achieve Reg_{DR}^n (required regulation service via DR) to match Reg^n. The network diagram representing the ancillary services market for providing regulation services via DR is illustrated in Fig. 6.2.

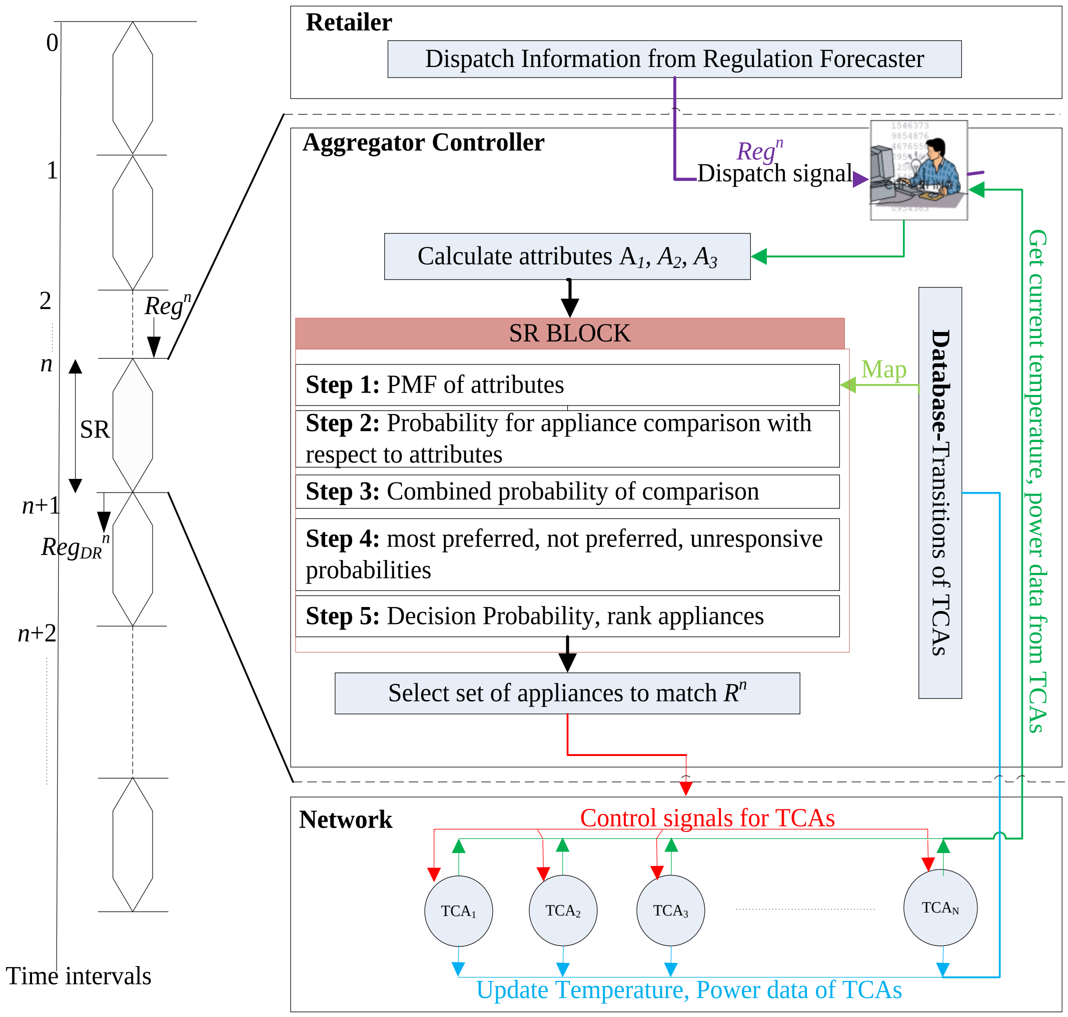

Fig. 6.3. Schematic Control Diagram of Aggregator Controller

6.2.2. SR algorithm performed by Aggregators

Aggregators perform SR algorithm to provide regulation services via DR mechanism. SR algorithm uses probabilistic measures of different attributes and uses stochastic programming (SR block) to rank them for achieving desired regulation response (Reg_{DR}^n). SR block consists of five steps as shown in Fig. 6.3. Using the

Probability Mass function (PMF) of various attributes (Step 1), the probabilities of appliances pairwise comparisons are calculated (Step 2). In step 3, the overall pairwise comparisons of appliance probability are obtained and are categorized according to preference (Step 4). In Step 5, the decision probability to rank appliances is calculated. Finally, the selected appliances according to ranking order are subjected to control. Information of TCAs is updated and stored in database which aids for calculation of attribute PMFs. Detailed description of SR algorithm (as summarized in Fig. 6.3) is discussed below:

6.2.2.1. ***Calculation of Attributes***

Among many attributes of load appliances, temperature variation, switching state and power rating are most important and are discussed below:

Attribute 1 (Temperature variations): As the appliances are subjected to curtailment when regulation raise service is required, only those appliances having higher probability to reach maximum comfort are selected i.e. heating appliances with higher temperature and cooling appliance with the lower temperature are suitable. Similarly, during regulation lower services, appliances are re-connected to the network, and therefore only those appliances having higher probability to reach minimum comfort are chosen. Therefore, attribute 1, $AT_{1i}^{n} \in [0,1]$ for i^{th} appliance at n^{th} time step, is defined as a normalized measure of temperature (room temperature for an AC and tank water temperature for a WH) as per (6.1). AT_{1i}^{n} can be used as a measure of customer comfort.

$$AT_{1i}^{n} = \begin{cases} \dfrac{T_{i,actual}^{n} - T_{i,\min}^{n}}{2T_{i}^{db}} & \text{if } i \text{ is a heating load} \\[2ex] \dfrac{T_{i,\max}^{n} - T_{i,actual}^{n}}{2T_{i}^{db}} & \text{if } i \text{ is a cooling load} \end{cases} \tag{6.1}$$

Where T_i^{db} is dead-band of i^{th} appliance; $T_{i,actual}^{n}$, $T_{i,min}^{n}$ and $T_{i,max}^{n}$ are actual, minimum and maximum allowable temperature for i^{th} appliance at n^{th} time step respectively. For the easiness of probabilistic computation, a continuous variable, $AT_{1i}^{n} \in [0,1]$, is converted to a discrete grey stochastic variable, $AT_{G1i}^{n} \in [1,10]$, with a discrete step size of 0.1 [131]. In general, a grey variable can be defined as a number to represent a range of values. For example, Table 6.1 shows the values of the grey stochastic variable, AT_{G1i}^n, for AT_{1i}^n under different regulation request.

Table 6.1 Definition of Grey Variables for AT_{1i}^n

$\boldsymbol{AT_{1i}^n}$	[0,0.1)	[0.1,0.2)	[0.2,0.3)	[0.3,0.4)	…	[0.9,1.0)
Reg^n>0	1	2	3	4	…	10
Reg^n<0	10	9	8	7	…	1

For regulation raise services (Reg^n>0), AT_{G1i}^n is incremented from 1 to 10, with an increment of 1. Whereas, for regulation lower services (Reg^n<0), AT_{G1i}^n is decremented from 10 to 1.

Attribute 2 (Switching states of TCAs): The status of the appliance is another important attribute for regulation services as it provides probabilistic information of appliances' current switching state. It helps to find appliance with correct switching state for control. Therefore, attribute 2, $AT_{2i}^n=\{0,1\}$ for i^{th} appliance at n^{th} time step, is defined as either 'OFF'= '0' or 'ON'= '1'. Although, AT_{2i}^n , is discrete variable, the grey variable, AT_{G2i}^n, is introduced for the purpose of grading appliances with higher probability of being in 'ON' status during regulation raise services and 'OFF' status during regulation lower services. For regulation raise services (Reg^n>0), AT_{G2i}^n is assigned 'OFF'= '1' and 'ON'= '2'. Whereas, for regulation lower services (Reg^n<0), AT_{G1i}^n is assigned 'OFF'= '2' and 'ON'= '1'.

Attribute 3 (Power rating of TCAs): The power ratings of TCAs can be used to grade appliances so that appliance with higher power rating is chosen for regulation services. Hence, attribute 3, AT_{3i}^n, for i^{th} appliance at n^{th} time step, is introduced and takes the value of the rating of i^{th} appliance for both regulation raise (Reg^n>0) and regulation lower (Reg^n<0) requirement. The importance of AT_1 is to provide maximum comfort to customers during regulation control. Attribute AT_2 aids to choose appliance with the correct switching state to satisfy requirements. Furthermore, attribute AT_3 is introduced to select appliances with the high power ratings so that number of control commands is reduced.

6.2.2.2. ***SR block***

Using the information from three attributes, the SR block performs following five steps to rank the loads:

Step 1: Defining Probability Mass Function (PMF) of attributes- PMF of $AT_{G1i}{}^{n}$ and $AT_{G2i}{}^{n}$ for i^{th} appliance at n^{th} time step is calculated using historical data of appliance consumption pattern. It is assumed that the first two attributes follow Markov process. Markov property of a stochastic variable illustrates that given the present value, the future is independent from the past. If $AT_{Gki}{}^{n}$, the k^{th} attribute, is currently in $h_x{}^{\text{th}}$ grey score, the probability of it being in $h_y{}^{\text{th}}$ grey score at next time step can be defined as $\mathbf{P}_{xy,i}{}^{n+1}$ as in (6.2) and is computed using the algorithm below.

$$\mathbf{P}_{xy,i}^{n+1} = \mathbf{P}(AT_{Gk,i}^{n+1} = h_y \mid AT_{Gk,i}^{n} = h_x) \tag{6.2}$$

Computation of Probabilities for Attribute Transitions

for time step $n = 0$ to $24\,hrs$ (5 min increment)

initialize count $N_{xy}^{i} = 0$

 for day $d = 1$ to 91

 Define grey score $AT_{Gki}^{n}(d)$ as in (4)

  for score $x = 1$ to M

   for score $y = 1$ to M

    if $AT_{Gki}^{n}(d) = h_x \cap AT_{Gki}^{n+1}(d) = h_y$

    $N_{wy}^{i} = N_{xy}^{i} + 1$

    end if

   end for loop of state y

   $\mathbf{P}(AT_{Gk,i}^{n+1} = h_y \mid AT_{Gk,i}^{n} = h_x) = N_{xy}^{i} \Big/ (\sum_{y=1}^{M} N_{xy}^{i})$

  end for loop of state x

 end for loop of day d

end for loop of time step n

Historical data of appliance consumption pattern for 91 days in a season is obtained. Number of days ($N_{xy}{}^{i}$) is counted subjected to transitions of grey scores from h_x to $h_{y.}$ for k^{th} (k=1,2) attribute of i^{th} appliance at n^{th} time step. It is repeated for all possible grey scores, and the total number of days are obtained as $\sum N_{xy}{}^{i}$, where y={1,2,…,M}. Ultimately, transition probability, $\mathbf{P}_{xy,i}{}^{n+1}$, is computed as a ratio of

$N_{xy}{}^i$ and $\sum N_{xy}{}^i$. This process is repeated for each appliance at each time step in a day. Furthermore, a transition block is created at n^{th} time step for a particular season as in (6.3). Here, M is number of grey scores. This transition block (TR) is used to compute PMF, $g_i{}^n(AT_k)$, for i^{th} appliance at n^{th} time step for k^{th} (k=1,2) attribute as represented in (6.4). If the grey score at current time step is known as h_x, then $h_x{}^{\text{th}}$ row of transition block gives the values of PMF as the probabilities of all grey scores at $(n+1)^{\text{th}}$ or next time step. Here, h_m is M^{th} grey score.

$$TR^n_{AT_{ki}} = [\mathbf{P}^{n+1}_{xy,i}]_{M\times M} \quad 1 \le x, y \le M \tag{6.3}$$

$$g_i^n(AT_k) = \left[TR^n_{AT_{ki}}\right]_{h_x \times (1 \to h_m)} \tag{6.4}$$

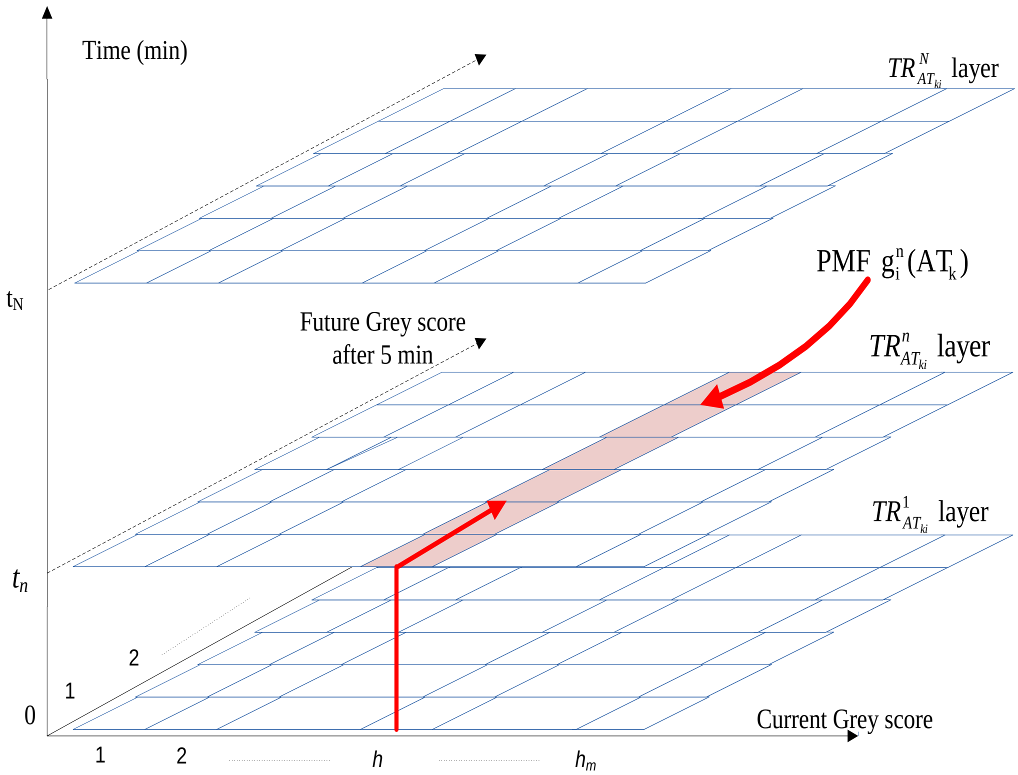

Fig. 6.4. Obtaining PMF from transition block

Fig. 6.4 further illustrates the way of obtaining PMF from transition block. $AT_{Gki}{}^n$ and $AT_{Gkj}{}^n$ of i^{th} and j^{th} appliances are considered as two independent discrete random variables with PMF of $g_i{}^n(AT_{Gk})$ and $g_j{}^n(AT_{Gk})$, where $\sum g_i{}^n(AT_{Gk})=1$ and $\sum g_j{}^n(AT_{Gk})=1$ for $-\infty < AT_{Gk} < +\infty$.

Step 2: Pairwise comparison of probability for individual attributes- The PMF of (AT_{Gki}^{n}-AT_{Gkj}^{n}) is defined as $f_{ij}^{n}(AT_{Gk})$, which represents the comparison of i^{th} and j^{th} appliances with respect to k^{th} attribute as in (6.5). Furthermore, $\mathbf{P}(AT_{Gki}^{n}=AT_{Gkj}^{n})$ is defined as in (6.6). Finally, the pairwise comparison of probability for AT_{Gki}^{n} being greater than AT_{Gkj}^{n} is defined as in (6.6).

$$f_{ij}^{n}(AT_{Gk}) = \sum_{AT_{Gk}\to-\infty}^{+\infty} g_{j}^{n}(AT_{Gki}^{n} - AT_{Gk})g_{i}^{n}(AT_{Gki}^{n}) \tag{6.5}$$

$$\mathbf{P}(AT_{Gki}^{n} = AT_{Gkj}^{n}) = f_{ij}^{n}(0) \tag{6.6}$$

$$\mathbf{P}(AT_{Gki}^{n} > AT_{Gkj}^{n}) = \sum_{AT_{Gk}=0}^{M} f_{ij}^{n}(AT_{Gk}) - 0.5 f_{ij}^{n}(\mathbf{0}) \tag{6.7}$$

Unlike the first two attributes, AT_{G1i}^{n} and AT_{G2i}^{n}, the third attribute, AT_{G3i}, is not time varying and the probability for pairwise comparison of appliance is defined deterministically as in (6.8).

$$\text{If } E_{i}^{rating} > E_{i}^{rating} \quad \begin{cases} \mathbf{P}(AT_{Gki} > AT_{Gkj}) = 1 \\ \mathbf{P}(AT_{Gkj} > AT_{Gki}) = 0 \end{cases} \tag{6.8}$$

If the energy rating (E_{i}^{rating}) of i^{th} appliance is greater energy rating (E_{j}^{rating}) of j^{th} appliance, probability of AT_{G3i} being greater than AT_{G3j} is '1', otherwise '0'.

Then, a block of pairwise comparison of probabilities for each attribute is constructed as in (6.9) and (6.10), using the above probability computations [132] . The diagonal elements of these blocks do not comprise of useful values. Here, N_{app} in the number of total available appliances in the network for regulation.

$$\mathbf{P}_{AT_k,comp}^{n} = [\mathbf{P}(AT_{Gki}^{n} > AT_{Gkj}^{n})]_{N_{app}\times N_{app}} \quad 1 \le i, j \le N_{app} \tag{6.9}$$

$$\mathbf{P}_{A_3,comp} = [\mathbf{P}(AT_{G3i} > AT_{G3j})]_{N_{app}\times N_{app}} \quad 1 \le i, j \le N_{app} \tag{6.10}$$

Step 3: Computation of probability with combined attributes- In step 2, pairwise probabilistic comparison of appliances based on individual attributes are obtained. However, analyzing the overall performance of appliances with a proper coordination of three different attributes is vital. Therefore, the overall probability for pairwise comparison of appliances is computed in Step 3.

There are two possible outcomes during comparison of i^{th} and j^{th} appliance with respect to k^{th} attribute. (i.e. if $AT_{Gki}^{n} > AT_{Gkj}^{n}$ is true, a binary outcome is defined as $u_{k,ij}^{n}$='1' and otherwise '0'. It shows that, there are 2^3=8 combinations of possible outcomes for pairwise comparison with the proposed three attributes. These combinations are shown in (6.11) where U_{ij}^{nq}={(0,0,0), (1,0,0), (0,1,0),…….., (0,1,1), (1,1,1)} for all q={1,2,…..,8}.

$$U_{ij}^{n,q} = \left\{u_{1,ij}^{n,q}, u_{2,ij}^{n,q}, u_{3,ij}^{n,q}\right\}, \quad q = 1,2,...,2^3 \tag{6.11}$$

$$\mathbf{p}_{i>j,overall}^{n,q} = \prod_{k=1}^{3} \left(\mathbf{P}_{AT_k,comp}^{n,ij}\right)^{u_{k,ij}^{n,q}} \left(\mathbf{P}_{AT_k,comp}^{n,ji}\right)^{(1-u_{k,ij}^{n,q})}, q = 1,2,...,2^3 \tag{6.12}$$

$$\mathbf{P}_{overall}^{n,q} = [\mathbf{p}_{i>j,overall}^{n,q})]_{N_{app} \times N_{app}} \quad 1 \le i, j \le N_{app} \tag{6.13}$$

Finding the probability ($\mathbf{p}^{n.q}_{i>j,\ overall}$) of obtaining q^{th} possible results when i^{th} appliance is compared with j^{th} appliance with respect to all three attributes is represented as in (6.12), which is used to form an overall probability, $\mathbf{P}^{n.q}_{overall}$, as in (6.13) and contains probabilities of pairwise comparison for all appliances in the network at n^{th} time step.

Step 4: Classification of possible outcomes- As there are 2^3 combinations of possible pairwise comparisons, the classification for $U_{ij}^{n.q}$ will help in improving computational speed and avoid the negative effect of undesirable values of $U_{ij}^{n.q}$. The three classes, as per classification rule [131], are as below:

Most preferable $U_{ij}^{n.q}$: If sufficient results exist to prove that i^{th} appliance is preferable than j^{th} appliance

Unresponsive $U_{ij}^{n.q}$: If there is no sufficient results exist to prove that appliance i^{th} appliance is preferable than j^{th} appliance

Not preferable $U_{ij}^{n.q}$: If sufficient results exist to prove that i^{th} appliance is not preferable than j^{th} appliance

This helps in providing conditions for deciding one attribute over the other. A threshold value, λ, and the weightage of the three attributes are chosen as 0.6 and [0.4 0.3 0.3] respectively. Rule used for classification is shown in Table 6.2 and Fig.

6.5. It shows the influence of attributes with their respective weights. At least two indicators are essential for making decisions.

Fig. 6.5. Categorizing the possible results into groups

Next, probabilities for the above classified groups are computed, which is the addition of $\mathbf{P}^{n.q}{}_{overall}$ for the selected combination of attributes (i.e. z^{th} classification Cl_z) as in (6.14).

$$\mathbf{P}^{n}_{Cl_z} = \sum_{q \in q_{clz}} \mathbf{P}^{n,q}_{overall} \quad Cl_z = Cl_1, Cl_2, Cl_3 \tag{6.14}$$

Table 6.2 Categorizing possible results

Classification	**Condition**	***q***	$\boldsymbol{U_{ij}^{n,q}}$
Most Preferable	if $U_{ij}^{n,q}$ x $w^T \geq \lambda$	{4, 6, 7, 8}	{(1,1,0), (1,0,1), (0,1,1), (1,1,1)}
Unresponsive	if $U_{ij}^{n,q}$ x $w^T \leq \lambda$	{}	{}
Not preferable	if (1- λ)< $U_{ij}^{n,q}$ x w^T<λ	{1, 2, 3, 5}	{(0,0,0), (1,0,0), (0,1,0), (0,0,1)}

Step 5: Ranking based on decision probability: Finally, (6.15) is used to calculate the combined probability matrix for appliance ranking.

$$\mathbf{P}^{n}_{D} = \mathbf{P}^{n}_{Cl_1} + 0.5\mathbf{P}^{n}_{Cl_2} \tag{6.15}$$

$$\mathbf{P}^{n}_{D} = \begin{bmatrix} - & \mathbf{P}^{n}_{D,1>2} & \mathbf{P}^{n}_{D,1>3} & \cdots & \cdots & \mathbf{P}^{n}_{D,1>N_{app}} \\ \mathbf{P}^{n}_{D,2>1} & - & \ddots & \ddots & \ddots & \mathbf{P}^{n}_{D,2>N_{app}} \\ \mathbf{P}^{n}_{D,3>1} & \mathbf{P}^{n}_{D,3>2} & - & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & - & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & - & \vdots \\ \mathbf{P}^{n}_{D,N_{app}>1} & \mathbf{P}^{n}_{D,1N_{app}>2} & \cdots & \cdots & \cdots & - \end{bmatrix} \tag{6.16}$$

$$\mathbf{P}((i>1)\cap(i>2)\cap\cdots\cap(i>N)) = \mathbf{P}^{n}_{D,i>1} \times \mathbf{P}^{n}_{D,i>2} \cdots \times \mathbf{P}^{n}_{D,i>N} \quad x \neq i \tag{6.17}$$

$$\mathbf{P}_{rank}^{n} = \left[\prod_{x=1,\ x\neq i}^{N_{app}} \mathbf{P}_{D,i>x}^{n} \right]_{N_{app}\times 1} \qquad i = 1,2,\ldots\ldots, N_{app} \tag{6.18}$$

The decision probability matrix, $\mathbf{P}_D{}^n$, is the addition of most preferred probability matrix and 50% of the unresponsive matrix as shown in (6.15) and gives the probabilities of i^{th} appliance being greater than the j^{th} appliance in n^{th} time step as shown in (5.16). $\mathbf{P}_D{}^n$, comprises of overall stochastic comparison of appliances which is used for ranking appliances.

The events represented by each row of $\mathbf{P}_D{}^n$, are independent such that probability of occurrence of one event does not influence the probability of other. Hence, the probability of i^{th} appliance is being greater than x^{th} appliance where x=1,2,…….,N $x \neq i$ can be easily obtained as using (6.17). Finally, the probability of every appliance being greater than the i^{th} appliance is calculated using (6.18) using $\mathbf{P}_D{}^n$. The appliances are ranked from the maximum to minimum probability of $\mathbf{P}_{rank}{}^n$. Appliance with a highest rank has the maximum probability to be greater than other appliances considering all attributes.

6.3. Modeling and Simulation Results

A test aggregator network consisting of 30 houses is considered to verify the algorithm for regulation services. Network topology as in chapter 3 is considered during the study with 10 houses per phase in a feeder. A sample regulation signal is taken, which is send from a retailer to the aggregator. All houses are assumed to have both ACs and WHs and are connected through in-home energy management units. These units have the capability to obtain time varying temperature and appliance power data, which is required by retailers for providing regulation services. MATLAB software is used to perform all simulations with 5 minute time step for 24 hours.

6.3.1. **Mathematical models for TCAs (ACs and WHs)**

ACs and WHs are considered as TCAs which operate within a predefined dead-band around a temperature set point. A continuous time varying models of WH and AC are used in this study and are discussed below.

AC: A thermal model of a house, based on a heat flow circuit is developed and the room temperature variation is modeled as in (19).

$$\frac{dT_r^n}{dt_n} = -\left(\frac{U_a + H_m}{\psi_{ac}}\right)T_r^n + \frac{1}{\psi_{ac}}\begin{bmatrix} U_a & H_m & Q_{ac} \end{bmatrix} \times \begin{bmatrix} T_a^n \\ T_m^n \\ K_{ac}^n \end{bmatrix} \tag{19}$$

Here, n- n^{th} time step in a day, T_a- ambient temperature, T_m- mass temperature of the house, T_r- room temperature of the house, ψ_{ac}- thermal mass capacity of inter ior air, U_a- heat loss coefficient, H_m- interior mass conductance of the house, Q_{ac}- energy input rate of AC and K_{ac}- state of AC thermostat (if K_{ac}=1 AC is switched ON and OFF otherwise) [54], [130]. Heating and cooling set points of AC have a nominal value of 75°F and 80°F respectively. Further dead-band of AC is considered to have a nominal value of 1°F during simulations. The variation in the capacity of ACs across different houses is modeled as normal distribution with mean of 2.5kW and variance of 0.1.

WH: A first order differential equation as in (20) for the energy flow of a WH is used to model their temperature characteristics [119], [53].

$$\frac{dT_{wh}^n}{dt_n} = \left(\frac{G + B}{\psi_w}\right).T_{wh}^n + \frac{1}{\psi_w}\begin{bmatrix} G & B & Q_{wh} \end{bmatrix} \times \begin{bmatrix} T_a^n \\ T_{in} \\ K_{wh}^n \end{bmatrix} \tag{20}$$

Here, T_w- water temperature, T_{in}- inlet cold water temperature, Q_{wh}- energy input rate, G- standby heat loss of the tank, B- heat consumption rate of water, ψ_w- thermal capacity of water in the tank, K_{wh}- state of WH thermostat. Set point and dead-band of WH have a nominal value of 120°F and 2.5°F respectively. The variation in the capacity of WHs across different houses is modeled as normal distribution with mean of 3.5kW and variance of 0.1. Detailed model of ACs and WHs are discussed in Appendix A.

For example, in a typical winter day (in Brisbane Australia), the power consumption profile of a single AC and WH is shown in Fig. 6.6 and Fig. 6.7 respectively. AC maintains room temperature within preferable limit by its switching actions performed by thermostat. Room temperature is compared with ambient temperature as in Fig. 6.6.

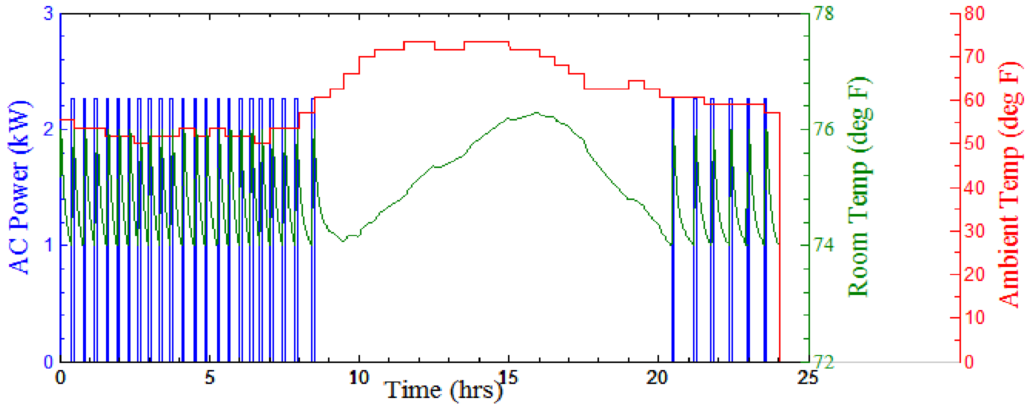

Fig. 6.6. Normal operation of an AC of a house

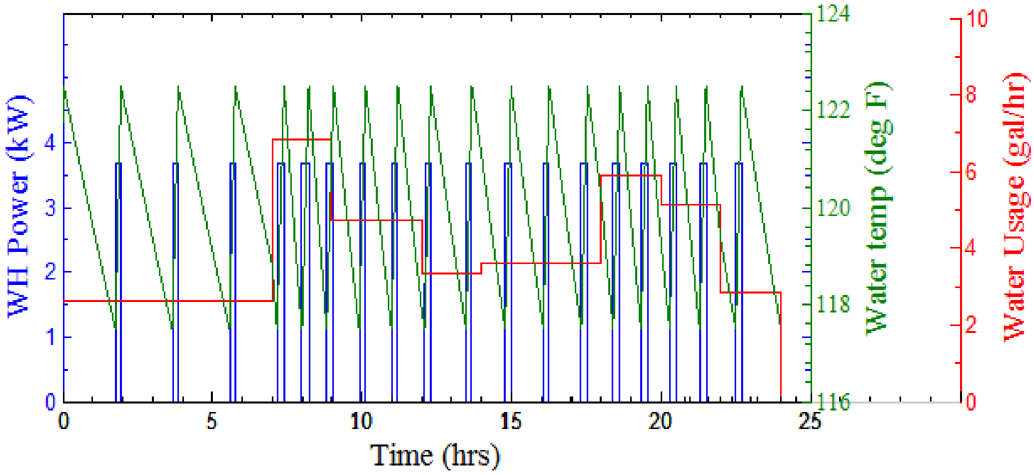

Fig. 6.7. Normal operation of a WH of a house

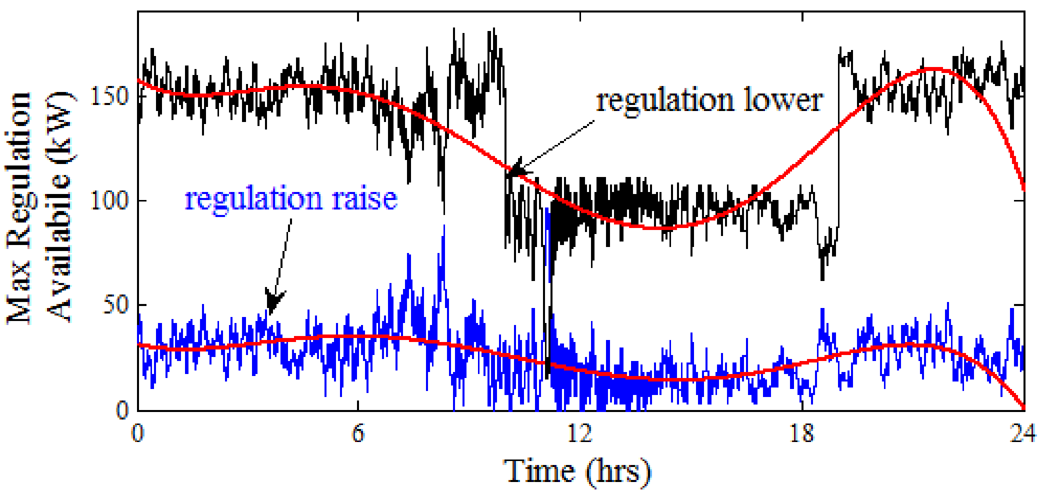

Fig. 6.8. Maximum available loads for regulation in 30 houses network

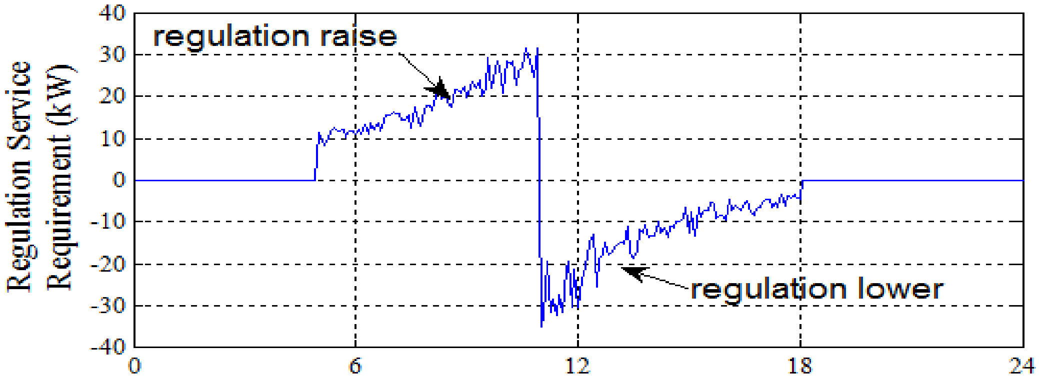

Fig. 6.9. Regulation requirement for network with 30 houses

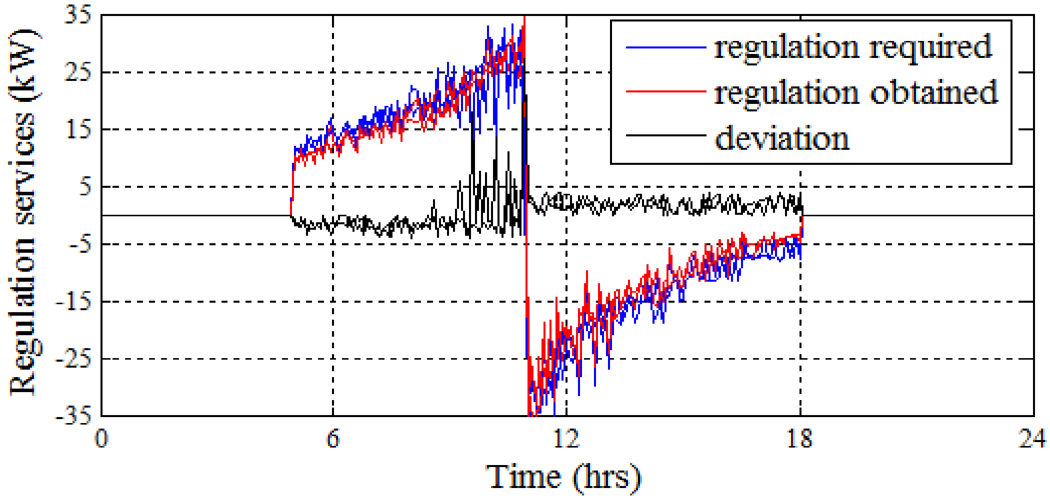

Fig. 6.10. Comparing network performance for a sample regulation service

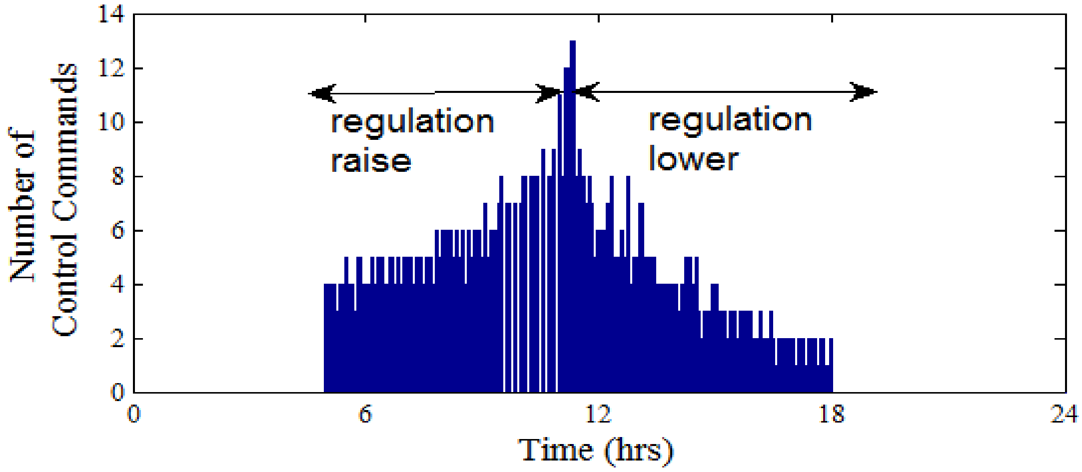

Fig. 6.11. Number of controls during regulation

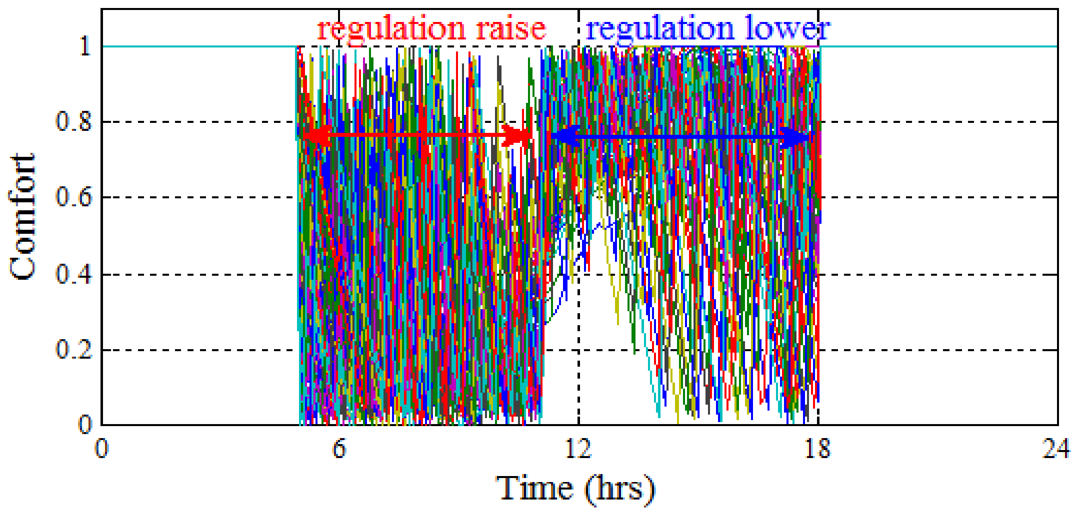

Fig. 6.12. Comfort of TCAs in the network as per (1)

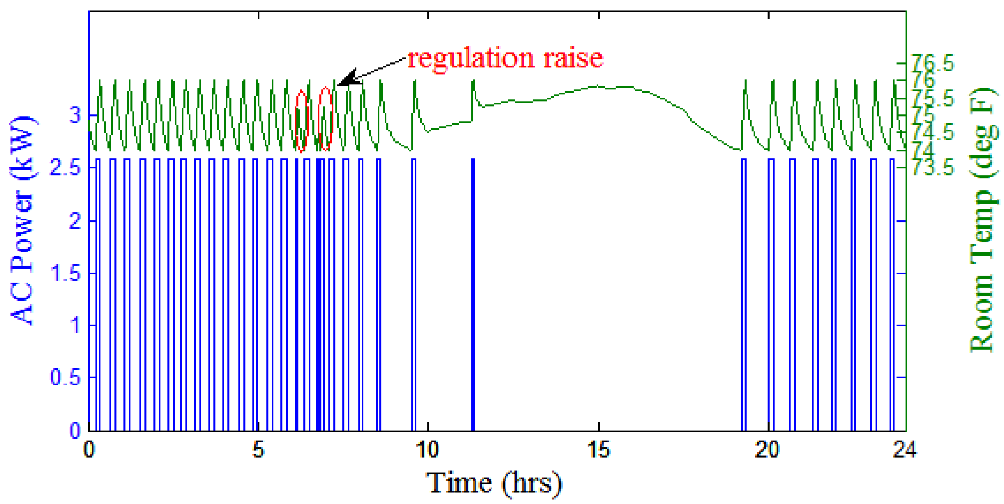

Fig. 6.13. Operation of an AC when providing regulation services

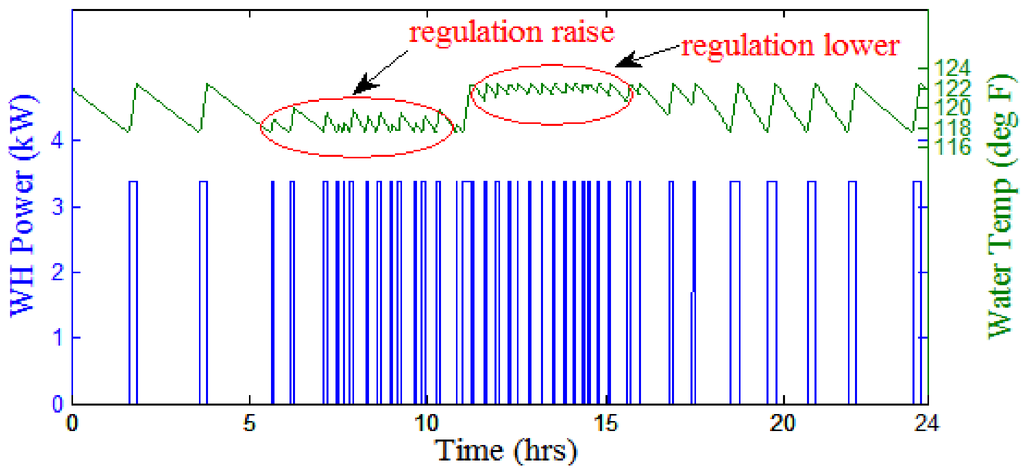

Fig. 6.14. Operation of a WH when providing regulation services

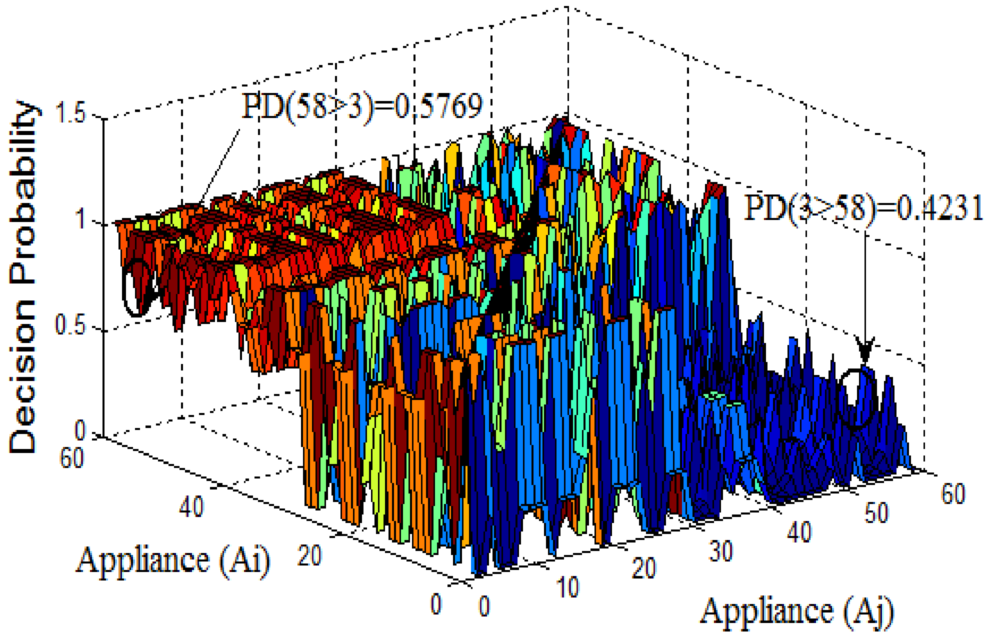

Fig. 6.15. Decision Probability at 1000 hrs (regulation raise services)

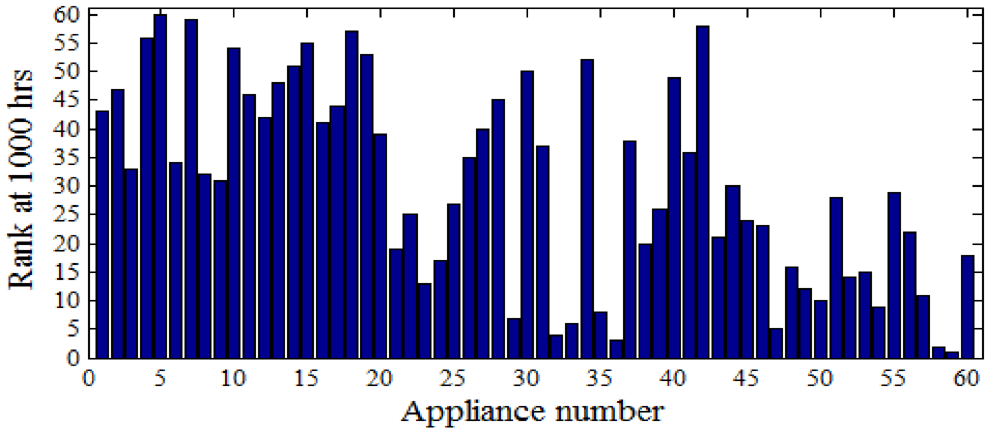

Fig. 6.16. Ranking of appliances at 1000 hrs

The power consumption profile of AC to maintain this room temperature is also shown in Fig. 6.6 Similarly, WH maintains temperature of hot water within a preferred limit is shown in Fig. 6.7. Respective power consumption profile of WH along with the water consumption of a house is also illustrated in Fig. 6.7.

6.3.2. **Small network with 30 houses**

Using weather forecasting data for a given area and the availability of appliances in the previous day, the expected load availability for the network is calculated by the retailer. Day-ahead network simulations are run without any controls to calculate the maximum amount of regulation services that can be offered in next 24 hrs. It is obtained by calculating available TCAs, which can be used for both regulation raise and lower services without violating comfort. The maximum possible regulation services that can be offered by the given test network are shown in Fig. 6.8. This is required for biding purposes and retails can provide regulation services up to this maximum limit.

Fig. 6.9 shows a sample regulation signal having a “regulation raise” requirement of 15kW between 500 hrs- 1100 hrs and a “regulation lower” requirement of 21kW between 1100 hrs and 1700 hrs. A simple exponential function with normal Random variable is used to generate this signal. Here, it is assumed that the same signal is send to the aggregator to provide regulation services. Fig. 6.10 shows the regulation services provided by the network, which matches well the required regulation signal. The number of control commands issued by the aggregator is shown in Fig. 6.11. Thirteen numbers of appliances are adjusted to satisfy the peak regulation requirement of 35 kW at 1100 hrs. Appliance comfort level is maintained within the allowable temperature range as shown in Fig. 6.12.

Table 6.3 Comparison of regulation services with three different networks

No of Houses	**Time**	**Average “regulation raise” capability (kW)**				**Average number of controls**				**Error%**
		Winter	Autumn	Summer	Spring	Winter	Autumn	Summer	Spring	
30	0700 hrs	15.73	13.48	18.82	13.72	6.210	4.84	8.10	4.42	**10.84**
	0900 hrs	**28.83**	**17.74**	**25.58**	**22.57**	7.00	5.69	7.59	5.19	**12.01**
	1230 hrs	28.60	25.39	48.87	21.94	8.220	7.21	**10.15**	6.35	**04.77**
	0230 hrs	14.59	11.22	18.83	10.85	4.610	2.86	4.91	2.85	**12.88**
120	0700 hrs	70.72	45.64	79.23	59.11	25.74	19.06	21.84	16.41	02.04
	0900 hrs	118.39	63.58	131.61	83.61	26.25	22.42	28.46	21.48	02.65
	1230 hrs	139.42	109.5	200.06	85.11	30.63	26.59	40.50	25.86	01.76
	0230 hrs	54.69	45.98	73.65	52.43	18.51	10.55	19.31	12.35	02.88
960	0700 hrs	563.30	428.3	544.9	474.52	203.9	148.8	270.1	146.4	00.85
	0900 hrs	**873.10**	**563.3**	**777.0**	**609.27**	237.3	180.6	248.1	172.4	00.94
	1230 hrs	1032.4	732.7	1661.3	755.48	256.1	216.4	328.6	191.6	00.17
	0230 hrs	468.10	426.5	553.0	383.22	162.6	95.05	159.5	87.71	00.52

The power consumption and temperature variation of TCAs in a single house in the network, while providing regulation services are shown in Fig. 6.13 and Fig.

6.14. During “regulation raise” requirement, as the selected appliance is switched off, it remains switched off until it reaches minimum temperature. For example, selected WH as in Fig. 6.14 is subjected to its first “regulation raise” control action at 0550 hrs and switched off. It remains switched off until it reaches its minimum temperature level at 0610 hrs and is reconnected. Similarly, during “regulation lower” requirement, as the selected appliance is switched on, it remains on until it reaches the maximum allowable temperature. For example, selected WH as in Fig. 6.14, is subjected to its first “regulation lower” control action at 1136 hrs and is switched on. It remains switched on, until it reaches its maximum temperature level at 1146 hrs and is disconnected. Similar behavior of all other TCAs in the network is observed.

The aggregator ranks the appliances using probabilistic pairwise comparison. The graph of decision probability of comparing i^{th} and j^{th} appliances at 1000 hrs, during regulation raise services, is shown in Fig. 6.15. It shows that $P_{D,i>j}$=1- $P_{D,j>i}$. For instance, decision probability of 58th appliance being greater than 3rd appliance is $P_{D,58>3}$=0.57 and decision probability of 3rd appliance being greater than 58th appliance is $P_{D,3>58}$=0.42. Then, the ranking probability as in (6.18) is computed using decision probability in Fig. 6.15 and obtains appliance ranking as shown in Fig. 6.16.

6.3.3. **Providing regulation services in different season in a year**

For a network with 30 houses, the maximum possible “regulation raise” services provided by the network in four different seasons are shown in Table 6.3. The regulation raise availability from the network is available in 5 minute interval, only the average value for that hour is listed here. The ambient temperature data for different seasons in Brisbane, Australia is used for this analysis [91]. Further, hot water consumption rate for different seasons in a weekday of a typical household with four members is also used for this simulation [133].

Due to the availability of more AC units, more “regulation raise” service is possible during 0500-0900 hrs in winter season. Here, the average possible regulation during winter is 28.83 kW, compared to 17.74kW in autumn; 25.58 kW in summer and 22.57 kW in spring. However, during summer, “regulation raise” is possible due to the availability of AC units mostly throughout the day. For instance, at 1230 hrs, the average possible regulation during summer is 48.87 kW, which is the highest value comparing to other seasons (winter: 28.60, autumn: 25.39, spring: 21.94 kW). This is true for any time during a day except 0500-0900 hrs.

Error percentage in Table 6.3 shows the deviation of required average regulation with the actual regulation provided by the network (using regulation signal of Fig. 3.9). The value shown is an average for all four seasons. For example, in a network with 30 houses, the error percentage is minimum (4.77%) at 1230 hrs compared to any other time of the day (0700 hrs: 10.84%, 0900 hrs: 12.01%, 0230 hrs: 12.88%). The more is the "regulation raise" available capability, the lesser is the error percentage. The network has more availability of distributed loads to match the required signal at noon time. Further, the average number of control actions for the network with 30 houses can reach up to 10.15, during summer season, when there is 48.87 kW of "regulation raise" capability.

6.3.4. **Providing "regulation raise" services from the network of different sizes**

Analysis of regulation data for three networks of 30, 120, 960 houses is presented in Table 6.3 for four seasons. During winter, more regulation service is possible during 0500-0900 hrs. For instance, consider network with 960 houses at 0900 hrs. There is a maximum possible regulation of 873.10 kW in comparison with only 563.3 kW in autumn and 777 kW in summer. During summer season, average "regulation raise" capability of the network is at its maximum of 1661.3 kW at 1230 hrs when compared with other seasons in a year (winter: 1032.4 kW, autumn: 732.7 kW, spring: 755.48 kW).

Furthermore, the error percentage is reduced as the number of appliances available for regulation services increase. This is because of the accuracy in balancing power signals with increased number of controls. Hence, the network with 960 houses has a reduced error percentage, compared to the networks with 30 and 120 houses. For example, at 1230 hrs, the error percentage is 0.17% in 960 house network, compared to 4.77% in 30 house network.

6.4. Conclusion and Summary

This part of research work, proposes a new control method for a pool of TCAs utilized for regulation services. Market operator will broadcast the regulation signal to retailer in real-time. The retailers pass it on to the aggregators, who perform direct load control using stochastic ranking method.

A stochastic pairwise comparison of appliances is conducted based on three attributes such as temperature variation, status and power rating of TCAs. Probabilistic nature of these attributes are computed using Markov property where probability of attribute at a future time step can be found based on its current status. Efficiency of this scheme is verified through network simulations for a given “regulation raise” and “regulation lower” signals. Required regulation is achieved with the allowable limit of overrides. It shows the robustness of the system. A minimum deviation of less than 1% from expected regulation services is obtained and system robustness is assured with the capability of providing regulation even with 10-40% of unexpected customer override signals.

The TCAs connected to the network are adjusted for the next time step. However, uncertainty in appliance consumption and seasonal temperature variations make appliance selection process difficult.

Chapter 7

Conclusions

In this thesis, the four important contributions made by DR to the future smart distribution grid are addressed and efficient approaches are proposed to improve system reliability and customer satisfaction. This chapter summarizes the proposed methods and draws the conclusions from the research. The limitations of the study are noted, and recommendations are made for future work.

7.1. Research Summary and Contributions

The initial part of this research proposed an improved DR option for a residential distribution system using a customer reward scheme. This work was done with the primary purpose of reducing network peaks and improving voltage in residential feeders. The deployment of two-way communication infrastructure with smart meters and in-home display units is required for this scheme. A decision-making process to appropriately adjust residential appliances was developed, reflecting appliance flexibility, satisfaction and priority. Customers would be encouraged to participate in this scheme through a fully-fledged reward mechanism. This reward mechanism is based on customer participation in load shifting and associated voltage improvement within the feeder. The impacts of the proposed method on both the electric utility and customers were analyzed. It was concluded that the electric utility would benefit from the improved feeder voltage and removal of the network peaks. Customer satisfaction and appliance usage patterns in this reward scheme were investigated. The results showed that considerable discomfort was tolerated by customers, which was compensated by the proposed rebate program. Hence, the proposed DR via customer reward scheme can be successfully implemented in a real electricity distribution network to defer the transformer upgrade costs and also maintain network reliability. In addition, customer satisfaction can be confirmed through the rebate scheme.

Current electricity networks apply price-responsive demand schemes for the residential distribution network. RTP is a promising option which benefits the electric utility by removing the peak demand and wholesale price spikes in the network. It has an added advantage of providing flexibility to customers to adjust their loads in contrast with the proposed reward-based DR scheme. Hence, an improved real-time pricing scheme for customers is proposed to alleviate voltage violations, peak load problems and unexpected wholesale price spikes. This RTP scheme contains three price components reflecting power consumption, adverse network voltage conditions and unexpected wholesale price spikes. It was tested on a sample residential distribution system and the performance was analyzed. The results showed that the active participation of customers can lead to a reduction in the cost of their consumption through appropriate load adjustments. In addition, an algorithm was proposed for indicating appropriate loads that can be controlled by a customer. In the proposed RTP scheme, customers are given the flexibility to make decisions for appliance control in a smart home environment. The results validated that the impact of the proposed RTP scheme did not hamper the appliance usage patterns among customers. The proposed scheme also ensured the elimination of network peaks, adverse feeder voltage conditions and wholesale price spikes.

DR via customer reward scheme and the RTP scheme provides benefit to customers through incentives and cost reduction respectively. Incentive provided to an average household through a DR via customer reward is found to be 28.9 % whereas the cost reduction achieved by an average household from a RTP scheme is 20.8 %. Hence, DR via customer reward provides more economic benefit to the customers for allowing forced load adjustments in comparison with RTP scheme. Residential customers are only considered for both studies.

Active and effective customer participation in the proposed RTP scheme would only be possible with a guaranteed automated HEM system. Hence, this research continued to focus on an efficient algorithm for real-time HEM units for reducing the cost of energy consumption in a house. This research work is unique in regard to the proposed appliance scheduling, as it considers the uncertain nature of RTP and appliance power consumption. The operation of the proposed HEM scheduler is divided into three phases, namely, real-time monitoring, stochastic scheduling and real-time control of appliances. Simulations are conducted every four minutes in a day. During the real-time monitoring phase, the electric utility remotely monitors appliances connected to the HEM system at every time step. The electric utility also obtains wholesale price information from the electricity market to broadcast the real-time price to customers. When the cost of consumption in a house is above an average limit, the electric utility defines the operating status of appliances considering the operating characteristics and customer input of controllable appliances connected to HEM system. The information obtained during the real-time monitoring phase may not be sufficient to make appropriate control decisions for scheduling appliances. This is due to the uncertainties in electricity price variation, appliance operation, user behavior and preferences. Hence, the real-time monitoring phase is followed by a stochastic scheduling process which utilizes the information obtained in the real-time monitoring phase to stochastically schedule the appliances. The main objective of the stochastic scheduling phase is to minimize the cost of the energy consumption. The Markov decision process is used to achieve the objective by accurately predicting the appropriate curtailment of appliances based on the stochastic behavior of the cost of consumption. Constraints are added to intrinsically maintain customer comfort and appliance priority. Constraints for allowable interruptions are also included in order to prevent reducing the life-span of the appliances while also maintaining customer satisfaction. Subsequently, the appliance selected during stochastic scheduling phase is subjected to control in the real-time control phase. The stochastic decision process ensures the incorporation of uncertainties. Simulations are conducted in short timeframes to achieve the four minute control steps. The outcomes validated a significant reduction in the cost of energy consumption and the maintenance of customer satisfaction. This ensures the efficient utilization of the RTP scheme.

The DR option can be utilized for the purpose of providing regulation services. Hence, a new control method applied on a pool of thermostatically controllable appliances for providing regulation services was recommended as part of this research. In the proposed method, an ancillary services market environment is created with a market operator, broadcasting regulation signals to retailers in real time. Retailers pass the obtained signal to aggregators, who are responsible for performing load control actions using a stochastic ranking method. A probabilistic pairwise comparison of appliances is conducted based on appliance attributes (namely, temperature variation, appliance power status and appliance power rating). The Markov property is utilized to compute the probabilistic nature of these attributes. This is done by assuming that the probability of an attribute at a future time step can be found based on its current status. The ranking method incorporates the contribution of all three attributes. The efficiency of this scheme is verified through a given regulation raise and lower signals. This ensures that the required regulation can be achieved by allowing limited overrides in the network. In this study, the deviation of the actual load curtailment from the required regulation signal was calculated. It confirmed that less than one percent of deviation can be expected in a network with 960 houses. It also allows 10-40% of unexpected customer override signals during simulations.

7.2. Proposed Future Work and Suggestions

The initial part of this research proposed a DR technique via a customer reward scheme. This reward scheme is based on the benefits obtained by the electric utility by time-shifting demand and removing voltage violations. However, the benefits obtained by deferring the system upgrade costs were not studied. The investment in communication infrastructure in the residential distribution network should also be considered when identifying the benefits of this scheme. Hence, a detailed study based on the cost-benefit analysis should be conducted.

In addition, the proposed RTP scheme reflects power consumption, adverse voltage conditions and wholesale price spikes. It can be further improved by including the feed-in tariffs from roof-top PV cells and special provisions for plug-in electric vehicles. The introduction of PV cells and plug-in electric vehicles to the residential distribution network has a significant impact on creating adverse network conditions. Hence, improvement in RTP is a promising research area which can be studied on a future electricity grid.

The proposed RTP scheme in Chapter 4, considers fixed energy limit for every house, in order to define the electricity price components. Similarly, rebate scheme developed in Chapter 3, considers a fixed energy limit for every house to define the rebate values due to load curtailments. However, different energy limit for each house should be considered in order to prevent adverse effect on customers who consume less than the average customer. This can be achieved by computing the annual average energy consumption limit for each house. Therefore, energy limit for each house due to diversified load profiles is expected to be included in future.

The proposed HEM scheduler to facilitate the RTP scheme ensures that the cost of energy consumption in a residence is reduced. However, the uncoordinated control of the proposed HEM scheduler may create unexpected network peaks during off-peak periods. Hence, the stochastic coordination of the HEM scheduler in a residential electricity network should be studied extensively to ensure a reliable network.

HEM scheduler developed in third phase of the research can include both market variability and weather forecast as separate Markov processes. The stochastic nature of market variability, temperature sensitivity effects scholastic scheduling of loads. Therefore, an improved HEM scheduler can be developed in future, with the incorporation of both variables.

Furthermore, different perceptions of appliance models can be included. For example, characteristics of air-conditioners such as fan and cooling operation can be considered. The lock-out time of air-conditioners has an implication in real time control. Therefore, a delay should be added during the control actions, reflecting the lock-out time. Moreover, different operation status of clothes washer can also be considered such as ‘cold water wash’.

This research is carried out in four different phases. Reducing network peak and voltage violations are the main objective of first research phase. Second phase includes the reduction of wholesale price spikes as well. Reduction in the cost of energy consumption in each house is considered in third phase whereas the fourth phase considers frequency regulation services. However, a demand response method considering all four objectives together is not yet studied. Therefore, a study which considers the objectives of all four phases should be conducted in future.

Incorporation of batteries with the demand response developed by the integration of four objectives can also be studied in future.

Additionally, communication capabilities of the DR schemes developed during this research should be studies. Sociological aspects of the developed schemes should also be focused to find the customer interest and participation rates.

APPENDICES

Appendix A

Detailed controllable appliance models such as WH, AC, PEV, DW, WA, DR and PP are discussed here. They are used for the research simulations.

- **Model of WH**

Energy flow equation in a WH is used to model the characteristics of it. It represents a first order differential equation for water temperature as in (A.1). It is briefly discussed in section 5.2.1 and section 6.3.1.

$$\frac{dT_{wh}^{n}}{dt_{n}} = \left(\frac{G+B}{\psi_{w}}\right).T_{wh}^{n} + \frac{1}{\psi_{w}}\begin{bmatrix} G & B^{n} & Q_{wh} \end{bmatrix} \times \begin{bmatrix} T_{a}^{n} \\ T_{in} \\ K_{wh}^{n} \end{bmatrix} \tag{A.1}$$

Where, n- time step, $T_{wh}{}^{n}$- hot water temperature at time n^{th} time step, T_a- ambient temperature, T_{in}- inlet cold water temperature, ψ_w- thermal capacity if water in the tank, Q_{wh}- energy input rate, G- standby heat loss of the tank, B- heat consumption rate of water, K_{wh}- state of WH thermostat [119], [53]. Here, G, B and ψ_w can be calculated from (A.2), (A.3) and (A.4).

$$G = U \times SA \tag{A.2}$$

$$B^{n} = F_{w}^{n} \times \sigma_{w} \times \Omega_{w} \tag{A.3}$$

$$\Psi_{w} = Vol \times \sigma_{w} \times \Omega_{w} \tag{A.4}$$

Where, U- stand-by heat loss coefficient, SA- surface area of the tank, σ_w- density of water, Vol- volume of water tank, Ω_w- specific heat of water and $F_w{}^n$ average hot water draw at n^{th} time step. Values used for a WH model is tabulated in Table A.1 as per [119], [136]. Ambient temperature data is obtained from [91] for Brisbane, Australia. Furthermore, hot water flow rate hourly profile as per [133] is obtained with the information as in (A.5). Values proposed in [133] are used for constant values from a_1-a_{13}.

Meanings for the symbols in (A.5) are as follows. $F_w(n_H)$ – hot water use in a house per hour; N_{person}- number of persons in a house; $N_{infants}$- Number of children between 0-5 years old; $N_{children}$- Number of children between 5-13 year old; N_{adults}- number of adults over 14 years old; $T_{set}{}^{nH}$- set point of WH; Vol- Volume of WH tank; T_{in}- WH inlet water temperature; T_a^{nH}- ambient temperature, $K_{at\ home}$- presence of adults at home; K_{spring}, K_{summer}, K_{autumn} and K_{winter} are binary state to represent respective seasons; K_{WA}- coefficient for the impact of clothes washer; K_{DW}- coefficient for the impact of dish washer; K_{senior}- coefficient for representing senior only house; $K_{not\ paying}$- Coefficient for house which does not pay for hot water. Hot water consumption rate $F_w(n_H)$, used in our study for a particular house in a day in shown in Fig. A.1.

Table A.1 Data used for WH model

Symbols	Values	Values in SI unit
T_{in}	60°F	15.56 °C
σ_w	8.34 lb/gal	0.02 kg/liters
Vol	50 gal	189.27 liters
Ω_w	1 Btu/lb°F	6.461x10^{-4} kWh/kg°C
$K_{wh}^{\ n}$	1-'*ON*', 0-'*OFF*'	1-'*ON*', 0-'*OFF*'
kW to Btu/hr unit conversion	3413	-
G	3.6 *Btu/*°F hr	0.0011 kW/°C
Q_{wh}	3.5 *kW*	3.5 *kW*

$$
\begin{aligned}
F_w(n_H) = [&a_0 + a_1.N_{person} + a_2.N_{infants} + a_3.N_{children} + a_4.N_{adults} \\
&+ a_5.T_{set}^{n_H} + a_6.Vol + a_7.T_{in} + a_8.T_a^{n_H} + a_9.K_{athome} \\
&+ a_{10}.K_{spring} + a_{11}.K_{summer} + a_{12}.K_{autumn} + a_{13}.K_{winter} \\
&- K_{WA} - K_{DW}] \times K_{senior} \times K_{not\ paying}
\end{aligned}
\tag{A.5}
$$

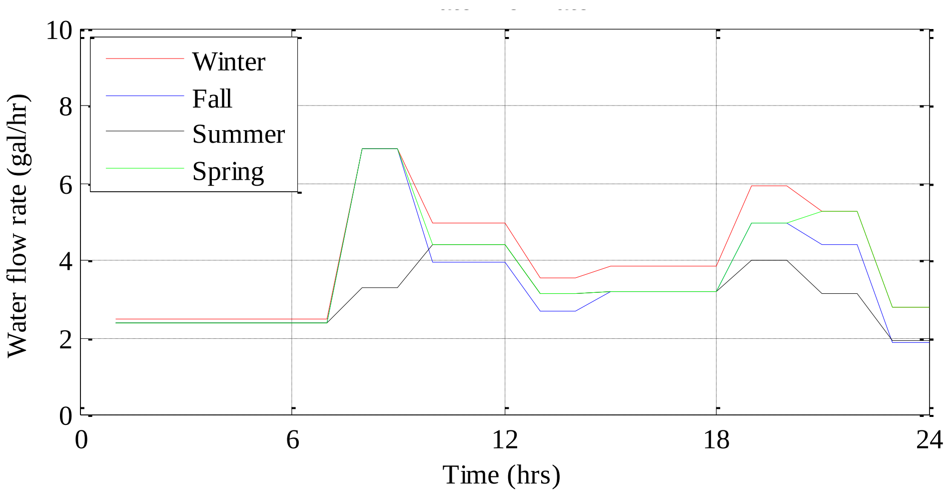

Fig. A.1. Hot water flow rate of a house in a day during each season

Thermostat operation is achieved by monitoring water temperature $T_{wh}{}^{n}$ at n^{th} time step. Logic controls as in (A.6)-(A.7) are used. (i.e. thermostat maintains water temperature in between ($T^{set}{}_{wh}$ ± $T^{db}{}_{wh}$) by controlling operation of water heater). Here, $K_{wh}{}^{n}$ is the control logic for thermostat (if $K_{wh}{}^{n}$=1 WH is switched ON and OFF otherwise). $T^{set}{}_{wh}$ is the set point of water heater and has a nominal value of 120 °F. $T^{set}{}_{wh}$ variation can be allowed in between 100- 140°F as per [119]. Further, temperature deadband $T^{db}{}_{wh}$ is considered as 2.5 °F and P_j^n is power rating of WH modeled as normal distribution with mean of 3.5kW and variance of 0.1.

$$K_{wh}^{n}=1,\, P_j^n=1\begin{cases} T_{wh}^{n}<T_{wh}^{set}-T_{wh}^{db} \\ T_{wh}^{set}-T_{wh}^{db}<T_{wh}^{n}<T_{wh}^{set}+T_{wh}^{db} \quad \& \quad \dfrac{dT_{wh}^{n}}{dt}>0 \end{cases} \tag{A.6}$$

$$K_{wh}^{n}=0,\, P_j^n=0\begin{cases} T_{wh}^{n}>:T_{wh}^{set}+T_{wh}^{db} \\ T_{wh}^{set}-T_{wh}^{db}<T_{wh}^{n}<T_{wh}^{set}+T_{wh}^{db} \quad \& \quad \dfrac{dT_{wh}^{n}}{dt}<0 \end{cases} \tag{A.7}$$

- **Model of AC**

Similarly, model of an AC is studied as in [54], [130]. Here, room temperature of a house is modeled as in (A.8).

$$\frac{dT_r^n}{dt_n}=-\left(\frac{U_a+H_m}{\psi_{ac}}\right)T_r^n+\frac{1}{\psi_{ac}}\begin{bmatrix}U_a & H_m & Q_{ac}\end{bmatrix}\times\begin{bmatrix}T_a^n\\ T_m^n\\ K_{ac}^n\end{bmatrix} \tag{A.8}$$

Where, n- n^{th} time step in a day, T_a- ambient temperature, T_m- mass temperature of the house, T_r- room temperature of the house, ψ_{ac}- thermal mass capacity of interior air, U_a- heat loss coefficient, H_m- interior mass conductance of the house, Q_{ac}- energy input rate of AC and K_{ac}- state of AC thermostat (if K_{ac}=1 AC is switched ON and OFF otherwise). Table A.2 shows the data used for the modeling of an AC.

Heating and cooling set points of AC have a nominal value of 75°F and 80°F respectively. Further dead-band of AC is considered to have a nominal value of 1°F during simulations. The variation in the capacity of ACs across different houses is modeled as normal distribution with mean of 2.5kW and variance of 0.1. Thermostat operation of an AC as a heating load is illustrated in (A.9)-(A.10). Equations (A.11)-(A.12) shows the thermostat operation of an AC as a cooling load.

Table A.2 Data used for AC model

Symbols	Values	Values in SI unit
U_a	522.12 *Btu/°F.hr*	0.153 *kW/°C*
H_m	7052.9 *Btu/°F.hr*	2.067 *kW/°C*
ψ_{ac}	1080 *Btu/°F.hr*	0.317 *kW/°C*
Q_{ac}	1.2 *kW*	1.2 *kW*
kW to Btu/hr unit conversion	3413	-
K_{ac}^{n}	1-'*ON*', 0-'*OFF*'	1-'*ON*', 0-'*OFF*'

$$K_{ac}^{n}=1, P_j^n=1 \quad \begin{cases} T_r^n < T_{ac}^{set\,heat} - T_{ac}^{dbheat} \\ T_{ac}^{set\,heat} - T_{ac}^{dbheat} < T_r^n < T_{ac}^{set\,heat} + T_{ac}^{dbheat} \;\&\; \dfrac{dT_r^n}{dt} > 0 \end{cases} \tag{A.9}$$

$$K_{ac}^{n}=0, P_j^n=0 \quad \begin{cases} T_r^n > T_{ac}^{set\,heat} + T_{ac}^{dbheat} \\ T_{ac}^{set\,heat} - T_{ac}^{dbheat} < T_r^n < T_{ac}^{set\,heat} + T_{ac}^{dbheat} \;\&\; \dfrac{dT_r^n}{dt} < 0 \end{cases} \tag{A.10}$$

$$K_{ac}^{n}=1, P_j^n=1 \quad \begin{cases} T_r^n > T_{ac}^{set\,cool} + T_{ac}^{dbcool} \\ T_{ac}^{set\,cool} - T_{ac}^{dbcool} < T_r^n < T_{ac}^{set\,cool} + T_{ac}^{dbcool} \;\&\; \dfrac{dT_r^n}{dt} < 0 \end{cases} \tag{A.11}$$

$$K_{ac}^{n}=0, P_j^n=0 \quad \begin{cases} T_r^n < T_{ac}^{set\,cool} - T_{ac}^{dbcool} \\ T_{ac}^{set\,cool} - T_{ac}^{dbcool} < T_r^n < T_{ac}^{set\,cool} + T_{ac}^{dbcool} \;\&\; \dfrac{dT_r^n}{dt} > 0 \end{cases} \tag{A.12}$$

- **Model of PEV**

Mathematical model in PEV is built using the data in [118]. Initially, the charging slope of PEV battery is calculated. Charging slope of the battery can be defined for two different modes of battery operation. They are, slow (CH_1) and normal charging (CH_2). Power consumption of slow ($P_{charging}^{CH1}$) and normal charging ($P_{charging}^{CH2}$) of battery can be found in Table A.3. Power consumption data is used for the calculation of total charging cycle duration of the battery as in (A.13). Charging cycle duration (Γ_{total}^{CHk}) is found by dividing the nominal capacity of the battery ($E_{nominal}$) by the power consumption ($P_{charging}{}^{CHk}$) for k^{th} charging mode. Then, the slope of charging ($Sl_{charging}$) is found as the inverse of charging cycle duration as in (A.14).

Table A.3 Data used for PEV model

Symbols	Values
$E_{nominal}$	N(16,0.1) *kWh*
$P_{charging}{}^{CHk}$	$P_{charging}{}^{CH1}$ – 2 *kW* $P_{charging}{}^{CH2}$ – 3.3 *kW*
$SOC_{initial}$	N(0.5,0.1) *p.u.*
t_{dept}	N(0800,0006) *hours*
$t_{arrival}$	N(1900,0006) *hours*
$Sl_{discharging}$	N(0.3333,0.1) *p.u./hour*

Arrival ($t_{arrival}$) and departure (t_{dept}) time of PEV is modelled as a normal random variable as in Table A.3. Initial state of charge ($SOC_{initial}$) of the battery during $t_{arrival}$ is assumed as a normal random variable with 0.5 *p.u.* mean and 0.2 *p.u.* variance. The battery discharging slope ($Sl_{discharging}$) is also assumed as a normal variable as in Table A.3. Fig. A.2 illustrates power profile and state of charge of a PEV in a selected house in two subsequent days. Here, the slow charging mode is used. Average charging and discharging patterns of PEVs in each house will vary. Therefore values of parameters of PEV in individual house are defined separately.

$$\Gamma_{total}^{CH_k} = \frac{E_{nominal}}{P_{charging}^{CH_k}} \tag{A.13}$$

$$Sl_{charging} = \frac{1}{\Gamma_{total}^{CH_k}} \tag{A.14}$$

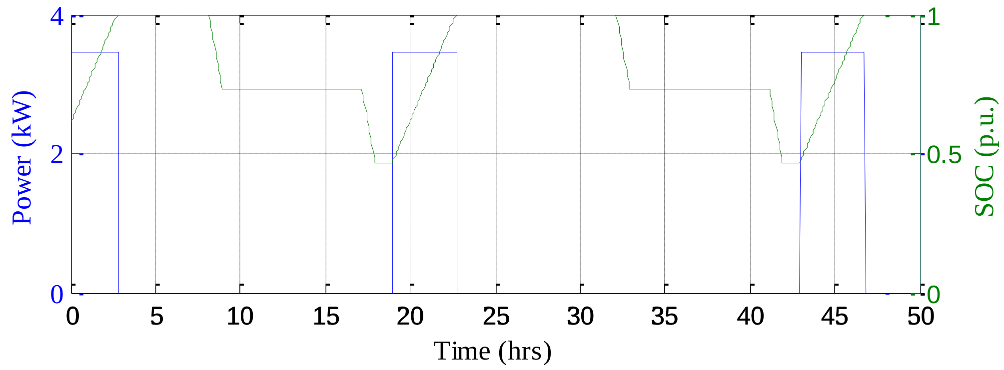

Fig. A. 2 Power profile and SOC of a selected PEV

- ***Model of DW, WA and DR***

Mathematical models of DW, WA and DR are simulated using the data in Table A.4. Here, power rating, starting (t_{start}) and operating time (t_{oper}) of appliances are generated using normal random variables. The operating range of DW, WA and DR in a week day is illustrated in Fig. A.3. Data in [137] is used for the modelling. Power profiles of DW, WA and DR in a typical house used in the simulated mathematical model for two subsequent weekdays are shown in Fig. A.4.

Table A.4 Data used for DW, WA and DR models

Parameters	DW	WA	DR
Power (kW)	N(1,0.1)	N(1.2,0.1)	N(2.5,0.1)
t_{start}: Starting time (hrs)	N(1800,0012)	N(1900,0012)	t_{start}^{WA}+t_{oper}^{WA}+N(1900,0012)
t_{oper}: Operating time (hrs)	N(0050,0010)	N(0100,0010)	N(0110,0010)

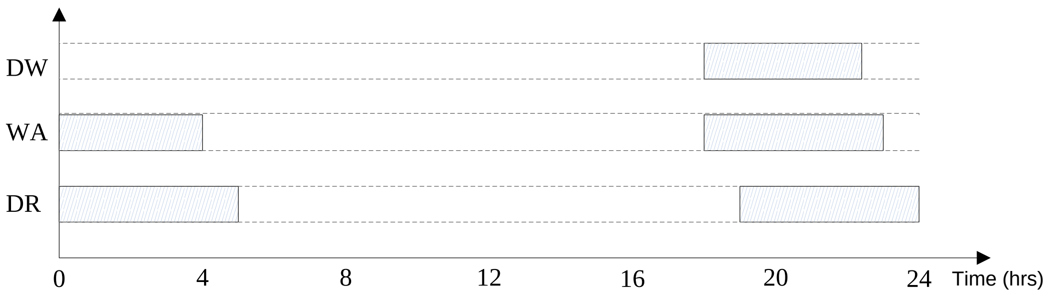

Fig. A.3 Operating range of DW, WA and DR in weekdays

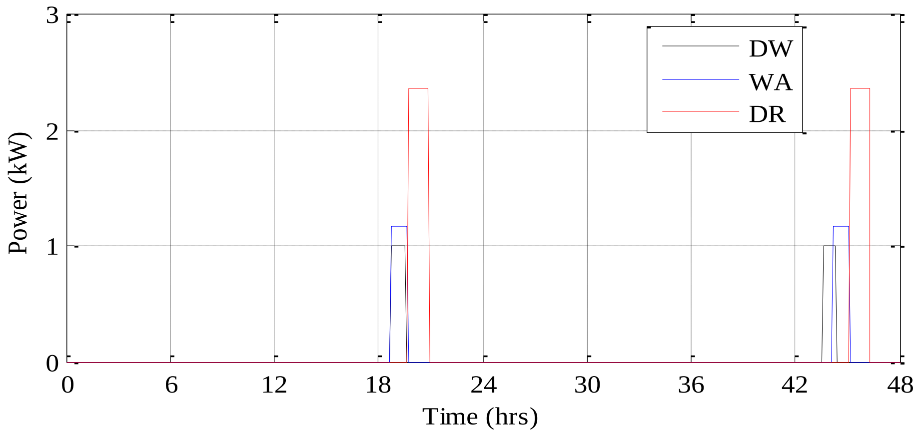

Fig. A.4 Power Profiles of DW, WA and DR in two subsequent weekdays of a house

- ***Model of PP***

Mathematical model of a swimming pool pump (PP) is built using a normal random variable for power rating, starting and operating time of it. Table A.5 shows the values for the PP parameters. Power profile of a PP in a selected house is shown in Fig. A.5.

Table A.5 Data used for PP models

Parameters	Values
Power rating (kW)	N(1.8,0.1)
t_{start}: Starting time (hrs)	N(1800,0012)
t_{oper}: Operating time (hrs)	N(0800,0030)

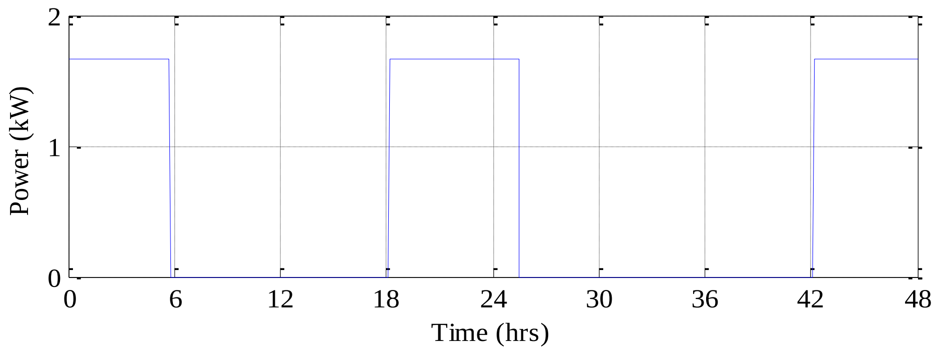

Fig. A.5 Power Profile of PP in two subsequent weekdays of a house

- ***Total House Consumption***

Controllable appliances such as WH, AC, PEV, DW, WA, DR and PP are modelled according to the above mathematical data. The non- controllable appliances such as lighting, fridge, freezer, cooker, electric oven, microwave, television, computer, stand-by appliance, and miscellaneous appliance are also considered during the study as in [32]. The detailed models of these appliances are not included in this appendix. The total house consumption profile for a selected house is obtained as in Fig. A.6. It is for two subsequent days in winter.

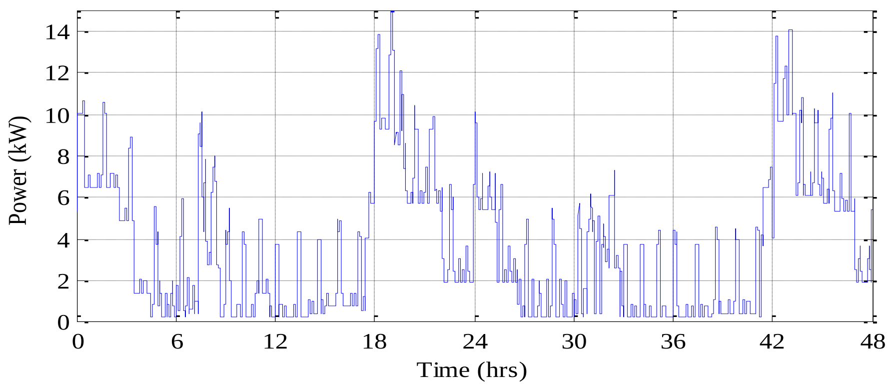

Fig. A.6 Power Consumption Profile of a selected house in two subsequent days

Appendix B

Three Phase Load flow program

Three phase load flow program is based on Newton Raphson algorithm. It solves a three phase nonlinear load flow problem assuming the loads are considered as constant power sinks in a specific unbalanced state. It is also assumed that the system contains only PQ buses and a slack bus. The mismatch equations and the Jacobian matrix for the load buses are derived separately for all three phases. The three phase Y- bus matrix is simplified to a 3*N*x3*N* matrix using Kron's reduction [134], where *n* is the number of buses. Instantaneous voltage values are calculated according to the time varying power values at each node/ house. The per- unit complex power for p^{th} phase at bus bar *k* at all nodes *n* is given by equation (B.1).

$$-S_k^p = V_k^p (I_k^p)^* = V_k^p \sum_{i=1}^{n} \sum_{m=1}^{3} (Y_{ki}^{pm} V_i^m)^* \tag{B.1}$$

Here, *Y* represents the admittance matrix and the negative sign indicates that the total current is entering the network. This proposed method is better for a distribution system due to large voltage angles and non-convergence problems in. The derived mismatch equations for the load buses are (B.2) and (B.3).

$$\Delta P_k^p = P_k^p + \sum_{i=1}^{n} \sum_{m=1}^{3} \left|V_k^p\right| \left|V_i^m\right| \left\{G_{ki}^{pm} \cos(\theta_k^p - \theta_i^m) + B_{ki}^{pm} \sin(\theta_k^p - \theta_i^m) \right\} \tag{B.2}$$

$$\Delta Q_k^p = Q_k^p + \sum_{i=1}^{n} \sum_{m=1}^{3} \left|V_k^p\right| \left|V_i^m\right| \left\{G_{ki}^{pm} \sin(\theta_k^p - \theta_i^m) - B_{ki}^{pm} \cos(\theta_k^p - \theta_i^m) \right\} \tag{B.3}$$

A Jacobian matrix(*J*) for a 3- phase system is derived with matrix blocks of 6x6 with diagonal and off- diagonal block elements following the similar pattern as in [135]. The above mismatch equations are used to form a 6*N*x6*N* Jacobian matrix. The mismatch quantities (ΔM) and *J* is used to form incremental voltage quantities ΔV as in (B.4). Iterative procedure is used to achieve convergence and the voltages are updated as in (B.5). The form of ΔM and ΔV are given in (B.6) and (B.7).

$$\Delta M = -J \Delta V \tag{B.4}$$

$$V = V + \Delta V \tag{B.5}$$

Whereas;

$$\Delta M = \left[\Delta P_k^a ; \Delta Q_k^a ; \Delta P_k^b ; \Delta Q_k^b ; \Delta P_k^c ; \Delta Q_k^c \right] \tag{B.6}$$

$$\Delta V = \left[\frac{\Delta\left|V_k^a\right|}{\left|V_k^a\right|} ; \Delta\theta_k^a ; \frac{\Delta\left|V_k^b\right|}{\left|V_k^b\right|} ; \Delta\theta_k^b ; \frac{\Delta\left|V_k^c\right|}{\left|V_k^c\right|} ; \Delta\theta_k^c \right] \tag{B.7}$$

The diagonal block elements of a 3 phase Jacobian matrix are represented by the following equations from (B.8) to (B.15).

$$\frac{\partial \Delta P_k^p}{\partial \theta_k^m} = \left|V_k^p\right|\left|V_k^m\right|\left\{G_{kk}^{pm}\sin(\theta_k^p - \theta_k^m) - B_{kk}^{pm}\cos(\theta_k^p - \theta_k^m)\right\} ; m \neq p \tag{B.8}$$

$$\frac{\partial \Delta P_k^p}{\partial \theta_k^m} = \left\{-Q_k^p - B_{kk}^{pm}\left|V_k^p\right|^2\right\} ; m = p \tag{B.9}$$

$$\frac{\partial \Delta Q_k^p}{\partial \theta_k^m} = -\left|V_k^p\right|\left|V_k^m\right|\left\{G_{kk}^{pm}\cos(\theta_k^p - \theta_k^m) + B_{kk}^{pm}\sin(\theta_k^p - \theta_k^m)\right\} ; m \neq p \tag{B.10}$$

$$\frac{\partial \Delta P_k^p}{\partial \theta_k^m} = \left\{P_k^p - G_{kk}^{pm}\left|V_k^p\right|^2\right\} \quad ; m = p \tag{B.11}$$

$$\left|V_k^m\right|\frac{\partial \Delta P_k^p}{\partial\left|V_k^m\right|} = -\frac{\partial \Delta Q_k^p}{\partial \theta_k^m} \qquad ; \; m \neq p \tag{B.12}$$

$$\left|V_k^m\right|\frac{\partial \Delta P_k^p}{\partial\left|V_k^m\right|} = \left\{2\left|V_k^p\right|G_{kk}^{pm} + \frac{\partial \Delta Q_k^p}{\partial \theta_k^m}\right\} ; \; m = p \tag{B.13}$$

$$\left|V_k^m\right|\frac{\partial \Delta P_k^p}{\partial\left|V_k^m\right|} = -\frac{\partial \Delta P_k^p}{\partial \theta_k^m} \qquad ; \; m \neq p \tag{B.14}$$

$$\left|V_k^m\right|\frac{\partial \Delta Q_k^p}{\partial\left|V_k^m\right|} = \left\{-2\left|V_k^p\right|B_{kk}^{pm} + \frac{\partial \Delta P_k^p}{\partial \theta_k^m}\right\} \qquad ; m = p \tag{B.15}$$

The off- diagonal block elements of the 3 phase Jacobian matrix for all values of *i* except *i*=*k* are represented by the following equations from (B.16) to (B.19). Table B.1 shows the important parameters used in this study.

$$\frac{\partial \Delta P_k^p}{\partial \theta_i^m} = \left|V_k^p\right|\left|V_i^m\right|\left\{G_{ki}^{pm}\sin(\theta_k^p - \theta_i^m) - B_{ki}^{pm}\cos(\theta_k^p - \theta_i^m)\right\} \tag{B.16}$$

$$\frac{\partial \Delta Q_k^p}{\partial \theta_i^m} = -\left|V_k^p\right|\left|V_i^m\right|\left\{G_{ki}^{pm}\cos(\theta_k^p - \theta_i^m) + B_{ki}^{pm}\sin(\theta_k^p - \theta_i^m)\right\} \tag{B.17}$$

$$\left|V_i^m\right|\frac{\partial \Delta P_k^p}{\partial \left|V_i^m\right|} = -\frac{\partial \Delta Q_k^p}{\partial \theta_i^m} \tag{B.18}$$

$$\left|V_i^m\right|\frac{\partial \Delta Q_k^p}{\partial \left|V_i^m\right|} = \frac{\partial \Delta P_k^p}{\partial \theta_i^m} \tag{B.19}$$

Table B.1 Parameters used during the load flow study

Parameter	Value
Reference voltage	1*pu*
Load impedance (Z_{load})	(0.0361+0.0149j) *pu*
Source impedance	(4.46+1.24j)x10^{-4} *pu*
Transformer impedance	0.05j *pu*
Distance between houses	20 meters
Number of buses/ phase	11
Apparent power base	100 MVA

Appendix B

Simulations in Chapter 3-6 were performed using MATLAB software platform in a 64 bits operating system with 2.10 GHz processor using m-files. Block diagram to illustrate the software being utilized for each chapter is presented from Fig. C.1 to Fig. C.4.

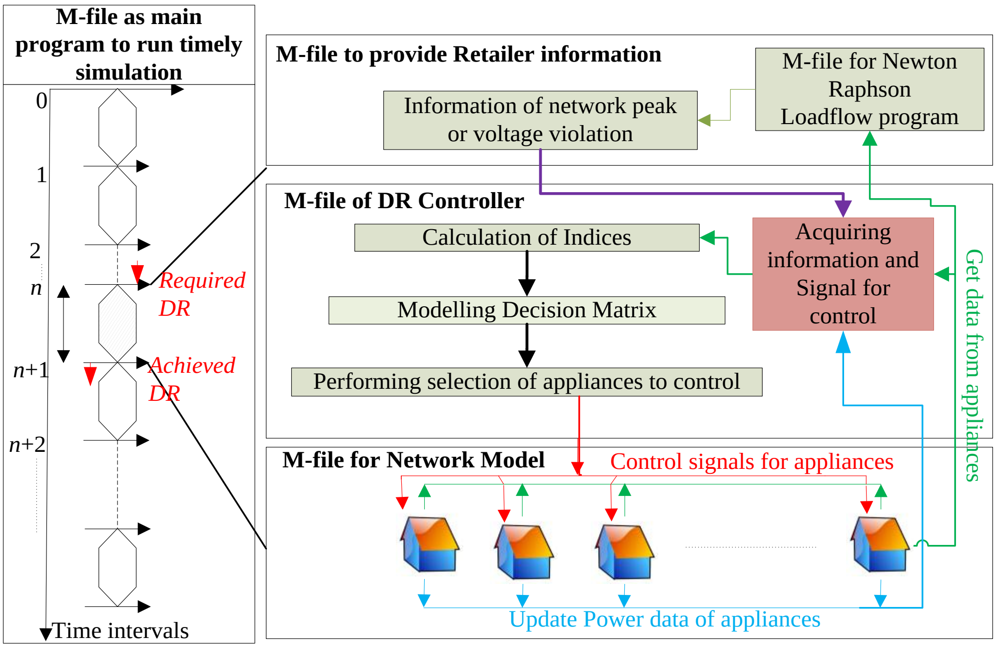

Fig. C. 1 Developed software program in MATLAB for Chapter 3

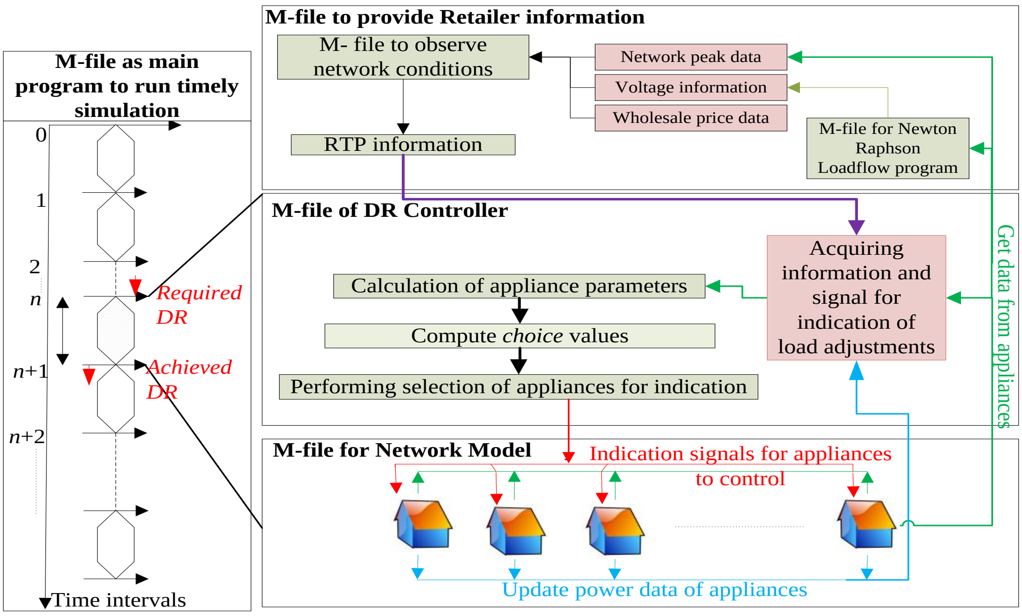

Fig. C. 1 Developed software program in MATLAB for Chapter 4

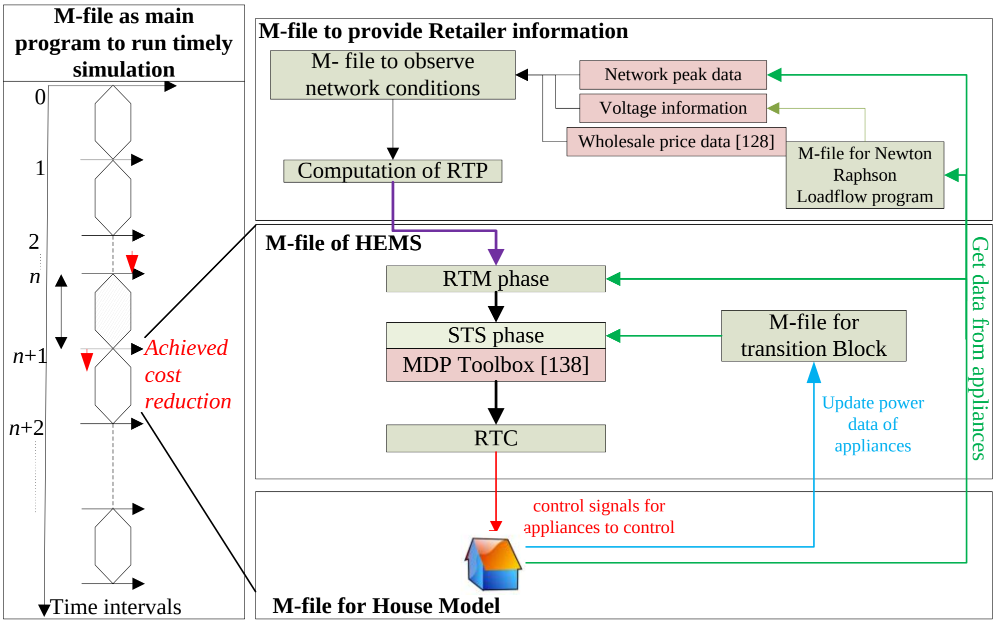

Fig. C. 4 Developed software program in MATLAB for Chapter 5

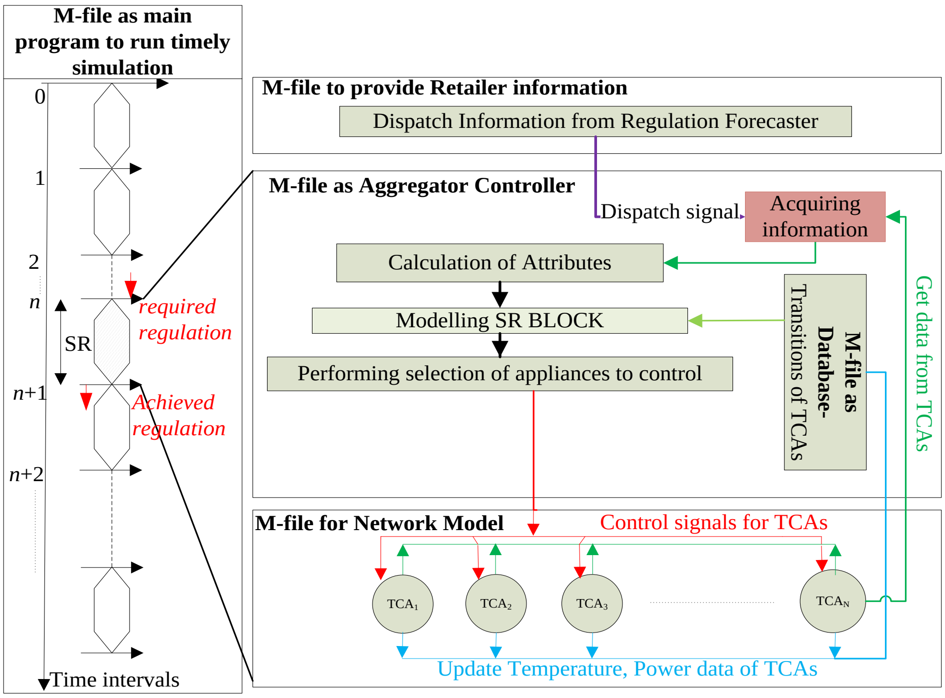

Fig. C. 4 Developed software program in MATLAB for Chapter 6

Separate m-files for retailer information, DR controller and network model are developed during the studies. A main program is developed in a separate m-file which is linked with the other m-files. It runs the timely simulation of the DR processes.

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