STOCHASTIC LEARNING ALGORITHMS FOR RESIDENTIAL LOAD SCHEDULING WITH PHOTOVOLTAIC SOURCE IN SMART GRID

Thesis submitted to

UNIVERSITY OF CALICUT

in fulfilment for the award of the degree of

DOCTOR OF PHILOSOPHY

By

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June 2018

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Certificate

This is to certify that the thesis entitled "**Stochastic Learning Algorithms for Residential Load Scheduling with Photovoltaic Source in Smart Grid**" is the record of bonafide research work done by **Ms. Remani T.** under my supervision and guidance at Department of Electrical Engineering, Govt. Engineering College, Thrissur in partial fulfillment of the requirements for the Degree of Doctor of Philosophy under the Faculty of Engineering, University of Calicut.

Thrissur-9 **Dr. E. A. JASMIN**

28.06.2018

DECLARATION

I **Remani T.**, hereby declare that the thesis entitled "**Stochastic Learning Algorithms for Residential Load Scheduling with Photovoltaic Source in Smart Grid**" is based on the original work done by me under the guidance of **Dr. Jasmin E. A.**, Associate Professor, Department of Electrical Engineering, Govt. Engineering College, Thrissur for the award of Ph.D programme under University of Calicut. I further declare that this work has not been included in any other thesis submitted previously for the award of any Degree, Diploma, Associateship or Fellowship or any other title for recognition.

Thrissur-9 **REMANI T.**

28.06.2018

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Abstract

One of the major operational issues in power system, with continuously growing energy demand is balancing power generation to the instantaneously varying load. Under smart Grid (SG) paradigm, utilities have realized that through Demand Side Management (DSM) and various Demand Response (DR) programs, co-operation of consumers can be utilized in an efficient way for this balancing procedure. In the present energy scenario, a major part of the flexible demand arises from the residential power sector. With the development in information and communication systems, the Price Based DR (PBDR) programs can be effectively used for controlling the loads of smart residential buildings thereby reducing consumer electricity bill and maximum demand on the system. The comfort aspect of the consumer due to delay in scheduling the loads is a factor to be considered while time scheduling the loads. Nowadays there is a large scale deployment of small renewable Distributed Generation (DG) sources like roof top Photovoltaic (PV) system by residential consumers. The power generated from such intermittent renewable energy sources is random in nature. For predicting the availability of energy the uncertainty associated with intermittent PV power generation

is to be modeled using suitable method. Efficient utilization of all such available resources along with suitable load scheduling methods will certainly result in reduction in the cost of electricity for the consumer and will also benefit the utility. In SG scenario, the future residential consumer will have renewable sources, flexible loads, nonflexible loads and various time dependent tariff schemes and at the same time will provide operational flexibility through improved data and communication infrastructures. The residential load scheduling problem turns to be a complex one while considering the constraints on operation of devices, comfort level associated with different appliances, stochastic nature of renewable power generation and time varying tariff. This necessitates a comprehensive model with implementable solution for the residential load scheduling problem. The solution method should also be able to handle the uncertainty of the solar power generation.

The objectives of the thesis are,

1. Develop a generalized mathematical model for load scheduling problem including renewable sources.

2. Formulate stochastic learning algorithms using Binary Particle Swarm Optimization, Learning Automata and Reinforcement Learning for the solution of residential load scheduling problem.

3. Model the uncertainty associated with PV generation using suitable probability distribution function.

4. Develop an algorithm using Reinforcement Learning for the solution of residential load scheduling problem with PV source.

5. Realize a prototype implementation of the developed stochastic learning algorithm using RL for a residential energy management system.

The first step is concerned with the development of a generalized mathematical model for the load scheduling problem which can include different types of sources. Starting with the basic load scheduling problem with a single power source, a generalized mathematical model which can include different sources such as utility grid, DG sources etc is developed. The load model considered is capable of handling the consumer comfort aspect. Basic load scheduling problem is considered taking into account the operational needs of the loads and with utility grid as the power source. A solution to this problem is developed using Binary Particle Swarm Optimization (BPSO) algorithm. The algorithm is validated and obtained the load schedule with minimum cost and satisfying various operating constraints. With a case study of a residential consumer with different types of loads, the algorithm is verified. Considering consumer comfort and uncertain PV source the complexity of the problem is increased and it is difficult to get solution with this algorithm. In the next stage, the load scheduling problem including the consumer comfort aspect is considered. The simple load model is modified in this case by including a factor *udc* to account for delay in scheduling. The load scheduling problem is formulated as a multistage decision making problem and a stochastic learning algorithm using Reinforcement Learning (RL) is developed to solve the problem with the modified load model and the grid power. The results obtained are validated and compared with that of Learning Automata (LA) algorithm which is a stochastic learning algorithm for single stage decision making problem. The RL algorithm is verified considering the case study of a residential consumer and the load schedule obtained corresponds to minimum cost. The method is found to be efficient compared to LA and BPSO algorithms.

The integration of renewable DG source in the load scheduling is the next stage. In this case in addition to grid connection, the residential consumer is provided with a roof top PV system from which the power generation is not constant. The uncertainty associated with PV generation need to be modeled. The historical solar irradiance data collected from the national solar radiation data base is used to model the random nature of irradiance using Beta Probability Distribution Function. This can be used to calculate the random power output produced from the PV source. A solution to the load scheduling problem, which is complex due to the presence of uncertain PV power generation, consumer comfort aspect, operating constraints of various loads and time dependant tariff, is developed using Reinforcement Learning (RL) method. The RL algorithm is validated and found to be effective in providing the best load schedule with minimum energy cost, efficiently utilizing the resources. The developed RL algorithm is analyzed for a variety of load data.

Finally the developed RL algorithm is realized by implementing a prototype model of Residential Energy Management System using a NodeMCU IoT setup and the results are verified.

Large scale deployment of roof top PV system by residential consumers together with variable pricing schemes introduced by the utilities impose the need for efficient algorithms. Consumers are thus enabled to intelligently schedule their appliances with minimum inconvenience. The stochastic learning algorithms developed can be a step towards a solution to this problem as it is beneficial to both consumer and utility.

Keywords: Smart Grid, Demand Response, Load Scheduling, Distributed Generation, Photovoltaic source, Reinforcement Learning

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Chapter 1

Introduction

One of the major operational issues in power system operation is balancing generation and load. Continuously growing energy demand, the deteriorating fossil fuel, environmental concerns and emerging renewable distributed generation necessitated a change in the conventional energy infrastructure. One of the proposed solutions is the concept of smart grid (SG). The smart grid is intended to ensure supply of clean, safe, secure, reliable, resilient, efficient, and sustainable energy. It provides monitoring, protecting and optimizing automatically the operation of the interconnected elements.

The major systems involved in SG are smart infrastructure system, smart management system and smart protection system. Smart infrastructure system can be further subdivided into three subsystems. The smart energy subsystem which deals with electricity generation, delivery, and consumption. The smart information subsystem considers the advanced information metering, monitoring, and management. The smart communication subsystem is for communication connectivity and information transmission. Smart management system in SG provides advanced management and control services. The smart protection system provides advanced grid reliability analysis, failure protection, and security and privacy protection services. Thus, smart grid aims to provide an efficient and reliable power supply for all at every point. Basic features of SG include infrastructure for information and power flow at various levels, making efficient use of renewable energy sources, incorporation of sufficient energy storage media, economic and efficient use of available energy. One of the management objectives of SG is the efficient use of available energy. Also in power system operation, generation and load balance should be ensured always. Traditionally, the electric utilities try to match the supply to the demand for energy. But in smart grid, electricity consumption of customer can also be managed to meet supply conditions. This makes it possible to provide reliable power supply with the existing generation and transmission capacities. Thus one of the important functions of SG is demand side management (DSM).

Demand side management refers to programs implemented by the utility to control the energy consumption at the customer side of the electric meter. DSM also promotes distributed generation, in order to avoid long distance transport, locally generated energy could be consumed by local loads, immediately when it is available. This results in increased sustainability of the smart grid, as well as reduced overall operational cost and carbon emission levels. Demand side management alters customers electricity consumption patterns to produce the desired changes in the load shapes of power distribution systems. DSM techniques that can be employed are load shifting, peak clipping, valley filling, strategic conservation, strategic load growth, and flexible load shape. Three concepts in DSM are identified as energy efficiency, energy conservation and demand response (DR). These programs are employed to utilize the available energy more efficiently without installing new generation and transmission infrastructure. Energy efficiency refers to permanent installation of energy efficient technologies or elimination of energy losses in eixisting system. Energy conservation involves using less of a resource, usually by making a behavioral choice or change. DR is related to electricity market and price signals, in the form of load management.

Demand Response is a program established to motivate changes in electricity use by end-use customers, in response to changes in the price of electricity over time or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized. Demand response programs are mainly categorized as: 1) Incentive based Programs and 2) Price based Programs. The incentive based program pays participating users for demand reduction during periods of system stress. The incentives can be payments or bill credits for their participation in the programs. This program includes Direct Load Control programs, Interruptible/Curtailable Load programs, Demand Bidding/Buyback Programs, Emergency Demand Response Programs etc. The concept of these programs are explained below.

Direct load control: In this case utility has the ability for remotely controlling (shuts down or cycles) a customers appliance (e.g. air conditioner, water heater) on short notice. The participating customers are provided with incentive in the form of an electricity bill credit.

Interruptible/curtailable (I/C) service: The customers who agree to reduce

their load to a pre-specified value during system contingencies are provided with an incentive payment or rate discount on electricity bill. If the participating customers fail to reduce the load, they will have to pay penality.
Demand Bidding/Buyback Programs: Customers bid on specific load reductions in the electricity whole sale market and load curtailment must be done as per the bid otherwise are liable to penalities.
Emergency Demand Response Programs: Incentive payments are provided to customers for measured load reductions during emergency conditions.

In price based program the price of electricity will be different for different time periods and the goal is to obtain a flattened demand pattern by providing low price for off-peak time and higher prices for peak times. By this the consumers are indirectly induced to change the energy consumption in accordance with price variation. From the consumer's perspective the price based DR schemes can be intelligently used to reduce the electricity bill. From the utility's perspective these are introduced to motivate the consumers to change their electricity usage pattern and thus reduce the Maximum Demand on the system. Utilities have designed various time varying tariffs such as Time of use (ToU) pricing, Critical peak pricing (CPP), Real time pricing (RTP) and Inclining block rate (IBR) to attain this objective.
Time-of-use (ToU) Pricing: The electricity price per unit consumption is different during different periods of time of a day or different seasons of a year. The price is more at peak periods compared to other time periods. ToU pricing is usually pre-determined for a long time period.
Critical Peak Pricing (CPP): During critical peak periods such as system contingencies or high wholesale electricity prices,a pre-specified higher rate

is used. CPP rates may also be added with a TOU or time-invariant price. It is employed only for short period such as few days or hours in a year.
Real-time pricing (RTP): The price for electricity typically fluctuates hourly reflecting changes in the wholesale price of electricity. RTP prices are usually informed to the consumers hour-ahead or day ahead basis.
Inclining block rate (IBR): The tariff has two different rates based on the energy usage of the consumer. If the consumption is more than a specified limit, the consumer has to pay a higher rate. The consumers get incentive by avoiding higher rates if they shift the operation of the loads to different time periods.
In global power sector, demand response programs are implemented in various countries such as USA, Norway, Italy, Spain, China etc. Time dependent tariff is relevant in the smart grid scenario and in India, demand response is in its nascent stages.

The type of consumer also is to be considered for effective application of the DR programs. There are mainly three different sectors of electricity consumers such as residential, commercial and industrial sectors. Generally residential consumers with large number of flexible appliances are chosen for performing demand response.

Nowadays the residential buildings are also becoming smarter with the use of smart appliances and integration of information and communication technology. Residential loads can be categorised into two groups, critical loads and controllable or flexible loads. Critical loads are must-run loads which are being turned on during a fixed time period and the time of use can not be shifted. Lighting loads, TV, PC etc. come under this category. For these type of loads, the customer should have the freedom to switch ON and OFF the loads as he desired. Controllable loads can be switched on at any time slot in the specified interval. Their operation can be delayed and/or interrupted if needed. Such loads include cloth washers, cloth dryers, dish washers, Heating Ventillating and Air Conditioning (HVAC) systems, water heaters, plug in electric vehicles, battery chargers for consumer electronics etc. Delaying the operation of some loads may cause discomfort to the consumer. The consumer may require to minimize the electricity bill without compromising on the comfort.

With the exploration of renewable sources, there is large scale deployment of small renewable generation systems. A large number of consumers tend to cover their electricity demand by their own local generation using renewable Distributed Genertion (DG) sources such as Photovoltaic (PV), wind turbine based power generation systems etc. Among the various DGs the most common and abundant resource is the PV. Recently, there is an increase in the number of residential consumers who install roof top PV systems to meet their load demand fully or partially. But the power generation from a PV source is uncertain in nature.

The major aspects to be considered with respect to residential load scheduling include comfort level associated with different appliances, constraints on operation of devices, availability, price and nature of energy supply. It is difficult or impractical for the consumers to control the loads manually considering all these aspects. So there is a need for automation and decision making tools for scheduling the residential loads with efficient utilization of all the resources and satisfying various constraints. In the past, big utilities were supplying power to big and small loads. In conventional power system, the balancing of generation and loads was achieved by scheduling the generating units. These problems were well formulated as Unit Commitment Problem (UCP), Economic Dispatch (ED), and Automatic Generation Control and different solutions were proposed and the area has matured. Now, with new concepts of power balancing, a mathematical model is very necessary for residential load scheduling. The following section describes the concept of modeling in respect of the load scheduling problem. The uncertainty modeling of PV source is explained in Section 1.1.2. The solution methods of the residential load scheduling problem is discussed in Section 1.1.3. The objective of the research work is given in 1.2 and the concluding section gives the outline of the thesis.

1.1 Research Focus

1.1.1 Generalized Mathematical Model for Residential Load Scheduling

The future residential consumer will have renewable sources, flexible loads, nonflexible loads and various time dependant tariff. Power generated from renewable sources, RTP and arrival of non-schedulable loads are random. The consumer will want to minimize his electricity bill without compromising on the comfort. Thus the problem is a decision making problem under uncertain environment.

So for residential load scheduling problem, a generalized mathematical model is formulated. Also the uncertainty associated with the PV source should be modeled to take into account the random variation of power output from such sources. Stochastic learning algorithms are appropriate tool for solving such problems. The objective is to minimize the total daily energy cost of the consumer, satisfying the various constraints. A general mathematical model for the load scheduling problem is developed which includes power from n number of different sources such as PV, grid, wind turbine etc. The inconvenience or discomfort caused due to delay in scheduling the load is also taken into account in the load model.

1.1.2 Uncertainty Modeling of PV Power

The power output from DG sources such as PV and wind power generation are fluctuating in nature. The uncertainty associated with PV power generation is due to the random nature of solar irradiance. If a lot of previous data of irradiance is available, a suitable probability distribution can be selected to model the random nature of irradiance. The best fitting distribution for the irradiance data is determined and this is done by historical data processing.

1.1.3 Residential Load Scheduling

The main objective of the price based DR (PBDR) programs is reduction in maximum demand, by motivating consumers with time dependant tariff to change their electricity usage pattern that helps to reduce their energy bill. Flexible loads are a good candidate for achieving this objective for residential consumers where the operating constraints of loads are specified by the consumer. Residential buildings are becoming smarter with wide use of smart appliances and integration of information and communication technology. In addition to the power from utility grid, now the power from roof top PV systems which is random in nature is also a source of energy for residential consumers. This necessitates efficient stochastic learning algorithms to schedule the consumer load optimally so as to minimize the energy bill.

Binary Particle Swarm Optimization (BPSO) algorithm is a population based stochastic search algorithm. Using BPSO algorithm, the load scheduling problem without considering consumer comfort and PV source is solved. Utility grid is the only source of energy in this case. The algorithm is validated with a case study of a residential consumer and this algorithm is found to be capable of handling problem with small solution space.

Next, the load scheduling problem is considered with incorporating consumer comfort in the load model. It is modeled as a multistage decision making problem so as to apply Reinforcement Learning (RL) strategy. RL is a stochastic learning method which involves learning from interactions with the environment to optimize the reward. The solution obtained is validated and is compared with the solution using Learning Automata algorithm.

In the next step, RL algorithm is developed for the residential load scheduling problem considering the consumer comfort and PV source along with grid power. The uncertainty of PV source is modeled using Beta PDF and PV output power is calculated. This is used for load scheduling. Verification and validation of the algorithm is carried out by considering the case study of a residential consumer also.

Finally the developed RL algorithm for load scheduling is tested by implementing a prototype model using NodeMCU IoT setup.

1.2 Objectives

In the smart grid paradigm, PBDR programs can be effectively utilized for controlling the loads of smart residential buildings. Recently, the use of stochastic renewable energy sources like Photovoltaic by small domestic consumer is increasing. A generalized model for the residential load scheduling problem in the presence of renewable sources for any type of tariff is essential to explore an implementable solution. Stochastic learning method like Reinforcement Learning (RL) is an efficient tool which has been used to solve decision making problem under uncertainty. The objective is to find an implementable solution for the residential load scheduling problem considering consumer comfort, stochastic PV power and time varying tariff.

The main objectives can be enumerated as,

1) Develop a generalized mathematical model for load scheduling problem including renewable sources.

2) Apply stochastic learning methods like Binary Particle Swarm Optimization, Learning Automata and Reinforcement Learning for the solution of residential load scheduling problem without PV source.

3) Model the uncertainty associated with PV generation using suitable method.

4) Develop an algorithm using Reinforcement Learning for the solution of residential load scheduling problem with PV source.

5) Prototype implementation of the developed stochastic learning algorithm using RL with PV for a residential energy management system.

1.3 Outline of the thesis

The thesis focuses on solution to residential load scheduling problem using stochastic learning algorithms. Load scheduling problem and the various constraints associated with it are studied. The different formulations and solution methodologies existing for residential load scheduling problem are reviewed in detail emphasizing the advantages and limitations.

As a first step a the mathematical model for the load scheduling problem with a single source is considered. From this a generalized model which can include different sources is developed so as to incorporate DG sources. A simple load model without the comfort aspect of the consumer is initially taken for the study. The load model with a factor *udc* which takes into account the delay in switching on a device is next considered. A solution to the load scheduling problem with one source, the utility grid and neglecting consumer comfort is first tried using Binary Particle Swarm Optimization (BPSO) algorithm. The algorithm is validated and is applied to a residential case study. But BPSO algorithm has certain limitations as the complexity of the problem increases with respect to the convergence of the algorithm.

Reinforcement Learning is a stochastic learning method which had been applied for solution of several search and optimization problems. The application of this method for load scheduling with PV source has not been fully explored yet. The load scheduling problem without PV source is considered but incorporating the comfort aspect in the load model. To apply RL strategy, the problem is modeled as a mulistage decision making problem.

The application of RL method to the load scheduling problem with PV source is to be investigated. The power output of the renewable DG unit like

PV source is stochastic due to the uncertain nature of solar irradiance. The uncertainty associated with these sources should be modeled using suitable probability distribution function. Beta PDF is used to model the uncertainty associated with the hourly solar irradiance, by historical data processing. The random power output of the PV source is obtained and is used for load scheduling.

The developed RL algorithm is used for the load scheduling problem with two sources, the utility grid and PV source. The result obtained is validated and verified to be the schedule with minimum cost satisfying the constraints. The RL algorithm is validated with a case study for a residential load scheduling.

Finally the developed stochastic learning algorithm using RL with PV source is verified by realizing a prototyype implementation of a residential energy management system.

The different chapters of the thesis are organized as follows.

DSM is one of the important functions of smart grid. Among the various DR programs to achieve DSM, price based DR can be employed to reduce the electricity bill of the residential consumers by properly scheduling the flexible loads. Load scheduling is a complex optimization problem with different operating constraints. There are a large volume of work with different formulations and solution methods for the load scheduling problem. A thorough review of existing methods for load scheduling in general and with regards to residential load scheduling with DG source in particular has been carried out for identifying the problem and solution strategies. *Chapter* 2 gives the review of the existing methods for load scheduling in the smart grid scenario.

The formulation of a generalized mathematical model for the residential load scheduling problem is explained in *Chapter* 3. The model takes into account a number of different sources so that any type of DG source can be included. The load model reflects the comfort aspect of the consumer also.

The solution of the load scheduling problem using Binary Particle Swarm Optimization algorithm is given in *Chapter* 4. Here the scheduling considering the basic load model is done with power from utility grid alone.

The load scheduling problem is formulated as a multistage decision making problem and RL solution is given in *Chapter* 5. First the basic RL algorithm is reviewed. The solution to the problem with a single source is presented and is compared with the solution available with LA algorithm which is also reviewed.

The solution to the load scheduling problem with PV source is introduced in *Chapter* 6. The power output from PV source is used for load scheduling and this power is random in nature due to random variation of solar irradiance. The uncertainty associated with the PV source is modeled using Beta PDF. Modeling of solar irradiance using Beta PDF is also explained. Simulation studies are also presented. A case study of a residential load scheduling with PV source is also discussed.

The performance of the developed algorithm is investigated by implementing a Residential Energy Management System (REMS)using a NodeMCU IoT setup, for a residential consumer with different appliances along with a PV source. The prototype implementation is explained in *Chapter* 7.

The important contributions are given in the concluding chapter, *Chapter* 8. The limitations and the scope for further work are also explained.

Chapter 2

Literature Survey

2.1 Introduction

Demand side management (DSM) is one of the important functions of smart grid (SG) that aims to provide an efficient and reliable power supply for all at every point. DSM programs are intended to manage the energy consumption of the consumer in the most reliable and economic manner. Various demand response (DR) programs are there to motivate the consumers to control the electricity usage as a means to achieve this goal. To investigate the residential load scheduling problem in the SG scenario, the concepts of smart grid, demand side management and demand response are to be familiarized. Several works have been done to address the residential load scheduling problem and a thorough literature survey has been conducted to study the residential demand response and various approaches existing for the solution of the residential load scheduling problem. Nowadays the integration of photovoltaic sources in the residential power sector is increasing. But the power output from this source is fluctuating due to the random variation of solar irradiance. The uncertainty associated with PV source need to be modeled so that the power output can be predicted in advance. Review of various methods available for uncertainty modeling is done. The literature on residetial load scheduling with DG is also reviewed. The solution method that is chosen for residential load scheduling should necessarily be a stochastic optimization technique.

The chapter is organized as follows. The various literatures that provide an overview of SG are discussed in Section 2.2. Section 2.3 describes the literature on different aspects of DSM and DR. Section 2.4 provides a review of works on residential load scheduling. The review of methods used for uncertainty modeling of photovoltaic source and load scheduling considering DG are also included in this section. The various methods used for residential load scheduling is reviewed in Section 2.6. Section 2.7 discusses various applications of reinforcement learning. The conclusion of the literature review is presented in Section 2.8.

2.2 Overview of Smart Grid

Smart grid is considered as the next generation power grid. The smart grid can be regarded as an electric system that uses information, two-way, cyber-secure communication technologies and computational intelligence in an integrated fashion across the entire spectrum of the energy system from the generation to the end points of electricity consumption.

The security, agility, and robustness of a large-scale power delivery infrastructure that faces new threats and unanticipated conditions are addressed by (Amin and Wollenberg, 2005) and suggested locally self regulating smart grid as an alternative. The SG is described as the intelligent grid which is expected to address the major shortcomings of the existing grid by (Farhangi, 2010). It needs to provide the utility companies with full visibility and pervasive control over their assets and services. Also it is required to be self-healing and resilient to system anomalies. It needs to empower its stakeholders to define and realize new ways of engaging with each other and performing energy transactions across the system.

The enabling technologies on smart grid are surveyed and given by (Fang et al., 2012). According to this, the major systems involved in SG are smart infrastructure system, smart management system and smart protection system. Smart infrastructure system can be further subdivided into three subsystems. The smart energy subsystem which deals with electricity generation, delivery, and consumption. The smart information subsystem considers the advanced information metering, monitoring, and management. The smart communication subsystem is for communication connectivity and information transmission. Smart management system in SG provides advanced management and control services. The smart protection system provides advanced grid reliability analysis, failure protection, and security and privacy protection services.

The smart grid technologies and its characteristics are described by (Hassan and Radman, 2010). Smart Grid goals, challenges and benefits are also explained. Suggested recommendations for smart grid standards, taking into account relevant approaches of smart grid standardization studies is given in (Rohjans et al., 2010). Smart grid and associated technical, environmental and socio-economic, and other non-tangible benefits to society is presented in (El-Hawary, 2014). The potential promise of the SG, which is embedded in its attributes such as efficiency, accommodating, quality focus, enabling and self-healing are explained. The concerns and issues confronting its forward progress, adoption and acceptance are also discussed. Some key issues related to the future grid such as distributed cooperation and control, data and application integration, and knowledge based comprehensive decision are pointed out by (Li and Zhou, 2011).

The Advanced Metering Infrastructre (AMI) supports the bidirectional information flow in SG. The utilization of AMI networks to realize Smart Grid goals is described in (Hart, 2008). Key AMI attributes are described as, communication to the electric meter to enable time stamping of meter data, outage reporting, communication into the customer premise, service connect/disconnect, on-request reads, and other functions. A Smart Grid key management framework with application to AMI networks is proposed by (Das et al., 2012). The potential application and communication requirements essential for Smart Grid implementation is presented in (Gungor et al., 2013). The challenges related to smart grid communication infrastructure are described in (Yan et al., 2013) such as complexity, efficiency, reliability and security. A survey of complex network theory to modern smart grid applications is given by (Chu and Iu, 2017).

Thus, basic features of Smart Grid include infrastructure for information and power flow at various levels, making efficient use of renewable energy sources, incorporation of sufficient energy storage media, economic and efficient use of available energy. One of the management objectives of the SG is the efficient use of available energy. Traditionally, the electric utilities try to match the supply to the demand for energy. But in smart grid, customer consumption of electricity is managed to meet supply conditions. Therefore one of the important functions of SG is recognized as demand side management.

2.3 Demand Side Management and Demand Response

With continuosly growing energy demand the importance of demand side management is increasing in smart grid. DSM refers to programs implemented by the utility to control the energy consumption at the customer side of the electric meter. DSM also promotes distributed generation, in order to avoid long-distance transport, locally generated energy could be consumed by local loads, immediately when it is available. This results in increased sustainability of the smart grid, as well as reduced overall operational cost and carbon emission levels. Demand side management alters customers electricity consumption patterns to produce the desired changes in the load shapes of power distribution systems. The DSM techniques that can be employed in future Smart Grids can be considered as peak clipping, valley filling, load shifting, strategic conservation, strategic load growth, and flexible load shape.

The three concepts in DSM are identified as energy efficiency, energy conservation and demand response by (Boshell and Veloza, 2008) . These programs are employed to use the available energy more efficiently without installing new generation and transmission infrastructure. Energy efficiency refers to permanent installation of energy efficient technologies or elimination of energy losses in eixisting system. Energy conservation involves using less of a resource, usually by making a behavioral choice or change. Demand response is related to electricity market and price signals, in the form of load management.

Various researches are being carried out on different outlooks for implementation of DSM in smart grid. Many works focus on the salient characteristics, technology implementation strategies, energy management and economic analysis of DSM. An overview and a taxonomy for DSM is presented in (Palensky and Dietrich, 2011). Analysis of different types of DSM and outlook on the latest demonstration projects in this domain are also included. They categorize DSM into energy efficiency, Time of Use, demand response and spinning reserve based on the timing and the impact of the applied measures on the customer process. Along with the different aspects of DSM, the concept of load based virtual storage power plants and various communication protocols for load management are also discussed.
The economic effects of DSM in a grid where generation cost is considered as a parameter to be analyzed is presented in (Verma et al., 2016). Differential Evolution is implemented to solve the DC-OPF in each hour and also to find the new load curve from DSM implemented in the system. It is shown that DSM has an effect to reduce the cost of generation over a span of time at overall grid level.

In the technical report by U S Department of Energy (Qdr, 2006), demand response is defined as the changes in electricity usage by end use customers from their normal consumption patterns in response to, changes in the price of electricity over time or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized. DR includes all intentional electricity consumption pattern modifications by end-use customers that are intended to alter the timing, level of instantaneous demand, or total electricity consumption. Demand response represents the outcome of an action undertaken by an electricity consumer in response to a stimulus and typically involves customer behavioral changes.

A summary of DR in deregulated electricity markets is presented in (Albadi and El-Saadany, 2008) which includes the potential benefits and associated cost components. The customer response can be achieved by three general actions. First, customers can reduce their electricity usage during critical peak periods when prices are high without changing their consumption pattern during other periods. Secondly, customers may respond to high electricity prices by shifting some of their peak demand operations to off-peak periods. The third type of customer response is by using onsite generation, customer owned distributed generation.

The different technologies, models and algorithms for demand response are addressed by various researchers. Good literatures on various aspects of demand response programs in smart grid are presented in (Siano, 2014), (Deng et al., 2015) and (Vardakas et al., 2015). A detailed survey of DR and smart grid which includes customer classifications, conceptual model for the customers domain, different DR programs, Potential benefits of DR, Enabling smart technologies, Control devices, Monitoring and Communications systems for DR are described in (Siano, 2014). Customers are classified as large commercial and industrial, small commercial and industrial, residential, individual plug-in electric vehicles (PEVs) and fleet of PEVs. Different DR programs are explained as price based, incentive based and demand reduction bids. The concepts of smart metering and Advanced Metering Infrastructure (AMI), Energy Management System (EMS), Energy Information Systems (EIS) are presented in this paper. Some idustrial case studies are also briefly reviewed and it shows that enabling technologies, such as smartmeters, AMI, home energy controllers, EMS, wired and wireless communication systems support the coordination of DR in smartgrids.

Mathematical models and approaches employed in DR programs are presented by (Deng et al., 2015). In this paper, they first give a review of incentive based and price based DR progrms employed by the utility to motivate consumers to reshedule their energy consumption patterns. The existing mathematical models corresponds to utility maximization, cost minimization, price prediction, renewable energy, and energy storage oriented problems. The DR approaches are identified as convex optimization, game theory, dynamic programming, Markov decision process, stochastic programming, and particle swarm optimization.

DR schemes based on pricing methods and optimization algorithms are surveyed in (Vardakas et al., 2015). They classify DR schemes into three- according to the control mechanism, the motivations offered to reduce the power consumption and the DR decision variable. It can be centralized or distributed based on control mechanism. The consumers can be motivated by price based or incentive based DR progrms. They identify the decision variable, based on task-scheduling or energy-management DR shemes. Though the the main electricity consumers are transportation, residential, commercial and industrial sectors , DR programs are mostly applied to residential, commercial and industrial consumers. A detailed classification of the optimization models and the solution methods is presented in the paper. It is identified that in future, the issues to be addressed are the stochastic nature of the renewable sources and random nature of the appliance usage, to arrive at optimal decision for DR implementation.

An optimization model that permits a consumer to adapt the hourly load level in response to hourly electricity prices is proposed by A. J. Conejo et al (Conejo et al., 2010). The objective of the model is to maximize the utility of the consumer or minimizing the energy cost. Robust optimization techniques are used to model price uncertainty. A linear programming algorithm is used to realize the real time DR model.

The main industry drivers of smart grid are identified as the environment, system reliability and operational excellence by (Rahimi and Ipakchi, 2010). They address demand response as a market resource and give an outline of the various product markets and DR facilitated by the existing ISOs/RTOs in the United States. The challenges associated with variable generation and potential solutions are also explained.

A DR simulator to study the demand response actions and schemes in distribution networks is described in (Faria and Vale, 2011). In the case of an energy shortage, reduction in load is achieved with the help of a consumer based price elasticity approach using real time pricing. The problem is addressed in a retailer's perspective. Optimal solution for load reduction is determined using non-linear programming. With a case study it is shown that the customer's demand depends on price elasticity of demand, and on the real-time pricing tariff.

Load shifting and load curtailment are two methods for DR implementation. A multi agent system for demand side management based on load shifting and load curtailment techniques is proposed in (Logenthiran et al., 2011). The multi-agent system provides an autonomous electronic platform for demand side management in smart grid which are equipped with intelligent devices. The operational cost and peak demand of the system are minimized by shifting the energy demand within certain boundaries from peak hours to off peak hours. The best possible load scheduling is found by the shifting algorithm using a quadratic program. The objective of the curtailment algorithm is to minimize the use of expensive generators like diesel generators.

A demand side management strategy based on load shifting technique considering a large number of devices of different types that include residential, commercial and industrial customers is presented by same authors in (Logenthiran et al., 2012). A heuristic-based Evolutionary Algorithm is used for solving the problem. The proposed strategy achieves substantial savings and reduces the peak load demand of the smart grid.

The effect of impacts of DR on distribution network is also addressed in some works. A quantitative study of the impacts on major attributes of a residential distribution network operation is given in (Safdarian et al., 2016).

The appliance level load profile of more than 1600 residential consumers from Kainuu, Finland, is used for the study. The result obtained is then applied to a network, and the impacts of the DR on network operation such as the network losses, voltage profiles, and service reliability are studied. It was shown that realization of only 10% of DR potentials would improve the system peak load, network losses, and service reliability by 5.6%, 1.3%,and 1.7%, respectively.

Renewable energy sources are an integral part of the smart grid. A renewable energy buying-back schemes with dynamic pricing to achieve the goal of energy efficiency for smart grid is proposed by (Chiu et al., 2017). The dynamic pricing problem is formulated as a convex optimization dual problem and a day-ahead time-dependent pricing scheme in a distributed manner is proposed. It is suggested as a better option compared to net metering and feed-in-tariff. Both the electric company and its users are benefitted by this pricing strategy and improves significantly the system-wide energy provision balance. The key review findings are given in Table 2.1

Demand response has been evolved from theoretical algorithmic solution to more practical implementable strategy with due consideration to energy and economic analysis in SG.

2.4 Residential Load Scheduling

Residential power sector is equipped with a number of schedulable loads. As residential consumers are large in number, proper implementation of DR programs in this sector will bring out a significant opening for energy manage-

Table 2.1: DSM-DR Review Findings

Year	Author	Review Findings	
		Key findings	**Parameters**
2008	Boshell and Veloza	The three concepts in DSM are identified.	Energy efficiency, energy conservation and demand response.
2011	Palensky and Dietrich	An overview and a taxonomy for DSM is presented.	Analysis of different types of DSM and outlook on the latest demonstration projects in this omain are also included.
2014	Siano	A detailed survey of DR and smart grid are described.	Customer classifications, conceptual model for the customers domain, different DR programs, Potential benefits of DR, Enabling smart technologies, Control devices, Monitoring and Communications systems for DR are described.
2015	Deng et al.	Mathematical models and approaches employed in DR programs are presented patterns.	The existing mathematical models corresponds to utility maximization, cost minimization, price prediction, renewable energy, and energy storage oriented problems. The DR approaches are identified as convex optimization, game theory, dynamic programming, Markov decision process, stochastic programming, and particle swarm optimization.
2015	Vardakas et al.	DR schemes based on pricing methods and optimization algorithms are surveyed.	It is identified that in future, the issues to be addressed are the stochastic nature of the renewable sources and random nature of the appliance usage for DR implementation.

ment. A detailed literature survey is conducted to study the various existing models and approaches for the solution of the residential load scheduling problem. There are many works in literature for modeling and solving DR in residential sector. The objective of the scheduling algorithm is to minimize the consumers electricity bill and reducton of maximum demand on the system with the tariff provided by the utiility. Different tariff structures such as Time of Use pricing (ToU), Critical Peak Pricing (CPP), Real Time Pricing (RTP) etc. are introduced as demand response initiatives in this case. Demand response problem may be addressed in two perspectives: consumer perspective to reduce the energy bill and utility perspective to reduce the maximum demand. The basic modelling is to arrive at an objective function which is to be optimized with proper scheduling strategy. The main aim of this task is to minimize energy cost.

The works presented by (Kin Cheong Sou, 2011), (Alessandro Di Giorgio, 2012), (Xiao et al., 2010) and (Julien M. Hendrickx and Wolsey, 2013) consider simple residential models. The problem of residential appliances scheduling with an objective to minimize total energy cost for operating the appliances based on their power profiles is addressed by (Kin Cheong Sou, 2011). It assumes a 24-hour ahead electricity tariff which is piecewise constant. A power safety constraint for limiting maximum demand by the power grid operator is also considered. The problem is modeled as a mixed integer linear program problem. The same authors proposed an automatic decision framework considering the effect of CO_2 emission to schedule smart home appliances so as to minimize electricity bill in (Kin Cheong Sou, 2013). A day ahead electricity tariff and CO_2 footprint, are assumed as the DR signals.

These signals are first considered as piecewise constant and then arbitrary. A dynamic programming formulation is used in this case. The design of a smart home control strategy to maximize the economic savings of the customer is proposed in (Alessandro Di Giorgio, 2012). The problem is formulated as an event driven binary linear programming problem. The event can be a consumer request to operate a load and DR signals such as price or power threshold reduction for a spcific period. Its solution specifies the best time to run of smart household appliances under a virtual power threshold constraint and ToU tariff. Energy price, peak and average load profiles and the available power threshold are considered as time varying. Using real time pricing scheme a min max scheduling algorithm is suggested by (Xiao et al., 2010) and it provided near optimal solution for peak shaving, cost reduction and risk aversion for consumers. They also proposed another algorithm for home energy management in (Xiao et al., 2012). The problem is formulated as a mixed problem between discrete appliance scheduling with dead lines and continuous Heating, Ventillation and Cooling (HVC) device control. Here an air conditioner is used as an example for HVC control with energy consumption modelled as a continuous function. It models user comfort by placing constraints on algorithm and assumes day ahead pricing with hourly prices based on real energy pricing and consumption data in South Korea. Energy price in peak hours is considered exponentially expensive while energy price in early hours of a day are significantly discounted. The problem of scheduling different energy consuming tasks when the energy price profile is given and fixed for a prescribed period is discussed by (Julien M. Hendrickx and Wolsey, 2013). They proposed a discrete time formulation for this problem and solved it by a minimum cut algorithm. Near-optimal cost is obtained with a reduced time of computation.

A dynamic programming model for the demand side control problem to minimize cost considering the level of discomfort is proposed by (Young Liang and Shen, 2013). This model consider stochastic demand arrivals. The objective is to design a general central controller that minimizes the cost of electricity and the discomfort from deferring the demands under time varying prices. It is assumed that users are equipped with smart appliances and allowable delays are specified by users. To overcome the dimensionality problem with dynamic programming, two solutions methods are proposed, one is a decentralization based heuristic approach and another approach based on Q learning. Both the methods resulted in near optimal solutions.

A consumer automated energy management system for residential demand response is presented by (O'Neill et al., 2010) which models both consumer energy reservations and energy prices as Markov chains and uses Q learning to optimally make energy consumption decisions to reduce the energy cost. The algorithm takes the sequence of consumer reservation vector and sequence of energy prices as inputs. It includes a disutility function to account for consumer dis-satisfaction of weighting.

A reinforcement learning based method to solve demand response problem is proposed by (Ahamed et al., 2011). The problem is modeled as a Markov Decision Process and the objective is to minimize the electricity bill considering the operating constraints of the load alongwith the consumer discomfort due to delay in scheduling the load. The optimum schedule is obtained with time varying price.

The load scheduling problem is formulated as a simple decision making problem by (Syed Q. Ali and Malik, 2013a). In this, the objective is to decide the best time slot for scheduling the load to reduce the energy cost. The decision maker is modeled as a learning automata. Discomfort due to delay in scheduling is also considered. They also considered the load scheduling problem as a combinatorial optimization problem constrained by the maximum demand limit (S. Q .Ali and .Malik, 2013). It is assumed that the utility is using a time of use pricing based two part tariff with a limit on the maximum demand. In this formulation Maximum Demand limit is taken as a constraint for optimization.

Demand arrivals and real time price variations are random in nature. Uncertainity and stochastic nature of the demand and pricing are also being addressed (T and Poor, 2011). They formulated power consumption scheduling problem with future price uncertainity and proposed an algorithm to minimize expected cost at the consumer side. Both non interruptible and interruptible loads are considered. The scheduling problem is formulated as a Markovian process. It models the future prices within 24 hour time frame by Gaussian random variables with known means, which are the expected prices and some estimated variance.

A real time price based DR management for residential appliances by stochastic optimization and robust optimization approaches is proposed in (Chen et al., 2012). It determines the optimal operation in the next five minute time interval while considering future electricity price uncertainities. Monte Carlo simulation method is utilized to generate scenarios for simulating real time price uncertainities in the proposed stochastic model. Operation task of appliances are divided into three different categories. Both approaches achieve lower electricity bill cost as compared to current flat rate electricity price.

A method to obtain the optimal scheduling of home appliances under time of use electricity tariff is presented in (Setlhaolo et al., 2014). The problem is modeled as a mixed integer nonlinear optimization problem in which maimum demand limit is ensured by providing an incentive part along with cost of electricity in the objective function. It also puts a bound on the electricity bill and suggests a method to capture the cost of inconvenience. The difference between baseline schedule and optimum schedule is taken as the inconvenience level. But no general guideline is provided to choose the weighting factor that represents the inconvenience level of each appliance.

One of the major category of schedulable loads come from thermostatically controlled appliances. Specific appliance models and solutions are also proposed in literature, such as electric water heater, air conditioner etc . An appliance commitment problem using an electrical water heater load as example is described by (Du and Lu, 2011). The objective is to minimize the energy being subject to comfort constraint which is solved based on the constraints of hot water thermal dynamics and temperature bounds specified by users for discomfort. The problem is solved by a linear sequential optimization enhanced multiloop algorithm. This algorithm is useful in getting optimal schedules of thermostatically controlled loads.

Scheduling a group of interruptible loads is proposed by (M.A.Pedrasa and Gill, 2009b). A Binary Particle Swarm Optimization (BPSO) method is used for obtaining the curtailment schedule that minimizes the total payment and frequency of interruptions. This algorithm provides certain limitation regarding the flexibility on scheduling and constraints pertaining to the different loads as only interruptible loads are considered for scheduling.

Apart from scheduling of flexible and interruptible loads in a single residential building, there are many works that focus on a group of consumers so that the cost reduction is more effective for the utility alongwith the bill reduction for the consumer. (Mohsenian-Rad et al., 2010), (Chen Chen, 2011) and (Chavali et al., 2014) proposed residential DR models considering group of consumers. An autonomous and distributed demand side management system for energy cost minimization in which multiple users interact with each other and utility to coordinate their energy usage is proposed in (Mohsenian-Rad et al., 2010). Utility provides the time dependant tariff. Each customer is equipped with an automatic energy consumption scheduler. Game theory is used to formulate an energy consumption scheduling game among the users. The objective is to minimize Peak to Average Ratio (PAR) and energy cost. Each user has control over the operation of the shiftable and non shiftable appliances. An automatic energy consumption scheduler using a distributed algorithm, provides an optimal schedule for the energy consumption for each user. Quadratic energy cost function is assumed with two different coefficients for day time and night hours. The method is effective to reduce the PAR, if a group of consumers are willing to act in a coordinated way. Real time pricing based residential power scheduling scheme using game theory is proposed by (Chen Chen, 2011). Energy Management Controller(EMC) in each home and the service provider form a Stackelberg game model and is formulated to analyze the interaction between consumer's EMC and the service provider. The leader level game is played by the service provider and the follower game is played by the EMC. The objective is to reduce the peak load and consumer electricity bill. A distributed energy scheduling algorithm based on cost optimizaion as a demand response for a group of customers is proposed by (Chavali et al., 2014). In response to the varying electricity prices, each user in the system will find an optimal start time and operating mode for the appliances. An approximate greedy iterative algorithm is used for obtaining the appliance schedule with a day ahead pricing scheme.

Another formulation of DR in terms of an energy service decision support tool for residential consumers to optimize their utilization of electrical energy services is presented by (M.A.Pedrasa and Gill, 2009a). It is based around an energy service model that place a received benefit on energy services. The total energy service benefits minus cost of energy accounts for the net benefits of the end user and a scheduling algorithm maximizes the net benefits. They presented enhancements to the energy service decision support tool in (M.A.Pedrasa and Gill, 2010). The basic formulation of cooperative PSO is improved by introducing stochastic repulsion among particles. Four controllable DER, plug in hybrid vehicle, space heater, storage water heater and pool pump are considered. They also determined the value of co-ordination by comparing the results when optimal DER operation solved in a co-ordinated manner versus when they are scheduled independently. They investigated the cases with three tariff structures, ToU energy with ToU feed-in rates, ToU energy with no feed-in compensation and ToU energy with ToU feed-in rates and peak demand charges.

The market-related problems of modern electric grids and possible solutions to address them are reviewed and presented in (Muratori et al., 2014). The residential demand response programs is analyzed and both on economic and policy perspectives, the implications of this solution are discussed. With a case study they showed that peak demand is not effectively reduced by Time of Use programs, though they effectively shift the time of occurrence of the peak demand. A review of smart home energy management system technologies is given in (Amer et al., 2014). The Energy Management System (EMS) in a smart home intelligently controls household load in association with smart meters, smart appliances, Plug-in Hybrid Electric Vehicles (PHEVs), and home power generation and storage equipments. The concept and background of smart home energy management system technologies are discussed. The review is done by classifying the home energy management works as consumption scheduling or home area networks. The challenges such as cost, implementation and privacy issues of smart technologies are also discussed.

Storage space heating also can be economically controlled by DR. Demand Response associated with electric storage space heating loads of residential consumer is presented in (Olli Kilkki, 2013) proposed a game theoritic approach to optimize the electricity price of storage space heating consumers and to maximize the daily profit of the retailer. The consumers are given the decided price vector and charging can be scheduled by minimizing the total hourly cost of electricity. The problem is addressed from the retailer's perspective.

A multiobjective optimization problem for home energy management with internal energy sources is proposed by A. Moghaddamin et al. (Anvari-Moghaddam et al., 2015). The home energy is provided by the utility and internal energy sources such as micro cogeneration systems and underfloor heating/cooling units. To obtain optimal energy use, a multiobjective mixed integer nonlinear programming model is developed.

The models and solutions for residential load scheduling problem proposed in these papers suggest methods to minimize both the energy cost of the consumer as well as the maximum demand on the system. It is well known that, there is a large scale deployment of roof top PV systems by residential consumers these days. The aim of Jawaharlal Nehru National Solar Mission (JNNSM)launched by the Government is to achieve the installed solar capacity of 100 GW by 2022 of which 40 GW is to be contributed by the rooftop panels (mnre, 2017). As a result of many initiatives taken by the central and state government, the installed capacity of the solar photovoltaic has reached 17.05 GW in 2017. The presence of PV source is not considered in the works discussed above.

2.4.1 Uncertainty Modeling of Photovoltaic Power Generation

Recently there is an increase in the number of residential consumers who install roof top PV system to meet their electricity demand. But the power generation from these sources are intermittent in nature. The uncertainity associated with the renewable power generation is to be modeled accurately and a review of various methods avilable in the literature is given below.

There are mainly three types of modeling methods for PV source known as, time series based method, probabilistic methods and stochastic methods. Time series based methods use models such as Unobserved Component Models (UCM), Autoregressive Integrated Moving Average (ARIMA), Neural Network, transfer function, hybrid models etc. In (Reikard, 2009) a comparison of predicting global horizontal irradiance at different sites and at different resolutions is given and performance of ARIMA model is found to be best compared to other models. For transfer function using cloud cover better result is obtained at high resolutions than ARIMA.

Three different methods using time series analysis to forecast solar irradiance components such as global horizontal irradiance, diffuse horizontal irradiance and direct normal irradiance with cloud cover effects are proposed by (Yang et al., 2012). ARIMA model is used to forecast the irradiance in all cases. It was found that the forecasts using the information of cloud cover gave more accurate results. Modeling the variations in solar irradiance using time series analysis is difficult as it requires a large amount of data.

In prbabilistic methods a suitable probability distribution function is required to model the random nature of solar irradiance based on historic data. In (Salameh et al., 1995) Probability Density Functions (PDF) such as Beta, Weibull and Log-Normal are studied to model the solar irradince using long term irradiance data and it was found that the Beta distribution fits the best. Beta PDF is used by several authors to model the uncertainty associated with solar irradiance and PV power generation. Beta distribution was used by (Assuncao et al., 2003) to model 5 minute averaged solar radiation indices in terms of optical air mass. In the study conducted using sequential

Monte Carlo method by (Mohamed and Hegazy, 2015) with Beta, Weibull and Normal distributions it is found that Beta distribution is the best fit distribution to accurately model stochastic PV generation. In (Atwa et al., 2010), Beta PDF was used in generating a probabilistic PV generation model to minimize the energy losses in the distribution system.

Stochastic methods are also used for predicting the solar irradiance such as neural network (Kayal and Chanda, 2015) and fuzzy methods (Wang et al., 2015). Another stochatic method given by (Miozzo et al., 2014) uses Markov Processes to model PV uncertainty.

From the literature, it can be concluded that, when sufficient data is available, uncertainty associated with the solar irradiance can be efficiently modeled by Beta distribution.

2.4.2 Residential Load Scheduling Considering DG

There is a large scale deployment of small renewable energy sources in the consumer premises (Akash T.Davda and D.Desai, 2014). Renewable energy source such as Photovoltaic and wind energy sources are generally used by residential consumers. Also with the development in power electronic interface and decrease in cost of PV panels this trend is expected to grow (Carrasco et al., 2006), (Kouro et al., 2015). Sophisticated planning and operation scheduling of Renewable Energy Resources with Demand Response is presented in (Fahrioglua, 2012) and (Jamshid Aghaei, 2013). Residential load scheduling in the presence of DG is an active research area now. Various existing models and approaches for the solution of the residential load scheduling problem in the presence of PV are reviewed and given below.

The development of a control system using Artificial Neural Networks (ANNs) tuned by Genetic Algorithms(GAs), for the residential sector with distributed generation is described by (E.Matallanas, 2012). It incorporates local PV energy generation and the controller maximizes self consumption. The system is made up of several ANNs placed at the various appliances and the realized load shifting strategy provides a load schedule for the next day. The model does not consider the inconvenience due to shifting the operation of the loads. Though the method focuses on maximizing self consumption of local generation, the uncertainty of PV power is not modeled in this work.

Guo et al. proposed a residential energy management system to minimize the electricity cost under real time electricity tariff considering renewable generation such as PV modules or small wind turbines (Guo et al., 2012). The problem is formulated as a stochastic optimization problem and is solved by Lyapunov optimization technique. Without the use of stochastic models, storage aspect is taken into account in this case.

A methodology for making robust day ahead operational schedules for controllable distributed energy resources (DER) including a PV system is suggested in (M.A.Pedrasa and Gill, 2011). The consumer net benefit is maximized over a set of scenarios that model the range of uncertainity. The optimal scenario set is derived by heuristic scenario reduction techniques. Robust operational schedules are formulated under stochastic energy service demand, availability of storage DER and status of dynamic peak pricing. Stochastic programming method based on cooperative particle swarm optimization with stochastic repulsion among particles is used to derive the schedule. In this work a different approach is used in which energy service demand is modeled by considering the hourly occupancy state probabilities. The method used for selection of scenario set reduction is only approximate and time consuming that limits practical implementation.

Considering DGs such as solar panel and wind turbine, a load management method by energy cost minimization under real time pricing is proposed by (Bingjie Ruan and Yan, 2014). The load management approach includes DG based scheduling and RTP based scheduling using Genetic Algorithm. The optimal appliance scheduling is obtained without considering the effect of delay in scheduling the appliance. A Smart Home Energy Management System with storage battery along with PV and wind turbine is proposed by (Jidong Wang and Dai, 2012). A mixed integer non-linear programming is used to solve the problem. Forecast of DERs is not considered.

The real time price is also forecasted for a home load management system with PV installation using auto regressive moving average technique by (Kiaee et al., 2014). The problem is formulated in a Mixed Integer Linear Programming format and is solved in the General Algebraic Modelling System(GAMS) using CPLEX solver. The PV is capable of selling energy to the distribution network.

M. Arora et al proposed an optimal scheduling of appliances in a smart home with PV and energy storage device by (Arora and Chanana, 2014). Residential loads are categorised as heating ventilating and air conditioning (HVAC) load and non-HVAC load. Load power is met either from PV panel/battery or from grid on priority. ESD is charged from PV panel or from grid during low priced period.

An autonomous demand side energy management system for a grid connected household with a roof top PV system is given in (O.Adika and Lingfeng-Wang, 2014). The load scheduling problem is approached in a slightly different way by introducing load clustering, wherein the appliances with similar schedules are grouped together into a cluster instead of considering each individual appliance. In the proposed approach the appliances Time of Use (ToU) probabilities is used to predict the customer's load pattern. The hourly price signals are also designed based on ToU probabilities. Three pricing scenarios are considered for analysis, Real time pricing, Feed in Tariff and Net purchase and Net sale plan.

Suyang et al. proposed a home energy management system in which the maximum demand and DR incentive are combined together for the DR mechanism (Suyang Zhou and Zhang, 2014). The home is equipped with PV and battery system. In this scheme excessive power drawn from grid is charged and the household can also sell the excess energy. The loads considered are controllable loads such as electric water heater, air conditioner, clothes dryer and electric vehicles along with critical loads. Half hour ahead rolling optimization and a real time control strategy are combined to realize the energy management of the household. It also utilizes a fuzzy logic controller to determine battery charging/ discharging power and to control it under the real time electricity price. The proposed control stratey is tested using a Zigbee based real test environment.

The delay in scheduling the loads affect the convenience of the consumer. Consumer comfort also is taken into account by some authors, in load scheduling with PV. (Paterakis et al., 2015), (Park et al., 2017) and (Arun and Selvan, 2017) consider comfort aspect in their works. A mixed integer linear programming model of a home energy management system is presented in (Paterakis et al., 2015). A household including electric vehicles, distributed generation such as roof-top PV units and energy storage systems along with controllable loads is considered. Most of the operational possibilities of demand response are addressed in this work and the system is proved to be efficient in minimizing the energy cost under dynamic pricing and reshaping the consumer load profile. Though the comfort associated with thermostatically controlled loads is included, inconvenience caused to the consumer due to scheduling of all controllable loads is not considered. The uncertainty of solar power is also not addressed in the model proposed. Algorithms for residential demand response considering user convenience under real time and progressive pricing policies are presented by (Park et al., 2017). The algorithm for reformulated problem guarantee optimal solution for real time pricing policy. The heuristic algorithm for progressive pricing formulation gave near optimal solutions. An intelligent residential energy management system for smart residential buildings with renewable energy resources (RER) is proposed by (Arun and Selvan, 2017). The objective is to minimize the electricity bill and maximize the utilization of renewable energy with the real time price provided by the utility. Optimal sizing of RER and battery units are also done to achieve this. Though the optimal sizing of the RER is considered, the uncertainty modeling of power production by RER and the consumer comfort aspect are not fully addressed in this work.

The key review findings are given in Table 2.2 and 2.3.

From the literature, it can be concluded that the most of the research

Table 2.2: Residential Load Scheduling- Review Findings 1

Year	**Author**	**Review Findings**	
		Key findings	**Analysis**
2012	Guo et al.	The problem is formulated as a stochastic optimization problem and is solved by Lyapunov optimization technique.	Without the use of stochastic models, storage aspect is taken into account in this case.
2014	Bingjie Ruan and Yan	The load management approach includes DG based scheduling and RTP based scheduling using Genetic Algorithm.	The optimal appliance scheduling is obtained without considering the effect of delay in scheduling the appliance.
2014	Arora and Chanana	Load power is met either from PV panel/battery or from grid on priority. Optimization problem is solved using Mixed Integer Linear Programming.	A real time price based scheduling mechanism is introduced without considering the PV power uncertainty.
2014	Suyang Zhou and Zhang	The home is equipped with PV and battery system. Half hour ahead rolling optimization and a real time control strategy are combined to realize the energy management. It is tested using a Zigbee based real test environment.	The uncertainty associated with PV power generation and user comfort aspects are not included.

Table 2.3: Residential Load Scheduling- Review Findings 2

Year	Author	Review Findings	
		Key findings	**Analysis**
2015	Paterakis et al.	A household including electric vehicles, roof-top PV units and energy storage systems is considered. The comfort associated with thermostatically controlled loads is included.	Most of the operational possibilities of demand response are addressed in this work but inconvenience caused to the consumer due to scheduling of all controllable loads is not considered. The uncertainty of solar power is also not addressed in the model proposed.
2017	Park et al.	Residential demand response considering user convenience under real time and progressive pricing policies are presented. The algorithm guarantee optimal solution for real time pricing policy.	Though the heuristic algorithm for progressive pricing formulation gave near optimal solutions, the stochastic nature of PV is not considered.
2017	Arun and Selvan	In the residential energy management system proposed, optimal sizing of RER and battery units are also done. Genetic Algorithm is used to get the optimal sizing and load schedule.	The uncertainty modeling of power production by RER and the consumer comfort aspect are not fully addressed in this work.

works discussed have not taken into account the random nature of the PV power for the load scheduling of the residential consumers. The comfort of the consumer due to delay in scheduling also need to be addressed more effectively.

2.5 Residential DR Models

The basic modeling is to arrive at an objective function which has to be optimized with proper scheduling strategy. Major aim of this task is to minimize energy cost satisfying the operating constraints.

A real time pricing based residential power scheduling scheme is proposed by (Chen Chen, 2011). EMC in each home and the service provider form a Stackelberg game model.The EMC schedules by minimizing the function,

$$min_s(s - t_0)\Psi_{n,a} + \sum_{r=s}^{s+l_{n,a}} \pi_r c_{n,a}$$

subject to

$$t_0 \leq s \leq t_0 + d_n$$

An appliance commitment problem using an electrical water heater load as example is proposed by (**?**). The objective is to minimize the energy being subject to comfort constraint. It is given as

$$min_{u_n}[\sum_{n=1}^{N}(p_n.u_n.P_e.\Delta t)]$$

(Syed Q. Ali and Malik, 2013b) formulated the problem as a simple decision making problem. In this, the objective is to decide the best time slot for scheduling the load to reduce the energy cost given by

$$Total\ cost = \sum_{j \in J} \sum_{h \in H} C^h r_j$$

r_j - power rating j^{th} load and C^h is the hourly tariff.

The same problem is modeled by providing an incentive part in the objective function (Setlhaolo et al., 2014). It suggests a method to capture the cost of inconvenience also by extending the objective function as,

$$Cost = \sum_{t=1}^{T} \sum_{i=1}^{l} P_i [c_t u_{it}^{opt} - \beta_t \lambda (u_{it}^{bl} - u_{it}^{opt})] \delta t$$

Here, $\lambda(u_{it}^{bl} - u_{it}^{opt})$ denotes the state of consumer to earn incentive and β_t is the incentive.

Both the maximum demand and DR incentive are combined together to form the DR mechanism (Suyang Zhou and Zhang, 2014). The DR mechanism is modeled as,

$$Cost\ in\ time\ interval\ \Delta t = C_{rt}^{t}.P_{grid}^{max}.\Delta t + ((1 + \delta_{pun}) C_{rt}^{t})(p_{grid}^{t} - P_{grid}^{max}) \Delta t$$

C_{rt} is the real time price, Δt is the time interval, δ_{pun} is the punishment factor.

The energy management system proposed schedule the loads so as to minimize the cost of net energy utilized,E_{DG}^{h} during the interval h (Arun and Selvan, 2017). The objective function is given by,

$$min[\sum_{h}(E_{DG}^{h}.C^{h})],\ h \in H$$

There is lot of divergence in the models discussed and are not complete considering all categories of loads focussing on the comfort constraints and the DG sources. A generalized mathematical model including all these aspects is necessitated.

2.6 Solution Methodologies for Residential Load Scheduling

Residential Demand Response problem is a complex optimization problem with different operating constraints. The optimization task is to minimize the single or multiobjective function given by the cost equation satisfying various conditions and constraints. DR problems are being solved by various analytical and soft computing methods.

2.6.1 Analytical Methods

An analytical approach termed as linear sequential optimzation enhanced multiloop algorithm for water heater load is given by (Du and Lu, 2011). Event driven binary linear programming method is used for solving the scheduling the events of appliances in (Alessandro Di Giorgio, 2012). A minmax scheduling algorithm to reach near optimal solution of the problem for general residential scheduling task is presented in (Xiao et al., 2010).

They also proposed a minmax solution considering comfort level for heating, ventillation and cooling devices in (Xiao et al., 2012).

A mixed integer linear programming method is used for sheduling the smart home appliances by (Kin Cheong Sou, 2011) and (Chen et al., 2012). (Arora and Chanana, 2014) also proposed a mixed integer linear programming method for optimization problem of residential load scheduling considering heating ventilating and air conditioning (HVAC) load and non HVAC load.

A mixed integer non-linear programming is used to solve the problem by (Jidong Wang and Dai, 2012). Mixed integer non linear optimization method used for the solution of constrained demand response program for minimization of cost and discomfort is proposed in (Setlhaolo et al., 2014). A multiobjective mixed integer nonlinear programming model is proposed for a home energy system with internal energy sources such as micro cogeneration systems and underfloor heating/cooling units in (Anvari-Moghaddam et al., 2015). Dynamic programming is another approach used for solution of several optimization problems. In dynamic programming the complex problem is decomposed into a sequence of subproblems, which are solved backward over each stage to obtain the optimum solution. A dynamic programming model is presented in (Young Liang and Shen, 2013) for the demand side control problem to minimize cost. Rolling optimization is another technique used for load scheduling solution. Half hour ahead rolling optimization and a real time control strategy are combined to realize the energy management of the household (Suyang Zhou and Zhang, 2014).

2.6.2 Soft Computing Methods

a. Stochastic Programming

Stochastic programming is leveraged to deal with uncertain optimization problems. Stochastic dynamic programming algorithm for solving Markov Decision process is put forward in (T and Poor, 2011). The solution has given optimal scheduling pattern for different energy consuming devices. A Q learning algorithm to reduce energy cost for a home energy management system is proposed by (O'Neill et al., 2010). Guo et al. formulated a stochastic optimization problem to minimize the electricity cost of a residential consumer, under real time tariff considering renewable generation and is solved by Lyapunov optimization technique (Guo et al., 2012). The load scheduling problem is formulated as a combinatorial optimization problem and an algorithm for solution is presented by (S. Q .Ali and .Malik, 2013) which is a simple approach to find the load schedule of different appliances. Learning Automata is another strategy which is used for solving optimization problems and has been applied for the demand response problems used by (Syed Q. Ali and Malik, 2013a). Heuristic based evolutionary algorithm is also used based on load shifting technique for demand side management with large number of devices in (Logenthiran et al., 2012).

b. Game Theory

Game theory is a solution method based on a model of interactive decision-making processes. Demand response involves the game relationship between the power utility and users which is used as an effective approach to facilitate intelligent decision-making in demand response frameworks. A game theoritic approach is used by (Mohsenian-Rad et al., 2010) to a demand side management system for energy cost minimization in which multiple users interact with each other and utility to coordinate their energy usage. An automatic energy consumption scheduler using a distributed algorithm, provides an optimal schedule for the energy consumption for each user. Another real time pricing based residential power scheduling scheme using game theory is proposed by (Chen Chen, 2011). Energy Management Controller (EMC) in each home and the service provider form a Stackelberg game model and is formulated to analyze the interaction between consumer's EMC and the service provider. The leader level game is played by the service provider and the follower game is played by the EMC.

c. Artificial Neural Networks

Artificial Neural Networks (ANN) consists of interconnected parallel processing elements used as computationl models. They can be trained to provide optimum output for the input data given to the network. The control system using Artificial Neural Networks (ANNs) tuned by Genetic Algorithms(GAs), for the residential sector is described by (E.Matallanas, 2012). It incorporates local PV energy generation and the controller maximizes self consumption. A real time control strategy including fuzzy logic control and half hour rolling optimization method given by(Suyang Zhou and Zhang, 2014) is used for finding the optimum solution for demand response under complex operating environments and with different categories of devices.

d. Genetic Algorithm

Genetic Algorithm is a popular stochastic method used for optimization task. In Genetic Algorithm based solution methods, a population of chromosomes are considered and evaluated by changing the chromosome string using crossover and mutation operations. Application of Genetic Algorithm for a domestic load management system with DGs is presented in (Bingjie Ruan and Yan, 2014). The optimal appliance sheduling is obtained using this method. Genetic Algorithm is also used to get the optimal sizing of DG and load shedule in (Arun and Selvan, 2017) to realize an intelligent residential energy management system for smart residential buildings with renewable energy resources.

e. Particle Swarm Optimization

Particle swarm optimization (PSO) is an evolutionary computation technique developed by Kennedy and Eberhart in 1995 (J.Kennedy, 1995). It is a population based stochastic search algorithm. The method was formulated based on the social behaviour of bird flocking or fish schooling when searching for food. Potential solutions to the problem are considered as particles in PSO. Particle Swarm Optimization method for solving the energy management with Distributed Energy Resources is proposed by M.A.Pedrasa et al. (M.A.Pedrasa and Gill, 2009a). They enhanced the algorithm by incorporating decision support tool by stochastic repulsion (M.A.Pedrasa and Gill, 2010). Binary Particle Swarm Optimization method is also used by (M.A.Pedrasa and Gill, 2009b) for curtailment of interruptible loads.

2.7 Reinforcement Learning and Applications

Reinforcement Learning (RL) is a computational approach based on goal directed learning from interaction with the environment (R.S.Sutton and A.G.Barto, 1998). RL combines the features of dynamic programming and supervised learning. In the learning process the agent continuously observes the present state of the environment and performs an action chosen from the permissible set of actions. The state transition occurs when an action is performed and an immediate reward is obtained based on the state and action performed. The objective of RL is to maximize the long term sum of the reward. This is done by exploring new possibilities and exploiting available information. The learning methods help to maintain a balance between exploration and exploitation to achieve the goal with optimal reward.

Reinforcement Learning has been used as an effective computatiional tool for building autonomous systems for various fields of control. Its applications include game playing, process control, power system, robotics etc. Some of the applications of Reinforcement Learning are discussed in the next section.

2.7.1 Game Playing

Reinforcement Learning algorithms are used for various types of game playing. The application of Reinforcement Learning to the game of Go is given by (Silver et al., 2007). The method used a linear evaluation function and large numbers of binary features to solve the problem. Game of Go is a challenging one due to the large search space. AlphaGo program proposed by D. Silver et al. by combining the application of RL and neural networks provided improved winning rate for the game (Silver et al., 2017).

A First-Person-Shooting (FPS) game in a 3D environment using Reinforcement Learning is presented by (Lample and Chaplot, 2017) . This task a challenging one and it is solved by dividing into two phases namely navigation and action. The navigation phase explores the map to find enemies and in action phase fight enemies.

2.7.2 Robotics and Control

Reinforcement Learning methods have been applied for deriving proper control strategy for robotic applications. The batch reinforcement learning algorithm was applied for solving a robotic soccer problem in (Riedmiller et al., 2009). With case studies it was demonstrated that batch learning framework of RL is very useful in the case of soccer-playing robots. The different framework and tools offered by Reinforcement Learning to robotics are described in detail by (Kober et al., 2013).

Autonomous helicopter flight represents a highly challenging control problem with non-minimum phase and complex dynamics. An application of Reinforcement Learning for the implementation of an autonomous helicopter flight is presented in (Abbeel et al., 2007).

2.7.3 Power system

The Automatic Generation Control (AGC) problem is formulated as a stochastic multistage decision problem and solved using Reinforcement Learning algorithm by (Ahamed et al., 2002). The RL approach allows the control objectives of AGC to be stated more qualitatively. Also, the algorithm can handle systems whose dynamics are not fully known or modeled. These features of RL algorithm make it very effective for the application of AGC.

Ernst et al. used RL to solve stability problem of power system in (Ernst et al., 2004). The application of RL to the oscillation damping problem in power system is proposed by (Ernst et al., 2009). The considered RL approach decided closed loop policies based on a set of system trajectories and cost values in a model free environment. The same problem was solved with model predictive control (MPC) using analytical model and on comparison RL is found to be competitive with MPC.

The economic dispatch problem is formulated as a multi stage decision making problem by (Jasmin et al., 2011) and Reinforcement Learning method is used to get the solution. Two learning algorithms, ϵ - greedy and pursuit algorithms, are employed to distribute the power demand among different generating units with minimum operating cost. Another algorithm that takes into account the transmission losses was also developed. The flexibility and efficiency of the algorithm is demonstrated considering different systems.

An intelligent Maximum Power Point Tracking (MPPT) algorithm using Reinforcement Learning for wind energy conversion systems is described by (Wei et al., 2015). Without the knowledge of wind turbine parameters or wind speed information, a fast and real time MPPT control of the system is achieved. Q-learning algorithm is used to realize to optimal control actions.

2.7.4 Multi Agent Reinforcement Learning

Reinforcement learning finds applications in multi agent systems also. Many real-world tasks involve multiple agents with partial observability and limited communication. Learning is challenging in these cases due to local view points of agents. The world is perceived as non-stationary due to concurrently exploring teammates. A unified policy that performs well for multiple related tasks, without explicit provision of task identity is presented in (Omidshafiei et al., 2017).

2.8 Conclusion

A detailed review of the different models and methods employed for residential load scheduling is carried out in this chapter. Different researchers have formulated the problem in different perspectives. Various solution methods are also suggested. From the literature, it can be seen that future residential consumer will have renewable sources, schedulable loads, non-schedulable loads and various time dependant tariff. Power generated from renewable sources, RTP and arrival of non-schedulable loads are random. The consumer will want to minimize his electricity bill without compromising on the comfort. Thus the problem is a decision making problem under uncertain environment. A complete and comprehensive model is yet to be developed considering all these aspects and optimization of the load scheduling based on the same is to be explored. Stochastic learning algorithms like Reinforcement Learning (R.S.Sutton and A.G.Barto, 1998) is a powerful tool to solve such problems.

Chapter 3

Residential Demand Response Model

3.1 Introduction

The conventional power system was relaying on hydro, thermal and nuclear power generation as the main source of electrical energy. The balancing of generation and loads was achieved by scheduling these generating units. These problems were well formulated as Unit Commitment Problem (UCP), Economic Dispatch (ED), and Automatic Generation Control and different solutions were proposed (Wood and Wollenberg, 2003). It is well known that there is large scale deployment of small renewable resources within the consumer premises (Akash T.Davda and D.Desai, 2014). With the development in power electronic interface and decrease in cost of PV panels, this trend is expected to grow. With the development in communication and automation technologies many consumer loads have become controllable. Utilities have realized that through various demand response (DR) programs under smart grid paradigm, co-operation of consumers can be utilized in an efficient way for the balancing act. That is, it is possible to bring down the cost of production by shifting the load rather than starting expensive generators.

The consumer behavior can be be influenced by incentives and in price based DR, this is achieved by designing appropriate tariff. Thus to achieve the goal of price based DR, utility has to design innovative tariff schemes which is attractive for the consumers and consumers require hardware and software to schedule his/her loads. These two problems: designing of tariff and scheduling of loads could be viewed as decoupled problems. If these problems have to be addressed as a coupled problem, it should be done by analyzing the business relationship between the utility and the consumer. From the consumer's perspective, it can be assumed that the tariff is specified by the utility and a typical consumer schedules the load with the sole objective of minimizing the electricity bill. Most of the residential consumers in the near future will have renewable sources such as roof top PV. A typical consumer will have various kinds of loads. Some may be flexible, some may be interruptible, some loads when shifted may cause some difficulty to the consumer. From the literature it is observed that, there is lot of divergence in the terminology and models used. For example loads are classified and termed as elastic and inelastic, controllable and critical, flexible and inflexible. Loads are also categorized as schedulable, noninterruptible and nonschedulable, interruptible and nonschedulable, atomic and nonatomic ,nonpre-emptive and pre-emptive shedulable loads. A unified terminology is introduced as critical loads for all inflexible/nonshedulable/inelastic/baseline loads and flexible/shedulable loads with nonpre-emptive and pre-emptive status are termed as atomic and nonatomic respectively. Thus, there is a need for a unified model for residential load commitment problem which takes into account various types of loads and distributed generators having stochastic nature of power generation. This chapter describes the development of a generalized mathematical model for the load scheduling problem.

Following are the assumptions:

Schedulable loads are included in the residential energy management system. Each load is associated with a start time, end time and a specified ON duration of operation. The consumer comfort constraint is included.

The limitations are:

Battery is not included while considering the DG source. Generation scheduling is not addressed together with load scheduling.

3.2 Generalized Mathematical Model

The system model considers a single household with a number of loads. It can communicate with the utility and receives the electricity tariff. DR problem is modeled as an optimization problem. The load model, tariff and the scheduling algorithm are required for the simulation framework. To develop the mathematical model, at first a timeline is to be defined.

3.2.1 The Timeline

A vector $\mathcal{K}$ is chosen to represent the timeline model such that there are $|\mathcal{K}|$ time slots in a day. The value of $|\mathcal{K}|$ varies depending on the duration of the interval selected. e.g. $|\mathcal{K}|= 96$, if the duration of interval is 15 minutes and $|\mathcal{K}| =48$, for an interval of 30 minutes duration. Here, it is assumed that the interval is 1 hour, i.e. $|\mathcal{K}| =24$, with the first interval starting from 12 am to 1 am. Then the second interval is the hour between 1 am to 2 am and so on. Also, any time between 12 am to 1 am is counted in the first time slot. The timeline for 1 hour interval is shown in Fig. 3.1.

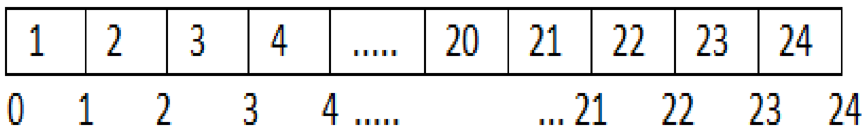


Figure 3.1: Timeline for one hour intervals

3.2.2 Load Model

Residential loads can be categorized into two groups, critical loads and controllable or flexible loads. Critical loads are must-run loads which are being switched on for a fixed period of time and the time of use can not be shifted. Lighting loads, fan, TV, PC etc. come under this category. For these type of loads the customer should have the freedom to switch ON and OFF the loads as he desires. Controllable loads can be turned on at any time slot within the given interval. Their operation can be delayed and/or interrupted if needed. They include cloth washers, cloth dryers, dish washers, Heating Ventilating and Air Conditioning (HVAC) systems, water heaters, plug in electric vehicles, battery chargers for consumer electronics etc. Controllable loads can be further classified as atomic and non-atomic loads. Atomic loads are non-interruptible loads and once switched on, will remain ON continuously for the specified duration. Non-atomic loads are interruptible loads and once turned ON can be turned OFF any number of times during the specified interval.

a. Basic Load Model

It is assumed that the consumer has total m number of flexible and nonflexible loads such that m= $|\mathcal{J}|$ where $\mathcal{J}$ is the set of all loads in the household. The flexible loads are assumed to be atomic in nature. Each load, $j \in \mathcal{J}$ is modeled by a 4-tuple denoted by,

$$d_j = (s_j, f_j, l_j, r_j) \tag{3.1}$$

where $\{s_j, f_j\}$ is the interval of operation of the load with s_j and f_j as the beginning and ending time slots respectively. l_j is the time duration for which the load is ON. r_j is the rated load power in kW (Ali et al., 2013). That is, $d_j = (7, 16, 4, 5)$, means that, a load d_j of 5kW power rating needs to be switched ON in the interval {7,16} for a duration of 4 hours. Flexible loads can be turned ON at any time slot in the permitted interval but once switched ON, it remains ON for l_j hours. Now the problem is to obtain the optimum time slots for which the load is to be turned ON, subjected to different constraints.

b. Load Model Considering Consumer Comfort

In this case, assumption regarding the flexible loads to be atomic is relaxed. The loads can be non-atomic, i.e. these loads can be turned OFF any number of times during the permitted interval while satisfying the total ON period duration of l_j hours and are more flexible compared to atomic loads. Non atomic loads also can be represented by the same load model as given in the previous section, for atomic loads.

The objective is to minimize the total daily energy cost of the consumer, satisfying the various constraints. This results in scheduling the loads in time slots where price of electricity is low. There are some loads for which this scheduling may cause discomfort to the consumer. The switching ON time of a flexible load e.g. cloth washer can be delayed so as to operate it at a low cost period. This delay causes some inconvenience or discomfort to the consumer. A parameter *udc* is incorporated in the load model to capture the degree of discomfort. Now, each load, $j \in \mathcal{J}$ is modeled by a 5-tuple denoted by,

$$d_j = (s_j, f_j, l_j, r_j, udc_j) \tag{3.2}$$

If the consumer is willing to accept delay, choose a low value of *udc*. Large value of *udc* indicates that consumer can not tolerate delay and results in high energy cost. Guidelines for choosing *udc* is developed and is explained later in chapter 5.

3.2.3 Energy Cost Model for Load Scheduling

Let C^k denotes the hourly tariff provided by the utility. It is assumed that C^k is available day ahead in the case of ToUP or CPP. It is available one hour in advance in the case of RTP. A Maximum Demand (MD) limit is also specified by the utility. So the total demand for any time slot should not cross the MD limit.

a. With one source of energy, the utility grid

The objective is to minimize the daily energy cost of the consumer. The consumer has to take decision on the switching schedule of the different loads. Let u_j^k denotes this decision variable. i.e., u_j^k denotes the ON/OFF status of j^{th} load in the k^{th} time slot. If j^{th} load is ON, $u_j^k = 1$ and if OFF $u_j^k = 0$, during k^{th} time slot.

The load scheduling problem is to obtain a vector, $u = [u_1^1, u_1^2, \ldots, u_1^{24}, u_2^1, u_2^2, \ldots, u_2^{24}, \ldots, u_m^1, u_m^2, \ldots, u_m^{24}]$ so as to minimize the total electricity cost, $f(u)$ for a day.
Now, the load scheduling problem is,
Minimize, total cost $f(u)$

$$f(u) = \sum_{k=1}^{24} \sum_{j=1}^{m} C^k r_j u_j^k \tag{3.3}$$

subject to,

$$\sum_{k=s_j}^{f_j} u_j^k = l_j; \quad u_j^k = 0, for \quad k < s_j \quad or \quad k > f_j$$

$$\sum_{j=1}^{m} r_j u_j^k \leq MDL, \quad k \in \mathcal{K}$$

where, MDL is the Maximum Demand Limit and C^k denotes the hourly tariff, ToUP or RTP.

The solution space is defined as,

$$U = [u_1^1, u_1^2, \ldots, u_1^{24}, u_2^1, u_2^2, \ldots, u_2^{24}, \ldots, u_m^1, u_m^2, \ldots, u_m^{24}]$$

$$\forall u_j^k \in \{1, 0\}$$

Then the aim is to find the optimum values of u_j^k.

b. General case with n sources

Consider the case with n sources such as PV, grid, wind turbine, energy storage etc. A general mathematical model for the load scheduling problem is developed to include all the sources.

Now the load scheduling problem is to find a sequence of decisions,
$u = [u_{1i}^1, u_{1i}^2, \ldots, u_{1i}^{24}, u_{2i}^1, u_{2i}^2, \ldots, u_{2i}^{24}, \ldots, u_{mi}^1, u_{mi}^2, \ldots, u_{mi}^{24}]$,
$\forall i \in \{1, ...n\}$,$\forall u_{ji}^k \in \{0, 1\}$ such that total electricity cost , $f(u)$ for a day is minimized.

The power output of the renewable sources can be random in nature. So the expected total cost is considered and the cost function $f(u)$ can be generalized as,

Minimize,

$$f(u) = E[\sum_{k=1}^{24} \sum_{j=1}^{m} \sum_{i=1}^{n} C_i^k r_j u_{ji}^k] \tag{3.4}$$

subject to,

$$\sum_{i=1}^{n} \sum_{k=s_j}^{f_j} u_{ji}^k = l_j, \forall j \in \{1 \ldots m\}$$

$$u_{ji}^k = 0, for \quad k < s_j \quad or \quad k > f_j$$

$$\sum_{j=1}^{m} r_j u_j^k \leq MDL$$

where, C_i^k is the hourly energy cost of i^{th} source

u_{ji}^k is the binary status of j^{th} load at k^{th} hour, with i^{th} source.

Here $i = 1, 2, 3 \ldots n$ denotes different sources such as PV, grid, wind turbine, energy storage etc.

3.3 Conclusion

In future, consumers will have renewable sources, flexible loads, nonflexible loads and various time dependant tariff. The consumer desires to minimize his electricity bill without compromising on the comfort. Thus the problem is a decision making problem under uncertain environment. The Residential DR problem is modeled as an optimization problem. The development of a generalized mathematical model for the load scheduling problem is presented in this chapter. Now it is required to explore methods to develop load scheduling algorithms based on the generalized mathematical model for the DR problem.

Chapter 4

Load Scheduling using Binary Particle Swarm Optimization

4.1 Introduction

With the development in communication and automation technologies many consumer loads have become controllable. Controllable loads at the consumer premises are the best candidate for implementing residential DR programs and proper scheduling of these loads reduces consumer's energy bill and peak demand. The mathematical formulation of the problem has lot of similarity to Economic dispatch and Unit commitment problem. Different authors addressed the problem with different formulations, load models, constraints and tariff patterns.

Load scheduling is a complex optimization problem with various operating constraints. It is required to develop an implementable solution to the load scheduling problem considering the complex behaviour of the demand resources. There are many works related to development of scheduling algorithm considering different types of loads. Soft computing method like Particle Swarm Optimization (PSO) can be effectively used for solving scheduling problems and the related works are reviewed in Chapter 2. Solution of unit commitment problem using hybrid PSO is described in (Ting et al., 2006). H. Song et al applied PSO for photovotaic system allocation also (Song et al., 2009). The solution to curtailmemt problem of interruptible loads using PSO method is presented in (M.A.Pedrasa and Gill, 2009b) but the proposed method has the limitation with respect to flexible load scheduling considering non-interruptible demand constraint. A more reasonable sheduling method is essential for solving and implementing residential load scheduling problem. Load scheduling is a commitment problem with ON/OFF status at each time slot. Optimization algorithms which take binary values in the solution space are more suitable and Binary Particle Swarm Optimization (BPSO) belongs to such a category. Thus BPSO is an effective tool for solving load scheduling problem. The objective of the load scheduling problem is to minimize the consumer's electricity bill and to reduce the maximum demand on the system, satisfying various constraints. It is required to find the optimal load schedule for minimum energy cost, subject to the given MD limit, tariff and load parameter specifications. In this chapter the development of load scheduling algorithm using BPSO method is presented.

4.2 Particle Swarm Optimization

Particle swarm optimization is an evolutionary computation technique developed by Kennedy and Eberhart in 1995 (J.Kennedy, 1995). It is a population based stochastic search algorithm. The method was formulated based on the social behaviour of bird flocking or fish schooling when searching for food. Potential solutions to the problem are considered as particles in PSO and these particles communicate with each other. The particle locations are assigned in a random fashion initially, in the solution space. The particles fly around the solution space and coordinate their movement similar to bird flocking or fish schooling. They are influenced by its own best performance and the best performance of the particles in the neighbourhood. Each particle remembers its own best position found so far in the exploration. This position is called personal best. Also the position of the best performing particle is called global best. The position and velocity describe the motion of the particle and can be represented as vectors $xi = [x_{i1}, x_{i2}, ..., x_{in}]$ and $vi = [v_{i1}, v_{i2}, ..., v_{in}]$ in an n dimensional search space for i^{th} particle. Using a fitness function, the performance evaluation of each particle is done iteratively. The new velocity of each particle is calculated based on its previous velocity, the best position attained by the particle and the position of the best performing particle.

Let *pbest* (personal best) be the best position achieved by a particle and *gbest* (global best), the position of the best performing particle. Then at each iterative learning step the velocity and position of that particle are updated using the Eqns 4.1 - 4.2.

$$v_i^{k+1} = wv_i^k + c_1 rand()(pbest - x_i^k) + c_2 rand()(gbest - x_i^k) \tag{4.1}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{4.2}$$

where, c_1, c_2 - Acceleration coefficients
w - Inertia coefficient
v_i^k - Velocity at k^{th} iteration for i^{th} particle
x_i^k - Position at k^{th} iteration for i^{th} particle
$rand()$ generates a uniform random number in the interval [0,1]. At each iteration, the position of the particle will be updated and this process will be continued until the maximum number of iterations is attained. At the end of the iterative procedure, the global best value gives the solution to the problem.

In PSO the particle changes its velocity at each step targetting towards $pbest$ and $gbest$ positions. The acceleration constants c_1 and c_2 represents the weightage of the accelaration terms. c_1 pulls the particle towards $pbest$ position and c_2 pulls it towards the $gbes$ position. Usually these parameters are selected in the range of 0 to 4 (Chaturvedi et al., 2008). The use of inertia weight results in convergence to a sufficiently optimal solution in fewer iterations. The inertia weight w is decreased linearly as the iteration proceeds and is given by $w = w_{max} - \dfrac{(w_{max} - w_{min}) * iter}{iter_{max}}$, where $iter_{max}$ is the maximum iteration number, $iter$ is the current iteration number and v_{max} and v_{min} are the final and initial inertia weights respectively (Mahor et al., 2009).

4.2.1 Particle Swarm Optimization Algorithm

Similar to Genetic Algorithm, PSO is also initialized with a population of random solutions. A random velocity is assigned to each solution or particle. The particles keeps track the position of best solution it has achieved so far and the position of the overall best solution obtained by any particle in the population. By changing the velocity, at each time step the particles move towards the *pbest* and *gbest* locations. The PSO algorithm is described below.

> *Initialize a population of particles with random positions and velocities.*
>
> > *Evaluate the fitness function for each particle*
> >
> > *Compare the fitness of the particle with pbest of the particle. If present value is better than pbest, set pbest equal to the present value and pbest position equal to the present position.*
> >
> > *Compare the fitness of the particle with gbest of the population. If present value is better than gbest, set gbest equal to the present value and gbest position as the present position.*
> >
> > *Change the velocity of each particle using equation 4.1 and position using equation 4.2.*
> >
> > *Repeat till a termination criteria is met or the maximum number of iterations is reached.*
>
> *Fitness value is the gbest value and particle with gbest is the optimal solution.*

The values for the different particles are continuous in basic PSO approach. For problems with discrete solution space, binary version of PSO is used to obtain the solution. The next section explains the concept of binary particle swarm optimization (BPSO).

4.2.2 Binary Particle Swarm optimization

The original version of PSO operates on real values. The solution space of the load scheduling problem is discrete in nature. So the particles need to be defined in the discrete space. For the solution of problem with discrete decision variables, a discrete binary version of PSO is proposed by Kennedy and Eberhart in (J.Kennedy, 1997).

In BPSO, the value of x_i^k can be 0 or 1 only. In this case also the velocity is updated using Eqn 4.1, but is kept within the limits specified by $+V_{max}\ and -V_{max}$. The velocity will determine a probability threshold. The particle is more likely to choose 1 for higher values of v_i^k and 0 for lower values v_i^k. So the threshold should be a real value between 0 and 1. This can be achieved by using a Sigmoid function given by Eqn (4.3).

$$S(v_i) = \frac{1}{1 + exp(-v_i)} \tag{4.3}$$

Using the Sigmoid function, the velocity is mapped into [0,1]. A random number between 0 and 1 is generated using uniform distribution. $S(v_i)$ is then compared with the random number, $rand()$, and the position is updated as follows.

$x_i = 1$, if $rand() < S(v_i)$,

$x_i = 0$, else.

BPSO can be effectively used for load scheduling problem. In the next section the residential load scheduling problem is explained.

4.3 Residential Load Scheduling

4.3.1 Load Model

Consider a consumer with a number of flexible and nonflexible loads. It is assumed that all flexible loads are atomic or non-interruptible. So the basic load model explained in Chapter 3 is selected. A time line is defined such that a day consists of 24 equal time slots k, $k \in [1, 24]$. k=1 is the time slot between 12 am and 1 am and k=24 is the last time slot.
A single load is modeled by a 4-tuple denoted by,

$$d_j = (s_j, f_j, l_j, r_j) \tag{4.4}$$

where $[s_j, f_j]$ is the permitted interval of operation of the load with starting time slot, s_j and ending time slot, f_j. l_j is the time duration for which the load is ON. r_j is the rated load power in kW.

4.3.2 Mathematical model of the Load Scheduling problem

The objective of the load scheduling problem is to obtain the load schedule such that the daily energy cost of the consumer is minimized subject to the different operational constraints. The source of energy can be the utility grid and/or renewable energy sources in the consumer premise. In this case, it is assumed that there is only one source of electrical energy, the utility grid. Let C^k denotes the hourly tariff provided by the utility. It is assumed that C^k is available day ahead in the case of ToUP or CPP. It is available one hour in advance in the case of RTP. A Maximum Demand Limit(MDL) is also specified by the utility. So the total demand for any time slot should not cross the MDL.

The j^{th} load status , at k^{th} time slot is denoted as u_j^k. If the load is ON, then $u_j^k = 1$ and $u_j^k = 0$ if the load is OFF. It is assumed that there are m number of loads, which are flexible and nonflexible. Flexible loads can be turned ON at any time slot in the permitted interval but nonflexible loads are to be switched ON for fixed time slots.

With m loads and 24 time slots, now it is required to obtain a vector,
$u = [u_1^1, u_1^2, \ldots, u_1^{24}, u_2^1, u_2^2, \ldots, u_2^{24}, \ldots, u_m^1, u_m^2, \ldots, u_m^{24}]$
so as to minimize the daily energy cost, $f(u)$.
The mathematical model of the load scheduling problem is,

Minimize,

$$Total\ cost = \sum_{k=1}^{24} \sum_{j=1}^{m} C^k r_j u_j^k \tag{4.5}$$

subject to the constraints,

$$\sum_{k=s_j}^{f_j} u_j^k = l_j$$

$$u_j^k = 0, \quad k < s_j \ or \ k > f_j$$

$$\sum_{j=1}^{m} r_j u_j^k \leq MDL, \quad k = 1 \ldots, 24, \quad j = 1, \ldots, m$$

The objective function of the problem is the total cost of energy. The consumer specified load constraint is the time slots of operation of each load. Utility constraint is that the total power consumption of all the loads at any time slot should be within the MD Limit. The load scheduling problem is complex owing to the presence of several types of loads with diverse characteristics in the consumer premise and the different constraints and tariff imposed by the utility. The solution space is defined as,
$U = [u_1^1, u_1^2, \ldots, u_1^{24}, u_2^1, u_2^2, \ldots, u_2^{24}, \ldots, u_m^1, u_m^2, \ldots, u_m^{24}], \forall u_j^k \in \{0, 1\}$

In the next section a solution method for the residential load scheduling problem using BPSO is presented.

4.4 Residential Load Scheduling Using BPSO

In the load scheduling problem, it is required to find the ON/OFF status of the various loads and the corresponding decision variable u_j^k is discrete in nature as explained in the previous section. BPSO can be applied to obtain the solution of scheduling problems in dicrete space. To apply BPSO to the load scheduling problem, at first the particle is to be identified such that it should include the characteristics of all loads. A parameter $p_j = f_j - s_j - l_j + 1$ is computed for each load, from the given load parameters. A particle is constituted using p_j's of different loads. If the parameters of the j^{th} load is $d_j = (8, 12, 2, 4)$, then $p_j = 3$. The load d_j can be switched ON at any of the time slots 8+0, 8+1, 8+2 or 8+3. That is, the optimum time slot to switch on the j^{th} load is to be selected from $[s_j + n, n = 0, 1, 2..p_j]$. A four bit binary number is used to represent p_j.

The objective of the load scheduling problem is to minimize the cost function given by,

$$Total\ cost = \sum_{k=1}^{24}\sum_{j=1}^{m} C^k r_j u_j^k \tag{4.6}$$

subject to the given constraints. Hence the fitness function for BPSO is chosen as the cost function of the scheduling problem. The initial population is randomly selected from the binary p_j's of all loads. As the particle correspods to the switching ON time slot of the different loads, from the global best particle optimum schedule can be obtained and the minimum energy cost is the corresponding fitness value. The algorithm for solution of scheduling problem using BPSO is detailed below.

To start with, the population size, maximum iteration number, number of loads, *pbest* and *gbest* values are initialized. The input data required are the parameters of the consumer load, utility specified MD limit and tariff. Particles are generated and initial population is randomly selected. Velocity associated with each particle is also initialized. Using Eqn (4.6) the fitness of the particle is calculated. The fitness value is compared with *pbest* value and MDL condition is checked. Minimum of the fitness value and *pbest* is assigned as new *pbest* value. Minimum of the *pbest* and *gbest* is the updated global best solution. Velocity is updated using Eqn (4.1) and restricted within permissible limits. Using sigmoid function given by Eqn (4.3), $S(v_i)$ is computed and new position is obtained.

When the iterative process ends, the *gbest* value gives the minimum cost. The optimum load schedule is obtained from global best particle.

Load Scheduling Algorithm using BPSO

Initialize the Maximum Demand limit, Number of loads, Population size, Word length of each particle, V_{max}, Maximum iterations, pbest and gbest values

Read the load parameters (s_j, f_j, l_j, r_j)

Calculate $p_j = f_j - s_j - l_j + 1$ *for each load*

Generate initial population of binary particles randomly within the allowable range p_j

Initialize velocity parameters

Calculate the fitness of i^{th} *particle using Eqn (4.6)*

If $fitness(i) < pbest(i)$ *and the maximum demand limit is not violated for the current position,* $pbest(i) = fitness(i)$ *and save the position of particle.*

If $pbest(i) < gbest$, $gbest = pbest(i)$ *and save the global best particle position.*

Update velocity value of each binary element of the particle using the Eqn (4.1)

Limit the velocity values within the allowable range $+V_{max}$ *to* $-V_{max}$

Map the velocity to $S(v_i)$ *using Sigmoid function in Eqn (4.3)*

Compare $S(v_i)$ *with rand(), get the new position* x_i

Limit the new particle position within the permissible subset

Repeat for all particles

Repeat till the maximum number of iterations is reached

Schedule is obtained from the global best particle value and the cost is the gbest value.

4.5 Results and Discussion

The developed Load scheduling algorithm using Binary particle Swarm optimization has been validated for a system with 6 loads having the characteristics given in Table 4.1.

Table 4.1: Load Details

Load	s	f	l	r
1	2	11	2	4
2	4	18	3	4
3	6	8	3	4
4	4	12	3	5
5	5	10	6	5
6	11	19	4	6

Table 4.2: Parameters used in BPSO

c_1	2.05
c_2	2.05
w_{min}	0.4
w_{max}	0.9
No. of particles	20

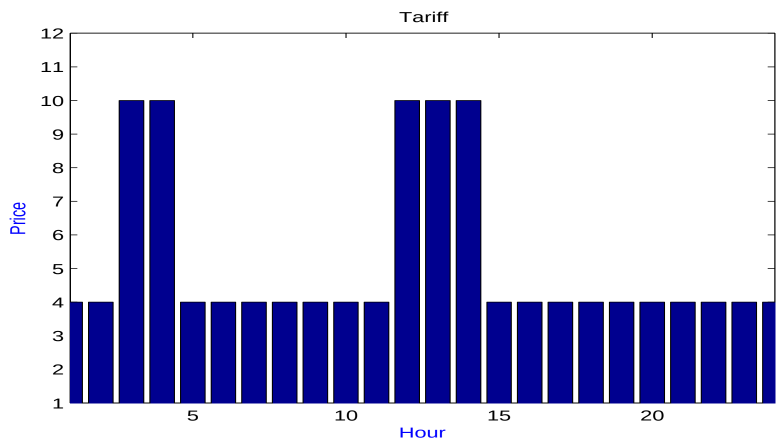


Figure 4.1: Tariff Structure

A two part tariff has been considered for simulation studies as given in 4.1. This tariff structure specifies two different rates for electricity usage varying with tine. The parameter used in the BPSO solution is given in Table 4.2. The algorithm converged in 100 iterations and the optimum schedule is obtained. The energy cost incurred has been reduced to 404 units from the unscheduled cost of 525 units for maximum demand constraint of 20kW.

To check the reliability of the algorithm, simulation is done for different values of the Maximum Demand and schedules obtained are tabulated in Table 4.3 and 4.4. The total energy cost is given in Table 4.5. The result has been validated by comparing with those given in (Ali et al., 2013). It can be seen that the non flexible loads, ie, 3^{rd} and 5^{th}, are scheduled at the sixth and fifth time slot respectively. The other flexible loads are scheduled between their respective s_j's and f_j's in the low cost period considering the MD constraint. The unscheduled demand is shown in Fig. 4.2. The scheduled demand allocations for different MD limits are shown in Fig. 4.3 and

Table 4.3: Schedule with MDL =10 kW

Hour	Load 1	Load 2	Load 3	Load 4	Load 5	Load 6	Total Dmand
1	0	0	0	0	0	0	0
2	4	0	0	0	0	0	4
3	4	0	0	0	0	0	4
4	0	0	0	0	0	0	0
5	0	0	0	0	5	0	5
6	0	0	4	0	5	0	9
7	0	0	4	0	5	0	9
8	0	0	4	0	5	0	9
9	0	0	0	5	5	0	10
10	0	0	0	5	5	0	10
11	0	0	0	5	0	0	5
12	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0
16	0	4	0	0	0	6	10
17	0	4	0	0	0	6	10
18	0	4	0	0	0	6	10
19	0	0	0	0	0	6	6
20	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0

Table 4.4: Schedule with MDL =20 kW

Hour	Load 1	Load 2	Load 3	Load 4	Load 5	Load 6	Total Dmand
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	5	0	5
6	0	0	4	0	5	0	9
7	0	0	4	0	5	0	9
8	0	0	4	0	5	0	9
9	0	4	0	5	5	0	14
10	4	4	0	5	5	0	18
11	4	4	0	5	0	0	13
12	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0
16	0	0	0	0	0	6	6
17	0	0	0	0	0	6	6
18	0	0	0	0	0	6	6
19	0	0	0	0	0	6	6
20	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0

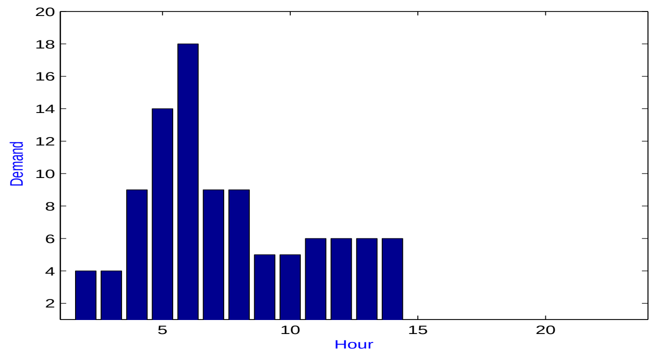


Figure 4.2: Unscheduled Demand

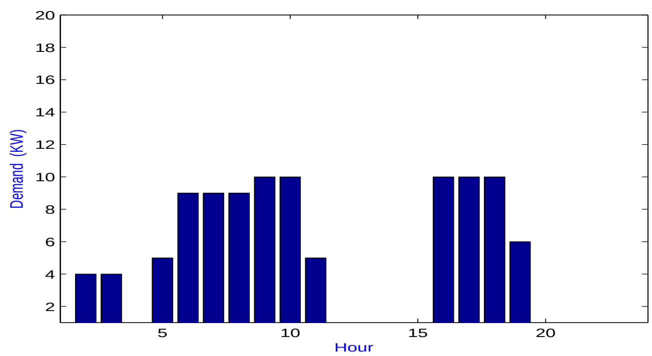


Figure 4.3: Scheduled Demand with MDL=10kW

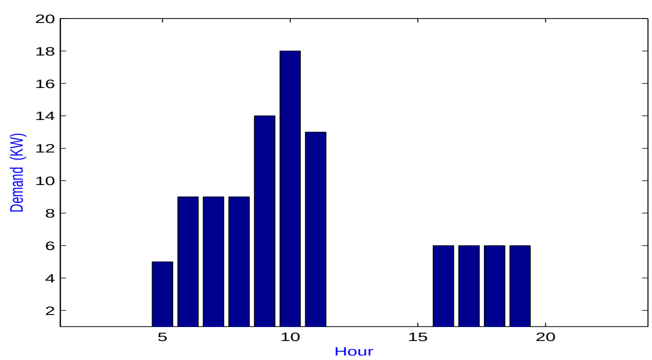


Figure 4.4: Scheduled Demand with MDL=20kW

Table 4.5: Effect of Maximum Demand on the Total cost (6 loads)

Demand	Cost
Unscheduled	525
Scheduled with MDL = 10kW	428
Scheduled with MDL = 20kW	404

Table 4.6: Effect of scheduling on the total cost for 100 loads

Demand	Cost
Unscheduled	3132
Scheduled	1028

Fig. 4.4.

For proving the efficacy of the developed algorithm for scheduling, the proposed alogirithm has been applied for 100 loads whose characteristics are developed through a Load generation program (Syed Q. Ali and Malik, 2013a). Table 4.6 shows the cost reduction on scheduling using the developed BPSO algorithm.

4.6 Case Study

To investigate the performance of the proposed BPSO algorithm for load scheduling, a smart home with different types of appliances is considered.

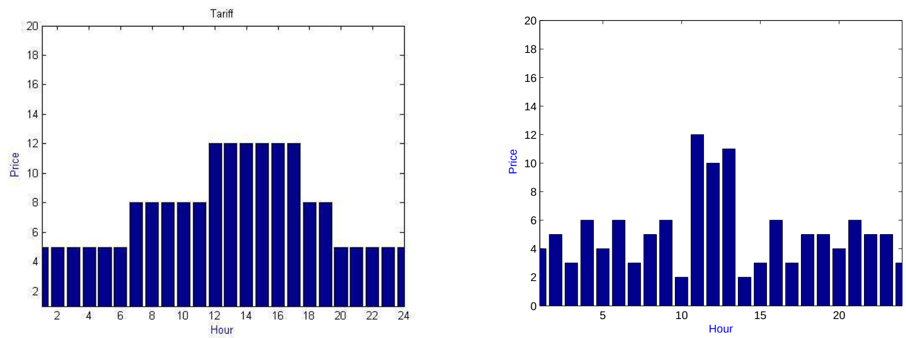
Lighting loads are considered as critical loads. Typical schedulable appliances in the home include Washing machine, Cloth dryer, Dish washer, Vacuum cleaner, Iron and Rice cooker, well pump and plug in hybrid electric vehicles(PHEV). These appliances operate with different time intervals, duration of operation and power ratings. The parameters of the household devices are given in Table 4.7. The electricity price and MD limit are received from the

Table 4.7: Parameters of Household Devices

Sl. No.	Appliance	s	f	l	r (kW)
1	Lighting	18	20	3	0.36
2	Washing machine	8	14	2	0.50
3	Cloth dryer	11	17	1	2.70
4	Dish washer	13	21	2	2.10
5	Vacuum cleaner	9	14	1	0.65
6	Iron	6	9	1	1.10
7	Rice cooker	7	10	1	0.30
8	Well pump	12	16	1	1.50
9	PHEV charging	10	24	2	2.30

utility. For simulation purpose, two different tariff templates are generated, ToUP given in Fig 4.5(a) and a random time varying price given in Fig 4.5(b). The time varying tariff is generated by adding a random number between +2 and -2 to the mean price during the particular interval. The energy cost for the unscheduled demand with all the domestic loads switched ON for l_j hours starting from s_j is found to be 118.65 units for ToUP and the corresponding maximum demand is 5kW.

The algorithm is tested for residential load scheduling using both the tar-



(a) (b)

Figure 4.5: Tariff (a)ToU Pricing (b)Real Time Pricing

iffs. Also, from the utility perspective the maximum demand on the system should not exceed the specified limit. The maximum value of the unscheduled demand for this case is 5kW. Hence for simulation the MD limits are chosen as 4 kW and 3kW, which are lower than the maximum unscheduled demand. The simulation is done first using ToUP and with a MD limit of 4kw. As expected all appliances are committed in the low priced period within the specified time slots without violating the MD limit of 4. For example, the duration of operation of lighting load is 3 hours starting from 18^{th} time slot. We can not shift the time of operation of a critical load such as lighting load. It is observed that lighting load is ON during the interval {18 - 20} itself. The flexible load such as washing machine is ON during the low priced interval {8 - 9}, which is within the specified time slot of {8 - 14}. The energy bill of the consumer is decreased to 89.25 units. The appliance schedule is given in Table 4.8.

Table 4.8: Schedule with MDL =4kW

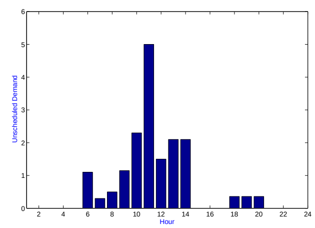
Hour	Lighting	Washing machine	Cloth dryer	Dish washer	Vacuum cleaner	Iron	Rice cooker	Well pump	PHEV charging	Demand Total
1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0.5	0.5
8	0	0.5	0	0	0	0	0	0	0	0.5
9	0	0.5	0	0	0	1.1	0	0	0	1.6
10	0	0	0	0	0	0	0.3	0	0	0.3
11	0	0	0	0	0.65	0	0	0	0	0.65
12	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0
15	0	0	0	2.1	0	0	0	0	0	2.1
16	0	0	0	2.1	0	0	0	1.5	0	3.6
17	0	0	2.7	0	0	0	0	0	0	2.7
18	0.36	0	0	0	0	0	0	0	0	0.36
19	0.36	0	2	0	0	0	0	0	0	0.36
20	0.36	0	0	0	0	0	0	0	0	0.36
21	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	2.3	2.3
23	0	0	0	0	0	0	0	0	2.3	02.3
24	0	0	0	0	0	0	0	0	0	0

The scheduling is repeated with 3kw MD limit. It can be seen that, for this case also the loads are scheduled within the specified s_j's and f_j's but with an increased energy cost of 93.8. This is expected as some loads are to be scheduled in high priced slots to restrict the demand within the specified MD limit. The appliance schedule is given in Table 4.9.

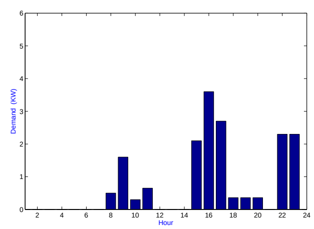
Table 4.9: Schedule with MDL =3kW

Hour	Lighting	Washing machine	Cloth dryer	Dish washer	Vacuum cleaner	Iron	Rice cooker	Well pump	PHEV charging	Demand Total
1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	1.1	0	0	0	1.1
8	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0
10	0	0.5	0	0	0	0	0.3	0	0	0.8
11	0	0.5	0	0	0	0	0	0	0	0.5
12	0	0	0	0	0	0	0	1.5	0	1.5
13	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0.65	0	0	0	0	0.65
15	0	0	0	2.1	0	0	0	0	0	2.1
16	0	0	0	2.1	0	0	0	0	0	2.1
17	0	0	2.7	0	0	0	0	0	0	2.7
18	0.36	0	0	0	0	0	0	0	0	0.36
19	0.36	0	0	0	0	0	0	0	0	0.36
20	0.36	0	0	0	0	0	0	0	0	0.36
21	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	2.3	2.3
24	0	0	0	0	0	0	0	0	2.3	2.3

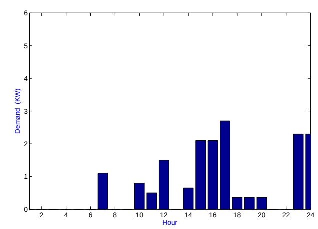
Next the scheduling is done using random time varying tariff for two different maximum demand limits. It is observed that in this case also, scheduling of all the loads are confined to the low priced periods, within the permitted interval satisfying the MD limit constraint . The cumulative demand in each hour is shown in Figure 4.6.



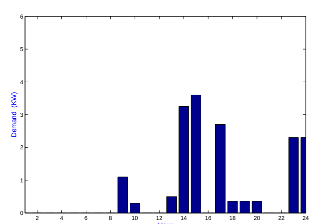
(a) Unscheduled Demand



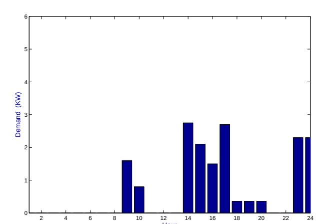
(b) Demand for MDL=4kW



(c) Demand for MDL=3kW



(d) Demand for MDL=4kW



(e) Demand for MDL=3kW

Figure 4.6: Demand Allocations (a)Unscheduled demand,
(b), (c) Scheduled Demands for ToUP and (d), (e), Scheduled Demands for RTP

The variation of energy cost with MDL is shown in Table 4.10. Also it can be observed that, the energy cost scheduled under RTP is low and is justified as it reflects the actual price at a particular time slot compared to ToUP which is fixed in advance.

Table 4.10: Effect of MDL on the total energy cost

Demand	Cost for ToUP	Cost for RTP
Unscheduled	118.65	128.84
Scheduled with MDL = 4kW	89.25	61.54
Scheduled with MDL = 3kW	93.8	63.54

4.7 Conclusion

A solution to residential load scheduling problem obtained through BPSO based algorithm is presented. Several simulation experiments are done, considering the case study of a domestic consumer with various demand resources and the results are analyzed for various MD limits and tariffs. The results show that the loads are scheduled with minimum cost satisfying the consumer as well as utility constraints, maintaining total demand below the Maximum Demand limit. This is beneficial to both the utility as well as the consumer. The effect of MD limit on energy cost is also analysed. But BPSO Algorithm has certain limitations. As the algorithm reaches to the optimum solution, the probability of changing the position of the particle must be near to zero. Since sigmoid function is used the position will change by taking the value of 1 or 0 with the probability of 0.5. When the complexity of the problem increases as renewable sources and comfort aspect are incorporated, the particle size increases. Convergence of the algorithm will be difficult and time consuming in this case. To incorporate consumer comfort and stochastic renewable source in the residential load scheduling problem, optimization tools which can solve decision making problem in the presence of uncertainty is needed and Reinforcement Learning is identified as one of the powerful tools.

Chapter 5

Residential Load Scheduling Using Reinforcement Learning

5.1 Introduction

In the previous chapter, a solution method to the residential load scheduling problem using Binary Particle Swarm Optimization method is presented. The developed BPSO algorithm is found to be capable of providing a load schedule with minimum cost satisfying the given constraints. However the following aspects are not addressed in the BPSO algorithm due to the increased complexity of the problem.

As the cost of electrical energy is only a fraction of the total house hold budget, consumer will be ready to schedule their load only if it does not affect their convenience. This is not addressed in majority of the works reported in the literature. Some research works are there in this direction considering inconvenience caused to the consumer but a quantitative modeling of household devices based on comfort level still lacks in these works. A parameter *udc* incorporated in the load model serves to capture the degree of discomfort.

It is well known that there is a large scale deployment of small renewable distributed generation (DG) sources within the consumer premises. Among the various DGs, the most common and abundant resource is the Photovoltaic. The uncertainty associated with time varying solar power should also be taken into account while considering the load scheduling problem. Now a load scheduling method is to be developed to solve the problem which is a decision making problem under uncertain environment and Reinforcement Learning is one of the tools to solve such prroblems.

In this chapter, the solution of load scheduling problem considering consumer comfort and a single power source (utility grid) is described and the solution method employed is stochastic learning algorithm, namely Reinforcement Learning (RL). Learning Automata algorithm is another stochastic learning algorithm used for single stage decision making problems. The solution obtained using RL and its comparison with LA algorithm is also presented.

5.2 Learning Automata Algorithm

Learning Automata (LA) (Thathachar and Sastry, 2011) are models used for adaptive decision making in random environments. LA algorithm can be used to learn the best decision in a single stage decision making problem with uncertain environment. Learning is achieved through repeated interactions with the environment. A simple decision making problem, the N arm bandit problem, is considered to explain the LA algorithm.

The N arm bandit is a game based on a slot machine with N arms. The player can play any arm of his choice by paying a fixed fee. The action of playing an arm is denoted as a. When the arm is played, a random reward is returned by the machine which is denoted as $R(a)$. The probability distribution for each arm is assumed to be fixed and is not known to the player. So the reward from each arm will be around a mean value with some value of variance. The mean value represents the goodness of choosing an arm or quality of an arm and is denoted by $Q(a)$. For example, playing on arm 2 results in return of a random variable beween 0.4 and 0.7, the mean value of which is $Q(4) = 0.55$. By playing the game, the goal of the player is to get maximum reward with minimum number of trials. The decision to be taken by the player is to play the arm with maximum mean value, as the reward from the arm is around a mean value. Here the play on an arm can be taken as the decision or action. Thus the objective is to find the best action corresponding to the arm with highest reward (best arm), from the action set consisting of the set of arms.

To find the best arm, a direct and simple method is to find the mean corresponding to each arm after a large number of trials on each arm and choose the best arm. Let the reward received for playing an arm in the i^{th} trial be denoted as R^i. Then the mean value estimated for the arm from n

trials, $Q^n(a)$ is given by the equation,

$$Q^n(a) = \frac{\sum_{i=1}^{n} R^i(a)}{n} \tag{5.1}$$

If mean value for all the arms are found, then the best arm i.e. the one with maximum mean, and the best action corresponding to it denoted as 'greedy action', a_g can be obtained as follows.

$$Q^n(a_g) = \max_{a \in A} Q^n(a) \Rightarrow a_g = \arg\max_{a \in A} Q^n(a) \tag{5.2}$$

Though simple, the above method is time consuming and not efficient. With number of arms $N = 50$ and number of trials $n = 1000$, the player is required to play $N * n = 50000$ times, to make a decision. An efficient method for solving this problem is the Learning Automata algorithm which make use of an iterative method for obtaining the mean values corresponding to each arm. The iterative formula for the estimates of the mean value can be derived as follows using equation 5.1.

$$\begin{aligned} Q^{n+1}(a) &= \frac{\sum_{i=1}^{n} R^i(a) + R^{n+1}(a)}{n+1} \\ &= \frac{nQ^n(a) + R^{n+1}(a) + Q^n(a) - Q^n(a)}{n+1} \\ &= Q^n(a) + \frac{1}{n+1}(R^{n+1}(a) - Q^n(a)) \end{aligned} \tag{5.3}$$

From the above equation, it can be noted that the new estimate based on the $(n+1)^{th}$ observation $Q^{n+1}(a)$ is the old estimate $Q^n(a)$ plus a small number times the error, $(R^{n+1}(a) - Q^n(a))$. Instead of $\frac{1}{n+1}$ a decreasing sequence

α_n can be used to get a recursive equation.

Starting with initial estimate $Q^0(0) = 0$, the estimate of the expected value can be found using this equation. Here, $Q(a) = E\{R(a)\}$ where $E\{R(a)\}$ is the expected value of the reward or observation related to an arm and $Q^n(a))$ is the estimate of $Q(a)$ obtained from n trials. The following recursive equation can be utilized to find the estimate of expected value of $R(a)$, if the observations are chosen independently.

$$Q^{n+1}(a) = Q^n(a) + \alpha_n[R(a) - Q^n(a)] \tag{5.4}$$

where α_n is the update factor, the value of which aids in the convergence of the algorithm.

Now, an efficient strategy for the selection of action need to be identified. An action taken with uniform probability is one method, in which all the arms are played equal number of times or the action space is explored throughout the learning. But it will be reasonable to play the best arm instead of playing all the arms. At any time during the play, there will be one action with maximum estimate of Q up to that time and is called the greedy action. If a greedy action is selected then the available knowledge regarding the values of actions is exploited. But there may be other actions better than the greedy action. Thus by trying a nongreedy action the other chances can be explored. So the action selection strategy should maintain a balance between exploitation and exploration. There are different algorithms for action selection. One such algorithm to balance exploration and exploitation is ϵ- greedy algorithm and is described next.

5.2.1 ε-greedy Method for Action Selection

The action corresponding to the best estimate of Q value is called the greedy action, which is based on the present estimate of Q. If a greedy action is selected then the available knowledge regarding the values of actions is exploited. It may be noted that, during the n^{th} episode the estimate of Q value, $Q^n(a)$ will be far from true value if n is small. Hence using the greedy action at this stage will not be a good idea. But there may be other actions better than the greedy action and these possibilities also have to be explored. So the action selection strategy should maintain a balance between exploitation and exploration. In the initial phase of the algorithm, the estimates $Q^n(a)$ may not be the true value. But, as the number of trials n increases the chance of the estimates approaching the true mean value increases and a_g becomes the best action. Hence it is preferred to get more information by exploring the unknown environment in the initial phase of the algorithm. As n increases, it is better to exploit the information already available.

The ϵ- greedy algorithm maintains a balance between exploration and exploitation by choosing a random action a with a probability of ϵ. Also a greedy action a_g is chosen with probability of (1- ϵ). It may be noted that if $\epsilon = 0$, the algorithm will always select greedy action, and if $\epsilon = 1$, the algorithm will always select random action. The value of ϵ decides the balance between exploration and exploitation. Initially, ϵ is chosen close to 1, to explore the unknown environment. As n increases ϵ is gradually reduced, so that the available information is exploited.

5.3 Reinforcement Learning

5.3.1 Introduction to Reinforcement Learning

Reinforcement Learning (RL) is a computational approach based on goal directed learning from interaction with the environment (R.S.Sutton and A.G.Barto, 1998). It is similar to how animals optimize their behaviour by learning, to obtain rewards and avoid punishments like learning of an infant to walk. In the learning process, the agent directly interacts with the environment without any supervisor as in the case of supervised learning. At each step the agent takes an action and the agent does not initially know the effect of its action on the state of the environment and the immediate reward of this action. By a trial and error process, the agent learns optimal actions so as to maximize the reward in each state.

The learning methodology developed in Reinforcement Learning combines the features of two disciplines namely dynamic programming and supervised learning. Dynamic Programming is a classical method in the field of mathematics that has been used to solve several optimization problems. But the application of Dynamic Programming is limited to problems with small size and complexity. Supervised learning methods like neural networks needs different sets of input- ouput pairs to train the network. Reinforcement Learning is a neuro-dynamic programming method in which an explicit goal is learned to achieve by trial and error interaction with the environment.

The learner or agent tries different actions at different states and learns to attain the best action at each state such that the long term reward is maximized. The action at any state affects the future state of the environment

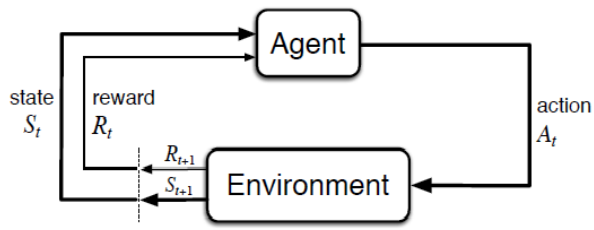


Figure 5.1: Interaction between Agent and Environment in Reinforcement Learning

and the agent tries to attain a control policy or rule for choosing an action. In RL, the agent can learn optimal policy or rule using simple learning algorithms.

The interaction between the agent and environment is illustrated in Fig 5.1 (R.S.Sutton and A.G.Barto, 1998). The agent interacts with the environment and at each step $t = 0, 1, 2, 3, ...$, some representation of the environment's state $s_t \in S$ is received, where S denotes the set of all possible states. At each state, an action $A_t \in A(s_t)$ is selected, where $A(s_t)$ is the set of actions in state s_t. After performing an action, the agent receives a numerical reward $R_{t+1} \in R$ and finds itself in a new state s_{t+1}.
The main elements of a Reinforcement Learning system are explained in the following section.

5.3.2 Elements of Reinforcement Learning Problem

The previous example considered in Section 5.2 had only one state. But in many problems it may be required to find the best action for different states. The characteristics of such general Reinforcement Learning problem and its

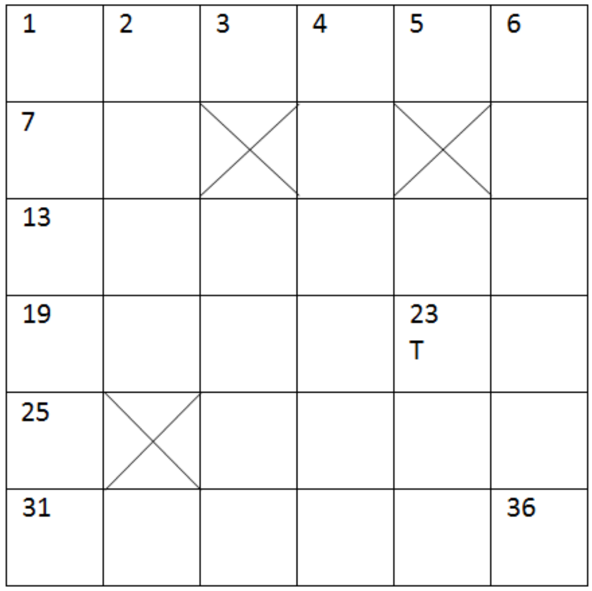


Figure 5.2: Grid world problem

various elements are explained in this section. Consider the example of a grid world problem to find the shortest path as given in Fig. 5.2.

The grid with 36 cells arranged in 6 rows and 6 columns is considered. The agent can be at any one of the cells, at any instant. The aim of the agent is to reach the goal state, denoted by T and the crossed cells have some obstacles. For each cell transition, a cost is incurred and the cost is high when passing through the crossed cells. The agent can follow different paths to reach the goal state, accordingly the cost also will vary. Starting from any initial position of the cell, the grid world problem is to find the optimum path to be followed to reach the goal. The different elements of the Reinforcement Learning Problem are now explained, with respect to this example.

1. State Space: The cell number describes the state of the agent at any time. The possible state the agent can occupy is the one from the entire cell space of 36 cells and it is called state space. In Reinforcement Learning, the state space is defined as the set of all possible states the agent can occupy at different instants of time. At any instant k, the state of the agent is denoted as $x_k \in X$ where X is the state space. From the initial state x_0, the agent performs a series of cell transitions or actions $a_o, a_1, a_2.....a_{N-1}$, to reach the goal state T.

2. Action Space: At any instant k, the agent can perform any action $a_k \in A_k$, where A_k, represents the set of permissible actions. The permissible set of actions depends on the current state x_k. For example, if the agent is in cell number 13, $x_k = 13$, then move to left is not possible, but move to right, up and down are possible. Thus for each cell there is a set of possible cell movements. The set of permissible actions at any instat k forms the action space.

3. System Model: Reinforcement Learning uses direct interaction with the system to learn and reach the goal. It may not be possible always. In such cases a mathematical or simulation model is required. In the grid world problem, the next position of the agent x_{k+1} depends on the present state x_k and the action a_k. It can be represented as,

$$x_{k+1} = f(x_k, a_k) \tag{5.5}$$

For example, if $x_k = 13, a_k = right$ then $x_{k+1} = 14$, and if $x_k = 13, a_k = down$ then $x_{k+1} = 19$. For simple systems like this, next state can be obtained easily by observation. But for systems with larger state space, a simulation model is needed to obtain x_{k+1}.

4. Policy: Based on the action taken a_k, trasition from current state x_k to the next state x_{k+1} occurs as given by equation 5.5. A policy in reinforcement learning can be defined as any mapping from state space X to the action space A and is represented by π. The action taken by the agent on reaching state x is denoted as $\pi(x)$. At any state x, there are many possible paths to reach the goal state. Each path can be treated as a policy denoted by $\pi_1(x), \pi_2(x)$, etc. It is required to find the optimum policy $\pi^*(x)$, corresponding to the minimum cost.

5. Reinforcement Function: The Reinforcement function should reflect the goal of the agent. In the case of shortest path problem, it can be assumed that each normal cell movement results in a cost of 1 unit and a cell with obstacle results in a high cost or penality. When the agent takes an action a_k that results in state transition from x_k to x_{k+1} then the reinforcement function is represented as $g(x_k, a_k, x_{k+1})$. The reinforcement function returned by each step is also called the reward, R_k. The agent learns to find a sequence of actions so that the total reward or cost for reaching the goal state $\sum g(x_k, a_k, x_{k+1})$ is minimized.

6. Value Function: Reinforcement function indicates the goodness of a policy in the immediate sense, whereas value function indicates the goodness of the policy in long run. In order to evaluate the desirability of a policy over N stages, one can measure the total expected dis-

counted cost. Value function of any policy π, V^{π} , returns the goodness of the policy in long-run. The total cost incurred by following a policy π over N stages starting from an initial state can be calculated as,

$$V^{\pi}(x) = \sum_{k=0}^{N-1} \gamma^k g(x_k, a_k, x_{k+1}) \tag{5.6}$$

Here γ which is called the discount factor accounts how much future rewards to be discounted in rating a good policy over N stages at the present state x. The value of discount factor is between 0 and 1. Here in the case of grid-world problem, the costs are same for a normal cell movement and therefore the value can be taken as 1.

A policy π_1 is better than policy π_2, only if $V^{\pi_1} \leq V^{\pi_2}, \forall x \in X$. The ultimate goal of the problem is to find an optimal policy π^* for which the total expected cost is minimum compared to all other policy $\pi \in \Pi$. This can be mathematically expressed as,

$$V^{\pi^*}(x) \leq V^{\pi}(x),\ \forall x \in X, \forall \pi \in \Pi \tag{5.7}$$

By following a policy, $\pi(x)$, the minimum cost is obtained which is denoted as $V^*(x)$. This value is called as optimal value function. There are many methods to find out the optimal policy π^* and one commonly used method is $Q - learning$ algorithm which is discussed in Section 5.3.4.

5.3.3 Multi Stage Decision Problem (MSDP)

Reinforcement Learning can be utilized to obtain solution of Multi Stage Decision Problems (MSDP). A problem in which a sequence of decisions is required to be taken for arriving at the solution is called a MSDP. The rewards obtained in each stage of decision making can be stochastic in nature. The application of reinforcement learning for the solution of MSDP is explained below.

By taking an action $a \in A$, the current state of the system $x \in X$ moves to a new state y with a transition probability of P_{xy} such that,

$$P_{xy} > 0 \quad \forall x, y \in X, a \in A \tag{5.8}$$

$$\sum_{y \in X} P_{xy} = 1 \quad \forall x \in X, a \in A \tag{5.9}$$

An immediate payoff or reward $g(x, a, y)$ is obtained based on the state and action taken in that state. The goal is to find a policy which decides the actions to be taken in each state of the environment such that the cumulative measure of rewards received is optimum. Also the corresponding policy is called optimal policy.

The value function $V^{\pi}(x)$ for a MSDP with N stages is given by equation 5.6. To explain the concept of value function, its application for MSDP is described below.

Consider a single stage problem with $N = 1$. At the first instant, $k = 0$, the state transition occurs from x_0 to x_1. Since $N = 1$, x_1 is the terminal state here. This transition is prescribed by a policy, $\pi(x_0)$ and results in an immediate reward $g(x_0, \pi(x_0), x_1)$ and reward $G(x_1)$ which is the terminal reward obtained from state 1. The value function is given by

$$V_1^{\pi}(x_0) = E[g(x_0, \pi(x_0), x_1) + \gamma G(x_1)] \tag{5.10}$$

For a two-stage problem, i.e when $N = 2$, upon taking action $\pi(x_0)$, the state transition occurs to x_1. Then the system reaches x_2 by adopting a policy $\pi(x_1)$ and returns a reward $G(x_2)$. The value function in this case is given by,

$$\begin{aligned}
V_2^{\pi}(x_0) &= E[g(x_0, \pi(x_0), x_1) + \gamma G(x_1)] \\
&= E[g(x_0, \pi(x_0), x_1) + \gamma(g(x_1, \pi(x_1), x_2) + \gamma G(x_2))] \\
&= E[g(x_0, \pi(x_0)x_1) + \gamma(g(x_1, \pi(x_1), x_2)) + \gamma^2 G(x_2)]
\end{aligned}$$

For a N-stage problem, the value function is given by,

$$V_N^{\pi}(x_0) = E[\sum_{k=0}^{N-1} \gamma^k g(x_k, \pi(x_k, x_{k+1}) + \gamma^N G(x_N)] \tag{5.11}$$

The policy that corresponds to the best action and best reward at a particular state is called as optimal policy π^*. The optimal cost that is given by adopting the optimal policy π^* is called optimal value function which is calculated using a recursive equation.

For the case $N = 1$, replacing the expectation operator with transition probability P_{xy},

$$V_1^{\pi}(x) = \sum_{y \in X} P_{xy}^{\pi(x)}[g(x, \pi(x), y) + \gamma G(y)], \quad \forall x \in X \tag{5.12}$$

For the system, the optimal value function is given by,

$$V_1^*(x) = \underset{\pi \in \Pi}{min} \sum_{y \in X} P_{xy}^{\pi(x)}[g(x, \pi(x), y) + \gamma G(y)], \quad \forall x \in X \tag{5.13}$$

If the policy, $\pi(x)$ is fixed for a state then,

$$V_1^*(x) = \underset{a \in A}{min} \sum_{y \in X} P_{xy}^{a}[g(x, \pi(x), y) + \gamma G(y)], \quad \forall x \in X \tag{5.14}$$

From the above equation, it is clear that, the optimal action and hence the optimal value functions depends upon the minimization of two terms $g(x, \pi(x), y)$ and $\gamma G(y)$. Here $g(x, \pi(x), y)$ represents the immediate reward and $\gamma G(y)$ represents the *cost to go*. If a k stage problem is considered, to obtain the optimal value, the *cost to go* in $k - 1^{th}$ should also be optimum. Thus the optimal value function for k^{th} stage is given by,

$$V_k^*(x) = \underset{a \in A}{min} \sum_{y \in X} P_{xy}^{a}[g(x, \pi(x), y) + \gamma V_{k-1}^*(y)], \quad \forall x \in X \tag{5.15}$$

To find the optimal value function for N stages, recursive equations can be used starting from the first stage by applying the equation $V_0^*(x) = G(x)$ and searching the action space A, N times.
The value function under policy π is given by,

$$V^{\pi}(x) = \sum_{y \in X} P_{xy}^{\pi(x)}[g(x, \pi(x), y) + \gamma V^{\pi}(y)] \tag{5.16}$$

With transition probabilities known, equation (5.16) can be solved to obtain $V^{\pi}(x)$. The optimal policy π^* which corresponds to optimal value function can be defined as one for which

$$V^{\pi^*(x)} \leq V^{\pi(x)}, \forall x \in X, \forall \pi \in \Pi \tag{5.17}$$

Then the optimal value function for an N-stage problem can be defined as in Dynamic programming steps as,

$$V_k^*(x) = \min_{a \in A} \sum_{y \in X} P_{xy}^a [g(x, \pi(x), y) + \gamma V_{k-1}^*(y)], \quad \forall x \in X \tag{5.18}$$

starting from the initial condition $V_0^*(x) = 0$.

Thus a mathematical formulation of the MSDP is obtained. The steps to be followed to reach the optimum policy is also explained. The solution method for reaching the optimal policy called Q-learning is described in the next section.

5.3.4 Q Learning Algorithm

Q-learning is a solution method used to find the optimal policy by learning the values of function $Q(x, a)$ which can be used even if transition probabilities are unknown. The value of the Q function is the value of taking an action in a state under policy π. The Q-value corresponding to a policy π is defined as,

$$Q^\pi(x, a)) = \sum_{y \in X} P_{xy}^a [g(x, a, y) + \gamma V^\pi(y)] \tag{5.19}$$

Comparing equation (5.19) with equation (5.16),

$$Q^\pi(x, \pi(x)) = V^\pi(x), \quad \forall x \in X \tag{5.20}$$

For optimal policy π^*, the above equations can be written as $Q^{\pi^*}(x, \pi^*(x)) = V^{\pi^*}(x) = V^*(x), \forall x \in X$ which returns optimum value of Q for the state action pair (x, π^*). For a minimization problem, the optimal Q-value can be defined as

$$Q^*(x,a) = \underset{\pi}{min} Q^{\pi}(x,a) \tag{5.21}$$

which implies

$$Q^*(x,a) = Q^{\pi^*}(x,a) \quad \forall x \in X, \forall a \in A \tag{5.22}$$

The optimal policy is given by,

$$\pi^*(x) = argmin_{a \in A} Q^*(x,a) \tag{5.23}$$

The Q-learning method can be employed by generating a sequence of samples which can be used to update the value of Q. At each iteration, the agent takes an action from the state x using some strategy to reach the new state y and receives an immediate reward given by $g(x,a,y)$ that is used to update the value of Q.

$$\begin{aligned} Q^{n+1}(x,a) = Q^n(x,a) + \eta[g(x,a,y) + \gamma \underset{a' \in A}{min} Q^n(y,a') - Q^n(x,a)] \\ \forall x \in X, \forall a \in A \end{aligned} \tag{5.24}$$

The above update equation consists of two parameters, η and γ. Learning index η indicates how much the Q- values are modified at each of the learning steps. Discount factor $\gamma \in (0,1)$ indicates how much the future rewards are to be discounted. Learning parameter $\eta \in (0,1)$ and with small value of η, Q^n converges to Q^* and therefore for large values of n, $Q^*(x,a)$ can be approximated as $Q^n(x, a)$.

The Q-learning algorithm for a MSDP with N stages is given below.

For all states $x \in X$ *and* $a \in A$

Initialize the value of $Q^0(x, a) = 0$

For $i = 1 : max\_iter$

Observe the current state x_0

For k=1:N

Select an action a_k *using action selection strategy*

Perform action a_k *and reach state* x_{k+1}

Obtain the immediate reward $g(x_k, a_k, x_{k+1})$

Update the value of $Q_(x_k, a_k)$

Update the state from x_k *to* x_{k+1}

End

End

End

Updating of Q value estimates are repeated a large number of times. When each action is performed sufficient number of times in each state, the estimated Q-values converge to true Q-values. To select an action from the action set various action selection strategies are used and most commonly used method is the ϵ-greedy algorithm described earlier in Section 5.2.1.

5.4 Load Scheduling

5.4.1 Load Model

The switching ON time of a flexible load, can be delayed so as to operate it at a low cost period. This delay causes some inconvenience or discomfort to the consumer. This aspect also need to be addressed while scheduling the loads. Here, a load model that include the consumer comfort as explained in Section 3.2.2 is considered. The objective of the load scheduling problem is to minimize the total cost of electricity consumed in a day subjected to various constraints.

A time line as explained in Section 3.2.1 consisting of 24 equal time slots, k in one day is chosen. The time between 12 am and 1am is denoted as k=1, the first time slot and k=24 is the last time slot. Each individual load is modeled by a 5-tuple represented as,

$$d_j = (s_j, f_j, l_j, r_j, udc_j) \tag{5.25}$$

where $[s_j, f_j]$ represents the operating interval of load d_j. l_j denotes the total duration for which the load should remain ON. r_j is the power rating in kW. If j^{th} load is switched on at s_j, it will remain on from $k = s_j$ to $k = s_j + l_j - 1$.

The problem is to obtain the optimum time slots at which the loads are to be switched ON, subject to different constraints. udc_j is a parameter called unit delay cost introduced to capture the degree of discomfort due to the delay in switching (Ahamed et al., 2011). The parameter *udc* incorporated in the load model serves to capture the degree of discomfort. The guidelines for choosing *udc* also is formulated.

5.4.2 Load Scheduling with One Source of Energy (Utility Grid)

The load scheduling problem is considered with a single source of energy, the utility grid.

The objective is to minimize the total energgy cost for one day satisfying various constraints. i.e., Minimize,

$$Total\ cost = \sum_{k=1}^{24}\sum_{j=1}^{m} C^k r_j u_j^k \tag{5.26}$$

subject to,

$$\sum_{k=s_j}^{f_j} u_j^k = l_j; \quad u_j^k = 0, for \quad k < s_j \quad or \quad k > f_j$$

where, $k = 1\ldots, 24, \quad j = 1, \ldots, m$

The solution space is defined as,

$$U = [u_1^1, u_1^2, \ldots, u_1^{24}, u_2^1, u_2^2, \ldots, u_2^{24}, \ldots, u_m^1, u_m^2, \ldots, u_m^{24}]$$

$$\forall u_j^k \in \{1, 0\}$$

Then the aim is to find the optimum values of u_j^k.

A solution method based on Reinforcement Learning for the load scheduling problem is explained in the next section.

5.5 RL Algorithm for Load Sheduling

There exist a variety of machine learning strategies which takes the stochastic nature of problem environment effectively. Reinforcement Learning (RL) is a neuro-dynamic programming method in which an explicit goal is learned to achieve by trial and error interaction with the environment. RL combines the features of dynamic programming and supervised learning. The main objective of Reinforcement Learning is to find an optimal policy that maximizes the reward. The agent learns to attain the best action at each state such that the long term reward is maximized. In RL, the agent can learn optimal policy using simple learning algorithms. In this section, the RL algorithm for Load scheduling without PV source is given (Ahamed et al., 2011).

The Load scheduling problem is to find a decision or commitment schedule $u_1, u_2, u_3, \dots u_m$, where u_j is a vector representing the status of the j^{th} load. $u_j = [u_j^1, \dots u_j^{24}]$
The optimization problem is given by,

$$f(u) = min_{u_j^k} \sum_{k=1}^{24} \sum_{j=1}^{m} C^k r_j u_j^k \tag{5.27}$$

Since there are no coupling constraints, the above problem can be written as

$$\sum_{j=1}^{m} [min_{u_j^k} \sum_{k=1}^{24} C^k r_j u_j^k] \tag{5.28}$$

Now the problem is converted to m minimization problems which can be solved independently.

Now it is required to solve the following equation,

$$min_{u_j^k} \sum_{k=1}^{24} C^k r_j u_j^k \tag{5.29}$$

subject to,

$$\sum_{k=s_j}^{f_j} u_j^k = l_j \quad u_j^k = 0, for \quad k < s_j \quad or \quad k > f_j \tag{5.30}$$

The above problem is modeled as a Markov Decision Process (MDP). If a system satisfies Markov Property, then the response of the environment at $k+1^{th}$ instant depends only on the state and action at instant k. Thus in the case of an MDP next state depends on the present state and present decision. To formulate the load scheduling problem as a MDP and to make use of RL (R.S.Sutton and A.G.Barto, 1998), state, state space, transition function, action set and reward function which are explained in 5.3.2 are to be identified with respect to the load scheduling problem.

The information needed to arrive at the decision should be contained in the state of the system. The decision to be taken in each step is, which loads are to be turned ON. This in turn depends on the price of electricity at the time of use and ON duration of the load. So in the case of load scheduling problem, the state at any stage k is represented by a two dimensional vector $[x(1), x(2)]$, where $x(1)$ is the current time slot and $x(2)$ is the ON duration of the load. Here the optimal actions need to be found only from $k = s_j$ to $k = f_j$ since $u_j^k = 0$, for for $k < s_j$ or $k > f_j$. The MDP starts with $x(1) = k = s_j$ and $x(2) = 0$ and terminates when $x(1) = f_j$ or $x(2) = l_j$.

The state space is given by,

$$\chi = \{(x(1), x(2));\ x(1) \in \{s_j, \ldots, f_j\}, x(2) \in \{0, 1, \ldots, l_j\}\}$$

At each state, the action to be taken is whether to switch ON or OFF the load. The action set $\mathcal{A} = \{0, 1\}$. The process starts from $k = s_j$. At each step, k is incremented by one so $x_{k+1}(1)$= $x_k(1)$+1. If a=1, the load is switched ON and $x_{k+1}(2)$=$x_k(2)$+1. Also if a=0, the load is OFF, then $x_{k+1}(2)$=$x_k(2)$+0. The transition from current state to the next state by the application of an action is defined by the transition function. In this case, from the present state the new state is obtained using the equation,

$$[x_{k+1}(1),\ x_{k+1}(2)] = [x_k(1) + 1,\ x_k(2) + a] \tag{5.31}$$

The objective is to minimize the cost of electricity subject to the constraints. To capture this objective the cost incurred when the process moves from x to x_{new} can be used to formulate the reward function, $g(x, a, x_{new})$. For MSDP having N stages, the requirement is to find the optimal sequence of actions, $a_0, a_1, a_2, ...a_{N-1}$ such that observed cost $\sum_{k=1}^{N-1} \gamma g(x_k, a_k, x_{k+1})$ is minimized. The cost for a sequence of actions is the same as the objective function when all constraints are satisfied i.e. $\sum_{k=1}^{24} g(x, a, x_{new})$=$\sum_{k=1}^{24} C^k r_j u_j^k$. If any of the constraints is violated a high penality is assigned to the reward function $g(.)$. Also, when a load with a non zero value of *udc* is not committed, a penality proportional to the rating r_j and udc of the load is given.

Therefore, the reward function is given by,

$$
\begin{aligned}
g(x,a,x_{new}) &= C^k r_j; \quad if\ a=1 \\
&= udc_j r_j; \quad if\ a=0 \\
&= penality; \quad if \\
&\quad x_{new}(1) = f\ and\ x_{new}(2) < l
\end{aligned}
\tag{5.32}
$$

Now to solve the MSDP the Q learning algorithm explained in Section 5.3.4 is used which involves learning Q values. To learn the Q values, start with an initial guess $Q^0(x,a)$, for all state action pairs. At each time instant k, the system is in state x_k, and we take an action a_k based on the current estimate $Q^n(x_k,a_k)$. Based on the action chosen, a new state x_{k+1} is reached and a cost of $g(x_k,a_k,x_{k+1})$ is incurred. Using this data the Q value for the current state action pair is updated using the Eqn (5.33).

$$
Q^{n+1}(x_k,a_k) = Q^n(x_k,a_k) + \eta[g(x_k,a,x_{k+1}) + \gamma \underset{a' \in A}{min} Q^n(x_{k+1},a') - Q^n(x_k,a_k)] \quad \forall x \in X, \forall a \in A \tag{5.33}
$$

The update equation consists of two parameters, i.e. η and γ. Learning index η indicates how much the Q values are modified at each of the learning steps. γ is the discount factor which is assumed to be 1. In the initial part of the algorithm, $Q^n(x_k,a_k)$ will not be a good approximation of $Q^*(x_k,a_k)$. Updating of Q value estimates are repeated a large number of times. If η is sufficiently small and if all possible (x,a) combinations of state and action are sufficiently visited then the iteration given by Eqn (5.33) will result in Q^n converging to the optimal value Q^*. The RL algorithm is given below.

REINFORCEMENT LEARNING ALGORITHM FOR LOAD SCHEDULING WITH ONE SOURCE (UTILITY GRID)

Read the load data $(s_j, f_j, l_j, r_j, udc_j)$ *for all loads*

Initialize Max_episodes, the parameters η *and* γ

For j=1 to m

    Initialize $Q^0(x, a) = 0, \quad \forall x \in \mathcal{X} \ \ \& \ \ \forall a \in \mathcal{A}$

    Initialize ϵ

    For n = 1 to Max_episodes

        $x(1) = s_j$; $x(2) = 0$;

        $x = [x(1) \ x(2)]$; $k = x(1)$

        while $(x(1) < f_j$ *AND* $x(2) < l_j)$

            Find the set of permissible actions

            Select greedy action with probability $1 - \epsilon$ *or a random exploratory action with probability* ϵ

            Find the new state x_{new} *using Eqn.(5.31)*

            Find the cost corresponding to the transition using Eqn.(5.32)

            Update the Q-value corresponding to the state action pair using Eqn.(5.33)

            $x = x_{new}$

$k = k + 1$

end

Update ϵ

end

Save the commitment schedule u_j^k for the j^{th} load.

end

The result of RL algorithm is compared with that of Learning Automata algorithm (Syed Q. Ali and Malik, 2013b). If we consider only atomic loads, the load scheduling problem will become a SSDP. The load scheduling problem with m loads is viewed as m independent single stage decision-making problems. The reward obtained on taking an action 'a' is, $R(a) = \sum_{k=s_j+a}^{s_j+a+l_j-1} C^k r_j$.

$$R(a) = \sum_{k=s_j+a}^{s_j+a+l_j-1} C^k r_j \tag{5.34}$$

. The objective is to find the best action a^* that minimizes the expected value of the reward $Q(a) = E\{R((a)\}$, which can be obtained using the following equation.

$$Q_j^{k+1}(a) = Q_j^k(a) + \eta(R(a) - Q_j^k(a)) \tag{5.35}$$

. The LA algorithm for load scheduling is given below.

LEARNING AUTOMATA ALGORITHM

Read the load data (s_j, f_j, l_j, r_j) for all loads

Initialize Max_episodes, the learning parameters η, ϵ

Calculate $p_j = f_j - s_j - l_j + 1$

Initialize $Q_j^0(a)=0$, *for* $a = 1, \dots, p_j$

For $n = 1$ *to Max_episodes*

Select random action a *with probability* ϵ *or greedy action* a_g *with probability* $1-\epsilon$

Calculate the observed cost using Eqn.(5.34)

Update the estimates using Eqn.(5.35)

Update ϵ

end

Find the best action for the j^{th} *load:* $a^* = argmin_{a \in \mathcal{A}} \{Q_j(a)\}$

5.6 Results and Discussions

To test the efficacy of the Reinforcement learning algorithm for load scheduling, several simulation experiments are conducted. Max_episodes, the learning parameters η and ϵ are initialized as 1000, 0.1 and 0.5 respectively. ϵ is updated to $0.9 * \epsilon$ after every 100 episodes. Initially a system consisting of 6 loads is considered and the load characteristics is given in Table 5.1. The price of electricity is given in Table 5.2.

The simulation is done and the load schedule obtained is given in Table 5.3. It is observed that all the loads are scheduled in the low priced period within their specified time slots. For example, if load number 5 is considered it can be turn on at any time slot in the interval {20 - 24} for a duration of 2

Table 5.1: Load Details

Load	s	f	l	r	udc
1	9	17	3	5	1
2	8	15	4	3	1
3	11	19	5	7	2
4	10	24	7	5	1
5	20	24	2	5	3
6	6	18	8	5	1

Table 5.2: Price of Electricity

Time,k	Price,C_k
1...12	5
13,14	12
15...18	5
19,20,21	10
22,23,24	5

hours. The schedule obtained for this load is {22 - 23} which are low priced periods. The total energy cost obtained is 735 units which is the minimum total energy cost corresponding to the given tariff and load details.

With same set of loads simulation is repeated with different values of udc ranging from 0 to 20, to study the effect of *udc*. It is observed that the total cost of energy increased with *udc*. The results are tabulated in Table 5.4. From the table we can see that when *udc* increases, the cost increases as consumer convenience is given importance. Moreover, we can also see that when *udc* is above 7 there is little impact. Here the daily average tariff of electricity is around 7 units. From this we can give guidelines for choosing udc. If convenience is of utmost importance choose udc greater than the

Table 5.3: Load Schedule

Hour	Load 1	Load 2	Load 3	Load 4	Load 5	Load 6	Demand from grid
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	1	5
7	0	0	0	0	0	1	5
8	0	1	0	0	0	1	8
9	1	1	0	0	0	1	13
10	1	1	0	1	0	0	13
11	1	1	1	1	0	1	25
12	0	0	1	1	0	1	17
13	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0
15	0	0	1	1	0	1	17
16	0	0	1	1	0	1	17
17	0	0	1	1	0	0	12
18	0	0	0	1	0	0	5
19	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0
22	0	0	0	0	1	0	5
23	0	0	0	0	1	0	5
24	0	0	0	0	0	0	0

average tariff (C_{av}) and choose a value between 0 and C_{av} if delay can be tolerated.

Table 5.4: Effect of *udc* on cost

udc (for all loads)	cost
0	735
3	735
5	795
7	890
8	988
20	988

The algorithm is validated and compared with Learning Automata algorithm proposed in (Syed Q. Ali and Malik, 2013b). To compare with Ali et. al., a load generator is programmed to generate 100 loads, assuming $udc = 0$ for all loads. Five categories of loads based on the time of occurrence are considered. Category 1 is assumed to be non flexible loads that can occur at any time of the day with a duration of one to four hours. The other categories include flexible loads occuring at load peak of the day, load peak at night and off peak hours. So category II load is with s_j randomly selected between the 8^{th} and 15^{th} interval and the scheduling window is randomly selected between one to seven intervals. The length is chosen anywhere between one to three intervals. Category III load is chosen such that it starts between 17^{th} and 20^{th} interval. The scheduling window is randomly chosen between one to five intervals and the length is between one to two intervals. Category IV load is assumed to occur between 1^{st} and 8^{th} interval, the off-peak hours after midnight. The length is chosen anywhere between one and three intervals and the scheduling window is randomly chosen between one to five intervals. Category V is with a start time randomly selected between the 13^{th} and 15^{th} interval, a scheduling window of one to five intervals and length between one to three intervals. The differential tariff used is shown in Fig. 5.3. The performance comparison of the algorithms is given in Table 5.5.

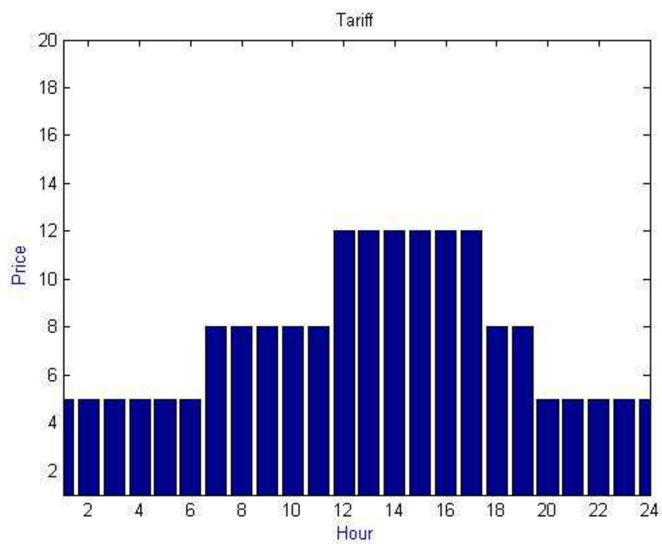


Figure 5.3: Tariff

All loads are committed in the low priced time slots and the total price of electricity for the learned schedule is 5014 units. With unscheduled load the total price of electricity is found to be 5161 units. When we generate the load a second time using the program, the load profile may change due to randomness. The computation time of RL algorithm 100 loads is found to be 3.89s, which is less than that of Learning Automata algorithm. The performance comparison of the algorithms is given in Table 5.5.

Table 5.5: Performance Comparison with LA

Scheduled Cost	Unscheduled Cost	Computation Time(s) with RL	Computation Time (s) with LA
5014	5161	3.89	6.76

LA is used for solving single stage decision making problems and load scheduling problem is solved using LA considering it as an SSDP. In LA the performance index of each action is updated on computation of reward for that action. But in MSDP, RL is suitable since it updates the Q value or performance index of each state action pair considering the discounted reward of future action. Hence, the chance of finding the best action corresponding to a particular state is improved in RL compared to LA. Thus the computation time is reduced in RL.

5.7 Case Study

To investigate the performance of the proposed scheduling algorithm, a smart home with schedulable and unschedulabe appliances is considered. Typical schedulable appliances in the home include Washing machine, Cloth dryer, Dish washer, Vacuum cleaner, Iron and Rice cooker and the residential loads are considered by referring several case studies in the literature. These appliances operate with different time intervals, duration of operation and power ratings. Typical residential loads are considered by referring several case studies in the literature.Also the consumer's willingness to tolerate delay in operation of the schedulable devices is reflected through the choice of *udc* value. The parameters of the household devices are given in Table 5.6.

Table 5.6: Parameters of Household Devices

Sl. No.	Appliance	s	f	l	r	udc
1	Lighting	18	20	3	0.36	8
2	Washing machine	8	14	2	0.50	1
3	Cloth dryer	11	17	1	1.80	0
4	Dish washer	14	19	2	1.20	9
5	Vacuum cleaner	9	14	1	0.65	1
6	Iron	6	9	1	1.10	1
7	Rice cooker	7	10	1	0.30	0

The dish washer assigned with $udc = 9$ indicates that the consumer is not willing to accept the inconvenience caused by delay. We can not shift the time of operation of a non flexible load such as lighting load. The duration of operation is 3 hours starting from 18^{th} time slot. The study is first conducted without considering the DG source. As expected the appliances are committed satisfying all the specified requirements with an energy cost of 53.65 units. The appliance schedule is given in Table 5.7. If the consumer is willing to tolerate delay for the operation of the dish washer, then a low value of udc can be set for this load. Simulation is repeated with udc=0 for the dish washer load. It was observed that the appliance schedule shifted to the low priced periods with a minimum total energy cost of 45.25 units.

For the same residential loads given in Table 5.6 with $udc = 0$ for all loads, simulation is also done with Binary Particle Swarm Optimization (BPSO) algorithm proposed in (Remani et al., 2015). The results are compared with the results obtained using RL algorithm and is shown in Table 5.8. It is

Table 5.7: Home Appliance Schedule

Hour	Lighting	Washing machine	Cloth dryer	Dish washer	Vacuum cleaner	Iron	Rice cooker	Grid Power
1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0
6	0	0	0	0	0	1	0	1.1
7	0	0	0	0	0	0	1	0.3
8	0	1	0	0	0	0	0	0.5
9	0	1	0	0	1	0	0	1.15
10	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0
12	0	0	1	0	0	0	0	1.8
13	0	0	0	0	0	0	0	0
14	0	0	0	1	0	0	0	1.2
15	0	0	0	1	0	0	0	1.2
16	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0
18	1	0	0	0	0	0	0	0.36
19	1	0	0	0	0	0	0	0.36
20	1	0	0	0	0	0	0	0.36
21	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0

observed the scheduled cost obtained in both the cases is the same, minimum cost of 45.45. But the computation time is less in the case of RL algorithm (1.34s) compared to BPSO algorithm (16.51s). With PV source and comfort constraint, the load scheduling problem is more complex and it is difficult to obtain solution with BPSO.

Table 5.8: Performance Comparison with BPSO

Scheduled Cost	Unscheduled Cost	Computation Time(s) with RL	Computation Time (s) with BPSO
45.45	53.65	1.34	16.51

5.8 Conclusion

A solution to the residential load scheduling problem using Reinforcement Learning approach is developed. The discomfort caused due to delay in scheduling a load is also considered in the load model by including a factor *udc*. A large number of simulations are done and the results obtained are analyzed and verified. The algorithm is also verified with the case study of a home with different types of loads. From the simulation results it is found that using the utility grid power, the loads are scheduled with minimum total energy cost, satisfying the constraints. Also the RL algorithm is found to be a better approach compared to other methods. But the renewable energy source is not included in the problem considered. Next, the load scheduling problem in the presence of Photovoltaic (PV) source need to be addressed.

Chapter 6

Residential Load Scheduling with PV Using Reinforcement Learning

6.1 Introduction

The deployment of small intermittent renewable energy resources within the consumer premises is increasing nowadays. A large number of consumers tend to cover their electricity demand by their own local generation using renewable Distributed Genertion (DG) sources such as PV, wind turbine based power generation systems etc. They produce clean energy which helps in meeting the rising power demand with minimum environmental challenges. Among the various DGs the most common and abundant resource is the Photovoltaic. Recently, there is an increase in the number of residential consumers who install roof top PV systems to meet their load demand. With the development in power electronic interface and decrease in cost of Photovoltaic(PV) panels (Carrasco et al., 2006), (Kouro et al., 2015), this trend is expected to grow. If the power output from such renewable sources is utilized effectively depending on the availability, it will help in reducing the electricity bill of the residential consumer. But the power generation from such sources is not consistent. This is mainly due to the random nature of the solar irradiance. The uncertain nature of the power output should also be taken into account while considering the PV source for energy management. Even though there are many works that consider home energy management system with PV source, the uncertainty associated with the power generation of PV source is not modeled in most of the cases.

The solar irradiance can be modeled using probabilistic distributions, if sufficient data is available. (Salameh et al., 1995) used Probability Density Functions (PDF) such as Beta, Weibull and Log-Normal to model the solar irradince and it was found that the Beta distribution fits the best. Beta PDF is used by several authors to model the uncertainty associated with solar power generation (Assuncao et al., 2003), (Atwa et al., 2010). In this work, the historic solar irradiance data of the site selected is taken from National Renewable Energy Laboratory (NREL) solar radiation database and the solar irradiance is modeled using Beta PDF to represent the uncertainty.

For residential load scheduling the consumer comfort also is to be taken into account. Thus the future residential consumer will have renewable sources, schedulable loads, non-schedulable loads and various time dependant tariff.The consumer wants to minimize his electricity bill without compromising on the comfort. Thus the major aspects to be considered with respect to residential load scheduling include comfort level associated with different appliances, constraints on operation of devices, availability, price and nature of energy supply. A generalized mathematical model developed considering these aspects, is explained earlier in Chapter 3. Reinforcement Learning (RL) is an approprate tool to solve this load scheduling problem which requires decision making considering uncretainty.

In this chapter, the uncertainty modeling of PV power generation using Beta PDF is described. The solution for residential load scheduling problem considering the uncertain PV power generation using Reinforcement Learning method is also explained.

6.2 Uncertainty modeling of Photovoltaic System

The output of the renewable DG unit like Photovoltaic source is stochastic due to the uncertain nature of solar irradiance. When sufficient data is available, uncertainty associated with the solar irradiance can be modeled as a random variable for which probabilistic distributions are used. A lot of previous data of irradiance is available and for developing the uncertainty model for the same, Beta PDF is being used (Atwa et al., 2010).

$$\begin{aligned} f_b(s) &= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} * (s)^{\alpha-1} * (1-s)^{\beta-1} \\ &\qquad \text{for} \quad 0 \le s \le 1, \alpha, \beta \ge 0 \\ &= 0 \qquad\qquad\qquad \text{otherwise} \end{aligned} \tag{6.1}$$

where,

s	solar irradiance kW/m^2
$f_b(s)$	Beta distribution function of s
α, β	parameters of Beta distribution function

α and β are calculated from the mean(μ) and standard deviation(σ) of the random variable s.

$$\beta = (1-\mu) * \left(\frac{\mu * (1+\mu)}{\sigma^2} - 1 \right) \tag{6.2}$$

$$\alpha = \frac{\mu * \beta}{1-\mu} \tag{6.3}$$

To model the hourly solar irradiance using Beta PDF, the mean and standard deviation of the historical data is needed. This is obtained by historical data processing. In this study, the historic solar irradiance data of the site selected is taken from National Renewable Energy Laboratory (NREL) solar radiation database. The hourly solar irradiance of the site under study for a period of one year is considered. The year is divided into four seasons and each season with 3 months, is represented by any day in that season. The day is further divided into 24-h segments. There will be 90 irradiance values for each hour in a season, considering 30 days for a month(3months X 30days). For each hour, the mean and standard deviation of solar irradiance is computed from this data and Beta pdf is generated.

The Power generation of the PV module depends on the solar irradiance, ambient temperature and the module characteristics (Atwa et al., 2010). For a particular hour solar irradiation s is generated using the corresponding

Beta PDF.

Then, the PV output power P_S, is calculated using the following equations (6.4) - (6.8).

$$FF = \frac{V_{MPP} * I_{MPP}}{V_{oc} * I_{sc}} \tag{6.4}$$

$$T_c = T_A + s\left(\frac{N_{OT} - 20}{0.8}\right) \tag{6.5}$$

$$I_y = s[I_{sc} + K_i(Tc - 25)] \tag{6.6}$$

$$V_y = V_{oc} - K_v * T_c \tag{6.7}$$

$$P_S = N * FF * V_y * I_y \tag{6.8}$$

where

FF	Fill Factor
V_{oc}	Open-circuit voltage in V
I_{sc}	Short circuit current in A
V_{MPP}	Voltage at maximum power point in V
I_{MPP}	Current at maximum power point in A
T_A	Ambient temperature in ^{0} C
T_c	Cell temperature in ^{0} C
N_{OT}	Nominal operating temperature of cell in ^{0} C
K_v	Voltage temperature coefficient V/^{0} C
K_i	Current temperature coefficient I/^{0} C
s	solar irradiance in kW/m^2
P_S	Power output of the PV module

The PV power output obtained using Eqn (6.8) is utilized for load scheduling with PV. Load scheduling with PV is explained in the next section.

6.3 Residential Microgrid

The general block diagram of a residential microgrid with grid connected PV source is shown in Fig. 6.1 which includes the converters and controllers needed for actual implementation (Amrr et al., 2018). For integrating it with the PV source a dc-to-dc solar charge controller or power-conditioning unit (PCU) is used. The charging of battery is decided by the controller depending on the battery voltage level from the solar PV and/or utility grid.

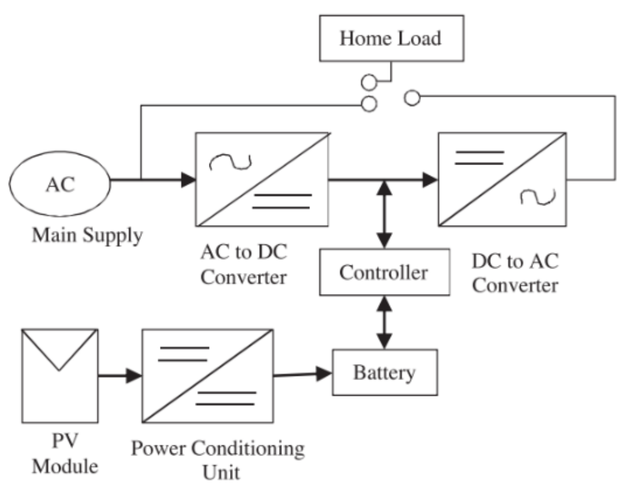


Figure 6.1: Micro grid

6.4 Load Scheduling with PV Source

6.4.1 Load Model

The same load model as considered in Chapter 5 is taken in this case also, which incorporates the parameter *udc* to capture the degree of discomfort. Each individual load is modeled by a 5-tuple represented as,

$$d_j = (s_j, f_j, l_j, r_j, udc_j) \tag{6.9}$$

where $[s_j, f_j]$ represents the operating interval of load d_j. l_j denotes the total duration for which the load should remain ON. r_j is the power rating in kW.

As explained, if the consumer is willing to accept delay, choose a low value of udc. Large value of udc can be selected if consumer can not tolerate delay but results in high energy cost.

6.4.2 Load Scheduling with two Sources (Grid and PV Source)

Consider the case with two sources, utility grid and PV source. The mathematical model of this problem can be obtained by substituting $n = 2$ in the general case explained in Chapter 3. The load scheduling problem is to find a sequence of decisions,
$u = [u_{1i}^1, u_{1i}^2, \ldots, u_{1i}^{24}, u_{2i}^1, u_{2i}^2, \ldots, u_{2i}^{24}, \ldots, u_{mi}^1, u_{mi}^2, \ldots, u_{mi}^{24}]$, $\forall\ i \in \{1, 2\}$ such that total electricity cost, for a day is minimized.

Minimize the total energy cost function given by,

$$Total\ cost = E[\sum_{k=1}^{24}\sum_{j=1}^{m}\sum_{i=1}^{2} C_i^k r_j u_{ji}^k] \tag{6.10}$$

subject to,

$$\sum_{i=1}^{2}\sum_{k=s_j}^{f_j} u_{ji}^k = l_j, \forall j \in \{1, m\}$$

$$u_{ji}^k = 0, for \quad k < s_j \quad or \quad k > f_j$$

where C_i^k is the hourly energy cost of i^{th} source,

u_{ji}^k is the binary status of j^{th} load at k^{th} hour, with i^{th} source.

Here $i = 1, 2$ denotes the sources grid and PV respectively.

6.5 RL Algorithm for Load Scheduling with PV Source

It is assumed that the grid connected home is equipped with a roof top PV system. The purchase of grid power can be reduced by making the best use of PV power. The task is to minimize the daily electricity cost considering the two sources, the PV and the grid, subject to the constraints.

That is,

$$min_{u_{ji}^k} E[\sum_{k=1}^{24}\sum_{i=1}^{2} C_i^k r_j u_{ji}^k] \tag{6.11}$$

subject to,

$$\sum_{k=s_j}^{f_j} u_{ji}^k = l_j \tag{6.12}$$

$$u_{ji}^k = 0, for \quad k < s_j \quad or \quad k > f_j$$

Here, i=1 for grid and i=2 for PV. u_{ji}^k indicates the status of load j, in the time slot k. That is, u_{ji}^k denotes ON/OFF status. E[] denotes the expected value.

The state is defined same as, $[x(1), x(2)]$, where $x(1)$ is the current time slot and $x(2)$ is the ON duration of the load. At each state, the action to be taken is whether to switch ON, from grid/PV or switch OFF the load. The action set is modified to $\mathcal{A} = \{0, 1, 2\}$. For switching OFF, the action is denoted as, $a = 0$. Action a is taken as 1 for switching ON the device using grid power. When the load is switched on from PV power, $a = 2$. This action causes a reduction in available PV power P_{pv}, during that particular hour and the PV power is updated to, P_{pvnew} given by,

$$P_{pvnew} = P_{pv} - r_j \tag{6.13}$$

In the reinforcement learning approach the stochastic nature of PV Power can be incorporated in the reward function and the the reinforcement function is defined as,

$$\begin{aligned} g(x, a, x_{new}) &= C_i^k r_j; \quad if \ a = 1 \ or \ 2 \qquad (6.14) \\ &= penality; \ if \ P_{pvnew} < r_j \ and \ a = 2 \\ &= udc_j r_j; \quad if \ a = 0 \\ &= penality; \\ &\qquad if \ x_{new}(1) = f \ and \ x_{new}(2) < l \end{aligned}$$

where, C_i^k denotes the cost of one unit of energy during the k^{th} time slot for i^{th} source. C_i^k depends on the nature of power source i, solar or grid and also on the type of tariff in the case of grid power. It is to be noted that, after load scheduling, the PV power availability at that time slot is updated to P_{pvnew}. If the power available is less than r_j a penalty is assigned as reward function.

State transition function is defined as,

$$[x_{k+1}(1),\ x_{k+1}(2)] = [x_k(1) + 1,\ x_k(2) + a'] \tag{6.15}$$

where, a'= 0 , if the device is in OFF state, that is a=0 and a'=1 , if the device status is switched ON, either from grid or PV, that is a=1 or a=2.

Before starting Q value updation, the α, β parameters are generated from historical data. Also the $(s_j, f_j, l_j, r_j, udc_j)$ data for each load is made available. The Q values are initialized to zero for each load. i.e. $Q^0(x, a) = 0$, where state $x = [x(1)\ x(2)]$, $a = \{0, 1, 2\}$. The PV power for the time slot is simulated using Beta PDF, which takes into account the randomness of PV power. Starting from $x(1) = s_j$ and $x(2) = 0$, action/decision is taken based on availability of PV power following ϵ-greedy strategy. Depending on the action taken state transition occurs and the Q-value as well as PV power availability are updated. After sufficient number of iterations, the learning phase converges, which is decided by the negligible updation in Q-values. The simulation phase gives the best action or source switching of each load corresponding to different time slots. The steps involved in RL algorithm for load scheduling with PV is given below.

REINFORCEMENT LEARNING ALGORITHM

Calculate α *and* β *from the past historical irradiance data*

Read the load data $(s_j, f_j, l_j, r_j, udc_j)$ *for all loads*

Initialize Max_episodes, the parameters η *and* γ

For j=1 to m

Initialize $Q^0(x,a) = 0, \quad \forall x \in \mathcal{X} \;\; \& \;\; \forall a \in \mathcal{A}$

Initialize ϵ

For n = 1 to Max_episodes

$x(1) = s_j$; $x(2) = 0$;

$x = [x(1)\ x(2)]$; $k = x(1)$

while $(x(1) < f_j$ *AND* $x(2) < l_j)$

if (First device in the kth hour),

Simulate the PV power for the hour using Beta PDF

else read the available PV power

Find the set of permissible actions

Select greedy action with probability $1 - \epsilon$ *or a random exploratory action with probability* ϵ

Find the new state x_{new} *using Eqn.(6.15)*

Find the cost corresponding to the transition using Eqn.(6.14)

Update the Q-value corresponding to the state action pair using Eqn.(5.33)

Update PV power availability for the hour if a=2 using Eqn.(6.13)

$x = x_{new}$

$k = k + 1$

end

Update ϵ

end

Save the commitment schedule u_{ji}^{k} *for the* j^{th} *load.*

end

6.6 Results and Discussions

6.6.1 Modeling the Uncertainty of PV Power

The output power of the PV module is dependent on the solar irradiance, the characteristics of the module and ambient temperature. The uncertainty in the solar irradiance is modeled using Beta PDF as stated earlier. In this study, the historic hourly irradiance data is taken from the solar radiation database of National Renewable Energy Lab (NREL) for the site Thrissur, Kerala (Latitude $10.52^{o}N$, Longitude $76.21^{o}E$). The parameters of the Beta PDF of solar irradiation is estimated from the hourly irradiance data. The four seasons in Kerala can be divided as winter, summer, south west monsoon and retreating monsoon. There are 90 data points corresponding to a season. The Beta pdf for each hour is generated and using this the hourly irradiance is simulated. The PV source is designed to meet about 50 percent of the total load for 24 hours. So a PV source with 160 modules is selected and

Table 6.1: PV module Parameters

Watt peak(W)	75
Open circuit voltage(V)	21.98
Short circuit current (A)	5.32
Voltage at maximum power(V)	17.32
Current at maximum power(V)	4.76
Voltage temperature coefficient(mV/^{0}C)	14.4
Current temperature coefficient(mA/^{0}C)	1.22
Nominal cell operating temperature(^{0}C)	43

the power output is simulated. The characteristics of the PV module (Atwa et al., 2010) is given in Table 6.1.

6.6.2 Load Scheduling with PV Source

Simulation is done with PV source for the same load details, given in Table 6.2. For the grid power the same tariff as shown in Table 6.3 is used, while the cost of PV power is assumed a low value of 1 unit. As mentioned earlier, to simulate random solar irradiation Beta distribution function is used. Hence while learning in each iteration the algorithm *sees* different PV power and in the simulations tested for each day the PV power will be different. One such scenario is shown in Fig. 6.2 .

The commitment schedule obtained using a simulated power scenario is given in Table 6.4. In the schedule, the ON status of load with power taken from PV source is denoted as 2 and that with grid power is denoted as 1. All the loads are scheduled between their respective s_j's and f_j's in the low priced period. At any time slot when the PV power is sufficient to meet the

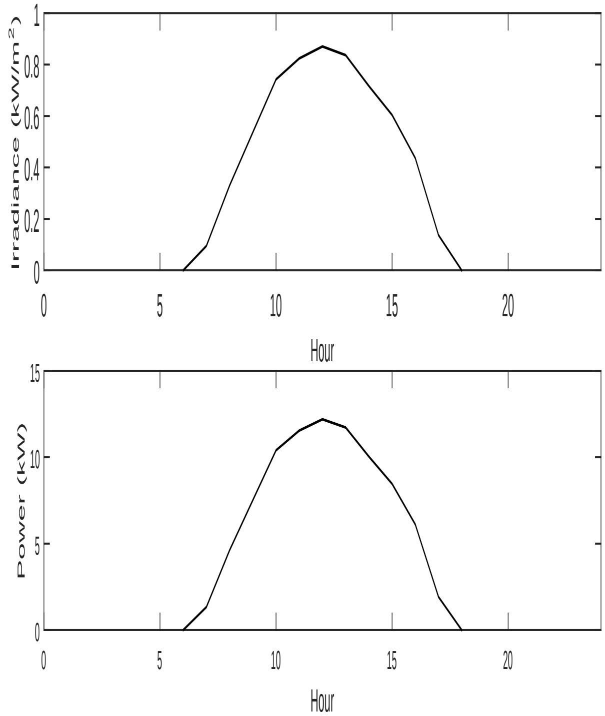


Figure 6.2: Simulated Irradiance and Power

load demand, the scheduling is done using PV power. The remaining loads are committed with grid power in the low priced period and satisfying the constraints. For example, load 1 is committed during the interval {9 - 11} and is powered by PV source. Load 3 is ON during {11 - 15}, with grid power for 11^{th} slot and PV power for slots {12 - 15}. It can be seen that slot 11 is a low priced period for grid power. For load 4, the schedule is {10 - 12} and {15 - 18} with 16^{th} slot powered from PV. With PV, the total energy cost is reduced to 495 and the demand from grid is also reduced. The simulations are repeated for a large number of scenarios. Even though there is variation in the simulated PV power due to uncertainty, it is observed that the load

Table 6.2: Load Details

Load	s	f	l	r	udc
1	9	17	3	5	1
2	8	15	4	3	1
3	11	19	5	7	2
4	10	24	7	5	1
5	20	24	2	5	3
6	6	18	8	5	1

Table 6.3: Price of Electricity

Time,k	Price,C_k
1...12	5
13,14	12
15...18	5
19,20,21	10
22,23,24	5

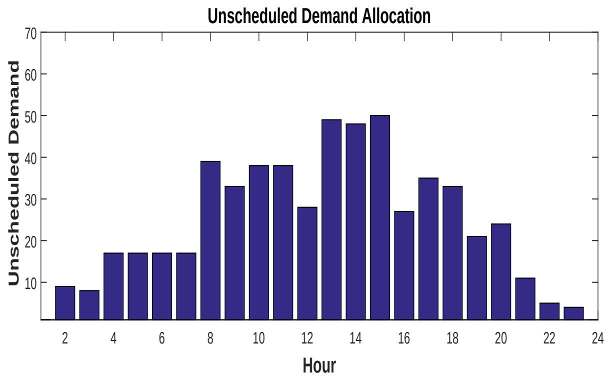
schedules obtained corresponds to the minimum energy cost.

Next, to demonstrate the scalability and validate the same, 100 random loads are generated, assuming $udc = 0$ for all loads. The PV source capacity is enhanced to account for the increased number of loads. The simulation is carried out with the same loads. In this case the total cost of electricity is reduced to 2130 units, whereas the cost with unscheduled demand is 5161 units and scheduled using RL without PV is 5014. The unscheduled load, the load scheduled using RL algorithm, without PV and with PV are shown in Fig. 6.3. It can be seen that without PV, as the load tries to avoid periods with higher price, though there is reduction in energy cost the maximum demand on the system is increased. The results show that, with PV there

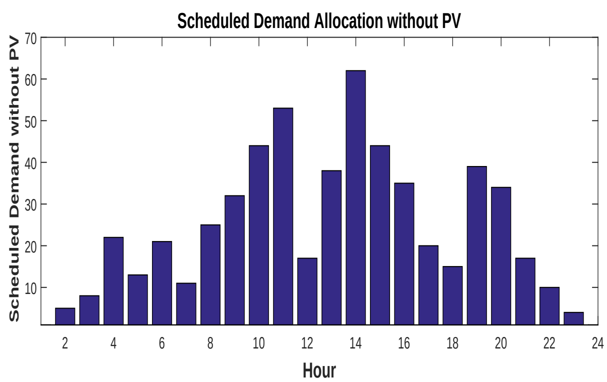
Table 6.4: Load Schedule with PV

Hour	Load 1	Load 2	Load 3	Load 4	Load 5	Load 6	Demand from grid
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	1	5
7	0	0	0	0	0	1	5
8	0	2	0	0	0	1	5
9	2	0	0	0	0	1	5
10	2	2	0	1	0	1	10
11	2	2	1	1	0	1	17
12	0	2	2	1	0	1	10
13	0	0	2	0	0	0	0
14	0	0	2	0	0	0	0
15	0	0	2	1	0	1	10
16	0	0	0	2	0	0	0
17	0	0	0	1	0	0	5
18	0	0	0	1	0	0	5
19	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0
22	0	0	0	0	1	0	5
23	0	0	0	0	1	0	5
24	0	0	0	0	0	0	0

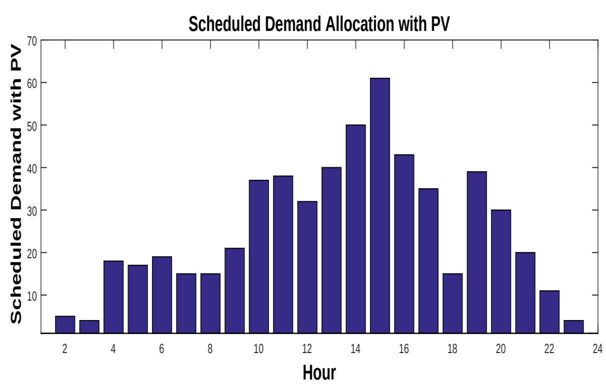
is reduction in energy cost and grid power consumption. This is achieved by maximum utilization of available PV power by effective load scheduling using RL algorithm.



(a)



(b)



(c)

Figure 6.3: (a)Unscheduled Demand (b)Scheduled Demand without PV using RL (c)Scheduled Demand with PV using RL

6.7 Case Study

To investigate the performance of the proposed scheduling algorithm, a grid connected smart home with PV source and schedulable and nonschedulabe appliances is considered. Typical schedulable appliances in the home include Washing machine, Cloth dryer, Dish washer, Vacuum cleaner, Iron and Rice cooker. These appliances operate with different time intervals, duration of operation and power ratings. Also the consumer's willingness to tolerate delay in operation of the schedulable devices is taken into account by proper choice of *udc* value. The parameters of the household devices are given in Table 6.5. The dish washer assigned with $udc = 9$ indicates that the

Table 6.5: Parameters of Household Devices

Sl. No.	Appliance	s	f	l	r	udc
1	Lighting	18	20	3	0.36	8
2	Washing machine	8	14	2	0.50	1
3	Cloth dryer	11	17	1	1.80	0
4	Dish washer	14	19	2	1.20	9
5	Vacuum cleaner	9	14	1	0.65	1
6	Iron	6	9	1	1.10	1
7	Rice cooker	7	10	1	0.30	0

consumer is not willing to accept the inconvenience caused by delay. We can not shift the time of operation of a non flexible load such as lighting load. The duration of operation is 3 hours starting from 18^{th} time slot.

The PV generation of the home considered is 5kW. The appliance commitment schedule with DG is given in Table 6.6. In the schedule, the ON status of load with power taken from PV source is denoted as 2 and that with grid power is denoted as 1. It can be seen that in this case for the lighting load which is unschedulable and required to be operated in time slots {18 - 20}, power is taken from grid, due to the non-availability of the PV power at that time slots. Also dish washer load is assigned a high *udc* to avoid delay in scheduling. Consequently it is ON during time slots {14 - 15}. With PV, the energy cost is reduced to 16.25 units.

Table 6.6: Home Appliance Schedule with PV

Hour	Lighting	Washing machine	Cloth dryer	Dish washer	Vacuum cleaner	Iron	Rice cooker	Grid Power
1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	2	0
8	0	2	0	0	0	2	0	0
9	0	2	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0
13	0	0	0	0	2	0	0	0
14	0	0	0	2	0	0	0	0
15	0	0	0	2	0	0	0	0
16	0	0	2	0	0	0	0	0
17	0	0	0	0	0	0	0	0
18	1	0	0	0	0	0	0	0.36
19	1	0	0	0	0	0	0	0.36
20	1	0	0	0	0	0	0	0.36
21	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0

6.8 Conclusion

The output power of the Photovoltaic source is stochastic in nature due to the uncertainty associated with solar irradiance. The random nature of the solar irradiance is modeled using Beta PDF. The discomfort caused due to delay in scheduling a load is also considered in the load model by including a factor *udc*. A solution to the residential load scheduling using Reinforcement Learning approach is developed. A large number of simulations are done and the results obtained are analyzed and verified. From the simulation results it is found that the loads are scheduled with minimum energy cost, effectively utilizing the PV and grid, and satisfying the constraints, which will be beneficial to the consumer as well as the utility.

Chapter 7

Prototype Implementation of Residential Energy Management System

7.1 Introduction

The grid connected PV systems are beoming a promising source of energy for residential sector, which is one of the major power consumers. This has markedly influenced the power consumption pattern of residential consumers. Efficient microgrid control methods with optimal scheduling of loads will provide reliable and cost effective energy utilization. The PBDR programs including intermittent PV power generation enable consumers to utilize energy more efficiently, leading to energy savings and cost reduction. But it is difficult or impractical for the consumers to control the loads manually considering the complexity associated with it and necessitated efficient automated load scheduling algorithm. By simulation experiments it is found that the developed RL algorithm helps to attain the goal of cost reduction along with considering the various constraints and priorities associated with loads and generation resources. In the smart grid scenario, with the development and integration of information and communication technologies, the practical implementation of the algorithm proposed for load scheduling is to be explored by exploiting the two way communication feature between consumer and utility.

The performance of the load scheduling algorithm in a practical system is investigated by implementing a Residential Energy Management System (REMS) using NodeMCU IoT setup. In this work, only the load scheduling and communication technologies associated with it is focussed. For making it a real time system, suitable controller modules of the invereter also is to be developed. The prototype model developed to showcase the algorithm is described in this chapter.

7.2 Residential Energy Management System (REMS)

A residential consumer with a grid connected rooftop PV system is considered for study, with five different types of appliances. The architecture of REMS is explained below.

7.2.1 Architecture of REMS

The prototype Residential Energy Management System includes an Energy Management Controller (EMC), a user interface and device status indicators. The architecture of the proposed system is shown in Fig 7.1.

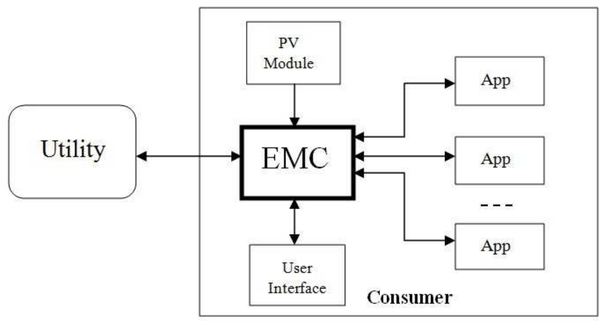


Figure 7.1: Architecture of REMS

The EMC receives the load details and constraints as entered by the consumer. Forecasting of PV power for the next day is done a priori using the probability distribution function. The forecasted PV power generation for different time slots is being communicated to the utility so that they can fix the tariff for different time slots. The tariff reflects the promotion of photovoltaic power instead of grid whenever it is available. The EMC receives the tariff from the utility through communication interfacing. Optimal load schedule for the different loads are generated by the consumer based on the tariff. The obtained ON/OFF status is communicated to the various relays connected to the loads at each and every time slot. The EMC also provides the facility to reschedule the loads automatically as desired by the consumer or demanded by the utility. Using the user interface the consumer can initialize the status of each load as per the requirement such as the power rating, duration of operation and flexible operating interval. Consumer is also having the flexibility to modify/reschedule in case if any change is needed.

7.2.2 Functionalities of REMS

The different functionalities of REMS can be described as follows.

- Add/Edit Device details

  This enables the consumer to enter and update the details such as start time s_j, finish time f_j, ON duration l_j, power rating r_j and udc_j value of each load j depending on the requirement.

- Forecast PV power

  The consumer can simulate the PV power using the PV power modeling and forecasting program and is communicated to the utility. Utility provides the tariff based on the availability of PV power at different time slots.

- Load scheduling

  The load scheduling is done using Reinforcement Learning algorithm based on PV power generation and real time tariff and optimal load schedule is obtained. The load scheduling program generates a matrix of arrays with values 0 or 1 or 2 at each slot, to indicate the appliance status. After scheduling the device status is indicated as 0 if device is OFF, 1 if connected to utility grid (source 1), 2 if connected to PV (source 2). This schedule is available to the consumer.

- Display device status

  The generated load schedule of the various devices are communicated and the status of these at different time slots displayed. Also based on the device status two power values, power taken from Grid and PV are updated and finally sent to utility.

The Signal flow in REMS is illustrated in Fig 7.2.

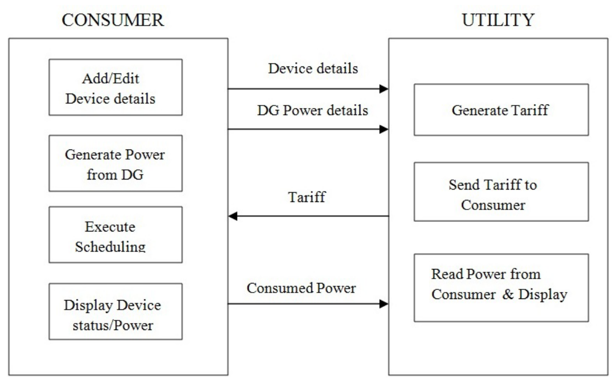


Figure 7.2: Signal flow in REMS

7.2.3 Prototype Implementation

The prototype implementation of the REMS is done using a NodeMCU. The NodeMcu is an open-source firmware and development kit that helps to Prototype the IoT product within a few Lua script lines or *C* codes. NodeMCU is like Arduino Hardware with a input output built in the board itself. It has also a Wi-Fi built in to connect directly to internet to control the things online using Nodejs Style network API for digital network applications, which facilitates developers to code running on the Board and speed up the Internet of Things application development process. The Development Board is based on ESP8266 Chip. The user interface is implemented using Visual Basic and communication is enabled through Wi-Fi. The prototype setup is shown in Fig 7.3. One day is divided into 24 time slots for scheduling and

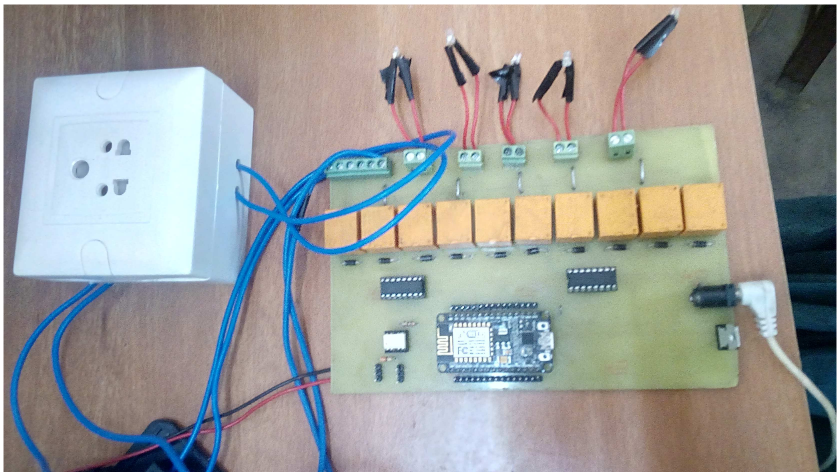


Figure 7.3: Prototype setup

tariff updates. In the proto type, the duration of one time slot is taken as one minute instead of one hour. The procedure for energy management is as follows:

- Initialize the status of each load such as, start time, finish time, ON duration, power rating and udc through the user interface by the consumer.

- Simulate the PV power using the PV power modeling and forecasting program and communicate to the utility. Utility provides the tariff based on the availability of PV power at different time slots.

- Obtain the optimal load schedule using Reinforcement Learning algorithm based on PV power generation and real time tariff. After scheduling the device status is indicated as 0 if device is OFF, 1 if connected to utility grid (source 1), 2 if connected to PV (source 2). This schedule is available to the consumer.

- The obtained ON/OFF status at each time slot is communicated to the various relays connected to the loads and power taken from Grid and PV are updated and finally sent to utility.

7.3 Results and Discussions

To investigate the performance of the proposed scheduling algorithm, a grid connected smart home with PV source and schedulable and nonschedulabe appliances is considered. The PV capacity is taken as 3kW. Typical schedulable appliances in the home include Washing machine, Cloth dryer, Dish washer and Vacuum cleaner. These appliances operate with different time intervals, duration of operation and power ratings. Also the consumer's willingness to tolerate delay in operation of the schedulable devices is indicated by proper choice of *udc* value. The parameters of the household devices are given in Table 7.1.

Table 7.1: Parameters of Household Devices

Sl. No.	Appliance	s	f	l	r	udc
1	Lighting	18	20	3	0.36	8
2	Washing machine	8	14	4	0.50	1
3	Cloth dryer	11	17	3	1.80	0
4	Dish washer	14	19	2	1.20	9
5	Vacuum cleaner	9	14	3	0.65	1

The PV power is simulated using PV power modeling and forecsting program and is communicated to the utility. The tariff provided by the utility is used for load scheduling. The optimum load schedule is generated by running the load scheduling program using RL algorithm. The screenshots showing consumer details entry through user interface, DG power generation and load scheduling are given in Figs 7.4, 7.5 and 7.6 respectively.

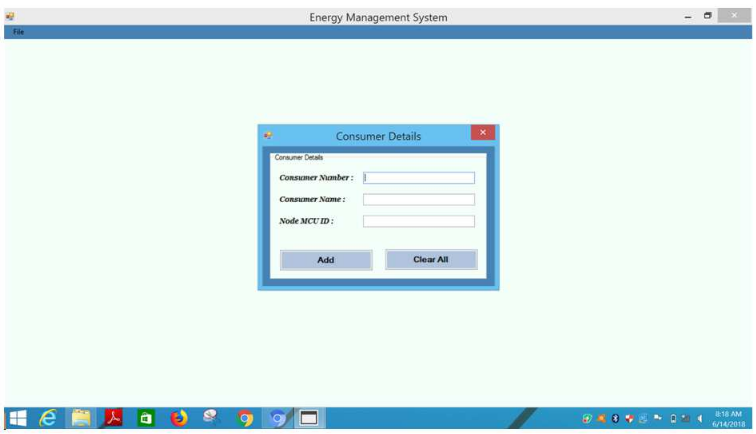


Figure 7.4: Consumer details

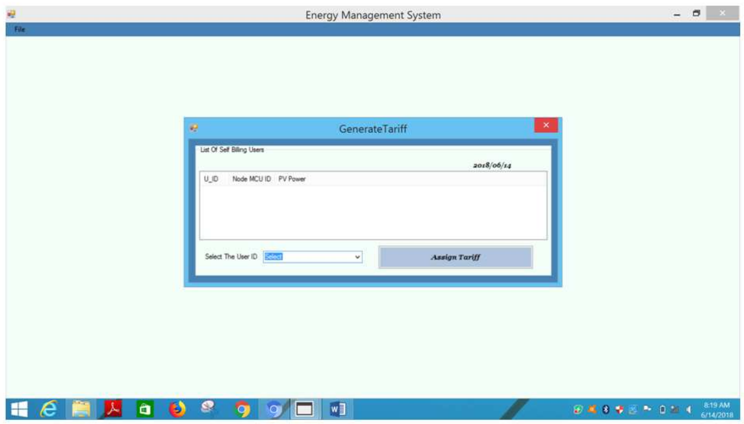


Figure 7.5: Tariff generation

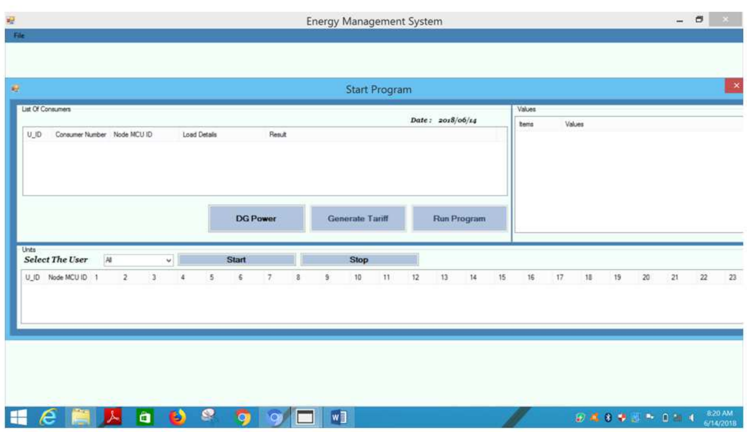


Figure 7.6: Load scheduling

Table 7.2: Home Appliance Schedule with PV

Hour	Lighting	Washing machine	Cloth dryer	Dish washer	Vacuum cleaner	Grid Power	PV Power
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0.40
8	0	2	0	0	0	0	1.05
9	0	2	0	0	0	0	1.92
10	0	2	0	0	0	0	2.64
11	0	2	0	0	2	0	2.77
12	0	0	2	0	2	0	3.07
13	0	0	2	0	2	0	2.95
14	0	0	2	1	0	0	2.31
15	0	0	0	2	0	0	1.74
16	0	0	0	0	0	0	1.07
17	0	0	0	0	0	0	0.56
18	1	0	0	0	0	0.36	0
19	1	0	0	0	0	0.36	0
20	1	0	0	0	0	0.36	0
21	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0

The load schedule obtained is given in Table 7.2. The schedule obtained corresponds to minimum enrgy cost of 33.95 units, effectively utilizing grid power and PV power. All the appliances are scheduled as per the requirement of the consumer. The switching ON of dish washer with a high value of *udc* should not be delayed and in the absence sufficient PV power, its swiching ON interval is found to be {14,15}, though 14^{th} time slot is a high priced slot for grid power.

7.4 Conclusion

The developed RL algorithm for load scheduling with PV is tested by implementing a prototype model of Residential Energy Management System using a NodeMCU IoT setup and verified the results through the display status of the devices in the set up. Thus the proposed RL algorithm is found to be implementable. But the real implementation demands more research in the direction of interfacing of controllers associated with PV sources. Here, just a status indicator alone is incorporated to indicate and prove the working of the developed scheduling algorithm. Recent government policies promote large scale deployment of grid connected roof top PV systems for residential consumers and the proposed implementable solution will be beneficial to both consumer as well as the utility and a step towards promoting clean energy.

Chapter 8

Conclusions and Future Work

8.1 Introduction

Continuously growing energy demand and associated challenges are of major concern in electric power sector currently. In the Smart Grid framework, price based Demand Response (PBDR) programs are identified as one of the means to address this issue by motivating changes in electricity use by consumers in response to time varying electricity price. In the present energy scenario a major part of the flexible demand arises from the residential consumers and PBDR programs can be effectively used for controlling the loads of smart residential buildings thereby reducing consumer electricity bill and maximum demand on the system. Recent advancements in energy usage of the residential consumer by way of integration of intermittent roof top PV sources increases the complexity of DR strategy. Residential load scheduling problem need to consider several factors like operational constraints of the appliances, consumer comfort related to delay in scheduling the appliance, uncertainty associated with PV generation, time varying tariff etc. Devising suitable method to obtain optimum load schedule with minimum energy cost by efficient utilization of all the available resources is significant in residential load scheduling and a step towards meeting the increasing demand.

Review of concept and different aspects of Smart Grid is carried out, to get an overview of various features of Smart Grid. One of the management objectives of the Smart Grid is identified as efficient use of available energy. Demand Side Management is thus found to be one of the important functions of Smart Grid. Review on various techniques used to realize DSM and DR in general is done. The main objective is to reduce the electricity bill of the consumer and to reduce the maximum demand. The various methods used for residential load scheduling is reviewed in detail. From the literature, it is seen that future residential consumer will have renewable sources, schedulable loads, nonschedulable loads and various time dependant tariff. Power generated from renewable sources like PV is random in nature. The consumer will want to minimize his electricity bill without compromising on the comfort. A complete and comprehensive model need to be developed considering all these aspects. Also, the problem is a decision making problem under uncertain environment.

Various analytical and soft computing methods are used to solve the problem. Most of these methods discussed in the review lack the ability to handle stochastic data. The stochastic learning algorithms are capable of solving such problems under uncertain environment.

8.2 Summary and Major Findings

The different features of smart grid and the significance of Demand Side Management and Demand Response are reviewed. Review of methods for residential load scheduling directed to the scope of formulating a generalized mathematical model and implementable solution for the residential load scheduling problem with intermittent PV source. In this research work application of stochastic learning algorithms for residential load scheduling with PV source is proposed in the smart grid context.

8.2.1 Generalized Mathematical Model

Future residential consumer will have renewable sources, flexible loads, non-flexible loads and various time dependant tariff. Power generated from renewable sources are random. The consumer desires to minimize his electricity bill without compromising on the comfort. This delay causes some inconvenience or discomfort to the consumer. A generalized mathematical model which can include different renewable sources is developed for the residential load scheduling problem taking into account all these aspects. A parameter *udc* incorporated in the load model capture the degree of discomfort.

8.2.2 Load Scheduling Using Binary Particle Swarm Optimization

A solution to basic load scheduling problem is developed using Binary Particle Swarm Optimization (BPSO) algorithm. This problem considered the operational needs of the loads and utility grid as the power source. The

BPSO algorithm is formulated as a minimization problem by taking fitness function as the total daily energy cost. Load schedule is obtained from the global best particle value and the minimum cost from the gbest value. The algorithm is validated and obtained the load schedule with minimum cost and satisfying various operating constraints. With a case study of a residential consumer with different types of loads, the algorithm is verified. With consumer comfort and uncertain PV source the complexity of the problem is increased and it is difficult to get solution with this algorithm.

8.2.3 Load Scheduling Using Reinforcement Learning

In this case, the simple load model is modified by including a factor *udc* to account for delay in scheduling. The load scheduling problem with the modified load model considering consumer comfort and grid power, is formulated as a multistage decision making problem and a stochastic learning algorithm using Reinforcement Learning (RL) is developed to solve the problem. The state variables are taken as the the current time slot and the ON duration of the load. At each state, the action to be taken is whether to switch ON or OFF the load. Based on the action taken, a new state is reached and a cost is obtained which is used to update Q-value. Using the Q-learning algorithm the optimum load schedule is obtained. With different types of loads, the results obtained using RL algorithm are validated and compared with that of Learning Automata (LA) algorithm. The RL algorithm is verified considering the case study of a residential consumer and the load schedule corresponding to minimum cost is obtained.

The method is found to be efficient compared to LA and BPSO algorithms.

8.2.4 Uncertainty Modeling and Load Scheduling Using Reinforcement Learning with PV Source

The fluctuating power generation from PV source is considered by modeling the uncertainty associated with the solar irradiance. The solar irradiance data of the site selected is taken from National Renewable Energy Laboratory (NREL) solar radiation database. The hourly solar irradiance of the site under study for a period of one year is collected and is modeled using Beta PDF. This is used to estimate the power output from the PV source.

The residential load scheduling problem including a roof top PV system is considered. A solution to the load scheduling problem is developed using RL, considering the presence of uncertain PV power generation, consumer comfort aspect, operating constraints of various loads and time varying tariff. At each state, considering the simulated PV power, here the action to be taken is whether to switch ON from grid or PV or switch OFF the load. Depending on the action selected the state changes and the corresponding cost incurred is used to update Q-value. The RL algorithm is validated and found to be effective in providing the best load schedule with minimum energy cost, efficiently utilizing the resources. The developed RL algorithm is analyzed for a variety of load data. Finally the developed RL algorithm is realized by implementing a prototype model of Residential Energy Management System using a NodeMCU IoT setup and the results are verified.

8.3 Major Research Contributions

The research work provides an implementable solution to the residential load scheduling problem considering PV source in the Smart Grid Scenario. A generalized model is developed incorporating the renewable DG sources. A solution method using BPSO algorithm is developed for basic load scheduling problem. The unceraínty associated with PV source is modeled using Beta PDF. Stochastic learnig algorithms are developed to find optimum load schedule with minimum cost and satisfying the various constraints. The algorithm is implemented by setting up a prototype model of Residential Energy Management System.

The main contributions of the thesis can be summarized as,

1) A generalized mathematical model for load scheduling problem including renewable sources is developed.

2)Stochastic learning algorithms using Binary Particle Swarm Optimization, Learning Automata and Reinforcement Learning are developed and are used in solving residential load scheduling problem so as to get optimal load schedule with minimum energy cost.

3) The uncertainty associated with the solar irradiance is modeled using Beta PDF and is utilized for calculating the power generation from PV source.

4) A Reinforcement Learning algorithm is developed for the solution of residential load scheduling problem with PV source to obtain the optimal load schedule with minimum energy cost, efficiently utilizing the resources.

5) The developed RL algorithm is verified by implementing a prototype model of Residential Energy Management System using a NodeMCU IoT setup and the results are verified.

Large scale deployment of roof top PV system by residential consumers together with variable pricing schemes introduced by the utilities impose the need for efficient algorithms that can be used by the consumers to intelligently schedule their appliances with minimum inconvenience and minimum cost. The stochastic learning algorithms proposed can be used to obtain a solution to this problem and it will be beneficial to both consumer and utility.

8.4 Limitations and Future Work

In this thesis work, only PV source is considered for residential load scheduling. Renewable DG sources such as wind turbine based generation, fuel cell etc can also be considered as power source for load scheduling to obtain optimum load schedule. The formulation can be made more general by including storage within the consumer premises into the model. Uncertainty associated with pricing and load arrivals also can be modeled. Generation scheduling can also be included.

As a future work, residential load scheduling including renewable generation with storage considering price and load uncertainties can be considered. Also load scheduling and generation scheduling can be combined to a single task for energy management.

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List of Publications

1. Remani T., E. A. Jasmin, T. P. Imthias Ahamed "Residential Load Scheduling with Renewable Generation in Smart Grid: A Reinforcement Learning Approach", IEEE Systems Journal - Accepted for publication.

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3. Remani T., E. A. Jasmin, and T. P. Imthias Ahamed "Load scheduling problems under demand response schemes: A survey." Signal Processing, Informatics, Communication and Energy Systems (SPICES), 2015 IEEE International Conference on. IEEE, 2015.

4. Remani T., E. A. Jasmin, and T. P. Imthias Ahamed "Load scheduling with maximum demand using binary particle swarm optimization." Advancements in Power and Energy (TAP Energy), 2015 International Conference on. IEEE, 2015.

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