DEVELOPMENT OF ADVANCED SMART ENERGY MANAGEMENT FRAMEWORK INTEGRATED WITH OPTIMIZATION TECHNIQUES AND PREDICTION MODELS FOR DEMAND SIDE CONSUMERS BASED ON IOT PLATFORM

Thesis

Submitted in partial fulfillment of the requirements for the degree of
DOCTOR OF PHILOSOPHY

by

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November, 2020

DECLARATION

by the Ph.D. Research Scholar

I hereby ***declare*** that the Research Thesis entitled ***"Development of Advanced Smart Energy Management Framework Integrated with Optimization Techniques and Prediction Models for Demand Side Consumers Based on IoT Platform"*** which is being submitted to the **National Institute of Technology Karnataka, Surathkal** in partial fulfilment of the requirement for the award of the Degree of **Doctor of Philosophy** in **Department of Electrical and Electronics Engineering** is a **bonafide report of the research work carried out by me**. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

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Place: NITK-Surathkal.

Date: 20-11-2020

CERTIFICATE

This is to certify that the Research Thesis entitled ***"Development of Advanced Smart Energy Management Framework Integrated with Optimization Techniques and Prediction Models for Demand Side Consumers Based on IoT Platform"*** submitted by Prakash Pawar (Register Number: 148047 EE14FV10) as the record of the research work carried out by him, is accepted as the ***Research Thesis submission*** in partial fulfillment of the requirements for the award of degree of Doctor of Philosophy.

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Abstract

Smart grid framework plays an indispensable role in dealing with the usage of available electrical energy proficiently. However, to manage power supply effectively, electrical appliances and devices at home and building environment should have smart energy management capability. Further, Smart Energy Management System (SEMS) can be unified with the smart grid for effective power consumption. SEMS can be used to control the status of the electrical appliances and devices by monitoring environmental conditions with the associated sensors and the context in which the appliance is being operated. In addition, SEMS can be used to reduce the standby power consumption of the appliances by turning off the supply to it. The SEMS system can be associated with a Grid or the distributed generation, and thus power negotiation techniques can be applied depending on the availability of the power or tariff information. In this research work, the emphasis is given to the design of a smart energy management system and deployment of power negotiating algorithms for effective power utilization. The proposed SEMS replaces the scenario of a complete power outage in a particular region with partial load shedding in a controlled manner as per consumer's priority. The hardware experiments are demonstrated assuming a demand response event, taking into account the constraints of maximum demand limits in various cases of changing priorities. The cost optimization algorithms are deployed by scheduling the appliances, considering the Time of Usage (ToU) and minimum slab rate. Sensory information's and indicators are used to control the loads with user comfort settings and alarm the user during peak hour usage, respectively. Reliable ZigBee communication is established in the Application Transparent (AT) mode of configuration with a self-diagnostic mechanism. Internet of Things (IoT) environment is created for uploading the data, storing it in the database with load wise data analysis daily and monthly basis with Graphical User Interface (GUI).

The challenge of energy shortages requires an optimized solution to demand-side consumer issues. Energy demand factors contribute to the implementation of variable tariff's and reward consumer's electricity usage during off-hours rather than during peak hours. In addition, the surge in tariffs and price volatility emphasize the need to carefully schedule the operation of large devices to minimize power consumption. In this task, a genetic algorithm is used to find the optimal load schedule that minimizes the cost spent on power according to considerations such as user comfort, maximum allowable demand, load characteristic's, environmental factors and so on. Further, this work will focus on testing the Binary Backtracking Search and Artificial Bee Colony algorithms against the Binary Particle Swarm algorithm benchmark to find the optimal load scheduling in terms of complexity, cost optimization, and execution time.

On the other hand, the challenge in energy management lays focus on the efficient utilization of available power sources without limiting power consumption. Above issue seeks for design and development of an intelligent system with day-ahead planning and prior forecasting of energy availability. Hence there is a need for accurate energy prediction technique to minimize imbalance in the power sector. In this context, an Intelligent Smart Energy Management Systems (ISEMS) is proposed to handle energy demand in a smart grid environment with penetration of renewable sources. The proposed scheme compares several prediction models for accurate forecasting of energy for hourly and day-ahead planning. Based on the predicted information, ISEMS negotiates the available power and dispatch the control action depending on the consumer assigned priority for an appliance. Several energy prediction models are evaluated and it is found that the Particle Swarm Optimization (PSO) based Support Vector Regressors (SVR) outperforms over other prediction models in terms of performance accuracy.

Keywords: Demand Response (DR); Demand Side Management (DSM); Internet of Things (IoT); Particle Swarm Optimization (PSO); Renewable Energy sources(REs); Smart Energy Management Systems (SEMS); Smart Grid (SG); Time of Use (ToU); ZigBee.

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List of Abbreviations

AMI	Advanced Metering Infrastructure
ABC	Artificial Bee Colony
ADC	Analog to Digital Converter
AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Network
AT	Application Transparent
BPSO	Binary Particle Swarm Optimization
BSA	Backtracking Search Algorithm
CPP	Critical-Peak Pricing
CMP	Capacity Market Program
DLC	Direct Load Control
DR	Demand Response
DSM	Demand Side Managemnt
DSEM	Demand Side Energy Management
EDRP	Emergency Demand Response Program
EMS	Energy Management System
ESS	Energy Storage System
GA	Genetic Algorithm
GUI	Graphical User Interface
HEMS	Home Energy Management System
HAN	Home Area Network
HIC	Heat Index in Celsius
HVAC	Heating ventilation and air conditioning
IoT	Internet of Things
ISEMS	Intelligent Smart Energy Management Systems
LED	Light Emitting Diode
LCD	Light Crystal Display
MAPE	Mean Absolute Percentage Error
MDL	Maximum Demand Limit
MRE	Mean Relative Error
NAN	Neighborhood Area Network
NREL	National Renewable Energy Laboratory

PAN	Personal Area Network
PLC	Power Line Carrier
PSO	Particle Swarm Optimization
PV	Photo-voltaic
REs	Renewable Energy sources
RF	Random Forest
RMSE	Root Mean Square Error
RTC	Real Time Clock
RTP	Real-Time Pricing
SG	Smart Grid
SM	Smart Meter
SEMS	Smart Energy Management System
SSM	Smart Socket Module
SVR	Support Vector Regression
ToU	Time of Use
WAN	Wide Area Network
WAMP	Windows Apache MySQL and PHP

Chapter 1

Introduction

This chapter presents an introduction of the thesis, including an overview and scope of the research work. Following, the description of research objectives. Finally, the overall organization of the thesis are included.

1.1 Overview

Modern electricity meters can measure power consumption with reasonable accuracy. However, it requires manual reading, which is tedious and depends on human resources. Outage management and recovery in the event of fault detection are time-consuming processes in traditional metering systems. It is therefore essential to upgrade our existing metering system. In this context, smart meters offer a practical solution with built-in communication capabilities. Smart meters support a two-way flow of information between the utility centre and consumers. Thus, Advanced Metering Infrastructure(AMI) contributes an integral part in the context of the Smart Grid(SG) framework, which facilitates full automation of various tasks related to power usage. The smart grid framework plays an integral role in addressing the utility and demand consumers and managing electrical energy efficiently. Overview of SG infrastructure for DSM is shown in Figure.1.1.

Further, Demand Side Energy Management(DSEM) mainly focus on the Demand Response(DR) program and Load management task at the consumer end. The DR program encourages the consumer to participate during peak hours by providing them economical and financial benefit and hence, balance the load profile curve (Gelazanskas and Gamage, 2014). Furthermore, load management allows the consumer to save

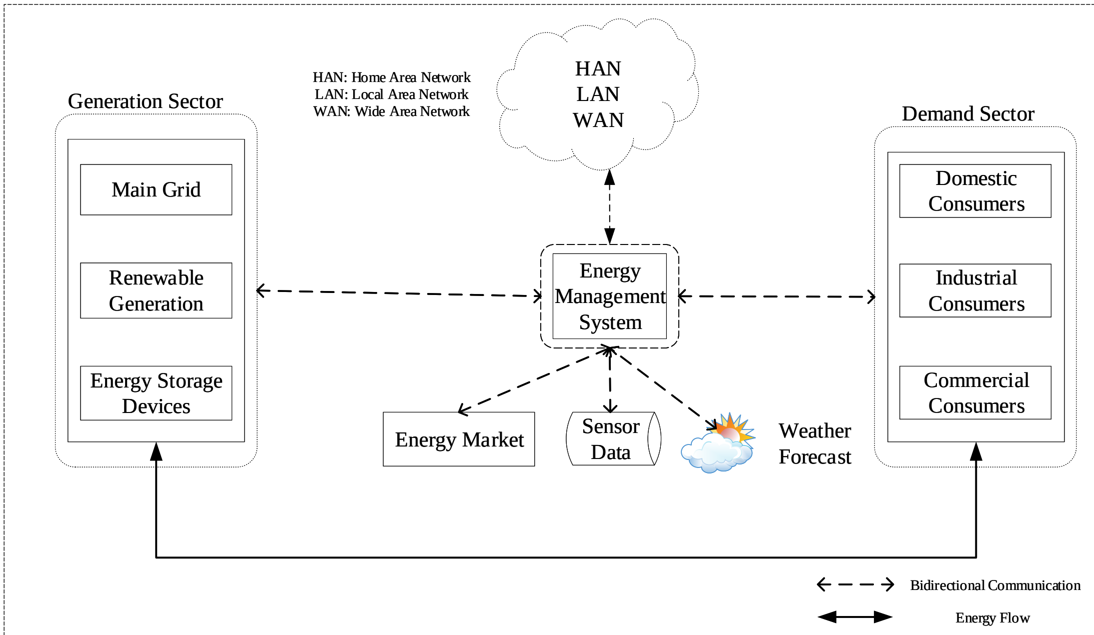

Figure 1.1: Overview of SG infrastructure for DSM consumers

electricity cost by having control over the individual appliance. However, to manage power supply effectively, electrical appliances and devices at home and building environment should have smart energy management capability. Further, the Smart Energy Management System(SEMS) can be unified with the grid for effective power utilization. Smart Energy Management System can be used to control the status of the electrical appliances and devices by monitoring environmental conditions with the associated sensors and the context in which the appliance is being operated. In addition, SEMS can be used to reduce the standby power consumption of the appliances by turning off the supply to it. The SEMS systems can be integrated with grid or distributed generation so that power negotiation techniques can be applied depending on the availability of power or tariff information. In this context, emphasis will be given to the design of smart sockets and deployment of power negotiating algorithms for effective power utilization.

The technology that connects everything in our daily lives to the Internet, exchanges information, and controls each other is called the Internet of Things (IoT). In addition, the use of IoT has enabled a variety of services that improve the convenience of living. As a familiar example, a location can be used to detect when a smartphone is approaching a house and automatically turn on air conditioning and home lighting. Moreover, an IoT environment can be used to monitor various services and energy management operations.

On the other hand, one of the main goals of the smart grid is to save energy consumption and minimize electricity costs. For residential, commercial and industrial sectors, interruptible loads can be properly scheduled to reduce peak demand and select lower tariff prices. Depending on the energy sector, load usage continues to change. Some loads can be interrupted continuously, while others can be more user-friendly based on time of use. Therefore, the increased load and random nature of usage make it difficult to schedule appliances optimally. Therefore, researchers have opted to solve this problem using optimization techniques. In literature, there are several approaches discussed for scheduling demand-side load considering constraint parameters, computational time, complexity, best accurate schedule and ease of implementation. Previously, authors have used linear, non-linear and mixed-integer programming methods to solve the scheduling problem and minimize the electricity consumption. The authors, (Pedrasa et al., 2009), have used Binary Particle Swarm Optimization (BPSO) algorithm to solve a complex problem with widely varied load constraints to obtain the best operational schedule and minimize the overall electricity cost. Maximum demand, usage time, and the number of hours the appliance is running determine the optimal schedule of load sets to save on electricity bills, taking into account user comfort. In this context, flexible loads are considered, as well as time-based tariffs that take into account peak times. Performance evaluation of various algorithms is performed in terms of computation time and optimal scheduling.

In the present scenario, the usage of renewable energy sources is of great interest in the modern community due to increased energy demand and growing concern over the hazardous environmental condition. Further, the availability of renewable energy sources such as solar or wind energy is very random and unpredictable. The deep penetration of renewable energy source integrated with smart grid environment makes the system more challenging in terms of the energy management task.

The potential benefits of renewable sources greatly depend on the availability of energy depending on the environmental factors. Further, due to its intermittent nature to handle renewable source integrated with smart grid environment poses a complex challenge in the efficient utilization of energy. The reliable solution could be, storing the excess energy during peak generation and using it later but at the cost of expensive investment on storage devices. One of the alternate solutions would be feeding surplus energy to the conventional grid system with the fixed tariff price and buyback during a deficit of energy. Thus, developing an intelligent energy management system is crucial to handle the uncertainties and provide reliable energy supply at a reasonable cost. It is necessary to take into account the change in the amount of solar power generation due to seasonal weather. Therefore, it is required to establish the correlation between the solar power generation amount and variation of weather parameters. Several parameters are influencing the generation of PV energy, which are identified as sun intensity, cloud cover, wind speed, ambient temperature, rain, geographical location along with sun-set and sun-rise time, etc. In literature several approaches and prediction models are discussed considering weather parameters (Gigoni et al., 2017),(Yona et al., 2013).

In this work, the emphasis is given to predict the availability of solar energy considering factors affecting the solar intensity due to seasonal variation. The historical data of solar irradiation and other dependent parameters from the NREL database is collected. Several machine learning-based prediction models are evaluated to find the accurate model. Further, the predicted power is assumed to demonstrate the different scenarios for optimal load strategy.

1.2 Research Motivation

In light of the literature survey, it is observed that the following topics motivate and finds the scope of research in the area of demand side energy management.

- In the energy sector, there is a need for an integrated co-operative operational mechanism taking into account of power supply and demand entity to reduce the mismatch.
- The power management operational task seeks for the development of inexpensive and efficient Smart Energy Management System(SEMS). Further, deployment of power negotiating algorithms with reliable communication capability is essential to reduce the overall power consumption and hence, minimize the electricity cost.
- A comprehensive initiative in smart grid is essential, which includes an energy management framework associated with an IoT environment that monitors and

visualizes power consumption at the consumer premises.

- Optimization techniques are to be evaluated to find the cost effective and computationally efficient approach for the given demand side consumer constraints.
- Accurate prediction of power generation or power availability is required for proper scheduling mechanism.

Considering the scope from the above literature, research objectives are framed to address the demand side energy management issues.

1.3 Organization of the Thesis

In this thesis, the overall content is organized into six chapters and three appendices. This section briefs about the overview information of each chapter and appendices. The outline of the thesis is highlighted in Figure 1.2.

- **Chapter 1:** This introductory chapter describes the outline and scope of the research, the motivation for the research, and the structure of the thesis.
- **Chapter 2:** In this chapter, a thorough literature survey has been carried out to introduce state-of-the-art technologies and to identify potential gaps in the area of demand-side energy management. It also describes the identified research gaps and research objectives.
- **Chapter 3:** This chapter describes the development of a smart energy management system that deploys a power negotiation algorithm with reliable communication capability. Several experimental demonstrations are performed, taking into account different configuration scenarios.
- **Chapter 4:** This chapter presents various optimization techniques for demand-side energy management applications to reduce costs and computational, time taking into account user-defined constraints.
- **Chapter 5:** This chapter discusses the accurate forecasting of renewable power for demand-side managed consumers considering historical data from the National Renewable Energy Laboratory (NREL) website. Performance evaluations of various machine learning models are carried out to find the best and accurate model to predict available power generation.
- **Chapter 6:** This chapter presents contributions and conclusive remark. A brief discussion on the future scope of the work is also included.

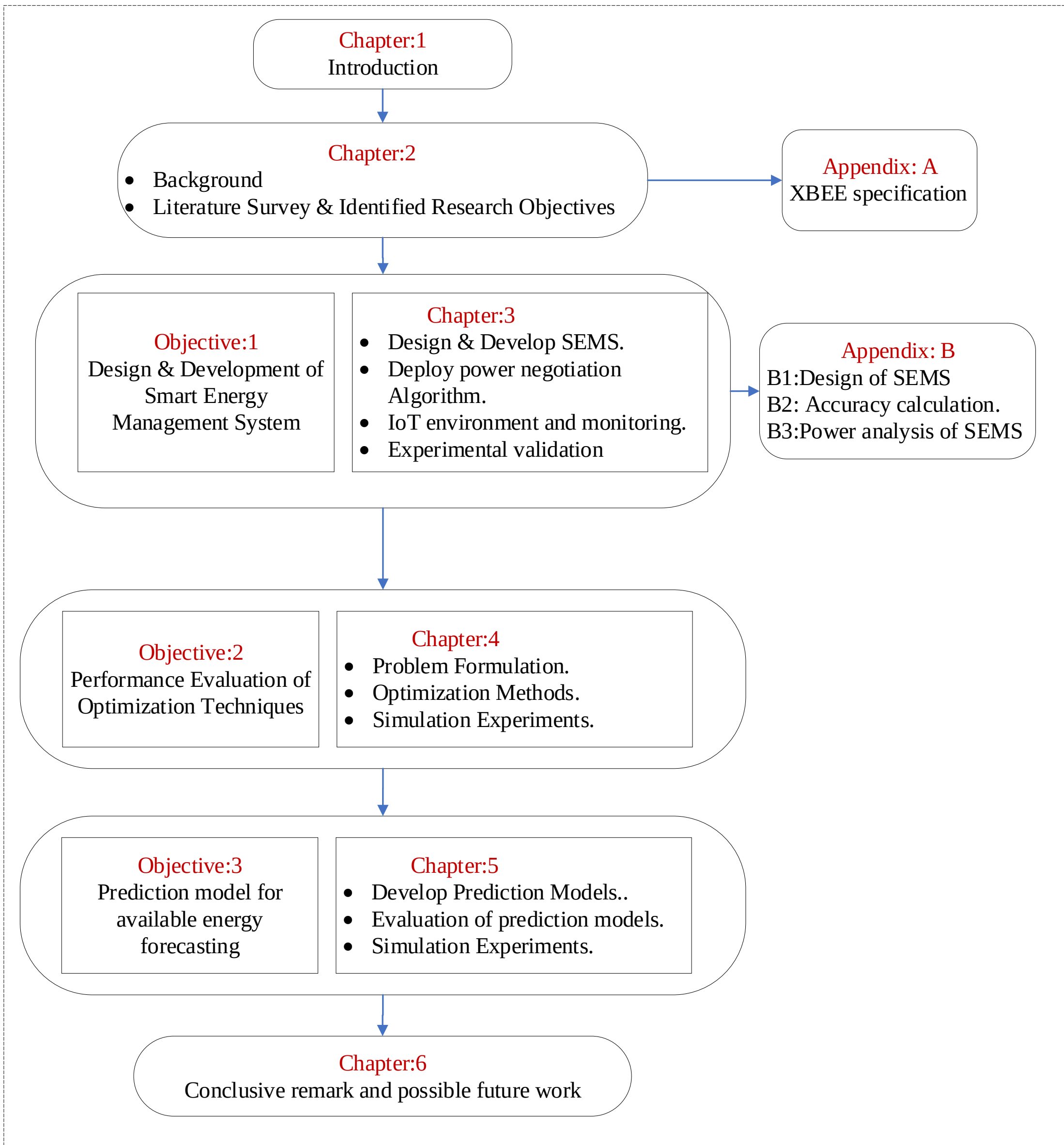

Figure 1.2: Outline of the thesis

Chapter 2

Literature Survey

The present study deals with the development SEMS, optimization techniques and prediction models for demand-side consumers. Hence, the detailed background study and the state-of-the-art related to SEMS, optimization techniques and prediction models are discussed in this chapter.

2.1 Background

2.1.1 Deregulation Move and Necessity of Automation

It is desirable to analyse why the deregulation of the energy market has made automation solutions essential and hence, it is advisable to understand the concept above. The following paragraphs briefly describe the idea and relevance of deregulation. For the past few years, utilities have been operating under a unique model set by government agencies. Electricity companies have the right to generate and supply electricity to certain areas based on regulatory regulations set by the Regulatory Commission to restore electricity rates and profit margins. Electricity industry regulations are rules and restrictions set by government agencies that define how a particular industry operates(Sharma et al., 2012).

- **Characteristics of Regulatory Industry:**

  Monopoly Franchise: Monopoly refers to situations where a single entity or one company manages the power sector industry. The above status, given by government agencies in that territory, allows only local utilities to generate, distribute, and sell electricity commercially.

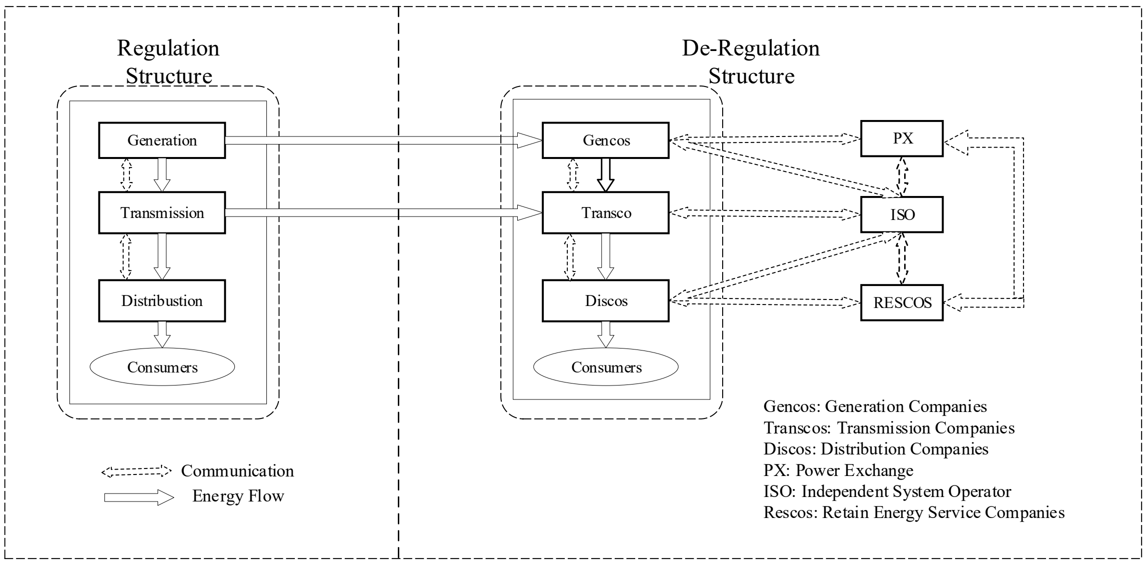

Figure 2.1: Power structure in a De-regulated environment (Lai, 2001)

Obligation to serve: The utility agrees to provide electricity to consumers in all categories in the region, regardless of profit margin.

Regulatory monitoring: Utilities should operate in a way that minimizes overall revenue requirements.

Regulatory Charges: Utilities charges are set in accordance with government regulatory rules and guidelines.

Assumed rate of return: The utility is assured a fair return on its investment, if it confirms to the regulatory guidelines and practices.

- **Deregulation:** Deregulation in Power Industry is a restructuring of the rules and economic incentives by expanding the role of customers in the pooled electricity market, including private participants. The transition of power sector from regulated to deregulated structure has many positive and negative consequences.

  Deregulation has brought several entities to the market, while redefining the scope of many of the existing players activities. There is variability among players in the market as to how each entity defines its role in the power system. However, at a broader level, the structure of the power sector can be identified after deregulation the as shown in the Figure 2.1.

- **Motivation for Deregulation:** There are many reasons that have led to deregulation of power systems. Deregulation will achieve the elimination of central control and improved economic efficiency of electricity. Due to competition, electricity prices can fall in the electricity sector, which benefits consumers (Abhyankar and Khaparde, 2013).

  For the following reasons, a major change in the scale of the economy is observed:

  1. Technological innovation improved the efficiency of small units for gas turbines, combined cycles, hydro and fuel cells over that of large ones.
  2. Improvement in materials, including new high temperature metals, special lubricants, ceramics, and carbon fiber, permit vastly stronger and less expensive small machinery to be built.
  3. Computerized control systems have been developed and often have zero staff in the field.
  4. Data communications and offsite monitoring systems can control the unit from a remote operations center. The Remote Operations Center allows one central operator to monitor multiple units at different sites, each as if they were present.

Thus, in many cases it was possible to build new power plants that could provide energy at a lower price than the customer was paying for the energy from the existing old giant power plant. Electricity industry and commercial users are now able to build and operate their own plants to produce cheaper electricity than utilities and sell surplus electricity to smaller customers.

2.1.2 Smart Grid Infrastructure and Smart Meters

Currently, the generation of power monitoring and billing technologies relies on traditional energy meters. These meters are installed in individual homes to measure electrical energy consumption. The energy consumed is recorded, and bills are calculated by a person who checks the energy meter in each household. This process is very inefficient and time-consuming. Besides, manual calculations can be erroneous, and the amount of human resources required to complete a task is so large that the entire process is not scalable. The major problem is that consumers are unaware of their daily behaviour. The monthly feedback given to consumers is not enough to

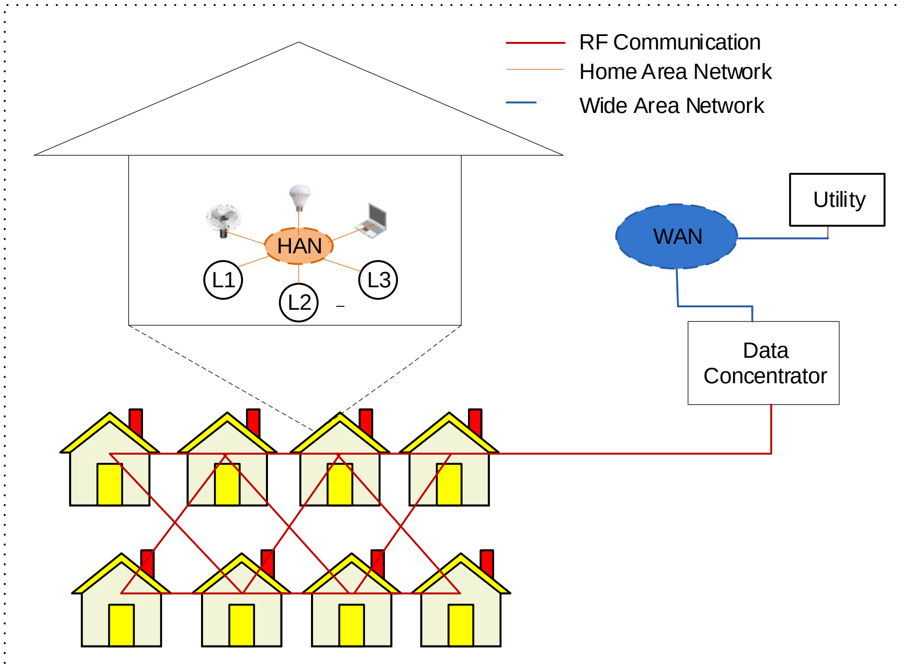

Figure 2.2: Smart meters in smart grid enviornment

measure how appliances consume energy. Smart meters are intelligent, network-based energy meters that solve most of the problems associated with traditional energy meters (Barai et al., 2015). Smart meters can provide consumers with usage alerts based on regular intervals of use of electrical energy. Also, the data collected by the smart meter is sent over the network to the regulatory committee, eliminating the need for manual calculations. Moreover, this reduces incorrect quotients in customs duty calculations and provides a better approximation of cost. Current energy meters have few limitations. Some of these meters lack a complete digital structure, leading to erroneous measurements due to their inability to accommodate mechanical components, the effort required to capture data, and the latest technological advances (Khalifa et al., 2010).

The next step in progress is implementing a smart grid system. Smart grid systems are built on the existing infrastructure of the power grid, but there are smart meters. Recent power grids make it challenging to notice fluctuations in the electrical load between appliances. As the population grows, the load on the power grid increases and the necessary changes must be made to improve the scalability of the system. The essence of smart grids is to increase grid efficiency through remote monitoring, reliability, and consumption measurement, and to communicate consumption by delivering data (in real-time) to consumers and suppliers (Selvam et al., 2012). Since conventional meters uses outdated technology, smart grid replaces traditional energy meters with promising meters that use computers to quickly calculate energy consumption and send information between homes and regulatory bodies. Moreover, it creates a much more scalable and efficient system. Smart Meter is the latest network-based energy meter, provides a medium for consumers to improve power consumption. Smart meters belong to the division of advanced measurement infrastructure or AMI and are responsible for automatically transmitting meter readings to energy suppliers. The benefits of smart meters are enormous, and almost all the problems associated with traditional meters can be solved by replacing traditional meters with smart meters. Figure 2.2 below shows an overview of the Smart Meter(SM) of the SG utility.

2.1.2.1 Advanced Metering Infrastructure (AMI)

AMI enables two-way communication between utility providers and consumers with the aid of a smart meter gateway. In addition, it allows customers to decide on better choices for their future energy usage. AMI comprises the transport of information on metering data to the aggregator of the energy provider (Liu et al., 2012). Because of the increased flow of information between the consumer and the utility providers, congestion and loss of information are prevalent. Hence, there is a need to improve the scalability of the network. Multi-channel capability can help achieve scalability. This can be achieved by introducing multiple subnetworks with different operating channels (Kulkarni et al., 2012).

2.1.2.2 Distribution System Automation

Distributed system automation plays a vital role in realizing the smart grid technology when implemented on local power lines and neighbourhood stations. Automation is a process of doing a particular task automatically in a sequence with faster operation rate and with minimal or no human assistance. It increases the reliability of the overall system with real-time monitoring and intelligent control mechanism. Further, the distribution system uses the sensory devices to gather the information and make a smart decision for the optimal flow of power. It is a very tedious job for a technician without the assistance of distribution system automation to identify and analyze system performance. Distribution automation system plays a vital role in early detection of the faults and preventing the outage or blackout of the system by regular maintenance (Mamo et al., 2009).

2.1.2.3 Smart Grids and Penetration of Renewable Energy Sources

The smart grid enables different entities like utilities, distributed generators and consumer premises to interface via communication and information technologies. The recent advancement in Renewable Energy sources (REs) is seen to be an excellent substitute for the diminishing conventional source of energy. Nowadays, to meet the energy demand and promote financial benefits to the consumer, renewable sources have made a deep penetration with the convention grid system (Eltigani and Masri, 2015). This phenomenal growth in the REs integrated with the grid system has a significant contribution to the energy sector. On the other hand, the intermittent and highly unpredictable nature of renewable sources poses a complex challenge in the reliability and stability of the system. Demand-side energy management techniques are an essential tool to monitor, store, and predict energy usage details and develop a sustainable energy framework.

2.1.3 Recent Developments in Energy Management System Associated with Smart Grid

Smart meters have a key role in the establishment of smart grid communication architecture. The conventional static digital meters do not account for the communication between utility and consumer premises. The automation of the metering system evolved with Advanced Metering Architecture (AMA), the meter is embedded with communication capability. In the AMA system, information related to energy usage, power outage and some fault conditions can be sent to the utility centre from the consumer premises periodically or on the occurrence of events. Thus, the AMA system facilitates automated billing and fast recovery from the power outages. Still, the system accounts for only one-way communication between the consumer end and the utility centre (Erol-Kantarci and Mouftah, 2015).

The next generation metering system evolved with an Advanced Metering Infrastructure (AMI), which incorporates two-way communication between the power utility and consumer premises. The AMI system includes Home Area Network (HAN) communication architecture, responsible for Home Energy Management System (HEMS), meter data management and smart meters communication. The architecture of AMI includes end-users, meter data management and communication layers. Hence AMI plays a major role in the metering system by alerting the consumers about energy usage parameters, which accounts for efficient power management.

2.1.3.1 Wireless Communication Technology for Energy Mangement System and Smart Meter Networks

Wireless communication supports the exchange of information between the transmitter and receiver through electromagnetic waves, without any physical connection. Wireless technology has an advantage over wired communication as it reduces the complication of cable installation. Wireless technology has been deployed over the last 30 years, and researches have put efforts to minimize cost, network complexity and power consumption. In smart metering, the communication network is classified into different categories based on the range of coverage such as Home Area Network(HAN), Neighborhood Area Network(NAN) and Wide Area Network(WAN). Home Energy Management System uses HAN to form a communication network within the consumer premises between different distributed appliances or loads. NAN collects the data from different HAN nodes. A survey shows widely used wireless technologies are Wi−fi, Wi-Max, Bluetooth and ZigBee for industrial automation. Hence it is required to choose suitable technology for the intended application(Gungor et al., 2011). A comparison of wireless technology based on power consumption, data rate, operation frequency and range of coverage is presented in the following Table 2.1.

Table 2.1: Comparison of various wireless technologies

	Bluetooth	Wi-fi	WiMAX	ZigBee
Standard	802.15	802.11a/b/g/n	202.16	802.15.4
Data Rate	1 Mbps	11–52 Mbps	70–80 Mbps	up to 250 Kbps
Operating Range	10 meters	50-100 meters	up to 50 kilometres	10-100 meters
Power Consumption	Medium	High	High	Very Low
Security	Yes	Yes	Yes	Yes
Complexity	Medium	High	Very High	Low

- **ZigBEE Devices**

XBEE wireless devices use the open global standard IEEE 802.15.4 ZigBee protocol to provide wireless connectivity between two terminals. ZigBee devices [1] consume low power due to long-lasting battery, low latency for low data rate transfer, and various networking options. These features make ZigBee the right candidate for the industrial and home automation sectors.The XBee device can be configured into three different modes as follows:

1. Coordinator
2. Router
3. End Device

- **Coordinator:** XBee as a coordinator module is responsible for forming the network connection by selecting a channel and Personal Area Network (PAN) ID. In a network coordinator module allows router and end devices to join the network. In this configuration, it has to monitor the network without sleep mode continuously and consumes more power compared to the other modules.
- **Router:** XBee as a router module has to join the PAN and further, and it can manage the router and end device to join the network. In this mode, it can also assist in data routing.
- **End Device:** XBee as an end device module joins the PAN to transmit or receive the data.

2.1.3.2 Demand Side Energy Management

Demand Response: Demand response program aids for energy saving with the curtailment of electricity by shifting the usage period. Further, demand response has two different schemes based on time and incentive, as shown in Figure 2.3.

Time-based demand response program: Based on the price motive of the day time, the program categorizes different schemes. (Palensky and Dietrich, 2011).

- Time-of-Use (ToU).
- Critical-Peak Pricing (CPP).

[1] https://www.digi.com/support/

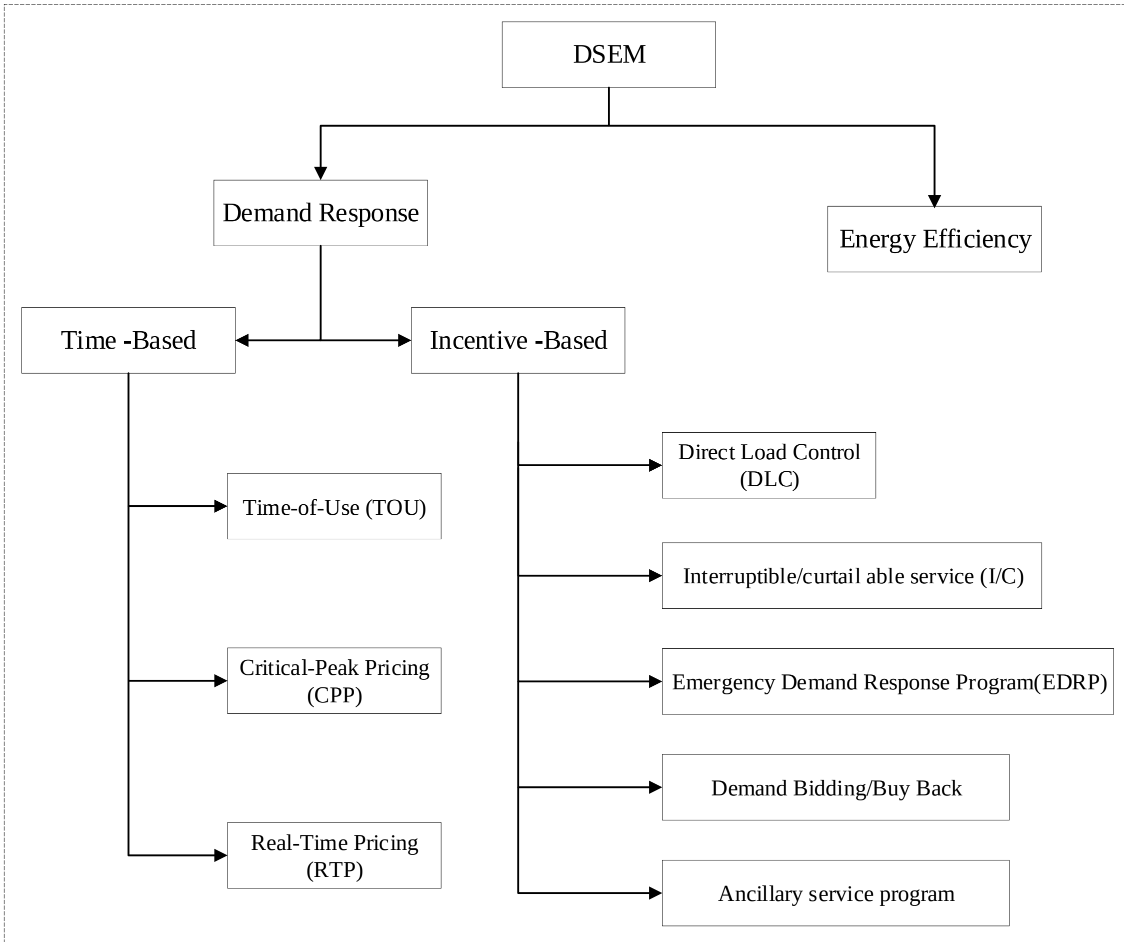

Figure 2.3: Classification of demand side consumer based on different schemes

- Real-Time Pricing (RTP).

Time-of-Use (ToU): The electricity provider provides tariff rates based on time of usage for a day.

Critical-Peak Pricing (CPP): The electricity provider provides tariff rates by considering peak hours.

Real-Time Pricing (RTP): In this scheme, tariff rates are decided on a real-time basis considering the current demand and peak usage details.

Incentive-based demand response program: Based on the customer response during high consumption of electricity, incentives are provided to motivate the customer and hence minimize the overall consumption.

- Direct Load Control (DLC)

- Interruptible/curtail able service (I/C)
- Emergency Demand Response Program (EDRP)
- Capacity Market Program (CMP)
- Demand Bidding/Buy Back
- Ancillary Service Markets (A/S)

Direct Load Control (DLC): DLC is a demand response program, in which the electricity provider has direct control over the consumer appliances and switch the appliance power with short prior notice. This method is best suitable for low consuming domestic and commercial consumers section.

Interruptible Load service : In the case of interruptible load service, the consumer appliance can be interrupted or curtailed during any uncertainty of the system.

Emergency Demand Response Program (EDRP) : In this program, the customer receives incentives for minimising the consumption in case of any system malfunction, breakdown due to operational failure and power shortage etc.

Demand bidding/Buy back: Demand bidding program encourages large consumption customers to bid for curtailment during high tariff or peak consumption. This program helps the consumer in cost-saving depending on their willingness to curtailment.

Ancillary service program: Ancillary service deals with the generator failure, transmission line fault and other system accidents caused.

2.2 Smart Energy Management Strategy for Demand Side Consumers

Demand Side Energy Management(DSEM) plays a significant role in the efficient utilization of energy. In literature, there are several approaches discussed based on appliance Time of Use (TOU), scheduling methods and demand response event. Further, sensor data integration and real-time data monitoring can make the system more efficient.

2.2.1 User Appliance Scheduling and Controlling Approach

Load shedding due to insufficient power generation is one of the significant issues, and hence, there is a need for efficient utilization of available power in the best optimal way. When the available power from generating stations is less than the required demand from the consumer's end, conventionally power distribution to some of the areas are tripped down by the utility in the order of their preference. The power consumption pattern is shifted to off-peak hours to balance the system, and hence, each affected area suffers the minimum possible blackout time. In recent years to overcome the issue of the complete blackout, a significant area of research focuses on the design of a Smart Energy Management System (SEMS) for consumers which benefit utilities as well as the end-users (Kuzlu et al., 2015). Today, interests in energy management systems have grown significantly, and now it is possible to optimize power utilization at consumer premises to get finer control of available resources (Díaz-Vilariño et al., 2015),(Barelli et al., 2018). The main goal of SEMS is to satisfy user comfort with available power, minimize energy consumption, and thus balance the demand and supply ratio. In demand-side energy management, during the peak consumption window, there are multiple constraints to schedule power optimally. Nevertheless, environmental weather sensor data can also contribute to a greater extent in minimizing and scheduling the available power effectively. Energy usage levels of Heat Ventilation Air Conditioning (HVAC) and other heating appliance(s) depend upon the weather condition in that region (Sehar et al., 2017). In general, the appliance can be categorized as schedulable and non-schedulable (Huang et al., 2016). Further, the schedulable appliance can be of interruptible or non-interruptible types. For example, a washing machine can be considered a schedulable non-interruptible device, and a pool pump can be a schedulable non-interruptible device (Zachar and Daoutidis, 2018),(Kumar and Saravanan, 2019).

A comparative study of different literature published in the area of building energy management system is discussed and listed in Table-2.2.

A considerable amount of literature focuses on algorithms deployed in demand-side energy management framework associated with a DR strategy. In literature (Han et al., 2011), authors propose a home energy management system to provide individual appliance usage details to the consumer and lets the consumer make a decision, but no automation mechanism to control appliance operation. The authors in (Ueno et al., 2006), have evaluated the effectiveness of Energy Management System (EMS)

Table 2.2: Building level energy management survey

References	**Proposed Approach**	**Parameters Considered**	**Appliances Type**	**Features incorporated**
Jo et al. (2013)	Linear transformation and optimization technique to find the best optimal schedule.	User comfort features and thermal properties of appliances.	-Intended for the use of Residential Consumer. -Heating and air conditioning appliances.	-Minimize inconvenience to the consumer. -Reduce energy consumption. -Utilize available resources.
Yang and Wang (2013)	A Multi-agent system is developed to enable interaction between occupants and environment parameters.	Indoor environment, illumination level, temperature and user characteristics.	-Adopted for the different building environment. -Considered HVAC and Lighting appliances.	-Satisfy occupants demand and minimize consumption. -Easily adopted into existing automation framework for add-on features.
Ogunjuyigbe et al. (2017)	Consumer satisfaction based Genetic algorithm (GA) is used.	-Predefined budget allocation. -Consumer achieved satisfaction level.	-Focusing on the residential consumer. -Home Appliances.	-Algorithm Controls based on user achieved satisfaction level and minimized cost.
Tenfen and Finardi (2015)	Mixed-integer linear programming is used.	-Demand Response and load shedding features are included in the EMS model.	-Focus on non-controllable loads in EMS model.	-Minimize the operational cost. -Measure the technical and economic impact of the EM system on the main grid.
Qureshi and Jones (2018)	Linear program and non-convex optimization problem using robust optimization method.	-Tracking temperature set-point level and load flexibility.	-Focus on HVAC appliance in a building environment.	A hierarchical control scheme is providing ancillary service involved with building thermodynamics and flexibility in the HVAC system.
Ghatikar et al. (2016)	Linear optimization techniques and openADR communication tool is used.	-Real-Time Pricing and Peak day Pricing. -Glopal temperature set-ponts, dimming lights and plug loads.	Common Loads such as heating, cooling, and lighting systems	Enables integrated environment for energy providers and consumers to provide load flexibility, cost effective system.

by considering power consumption data, ambient temperature, room temperature and consumer usage profile prior and after deployment of the EMS system. It is reported that significant power reduction can be made by changing the TV usage pattern, avoiding standby power consumption and by varying the refrigerator capacities based on the constraints above. In a recent work (Pedrasa et al., 2010), the authors proposed an optimized model using Particle Swarm Optimization (PSO) scheduler, which emphasis on minimizing electricity cost and reducing peak load consumption for a domestic consumer. Furthermore, authors (Ahmed et al., 2017) deployed algorithm for optimal real-time scheduling designed to shift the peak window and minimize the overall energy consumption by assigning priority to the appliances. (Kuzlu et al., 2012) presented a hardware demonstration of the energy management system at the appliance level based on the DR program considering maximum demand limit constraint and also communication delay involved with energy management set up was evaluated.

2.2.2 Energy Management Strategy Integrated with Sensory Data

In recent literature, various investigations have been carried out with environmental sensor data and user comfort integration to develop a more sophisticated energy management system. Authors (Klein et al., 2012) presents a multi-agent-based comfort energy management system, which can dispatch the controls actions considering occupants and sensory information data. It coordinates with the occupants in the building and real-world data like actual ambient temperature, user preference, and user schedules to maintain the user comfort and hence optimize the energy usage. Author's (Doukas et al., 2007), developed a knowledge database with building energy characteristics and sensor feedback. Further, a rule set based intelligent system incorporated with expert knowledge is designed to create a reliable energy profile to control energy activities with preserving consumer comfort and minimizing the electricity cost. Authors (Sehar et al., 2017) presents an integrated environment to control appliances in a commercial building, i.e., Heating, ventilation, and air conditioning (HVAC) demand to maintain Individual user satisfaction considering their preference. (Ogunjuyigbe et al., 2017) suggested a demand-side load management technique that focuses on maximizing the user satisfaction level based on a certain rule at a possible minimum cost with a predefined budget by the consumer. In this case, the acquired data can be used for predictive analysis and further optimization in energy usage pattern (Fabrizio et al., 2017).

Previous studies have suggested several optimal energy models for consumer-based on DR strategies and optimization approach. Author's (Tenfen and Finardi, 2015) proposed detailed modelling of optimal energy management to reduce the operational cost of the system, incorporated with shedding and scheduling of loads in demand side. In this work, authors also consider reducing the start-up, shutdown, and maintenance costs. Authors (Yin et al., 2016), present a novel DR estimation framework with regression models based on time of use and temperature set point for domestic and commercial consumers. The developed framework shows a DR potential and flexibility for peak load shed prediction. Author's (Lagorse et al., 2010) have developed a multi-agent EMS architecture for smart home energy management system with consumer intention and sensor feedback involving scheduling strategies and DR mechanism. Further, this technique has been implemented for renewable sources integrated with smart grid control. Author's (Paterakis et al., 2015) focus on scheduling and controlling in-home appliances to provide economic advantages for residential energy management, modelled using mixed-integer linear programming. Furthermore, battery-based Energy Storage System (ESS) considered along with DR strategy improved significantly in lowering the electricity cost.

In a recent work (Wang and Tang, 2017), proposed a novel supply based feedback control strategy. Global and local cooling distributors based on adaptive utility function are employed to properly distribute the chilled water/air flow among different zones to sustain the uniform thermal comfort. The proposed system helps resume operation quicker after the DR event and shows a significant reduction in power consumption. Authors (Qureshi and Jones, 2018), have proposed a hierarchical control scheme providing ancillary service for demand-side management involved with building thermodynamics and HVAC system by tracking temperature level and load flexibility. The developed method offers flexibility in load scheduling and also minimum operational cost.

2.2.3 Communication Infrastructure and Remote Monitoring of Energy Consumption

Several energy management frameworks are designed based on various communication technology, such as Wi-Fi, ZigBee, and power-line carriers. The suitable communication mode between the consumer loads and utility gateway is used to control the appliance with different operation strategy (Han and Lim, 2010),(Son et al., 2010). Authors (Son et al., 2010), proposed a home EMS with key features involving real-time data monitoring, intelligent control actions using power line communication. The designed system provides remote monitoring feature for better energy conservation with the use of Reduce model, a statistical model which examines the energy-saving choices by including many different factors. The Internet of Things (IoT) introduced in recent years has a wide range of application in the automation system. Integrating the IoT environment in SEMS aids for remote monitoring and controlling at the appliance level for efficient energy management (Abate et al., 2019),(Alavi et al., 2018). In a study author's (Ghatikar et al., 2016), developed new models using linear optimization techniques and communication open standards. In addition, this work presents a cost-effective solution to demand-side energy management challenges by exploring communication technologies and information models for distributed energy system integration and interoperability.

Most of the energy management implementations discussed in the literature focus mainly on domestic consumers. They are designed to schedule the appliance operations based on Utility signals assigned with fixed priority parameters. There is still a need to implement a flexible energy management system, which includes a variety of consumers which can manage power-intensive loads and limit peak household demand without significantly impacting user satisfaction or reducing overall power costs.

In addition, a reliable communication infrastructure with real-time monitoring and ease of scalability at the appliance level is essential in the design of SEMS. In this context, the proposed scheme emphasizes on design and development of real-time hardware prototype.

2.3 Optimization Technique in Demand Side Energy Management

In the demand-side energy management, researchers have used several approaches to solve optimization problems. A comprehensive and critical survey on various strategies has been carried out in the following subsections.

The Demand Side Energy Management(DSEM) and Demand Response(DR) plays a vital role in the energy sector for Residential as well as Industrial and Commercial Consumers. DSEM deals with load management to avoid blackout conditions, reduction of energy usage, etc. In contrast, DR involves the participation of consumers in the incentive-based programs to reduce the peak power usage and electricity bill (Mohsenian-Rad et al., 2010). Load scheduling is a technique that involves finding the best time to power on various loads in order to minimize their cost of energy. Moreover, this is subject to considerations like variable cost of power, the fact that some devices cannot remain on past certain times, the total maximum demand allowed in the system, and the ratings of each device (Du and Lu, 2011). This problem has many possible solutions, given that it is a standard constrained minimization exercise. One of the significant differences from continuous minimization is that the slots we considered give the problem a discrete characteristic per hour, and with this nature, variable tariffs mean that the curve cannot be easily aligned.

In DSEM, the main aim is to minimize the electricity bill, maximize the user comfort and reduce the aggregated power. In this aspect, different DSM techniques and algorithms have been discussed in the literature. In general, the optimization problem has an objective function and dependent parameter constraints. In an energy management strategy, the main objective function can be the minimization of the electricity cost or aggregated power consumption along with maximum user satisfaction level. Further, appliance operating parameters such as ToU, duration, priority etc. will be parameter constraints (Dong et al., 2012).

Depending on the constraint parameters and the nature of the objective function, optimization problems can be categorized as integer linear programming or integer nonlinear programming. In addition, deterministic and stochastic programming problems are categorized based on the nature of the uncertain constraint variables involved.

2.3.1 Minimization of Electricity Cost

The main objective of the optimization algorithm is to obtain the best optimal solution for the given problem. In DSM strategy, the aggregated energy cost can be reduced by shifting the peak hour consumption, minimizing energy usage, utilizing a maximum alternative source of energy like a renewable generation. The load scheduling strategy and features of each load are required to get the best optimal solution. Furthermore, a number of load parameter constraints and the objective function decides the computational complexity of the scheduler.

Integer Linear Programming (ILP) is a widely used method in the literature to solve the load scheduling problem. In a recent work Molderink et al. (2009), the control algorithm is designed for domestic customers at the local and global level based on the current state of the system and the external parameters that affect it. The proposed controller determines when the appliance should be turned on or off with the generator supply for a specific schedule. The proposed strategy maintains the level of user satisfaction. However, this method only considers fixed interval scheduling. In general, this technique is not best suitable for loads with different power consumption patterns.

In a similar work, using a Mixed Integer Linear Programming (MILP) method authors (Mohsenian-Rad and Leon-Garcia, 2010) proposed an optimal energy consumption scheduler for residential consumers to achieve minimum electricity bill. In addition, the trade-off between minimizing the electricity cost and waiting time of an appliance is considered.

An efficient home energy management scheme is proposed in (Zhou et al., 2014) using Binary Particle Swarm Optimization. The objective of this technique is to minimize the electricity bill with minimum interruption and to satisfy the different constraints considered. Different load curves are targeted by random, single and double optimal objectives.

2.3.2 Minimization of Aggregated Power Consumption

Reducing total power consumption depends on the optimum schedule obtained, considering the peak time. In this strategy, a good schedule relies on the DR event with an incentive-based program offered to consumers. In reducing total power, the load scheduling strategy should be carefully designed considering user preferences, schedul-

ing and non-scheduling loads and tariffs.
Authors (Logenthiran et al., 2012) presents DSM with load shifting techniques, based on a heuristic-based evolutionary algorithm to solve load scheduling problem. Various types of loads from different sectors were included in the simulation and showed better simulation results with electricity bill saving with reduced peak demand.

A Genetic Algorithm(GA) based DSM model is proposed in a article by (Khan et al., 2015), energy management for residential consumers is carried out by load shifting techniques for schedulable loads without reduction of electricity usage and appliances are classified based on user preference and their characteristics.

Pedrasa et al. (2009) have investigated the BPSO algorithm for solving multi-objective optimization problem by using a single aggregate objective function for a significant number of loads under different constraints. It is observed that BPSO achieved a near-optimal solution with less computation time for a relatively complex problem.

Miao et al. (2012) use a GA based algorithm for home energy management system. The main objective of his study is to reduce electricity cost by scheduling appliances in a predefined slot with satisfying the user constraints. A comparative study was carried out, and simulation results showed GA performs better and gives optimal solution than the greedy method.

An efficient heuristic-based approach is presented by (Ogwumike et al., 2015) to minimize the electricity cost scheduling the appliances in best available slots adhering to the appliance operational and peak usage constraints. It is shown that the exponential factor reduces the computational time, and hence heuristic algorithms can be embedded within a simple microcontroller for smart meter application.

From the analysis of literature, it is observed that most of the optimization techniques used in DSM are complex and takes more computational time, in turn, not easily scalable and achieves less user satisfaction. Hence, in this work, an advanced DSM technique is developed by considering load scheduling as a discrete optimization problem and given the nature of such problems, there are multiple possible solutions. We aim to find the optimal solution via the use of genetic algorithms, which performs better in terms of peak power reduction, user satisfaction and computational time.

2.4 Accurate Prediction Techniques for Renewable Source Generation

Renewable Solar PV power generation is an abundant and promising source of energy in the world. The main limitation remains that it is very unpredictable and intermittent as it depends on tropical region or zones, environmental factor and meteorological parameter like “irradiation”, “wind direction”, “wind speed”, “temperature”, “humidity” and also mainly on “Sun-rise” and “Sun-set” time (Di Santo et al., 2018). Efficient usage and management of these resources is very crucial to fulfilling the ever-increasing energy demand of the consumer. In the digital world with an IoT environment, it has made so many advancements in the energy sector for reliable data acquisition, remote monitoring and controlling.

2.4.1 Input Selection of the PV Power Prediction Model

Solar energy, which comes from the Sun as solar radiation, is accessible renewable energy. The photovoltaic effect converts the solar cells made up of semiconductors in the photovoltaic module into electricity. The output of PV power depends mainly on the amount of solar irradiance. Certain meteorological parameters such as temperature in the atmosphere, the temperature of the node, wind speed, direction and humidity are further regarded as possible parameters for estimating the PV energy output.

2.4.2 Classification of PV Power Generation Prediction

The researchers have categorized the estimates for PV power generation according to various factor categories. Nevertheless, the PV power forecast does not have set requirements. The PV power forecasts, analysis of solar irradiance and other weather data and predictions methods are categorized by most researchers according to the predictive horizons, as shown in Figure 2.4. A comprehensive analysis was performed on the basis of the following subsections for different classifications of PV generation forecasting.

In coming days standalone solar PV generation plays a major role in the power industry due to growing concern over the usage of fossil fuel (Kurczveil et al., 2014). Hence it is essential to predict PV output data accurately and plan the operation load/appliance at the consumer end for efficient utilization. Different approaches

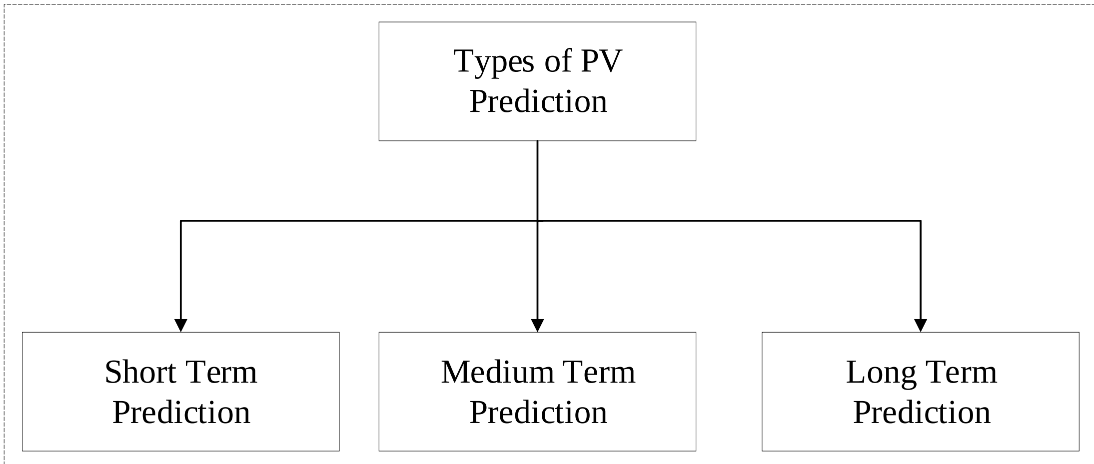

Figure 2.4: Classification of PV forecast types

can be considered for modelling of the solar irradiance depending on the availability of dataset length, parameters considered and usage. In literature use of Seasonal Auto-Regressive Integrated Moving Average (SARIMA), Radial Basis Function (RBF), wavelet decomposition network methods are employed (Ciabattoni et al., 2013). However, the widespread use of these time series based model may not show high performance since they are efficient with small range prediction. Authors deployed of fuzzy logic technique to estimate insolation considering humidity and cloud parameters, further used neural network technique to forecast solar energy with available data (Yang et al., 2014b). In a similar work, authors used historical data of solar irradiance along with weather condition for prediction of solar PV output using fuzzy logic method (Tanaka et al., 2011). Aunedi et al. (2013) have carried out an assessment of frequency regulated refrigerators with deep penetration of renewable and shown with the perspective of economic and environmental benefits. A weather-based hybrid model was developed combined with a different prediction model for accurate PV generation output (Yang et al., 2014a).

Accurate renewable forecasts for utilities, as well as energy consumers, have many benefits, such as monitoring the distribution potential, efficiency, and reliable and safe operation of utilities. Accurate forecasting information from renewable power generators helps energy sector to minimize power fluctuations and maintain overall reliability of the system. Continuous monitoring of the forecasting information may also help the energy producers to preserve the health of the system (Gigoni et al., 2018).

On the other hand, there are several works carried out towards deployment of Demand Side Energy Management system. In the power engineering context, it is also referred to be as "Demand Response" event, which allows the consumer to change their power consumption pattern considering ToU and Utility tariff price to avoid peak usage. In recent articles authors (Pedrasa et al., 2010) and (Mohsenian-Rad and Leon-Garcia, 2010) focus on scheduling and controlling in-home appliances to provide economic advantages for residential energy management. Authors (Sehar et al., 2017) presents an integrated environment to control appliances in a commercial building, i.e., Heating, ventilation, and air conditioning (HVAC) demand to maintain Individual user satisfaction considering their preference. In literature authors (Ogunjuyigbe et al., 2017) suggested a demand-side load management technique that focuses on maximizing the user satisfaction level based on the certain rule at possible minimum cost with a predefined budget by the consumer. Acquired data can be used for predictive analysis and further optimization in energy usage pattern (Fabrizio et al., 2017). In order to keep the power usage under a pre-determined limit authors (Busquet et al., 2011) have implemented event-driven scheduling algorithms by assigning priority class to home appliances. However, authors considered constant power supply from the grid but not for the dynamic generation like the renewable source.

In this work, solar irradiation data from NREL site is collected for Mangalore region, and the solar radiation output is usually available from 7 AM to 5 PM for a day. Dataset is used to train the different models and validate the results obtained to find the accuracy of the prediction. In order to make proper load scheduling or pre-scheduling, accurate forecasting of source generation plays a key role in the energy management system.

Based on state of the art, there is a need for more accurate renewable energy prediction model for demand-side SEMS to manage load/appliance efficiently without limiting user comfort. In this context, developing an accurate predictive model based on several machine learning techniques is considered for an efficient energy management system. Furthermore, it facilitates the user-configured dynamic priority assignment function associated with the IoT environment. The proposed architecture is evaluated at the laboratory level experimental set up, which shows a better SEMS with prediction model with reliable communication.

2.5 Objectives of the Research Work

1. Design and development of SEMS prototype for experimental validation.
    - Deployment of power negotiation algorithm and user defined functions with reliable communication.
    - IoT Environment for data storage, remote monitoring and analysis.
2. Performance evaluation of optimization algorithms for Demand Side Energy Management (DSEM) consumers.
3. Accurate prediction of power availability using different machine learning model for DSEM consumers.

Chapter 3

Design and Development of Smart Energy Management System

3.1 Introduction

The modern era has considerably increased the usage of power appliances, and research community has shown growing concern over minimizing the cause of the environmentally hazardous and alternative source of energy resources. The ever increasing demand for electricity consumption is a challenging issue to be addressed. Consumers in developing countries are affected severely due to the insufficient power supply from utilities during peak hours, leading to frequent unscheduled load shedding. To adapt to the above situation, a consumer has to invest in fuel generators and battery storage with additional financial burden counterpart inversely affecting the economic growth of the country. At the other end, utilities have to invest huge amounts in developing infrastructure for the generation plants to withstand peak hours, subsequently leading it to be underutilized. In order to maintain energy supply and demand, a reliable power network within the power generation, transmission and distribution sectors is required.

Smart Grid brings rapid transformation in the energy sector, enables the demand-side management system to quickly respond during outages, peak load shifting, and fault management. In addition, it facilitates the consumer to employ alternative renewable sources for minimizing electricity cost and efficient utilization of available power sources. Demand Response (DR) program in Demand-Side Energy Management (DSEM) is a viable solution to manage energy efficiently and in turn, benefit the consumer and utilities (Deng et al., 2015). Smart meters at the consumer's end have a crucial role to play in the power management of energy sectors (Beaudin and Zareipour, 2015). Bidirectional communication between consumer premises and the utilities provide a greater opportunity in the energy management system (Gelazanskas and Gamage, 2014). Currently, utilities provide different tariff rates based on the categories of consumers. The classification of consumers is mainly based on the usage of electricity and the business established in that region. Most commonly energy sectors divide consumers into different categories as Domestic, Commercial, and Industrial customer (Lilis et al., 2017). For each category, there are different tariff rates with Time of Usage (ToU) and penalty charged considering demand limit and power factor parameters. Tariff rates are low for residential customers and high for industrial customers, since industrial sector gives maximum profit for utilities, hence it is listed to be in the high priority section.

3.2 Development of Smart Energy Management System

This section describes the proposed Smart Energy Management System (SEMS) in detail with the algorithms embedded within the system.

3.2.1 Overview of Proposed SEM System

The concept of proposed smart energy management (SEM) system is shown in Figure 3.1. The overall system comprises of an SEM unit that provides a monitoring and control functionalities for a consumer and another end Smart Sockets gather electrical parameters from appliances and perform local control based on command signals received from the SEM unit.

SEM unit also acts as a gateway that provides an interface between the utility and a consumer. In such a scenario, the gateway receives the data of allocated maximum demand limit from the utility, which is used as an input for our SEM unit. Utility, on the other side, collects energy consumption data from all the SEM units in a city and analyzes this data for updating the maximum demand limit of each household. Collected data would also be used for billing purpose, and an e-bill would be generated for each household.

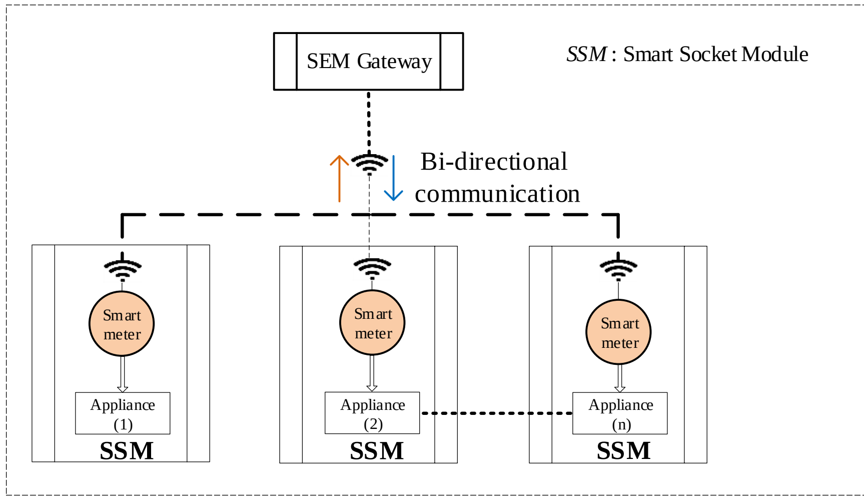

Figure 3.1: Overview of proposed smart energy management system

3.2.2 The Architecture of SEM Gateway

In general, SEM Gateway comprises of the following modules as shown in 3.2,

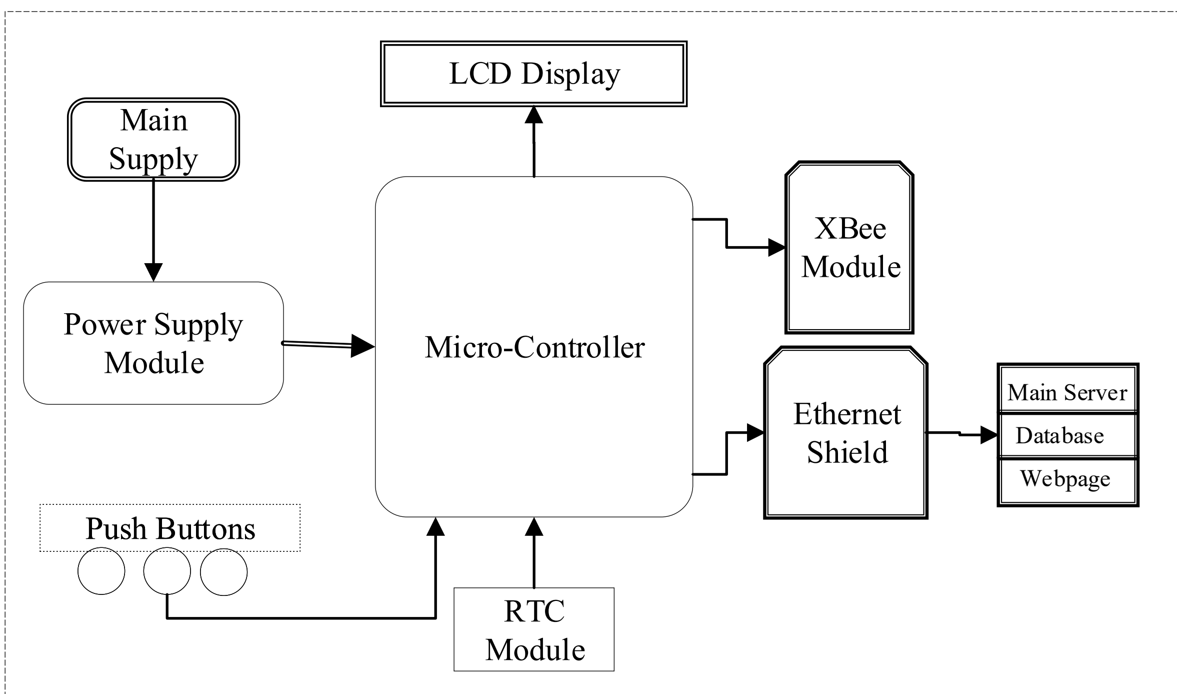

Figure 3.2: Functional block diagram of central gateway

The SEM unit (central controller) acts as an intermediate gateway between the utility and a consumer, and it is used here as the central control unit which runs a decisive (power negotiation) algorithm that serves as a brain of the SEM system. It decides to switch ON/OFF selected end-user appliances based on the utility signal received, as well as homeowner's load priority settings. During peak load hours, the SEM unit warns consumer while switching on a high power-consuming appliance to avoid high tariff charges. It is also responsible for collecting energy consumption data from all the load controllers through XBee modules and providing an LCD interface for homeowners to retrieve real-time energy consumption data and even with a provision to configure the priority of an appliance as intended.

3.2.3 The Architecture of a Smart Socket Module (Load Controller)

A load controller provides an interface between the SEM unit and a selected appliance through Smart Socket Module (SSM). It provides essential power management functions (i.e., control, communicate).

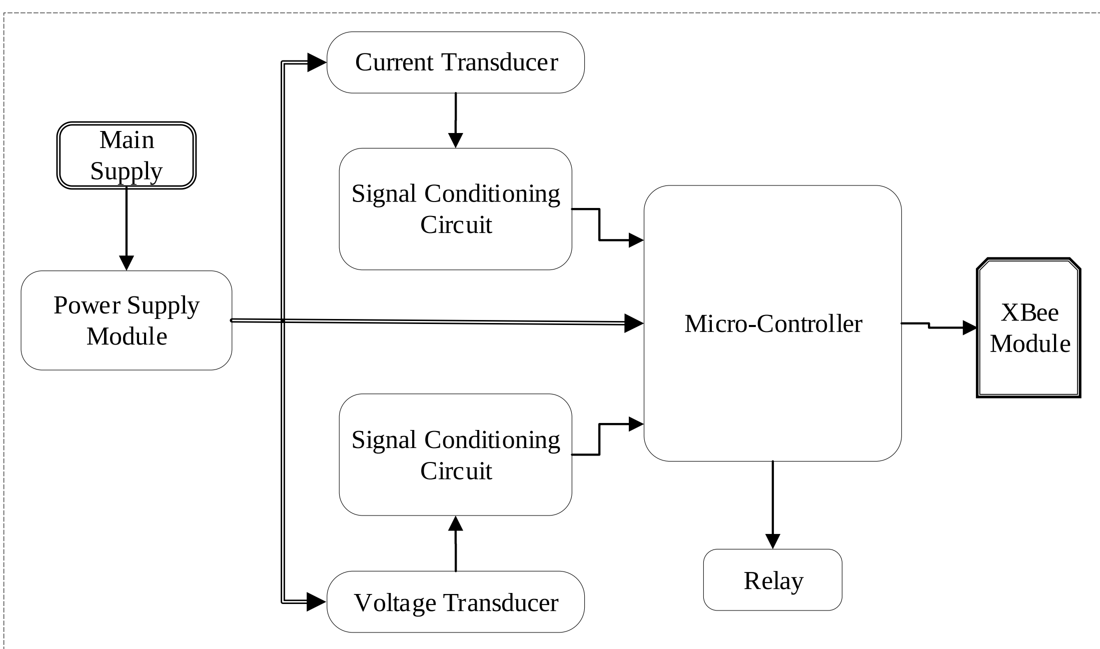

Figure 3.3: Functional block diagram of smart socket module

Different roles of functional module:

1. **A data collection and processing module:** The main task is to collects real-time electrical parameters such as RMS voltage and current values, further computes apparent power, real power, energy and power factor of an appliance. Hall effect based LEM sensors is used here for voltage and current measurement.

2. **A control module:** It is an electronic relay circuit used to switch a selected appliance ON/OFF, as per command sent by the SEM unit.

3. **A communication module:** It establishes a two-way communication path between an SSM and the SEM unit.

The collected power consumption data from a load controller is to be sent to the SEM Gateway counterpart commands from the SEM unit is received by a load controller. Communication is established using Application Transparent (AT) mode, and after collecting data from all load controllers, each load controller communicates directly with the SEM unit and in turn, executes decisive algorithms and sends control commands back to the load controller.

3.2.4 SEMS Communication and Web Based Data Archiving

The SEMS system establishes two communications between the controller and the appliance. In addition, real-time data monitoring and archiving is performed using a web-based interface through the SEM unit gateway.

3.2.4.1 Communication within Smart Energy Management System

Generally, the energy management system communication module is required at either end of the master node and the slave node. One of the communication modules is integrated with the SEM unit gateway and the other is associated with each smart socket or load controller module.In practice, wireless communication is established between the coordinator (user end) and the router (appliance end) module. The XBee Series-2 device is used here as a communication module, with an XBee module connected at either end to allow communication within the SEMS. The XBee module of the load controller is configured as a router (appliance end) and the other modules are configured as coordinators (user end). Once communication is established between the router and the coordinator of the SEM system, the SEM unit runs a power negotiation algorithm on the collected power consumption data, and the associated coordinator sends control signals to the router.

3.2.4.2 Network Configuration of SEMS and Ethernet Shield

Initially, the Arduino analog input and output ports are in a logic low state. All data pins anything connected to the Arduino Ethernet shield is set to a fixed baud rate. All required libraries required for communication is connected to run at startup. Input or output data type initial values are declared. Timing parameters are initialized globally to set the time interval between server and client communication. An additional reset switch is provided to restart the entire system configuration. All of the above configurations are displayed on the serial monitor to verify the following Input or output configuration.

The Ethernet shield (W5100) is located on top of the Arduino and communicates with the Arduino GPIO. Arduino peripherals such as reset, ground, power supply ($5V$) are connected directly without external equipment. A LAN (local area network) cable is connected to the board, allowing Internet connection. All configurations related to Ethernet shielding and data communication are programmed on the Arduino microcontroller. The library that defines the Ethernet commands is programmed into Arduino. These libraries and setup commands start running when the shield is activated. A static MAC address is assigned to the shield specified by the manufacturer. As the board starts communicating with nearby network nodes, a dynamic IP is assigned to the board. Arduino board and Ethernet shield are made as clients of this work. A static server IP is obtained which can work at different locations within the local area network and burned into the program code. Ethernet shield keeps assigning the same MAC IP address each time you communicate with the server. Ethernet shield sends a failure message to Arduino during network configuration malfunction. Every 5 minutes Arduino Ethernet clients connect to the server via a specific HTTP port (80). Currently available The data calculated by the Arduino microcontroller is sent to the server one by one. File-path is written in Arduino code for storing data on the server. After Arduino recognizes the ethernet shield, all electrical parameters will be successfully uploaded. A functional diagram of the Arduino and ethernet shield is shown in Figure 3.4.

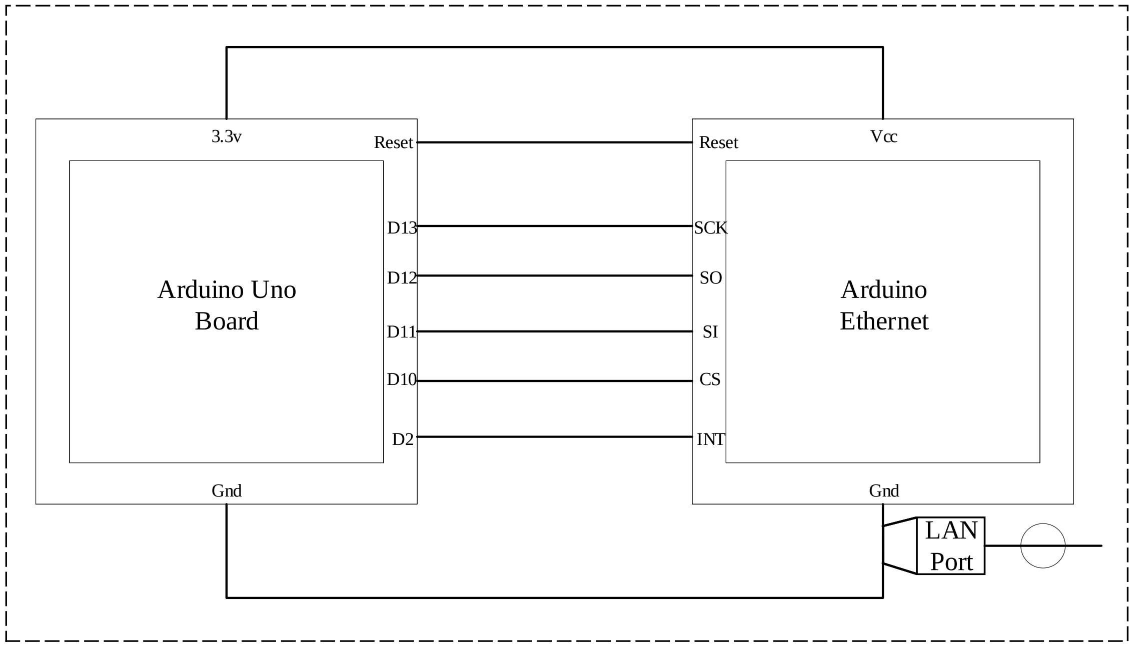

Figure 3.4: Functional block diagram of the Arduino and ethernet shield

3.2.4.3 Server and WebPage

WAMP (Windows, Apache, MySQL, PHP) server is a web development platform on Windows create dynamic web applications using Apache server, MySQL database and PHP scripting language. In smart metering applications, the WAMP server is used as a local server. Further, this application allows users to create a user ID and password for authentication. Additionally, MySQL can be used to create multiple instances and store it on the server. It is required to check configuration of the system before installing WAMP server. After successful installation, all the files will be stored in a particular folder specified by the user.

3.2.5 Smart Meter Firmware Requirement and Data Acquisition

This section discusses the details of the software and hardware involved in the development of SEMS. Figure 3.5 shows the firmware process involved in establishing a successful connection and data upload.

3.2.5.1 Software Requirement:

1. **Arduino IDE (ATMEGA328 Microcontroller):** Smart socket modules are build based on the Atmega328, 8-bit microcontroller compatible with the Arduino IDE open source platform.

   Features:

   (a) Operates with a clock speed of 16MHz
   (b) The Atmega328 has 32 KB of flash memory for code
   (c) Analog input pins :6
   (d) Digital input pins :14

2. **XCTU Software:** XCTU sofware is used to establish communication between two or more XBee RF modules.

   Features:

   (a) XCTU can detect and configure radio modules
   (b) Configure XBee module in AT or API mode
   (c) Firmware updation of XBee RF modules

3. **WAMP Server:** The WAMP server is used here to create a webpage using Apache, store the data using MySQL database and programme using PHP language.

   Features:

   (a) Different web-pages are created to access the user login page, power consumption data of and trend graphs.
   (b) All the power parameters along with time stamping are stored in th database.

3.2.5.2 Hardware Requirement:

1. SEM Gateway (Central controller)

The SEM gateway (central controller) uses the RF XBee module in AT mode to communicate with the smart socket module. The SEM gateway has a display unit for displaying power parameters. In addition, the RTC module is embedded for the real-time clock, and the Ethernet shield is embedded for uploading real-time data. The hardware component modules involved in the design are as follows.

(a) ATMEGA328 based Arduino Micro-controller [1]

(b) XBee Module[2]

(c) 16X2 LCD Module [3]

(d) DS3231 RTC module [4]

(e) Ethernet Shield1

2. Smart Socket Module

The smart socket module uses a DC power supply device and has a relay module to control the load status. LEM current and voltage sensors are used to measure power consumption data. Further, a signal conditioning circuit is used to obtain the desired signal. The XBee module is used to send data to or receive data from the central controller. The hardware component modules involved in the design are as follows.

(a) ATMEGA328 based Arduino Micro-controller1

(b) LEM55A Current Transducer[5]

(c) LEM25P Voltage Transducer 2

(d) Signal Conditioning Circuit

(e) Power Supply Module

(f) 5V RELAY Module and Socket

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[1] $https://www.microchip.com/wwwproducts/en/$

[2] $https://www.digi.com/resources/documentation/digidocs/$

[3] $http://www.datasheetmeta.com/pdf.php$

[4] $https://datasheets.maximintegrated.com/$

[5] $https://www.lem.com/sites/default/files/productsdatasheets/$

3.2.5.3 Data Acquisition and Uploading:

The ATMEGA328P based micro-controller is connected with a compatible Ethernet shield to configure it as a client part, which establishes the communication with the server. Arduino UNO microcontroller computes the different electrical parameters by fetching the analog values of voltage and current sensors. These transducers will give the stepped-down voltage signal in the range of less than 2.5V. Computation of different electrical parameters will be performed at microcontroller end. Arduino Ethernet shield is allocated with a unique MAC address and IP address during its boot-up there is a connection established between client and server. Once the MAC address and IP allocation are successful, all the information will be transferred between client and server, and it is also displayed in the serial window of Arduino through serial communication.

The controller reads the sensor values from the analog ports, which is a scaled-down signal of actual voltage and current signal. Further, these values are converted in digital values in the analog to the digital conversion process. The ATMEGA328P based micro-controller has 10-bit ADC and hence takes the analog values in the range of 0 to 1023. After performing several computations, the proportional analog values are converted into actual voltage and current value. The timer will be running parallel, which sends the signal to the ATMEGA328P controller. After every 5 min of an interval, Arduino sends the information to the server.

3.2.6 Calculations of Different Electrical Parameters

1. Instantaneous Voltage/Current:

   The signal conditioning is performed on the actual voltage and current signals before it could be processed with the microcontroller unit. ATMEGA328 Arduino Uno microcontroller kit is used to read the analog values from the circuit, which is sampled using built-in 10-bit ADC. The maximum sampling rate depends on the resolution of ADC, and each individual sampled signal gives the instantaneous values of voltage and current readings.

$$P_{inst} = V_{inst}(n) \times I_{inst}(n) \tag{3.1}$$

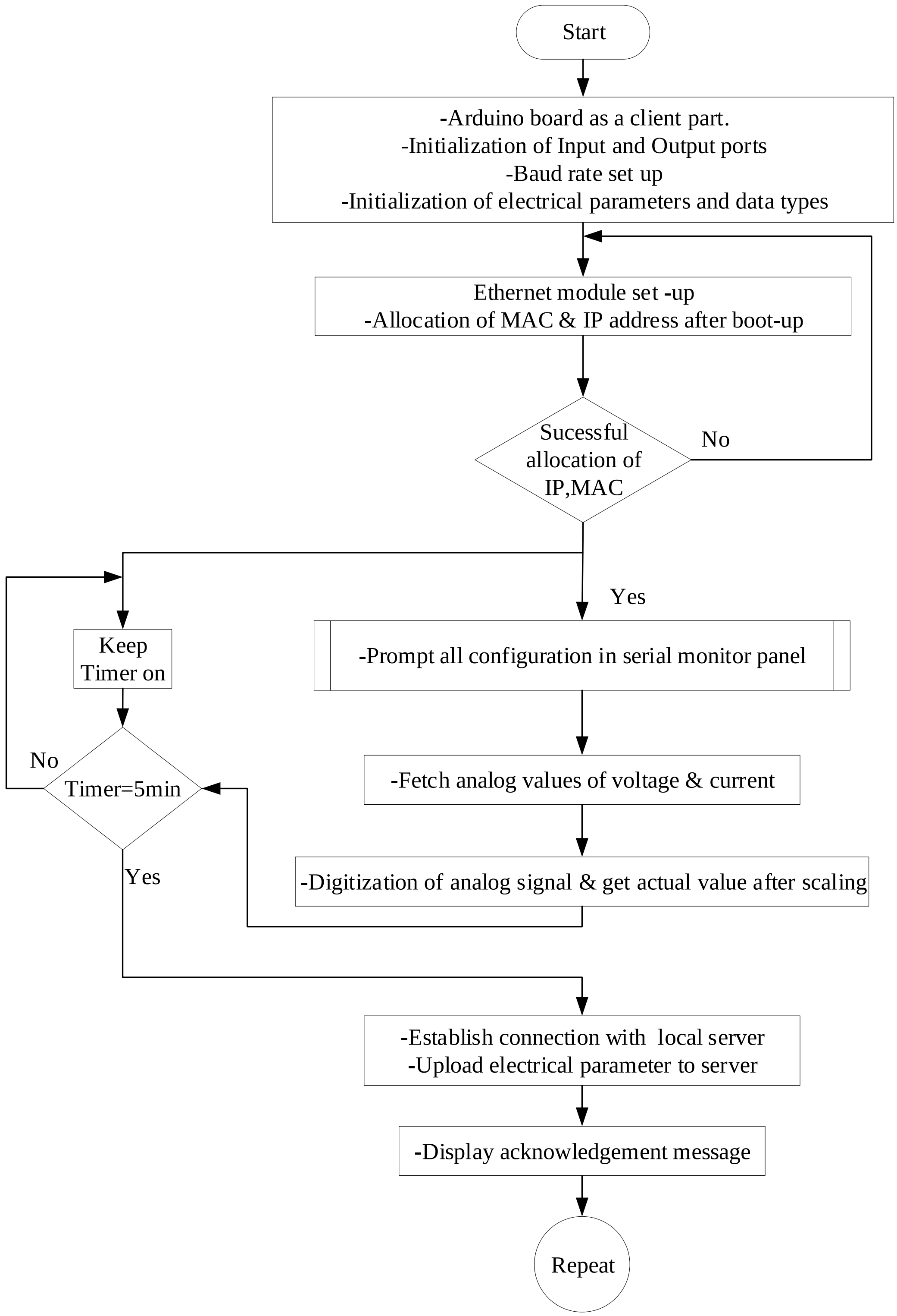

Figure 3.5: Firmware development of IoT environment for SEMS.

$$\sum P_{inst} = \sum V_{inst}(n-1) \times \sum I_{inst}(n) \tag{3.2}$$

$$P = \frac{\sum P_{inst}}{n} \tag{3.3}$$

2. Calculating the Real Power(P):

   The instantaneous values of voltage and current readings are used to estimate the real power of the circuit. The product of instantaneous voltage and current is calculated to find instantaneous power (P_{inst}), and the sum of instantaneous power is calculated by successive addition of instantaneous power. Finally, the sum of instantaneous power is divided by the number of samples(n) to get real power consumption.

3. Root Mean Square(RMS) Voltage:

   For the n no.of sample, the successive som of squared voltage from the instantaneous product of the voltage is calculated and divided by the n number of samples to get the average and RMS value of the voltage given by the equation.

$$V_{rms} = \sqrt{\frac{\sum V^2}{n}} \tag{3.4}$$

   Similarly, I_{rms} is given by

$$I_{rms} = \sqrt{\frac{\sum I^2}{n}} \tag{3.5}$$

4. Apparent Power(S):
   The product of RMS Voltage and RMS Current values gives the apparent power of the load, which is given by

$$S = V_{rms} \times I_{rms} \tag{3.6}$$

5. Energy (E):
   Energy of an appliance is calculated as product of power and the time of power consumption, which is given by

$$Energy(E) = P \times t \tag{3.7}$$

3.3 Algorithms Embedded with Smart Energy Management System

The proposed SEMS control technology consists of smart socket units associated with individual appliances to communicate with the SEM unit gateway (central controller) using the XBee module in AT communication mode. The SEM unit of the proposed method receives the maximum demand limit data allocated from utility and energy consumption data from all installed smart sockets. In addition, SEM uses a decisive algorithm for power negotiation to optimally schedule individual appliances. The proposed SEMS incorporates the following algorithms into the SEM unit gateway and Smart Socket Module (SSM) to address demand side energy management for optimal energy use.

1. SEM Gateway (Central controller)
   (a) Decisive algorithm operation during Demand Response(DR)
   (b) Self-diagnostic feature to handle non-responding appliance
2. Smart Socket Module (Appliance end)
   (a) Control actions dispatched at the appliance end
   (b) Cost optimization algorithm

3.3.1 Decisive Algorithm Operation During Demand Response

The decisive algorithm is the key element in the proposed SEMS technique, which considers the consumer priorities of appliances and operates the most critical appliances even when the utility allotted power is less than the maximum demand. The complete flowchart of the proposed SEMS technique with power negotiation algorithm is shown in Figure 3.6. Further, the stepwise explanation of the deployed algorithm is discussed in this section.

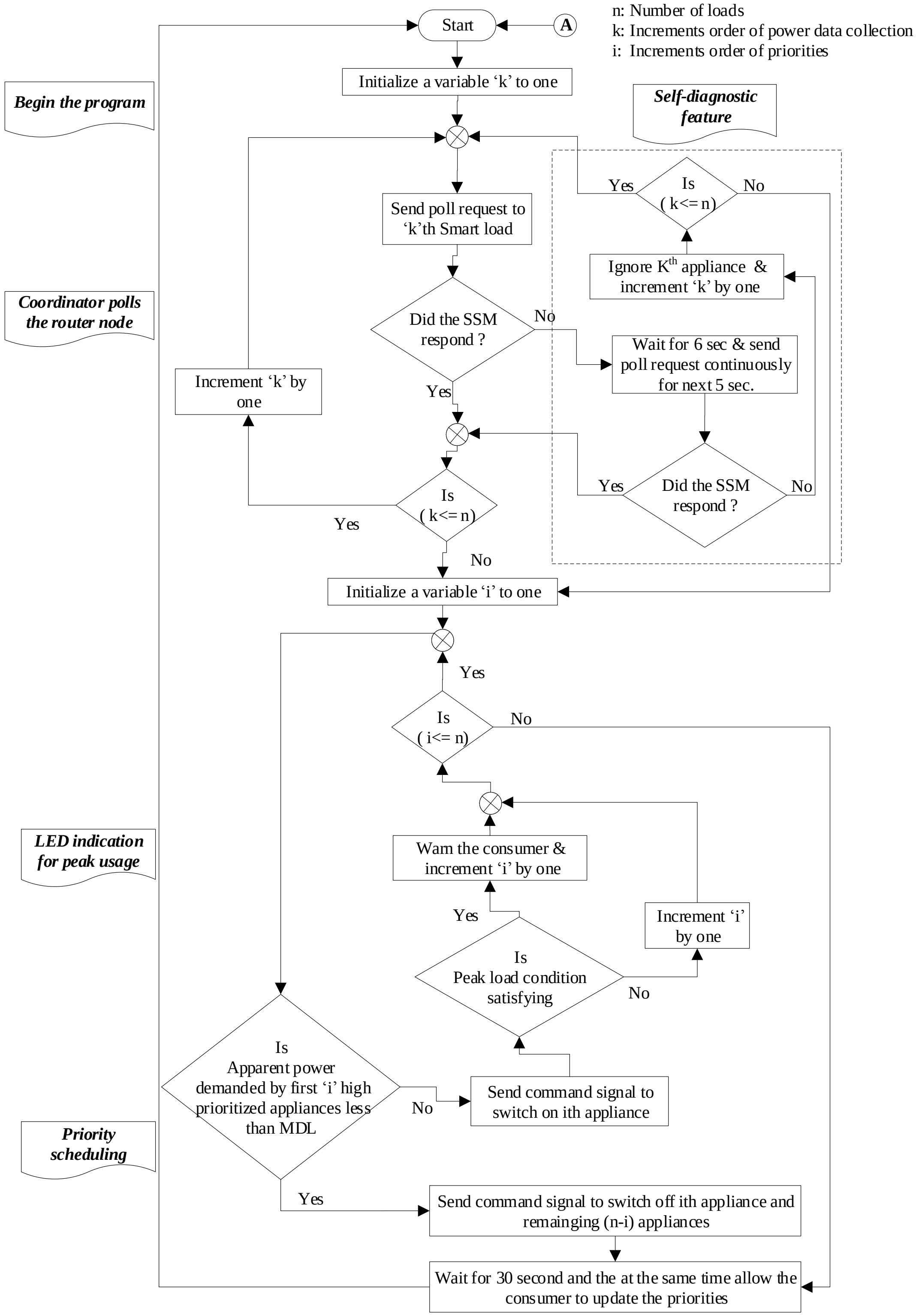

Figure 3.6: Flowchart of decisive algorithm with self-diagnostic capability

1. The SEM decisive algorithm starts by gathering power consumption data of all the appliances. This data collection would be done in a predefined order. If any load controller does not respond, the controller runs a self-diagnostic algorithm explained in section 3.3.2.

2. The collected data of power consumption is arranged in the order of consumer's priorities, and then SEM Gateway checks for following demand limit violations. Total Apparent Power consumed > Maximum Demand Limit(MDL).

3. SEM Gateway sends a command to switch ON the maximum number of high prioritized appliances such that the MDL is not violated and sends a command to switch OFF the remaining appliances.

4. For any appliance which is switched ON, the decisive algorithm also checks for following peak load condition (which depends on user convenient).

   Total Appliance Power > 1/4 (Maximum Apparent Power of previous month)

   In case, if the peak load conditions is being satisfied, the SEM unit gateway sends a command signal to the load controller to alert consumers that power consumption at peak load is high to avoid high tariff charges. Moreover, the load controller alerts consumers by turning on the buzzer and LED for one second.

5. After sending each command signal to all appliances, the SEM unit gateway waits 30 seconds before the next data sampling. In addition, consumers can update appliance priorities based on their satisfaction during the wait time. Then repeat steps 1-5.

A flowchart of the SEM decisive algorithm for "n" household loads is shown in Figure 3.6. It is to be noted that before running this algorithm, priorities of appliances are initialized with predefined settings. Also, two variables "i" and "k" are used in the flowchart. The variable "i" increases in priority order, while "k" increases in a predefined order to collect power consumption data for all appliances.

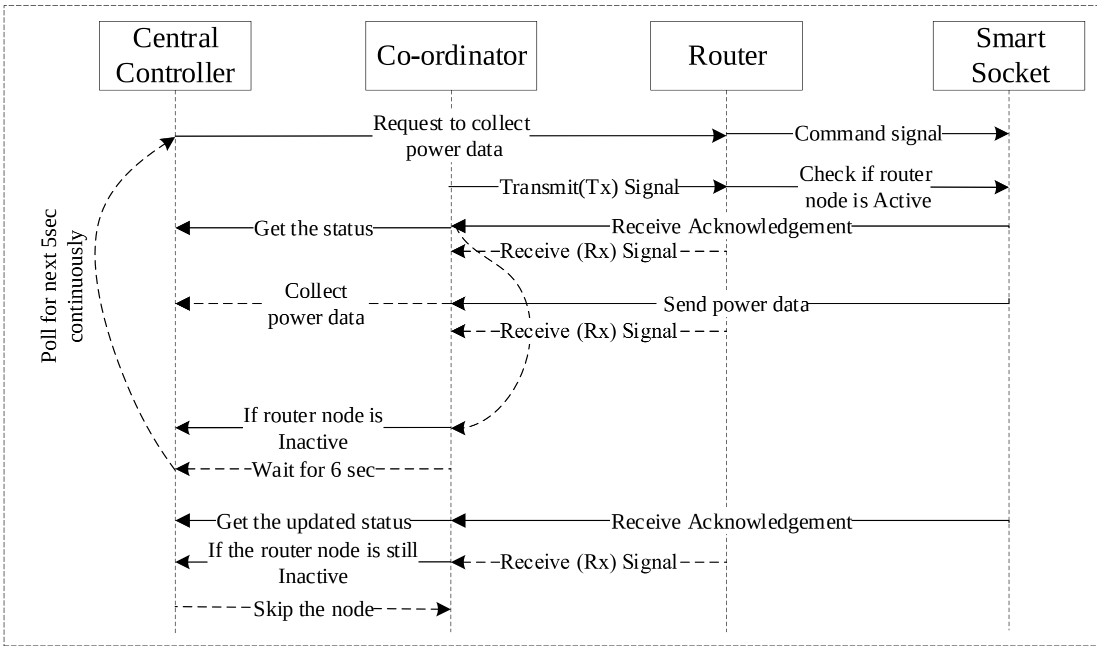

Figure 3.7: Sequential flow of of self diagnostic mechanism

3.3.2 Self-diagnostic Feature to Handle Non-Responding Appliance

Decisive algorithms provide reliable communication in case of failure. The operation sequence during the self-diagnosis mechanism is shown in Figure 3.7. The SEM gateway sends a request signal to each load controller to collect power consumption data. Under normal operating conditions, the load controller responds immediately with energy consumption data for that particular load. In unusual situations where the load controller's XBee module is temporarily inactive, the data transfer sequence is interrupted, and the load controller may not respond after returning to normal. In such a situation, the SEM gateway waits a set time of 6 seconds before running the self-diagnostic algorithm, continuously polling the load controller for the next 5 seconds, and simultaneously waiting for a response. Then, if the inactivity is due to a temporary failure, the load controller responds with the relevant data. Further, the SEM gateway continues to send requests to other load controllers. If the load controller does not respond after 5 seconds of continuous polling, the SEM gateway considers the load controller to be permanently inactive for that event, and it starts sending requests to other load controllers. Therefore, an idle load controller has little effect on the rest of the system.

3.3.3 Cost Optimization Algorithm

The various tariff plans and slab pricing introduced for consumers are listed in Table.3.1, and this subsection describes the evaluation of cost optimization techniques. ToU rates have a significant impact on consumer energy costs. To minimize energy costs, load scheduling algorithms have been developed, however not all appliances are suitable for this algorithm. Appliances in a household are categorized into schedulable and unscheduled devices that allow the appliance to be scheduled for operation based on the willingness of the consumer. This algorithm runs in the load controller of all schedulable appliances. Therefore, all schedulable loads are controlled by the decisive and the load scheduling algorithm that runs on the SEM unit and the load controller, respectively.

The ToU tariff of MESCOM for the fiscal year 2018 applicable to Low Tension (LT) industries (categorized as LT-5) [6] is mentioned in Figure 3.8. The ToU tariff mentioned above is considered for the design of load scheduling algorithm with an objective of cost optimization. SEM unit sends data of time to all schedulable appliances. Based on the time zone, the load controller of a schedulable appliance decides the status of the device. Also, based on the consumer's daily usage, there is a predefined period of time for a day during which the appliance must be operated.

The algorithm is designed in such a way that appliance is operated to the maximum possible extent during $22:00$ Hrs to $06:00$ Hrs so that consumer would be benefited with an incentive of Indian rupees 1/unit as presented in Figure 3.8. During peak load hours, the appliance is forced to be switched OFF irrespective of the required duration of operation in order to avoid penalty. During non-peak load hours when neither incentive is offered, nor penalty is levied, i.e., from 10:00 Hrs to $18:00$ Hrs, appliance can operate if the required duration of operation is more than eight hours else it is switched OFF so that it would be scheduled to operate between $22:00$ Hrs and $06:00$ Hrs as incentive would be provided during this period. Due to insufficient power generation, some appliances cannot operate for the required time due to control

[6] http://www.mesco.in/tariffs/Tariff-order2018.pdf

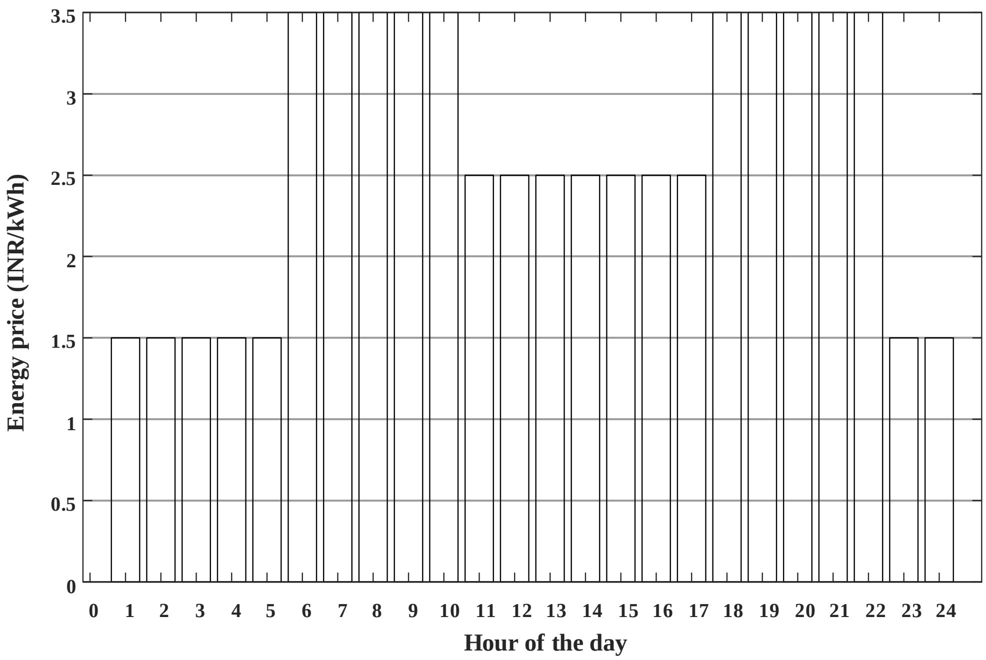

Figure 3.8: The approved ToU tariff for LT consumers

of the SEM decisive algorithm. In this case, the algorithm compensates for the loss by allowing it to run longer the next day. Every day at 10:00 pm, the required duration of the operation is updated by adding the previous day's pending requirements to the daily requirements.

Table 3.1: Tariff plans and slab rates

Tariff Plan	Slab Rate	ToU
Flat Rate	Medium	10AM to 6PM
Variable	Low	10PM to 6AM
	High	6AM to 10AM
		6PM to 10PM

3.3.4 Control Actions Dispatched on the Appliance End

The details inside the smart socket will be explained in detail in the next section, and the algorithm flowchart is shown in Figure 3.9, and the role of the smart socket algorithm is as follows. The Smart Socket decisive algorithm constantly checks requests received from the coordinator end and sends power consumption data.

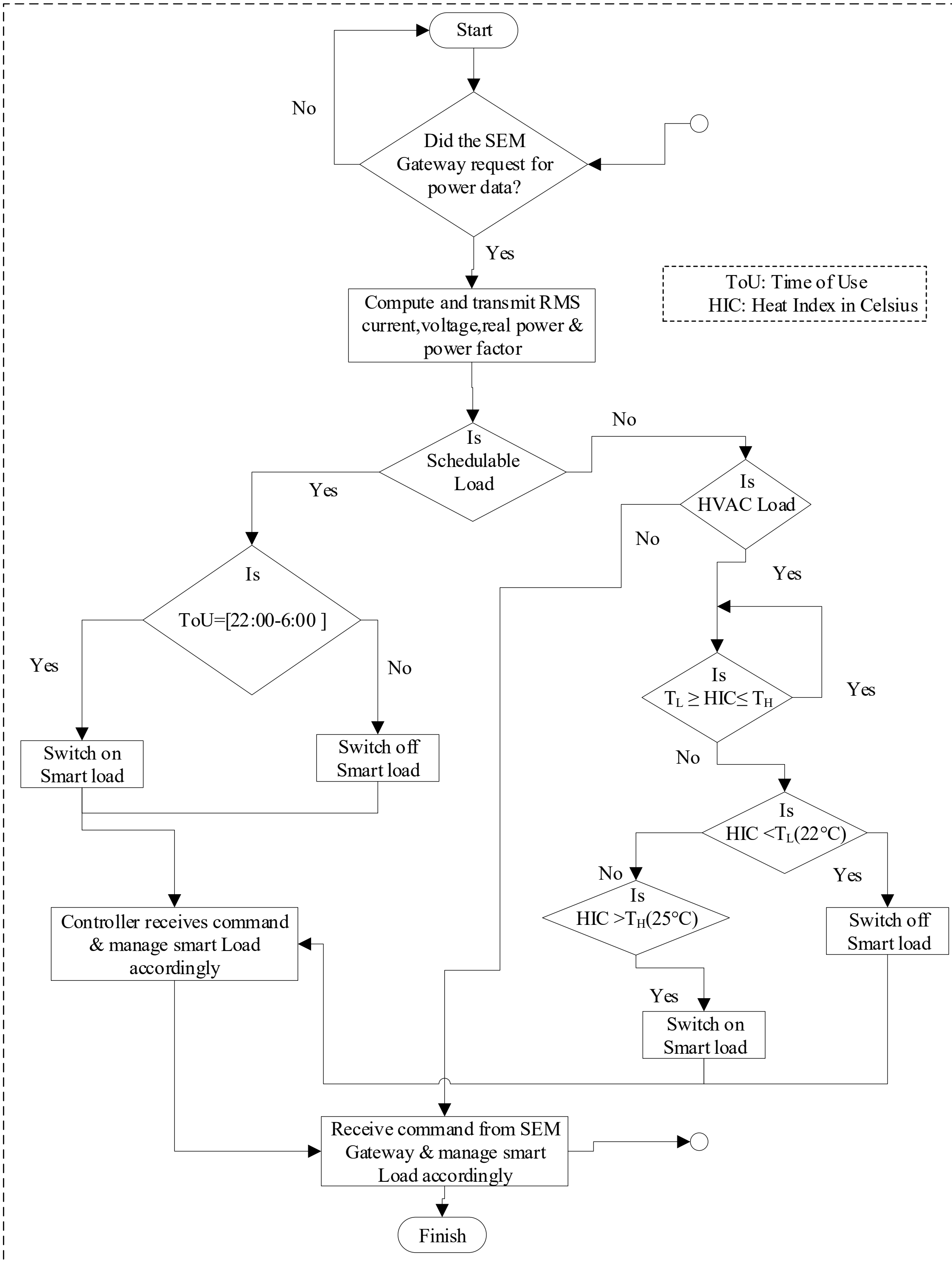

Figure 3.9: Flowchart of algorithm deployed in the smart socket module

The microcontroller unit associated with the smart socket calculates and sends RMS current, voltage, real power and power factor parameters. The smart socket receives command signals from the coordinator and controls relays to switch appliance status accordingly. In addition, smart sockets receive signals from the coordinator and provides any required warnings about the appliance consumption.

3.3.5 Configurable Priority Setting Feature

Configurable priority settings allow users to schedule appliance operations according to their requirements. In this context, three different appliances are considered to be assigned high, medium, and low priority. Critical appliances that take time-of-use (ToU) into consideration are assigned a higher priority than other appliances. A diagram of configurable priority scheduling is shown in Figure 3.10.

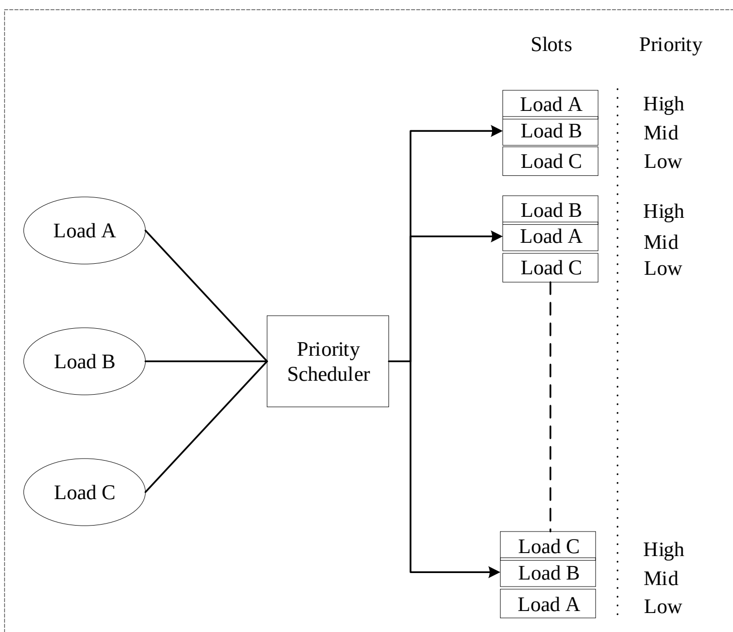

Figure 3.10: Illustration of the configurable priority scheduling

Consumer priorities for using appliances change every few hours in a day. For example, during the day AC is more important than lighting, but at night light is preferred over AC. As a result, prioritization is configurable to give consumers flexibility in situations where requirements change, allowing consumers to update at any time as needed. The priority of each load is displayed on the LCD screen in real-time.

3.3.6 IoT Environment with an Energy Monitoring System

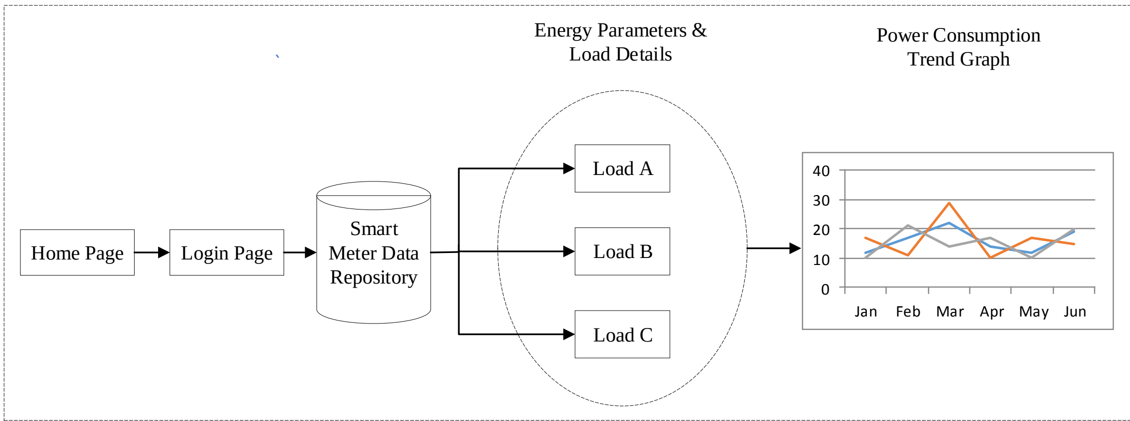

Figure 3.11: Overview of IoT environment

Smart meter housing development is used to monitor energy consumption in real-time. Developed SEMS power data can be uploaded to the server by establishing a connection through the Ethernet shield. In addition, uploaded data can be accessed and monitored using a data monitoring system or device. Collecting extensive metering data allows you to consider studies on managing energy systems. Currently, several research groups are exploring research areas such as real-time energy management solutions, big data analytics, machine learning, and energy cost solutions. A graphical view of the entire system is shown in Figure 3.11.

The energy monitoring system consists of a server and database management system for real-time monitoring and data acquisition, as shown in Figure 3.12. The server used is WAMP, and the overall application is accessed using localhost in intranet. The hostname can be changed from localhost to a specific domain name to access power parameters via the Internet. Multiple databases are created in the server to store different power parameters. Power data is uploaded to the server at the interval of 5min. In the web portal, only an authorized person can be able to login into the webpage using login credentials. Further, results and trend graphs are presented in section-3.4.6.

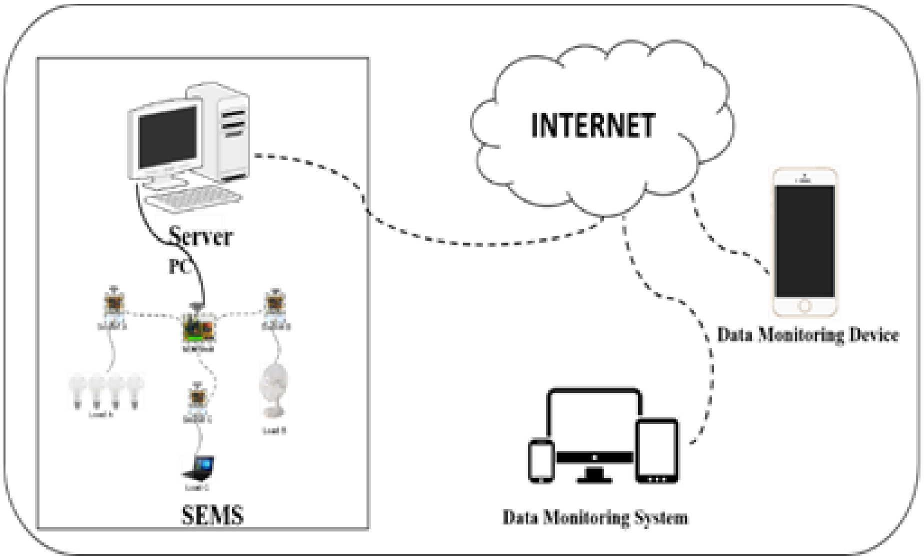

Figure 3.12: IoT environment for energy monitoring system

3.4 Demonstration and Result Analysis

In this section, results for different scenarios are demonstrated and are analyzed. Experiments are conducted by assigning an order of priority to appliance with different configurations, user comfort case and cost optimization technique are demonstrated to prove the effectiveness of the energy management system.

3.4.1 Smart Energy Management System Experimental Setup

In this section, emulation of demand response event is presented in laboratory environment for experimental verification of SEMS.

3.4.1.1 The Overall System Set-up

The overall SEM system is shown in Figure 3.13, which is set up in the laboratory environment with actual loads: a lighting load, a fan, and a charging laptop. Algorithms deployed in SEM unit are designed to run the appliances in the order of assigned priority during the Demand Response(DR) event considering the maximum demand limit, scheduling the appliance considering the Time of Usage (ToU) to accommodate it in the minimum slab rate.

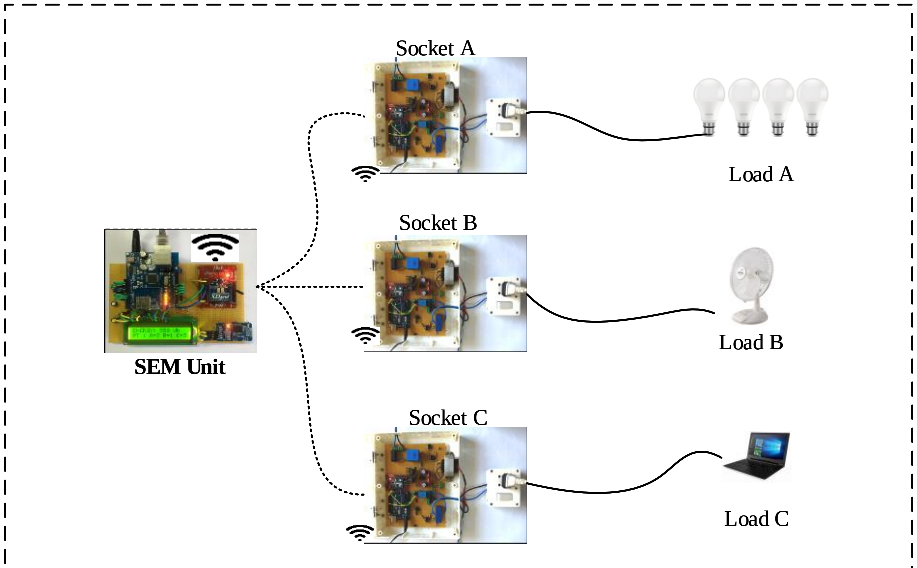

Figure 3.13: Experimental setup of SEMS

Actual loads are used in the experimental work in the laboratory environment, and an incandescent lighting bank is used as Load-A, which has the provision for varying the power consumption by switching on/off the status of the individual bulb within it. The fan is used as Load-B in the setup. Fans can change speed and are associated with humidity and temperature sensors to show how user comfort is integrated with the deployed algorithms. A charging laptop is included as Load-C. This load is deliberately chosen to indicate the scheduling of rechargeable loads with regard to ToU.

3.4.1.2 User End Interface with the Display Unit

The SEM unit has the LCD unit to display the essential electrical parameter such as energy consumption of the loads and the priority of the loads assigned. Switch buttons are included to change the priority of the appliance according to the consumer preference. The laboratory experimental setup of the SEM unit is shown in Figure 3.14.

3.4.1.3 Smart Socket Module as a Load Controller

The experimental setup uses three identical load controllers, which is named as smart socket as depicted in Figure 3.15, these are used as general-purpose socket built for switching the loads according to control signals received. Also, used for sub-metering application to measure the basic electrical parameters of the loads connected. The module is associated with an ATMEGA328 microcontroller unit, measurement modules, i.e., voltage(LEM LV-25P) and current sensors (LEM LA-55P), a relay module with 20A range for switching actions and XBee series-2 module for bidirectional communication.

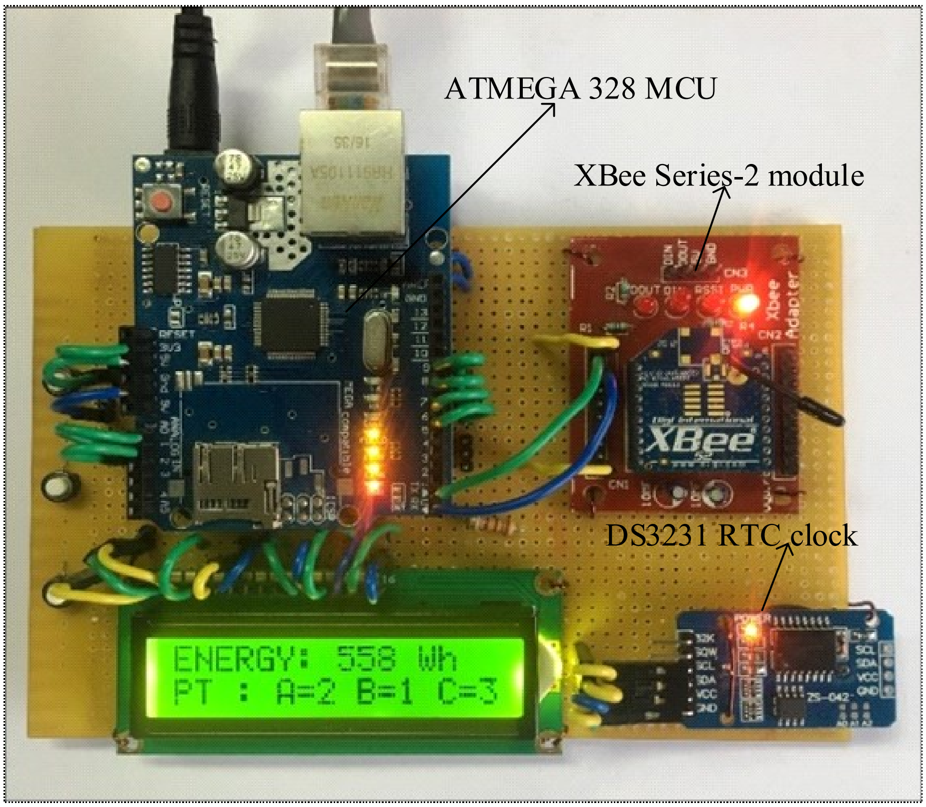

Figure 3.14: Experimental setup of SEM Gateway

3.4.1.4 SEM System Communication Modules

SEM systems use two identical XBee modules for ZigBee communication. XBee module with SEM unit configured as coordinator and XBee module with smart socket configured as a router. The experimental setup uses the application transparent (AT) mode of ZigBee communication. The coordinator in the SEM unit sends a broadcast data request message to the routers integrated with the smart socket in the predefined order, which collects all the power consumption data from the loads connected to the smart sockets. In turn, the router receives the control signal from the coordinator

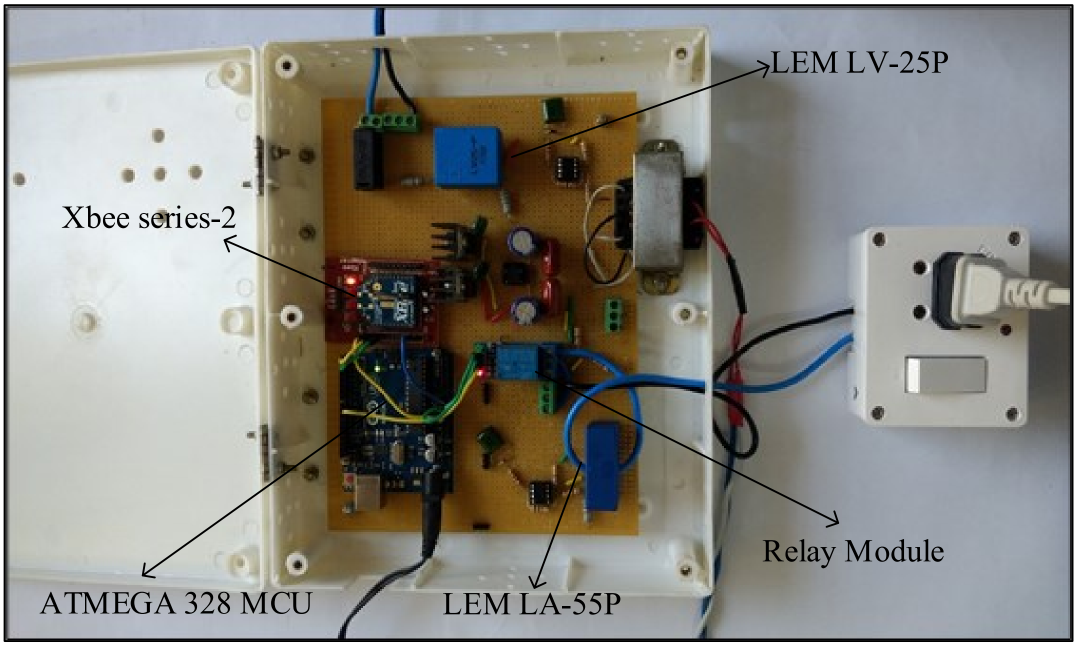

Figure 3.15: Experimental setup of Smart Socket Module

of the SEM unit. The data collected from the router is in the format of the string. In turn, it is converted to its equivalent decimal format to get the actual value of electrical parameters.

3.4.2 Operational strategy of the configured priority loads

The mechanism of how the load works in various configurations is described in the following subsections. Details of different cases are listed in the Table 3.2.

In this case, the incandescent bulb bank is considered as Load A and it is assigned with the highest priority. A fan load is assigned with mid priority and battery charging appliance is considered as a low priority, as it is a schedulable load. The SEM load scheduling operation is depicted in Figure 3.16.

Details of the step-by-step execution of load scheduling using set priorities are given below.

- **Step 1:** The SEM unit broadcasts a data request signal in the form of a string

Table 3.2: Different load priority configuration cases

Case	Priority Order	Load Type	Observation
I(a)	Load A>Load B >Load	Fixed	To show running of higher priority loads
I(b)	Load A>Load B >Load C	Variable	To show running of higher priority loads under dynamic consumption
II	Load C>Load B >Load A	Fixed	To show different priority configuration

"Ca".

- **Step 2:** Load A responds with its power consumption data: RMS voltage, RMS current, power factor, apparent power, active power, reactive power and energy.
- **Step 3:** Next, the SEM unit broadcasts a data request signal in the form of a string "Cb".
- **Step 4:** Load B responds with power consumption data.
- **Step 5:** Next, the SEM unit broadcasts a data request signal in the form of the string "Cc".
- **Step 6:** Load C responds with its power consumption data.
- **Step 7:** The SEM unit uses command signals in the form of the strings "raah", "rbbh", and "rcch" to turn on the relays for all three loads.

Case-I (a): Operational Strategy with Fixed Consumption of "Load a".

In Figure 3.16, it is shown maximum demand is set to be 530W (i.e., input from the utility). From the period 8.16.44 PM to 8.19.44 PM, all the three loads were turned since the maximum power consumption is less than the maximum demand limit (MDL). From Table 3.3, it is observed that the required power is below the maximum demand limit. Thus, according to the decisive algorithm, all three loads remain "on". In this case, since the total power demand is below the maximum demand limit, the SEM unit turns on the relays for all three loads using command signals in the form of strings "raah", "rbbh", "rcch".

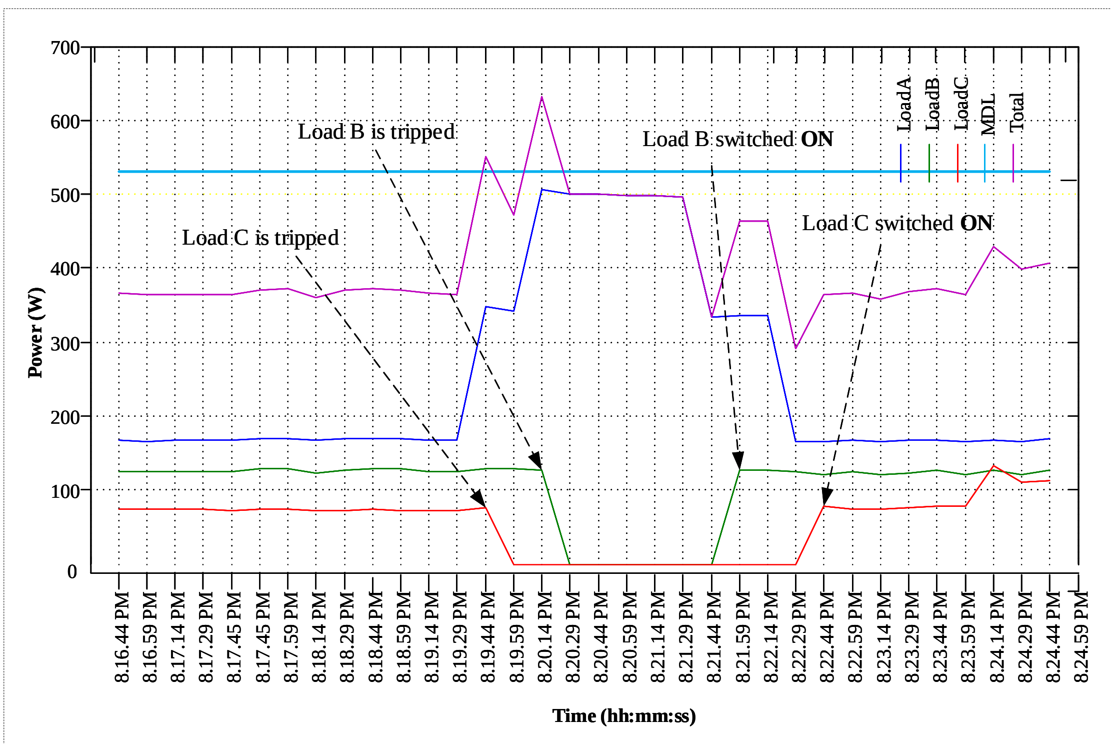

Figure 3.16: Experiment to demonstrate running of higher priority appliance with MDL constraint

Table 3.3: Appliance status after load scheduling case-I

Appliance	**Load A**	**Load B**	**Load C**
Appliance Status	On(1-bulb)	on	on
Apparent Power(W)	165	127	083
Power Demanded(W)		375	
Maximum Demand Limit (MDL)		530	
Appliance Status after power negotiation	on	on	on

Case-I(b)): Operational strategy with dynamic consumption of "Load a".

At the instant of 8.19.44 PM, the extra incandescent bulb in the bank is switched ((i.e., two bulbs ON) and the total power consumption exceeds the MDL.

The proposed SEM controller responds immediately to this scenario and turns off the battery charging load (Load-C). In addition, at the instant 08.20.29 PM, the lighting load alone consumes 497W of the 530W MDL, so switching the additional bulbs (i.e., three bulbs on) increases the power consumption of the lighting load. Therefore, the controller switches off the second load (Load-B) as well to balance the supply and demand. Finally, when Load A consumption is decreased, Load B and Load C are turned in the order of priority. Power consumption details and scheduling of appliances by SEM, in this case, are listed in Table 3.4.

Table 3.4: Appliance status after load scheduling case-II

Appliance	**Load A**	**Load B**	**Load C**
Appliance Status	On(1-bulb)	on	on
Apparent Power(W)	330	127	083
Power Demanded(W)		540	
Maximum Demand Limit (MDL)		530	
Appliance Status after power negotiation	on	on	off

3.4.3 Case-II: Operation Strategies for Configurations With Different Load Priority Order

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Figure 3.17: Experiment to demonstrate running of higher priority appliance with MDL constraint

Similar to Case-I, but the load priorities have been changed as described in the table ref tabe2 below in the graphical demonstration of Figure 3.17. The SEM unit compares the total apparent power of all the three loads (0.330 + 0.127 + 0.083 = 0.54 kW) with maximum demand limit of 0.53 kW. Since total power demand is more than the maximum demand limit and power demand of the first two priority loads(i.e. load C and load B) (0.083+0.127 = 0.210 kW) is less than the maximum demand limit. SEM unit switch ON relays of load 'c' and 'b' but switch OFF relay in series with a load 'A' using command signals in the form of strings "raal", "rbbh", "rcch".

Appliance operation based on a decisive algorithm with an assigned order of priorities is presented in the above Figure 3.17. The user wants to turn on all three loads. Initially, all the loads are turned since there is no violation of MDL. Load 'A' consumption is increased further, and it is observed that load 'A' is itself tripped off to avoid MDL violation since it is assigned with lower priority in this case.

3.4.4 User Preference Setting With Perceived Sensor Data

Most of the heating or cooling appliances are designed to operate at a fixed temperature or in a shorter range of temperatures which would force appliances to turn on or off frequently. For example, an air conditioner attains the desired temperature according to the temperature set by the consumer. The compressor in the air conditioner is turned on and stays on until the room temperature is equal to the set temperature.

While the desired temperature is reached, the compressor turns off until the room temperature rises again. Air conditioners consume a lot of power each time the compressor is turned on. This power is much higher than the power consumed by air conditioners for continuous operation (long cycles). Therefore, frequent short cycles will affect the efficiency of the air conditioner. On the other hand, the efficiency of an air conditioner increases as it operates for a longer time, i.e., longer cycle.

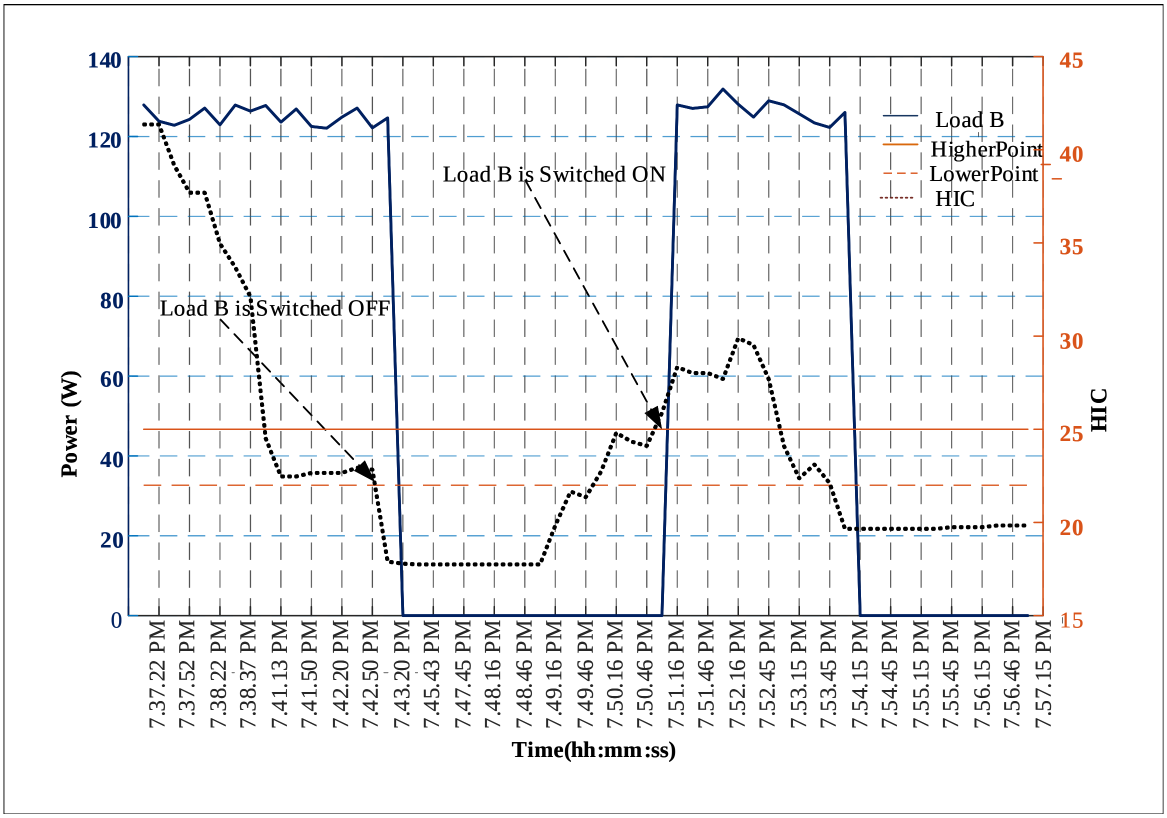


Figure 3.18: Experiment to demonstrate user comfort setting with the sensed parameter

In the proposed system, the consumer is given provision to set a larger range of temperatures to improve the efficiency of appliances, thereby reducing energy consumption. When SEM unit sends command signals to switch on a heating or cooling appliance, the load controller of that appliance also checks for comfort settings violation and controls appliance such that it always maintains the temperature within the range of consumer's comfort settings. In our case, data from humidity temperature sensor Heat Index in Celsius(HIC) is used as the threshold value with an upper limit $(25C)$ and the lower limit $22C$ to control the load status as shown in Figure 3.18. At the instant $7.43.20PM$, room temperature is below $22C$. Consequently, the controller turned off the fan load. Similarly, after some time (i.e., at 07.51.16 PM) temperature has crossed the upper limit $(i.e., 25C)$, the controller turned on the fan load.

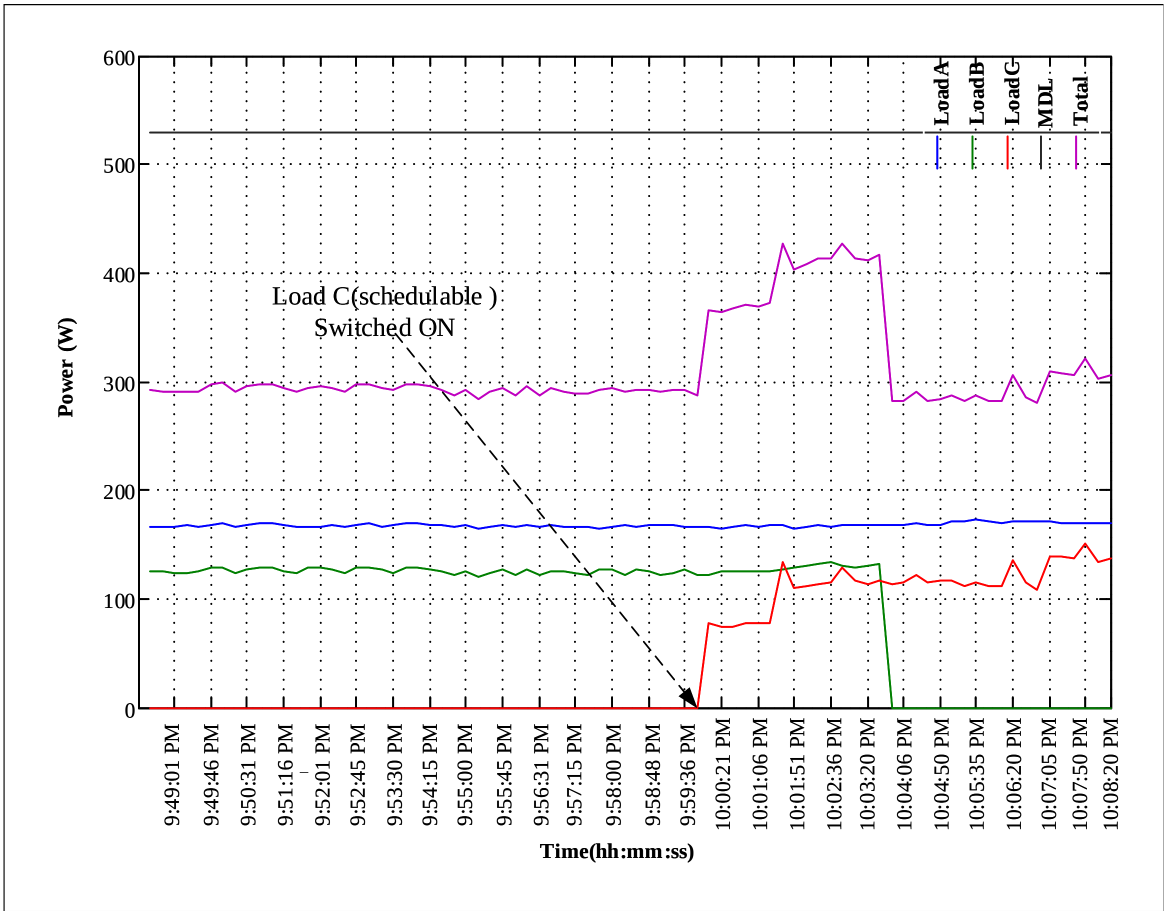


Figure 3.19: Experiment to demonstrate scheduling operation with ToU

3.4.5 Scheduling Considering ToU Tariff

As explained in the earlier sections, appliances in the household can be categorized into two groups, such as schedulable and non-schedulable. To reduce the electricity cost during the ToU tariff, the proposed controller shifts the schedulable loads to peak off hours. In this case, the controller uses the input from the RTC module and peak hours information from the utility. Load scheduling characteristics for ToU tariff system is shown in Figure 3.19. In this case, peak-off hours start from 10:00 PM. Thus the controller shifts the battery charging (i.e., schedulable load) to 10 PM to reduce the electricity cost.

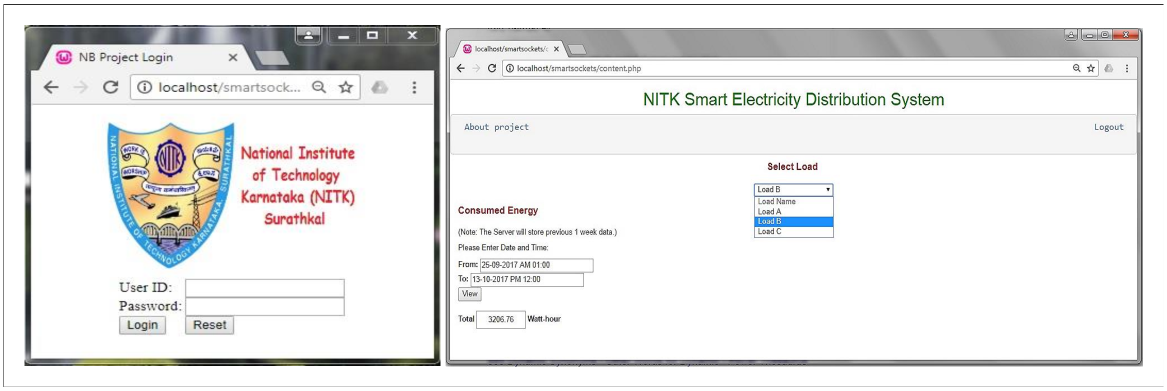
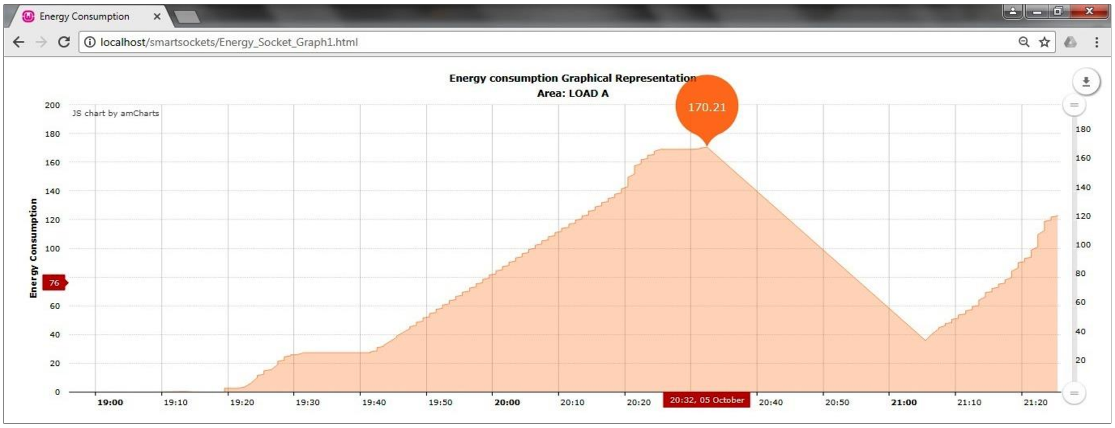


Figure 3.20: (a) Login Portal (b) Load and Time selection webpage

3.4.6 Iot Environment With Energy Monitoring System

The webpage is developed to display real-time energy consumption and other electrical parameters. The web portal is created in such a way that only an authorized person can be log into the webpage using login credentials. After successfully logging in, the user can access the smart meter data repository. For example: If a user wants to check the real-time energy consumption of any laboratory present on the webpage, the user needs to select that laboratory and specify the date and time as shown in Figure 3.20(a) and 3.20(b). By clicking view, it will enter into the next page, which displays the acquired electrical parameters. In the main page, there is a provision for checking the trend graph of power consumption of a different load, as shown in Figure 3.21(a). In addition, as shown in Figure 3.21(b), different electrical parameters will be displayed on this page. At the end of the page, it will show the total energy consumption of the selected laboratory.

The user needs to enter the login credentials in the login page, as shown in Figure 3.20(a) After successfully logged in to the webpage, the user can enter into the main page. In the main page, the user can have all the privileges to select the different laboratories, check the real-time energy consumption, power usage data, possible to view trend graph of energy consumption. If a user or guest wants to know the objective and project details can check it in about the project. The load wise power data such as RMS current, power demand, power factor, energy consumption, and assigned priority for a load of developed SEMS system is shown in Figure 3.21. In addition, due time in hours for the schedulable load is also shown in the power data table.



(a)

SERIAL.NO	TIME	RMS VOLTAGE IN VOLTS	RMS CURRENT IN AMPS	APPARENT POWER DEMAND IN VA	POWER FACTOR	ENERGY IN WATT-HOUR	PRIORITY
107	2017-10-05 19:41:35	227.40	0.00	0.00	0.00	27.38	1
108	2017-10-05 19:41:50	226.22	0.77	174.32	1.00	27.98	1
109	2017-10-05 19:42:05	226.37	0.77	174.27	1.00	28.69	1
110	2017-10-05 19:42:20	225.80	0.77	172.98	1.00	29.44	1

(b)

Figure 3.21: (a)Power consumption of the schedulable load (b) Power consumption trend graph

3.5 Summarry

The hardware prototype of SEMS is designed and developed in the laboratory environment, experiments are carried out to demonstrate the effectiveness and working of the power optimization algorithms deployed in the controller. The wireless ZigBee communication is established using XBee series-2 modules between the SEM controller and smart socket unit, incorporated with a new advanced self-diagnostic mechanism to form a reliable network. The first experiment demonstrates the novel configurable priority feature, where, in three different loads are considered, there is a provision to change the priority order of an appliance according to the consumer requirement. Secondly, in this work, different experimental scenarios are exhibited to show the running of only higher priority appliance during DR event and under MDL constraint. Furthermore, cost optimization algorithms are deployed in the SEM controller, which schedules the operation of a particular appliance during the off-peak hours considering ToU tariff and hence utilize the lower slab rate to minimize electricity cost. In order to avoid higher power consumption during peak hours, a warning is given to the consumer with buzzer and LED indicators. Finally, to access the power consumption data of individual load, secure web portal associated with an IoT environment is developed. The GUI provides a power consumption plot to display daily and monthly appliance power usage. A database is provided for the energy management system and can be used for further data analysis.

Chapter 4

Demand Side Optimization Approaches

4.1 Introduction

Smart grids integrate demand and supply entities with advanced communications technologies and employ a control mechanism framework to respond more efficiently to energy crises. The deep penetration of renewable energy sources, such as solar and wind energy, poses the additional challenge of distributing energy in smart grid environments. The above elements cover a variety of features in search of highly adaptable grid infrastructure. The main responsibilities of modern smart grids are focused on secure and reliable networks with high power quality, optimal power usage and maximum user satisfaction. In the previous chapter, the design and development of an energy management system for demand-side consumers taking into account power negotiation and user, adaptable features are considered. This chapter focuses on evaluating the performance of several optimization techniques for scheduling appliances based on appliance category, usage patterns and consumer preferences. A typical optimization model with dependent parameters and objective function for demand-side consumers is shown in Figure 4.1.

4.2 Optimization Techniques

This work uses several techniques of machine learning, and the underlying assumptions behind each are described in the next section.

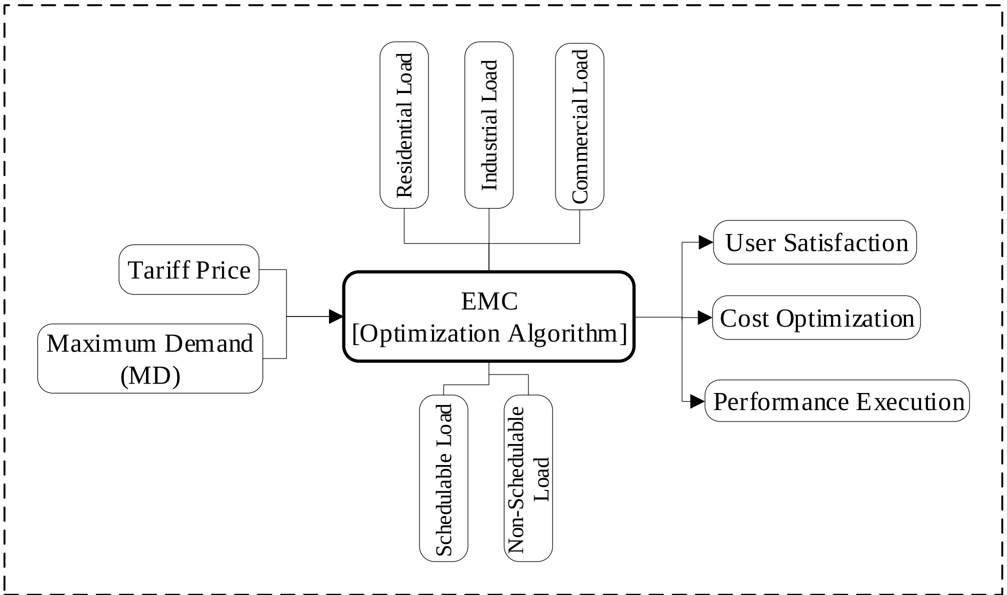


Figure 4.1: Optimization model for demand-side consumers

Genetic algorithms are based on natural selection by pseudo-random modification of the solution and filtering based on its suitability. Typically, these are the four key steps (initialization, selection, mutation, crossover), and the last three stages will be repeated several iterations or until the solution remains unchanged long enough. These new methods have been tested against binary particle swarm optimization algorithm as a benchmark and determined to be suitable for load scheduling, and are described in the next section.

In SG, DSM makes grid service more effective and more reliable. The two main functions are energy supply and end-user demand monitoring. Furthermore, at DSM Consumers, all smart premises have an energy management system (EMS) and smart meters to ensure that two-way communication between utilities and customers is stable and reliable. The controller is provided with all details, such as load and devices, sensors, local energy generation, energy storage and usage pattern (ESS), and the EMS optimally controls the appliance's scheduling.

4.2.1 Binary Particle Swarm Optimization

Binary Particle Swarm is a variant of the original Particle Swarm algorithm that Kennedy and Eberhart invented in the population optimization process. The solution to this problem is inspired and is seen as a swarm of particles by the behavior of flocking birds and schools of fish. Particles are initially randomly placed in solution space and move into solution space. Particle position is affected at each iteration by the most effective particle position. If the optimal position achieved by the particles is *pbest* and the particle position that performs best is *gbest*, then at each learning iteration the particle velocity and position can be updated as in equation 4.1 and 4.2.

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

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

where, v_i^k = velocity of particle i at iteration k.
w = inertia coefficient, specified by programmer.
c_1, c_2 = acceleration coefficients, specified by programmer.

The solution space must be discretized in order to use PSO for the load scheduling problem. Solution space needs to be discretized. Furthermore, the binary PSO is mapped to a range of $[0, 1]$ using sigmoid function as in equation 4.3, and uses same velocity criteria and velocity mapping between the range $+V_{max}, -V_{max}$ as conventional PSO.

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

The position is updated by comparing $S(v_i)$ to a random number. If $rand() < S(v_i)$,$x_i = 1$ else $x_i = 0$.

The $rand()$ function is a random generator number between 0 and 1. The particles modify the values before they fulfil the convergence criterion and achieve the maximum number of iteration. In this case, $rand()$ function guides the particle to the optimal global value that increases the iteration count.

4.2.2 Artificial Bee Colony Algorithm

Karaboga and Akay (2009) have developed the Artificial Bee Colony(ABC) algorithm, the bee colony algorithm uses a population-based optimization, with several differences from the PSO and finds an ideal solution based upon the bees drilling actions in a comparative nature. The particles in the solution space are modelled as 'food source' for the bees, and the bee colony consists of three groups of bees, each pertaining to one stage of the algorithm. For its simplicity and usability, the ABC implementation algorithm has received considerable attention in planning job optimization to solve many practical problems (Chen and Xiao, 2013).

The three classes of artificial bees are known as employed bees, scouts and onlookers. Bees make foraging decisions based on various factors. For example, distance to food, quantity and quality of honey all these factors made up the assessment of food sources and represented as profit.

In accordance with the classification, Scout bees are expected to search for new food sources randomly, and Employee bees must search for the sources of food to warn onlooker bees that are waiting for hives. The bees then calculate the health value of the onlooker and choose the optimal source of food for the selection of the bees. Once a food source has been selected, and all food has been collected, the bees working on that food source are converted to scouts and again search for a new food source randomly. Bees measure the consistency of food sources on the dance floor in real nature. The bees dance, called "Waggle dance", to inform others how far and how much quantity towards which direction. All food sources are comparable with the best ones by onlooker bees. The details of ABC algorithms are described in the following sections.

The key steps of an algorithm for artificial colony of bees are as follows. The initial parameters set are the number of bees used, the maximum number of the sources for food used (limit), and the maximum number of iterations (max cycle) and the number of bees being used, and the number of bees detected.
For random food sources selected under boundary constraints, the initialization and fitness value of Scout bees are determined. Thereby, our load particles already comply with start and end time and maximum demand constraints. In the algorithm, N is the number of food sources, or solution space particles, and $i = 1, ...N$. D is the number of decision variables, in our case the number of loads, and given by $j = 1, ...D$. A counter is used for each food source, i.e. $count_i = 0$ at start. Further, another food source will be provided during the search process for the employed bee stage using

equation 4.4.

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{4.4}$$

Where, ϕ_{ij} is a random number generated between 0 and 1, and j and i satisfy previously set limits. The fitness of the new source of food is then evaluated and modified in accordance with the cost function if the fitness level is better than the old one.

Roulette wheel selection is used in the onlooker bee process to produce probability of selecting each source of food using equation 4.5.

$$p_i = \frac{fitness_i}{\sum_{i=1}^{N} fitness_i} \tag{4.5}$$

Where, $fitness_i$ is the fitness cost of the i^{th} food source, N is the number of food sources and a random number r is generated between 0 and 1, and if $r < p_i$, a new food source is generated as above. If the new food source is better, the algorithm will greedily update the old one, and this will be repeated for all onlooker bees. In case, if some food sources have not been improved during a certain number of Scout Bee stages, those food sources will be abandoned. The algorithm thus avoids remaining at local minima and finds a new, randomly assigned food source.

4.2.3 Backtracking Search Algorithm

BSA is a search algorithm for adaptive analysis using three components of genetic operators, namely selection, mutation and crossover for generating individual trials (Civicioglu, 2013). BSA is a population-dependent algorithm that uses a single control parameter, unlike the earlier two. It also possesses internal memory that is used in generating a search matrix for generation of trial population. The BSA involves mainly five stages for execution as described below:

Initialization: Initialization generates the initial population according to the problem constraints. In this case, N is the size of the population and D is the dimension.

Selection-I: In this phase, historical population $oldP$ is found for calculation of search direction. The initial historical population is generated as as above in initialization stage. BSA determines the population that belongs to the randomly selected previous generation as the historical population and remembers it until changed. After oldP is changed, the order is altered to enhance the randomness of selection by $oldP := permuting(oldP)$.

Mutation: Mutation process generates the trial population as per equation-4.6.

$$Mutant = P + F.(oldP - P) \tag{4.6}$$

Where F, is an acceleration term for the search matrix, $(oldP - P)$, given by equation-4.7, thus allowing the BSA to take advantage of its experience.

$$F = 3r_n \tag{4.7}$$

Where, $r_n \in (0, 1)$, and M is a standard normal distribution, and F is the controlled parameter.

Crossover: The Crossover process of BSA generates the trial population's final form by evaluating the fitness of the trial population. In this phase a binary integer-valued matrix (map) of size $(N \times D)$ is calculated indicating individuals of trial population T to be manipulated via relevant individuals of P. If $map_{n,m} = 1$, where $n \in 1, 2, 3, ...N$ and $m \in 1, 2, 3, ...D$, T is updated with $T_{n,m} : P_{n,m}$. The unique mix rate parameter in the process controls the number of individuals in a trial that will mutate. After mutation, updates are made according to selection II.

Selection-II: In this phase, based on a greedy selection, the T_i individual with better fitness than the corresponding P_i individual is used to update P_i. Further, if the optimal T_i is a better fit than the global optimal, the global optimal is also updated.

The next section describes the formulation of the load scheduling problem under specified constraints and performs an evaluation of the optimal scheduling optimization algorithm.

4.3 The Problem Formulation

The work of (Remani et al., 2015) frames the load scheduling problem as a constrained optimisation problem. Thus, one day is divided into 24 slots and one hour in a day is every slot. In this case, slot 0 is the time between 12:00 AM and 1:00 AM, slot 2 between 2:00 AM and 3:00 AM, and so on. The individual load are modelled with four parameters as $d_j = (s_j, f_j, l_j, r_j)$, where, $[s_j, f_j]$ indicates the interval at which the load can be operated, for a load operation, s_j is the start time of the load and f_j is the end time of the load operation. l_j is the working load time, the minimum load time to be completed in order to operate efficiently and r_j the load rating value is in kW. Thus, a load $d_j = (1, 5, 2, 6)$ represents a load that may be operated from 1am to 6am, with its minimum on-time as two hours. In addition, it consumes 6kW of power when on.

The cost function used is one of the total costs of energy drawn by all loads during the day. The utility provides the ToU price in advance, and it is assumed that there is a maximum demand limit above which no-load operation is allowed. The total cost is a function to minimize, and the total demand must be below the maximum demand limit. This is calculated hourly as D_t, which is the demand at time t given by the following equation 4.8.

$$D_t = \sum_{j=1}^{k} r_j a_j^k \tag{4.8}$$

Where, r_j is an estimate of load j, and a_j^k is a binary value of 1 if load j is on and 0 if off at the time that demand is calculated. The prospect solution detects demand every hour and must always be below maximum demand. Therefore, the cost function can be estimated as in equation 4.9.

$$TotalCost = \sum_{k=i}^{24} \sum_{j=1}^{m} r_j C^k a_j^k \tag{4.9}$$

Where, r_j is the rating of load j, C^k is tariff rate and a_j^k is a binary value of 1 if load j is on and 0 if off at the k^{th} time Constrained by $s_j > k > f_j$; by given equation 4.10.

$$\sum_{k=s_j}^{f_j} a_j^k = l_j \tag{4.10}$$

Therefore, constrained optimization in the discrete solution space is used to find the optimal start time for each load, so that the cost function is minimized while the given constraints are satisfied.

4.4 Evaluation of Optimization Algorithms for Demand Side Energy Management

In this work, three different genetic algorithms are implemeneted, and the tic and toc function is used to find the algorithm execution time. However, flow is modified to suit the platform used, thereby altering the flow of algorithms as depicted in this section's flow charts.

In this case, simulation experiments are performed on the basis of PSO algorithms to achieve the best solution for the proposed objective function. The particles make up the element corresponding to each load selected from $m_j = (f_j - S_j - l_j + 1)$. For example, if $dj = (8, 12, 2, 4)$, then $mj = 3$. The ON time slot switch that can schedule the load j is $s_j + n$, where $n = 0, 1, 2...m_j$ and population is generated in binary. The optimal global particles can provide an optimum schedule, and the corresponding fitness values can achieve the lowest cost. The algorithm begins by initializing the maximum demand limit, the number of loads, population size, word length of each particle, the maximum number of iterations considered, pbest and gbest values.
The value of mj is calculated using the required load parameters such as start time s_j end time f_j load rating rj and lj, and schedules the appliance in the allowed slot. The initial population is generated within the tolerance of mj. Following, the velocity parameters are initialized. The fitness of the i-th particle is calculated using equation 4.1, $fit(i) < pbest(i)$, and if it does not violate the maximum demand limit of the current position, $pbest(i) = fitness(i)$ and location. $pbest(i) < gbest$, also stored if $gbest = pbest(i)$, and the global optimal particle position is saved.

The velocity value for each binary element of the particle is updated using the equation 4.1 and 4.2 within the acceptable range $+Vmax$ to $-Vmax$. The mapping of the velocity $S(v_i)$ is done using a sigmoid function as in equation 4.3, and $S(vi)$ is compared to $rand()$ to get a new position x_i. The maximum number of iterations is performed to get the schedule from the global best particle and get the best cost from

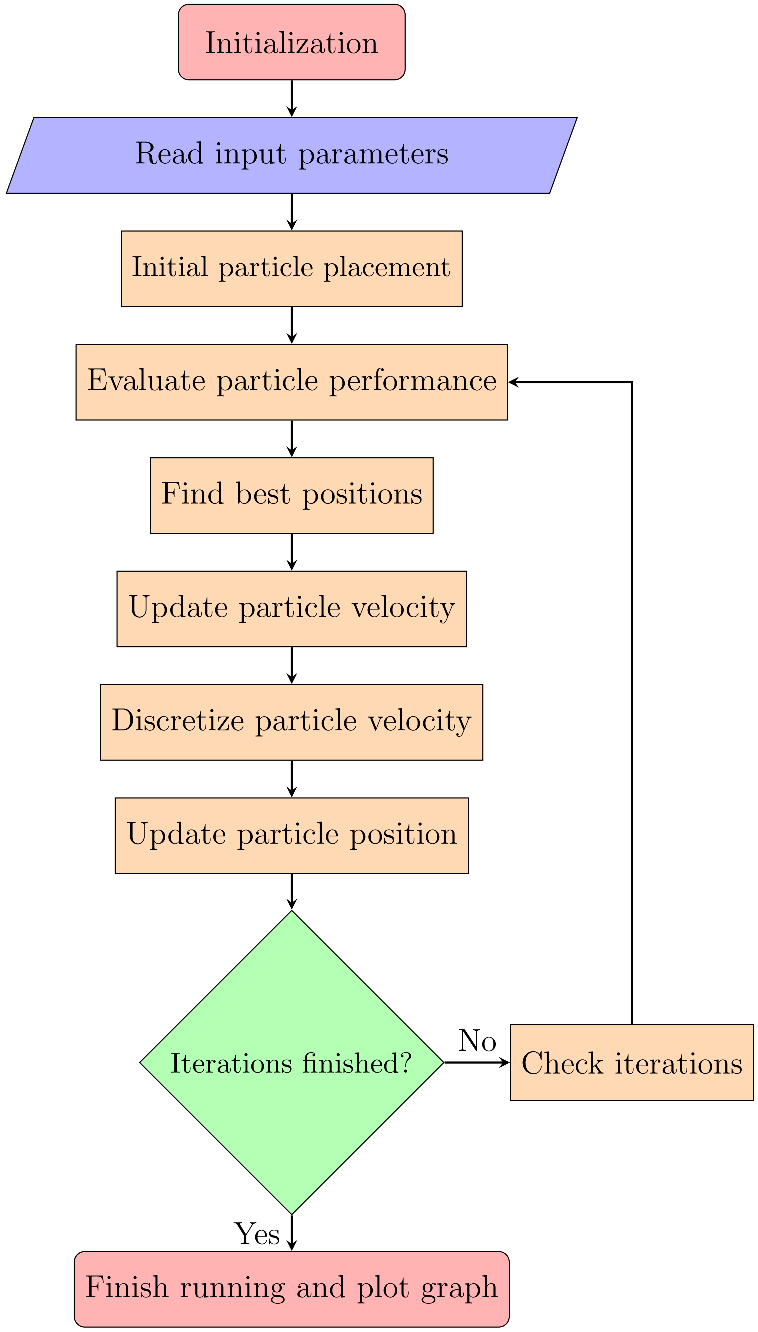


Figure 4.2: The flow of particle swarm optimization algorithm

gbest. Finally, the number of iterations is checked, and when the iterations are over, the algorithm ends. Otherwise, perform a further assessment of fitness and exit the loop, as shown in the Figure 4.2.

In the ABC algorithm, all load parameters are defined, such as the number of loads

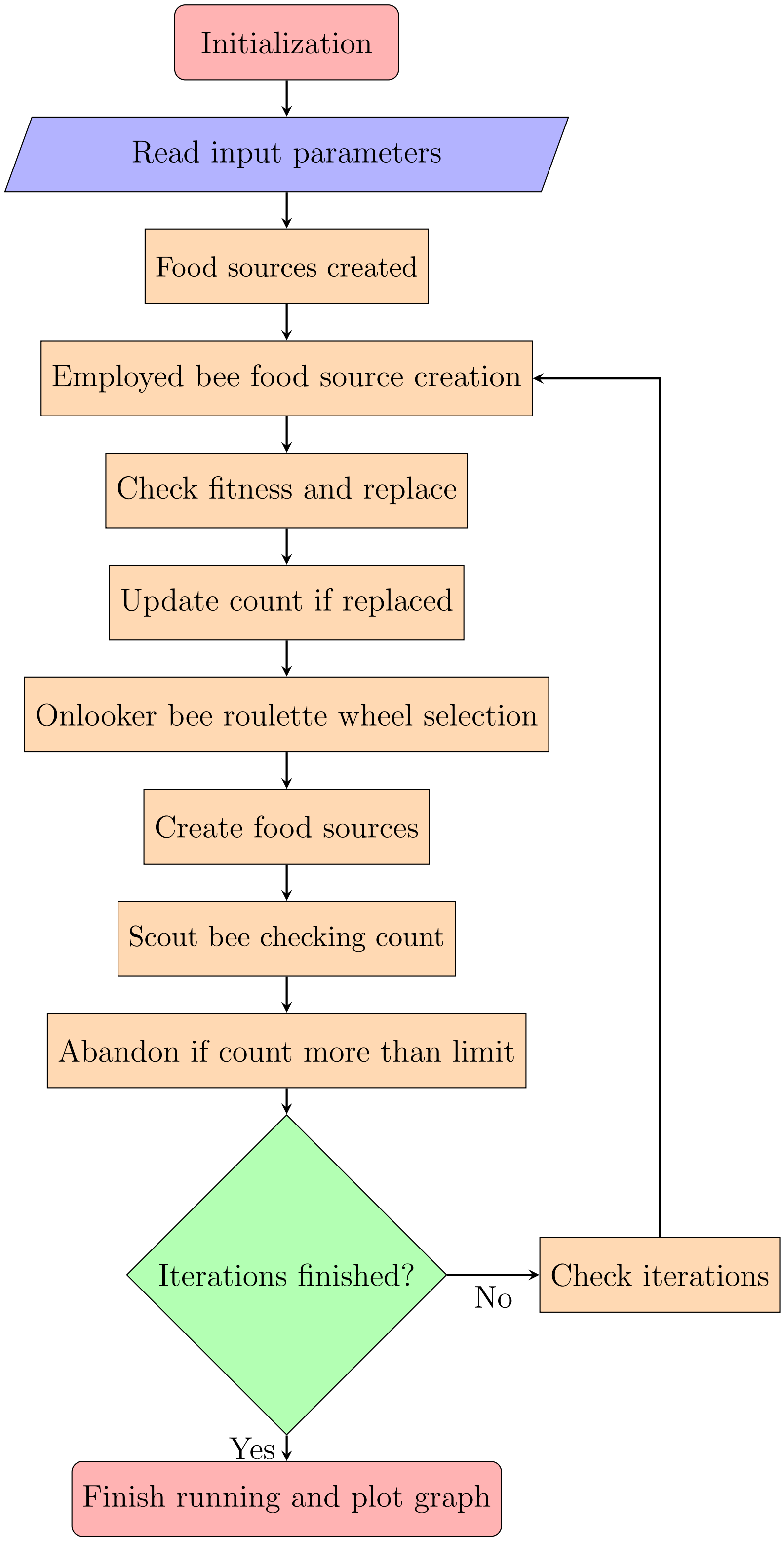


Figure 4.3: The flow of artificial bee colony algorithm

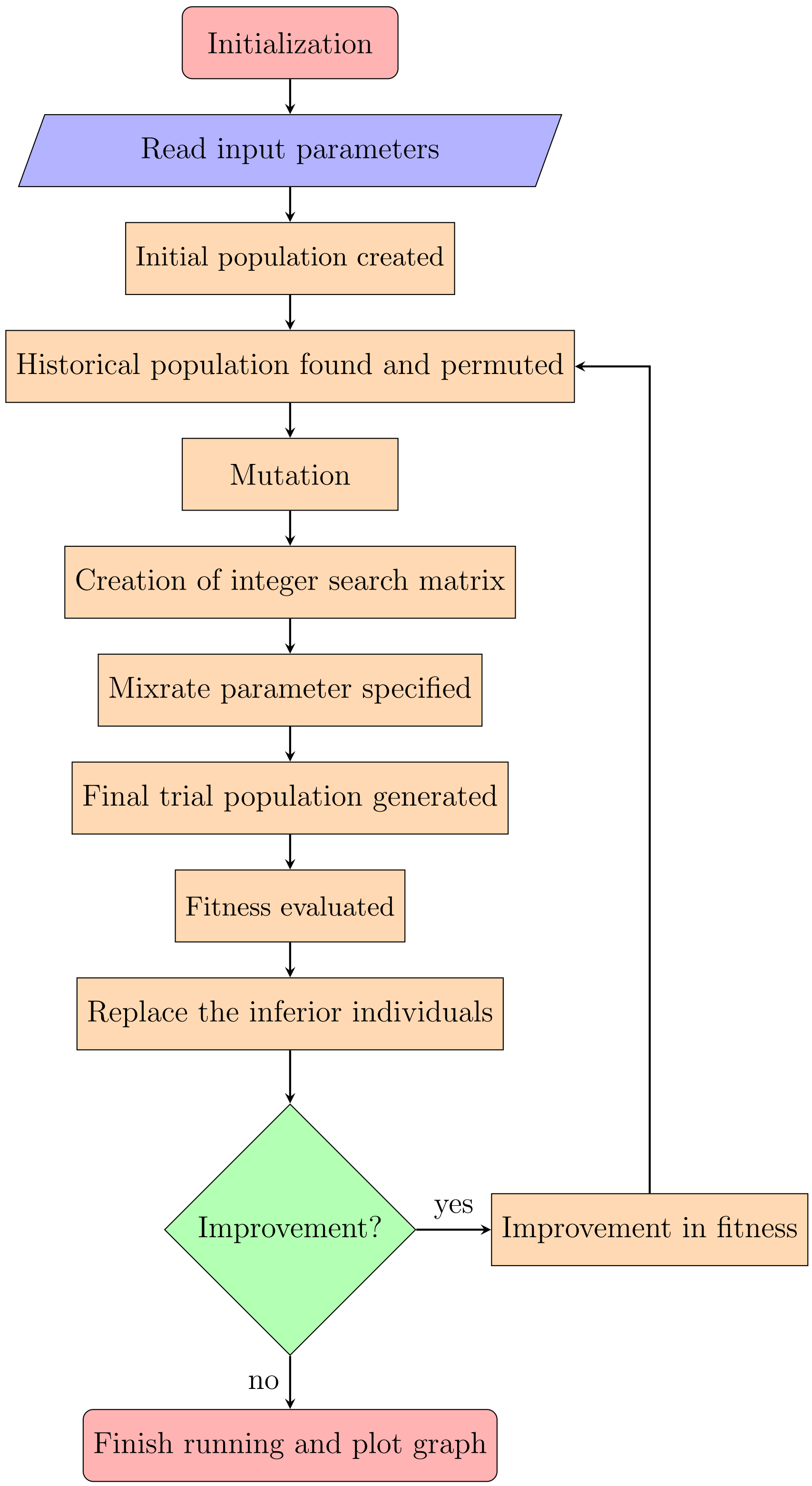


Figure 4.4: The flow of backtracking search algorithm

as decision variables, the size of the population, the number of onlookers bees, the demand limit, and the maximum number of iterations. The cost function is defined as equation **??**, and the maximum demand constraint is defined as equation 4.8. The algorithm flow is shown in Figure 4.3.

In this application, the initial cost calculation for a particular load schedule location is obtained according to f_{upper} bound (end time), $s_{lower(j)}$ bound (start time), and maximum demand limit constraints. Further, random creation of initial food sources is followed similar to the basic ABC algorithm. In the bee stage used, another food source is generated as follows in equation 4.11:

$$pop(i).Position(j) = randi([s_{lower(j)}, f_{upper}(j) - dur_{load(j)} - 1]) \tag{4.11}$$

Here, $pop(i).Position(j)$ is load schedule position as fitness function , j and i follow limits laid out earlier. The function $randi$ is a random number generated between 0 and 1. Corresponding to the fitness, cost function is evaluated as per in equation 4.9 to get the best solution.

The Employed bee phase is used to find the near fitness value (i.e. cost) using the number of population sizes (bees) at various schedule locations. The maximum iteration fit is evaluated and updated with the best solution. Following, in the onlooker bee phase roulette wheel section is run to get the probability value of the new and better schedule position to find the optimal fitness value. Similar to the previous case, fitness values are evaluated and updated with the best solution for a maximum number of iterations.

In the scout bee phase, fitness values are calculated randomly, and in case the trial particle has crossed the count limit than the evaluation is assumed to be struck, and it is eliminated. Finally, the best solution is updated among all the bee particle after global and local assessment to get the best cost value in our case. The best schedule is obtained for the best cost position since the demand limit condition is intrinsic.

The backtracking search algorithm (BSA) algorithm is used to schedule load equipment at specified times, taking into account user-defined constraints. The implementation of the algorithm is as depicted in Figure 4.4, starts by resetting the BSA parameters, mainly the population size (N), the maximum number of iterations performed (T), and the number of problem variables (D). This work uses 100 populations and 100-600 iterations to get the best results. In addition, it runs the BSA algorithm to schedule user-defined appliance load requests. Each population (Z_{ij}) takes into account user constraints such as appliance start time, end time, and the number of hours that must run with the maximum demand constraint. The initial population is calculated as in the following equation-4.12.

$$pop(i, j) = randi([low(j), up(j) - dur_{load(j)} - 1]) \tag{4.12}$$

Where, i is the population size, and j is the number of loads as decision variables, $low(j)$ is the start time and $up(j)$ is the end time of load.

Initially, historical population are created, if in case this is not the first attempt then available historical population are chosen. Next, a permutation of the historical population is used to enhance the mutation randomness. Population mutate carried out as per the equation 4.6, and binary integer search matrix is prepared to evaluate the fitness prior to crossover. The mix rate parameter is used to find the number of population members to mutate. The final population generated through crossover and fitness evaluation is carried out as per the cost function given by equation 4.9.

Finally, individuals are replaced in which it is found to have inferior fitness compared to the mutants generated. Furthermore, if the overall cost function among individuals is improved, the individual will be sent for another iteration. Otherwise, it is made to terminate the algorithm. Global minima are stored to get the best cost for the maximum iterations carried out, and the corresponding demand function gives the best schedule.

4.5 Results and Discussion

The MATLAB simulation tool implements three algorithms using trial values according to the author's work on (Remani et al., 2015) using PSO. Experiments are conducted to find the algorithm with the best runtime for the set number of iterations and the one that converges fastest. The best load scheduling algorithm is chosen based on convergence and speed of execution.

During the simulation, a different set of experiments is performed according to the problem statements described in section 4.3. In this case, the six loads are considered with four load parameters, such as load start time "s", load end time "f", number of hours the load has been running "l", and load rating "r". The first trial uses $s = [2, 4, 6, 4, 5, 11]$, $f = [11, 18, 8, 12, 10, 19]$, $l = [2, 3, 3, 3, 6, 4]$, and ratings $r = [4, 4, 4, 5, 5, 6]$. Thus six loads are present, each with one start time, end time, duration and rating. Maximum demand is at 10kW, and the tariff price for 24 hour time slot is given by $P = [4, 4, 10, 10, 4, 4, 4, 4, 4, 4, 4, 10, 10, 10, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4]$, having one cost value per hour. The second trial also uses same parameters with six number of loads with a maximum demand limit of 20kW.

4.5.1 The Binary Particle Swarm Optimization

The BPSO algorithm uses several parameters during execution. The initial acceleration factors $c1$ & $c2$, the inertial mass w_{min} & w_{max} that can be used to control the velocity of the particles and the number of particles used are listed in the table 4.1.

The flowchart of the BPSO algorithm is presented in Figure 4.2. From the analysis, it is observed that the binary PSO converges within eleven iterations for a small six-load optimization problem. The demand over time for six-load using BPSO is shown in Figure 4.6 also shows the power consumption demand pattern with maximum demand limit of 10kW. The minimum best cost obtained is 428 for the trial of six loads. It is also observed that to run through 600 iterations of the binary PSO for this problem takes close to two minutes - 117.7 seconds. The best cost obtained over iteration plot is shown in Figure 4.5.

Table 4.1: Parameters of BPSO algorithm

Parameter	Values
$c1$	2.05
$c2$	2.05
w_{min}	0.4
w_{max}	0.9
$No.of Particles$	20

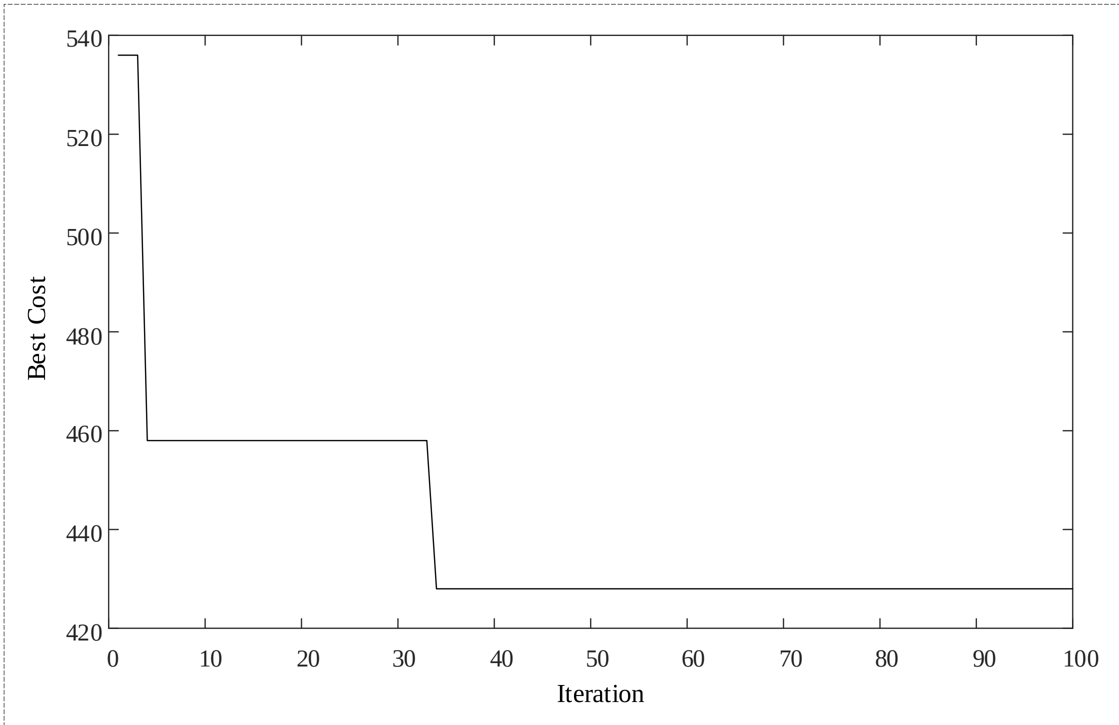


Figure 4.5: Best Cost over Iteration(Max n=100)

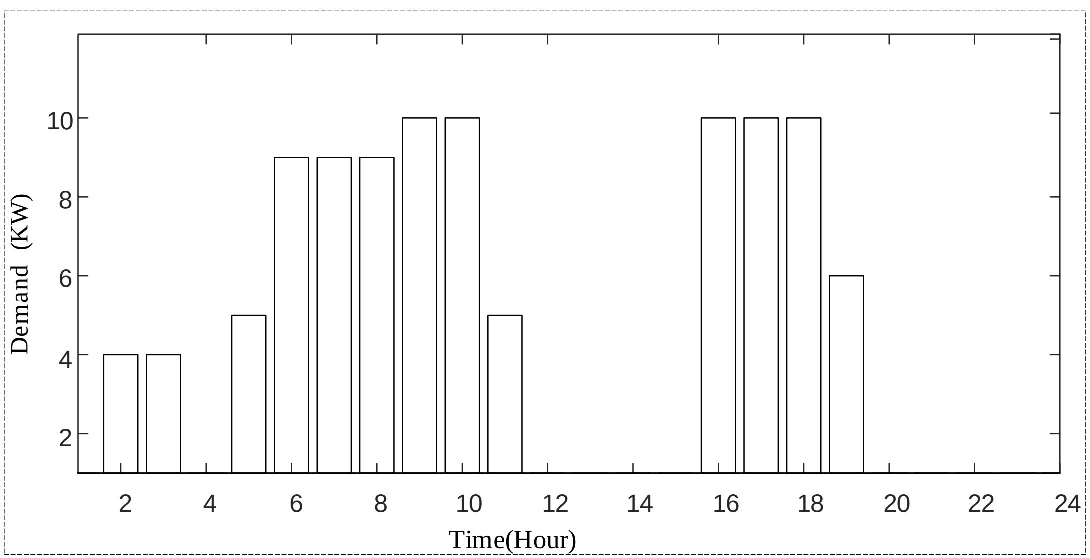


Figure 4.6: Demand(Max MD=10) over time for six-load BPSO

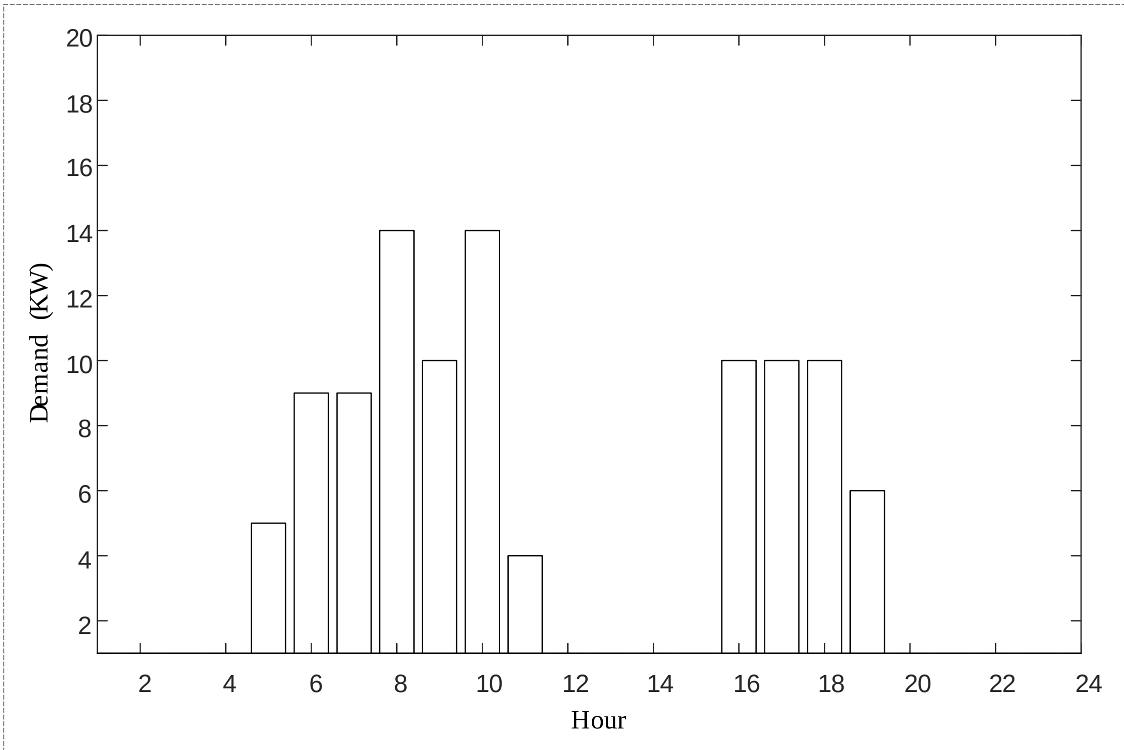


Figure 4.7: Demand (MD=20) over time for six-load BPSO

The demand over time for six-load using BPSO is shown in Figure 4.7 shows the power consumption demand pattern with maximum demand limit of 20kW and correspondingly cost minima obtained is 404. The second trial of six loads takes 4.52 seconds for 600 iterations.

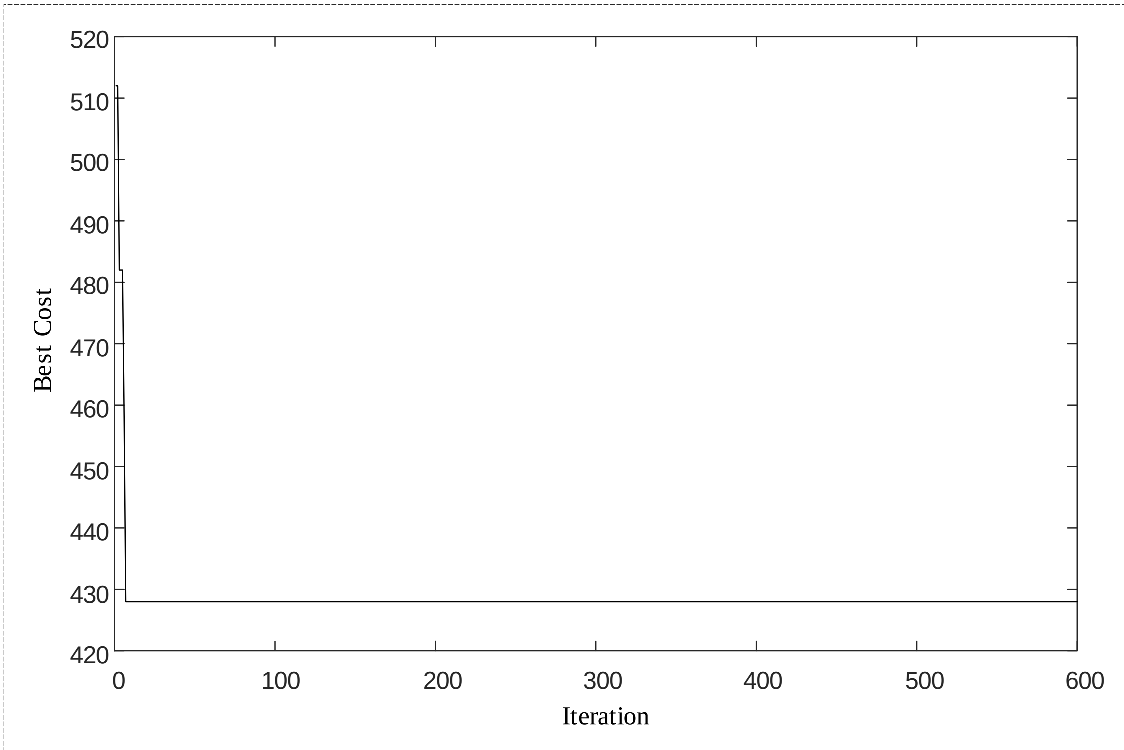


Figure 4.8: Best cost over iteration(Max n=600)

4.5.2 The Artificial Bee Colony Algorithm

The flow of the ABC algorithm is shown in Figure 4.3. Similar to the BPSO case, a different set of experiments are conducted considering maximum demand limit of 10kW and 20kW. The power demand consumption of the six load ABC over time is shown in Figure 4.9. The ABC algorithm appears to converge the second fastest of the three algorithms (within seven iterations). However, the execution time for 600 iterations is 9.27 seconds. The above scenario demonstrates the nature of the ABC algorithm for problems with a large number of decision variables, and at higher problem dimensions, it should perform better than the PSO. The best cost obtained from the iterative plot is shown in Figure 4.10. Further, a comparative discussion is presented in section 4.5.4.

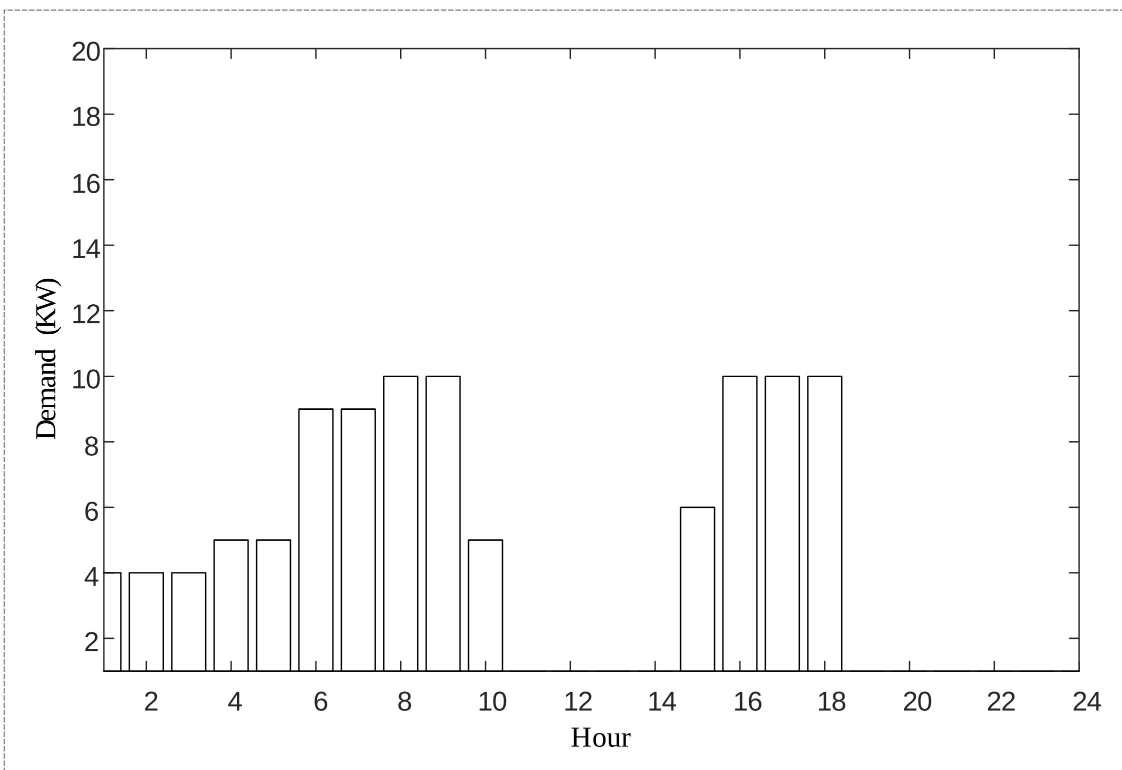


Figure 4.9: Demand (Max MD=10) over time for six-load ABC

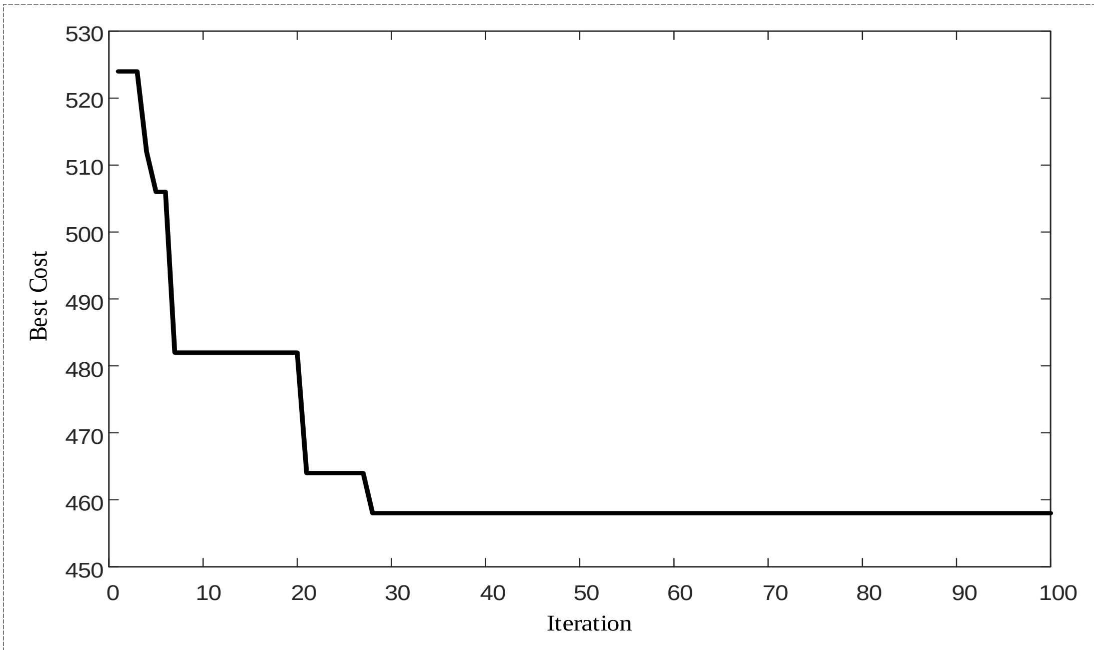


Figure 4.10: Best cost over iteration(Max n=100)

The demand over time for six-load using ABC is shown in Figure 4.11 shows the power consumption demand pattern with maximum demand limit of 20kW and correspondingly cost minima obtained is 404. Best Cost obtained over iteration plot is shown in Figure 4.12 for 600 number of iterations.

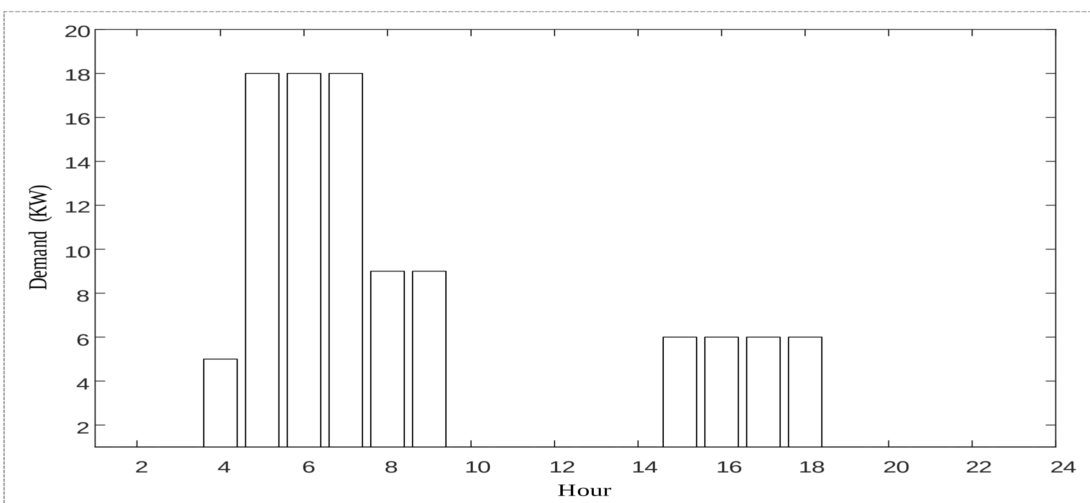


Figure 4.11: Demand (Max MD=20) over time for six-load ABC

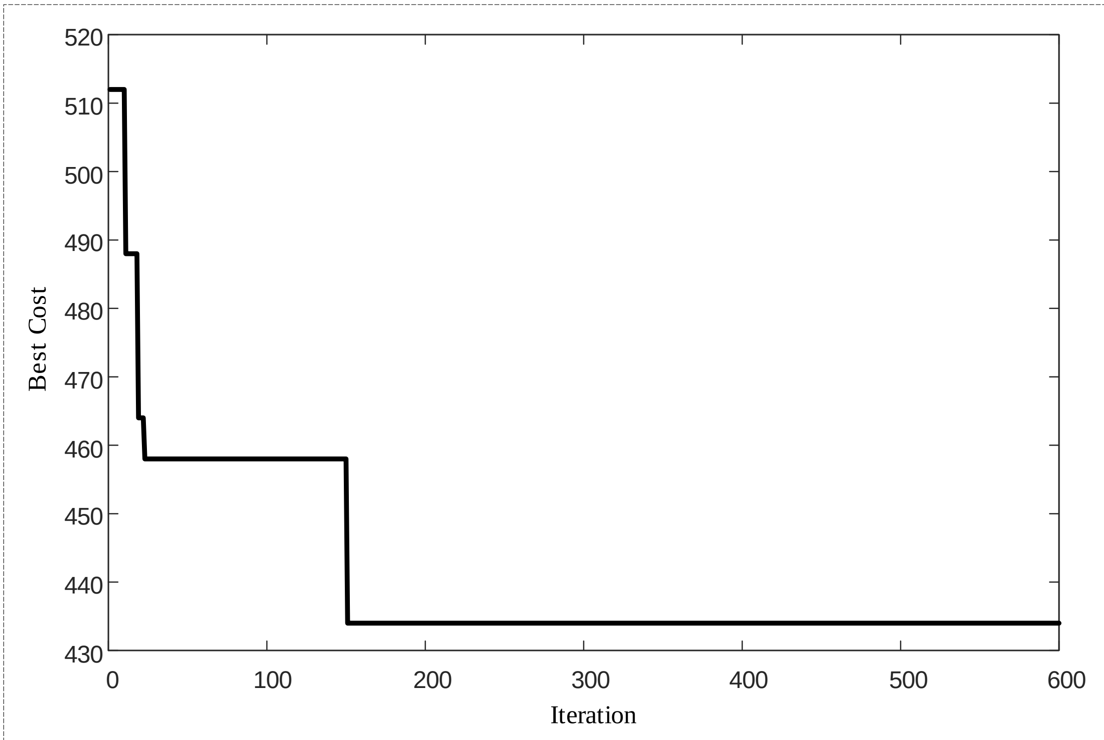


Figure 4.12: Demand over best cost iteration(Max n=600)

4.5.3 The Backtracking Search Algorithm

The analysis of the BSA algorithm is shown in Figure 4.4. Similar to the previous case, a different set of experiments are conducted considering maximum demand of 10kW and 20kW. The power demand consumption over time for six load BSA with maximum of 10kW demand is shown in Figure 4.15, which achieves a cost minimum of 434. The BSA terminates automatically after convergence due to its use of historical values. Once there is a little divergence from the historical values, the BSA algorithm ceases to count iterations and terminates. Here it is that convergence has occurred in four iterations that have taken 2.3s to run 600 number of iteration as shown in Figure 4.14 . Further, the comparative discussion is presented in section 4.5.4.

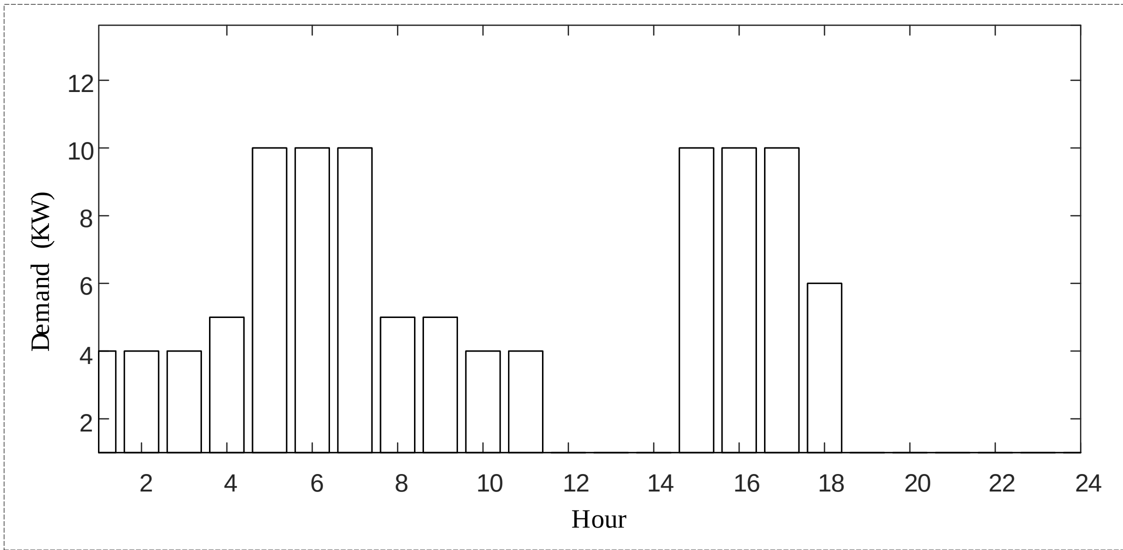


Figure 4.13: Demand (MD=10) over time for six-load BSA

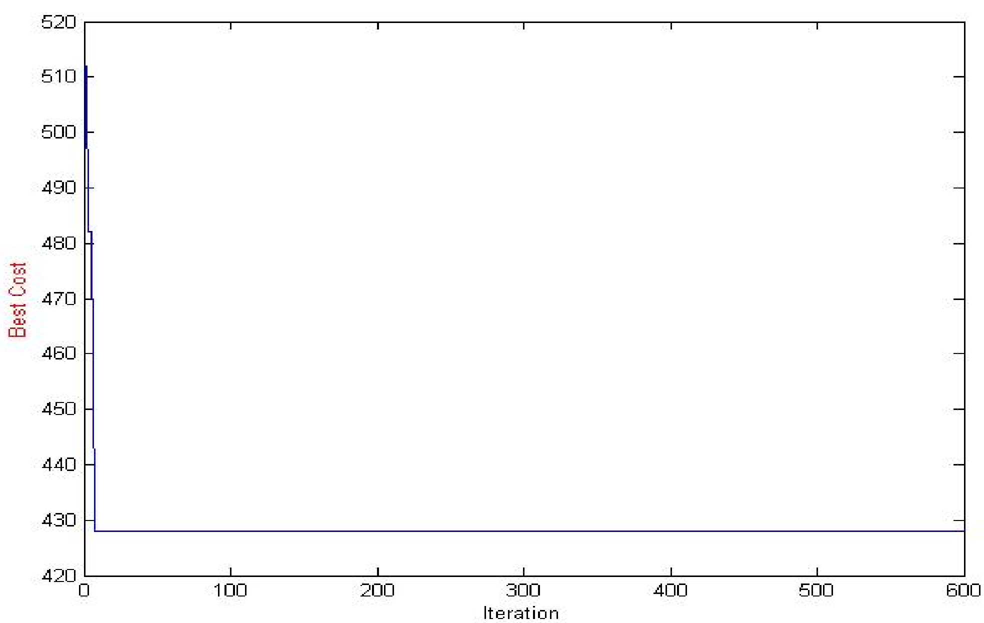


Figure 4.14: Best cost over iteration(Max n=600)

The BSA converges in four iterations once again, although it takes 1.9s to run those four, evidence of the greater complexity of the problem. It reaches the best cost minima of 404 for maximum demand of 20kW as shown in Figure 4.15. Best cost over iterations plot that has taken 1.9s to run 600 number of iteration is shown in Figure 4.16. Thus, the BSA algorithm seems to be better for this kind of small-dimension problem, although the use of a large matrix may complicate things at higher dimensions.

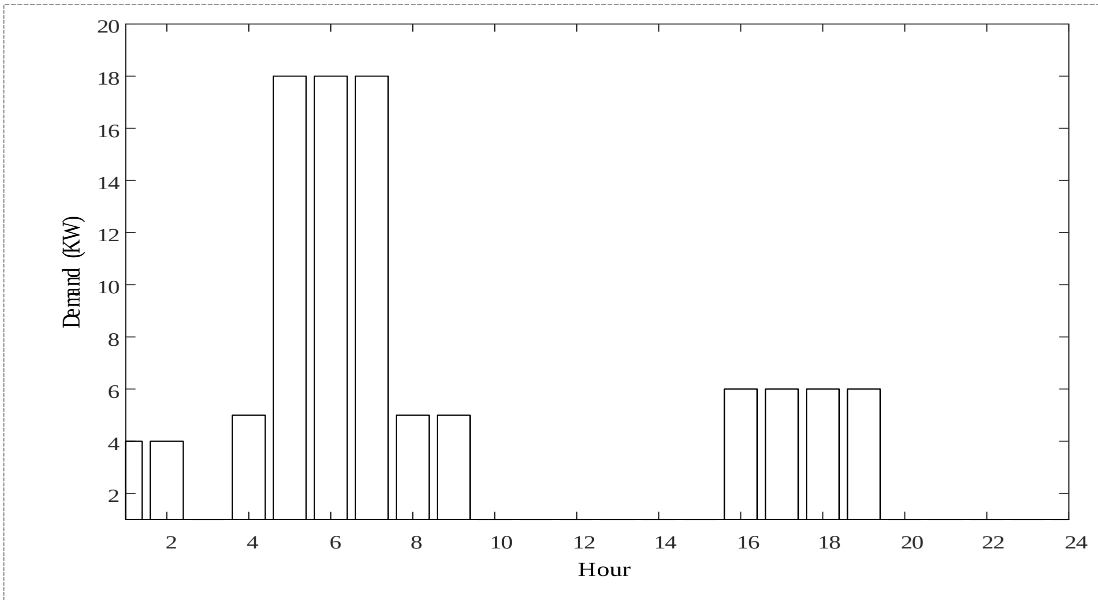


Figure 4.15: Demand (Max MD=20) over time for six-load BSA

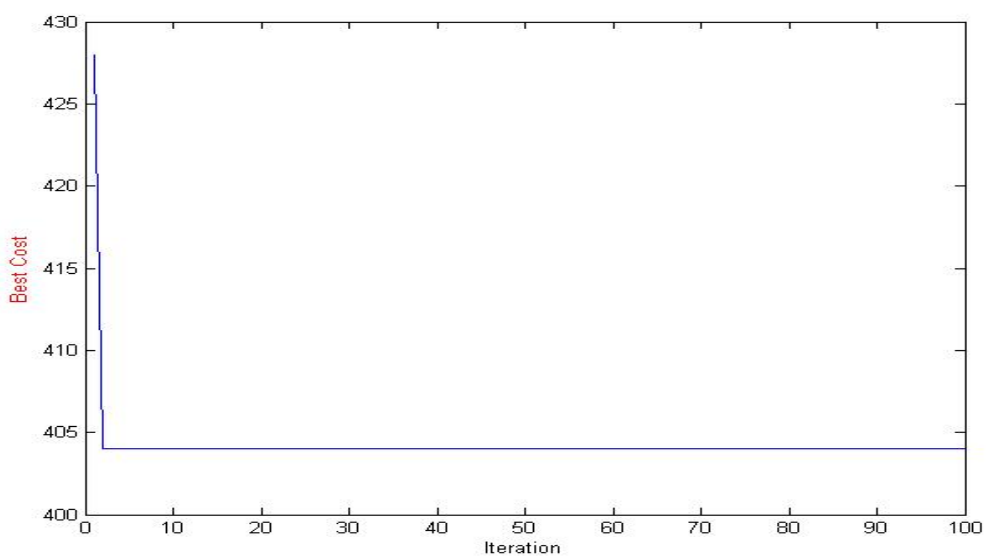


Figure 4.16: Best cost over iteration (Max n=100)

4.5.4 Comparison of BPSO, ABC and BSA in Terms of Cost Saving and Execution Time

The Table 4.2 and Table 4.3 shows the detailed comparison of execution time and best cost obtained for three different algorithms corresponding to maximum demand of 10kW and 20kW respectively.

Table 4.2: Execution time and best cost (MD=10)

Algorithm	Execution Time(sec)		Best cost	MD
	n=100	n=600		
BPSO	0.443596	4.526016	428	10
ABC	1.876166	9.277867	458	10
BSA	2.804660	2.334307	428	10

Table 4.3: Execution time and best cost (MD=20)

Algorithm	Execution Time(sec)		Best cost	MD
	n=100	n=600		
BPSO	0.479694	2.774221	404	20
ABC	1.887784	28.333441	434	20
BSA	0.987027	1.968387	404	20

The three different algorithms have been simulated and results are discussed in the previous section.Best cost value is obtained for BPSO and ABC algorithms however BSA algorithm has better execution time for small number of loads and need parameter tuning to get the accurate cost. It is also observed that for different demand limit constraint used 10kW and 20kW, cost reduction is significant due to more space availability for load scheduling in case increased demand.

4.6 Summary

In this work, three genetic algorithms have been implemented for the load scheduling problem, following the work of (Remani et al., 2015) as a benchmark. Among the implemented algorithms, the artificial bee colony algorithm as one that is well-suited to larger problem dimensions, and the backtracking search algorithm, as one that is well-suited to smaller problem dimensions. Additionally used the binary PSO as a benchmark in our evaluation. We conclude by saying that the ABC algorithm will likely prove superior to the PSO for larger problem dimensions, and that the BSA algorithm will prove superior to PSO for smaller ones. Due to the constraints of memory, use of BSA for larger problem dimensions is unlikely to yield positive results.

Chapter 5

Accurate Prediction of Renewable Energy Generation for DSM Consumers

5.1 Introduction

The next few years are expected to face rapid growth and challenges in power generation, distribution and use. For efficient electricity use, renewable and distributed energy needs to be integrated, and demand-side smart energy management systems need to be integrated. Renewable energy sources play an important role in the energy sector as the world of fossil fuels is depleted, meeting the growing demand of consumers and the need for more reliable and lower cost energy supplies. Renewable energy sources such as photovoltaic (PV), wind, and biomass microturbines are widely used (Du and Lu, 2011).

Recently, there has been a great deal of interest for urban domestic consumers in developing small rooftop photovoltaic (PV) systems. PV systems can be used in stand-alone mode (off-grid connection) or in hybrid mode (grid connection with other renewable energy sources such as wind energy or conventional supply).

Since the use of stand-alone PV requires an extensive storage system, typical grid-attached PV systems are preferred over stand-alone PV systems for uninterrupted supply in the maximum amount of time. As a result, there is a growing demand for hybrid systems that include elements of both off-grid and on-grid systems. Most grid-connected systems have no storage because unused power is exported to the grid.

However, in developing countries such as India, there is a problem when exporting power to the grid because the grid is not stable, and the grid is outage occurs.

PV storage is required as part of a modern grid-connected system. On the other hand, the potential benefits of including renewable energy sources in microgrids are often challenging to realize due to their intermittent nature and very unpredictable (Craparo et al., 2017). Grid-connected PVs can increase the mismatch between power generation and consumption and cause fluctuations in the entire power system. To overcome this problem, an accurate prediction of renewable energy is essential.

Furthermore, depending on the availability of the utility grid and PV energy, consumer loads need to be scheduled according to assigned priorities, and storage actions need to be performed. In this case, it is necessary to develop a reliable prediction model for predicting PV output based on solar irradiation levels and local weather conditions or other external factors (Agüera-Pérez et al., 2018).

In this context, an Intelligent Smart Energy Management System (ISEMS) architecture for demand-side energy management considering renewable energy sources has been proposed. The developed architecture includes PV-generated data collection, predictive smart energy management systems, and an IoT environment for users to access energy details and management. The proposed architecture uses a machine learning approach to predict accurate energy every hour and the next day. Based on the predicted information, the SEMS negotiates available power and dispatches control actions according to the assigned priority of the appliance.

5.2 Machine Learning Techniques for Prediction

- **Artificial Neural Network:** The ANN is a popular regression model, which uses input layer, hidden Layer and output as three different layers as shown in figure 5.1. The model uses Back Propagation Algorithm(BPA) (Li and Shi, 2010). The input variables, x_i, are mapped to the hidden layer neurons, v_j, and then to the output variables, y. The detailed mathematical formulations of the artificial neural network are given below. In order to calculate the hidden layer value, the following equation5.1 can be used.

$$v_j = (1 + exp(-1 * \sum_{i=1}^{I} x_i w_{ij}))^{-1} \tag{5.1}$$

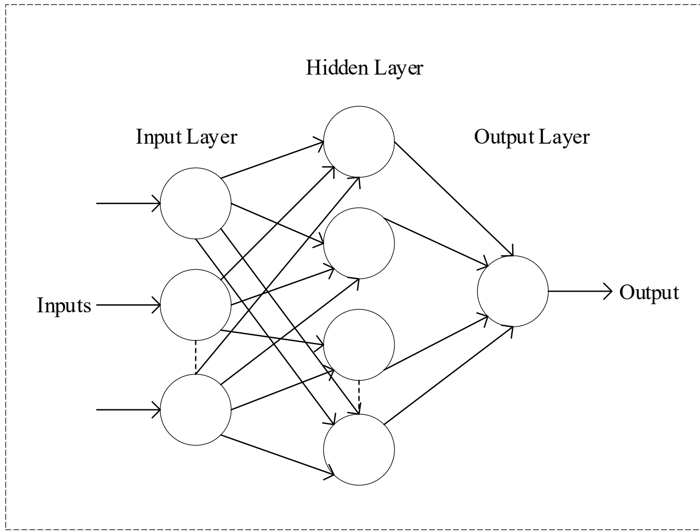


Figure 5.1: Flowchart of a basic prediction model.

Where, v_j represents node j in the hidden layer, x_i represents node I the input layer, and the weight between nodes are represented by w_{ij}.

The output layer node y value can be calculated by equation 5.2,

$$y = (1 + exp(-1 * \sum_{i=1}^{J} v_j w_{ij})) \tag{5.2}$$

The error parameter E between observed and predicted data can be calculated by equation 5.3.

$$E = 0.5(d - y)^2 \tag{5.3}$$

Where, d represents the observed data propagation from the output layer and a hidden layer that is represented by the following equations 5.7 respectively,

$$\delta_y = (d - y)(1 - y) \tag{5.4}$$

$$\delta_y = v_j(d - v_j)(1 - y)\delta_y w_j 1), j = 1........., J \tag{5.5}$$

The weight adjustment between hidden and output layers and input and the hidden layer can be carried out using below equation.

$$\Delta w_{ij}^{n} = \alpha \delta v_j, i = 1, ...I, j = 1, ...J \quad (5.6)$$

- **PSO-ANN approach:** The Back Propagation (BP) is a local search learning algorithm. Therefore, the optimal search process of ANN may fail and return an unsatisfactory solution. By adjusting the weight and bias value of ANN, PSO can be implemented as a global search algorithm and the performance of ANN can be improved. The detailed modeling of PSO algorithm is discussed in section 4.2.1. As mentioned earlier, BP-ANN PSO is more likely to converge at the minimum, and the global minimum can be found. Thus, the hybrid PSO-based ANN model has search properties for two PSO ANNs, where PSO finds the global minimum search space, and ANN uses optimized parameters to find the best result.

- **Support Vector Regressor:** The SVR uses a function that approximates the input domain-to-real mapping based on a training sample. The SVR, support vector regression, is the SVM utilization for function approximation and regression (Li et al., 2009). Different basic kernel functions are used in SVM models.The SVR model uses different optimization techniques than those used in logistic or linear regression, such as neural networks .

  The regression model is represented by the following equation 5.7

$$Y = f(X) = w.\phi(X) + b \quad (5.7)$$

  Where, $\phi(X)$ is a high dimensional space characteristics that maps to input vector, parameters w and b are normal vector and scalar. Variables w and b can be predicted by minimizing the regularized risk function after initiating positive slack parameters ζ_1 and ζ_2^* that represent upper and lower excessive deviations as following equation 5.8.

$$R_{SVMs} = \frac{1}{2}\left\| w \right\|^2 + C\frac{1}{N}\sum_{i=1}^{N}(\zeta_1 + \zeta_2^*) \tag{5.8}$$

with subject to the following constraints given by equation 5.8

$$\begin{cases} Y_i - w.\o(x_i) - b \leq \varepsilon + \zeta_1 \\ w.\o(x_i) + b \leq \varepsilon + \zeta_1^*, i = 1, 2, ...N \\ \zeta_1 \geq 0, \zeta_1^* \geq 0 \end{cases} \tag{5.9}$$

Thus, the SVR is modeled by equation 5.10 with Lagrange multipliers δ_i, δ_i^* as follows,

$$Y = f(X) = \sum_{i=1}^{N}(\delta_i - \delta_i^*)K(X_i, X_j) + b \tag{5.10}$$

Where, $K(X_i, X_j)$ represents the kernel function.

- **PSO-SVR approach:** The hyperparameters of the SVR model are derived from the pattern of data and random default settings. The values of these parameters determine the accuracy of the model. For a typical SVR model, these hyperparameters are not optimized, hence the accuracy may not be the best possible value. Using the hybrid PSO-SVR models, PSO algorithm is used to optimize these parameters. The PSO builds a SVR model for each of its iterations and find the smallest possible prediction error from and use the entire solution space and its information to reach the optimal value. The detailed modeling of PSO algorithm is discussed in section 4.2.1.

- **Ensemble Methods (ENS):** In ensemble learning approach, weak learners (or base models) models that can be used as building blocks for designing more complex models by combining several of them (John et al., 2015). Most of the time, these basic models perform not so well by themselves either because they have a high bias (low degree of freedom models, for example) or because they have too much variance to be robust (high degree of freedom models, for example). Then, the idea of ensemble methods is to try reducing bias and or variance of such weak learners by combining several of them together in order to create a strong learner (or ensemble model) that achieves better performance.

$$\left\{Z_1^1, Z_2^1, ...Z_B^1\right\}, \left\{Z_1^2, Z_2^2, ...Z_B^2\right\}, ... \left\{Z_1^L, Z_2^L, ...Z_B^L\right\} \tag{5.11}$$

L independent weak learners can be assembled by the following equation 5.12

$$w_1(), w_2(), ...w_L() \tag{5.12}$$

Further, in order to get ensemble models with small variance, model is aggregated to some kind of averaging process by the following equation 5.13 .

$$S_L(.) = \frac{1}{L}\sum_{l=1}^{L} w_l(.) \tag{5.13}$$

5.2.1 Data Processing and Validation

The basic idea of regression is to determine a function that approximates the target values accurately using a set of input values. In general, a regression model has three phases, such as data collection and preprocessing, building the model, training and testing phase, as shown in Figure 5.2.

1. **Data collection and preprocessing:** Collecting a suitable dataset is the first stage of designing a prediction model. This work involves collecting historical solar radiation data from the National Solar Radiation Database (NSRDB) on the NREL website for the Mangalore region and using data points for temperature, pressure, wind speed, global horizontal irradiance (W / m2). Further data preprocessing is done to solve the problem missing data by replacing it with an average data of the same day and normalization of the data is done.

2. **Building the Model:** At this stage, the designer must adjust various parameters related to the model, such as variables, maximum depth, and coefficients, to build an accurate model. The above forecast models are evaluated to decide the best suitable model which give better accuracy. Of the five models, the random forest regressor outperforms the other models in terms of accuracy. Therefore, the random forest regression model is used in the ISEMS prediction method.

3. **Training and Testing the model:** During the training process, the entire

dataset was split into a training dataset and a test dataset. In this case, the daily forecast uses the 2013 dataset for training and uses the 2014 dataset to predict any day in the trained model year. Similarly, for monthly forecasting, train the model using the 2013 dataset and test the same month of a year using 2014 data.

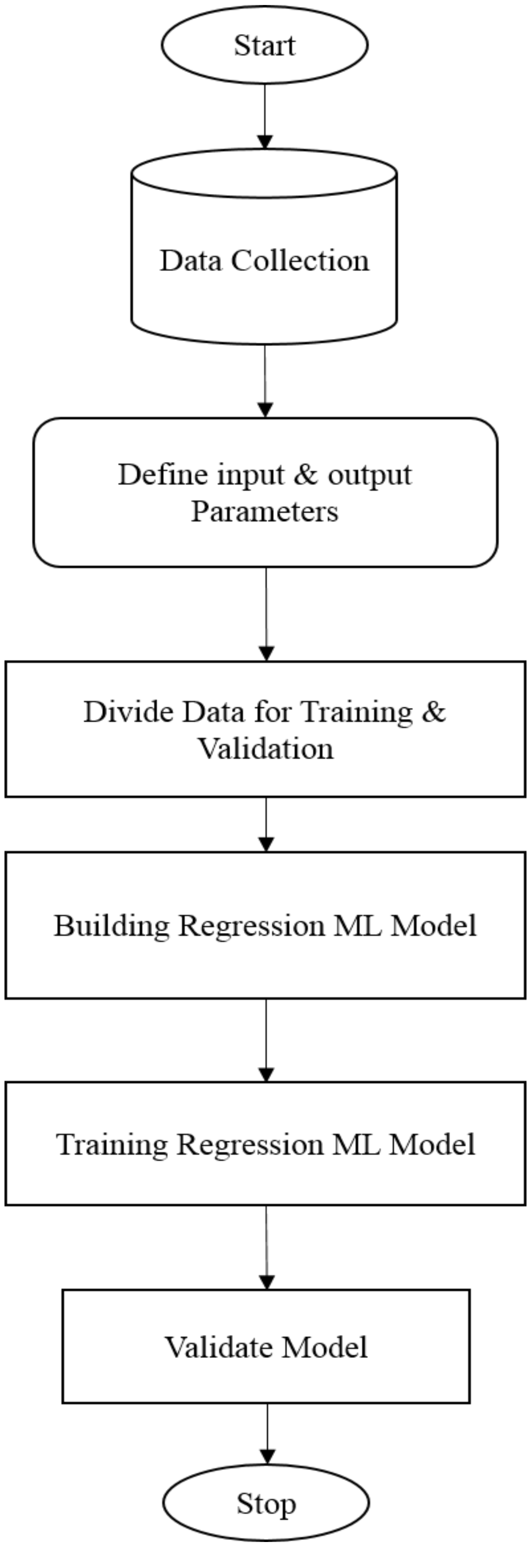


Figure 5.2: Flowchart of a basic prediction model.

5.2.2 Prediction Models for Energy Management System

The proposed Intelligent Smart Energy Management Systems(ISEMS) architecture shown in Figure 5.3 for demand-side energy management, taking into account the renewable source. It has three stages, which are PV generation and data collection, smart energy management system based on prediction and IoT environment for the user to access the energy details and management. The proposed architecture uses a machine learning approach to predict accurate energy for hourly and day ahead. Based on the predicted information, SEMS negotiates the available power and dispatch the control action depending on the consumer assigned priority of an appliance.

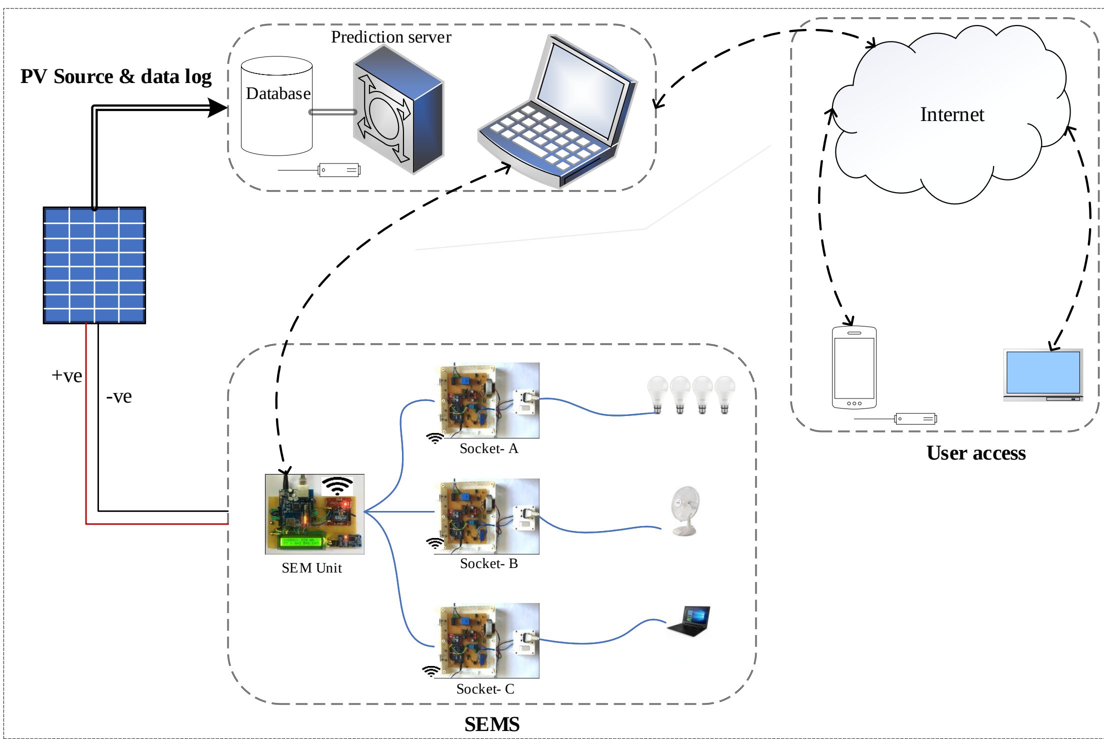


Figure 5.3: Overview of proposed intelligent smart energy management system.

The different machine learning methods discussed earlier in section 5.2 are modeled to predict solar irradiation level.

1. Artificial Neural Network(ANN):

   The ANN model is shown in the flow chart and includes historical data with various inputs, such as temperature, wind speed, day time, month, and so on.

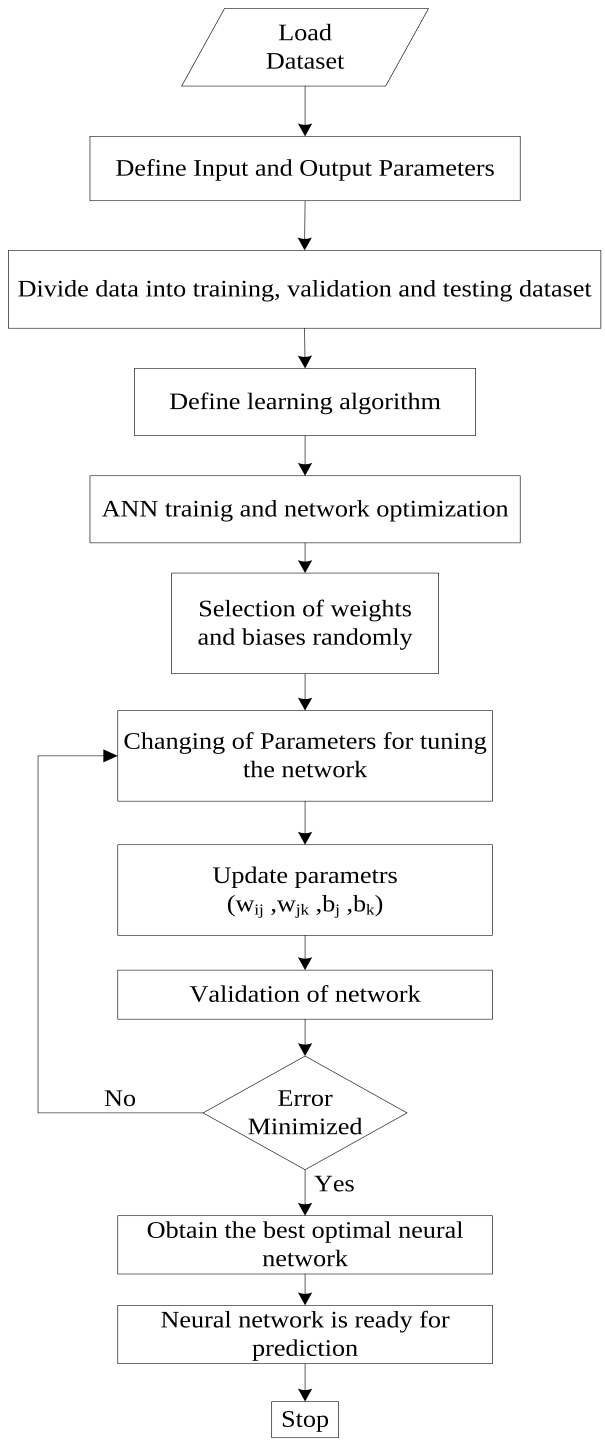


Figure 5.4: ANN Flowchart

Furthermore, the data is split into 75% as a training set and 25% a test data set. Several combinations of ANN parameters and some neurons and hidden layers are tried to get the best optimal value. After a number of trials, the best-trained model with minimal error will be selected. The flowchart of the ANN model is shown in Figure 5.5.

2. PSO based Artificial neural Network(PSO-ANN):

   Different analyzes are performed on various combinations of input parameters to find the best optimal parameter values. First, to find the optimal value of the PSO particle size, select fixed acceleration factors $c1$ and $c2$ and the number of hidden layers n for different combinations of variable particle sizes taking into account the minimum error. Additionally the optimal values of the acceleration factors $c1$ and $c2$ are obtained using the same size of the hidden layer n as the optimal particle size obtained in the initial analysis. Finally, a third analysis is performed to find the optimal number of hidden layers, taking into account previously obtained fixed optimal values of particle size and acceleration factor values $c1$ and $c2$ for different combinations.

3. Support Vector Regression(SVR):

   SVR uses different optimization techniques than those used in logistic or linear regression, such as neural networks.

   The meta parameter "Gama" defines the Gaussian kernel function. It determines how different similar features are related to each other and, thus imparts weight to the corresponding optimization functions. The Regularization parameter C controls the trade-off between hyperplanes and minimizes training errors. The hyperparameters of the SVR model are derived from data patterns and random initialization. The values of these parameters determine the accuracy of the model, and in case of SVR, $\gamma = 1.25$ and $C = 1$ are used as initial values. Additionally, tuning of these parameters using optimization algorithms is described in the next section.

4. PSO based Support Vector Regression(PSO-SVR): The hyperparameters of the SVR model are derived from data patterns and random initialization. The values of these parameters determine the accuracy of the model. In the SVR-based load forecasting model described in the previous section, these hyperparameters have not been optimized, and the resulting accuracy is sub-optimal. The PSO can be used in the PSO-SVR model to optimize these SVR parameters. The PSO

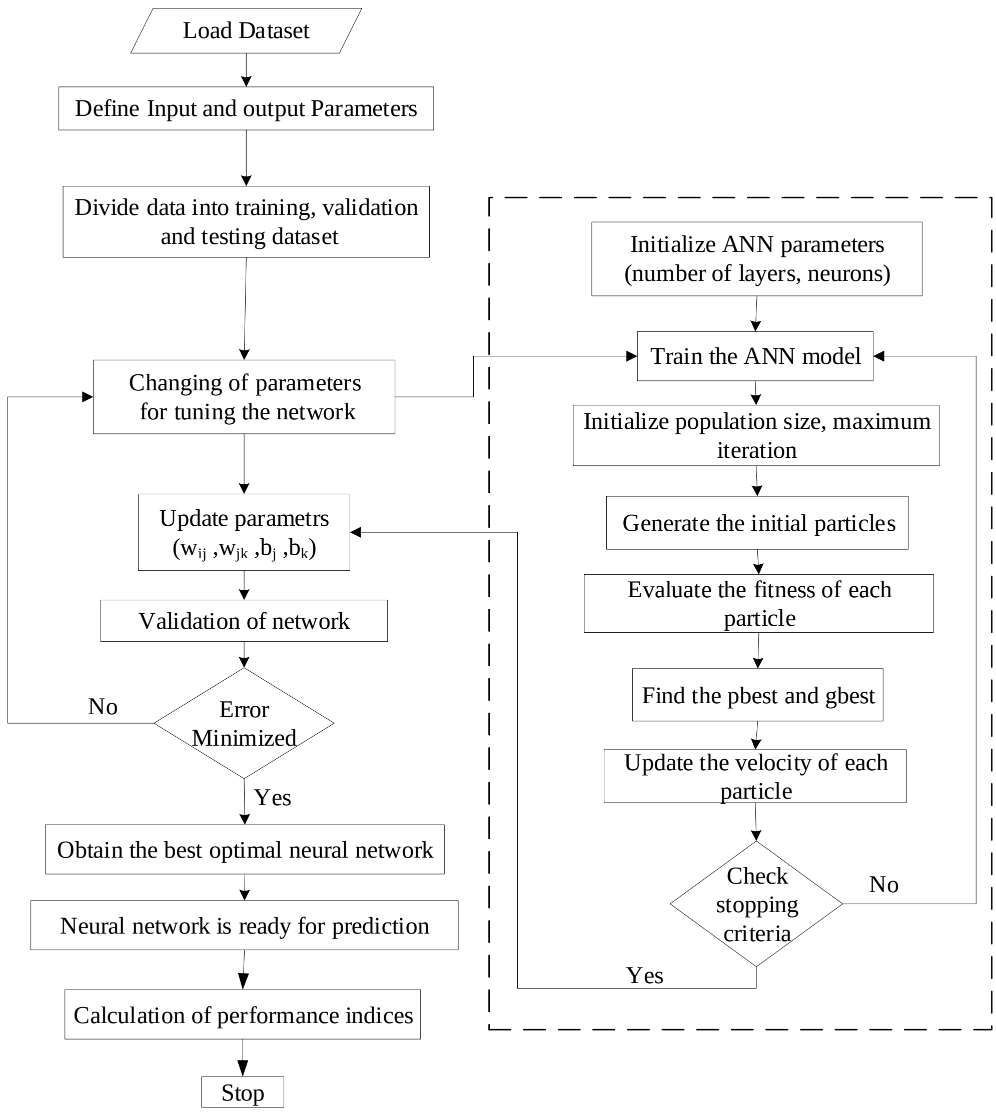


Figure 5.5: PSO based ANN flowchart

obtains the prediction error of the SVR model at each iteration, finds the smallest possible prediction error from the entire solution space and uses that information to arrive at the optimal value of the SVR parameter under investigation.

The operation of the PSO-SVR model flowchart 5.6. The hyperparameters of the SVR model are initialized with random values by the SVR function. The data is divided into a training set and a test set using a random index detailed in the following section. The SVR algorithm is then run in iterations, as directed

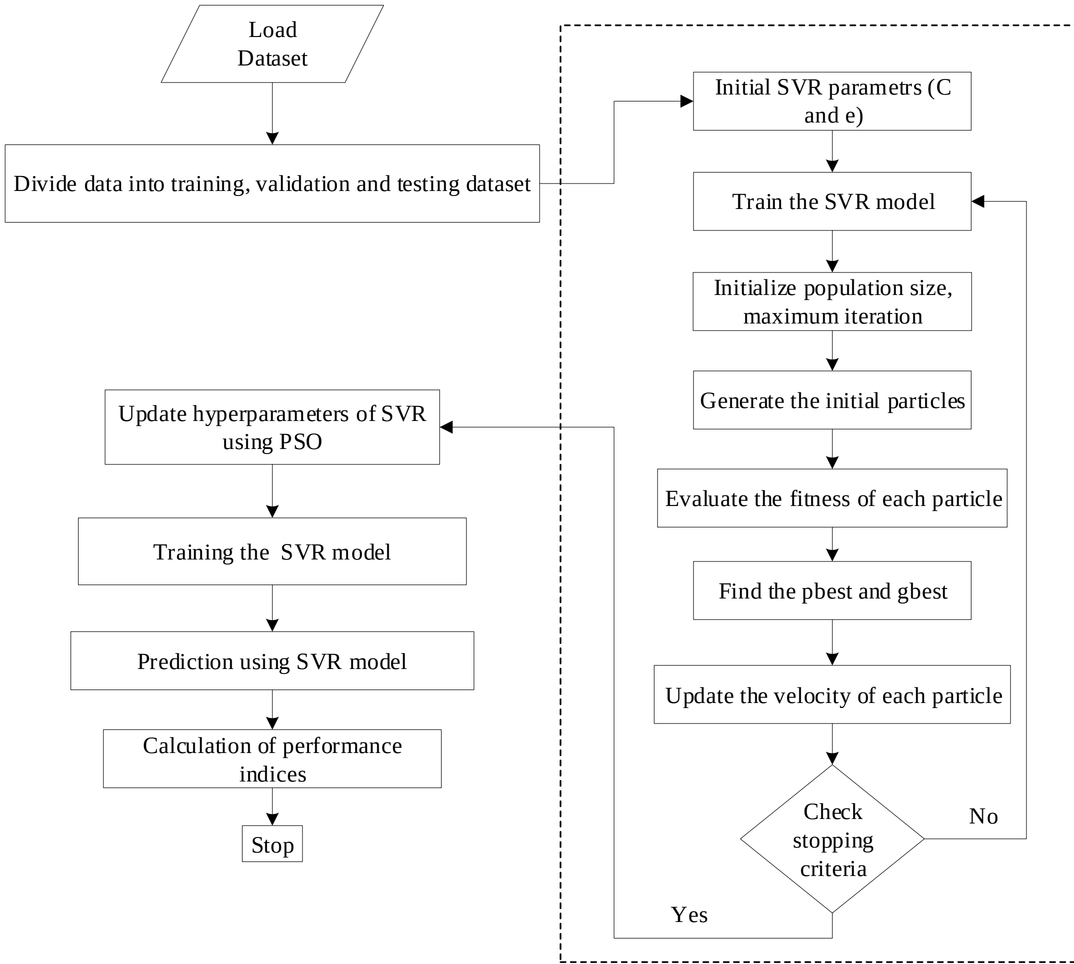


Figure 5.6: PSO based SVM flowchart

by the PSO, and the performance of the model is checked at each iteration. Also, the direction in which the iteration needs to be performed is determined by the PSO. Furthermore, PSO selects the value of the hyperparameter with the lowest error value as the best solution. Next, the model accepts test data and makes predictions using the optimal set of hyperparameters.

5. Ensemble Methods(ENS):

Feature selection is an essential criterion for data analysis and the decision tree algorithm has the advantage of performing a function selection that implicitly selects some top nodes if the dataset fits. Decision trees require little effort to prepare data, unlike the needs of other regression models. Furthermore, proportional scaling between the parameters used, improve performance without making linear assumptions, even when there is a non-linear relationship between parameters. In this method ensemble of decision trees, known as weak or base learners. In this work, 50 base learners are chosen by performing trial and error with a repeated number of experiments, which learn with lower computational cost and achieves higher prediction rate. Hence, this method shows better performance compared to other conventional techniques.

5.3 Performance Evaluation Metrics

The performance evaluation of a trained model is an important concern and defines the suitability of the model for a practical application. This work examines three key performance criteria that establish the accuracy of the model. These are described below.

1. Root Mean Square Error (RMSE).
2. Mean Relative Error (MRE)
3. Mean Absolute Percentage Error (MAPE)

5.3.1 Root Mean Square Error

The Root Mean Square Deviation(RMSD) or Root Mean Square Error (RMSE) expressed as in equation 5.14 is often used as a measure of the differences of samples and population values predicted by a model or an estimator and the values observed.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}|\frac{\hat{P}_i - P_i}{\hat{P}_i}|^2} \tag{5.14}$$

5.3.2 Mean Absolute Error

Absolute Error is the amount of error in the performance metric evaluation. It is the difference between the measured value and “actual” value. The MAE is expressed by the following equation 5.15.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\frac{\hat{P}_i - P_i}{\hat{P}_i}| \tag{5.15}$$

5.3.3 Mean Absolute Percentage Error

The mean absolute percentage error (MAPE), also known as mean absolute percentage deviation (MAPD), is a measure of prediction accuracy of a forecasting method in statistics. Further, it usually expresses accuracy as a percentage and is defined by the following equation 5.16.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|\hat{P}_i - P_i|}{P_n} * 100 \tag{5.16}$$

Where, P_i is the actual value at the ith hour, $\hat{P}_i$ is the predicted value and P_n is the nominal power and N is the number of test points.

MAPE has two advantages. First, the absolute value ensures that positive and negative errors do not cancel each other. Second, because the relative error is independent of the scale of the dependent variable, this measure allows comparing prediction accuracy between data at different scales. In this work, the primary importance is given to MAPE.

A detailed analysis of the performance of all models using the parameters described in this section is provided in the next section. Such analysis is obtained by performing several combinations and trials of the developed model.

5.4 Results and Discussion

In this section, simulation experiments are conducted for short-term to medium-term forecast models. Thus, different machine learning models are used to analyze the results and find out accurate predictions method. In this context, historical data is used for model training and model validation. Furthermore, it performs monthly and daily forecasts for various scenarios using the different models developed. In addition, error analysis is performed to find the best accurate model. The trend graph of historical data is shown in Figure 5.7.

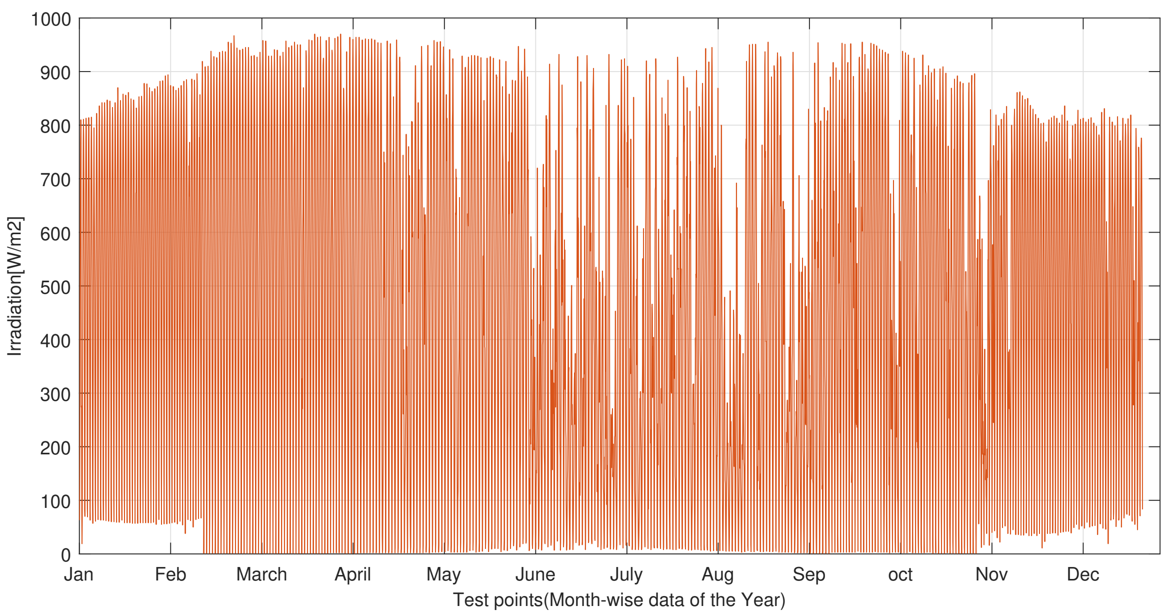


Figure 5.7: Month-wise actual data of a year

5.4.1 Day-Wise Solar Irradiation Prediction

The performance of different machine learning-based regressor models are compared for predicting the solar irradiance for a day. A plot of solar radiation versus time (in hours) is taken, with the time being considered from 7 AM to 5 PM on that day. The models were trained with a two-year dataset collected from NSRDB database and tested for a daily basis to check the performance of the prediction model on the dataset. Among all predictive regressor models, PSO-based SVM regressors outperform the other methods shown in Figure 5.8.

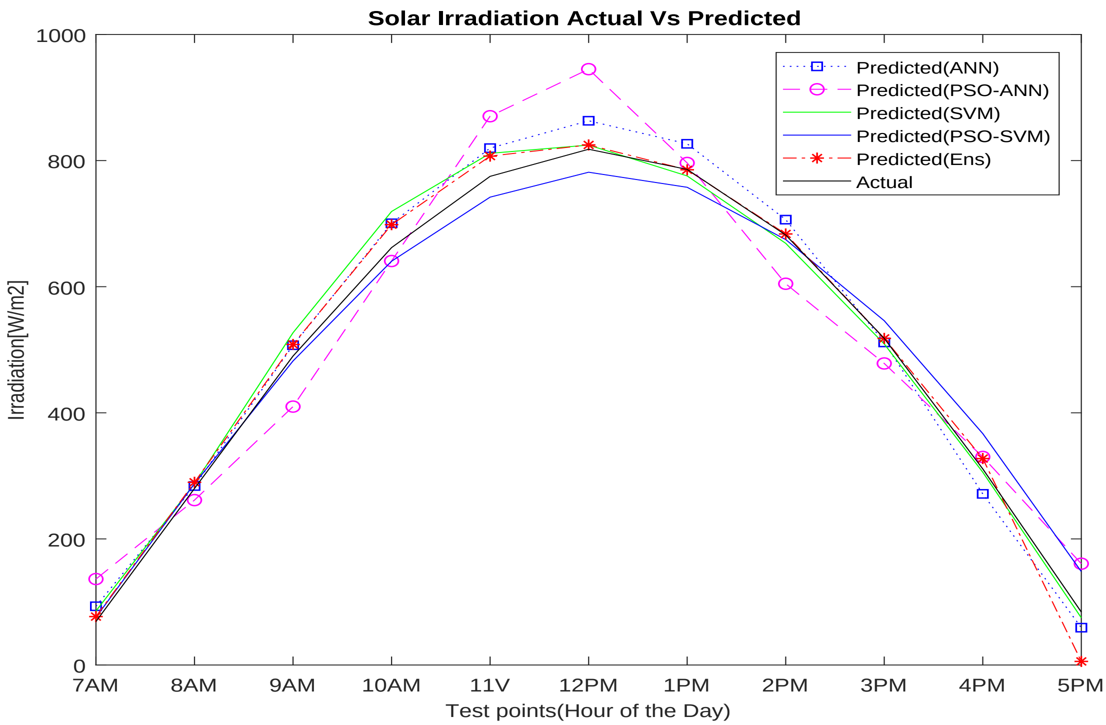


Figure 5.8: Day-wise prediction of different schemes

5.4.2 Month-Wise Seasonal Prediction Using ML Approach

Monthly forecasts for the Mangalore region use factual historical data each year to distinguish rainy months, summer months, and winter months on a monthly basis. Heavy rain was observed in July during the rainy seasons of June, July, August, September and October. Furthermore, May is considered the hottest month, and December is regarded as the coldest month.

Simulation experiments are performed using five different predictive models, such as ANN, PSO-ANN, SVM, PSO-SVM, and Ensemble techniques. Each analysis is performed using a different forecasting model considering season-wise. First, for sunny days the model is trained using the 2012 and 2013 datasets, validated using the 2014 dataset, and confirms the accuracy of the prediction model used. Various metrics, such as MAPE and MAE, are considered to determine the performance of the predictive model. From the prediction plot, it is observed that during sunny days, the solar radiation is periodic, and the prediction error is minimal, as shown in Figure 5.9. Among the various models compared, the PSO-based SVM is more accurate than all other models.

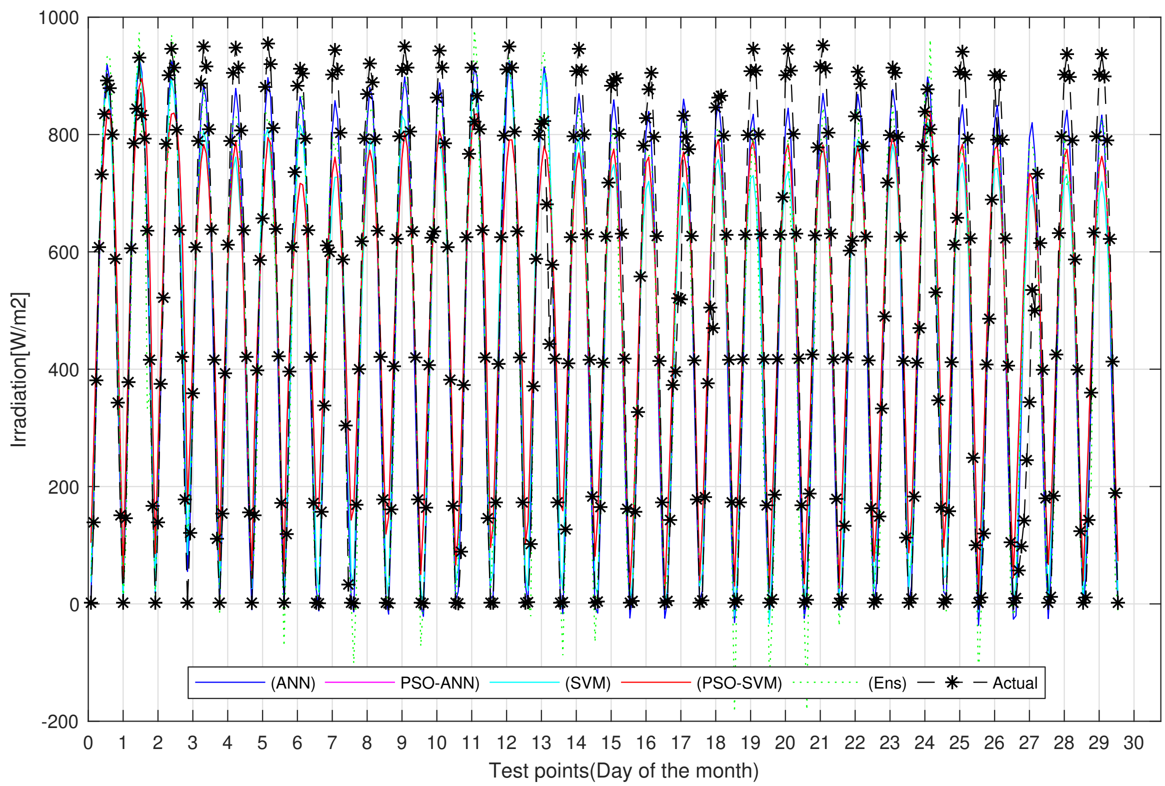


Figure 5.9: Prediction for sunny days(April-month) using different models

Similarly, a winter day simulation experiment is performed by training the 2012 and 2013 data sets and testing using the December 2014 data, as shown in Figure 5.10. However, the irradiation levels are periodic, which improves the accuracy of the prediction. PSO-based SVM models perform better than all other models.

Finally, a simulation experiment is performed for a rainy day by training the 2012 and 2013 datasets and testing using the July 2014 data, as shown in Figure 5.11. In this case, the irradiation is observed to be low and very random compared to sunny and winter days. Therefore, error rates are significant in the rainy season.

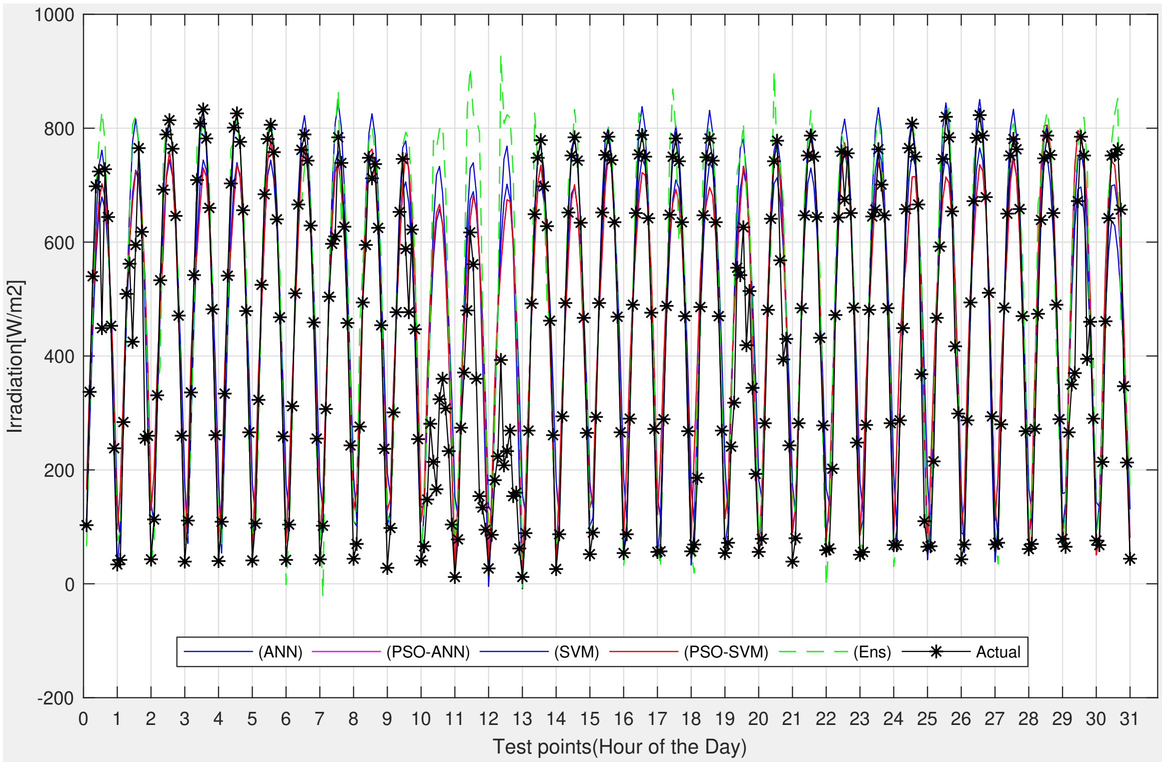


Figure 5.10: Prediction for winter days(Dec-month) using different models

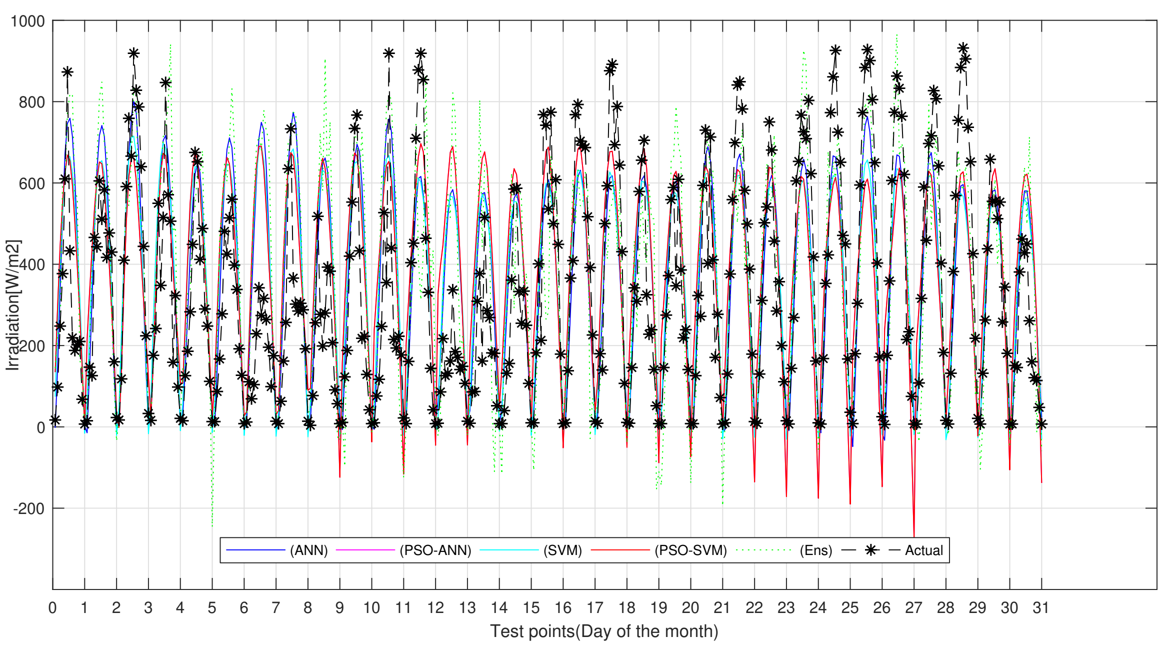


Figure 5.11: Prediction for rainy days(July-month) using different models

The summer season April month forecast of the PSO-based SVM model is shown in Figure 5.12 with error analysis, among all the different methods compared PSO-based SVM model shows the best accuracy. Similarly, error analysis plots for the winter and summer seasons are shown in Figures 5.13 and 5.14, respectively.

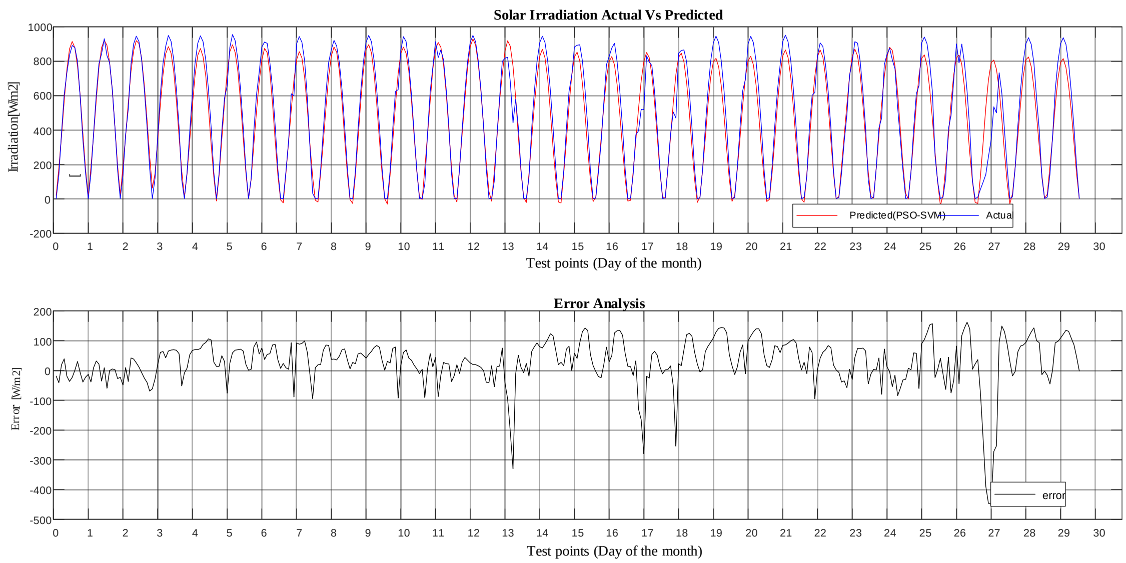


Figure 5.12: Month-wise(April) prediction for sunny days based on PSO SVM model

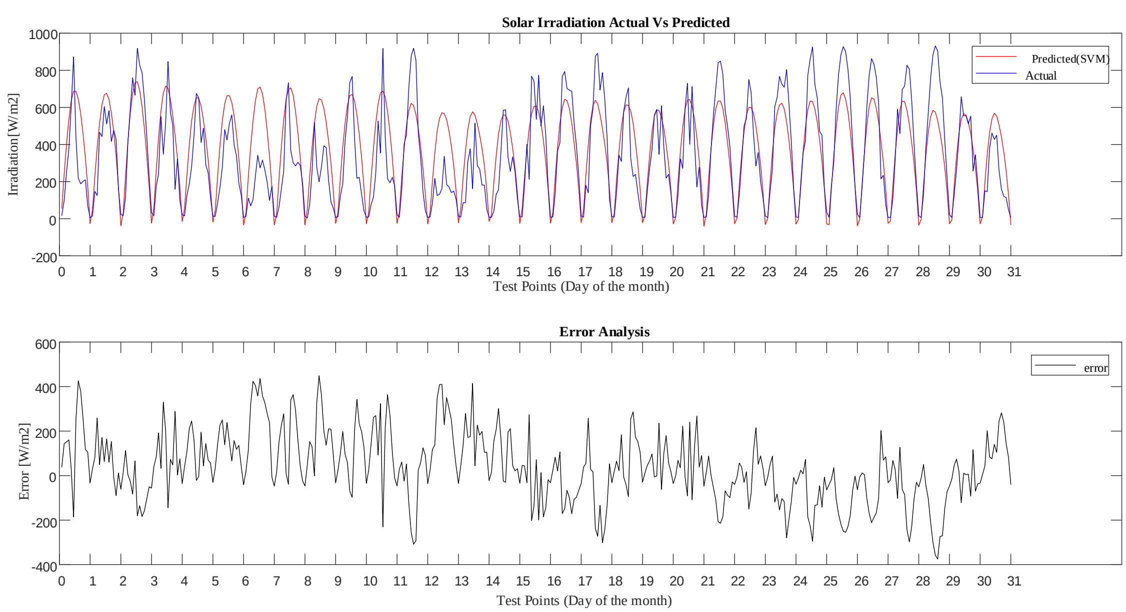


Figure 5.14: Month-wise(July) prediction for rainy days based on PSO SVM model

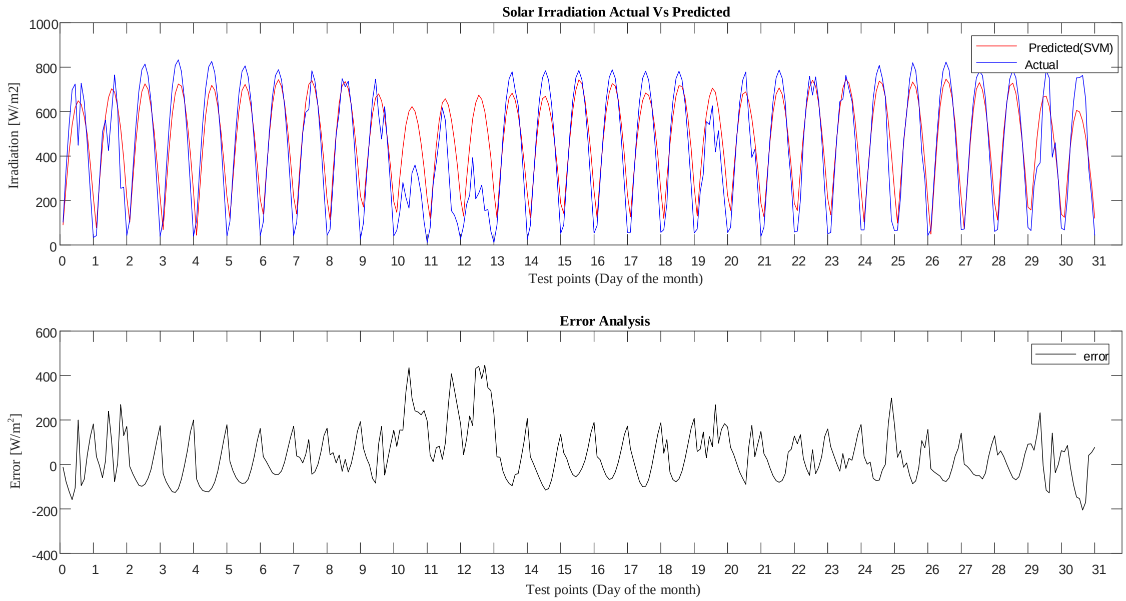


Figure 5.13: Month-wise(Dec) prediction for winter days based on PSO SVM model

A detailed month-wise comparison with various evaluation metrics is summarized in table 5.1. From the table 5.1, it is observed that the PSO based SVM model outperforms all other regressors in terms of Mean Absolute Percentage Error(MAPE). The ANN and Ensemble methods have also been shown to improve accuracy in December and April due to the more periodic data. On the other hand, in the rainy season, July month, historical data is very random and difficult to predict accurately.

Table 5.1: Month-wise error analysis

Month	Error Index	ANN	SVM	ANN-PSO	SVM-PSO	Ensemble
December	MAE	67.1241	81.8647	65.5030	60.4142	80.6328
	MAPE	6.71241%	8.18647%	6.55030%	6.04142%	8.06328%
	RMSE	108.1940	115.3036	119.5684	109.6596	138.8190
April	MAE	70.2847	74.5081	68.9326	61.6458	75.5474
	MAPE	7.02847%	7.45081%	6.89326%	6.16458%	7.55474%
	RMSE	91.9098	114.3410	118.4938	83.7416	100.7348
July	MAE	126.8701	128.8019	126.199	115.6627	130.7009
	MAPE	12.68701%	12.8802%	12.6199%	11.56627%	13.07009%
	RMSE	165.5247	162.9518	191.3242	157.9393	201.4113

5.5 Integrated Architecture of Smart Energy Management System

This section describes the proposed Integrated Architecture of Smart Energy Management System as shown in Figure5.15. The design and deployment of a configurable smart energy management system with power negotiating scheme is presented in the Chapter-3. Further, the performance of optimization techniques are evaluated to obtain the best cost and schedule considering various power parameter constraints. In addition, accurate prediction model are developed using the historical data from NREL NSRDB database for short term forecasting to facilitate day ahead planning in energy management system.

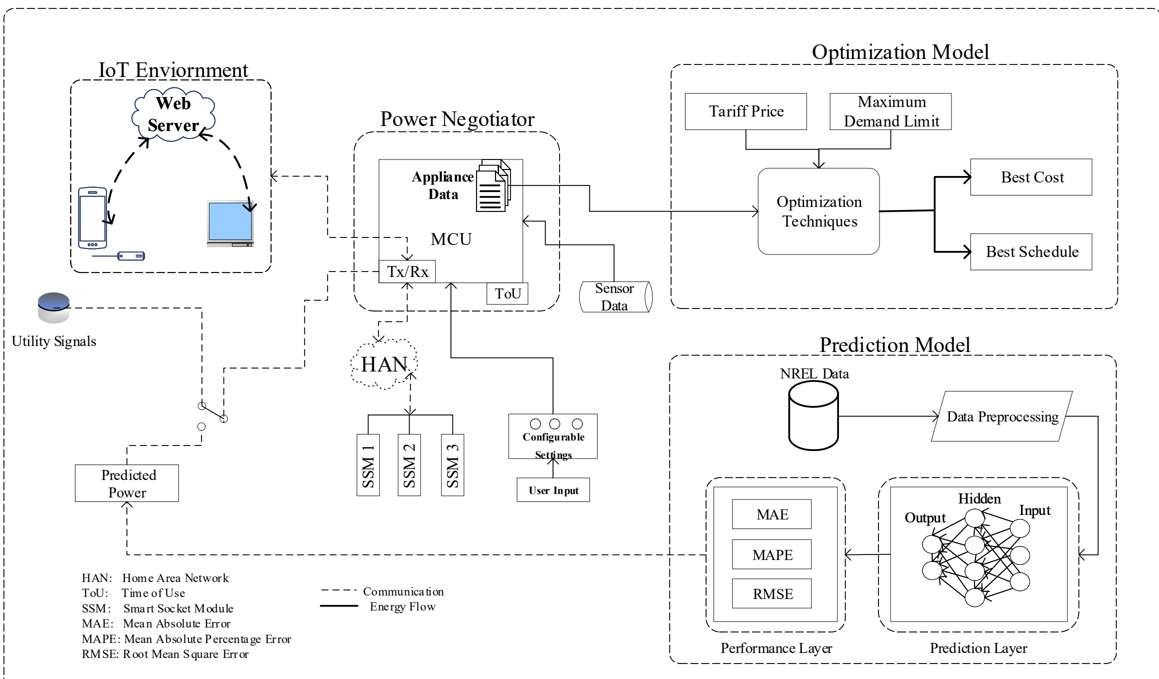


Figure 5.15: Proposed Integrated Architecture of Smart Energy Management System

5.6 Summary

With the spread of renewable energy, Intelligent Smart Energy Management Systems(ISEMS) are being developed to handle energy demands in smart grid environments. The proposed scheme explores the development of accurate predictive models by extensively comparing ANN, PSO-ANN, SVM, PSO-SVM, and Ensemble regression methods for hourly and day-to-day planning. Based on the predicted information, ISEMS negotiates the available power and dispatches control actions according to the priority assigned to the appliance. Among the several energy prediction algorithms evaluated, the PSO-based SVM regressor was found to outperform other prediction models in terms of performance accuracy.

Chapter 6

Conclusion and Future Scope

In this thesis, the emphasis is given to the design and development of a smart energy management framework benefiting the utility provider and the demand side consumer. Further, different optimization techniques are investigated to get the best optimal schedule for schedulable loads. Due to the deep penetration of renewable sources, accurate prediction models are developed for day-ahead planning.

6.1 Conclusion Summary

In Chapter 1, a brief overview of the research work is presented. Following, scope and motivation of the work is highlighted. Finally, the organisation of thesis is included.

In Chapter 2, the background of the research work is discussed. Next, a comprehensive literature review in the area communication technology and load management for demand-side consumers is presented. Further, a detailed investigation of the optimization approach and prediction models are discussed to find the potential gap in the research area. Finally, based on the identified research gaps research objectives are framed.

In Chapter 3, the hardware prototype of SEMS is designed and developed in the laboratory environment, and experiments are carried out to demonstrate the effectiveness and working of the power optimization algorithms deployed in the controller. The wireless ZigBee communication is established using XBee series-2 modules between the SEM controller and smart socket unit. SEMS also incorporates new advanced selfdiagnostics mechanisms to form a reliable network. The first experiment shows a new configurable priority feature that takes into account three different loads. There is also a provision for changing appliance priorities according to consumer requirements. Secondly, in this work, different experimental scenarios are exhibited to show the running of only higher priority appliance during DR event and under MDL constraint. Furthermore, cost optimization algorithms are deployed in the SEM controller, which schedules the operation of a particular appliance during the off-peak hours. It considers ToU tariff and hence utilize the lower slab rate to minimize electricity cost. In order to avoid higher power consumption during peak hours, a warning is given to the consumer with buzzer and LED indicators. Finally, to access the power consumption data of individual load, secure web portal associated with an IoT environment is developed. GUI is provided with power consumption plot to view power usage of an appliance daily, and monthly basis and also, database is provided for the energy management system with a provision to use it for further data analytics.

In Chapter 4, the evaluation of schedulable loads optimization algorithm that takes into account user constraints and load parameters are performed. The simulation experiments are conducted with three different optimization algorithms BPSO, ABC and BSA to find the best one in terms of optimal cost and execution time.

Further, in Chapter 5, due to the deep penetration of renewable energy, the development of an Intelligent Smart Energy Management System (ISEMS) that handles energy demand in a smart grid environment is proposed. The proposed scheme considers developing an accurate prediction model by extensively comparing ANN, PSO-ANN, SVM, PSO-SVM and Ensemble regression techniques for hourly and day-ahead planning. Based on the predicted information, ISEMS negotiates the available power and dispatch the control action depending on the consumer assigned priority for an appliance. Among the several energy prediction algorithms evaluated, it is found that the ensemble of PSO based SVM regressors outperforms over other prediction models in terms of performance accuracy. Finally, evaluation metrics MAE and MAPE are used to evaluate the performance accuracy of the model.

6.2 Scope for Further Investigation

In light of present work, further investigation can be carried out in the following research direction.

In the future, further investigation can be carried out on fine tuning parameters of hybrid optimization algorithms to get more accurate results and to include user satisfaction parameters.

In the present scenario, data analytics has wide scope with the evolving of IoT and machine learning techniques. In this context, a real time deployment of non-intrusive load monitoring for demand load disaggregation can be the study of interest.

Appendix A

Details of the hardware modules used in SEMS

This section presents the detailed specification and source of information about the proprietary hardware items used in design and devcelopment of Smart Energy Management System.

A.1

Appendix A

The ATmega328P is low power complementary metal-oxide semiconductor 8bit microcontroller, the architecture of this is based up on the AVR enhancement Reduced Instruction Set Computer(RISC) architecture. The high-performance micro-controller integrates 32 Kilo Bytes flash with writes, while read in progress features, 23 general purpose I/O lines, 1024B EPROM, 32 general purpose registers, 3 flexible timers with comparison mode, external and internal interrupts, 1 byte directional 2-wire serial interface, serial port SPI, 6-channel 10-bit analog-digital converter, a watchdog timer programmable using an internal oscillator, and 5 power saving mode options and software. The operating range of the device is 1.8-5.5 volts. The specifications of Arduino module, ATMEGA328 based controller is listed in table A.1.

The DHT11 sensor module consists of a temperature and humidity sensor, calibrated for digital signal output. DHT11 is reliable, highly efficient, and has long-term stability that exists with the help of digital signal acquisition technology. The detailed

Table A.1: Specification of ATMEGA328 based MCU 1

Parameters	**Description**
Operating Voltage	5V
Input Voltage (recommended)	7-12V
Input Voltage (limits)	6-20V
Digital I/O Pins	14 (of which 6 provide PWM output)
Analog Input Pins	6
DC Current per I/O Pin	40 mA
DC Current for 3.3V Pin	50 mA
Flash Memory	32 KB (ATmega328) of which 0.5 KB used by bootloader
Clock Speed	16 MHz

specification are listed in the following table A.2

Table A.2: Specification of Temperature and Humidity DHT11 module

Parameters	**Description**
Power Supply	3.3∼5.5V DC
Measurement Range	Temperature 0∼ 50°C
	Humidity 20-90% RH
Accuracy	Humidity +-5%RH
	Temperature 1°C
Resolution	Humidity 1%RH
	Temperature 1°C
Sampling Frequency	1Hz

The display unit used to interface with controller is known as Liquid Crystal Display (LCD), which has 16x4 (16 columns by 4 rows). Potentiometers are used to adjust the brightness of the LCD. The two terminals of the potentiometer are connected to VCC and GND, and the output terminal of the potentiometer is connected to the VEE of the LCD. The detailed specification of LCD module is listed in table A.3.

LEM creates a wide range of electrically isolated current and voltage transducers that have become the standards in the measurement field. The aspects of thermal, mechanical, thermal conditions and environmental conditions must be taken into account while selecting a transducer.Transducer selections for electrical requirements include power requirements, peak measurements, response times, di/dt, dv/dt, and more. The detailed specification of current and voltage sensor module is listed in

Table A.3: Specification of LCD module 3

Pin no.	**Symbol**	**Description**	**Function**
1	Vss (Ground)	Ground	0V (GND)
2	Vcc (+5V)	Powers the LCD with +5V (4.7V – 5.3V)	+5V
3	VEE	Decides the contrast level of display.	
4	RS	Instruction/data register selection	RS=0: Instruction Register RS=1: Data Register
5	R/W	Read/Write selection	R/W =0: Instruction Register R/W=1: Data Register
6	Enable	Enable Signal	
7	DB0	Data Input/output lines	8Bit: DB0-DB7
8	DB1		
9	DB2		
10	DB3		
11	DB4		
12	DB5		
13	DB6		
14	DB7		
15	LED +ve	+ve terminal	+5V
16	LED -ve	-ve terminal	0V

table A.4 and table A.5 respectively.

Table A.4: Specification of LEM LA-55P current sensor module module5

Attribute	**Value**
Current Ratio	55:1
Sensor Technology	Closed Loop
Supply Voltage	12 - 15 V
Input Current	55A
Output Current	25 mArms
Overall Height	27.2mm
Overall Width	36.5mm
Overall Depth	14.45mm
Minimum Temperature	-25°C
Maximum Temperature	+85°C
Series	LA
Mounting Type	PCB Mount

The DS3232 module is a low cost, accurate and an integrated temperature compensated crystal oscillator(TCXO). The device maintains time and date information in seconds, minutes, hour and in day, month and year correspondingly. The detailed

Table A.5: Specification of LEM LV-25AP current sensor module module5

Attribute	**Value**
Current Ratio	14:1
Sensor Technology	Closed Loop
Supply Voltage	12 - 15 V
Input Current	14A
Output Current	25 mA
Overall Height	16.45mm
Overall Width	26mm
Overall Depth	29.2mm
Minimum Temperature	0°C
Maximum Temperature	+70°C
Mounting Type	PCB Mount
Series	LV

specification of the module are listed in table A.6.

Table A.6: Specification of DS3231 RTC module module4

Parameters	**Description**
Operating Voltage Range	2.7V ∼5.5V (including 24C32).
Voltage Supply for RTC	2.2 V ∼5.5 V
Battery Holder	2032 Coin Battery.
I2C interface	Fast (400kHz) I2C Interface.
EEPROM	AT24C32 32Kbit Serial I2C.
Time and Date Format	Time: HH: MM: SS (12/24 hr). Date Format: YY-MM-DD-dd.
Operating Temperature Range	Commercial (0°C to +70°C) Industrial (-40°C to +85°C).
Digital Temp Sensor Output	10bit,$\pm 3°C$ Accuracy and $0.25C$ resolution.
Dimensions in mm (LxWxH)	38 x 22 x 14
Weight(gm)	8
Shipment Dimensions	$12x8x5cm$

A.2

Appendix B

In SEMS network, the coordinator builds a Zigbee network as shown in Figure A.1. After the network is formed, other nodes can join. The coordinator must configure XBee because the default system class for the XBee module is a router. In SEMS for

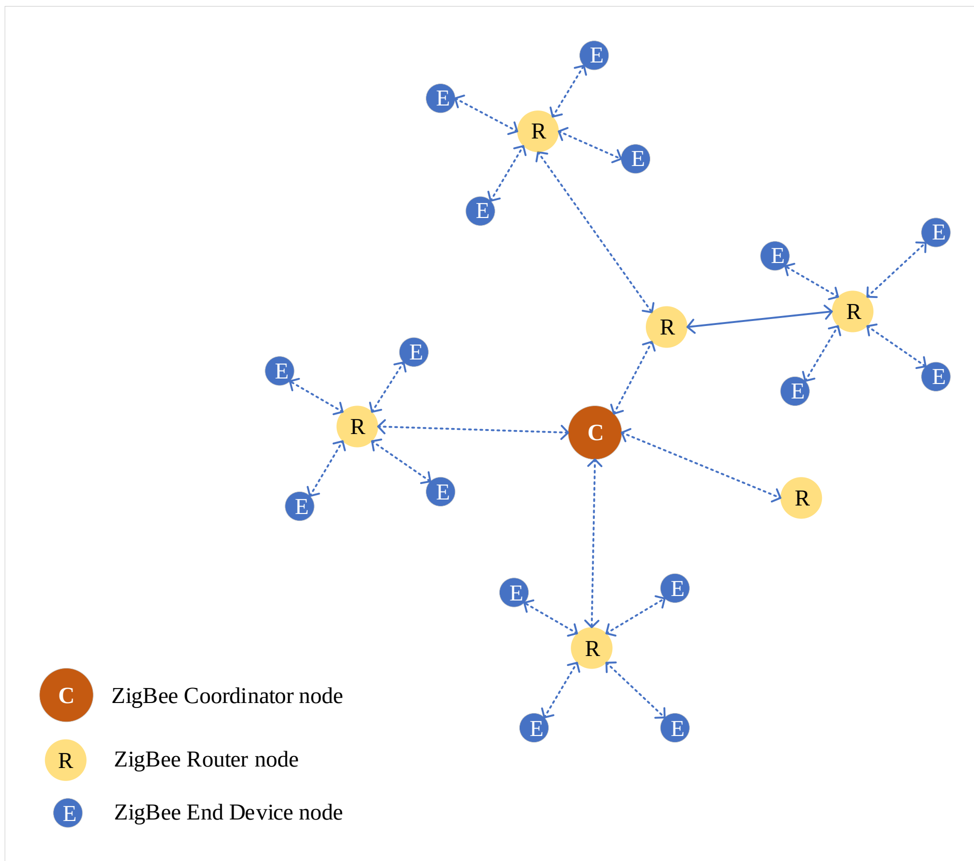


Figure A.1: XBee mesh network

offering wireless end-point connectivity to modules, XBee (Series-2) 2mw modules are used. The specifications of XBee modules are listed in Table A.7.

Table A.7: Specification of XBee module 2

Specification	XBee Series 2
Performance	
Indoor/Urban Range	up to 133 ft. (40 m)
Outdoor RF line-of-sight Range	
Transmit Power Output (software selectable)	2mW (+3dBm)
RF Data Rate	250,000 bps
Serial Interface Data Rate (software selectable)	1200 - 230400 bps (non-standard baud rates also supported)
Receiver Sensitivity	-95 dBm (1% packet error rate)
Power Requirements	
Supply Voltage	2.8 – 3.4 V
Operating Current (Transmit)	40mA (@ 3.3 V)
Operating Current (Receive)	40mA (@ 3.3 V)
Power-down Current	<1; 1 uA @ 25°C
General	
Operating Frequency Band	ISM 2.4 GHz
Dimensions	0.960" x 1.087" (2.438cm x 2.761cm)
Operating Temperature	-40 to 85° C (industrial)
Antenna Options	Integrated Whip, Chip, RPSMA, or U.FL Connector
Networking & Security	
Supported Network Topologies	Point-to-point, Point-to-multipoint, Peer-topeer & Mesh
Number of Channels (software selectable)	16 Direct Sequence Channels
Addressing Options	PAN ID and Addresses, Cluster IDs and Endpoints (optional)

Appendix B

Design Specification for Smart Socket Module

B.1 Design of Smart Socket for SEMS

The schematic design of the smart socket is shown in Figure B.1.Using the Hall Effect based voltage and current transducers, the single-phase power parameters (voltage and current) are stepped down to low-level voltage signals. Schematic of the voltage transducer is shown in Figure.B.1. Input resistance R_1 is chosen such that the measuring resistance R_M is selected in the range of $10 - 350ohm$. Similarly, the schematic of the current transducer is shown in Figure B.1. Measuring resistance, R_M is selected in such a way that, the output voltage shouldn't exceed 4.5V. These signals are further conditioned using a signal conditioning circuit to level shift the signal by $1.8VDC$ offset. This offset voltage is generated by the power supply module using a voltage divider circuit. Arduino Microcontroller can read only positive voltages $(0 - 5V)$. If the input voltage to the microcontroller exceeds 5V it may get damaged. So, in the signal conditioning circuit, a Zener diode with a cut-off voltage of $4.7V$ is used at the output stage to prevent the overvoltage. This signal conditioning circuit is tested by applying the stepped down signals from voltage and current transducers and found to be within 0-4V range. These output signals are given to the analog pins of the Arduino microcontroller. Relay module provides the capability to switch a selected appliance ON/OFF, depending on the command sent by the microcontroller unit.

The phase line from the load supply passes through the current transducer and is connected to the NC pin of the relay. In addition, the COM pin of the relay module is connected to one port of the socket. Finally, the neutral wire is connected to another port on the socket. The communication path is established using the Xbee series2 module. This module is connected to the SEMS unit (router) and allows the SEMS unit to send control commands to all load controllers. In the coordinator module, Arduino receives commands from the different router via Xbee module. It also collects energy consumption data from all routers via the XBee module and provides an LCD interface that allows consumers to get the entire energy consumption data. In addition, energy consumption data is uploaded to a local server (WAMP) using the Arduino ethernet shield.

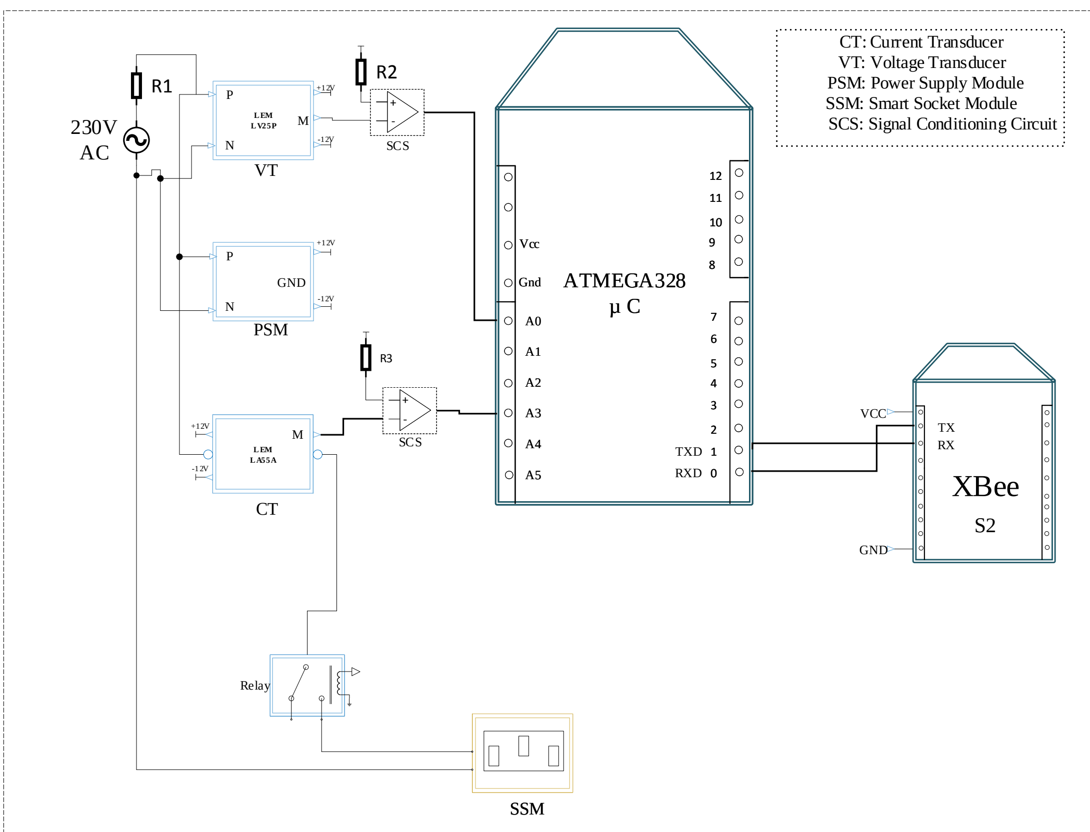


Figure B.1: Design of smart socket for SEMS.

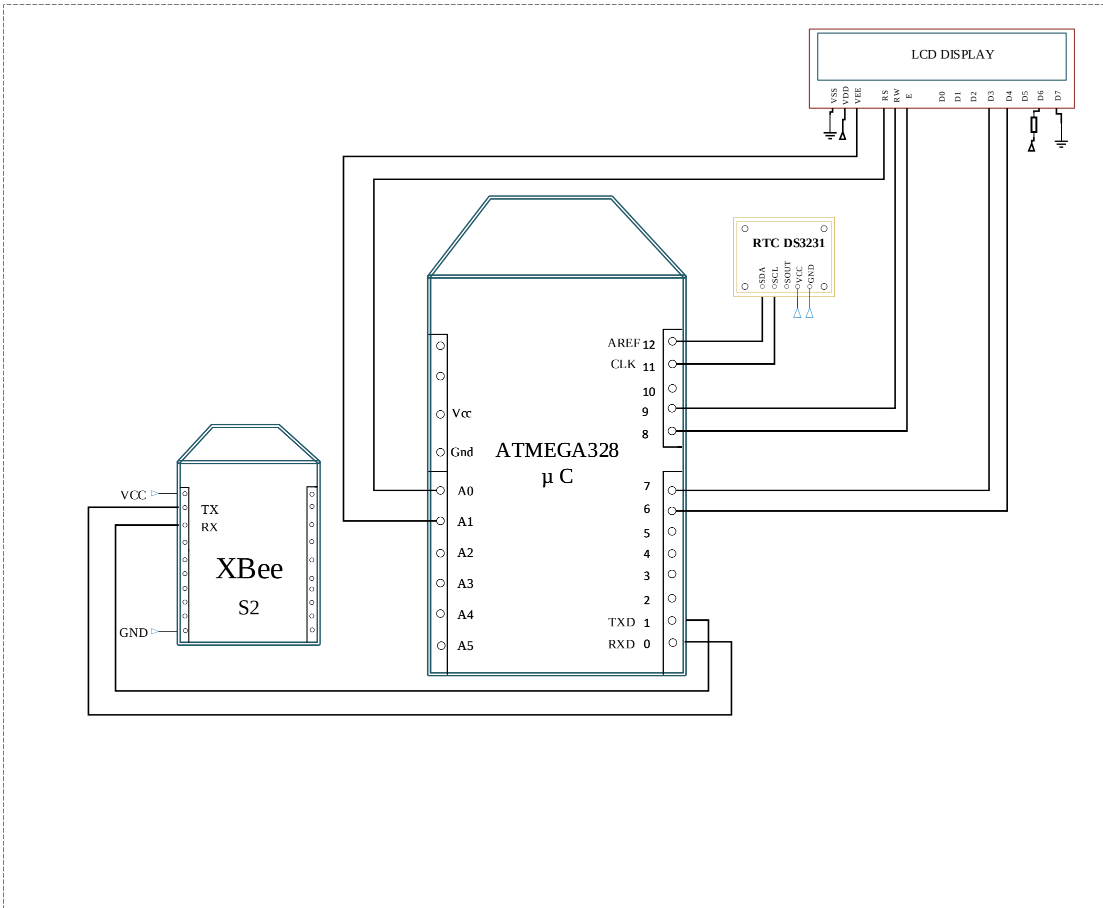


Figure B.2: Design of smart gateway for SEMS.

B.2 Accuracy Calculation and Power Consumption Measurement of SEMS Modules

Calibration in our study is performed with a power meter considered as reference. It is calculated as follows:

$(Measured\_value$ - $offset\_factor)$ * $k = Value\_observed\_in\_ref\_power\_meter)$

Where k is a scaling factor, at more than two load conditions, the power measured by the setup and reference meter measurements was recorded. As a result, the offset and scaling factors are determined. In this work, the experimental module must consider the following error cases to determine accuracy:

- Non-linearity of ADC

- Tolerance of resistors used
- Accuracy of op-amps used
- Accuracy of LEMs transducers

The ATMEGA 328 microcontroller is provided with successive approximation type analog to digital converter(ADC). The ADC module has a resolution of 10-bits. From the datasheet specification of ATMEGA328 controller it is found that there is an error of$\pm 1LSB$. Hence, the accuracy of the converter used is $\pm 0.125\%$. Further calculations are made, assuming that the tolerance of the resistor component is used as 0.05%. Power(P) is calculated using the instantaneous product value of Voltage(V) and Current(I) as in equation B.1.

$$P = V \times I \tag{B.1}$$

The designed power supply unit is supplied with $230V$ main supply, which outputs $\pm 12V$ to power up transducer. The power supply module has a possible measurement error of 2%. The resistor components used in the design of voltage divider circuit have a tolerance of 0.05%. Considering the internal reference voltage to be $0.9V$.Hence, the overall error might contribute to $2 + 0.05 \times 2 = 2.1\% = 0.0189v$.

To measure the instantaneous value of the voltage and current from the transducer output, which is multiplied by the appropriate scaling factor, the expression can be written as in equation B.2.

$$V = (0.9 \pm 0.0189) \times (1 + (\frac{R_f}{R_1})) - (\frac{R_f}{R_1}) \times V_{LEM(v)}) \times k_v \tag{B.2}$$

where, k_v is a Voltage scaling factor.

Similarly, for the current measurement, it can be calculated as given by the equation B.3.

$$I = (0.9 \pm 0.0189) \times (1 + (\frac{R_f}{R_1})) - (\frac{R_f}{R_1}) \times V_{LEM(i)}) \times k_i \tag{B.3}$$

where, k_i is a Current scaling factor.

The percentage of error in ADC is $\pm 0.125\%$.

B.2.1 Voltage Accuracy Measurement

The manufacturer's datasheet shows that the percentage error of the LEM LV 25P transducer at the secondary coil current I_S is 0.9%. The RMS output of the LEM transducer measures $1.89V$ for an input voltage supply of $230V$. Given that the tolerance of all resistors used in the circuit is 0.05 %, the percentage error of $V_{LEM(v)}$ is given by equation B.4.

$$V_{LEM(v)} = LEM(error) + R_f(error) + R_1(error) + R_2(error) + R_3(error) \quad \text{(B.4)}$$

Where, $R_2 = 100k\Omega, R_3 = 100\Omega$

$$V_{LEM(v)} = 0.9\% + 0.05\% + 0.05\% + 0.05\% + 0.05\% = 1.1\%0f1.89v = 0.02079v \quad \text{(B.5)}$$

Therefore, the above equation B.5 can be described as in equationB.6.

$$V = (0.9 \pm 0.0189) \times (1 + (\frac{R_f}{R_1})) - (\frac{R_f}{R_1}) \times 0.02079) \times k_v \quad \text{(B.6)}$$

$$V = (1.8 \pm 0.0586)) \times k_v \quad \text{(B.7)}$$

Hence, the percentage of error in voltage measurement is $\pm\frac{0.0586}{1.8} = \pm 3.25\%$.

Therefore, overall percentage of error in voltage measurement is calculated as: $3.25 + 0.125 = \pm 3.375\%$

B.2.2 Current Accuracy Measurement

The supplied main current to the load is measured by passing through a current transducer LEM LA 25P. A nominal current of $2A$ is considered to be passed through the transducer. In this case $I_S = 2mA$ which flows through a burden resistor of 100Ω leading to RMS output voltage of LEMs transducer proportional to $0.2A$.

Thus, the overall percentage error in current transducer can be expressed as in equation B.8. Further, modified as in equation B.9 and calculated as in in equation B.10.

$$I_{LEM(i)} = LEM(error) + R_f(error) + R_1(error) + R_2(error) + R_3(error) \quad \text{(B.8)}$$

Where, $R_2 = 100k\Omega, R_3 = 100\Omega$
$V_{LEM(i)} = 1.05\%$ of $0.2A = 0.02A$

$$I = (0.9 \pm 0.0189) \times (1 + (\frac{R_f}{R_1})) - (\frac{R_f}{R_1}) \times 0.02079) \times k_i \quad \text{(B.9)}$$

$$I = (1.8 \pm 0.0407)) \times k_i \quad \text{(B.10)}$$

The percentage of error in current measurement is $\pm\frac{0.0407}{1.8}$=2.26%.

The percentage of error in current measurement including ADC error is $2.26 + 0.125 = \pm 2.385\%$.

Therefore, the cumulative percentage of error in power measurement is calculated as, $2.625\% + 2.385\% = \pm 5.01\%$

B.3 Power Consumption Measurement of SEMS Modules

The deployment of SEM units, which runs 24 hours a day for 365 days a year, will add to the annual electricity consumption due to the SEM's residual power needs. Therefore, it is required to analyze the energy consumption of the proven SEM unit and load controller used in this experiment. The estimated power consumption is detailed in Table B.1.

Table B.1: Power consumption analysis of SEMS

SEM Module	Device	Approximate Power Consumption	Operating Duration	Annual Energy Consumption (kWh/Year)
SEM Unit (Coordinator)	16*2 LCD Display, XBee module, Microcontroller with Ethernet shield (data transmission at 1 min interval)	0.1945 Watts	Operates at 24/7 with energy display on LCD Screen	1.703 kWh/Year
Load Controller (Router)	Sensor Module, Power supply module, Microcontroller, ZigBee Module, Relays	0.8492 Watts	Operates at 24/7 with energy display on LCD Screen	7.438 kWh/Year

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A. Refereed International Journals

1. Pawar Prakash and Vittal K P. (2019). Design and development of advanced smart energy management system integrated with IoT framework in smart grid environment. *Journal of Energy Storage-Elsevier*, 25, 100846.(SCIE, IF=3.51).

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3. Pawar Prakash and Panduranga Vittal K. (2019). Performance analysis of a smart meter node for congestion avoidance and LoS coverage. *AIMS Energy*, 313, 2333-8334.(ESCI)

B. International Conference Proceedings:

1. Prakash Pawar and Vittal, KP (May, 2017), "Design of smart socket for power optimization in home energy management system", *IEEE,Recent Trends in Electronics, Information & Communication Technology (RTEICT)*, pp. 1739—1744, Bangalore.

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