Agent Base Modelling and Simulation of Domestic Electricity Load Profiles for effective Demand side Management

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Declaration

I hereby certify that I have developed this thesis titled as Agent Base Modelling and Simulation of Domestic Electricity Load profiles for effective Demand side Management on the basis of my personal efforts under the sincere guidance of my supervisor Dr. Azhar Ul-Haq. The sources used in this thesis have been cited and contents of this thesis have not been plagiarized. No portion of the work presented in this thesis has been submitted in support of any application for any other degree of qualification to this or any other university or institute of learning.

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Copyright Statement

Dedicated

to my father ***Mr. Abdul Mannan***

for encouraging and supporting me to achieve this daunting task,

and

to my mother ***Ms. Rehmat Begum***

who has been a source of motivation and strength during the moments of despair and discouragement.

Acknowledgments

And your Lord is going to give you, and you will be satisfied. Al-Quran [93:5]

First, I am thankful to my Creator ALLAH ALMIGHTY, Who gave me an opportunity to use best of my knowledge and encouraged me to carry out this work. Without His blessings I wouldn't have achieved this accomplishment. Whosoever guided me throughout the course of my thesis, whether my parents or any other individual was His will, so indeed none be worthy of praise but Him.

Second, peace and salutation always dedicated to our beloved HOLY PROPHET MUHAMMAD S.A.W.W, the last PROPHET who has brought us from the darkness to the brightness.

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I am grateful to my parents for their prayers and moral support. Their wish to see me achieve greater heights in my education and career has motivated me throughout my life. Words cannot express how grateful I am for all of the sacrifices that they had made on my behalf. My special words of thanks should also go to my siblings for my success as it's a result of their devoted prayers and encouragement.

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Nomenclature

EVs	Electric Vehicles
ABM	Agent base modeling
ABMS	Agent based modeling and simulation
AI	Artificial Intelligence
ANN	Artificial Neural networks
DERA	Distributed Renewables for energy access
GHG	Greenhouse Gases
SoH	State of Health
SoC	State of Charge
CC	Constant Current
CV	Constant Voltage
CB	Capacity of battery
CP	Power consumption
kWh	Kilo watts hour
M&S	Modeling & simulation
ToU	Time of use
Max D	Maximum Trip distance
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
A/C	Air conditioning
RTP	Real Time Price
SOCP	Second Order Cone Programming
ADMM	Alternating Direct Method of Multiplier
D	Daily trip distance
DAM	Day Ahead Market
TOU	Time of Use
P	Charging power consumption
IESO	Independent Electricity System Operator

T	Total charging time
DSM	Demand side management
DR	Demand response
DRM	Demand response management
PV	Photovoltaic
MINLP	Mixed integer nonlinear programming
DAP	Day ahead pricing
CE	Cost efficiency
EA	Quantum evolutionary algorithm
EMC	Energy management controller
DLC	Direct load control

Abstract

In Pakistan, domestic electricity consumption accounts for approximately 40% of the electricity sale share, stressing requirement of forecasting this consumption sector load profiles for establishing demand side management policies ever more important. It has become crucial for power generating companies to profile their clients' electricity consumption profiles in recent times. This process would allow them to optimize their grids by providing only enough power to serve their clients keeping in view the demand and thus avoid wastages and unnecessary strain on whole system particularly transmission system hence resultantly enables to bridge the gap between electrical supply and demand efficiently. Moreover, this step helps consider efficient electricity generation from renewable sources, like solar and wind, which require a power storage device. The best way for these companies to achieve this goal is by developing load profiling models that simulate consumers' domestic power consumption under different load conditions and factors effecting these. Efficient electricity infrastructure based on accurately monitored load profiles of consumer will help implement smart grid infrastructure and demand side management solutions in a developing country like Pakistan in near future. This work undertakes to develop a model which forecast household electricity consumption profiles using coherent technique i.e. agent-based modelling. It considers a population having 300 households and then uses the Any-Logic software to model their behaviour according to their activities investigated through variables and functions. Multi layered hierarchal scheme incorporating agents and their characteristics subject to actions taken in inter-related environment based on their habits, nature, occupancy profiles and patterns is considered. This work discusses the processes involved in Agent based modelling and simulation environment which reflects characteristics in respect of the modelled entities to simulate actual operating conditions of the appliances for generating a high resolution household energy demand profile. Results show that the agent-based simulated total electricity consumption in kWh for a given set of households in a month approximates real time validated data with difference of 2.4%. Hence, this approach proves viable for the purpose of obtaining this vital information i.e. electricity load profiles through observing daily, weekly, yearly patterns of the electrical appliance consumption by households.

Chapter 1
Introduction

1.1. Motivation

With necessity arising for utility companies to regulate and plan expansion of existing capacity of the network but before determining the storage capacity that they need, these companies must know the demands of their customers. It is not possible to approximate an individual's power usage using another data from other people’s consumption. Still, despite the complexity involved in this process, power companies still need to know their clients' power usage profile to plan their generation and distribution of the power and use appropriate equipment. Furthermore, many of these companies create smart grids, which optimize power generation and distribution to their clients [1]. These smart grids work best when the companies have usage profile data from their customers. They obtain this information using energy management systems, which use algorithms to simulate their users' power consumption while considering varying loads and generation capabilities [1]. If these companies fail to profile their clients' power consumption, they may end up in situations where they may need to use alternative power generation measures, such as propane-powered generators [2] [3]. Such a step would be more expensive than using appropriate storage and distribution of their power depending on their clients' usage profiles.

1.2. Introduction

This chapter presents overview of the proposed analysis framework in light of need of better insights for the planning of efficient electricity grid network. People use electricity for different purposes in their homes and at work. Electric loads include appliances like dishwashers, cookers, televisions, lights, personal computers, digital clocks, electric vehicles, and other devices. The number of these appliances keeps on rising, which increases the need for more power. Moreover, while people may have similar appliances, their usage profiles differ, which means that it is not possible to determine the power consumption pattern of a person using the data of another [4]. For instance, one person may spend more time watching television than another one who may be using their computer. This variation in power consumption makes it hard to determine how much power these two people need without data from them. In a world with increasing power demand, it is vital to find users' electricity load profile to decide how much power to generate to satisfy their needs. In recent times, more attention has shifted to the generation of electricity using renewable sources, including geothermal, solar, and wind sources [5]. However, these sources usually require storage for their power since they vary depending on environmental factors [6]. For instance, electricity generation using solar energy is only possible during the day. Moreover, using wind to generate electricity produces varying power depending on wind intensity. Since people's demand for power does not depend on these environmental variations, it is impossible to use them without a storage device, which will ensure the availability of power when needed. Consequently, companies generating power from these renewable sources need to have storage devices to ensure their grids' stability.

This work proposes an agent-based domestic electricity consumption of 300 households simulation and analysis framework while considering factors having influence on the outcome of the consumption profile and encompasses features such as occupancy patterns of the agents given different constraints like no. of residents of the house, no. of working occupants of a household, age of the occupants which enables to make a suitable assumption for processing a checking loop regarding occupancy pattern on a given time of the day, the number of rooms in the houses to cater for dynamics of variation in size of the house, and the appliances that these households have, categorized based on the power ratings and usages patterns accordingly. As described above, electric load profiling of users is of high importance to lay a basic framework for implementation of smart home energy mechanisms and demand side management policies. Data in respect of Household demand profiles carry most importance because of the fact that major consumer class of electricity is domestic sector with ranging to about 40%. Therefore, provision of such accurately monitored data is imperative to build on clean green smart grid technology. This work also looks at the impact of weather on inductive load like air conditioners and fans' usage and electric vehicles' ownership. Changing weather conditions in the real world demands simulation to include response towards alternating climatic conditions to replicate the real life scenario in true sense. It incorporates a function that allows to change the temperature condition at run time to see the impact of such a variation on the model. Modelling inductive load requires work to be carried out in respect of the variability of the load and phenomenon of the initial spikes associated with them. Considering all these factors leads to developing a comprehensive agent based electricity profile of daily, weekly and seasonal power usage for a given set of people in the population which closely approximates actual data differing by 2.4% as discussed in the Simulations chapter in detail.

Our proposed framework will support relevant stakeholders in understanding the diversified patterns of domestic electricity utilization to fulfil the On Peak, Off Peak and Mid Peak power demand. It will also help for the planning of efficient electricity transmission and distribution network.

1.3. Problem Statement

With ever evolving role of demand side management in view of the smart grid infrastructure to efficiently utilize the available resources, it requires an extensive load profiling simulator design incorporating in depth occupants related parameters hence leading to the problem statement as follows:

The problem is to develop a comprehensive Agent base modelled and simulated load profiling system for a set of domestic population which includes power usage variations influenced by the appliance design and occupant behavior while incorporating the dynamics of inductive loads usually found in domestic scenarios effectively given the randomness in its nature.

1.4. Research Objectives

The following are the research objectives of this thesis.

1. To develop an approach that maximizes monitored electricity profiling efficiency.
2. To present a methodology that focuses on the enhancement of ability to forecast under varying loads and weather considerations.
3. To develop the optimization framework which accounts for the randomness involved in problem and ensuring optimization of appliance power consumption levels based on the given inputs.
4. To perform the comparison of ABM electricity load profiling under the provision of actual consumption data from electrical distribution company.

1.5. Contribution

Main contribution of the study is listed as follows:

1. Proposed a suitable Agent based simulation & analysis framework which well captures the diversity of occupants nature and behavior for accurate monitoring of the electricity load profiles.
2. Presented modelling and analysis framework of domestic electricity load profiles which constitutes major chunk of consumer class, for forecasting future energy demand.
3. Impact of variable weather, inductive load dynamics and Load classification strategy is investigated to incorporate diverse appliance characteristics and occupants behavioral patterns in the proposed model for the purpose of analyzing hourly, weekly, monthly and total electricity consumption and appliance wise electricity consumption.

1.6. Thesis Organization

The organization of the thesis is as follows.

- **Chapter 2: Fundamentals**

  Chapter 2 presents a brief overview of basic concepts related to electricity load profiling and demand side management. It briefly describes factors related to agent base modelling and its importance in terms of advantages over other techniques.

- **Chapter 3: Literature review**

  Chapter 3 provides overview of the previous work done in forecasting of domestic load consumption profiles. It provides a critical analysis of the different techniques discussed in the respective papers to implement Demand side management through load profiling.

- **Chapter 4: System Model**

  This chapter explains the formulation of proposed approach and how it models domestic load consumption through agent base modelling. Input parameters and proposed simulation and analysis framework is explained in this chapter.

- **Chapter 5: Simulations**

  This chapter presents simulation of our framework. It describes the simulation model conditions and constraints and shows the output of our framework in terms of load forecasting.

Comparison of simulations results with actual data is also presented.

- **Chapter 6: Conclusion and Future work**

  The tasks completed during the course of this thesis are presented in this chapter. The conclusion of our work and the future work to carry out enhancement of the model is presented in this chapter.

Chapter 2

Fundamentals

The chapter provides description on the different components and parameters involved in demand side management and electricity load profiling environment. It discusses each concept involved for the better understanding of relevant concepts before going forward. These components are Load curves, Demand response, smart grid and pricing techniques. In addition, this chapter also briefs about the components and parameters used in Any-logic software. The pros and cons of each technology associated with DSM are discussed in detail.

2.1. Household Electricity Load Curve

The household's role in future electricity systems is evolving as now they are playing the role of prosumers, therefore a good understanding of the household electricity demand profiles is vital. Demand / Load Profile is a curve or chart illustrating the variation in demand/ electrical load over a specified time as shown in Fig. 2.1 below.

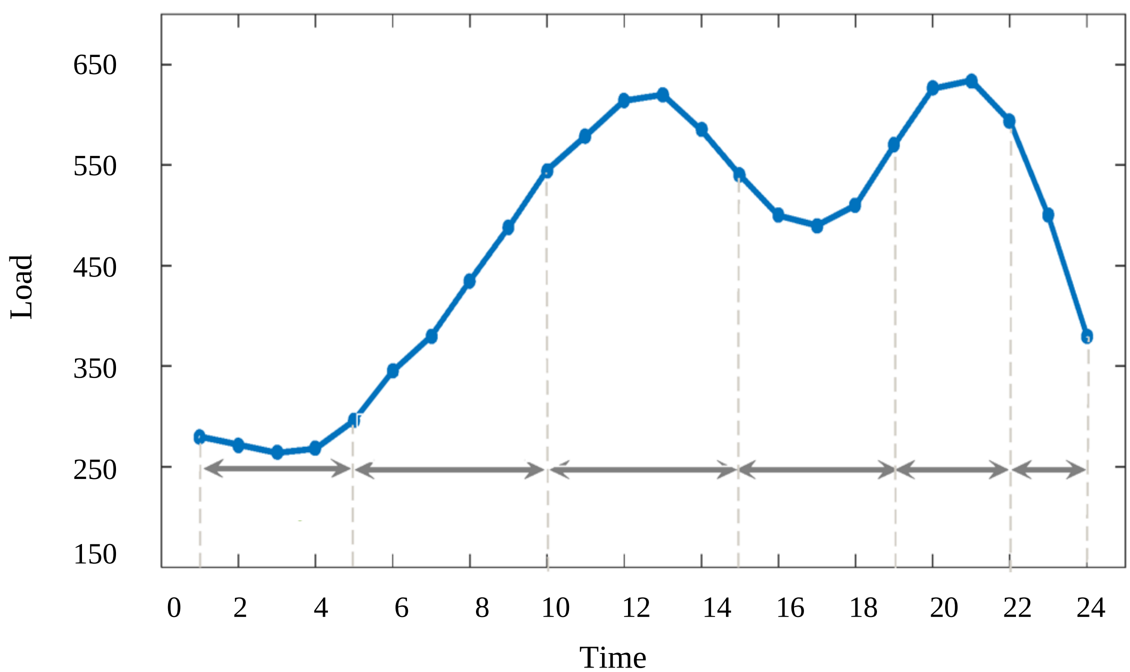


Fig. 2.1: Example of Load curve [7]

2.2. Smart Grid

A smart grid is an electricity network which provides a two-way flow of electricity and communication data with digital communications technology equipping system to ascertain, respond and pro-act to changes in user usage pattern and other co-existing multiple issues. Smart grids provide mechanism to electricity customers to become active participants in electricity network. A smart grid is a modern power generation, transmission and distribution system that can automate and efficiently deal with the increasing complexity and requirements of electricity in the 21st century. As illustrated in Fig. 2.2, the technology aims to; integrate and support renewable energy sources like solar, wind and hydro, empower consumers with real-time information about their energy consumption [8]. Current mode of electricity grid network calls for changes in it. This is because the grid technology has been the same with no major modifications in connection of flow of communication data for tracking and monitoring purpose. There has been a need of revamp in grid technology to incorporate ever evolving modern day dynamics of electrical usage and user satisfaction. Fig. 2.2 shows how communication and electrical flow of data operate in two way direction in an interconnected system ensuring overall tracking monitoring of electricity production and consumption.

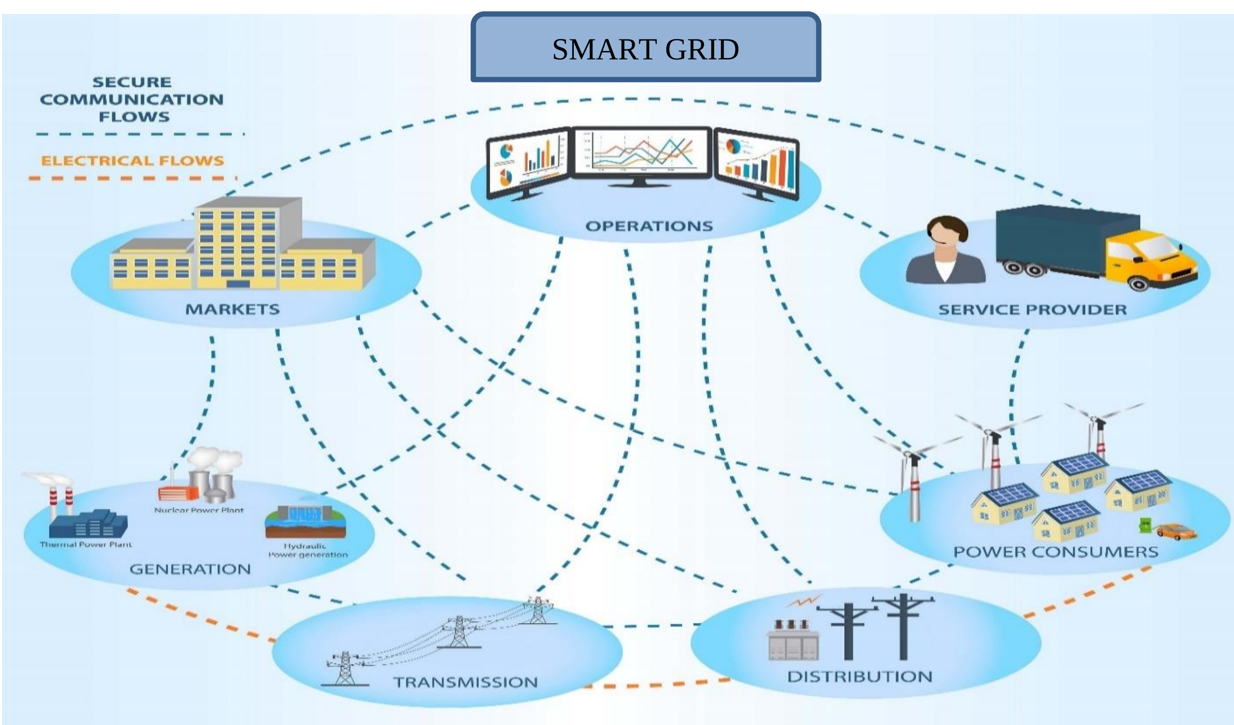


Fig. 2.2: Smart Grid System [8]

2.3. Demand side Management

Demand side management is an effective mechanism to efficiently utilize available generated energy for increased reliability and productivity of overall system infrastructure. Demand side management essentially modifies consumer demand for energy through various methods such as smart metering, indirect load control like incentive based schemes and direct load control which include monetary incentive for turning off loads or rescheduling loads. Fig. 2.3 shows categories of Demand side management in respect of time required for implementation and subsequent impact generated on electricity utilization patterns. This is explained in further detail in this chapter. DSM involves the process of collection of data of electricity consumption profiles through energy, load and occupancy forecasting and then applying different optimization algorithms to design a particular simulator which is able to regulate the loads accordingly for efficient utilization of energy at disposal. Demand side management is a technique which effectively removes the need of setting up new plants by managing load curve in conventional grid and also smart grid having renewable energy penetration.

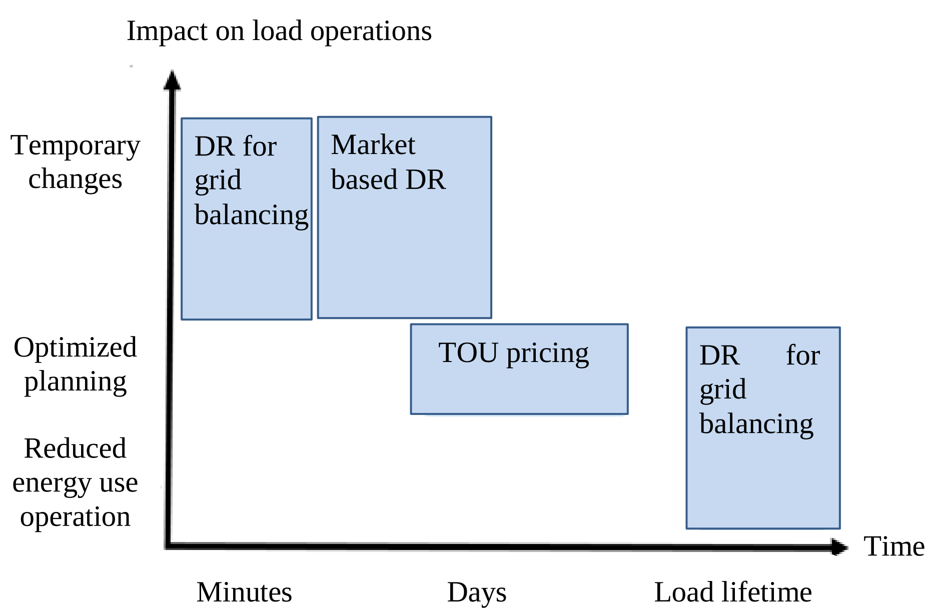


Fig. 2.3: Categories of Demand side management [9]

DSM is carried out essentially by using two approaches as follows.

- **Energy Efficiency:** Energy Efficiency is related with employing advanced efficient appliances to increase energy efficiency. Studies have shown that mostly electrical breakdown and failures have occurred due to non-efficient and improperly tested equipment usage. Implementing energy efficiency program under demand side management umbrella is rather difficult as it needs a major over haul of entire electrical power infrastructure.

- **Demand response:** Demand Response deals with behavioral change in consumer consumption patterns to increase efficiency by reducing peak demand of residential sector which constitutes major chunk of total cost incurred. It is essentially an energy conservation and efficient utilization technique for efficient usage and consumption of electricity by users to reduce and lessen the burden imposed on electrical generation, transmission and distribution network.

In Demand Response programs (DR) using Direct load control (DLC), clients give electricity distribution companies the choice to shut down appliances from a far apart distance during peak electricity demand duration or electric power supply contingencies through a preset program installed in controllable equipment, so that load profile can be maneuvered, and in return receive benefits on electricity bills for this partnership and cooperation with utility companies.

The rescheduling of peak load from one time frame to another results in one instability which needs to be taken care of through effective and thorough planning. The one big issue is instability, e.g., a "rebound" electricity peak demand may take place during an otherwise low demand time period due to a significant amount of switched load to same slot/period. Some methods used by utilities for price schemes are

- Price based methods

It is a day ahead pricing scheme. It utilizes day ahead price, when price is large, only high prioritized appliances are allowed to operate.

- Time of Use (TOU) method

Generally the commonly known peak demand time periods, morning and evening, are nominated as peak energy usage times and during these periods, fewer appliances are operated.

- Real time pricing (RTP) method

It is a dynamic pricing scheme. Its parameters are changed hourly or sub hourly.

- Critical Peak pricing (CPP) method

This scheme is very rarely used by utility companies. It is employed in the case of emergency and contingency conditions. Usually customers are charge 15-20 days of the year under this scheme. Prices are set very high during these hours. In Fig. 2.4 Time and price based demand response flow diagram is illustrated which takes into account the difference between real time pricing and time based pricing demand response strategy with former incorporating price signal at run time.

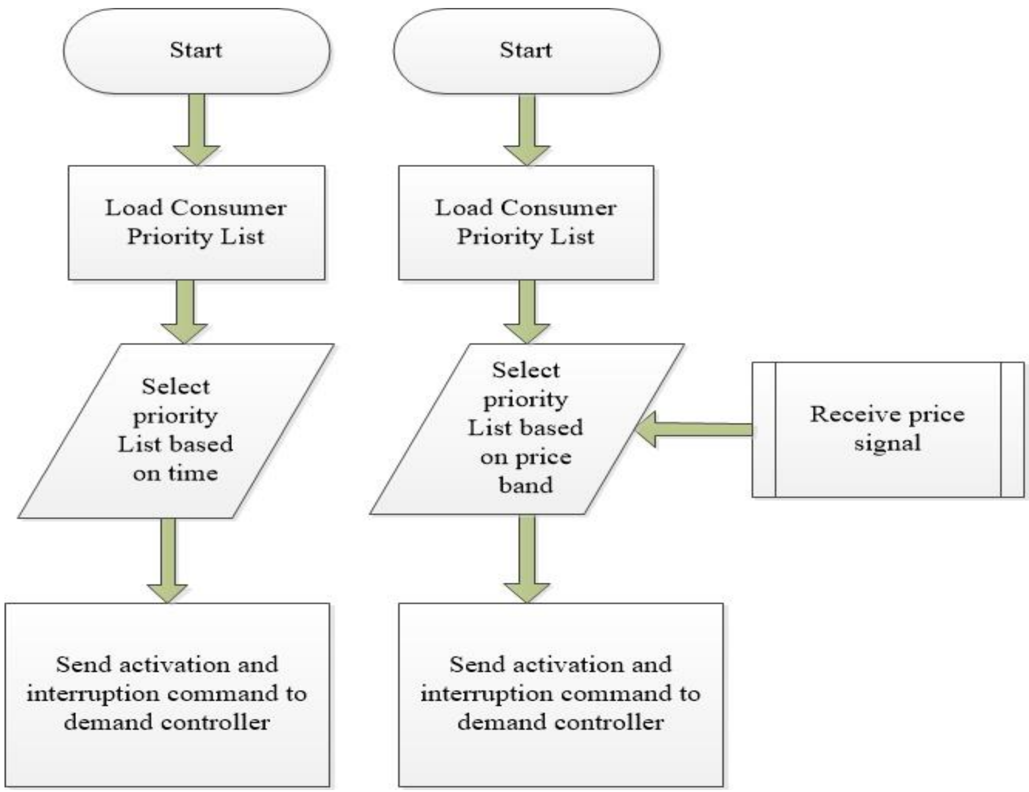


Fig. 2.4: Time and Price based Demand Response flow diagram

2.4. Components of Demand side Management

Some of the basic components that lead to implementation of Demand side management and terms related to it are described here.

Load / Demand profiling means to accurately monitored and forecasted electricity consumption patterns of users for implementing different techniques and optimization algorithms for achieving demand response desired results. Optimization algorithms such as particle swarm optimization, genetic algorithm, MOPSO, linear integer programming techniques are used to implement Demand side management by modifying user consumption pattern through demand response control strategies. Demand side management in renewable energy environment required power storage devices for its implementation. Power storage devices is any type of device used to store power for usage. It is used in context of smart grid to mostly refer to storage devices like batteries which provide electricity power to appliances once stored through solar or wind power systems. Agent base modeling is a relatively newer approach to forecast demand profiles which serve as pre requisite for DSM. There are three main simulation modeling paradigms:

1- Discrete event
2- Systems dynamics
3- Agent-based

System dynamics and discrete event are traditional simulation approaches, agent based is a newer one. Technically, system dynamics approach deals mostly with continuous processes whereas discrete event and agent-based models work mostly in discrete time, i.e. jump from one event to another. Agent base modeling implemented through software Any-logic has some basic components as follows.

- **Agents:** Agents may provide representation to a variety of things — people, vehicles, projects, utilities, commodities, pieces of land, etc. Agents serve as building blocks of Any-Logic model. Agent is a unit of model design that possesses behavior, memory, timing, contacts, etc.
- **Variables:** Agent consists variables in them. Variables generally serve the purpose of storing the results of simulation or to model some data units or object characteristics, changing over time.
- **Event:** Event is the simplest way to programme some activity / measures in the model. Thus, events are commonly used to model delays and timeouts.
- **Function:** Any-Logic enables defining your own functions. Function will return the value of an expression each time the user calls it from the model. Functions are helpful when you need to re-use the same function in multiple places in your model.

2.5. Agent Base Modelling & Simulation

This chapter discusses Agent based modelling & simulation (ABMS) in respect of modelling consumption profiles. Several methods can produce data that shows people's domestic power usage profiles. These approaches include using data mining methods and using performance simulations. These approaches are applicable, but data mining uses artificial intelligence and neural networks to produce useful power usage profiles. Its only challenge is that it involves intense data collection, and the developed models may not be readily applicable to old buildings [10]. On the other hand, performance simulations can solve this data collection challenge, but some simulations tend to fail to capture and account for randomness of power usage. Their data is not viable in developing load profiles. They are only applicable during building design, and not to produce power usage profiles. However, due to the challenges of implementing a data mining approach, simulations become more suitable in this case to capture the essence of electric load profiling.

2.6. Agent Base Modelling: Advantageous Approach

There are several methods of simulating power usage in domestic houses. The performance simulation approach uses system-wide data and considers their systems as a whole. For instance, when assessing a population of 100 items, these approaches will model one item and then apply its characteristics and behaviours to the rest of the items. This approach fails to consider the randomness of the individuals in the population. Application of such a modelling approach is not valid, since as discussed above, it is hard to use one individual's power usage profile to estimate that of a different person. The best tactic would be to use a method that considers all the population members differently and then combines their profile to find the whole system. This approach is called agent-based simulation since it considers the members in the system as having distinct features.

This approach defines the variables affecting an agent's behaviours and programs them in a model. Then the simulation software places all the agents in an environment, where they can act independently, and it then considers their combined response. When used to model the power usage profile for people in an area, the agent-based approach produces comparable results to real-life situations [11]. The advantage of using agent-based modelling in developing power usage profiles is that it does not use a generalized structure such as is the case with performance simulations. The agent-based approach considers the power usage of different people depending on their appliance usage tendencies. When using the performance simulation, the system may assume factors like the time subjects use appliances like the television. It will create a general assumption that will make the results fail to be realistic. This approach also defines the variable as random and then examines the results emerging from these appliances' ensuing random usage. This process produces realistic results.

It is possible to achieve real-life results when combining mathematical analysis and object-oriented programming to develop a simulation. However, this approach will produce a significantly large simulation, and it will be hard to make, especially in the case of inexperienced modellers [12] [13]. Instead of using such a challenging method, agent-based modelling provides an easy solution. It follows a more straightforward process and produces a much smaller model than object-oriented programming merged with mathematical analysis. Moreover, the results of agent-based modelling will be better than those of the former approach. Thus, agent-based is preferable when compared to the use of mathematical and object-oriented programming.

Based on the benefits of using the agent-based approach to simulate the power usage profile, this work adopts aforementioned technique. It used the *Any-Logic* software to develop and run the model. This paper will provide the process used in developing this model. It will discuss all the variables considered and show how the software varied and applied them to the chosen population of 300 households. The software makes it possible to model and simulate all these households' power usage and provide a viable model and results. This paper will also discuss this experiment's results and compare them with published data to validate them. Given these advantages of agent-based modelling, it emerges as more superior to other methods used in such instances. Besides, as discussed above, agent-based modelling provides more accurate results, and its implementation is more straightforward than its alternatives. As such, an agent based simulation model is a set of interacting objects that reflect relationships in the real world. The results make agent based simulation a natural step forward in understanding and managing the complexity of today’s business and social system.

Chapter 3

Literature Review

This chapter presents the literature review on the techniques / approaches being implemented for electricity load profiling. It provides a critical analysis of the approaches being discussed in the respective papers to implement Demand side management through demand load profiling and optimization algorithms and also highlights their advantages and disadvantages in comparison with keeping in view different conditions with respect to efficient load profiling resulting in close to real output.

3.1. Modelling & Simulation of Electricity Load profiles

Previous work carried out in the field of electricity load profiling and DSM can be classified as techniques followed on the basis of statistical / probabilistic / Time of use (TOU) models, agent base models, smart meters / home energy management systems / optimization algorithms such as particle swarm algorithm / genetic algorithms / neural networks / fuzzy logic and models based on effect of weather / occupancy on electricity consumption.

Demand Side Management (DSM) discussed in literature employing different control and heuristic optimization techniques is an effective tool for utilities to increase the flexibility of electrical distribution network, and augment the efficiency of electrical system in the presence of distributed generation facilities in a smart grid environment. Emergence of distributed generations and smart grid framework has accentuated the importance of having an optimization technique to address the problems created by peak load occurrence in distribution network. Research has shown that Demand side management finds it major benefits and advantages in residential areas distribution network. Residential areas which consist of a major chunk of electricity distribution users may help in making the whole electrical system more efficient and reliable if Demand side management (DSM) is employed properly. Demand side management can be explained as the name of averting or checking the need for investment in brand new electrical power plants, enhancing and improving the power quality, increasing energy efficiency and reliability by ensuring efficient production, transmission and distribution of available electricity.

This section discusses demand profile forecasting techniques as well as the heuristic optimization techniques employed thus far in research to implement Demand side management (DSM). Many researchers have focused to propose and devise mathematical and optimization techniques to schedule the peak load under optimal conditions. This enhances the efficient utilization of available energy in smart grid. In [15], latest DSM literature tilt towards stochastic modelling is presented. Credit based novel incentive scheme within stochastic planning environment is used. Fig. 3.1. Illustrates household smart energy management system including inflow of power from power utility to a home having Energy management controller (EMC) to implement control mechanism and thus enabling smart control on appliances connected.

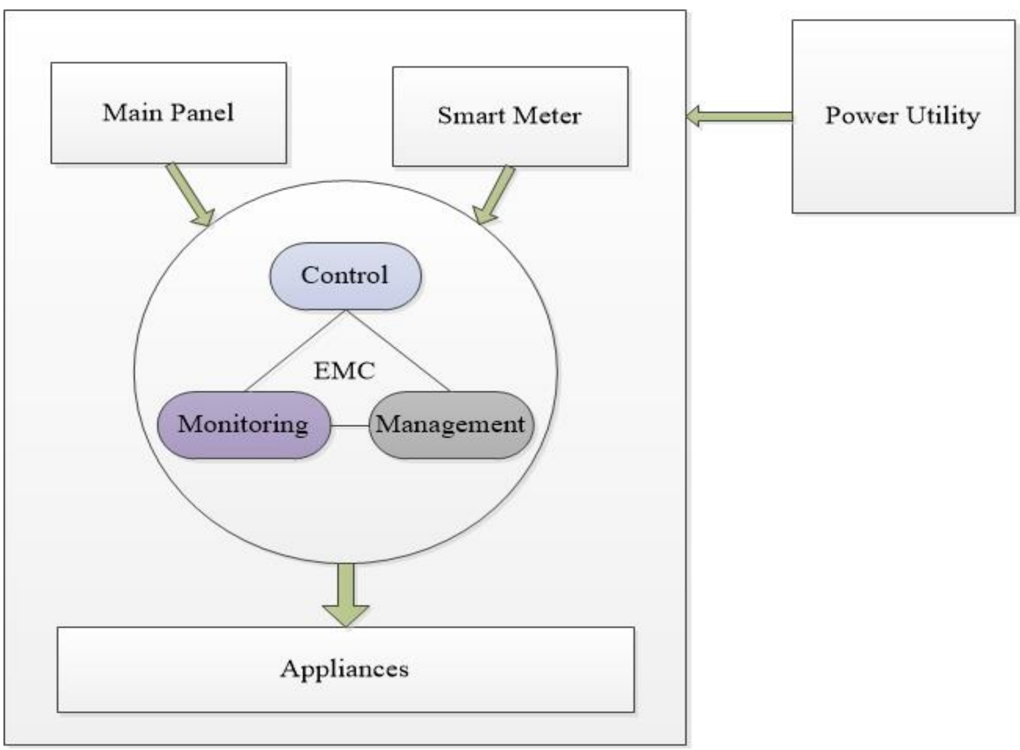


Fig. 3.1: Household Smart Energy Management system

Home energy management for distributed energy resources (DERs) comprising both electrical and thermal appliances scheduling (HEMDAS) [16]. The proposed technique aimed to minimize the energy usage price while considering the user comfort. The mixed integer non-linear programming (MINLP) along with dynamic pricing (DP) scheme is adopted.

In [17], Teacher learning based optimization (TLBO) is used. Load is classified into three classes: shift-able, shed-able and non-shed-able load. Cost efficiency is taken as the ratio of total energy consumption advantages to the total energy payments. CE is considered as a signal for customers to adapt and alter their energy consumption pattern. Moreover, the fractional programming (FP) technique combining with RTP and day ahead pricing (DAP) is adopted in this scheme. The performance results show that CE is increased with large number of DERs [18]. In [19], for a system with an integration of Photovoltaic (PV) to a wind mill as RESs, and uncertainties arising by RESs integration, fuzzy logic technique is used.

Fig. 3.2 illustrates hierarchical levels of DSM. An author named Safdarian, categorized DSM into two stages. In first category, there is a decentralized system with the objective to reduce the energy cost of consumers. Mixed integer non-linear technique (MILP) is used to formulate the problem. In second stage, the main goal of the proposed model is to provide benefits to the utility by maneuvering the load profile while also taking caution of guarding the parameters important to user i.e. cost and comfort. MIQP approach is adopted to get to the target of modified load profile curve [20].

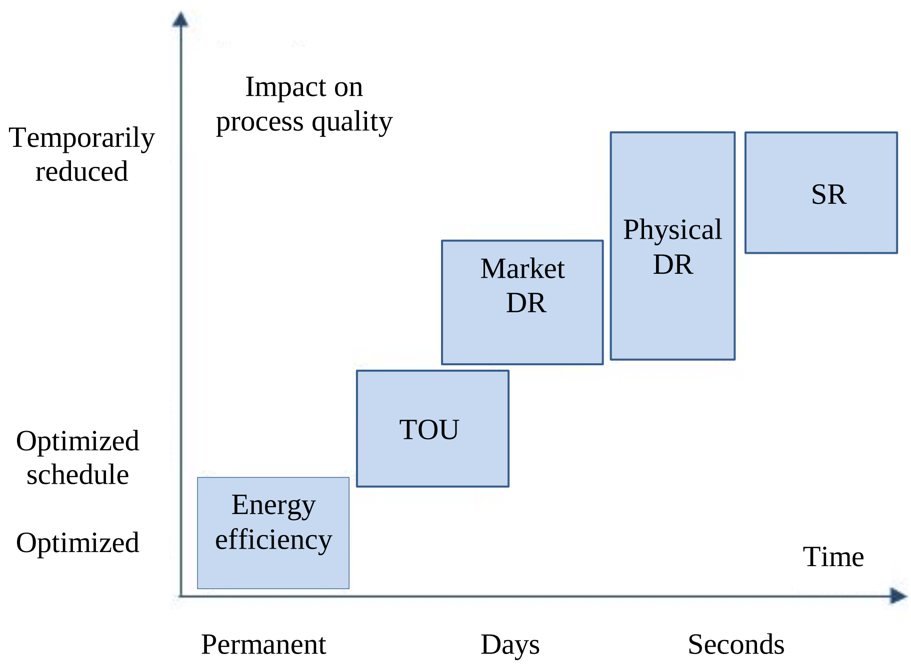


Fig. 3.2: Hierarchical levels of DSM

Agent-based Modeling and Simulation (ABMS) approach is used by researchers for complex socio-technical problems to serve as a pre-requisite for implementing DSM policies by forecasting electricity load profiles. Recently the framework is used for modeling of smart grid scenarios like demand response strategies, distribution generation, integration of renewable technologies and energy storage. [21] used the agent-based simulation approach by dividing the London urban area into zones using socio-demographic parameters. For each zone, a heterogeneous group of agents is created with an occupancy profile which simulates the hourly electricity consumption for heat-pumps, electric vehicles, and residential energy. The focus of the researcher was electric vehicles and residential use was represented as an aggregate in total electricity consumption. [22] used an agent-based model to study office building electricity consumption.

It has been observed in the literature that mathematical models tend to model structure & environmental data better and probabilistic models tend to model social behavior appropriately. However, what is required is a strategy which can incorporate both the structural-environmental and socio-anthropologic aspects within the simulation element. Though very effective, collecting data from the consumers for forecasting and planning has cost, legal and privacy concerns which make these systems less practical for the existing energy systems the sheer of collecting data from the consumers makes these models unlikely for use in the existing energy system. Table 3.1 gives summarized previous literature work analysis.

Table 3.1: Literature survey and identification of research gaps

S. N.	**Demo-graphics**	**Author (s)**	**Description / Technique**	**Data Source**
16	IEEE Transaction , Turkey	[15]	The proposed mechanism relies on providing energy credits to the end-users on the basis of their contribution during a DR event, which in turn can be used in periods outside the time span of a DR event in order to reduce their energy procurement cost.	Synthetic. 40 identical households having the structural parameters. Reference HVAC power is nonzero and initially assumed to be 12 kW from the total of the 40 households.

7	IEEE Transaction, UAE	[17]	DR scheme in the context of a day-ahead Bi-level electricity market for a VPP. A centralized DR aggregator then select an optimal combination of individual daily load profiles.	Synthetic. Considered a VPP system aggregating only solar PV generation with a total rated power of 1MW.
9	IEEE Transaction, Australia	[18]	The tool estimates the available domestic hot water loads in a controlled area, and determines optimal switching programs. The tool employs Monte Carlo simulations to generate hot water consumption profiles. Exporter block then exports the data to an external (Excel) file.	Parameters used in the simulations are based on the results of a survey conducted on 1000 randomly selected households and actual energy metering data of 279 households across Tasmania. Probabilistic simulations are incorporated.
1	Conference, Nepal	[19]	Used survey technique for actual and forecasted energy demand considering different scenarios of growth rate. LEAP (Long term energy alternative planning modeling software).	Actual. 96 households were surveyed for data collection. Family size and income are parameters. Primitive loads.
2	IEEE transaction, China	[20]	Cost efficiency based algorithm to optimize cost benefit per unit cost	Synthetic. 3 consumption patterns by clustering method.
25	IEEE Conference, Belgium	[21]	The model considered the factors of land use, energy landscape, and customer inclination. The area under consideration is divided into different zones by using socio-demographic parameters. An action based on activity is related with every agent and electricity load model and heat demand models are produced.	Synthetic.
26	Applied energy, USA	[22]	The four elements for office energy consumption are considered. These are Energy Management Policies, Energy Management Technologies, Energy User's behaviors, and Office	Synthetic.

			Electric Equipment and Appliances.	
3	IEEE Transaction , America	[23]	Energy Management controller using Markov modeling	Detecting User behavior pattern through preset reference models.
4	Int. Journal of Energy research, USA	[24]	Genetic algorithm is applied to implement each EMC and smart meter of users by categorizing loads into delayable (timed, regular appliances) and non-delayable.	The RTP data for 60 days (from January 1, 2014 to March 1, 2014) is obtained from Illinois Power Company.
5	IEEE Transaction s, Spain	[25]	Non-Cooperative game theory, Day ahead energy market is considered and minimization of cost in robust situations with distributed algorithm is presented.	Synthetic, general framework
6	IEEE Transaction s, Canada	[26]	Implemented DCCM, TSCM using SQ (state queuing) approach for refrigerator load to achieve hybrid scheme HCM for better regulation and load management capabilities.	Simulation of model uses Calgary city estimated 900 000 devices rated at 110W, resulting in 99 MW of power Capacity.
8	IEEE Conference , Germany	[27]	To measure the customers' electricity consumption 200 Smart Meters were installed at the participants measurement points. Half of the devices are working with Powerline Communication and the other half are using mobile GPRS.	Data is obtained from daily load consumption of users of small town of Germany
14	IEEE Transaction , Denmark	[28]	The control strategy at the aggregator consists of an model predictive control (MPC) design plus a manual controller. The setup consisted of an aggregator connected via Internet to a laboratory refrigeration system and a real HVac	The DERs available for the experiment are supermarket refrigeration system located at the refrigeration laboratory at the Danfoss headquarters in

			chiller in conjunction with an ice storage. The aggregator aimed to control the active power consumption of the consumers directly, such that the aggregated power consumption stays below a certain level during an activation time.	Nordborg, Denmark. The ice storage system is located at the Grundfos headquarters in Bjerringbro, Denmark
15	IEEE Transaction, Canada	[29]	This paper proposes a methodology to build a real time simulator by identifying the thermodynamic parameters for individual DEWHs and estimate individual DEWH water demand profiles, based on limited measurements. Results show that the simulator can accurately predict the actual load profile in the presence or absence of load shed control action. Therefore, the proposed simulator may be used for assessment and validation of control performance in DLC programs.	Using measurements of power consumption of DEWHs in the PowerShift Atlantic pilot project, thermodynamic parameters were identified and water usage profiles were estimated.
20	ICEIA Conference, Iran	[30]	Produced structures by DLC are optimized by Integer Genetic Algorithm that is discussed in this paper.	In residential area, it is assumed that 210 equipment are controllable out of 1650 and in industrial area, 50 equipment are controllable
18	IEEE Transaction, USA	[31]	Proposed approach utilizes the average consensus algorithm to distribute portions of the desired aggregated demand to each EMC in a decentralized fashion. The allocated portion corresponds to each building's aforementioned local power consumption target which its EMC then uses to schedule the in-building appliances. The result will be an aggregated demand over this	Synthetic. Typical residential appliances' power consumptions are considered, the power consumptions of appliances are uniformly distributed as (50 W, 2000 W). It is assumed the cycle durations of appliances follow a uniform distribution of (15, 135) min in the simulation.

			region that more closely reaches the desired demand.	
10	IET, China	[32]	Aggregate TCL's do not have Markov chain property which is necessary for SQ modelling to characterize loads. A modification method is proposed for the SQ model so that its accuracy is greatly improved. The modification is implemented by multiplying the original transition matrix *P* by a modification matrix *M*, which is derived through GA-based optimization	Synthetic. Considered 10,000 individual TCLs with normally distributed parameters of mean and relative standard deviations.
11	IEEE Transaction, China	[33]	Model determines proper amount of DR loads to be shifted from peak hours to off-peaks under the ISO direct load control for reducing the operation cost and ensuring that DR load payments will not deteriorate significantly after load shifting. The proposed model is solved in its original mixed-integer nonlinear programming formulation and the mixed-integer linear programming reformulation	Synthetic. A 6-bus system is adopted to illustrate the effectiveness of the proposed MINLP model. The modified IEEE 30-bus system is used to study the proposed approach on larger systems,
12	IET Journal, India	[34]	This paper considers CPSDS (Cyber physical smart distribution system) in which RLAs are presented with various categories of incentives and underlying operating conditions offered by DRAA for event-based DSM mechanism. Thereupon, customers are encouraged to select incentive category of their own depending on their load consumption pattern.	Synthetic. The proposed DSM framework for CPSDS is examined using IEEE 37 bus test system with three types of loads categorized as residential, industrial and commercial.

13	IEEE Transaction, Belgium	[35]	In this work, batch RL is used, where an estimate of the Q-function is obtained offline. A regression algorithm is used to generalize the estimate of the Q-function to unobserved state-action combinations.	Synthetic. Second-order model has been used to describe the dynamics of each building. the values are selected random from a normal distributions
17	Elsevier, Spain	[36]	Power constraints from the system operator are the input of this method. An algorithm, based on the Multi-Objective Particle Swarm Optimization (MOPSO), is applied to satisfy these constraints that modify the operation of the appliances. The main concern of this paper is how to adapt a MOPSO method to deal with a complex and dynamic system.	Synthetic. Parameterization of model is done by assuming 1350 households.
19	IEEE Conference, Ireland	[37]	The paper describes the modelling of simple DLC-DR and DR using a fuzzy system approach which is typically a rational decision making model.	Synthetic. Two peak periods (6am-9am, 6pm-9pm) are considered with peak of 3.1 kw.
21	IEEE Conference, India	[38]	PSO is implemented, hour breakdown scheme is used to arrange appliances according to particular type. RLM (Reducible load margin) scheme is used to make forecasted load nearer to objective load.	Synthetic. 14 different controllable types of appliances are considered.
22	Springer, Conference ,Pakistan	[39]	GA and Binary PSO are utilized to build a hybrid algorithm GAPSO. Peak and cost minimization with maximizing user comfort is considered.	Synthetic. 14 types of appliances considered.
23	Applied Energy Journal, USA	[40]	An agent-based model is developed for electricity consumption of a single representative household of U.S. to study demand response schemes.	Synthethic.

24	Applied energy Journal, Abu Dhabi UAE	[41]	In this paper, ABM framework is developed to model an urban area with several buildings along with the movements and actions of people within the environment and calculating key performance metrics such as indoor/outdoor thermal comfort and energy consumption levels. This test and propose strategies to optimize sustainable building operation.	Synthehic. Suitable assumptions were made in respect of stochastic techniques PMV and regression.

Chapter 4

System Model

This chapter provides understanding of how the proposed framework modelled different considerations of the system and the reason behind the decisions. It shows how the simulation considered the usage patterns of household appliances, the number of bedrooms in houses, occupancy patterns, loads having fixed and those having variable loads, and the effect of weather conditions on some loads. This chapter explains the proposed method of ABM implementation in a household scenario and its problem formulation. Fig. 4.1 shows proposed framework which is explained in this chapter in detail and the description of the proposed approach includes the detail of inputs applied to a model and its outcomes while considering external factors affecting the simulation parameters. The equations involved in model formulation are also discussed in detail where the purpose of using each equation is elaborated.

4.1. Modelling Household appliances and their usage patterns

A house would typically have appliances that exert different power loads. For instance, the load emerging from using a water heater will differ from that of lights. The usage of these appliances is typically independent of each other. For instance, one would use them for different durations, leading to varying power consumption for each power consumer. It is possible to classify these loads according to their usage. Specifically, some of them will always be on throughout the day, even when the houses are empty. For instance, loads, like digital clocks, will always be on throughout the day, even when they are not in the house [5]. Moreover, they run at constant power and therefore, in each household, they will always have similar loads per day.

Therefore, when modelling a house, this project considered and includes them in the developed model. This project considered baseloads to include refrigerators, routers, digital clocks, and freezers. These loads will always run throughout the day for houses having them. The project considered these loads

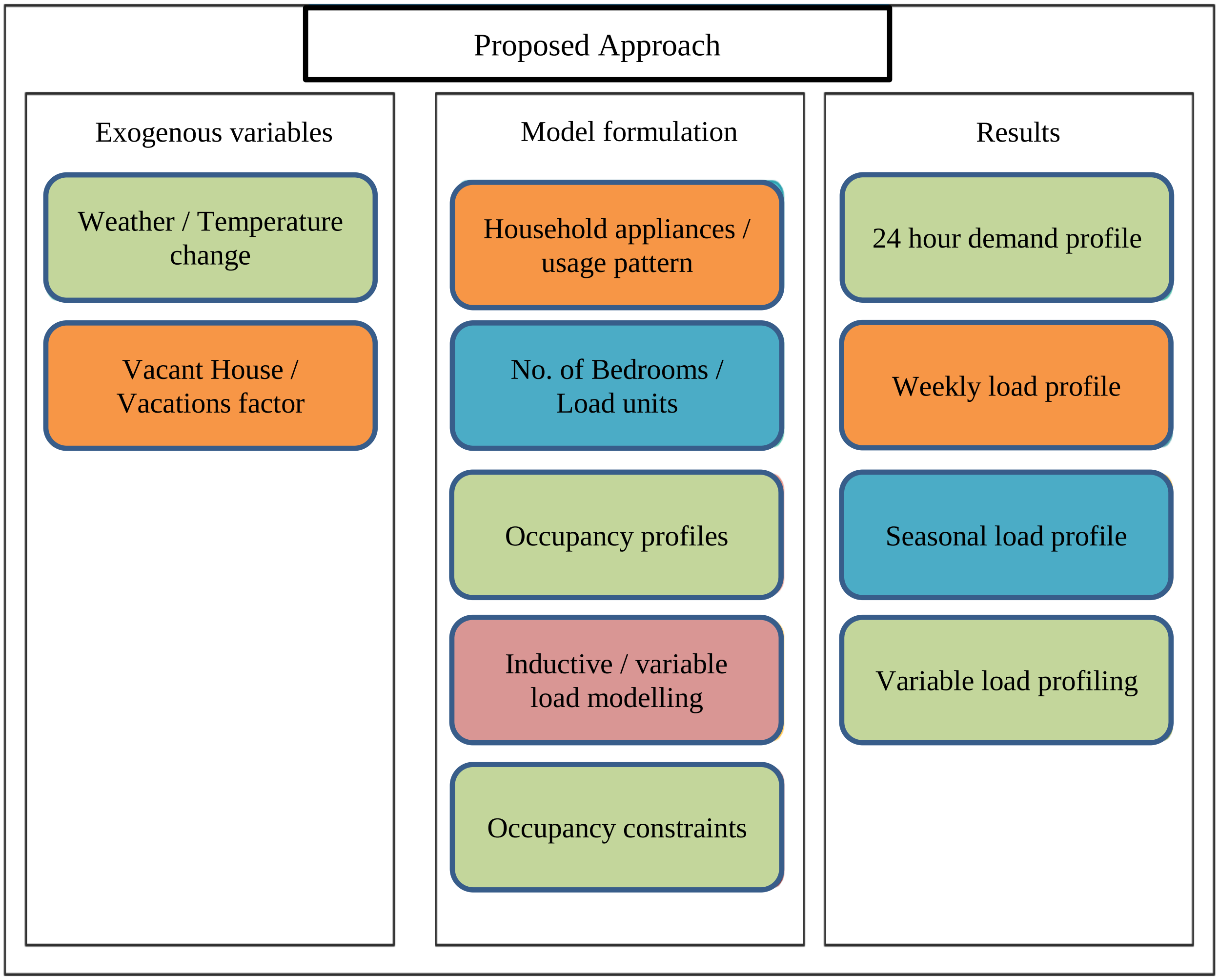


Fig. 4.1: Proposed Model Framework

to have power ratings as follows. Freezers have a rating of 80 W, the rating for routers is 4 W, that for digital clocks is 3 W, while for refrigerators is 50 W, and these values were obtained from [5]. While this project used these values, some variations in their power allowed some people not to have all these appliances, while others may have different power ratings.

Other loads found in a house do not fit in the categorization of the baseloads described above. They include loads, whose usage depends on occupancy of the house and activity of the residents. For instance, a computer load will only be connected when a person is in the house and needs to use it. Same is the case of other loads, such as domestic hot water, televisions, and cooking. A person will always connect these loads instantaneously when needed and disconnect them after finalizing using them. A good example is cooking, whereby a person will power a cooker before a meal, use it for a given duration, and then power it off. The usage patterns of these loads may not depend on their ratings. As shown, their power consumption is not constant in a house, and their usage has varying durations. This project considered different usage patterns for these loads.

Another category of loads exists, and it represents loads having adjustable power ratings. The power consumption of these loads will depend on the setting of a user. An excellent example of these loads is an air conditioner. Its load will depend on the prevailing weather condition, which will cause a user to select a power rating that gives them comfort. A person can vary the consumption of these loads from a minimum value of zero to 1000 W [5]. Another factor that determines their consumption is the climatic conditions. The name of the category containing these loads is adjustable loads, and the two most common examples of these loads are air conditioners and fans.

The final category of loads that this project considered is that a user can shift to different times. They include dishwashing, laundry, and charging of electric vehicles. While these loads are critical, a user does not need to connect them instantaneously. This factor makes it harder to model their power consumption compared to other loads. Some people will connect some of these loads when they are asleep and others when they are awake. For instance, a person can charge an electric vehicle and use the laundry machine once a week. Such factors make it hard to model these loads. This project considered all these varying usage patterns when modelling them. When a power generation company intends to optimize their grids' power consumption, they may encourage people to shift these loads to low-consumption hours [6]. Such a step would improve the efficiency of the grid. Recommended actions may include charging an electric vehicle when sleeping to avoid straining the grid during peak hours. This project also simulated this case to ensure that it reduces large spikes emerging from these transferrable loads.

Fig. 4.2 illustrates system model overview. The chapter in following sections discuss each sub-system design parameters and conditions in detail. The model considered categorised loads to have different usage patterns for each house. Since houses have different numbers of rooms, the baseloads would vary. This project update agent characteristics modelled this factor by creating a triangular distribution with its mode set at its average and a 30% variation from this mean. This variation accounted for the fact that some houses would have a higher or lower number of rooms than most households (mode). The model then multiplied the summation of all the baseloads by 24 hours a day to get the number of power units in KWh for the houses.

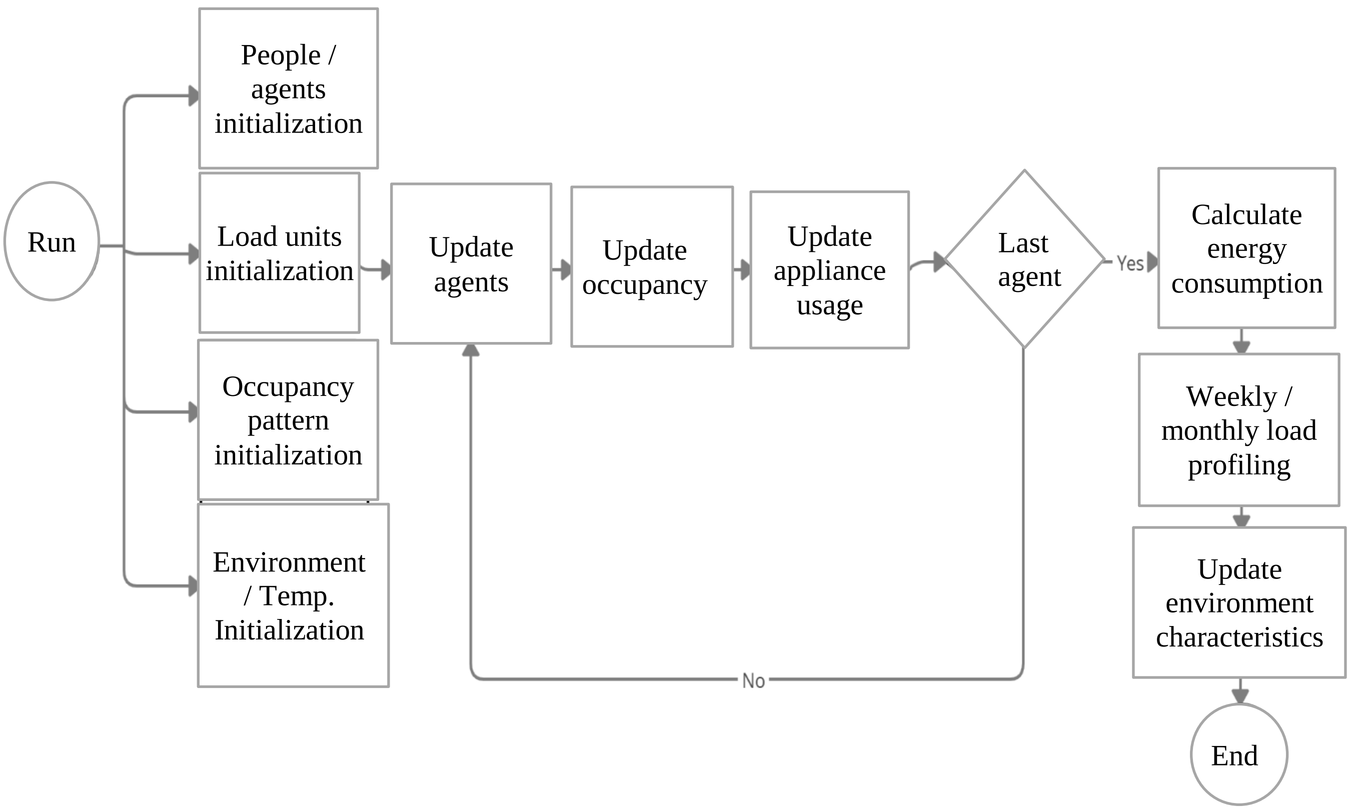


Fig. 4.2: System Model overview

4.2. Modelling of Households' size and Load units

Agent-based modelling makes it possible to simulate the behavior of complex domestic power usage profiles. As stated above, people do not follow similar power consumption profiles, making it hard to generalize their power usage. For instance, while one person may decide to use their personal computer while the television is on, others will only use one of these appliances, and therefore, they will have different power consumption profiles. This variation will emerge from loads, such as lighting, fans, air conditioners, phone charging, personal computer loads, other appliances, depending on the room numbers [11]. The number of rooms in a house, particularly bedrooms, significantly affects people's power usage variation. It is, therefore, vital to consider this factor when modelling the power usage of different households.

Assigning all houses in a system the same number of rooms and bedrooms would lead to an inaccurate model. Moreover, the results of such a simulation would not be viable for use in usage power profiling. A good model should consider this factor and then allow the simulation agents to have different room and bedroom numbers. Including this feature makes a model give results that approximate an actual setting. When developing this model, this project considered the number of occupants and their activities. At some times, a house will have no occupant, and therefore, even if it has many bedrooms, it will have close to no power consumption. Such times include during daytime when all the residents are out of the houses. Additionally, the residents will be asleep at other times, and therefore, the house's number of bedrooms will not affect its electric power consumption.

This project considered these factors when developing the simulation. It combined them with other variables discussed in this paper. For instance, these other variables include the usage patterns of appliances in a house, house occupancy patterns, and the climatic conditions. Combining these conditions led to the development of an actual modelling of its occupants' power usage profiles.

This project did not have a specific function that considers the number of rooms or bedrooms, instead, it incorporated it in each function. For instance, case described above of the appliances in a house, the project modelled their usage to vary according to some triangular distribution. These functions are defined to consider the number of rooms and bedrooms in the houses.

4.3. Modelling Household Occupancy patterns

As stated above, some electrical loads depend on the presence of a person in the house. They also depend on the person's activities in the house, whereby they must be using them for their load to exist. They include lights, air conditioners, televisions, radios, cooking, dishwashing machines, and other similar appliances. Such loads will only occur when a house has an occupant. A person in a house may still decide not to use such appliances, which causes the loads to cease existing. Precisely, an occupant will only use such loads when needed. In some cases, occupied houses will not have these loads. For example, a person can be in the house, yet asleep. Such an individual will not need loads, such as the computer, cooking loads, light, and television. Therefore, when modelling households' electric power consumption, it is crucial to consider this factor to produce a realistic simulation.

This project modelled household occupancy patterns to ensure that it simulates houses' actual condition to generate realistic power consumption. In order to achieve this, it modelled people sleeping, going to work, and being at home. Each of these states attracts varying electric loads. Precisely, when a person is at work, they cannot use electrical appliances in the house, and therefore, the only existing loads will the baseloads discussed above. Furthermore, if the person is asleep, they will not use as many electric loads as when they are awake. In such a case, the only loads that they will have are the transferrable loads discussed above. For instance, people with electric vehicles can charge them at night, and therefore, their electric consumption at these times will have to include the loads ensuing from this activity. Moreover, in cases where generation companies need to improve their grids' performance, they can encourage their clients to use such loads at low-power consumption hours [13]. These hours include at night when most users are asleep.

Characteristically, when people return to the house from their daily activities, they start engaging many loads, such as fans or air conditioners, lights, televisions, and many other instantaneous loads. This sudden connection of many loads in almost all houses leads to a sudden rise in households' total power consumption. Other individuals will also start charging their electric vehicles, contributing to the spike in power consumption. After some time, these people will disconnect some of these loads, which will cause a variation in power consumption.

This project modelled the houses' different occupancy patterns to ensure a variation that simulates actual household occupancy. It considered several factors when developing this model. Firstly, not all people wake up at the same time. Therefore, it modelled the occupants of the houses to wake at different times following a triangular distribution whereby the earliest person woke at

3:00 am, the last one at 5:30 am, and most people waking at 5:00 am. This project selected this pattern hypothetically and it devises strategy to model people's waking up to a close to real life scenario. It ensures that their loads do not experience a sharp peak at the same time. Secondly, while many people go to work at around 8 am, they do not leave at the same time. This project ensured that they leave their houses at different times, by setting them to leave for work from 6:00 am to 8:00 am and a majority to leave at 7:30 am.

Thirdly, while many people leave work at 5 pm, they do not arrive in their houses together. Some will return home earlier than others keeping in view different factors e.g distance from the house to workplace, time constraint etc. Moreover, when they enter houses, people do not always start engaging particular loads. Therefore, the project varied the number of appliances that they engage randomly to ensure a near-actual profile. It modelled their return home and loading of power devices using a triangular distribution varying from 5:00 pm to 9:00 pm, and a majority arriving at 6:30 pm. Furthermore, even with this variation, the model added a second layer of variation when calculating the power consumption of each household. It varied them accordingly to reflect the number of hours that the residents would use their appliances. This factor affected all the loads, and leads to a secondary variation, which closely approximates actual usage profile for these electrical appliances.

Fourthly, this project considered when occupants go to bed and ensured that it varies from one individual to another. It modelled the occupants to go to bed using a triangular distribution whereby the first person goes to sleep at 8:00 pm, the last one at 11:59 pm, and the average time being 9:30 pm. This distribution accounts for the gradual drop of power consumption recorded in the simulation. It approximates people's actual sleeping patterns. Fig. 4.3 shows a flowchart of how the occupancy pattern affects the total load consumption by considering different conditions under which certain load connects resulting into different electrical power consumption subsequently. Connected load depends on the occupancy state and patterns exhibited by the agents and in connection to consumption and utilization of a specific category of load. Four occupancy states which model the usage patterns are discussed in the next chapter.

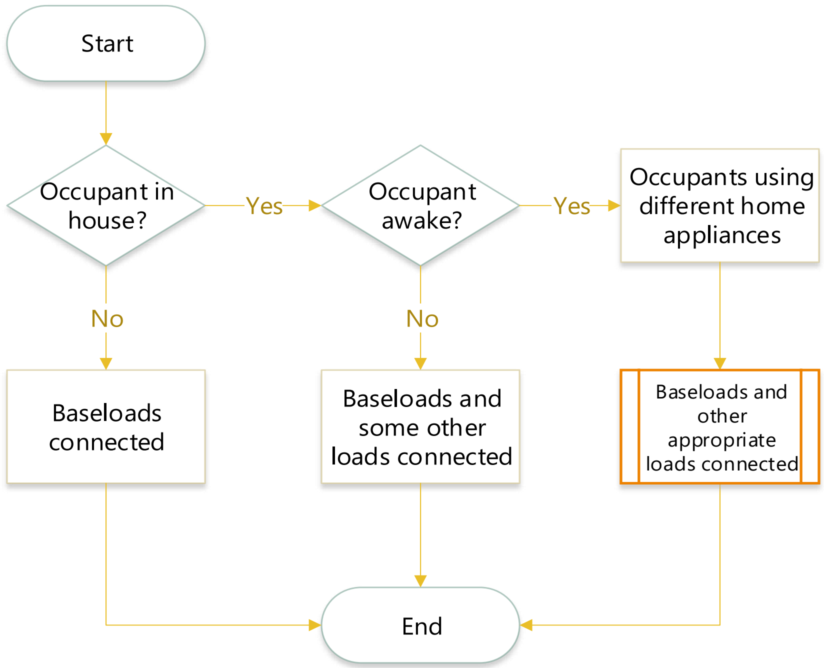


Fig. 4.3: Flowchart of occupancy pattern and power consumption

4.4. Modelling Impact of weather on usage of Air-conditioners and fans

Other than the factors described above, climatic and weather conditions can also affect people's power consumption in a community. High-temperature conditions bring discomfort to people, which causes them to use air conditioning appliances that bring their houses' temperatures to conducive conditions. Similarly, when the temperatures are too low, people use appliances that regulate it, making it comfortable for occupants of a house. These devices typically have high power ratings, which causes them to exert a large load on people's power consumption. For instance, air conditioners have a typical power rating of 1000 W. Such a rating has a significant impact on the total power consumption of a house. In extreme climatic conditions, such as during winter or summer, people are most likely to use fans and air conditioners more than in other periods. These loads may also be in use even when people are asleep. In such instances, they will not follow similar patterns as described above. When modelling people's power consumption profile, it is crucial to consider these loads since they can account for large consumption variations from other times.

While these loads are large and can cause a sudden surge in the total power consumed in a community, they are adjustable. For instance, a user can reduce or increase an air conditioner's power output without affecting their comfort. This variability in the operational power rating of these devices causes them to cause a substantial effect on the power variation between houses. Furthermore, just as in many other loads, people typically do not use them being high wattage equipment when they are not at home. Therefore, its usage depends on the occupancy of a house. They also relate to the number of rooms in a house, particularly bedrooms. A house with many rooms will typically have a higher load emerging from these loads since it has more air to heat or cool. Therefore, this project considers this dissimilarity and models it to produce a good simulation of its impact on the total load.

It is expected that in times of unfavourable temperature conditions, people would use these appliances more than at other times. Moreover, other than in times of extreme temperatures, people may also use these devices even when climatic conditions are not too high or low. In this operation, these loads are regulated by thermostats, which regulate their power depending on the house's heat conditions. Their power consumption will typically depend on the temperature of a room. When a room is warm enough, these loads will have a low value. However, when it is much farther from a set point, then the thermostat would cause these loads to have a significantly high rating, which would affect the overall load of a house. This variability of these loads causes them to contribute significantly to the power variations of different houses. Therefore, it is crucial to model their behaviour to produce a realistic simulation that approximates houses' actual power usage.

This project made it possible to change the temperature at runtime. This factor allows one to see the impact of temperature variation on the model. When the temperature is below 20℃ it engages the heater and when it is higher than 28℃ it starts the air conditioner. Moreover, being the inductive load, the wattage consumption of the heater or air conditioner depends on the extent of the heat or cold. This is discussed in the next chapter. Markedly, if the building is at 18℃, an occupant would select a lower power rating for the heater than when it is 5℃. The same applies to temperatures exceeding 28℃. When the household is at 30℃, the air conditioner will operate at a lower power rating than when it is 37℃.

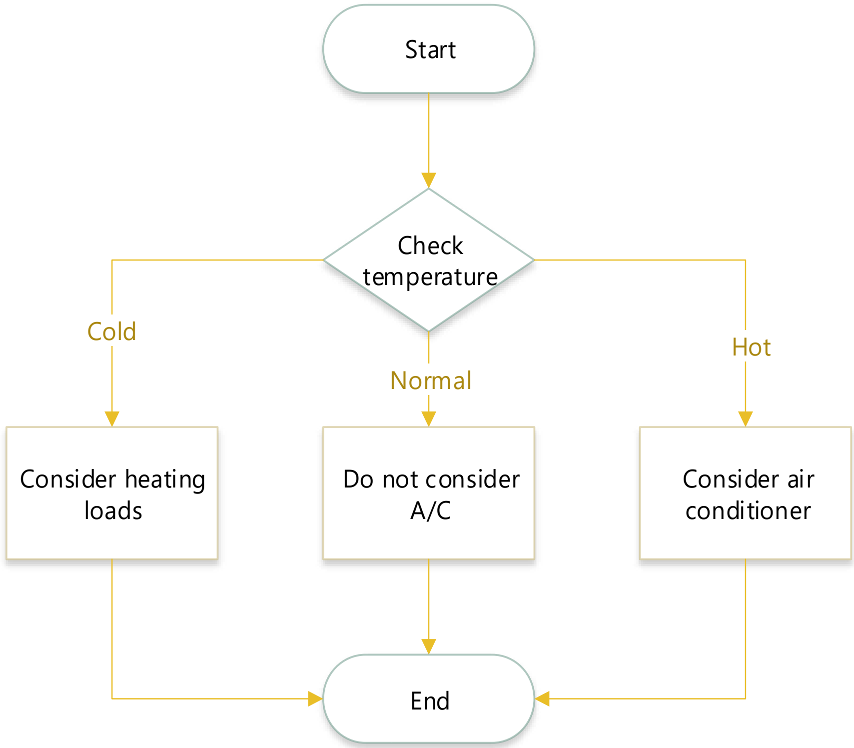


Fig. 4.4: Impact of climatic conditions on the model

The flowchart in Fig. 4.4 illustrates how the model responds to different climatic conditions. It shows that when the temperature is high (greater than 28°C), then the model considers air conditioning loads, and when it is cold (i.e. temperature lower than 20°C), it considers heating loads according to the rules described above.

4.5. Modelling Loads with Variable and Fixed Power consumption

Another crucial factor to consider when simulating domestic power consumption is the variability of loads of different appliances. In this case, there are two types of appliances, which include adjustable fixed loads. Variable loads include air conditioners and fans as discussed above. The operation of these loads depends on the need of the person using them. Another instance is the case of charting electric vehicles. The amount of time that this load would exist on the grid typically depends on equation (1) described below [5]. Charging duration is directly proportional to the amount of power consumed.

$$T = \frac{C - (C \times SoC)}{P} \tag{1}$$

Where T = total charging time.

C = Total battery capacity.

SoC = Current state of charge of the battery.

P = Charging power consumption.

Moreover, the value of SoC uses the relationship in equation (2) below.

$$SoC = 1 - \frac{D}{Max\ D} \tag{2}$$

Where D is the daily trip distance, while $Max\ D$ is the maximum trip distance that the vehicle can travel.

As equations (1) and (2) show, some vehicles may need more time to charge than others. Therefore, charging of electric vehicles is a variable load and thus, when modelling the power consumption of different people, it is crucial to include this variability. Such a load will be different from a fixed load, such as a digital clock's power consumption in a house. However, while it is not possible to adjust the power that fixed loads use, their value is usually not the same for all cases. This variability comes from the power usage differences between people as described above. Specifically, people will always use different appliances at dissimilar times and for varying durations. Consequently, when comparing two households, their power consumption emerging from fixed loads will also be different. Therefore, when developing a model, it is crucial to consider the variability of bot adjustable and fixed loads to produce a valid model.

This project modelled these variations differently. In the case of fixed loads, it only varied the usage patterns of users. Precisely, it gave the agents a different amount of time to use these fixed loads. However, in variable loads, it modelled different usage durations and their varying power ratings. The result was a load variation that remarkably simulates practical situations. This factor applied to the charging of electric vehicles and air conditioners in the project.

An important part of this model is its handling of inductive loads. These loads include fans, refrigerators, dishwashing machines, vacuum cleaners, water pumps, and many other appliances that have motors. Unlike with resistive loads, inductive loads usually have a spike in their power during starting, which gives them a different behaviour than resistive loads. It also makes it hard to model them using an on off step function [12]. Typically, these loads have a spike in their consumption, when starting after which they have a somewhat stable level. This project considered this factor and modelled it using the following reasoning. Firstly, the simulation focuses more on the power consumption given in units of kWh. Secondly, the spike noted above would significantly influence the power consumed in kW and since it occurs for a very short time during starting, it would not have a substantial influence on the kWh consumed. Thirdly, the variations are not significantly large compared to the power rating of these appliances. Therefore, when considering their consumption for a long period, such as a whole day, their usage can ignore these fluctuations. However, when the model shows the power consumption in kW for a short duration, such as an hour, then it has to consider this spike in the consumption.

Fig. 4.5 from [12] shows the influence of this fluctuation in a model that uses two hours. It can be seen that as the load switches on, a huge transient spike of electricity power occurs and as time (x-axis) passes by, wattage consumption begins to show decreasing trend. After about 15 min of initial spike and a decreased power consumption, there is an increasing trend for a short span of time, after which again power consumption moves downwards. This whole process can be seen to last for about 30 minutes after which power consumption steadies down to a normal power consumption value which comes up the around 20% less than initial spike value.

Fig. illustrates the process used in modeling inductive and non-inductive loads. Due to the large number of home appliances being inductive, and since their power consumption differs from that of resistive loads, it was crucial for this project to model them differently. It calculated their total consumption in kWh and then added a consumption equal to the initial spike in their consumption. Typically, these spikes last for not more than two minutes and might be up to 6 times more than the actual power of these appliances. This project incorporates this spike by adding a consumption that varies from ten seconds to five minutes and having a power rating of between two to seven times that of the load. This modelling approach is different from the fixed resistive loads, which only consider the rated power for the appliances. Using this approach helps the model to have actual power usage properties of a typical household.

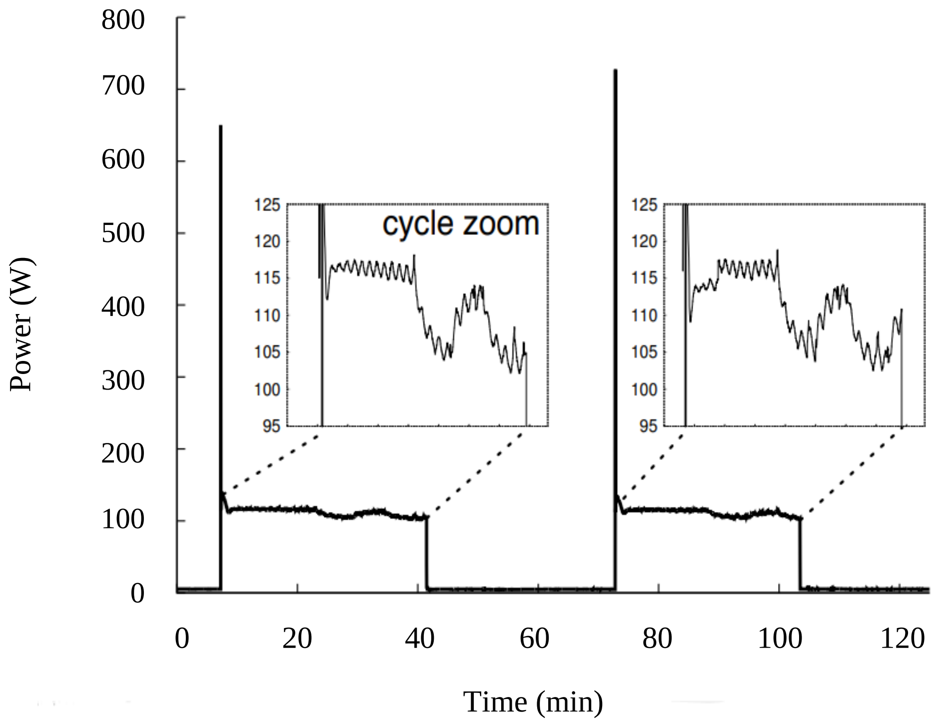


Fig. 4.5: The power consumption of a refrigerator [12]

A refrigerator is an inductive load, and as every time the motor starts, it records a large spike in the power consumed after which it stabilises. Moreover, even when the power appears stable, it still exhibits some fluctuations.

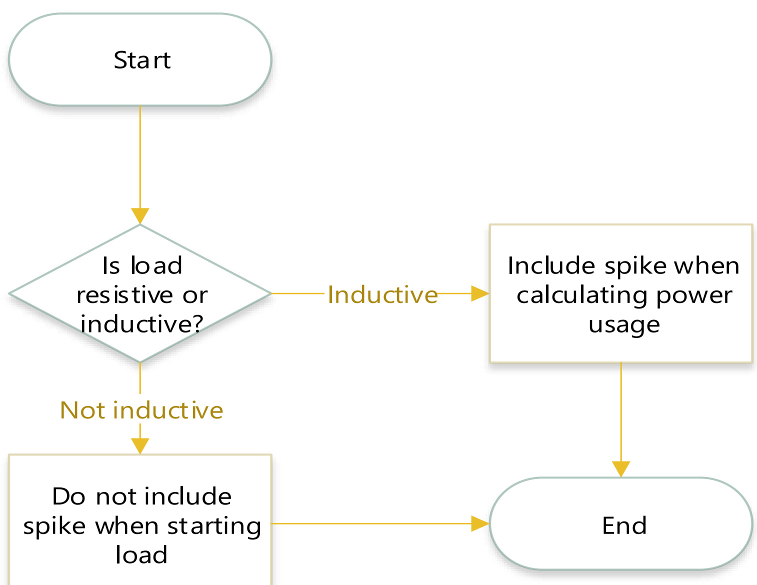


Fig. 4.6: Process flowchart showing modeling of inductive and non-inductive loads

Chapter 5

Simulations

The previous chapters have discussed the factors to consider when developing an excellent domestic power consumption agent-based model. This section will now describe the model in great details, and it will also provide the results emerging from the simulation of this developed system. As discussed above, the best method to create this model is to use an agent-based approach. This project used the Any-Logic software to develop and simulate the model described here. It considered a small population of 300 households. This software is ideal for making such models since it creates the agents and assigns them the defined characteristics and then runs them in an environment where they can interact. This feature leads to developing a practical model of people's power consumption profile in a population. This modelled population had similar characteristics as an actual population. Specifically, the residents of these houses could sleep, go to work, be at home, and choose when to use some electric loads and when not to use them.

Based on this project's complex nature and its potential significance, it was essential to ensure that the different loads do not affect each other. This way, it would be possible to monitor each independently. This project considered loads of the following appliances: light, television, personal computers, domestic hot water, cooking, laundry, dishwashing, air conditioners, and charging of electric vehicles.

Each of these loads was defined as a variable to make it easy to monitor it independent of the rest. This approach also makes it easy to plot the values of the different loads on a time plot. While it would be possible to achieve the same results without using variables, that alternative would be more complicated than the chosen approach. These variables also made it much easier to calculate the different consumption values than it would be without them. Had the model not used these variables, it would have had to define the loads every time it needed to use them. Such an approach would have led to some problems in the model's java code, making it complex, which would have increased the chances of errors in the programming. However, the chosen method eliminates the need for defining the loads anew. Whenever the model needs to use a variable, it only needs to call it. Besides, at runtime, the system shows the values of these variables, which helps in visualising their values. The model also considered the total loads, which is a sum of all the variables described above.

Another feature of this project is that it shows a modelled average duration within which the occupants of the households were at work, at home, and awake. As described above, these factors affect some appliances' usage and the model's total load. As the simulation runs, it shows these variables' values, making it possible to follow them and see their effect. This model also defined four independent phases in which the occupants can be. They define the house occupancy patterns of the people, including morning, working, evening, and sleeping. The morning phase includes the time after a person wakes and before leaving for work. Its duration depends on the time when an individual wakes and when they leave home for work. This duration affects the amount of power they will use on appliances, such as lighting, television, cooking, and other applicable loads. Between this phase and the working state is a transition that simulates people going to work. It models that many people leave for work from around 6 am to 8 am, with some variation in their time. The variation models the practical occurrence of this event. When a person is at work, their homes do not have many loads. The only ones that will continue occurring are baseloads as described above. The simulation should show a slight decline in the amount of power consumed in the houses at this phase. The duration that individuals spend at work is shown during the simulation, and it depends on a function in the model, which aims to make it realistic. Specifically, it would be incorrect to assume that all people work for the same amount of time.

After this state is a transition that models people returning to their homes, it acts as an interface between the working and evening states in the model. Just like the transition to work, this one also depends on a random function that makes the model simulate people returning to their homes. Upon reaching home, these individuals move to the evening state to continue using their electric appliances. It is here that most of the consumption occurs since people engage in many activities. Like the case of morning and working states, the duration that one spends in this state depends follows a modelled function that allocates the time randomly. After this state, a person goes through a transition named going to sleep, which comes before sleeping. The last phase is sleeping, in which time a person's consumption of electricity is lower than it was before. At this instant, most of the running loads are the baseloads and others that have been described above. This cycle takes 24 hours in model times, and it shows the amount of power that the occupants use throughout their day.

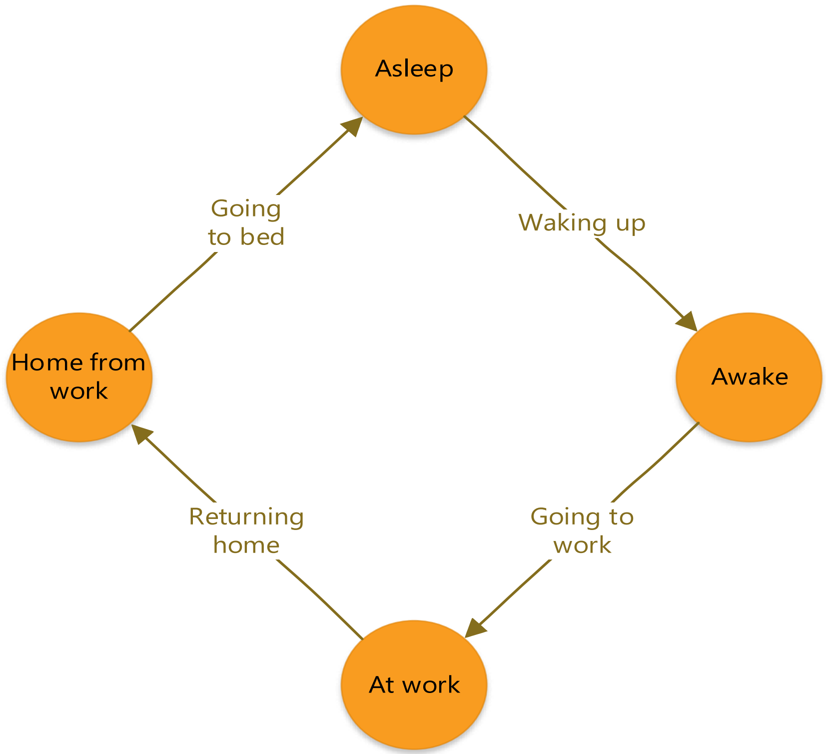


Fig. 5.1: The four states

Fig. 5.1 shows these four states and their respective transitions as modelled in this project. The mode presents its data in two ways. Firstly, it uses the numerical values of the variables described above. Secondly, it uses graphs that plot the values of these variables during run time. Using plots makes it easy to note higher than other variables, making it easy to compare them. Moreover, the variables offer an advantage to a person running the model, since they allow one to copy their historical data, which can then be analysed further using *Microsoft Excel* or any other statistical program. Moreover, other than showing the electric loads incurred in the model, the simulation also shows the occupants graphically as they move through all these states. It uses different colours to illustrate different activities. For instance, a person sleeping is shown in the colour lavender, one awake is yellow, working is lime green, while an occupant from work is coloured in gold. The plots indicate times of the day on the x-axis and power consumption on the y-axis. These features of the model make its analysis to be easy.

Table 5.1 lists the parameters for household appliances and load scheduling according to four different category of loads. EV load service time is determined by *SoC*, *P* and *C* values from Eq. (1) explained in previous chapter.

Table 5.1: Parameters for Appliance Agents

Load category	Appliances	Service time		Power rating
Baseload	Digital clocks	Continuous		3W
	Routers	Continuous		4W
	Refrigerators	Continuous		50W
	Freezers	Continuous		70W
Occupancy dependent load	Computer	State dependent		100W
	Television	State dependent		60W
	Lighting load	State dependent		40W
Adjustable power rating / Variable load	Air conditioner	Run time Temperature dependent		350-2400W
Shift able load	Washing machine	Cycle 1	20 min	1000W
		Cycle 2	40 min	400 W
	Dishwasher	Cycle 1	25 min	1800W
		Cycle 2	65 min	1200 W
	EV charging	*T* depending on *SoC* & *P*		5480 W

Table 5.2 gives the conditions and constraints linked to occupancy states. The model used triangular distribution varying from each time period while adding a second layer of variation when calculating power consumption to reflect number of hours that residents would use appliances.

Table 5.2: Occupancy conditions and constraints

State	Behaviours	Time constraint
1	Awaking up	0300-0530 hrs
2	Going to work / Leave home	0600-0800 hrs
3	Returning home	1700-2100 hrs
4	Going to bed	2000-2359 hrs

5.1. Results

The following are the results obtained from this simulation. These results use graphs of time on the x-axis and power units of kilowatt hours (kWh) along the y-axis. Each result was obtained in separate simulation. Since some required short time durations, such as a few hours per day like in 5.2 and 5.3, a week like in Fig. 5.4 and Fig. 5.5, and a year like in Fig. 5.6 and Fig. 5.7, the time scale was adjusted accordingly. Results for a few hours used a short duration on the x-axis, producing detailed power consumption data. When showing results for a week or a year, the time was adjusted accordingly to show seven or 366 days. Before running the simulation, it is important to adjust the time scale to provide the required graph. The power scale on the y-axis has been set to adjust automatically depending on the data to be plotted. When the power consumption is high, the scale adjusts itself to capture all the data. This scale shows the amount of power consumed in power units of kWh.

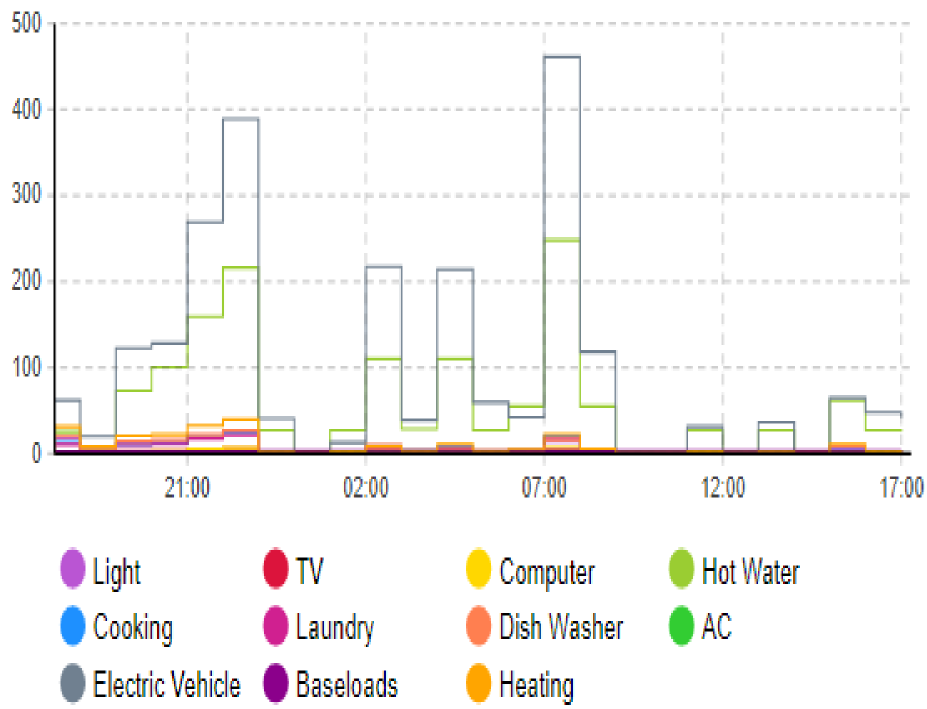


Fig. 5.2: Different loads from evening to sleeping time

The plot in Fig. 5.2 illustrating load curve has Time (24 hrs) on x-axis and units consumed (kWh) on y-axis. It shows individual load curve of each appliance modelled in the proposed framework. It shows a gradual rise in people's consumption around evening and in morning when people are about to go to work and then a sudden drop right before midnight. EV load shows maximum kWh consumption of

460 units in 24 hrs. The simulation also shows that the total power recorded i.e sum of all connected loads power varies depending on the individual loads, as shown in Fig. 5.3. Energy consumed (kWh) on y-axis shows increase in value when calculated for total power consumption for all appliances as a whole. Power consumption trend is noticeable with two portions of the day where kWh consumption is more than other parts, one being at night time before midnight when all occupants are at home 820 kWh and other – in the morning from 07:30 till 09:00 Hrs with 750 kWh units peak when people engage loads as most of the occupants set to leave home for respective work stations.

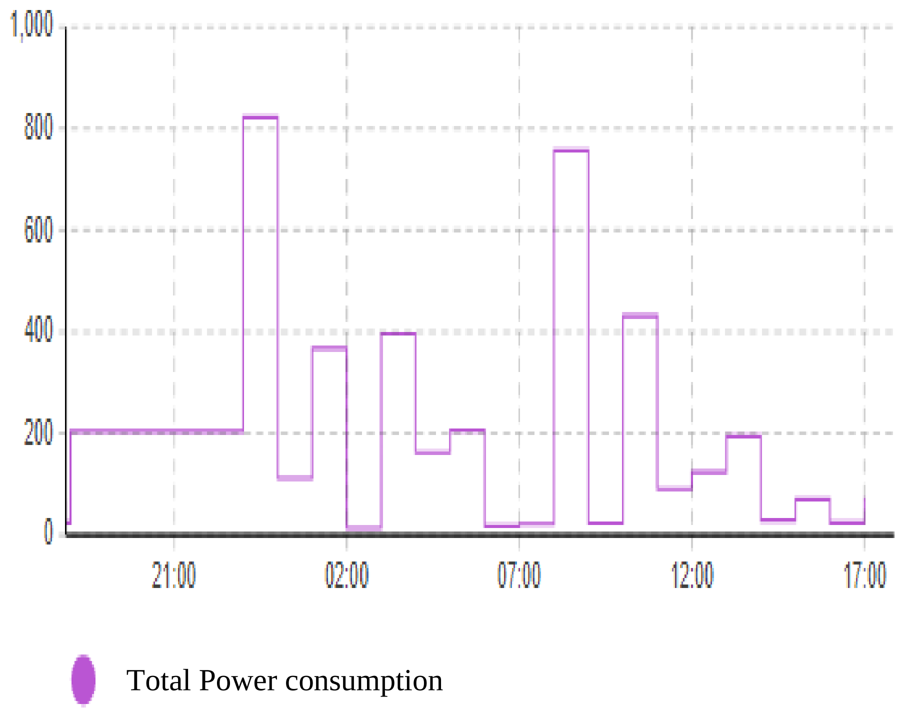


Fig. 5.3: Plot of total power consumption

When shown across a scale of one week, the plot shows a recurrent rise and drop in the power consumption throughout the week, as shown in Fig. 5.4. It shows major share of power consumed by EV load is 430 kWh in one day of the week which turns out to be weekend and Heater recording second most consumption given reading taken in month of winter season. Other loads such as baseloads are shown to consume less amount of power because of low power rating.

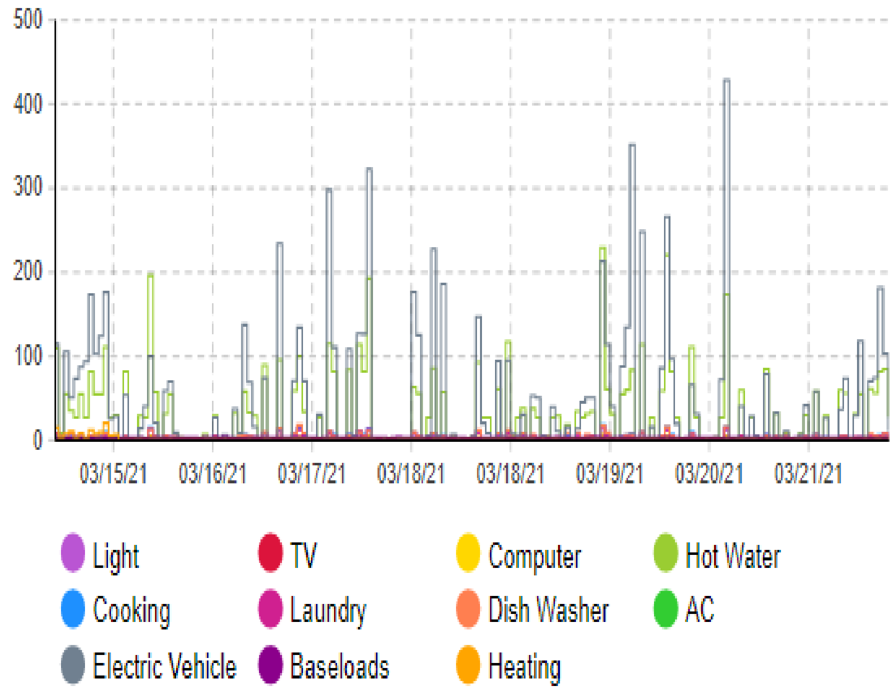


Fig. 5.4: Power of different loads within a week

Fig. 5.5 shows total power consumption recorded in a week. Graph shows maximum value of 700 kWh consumption on y-axis on a particular day of week while days of a specific week of month of March are shown as x-axis. Trend shows a relatively consistent power consumption throughout a day on weekends in comparison to week days given change in occupancy pattern of household due to vacation factor. People tend to leave home for less time on weekend than a weekday.

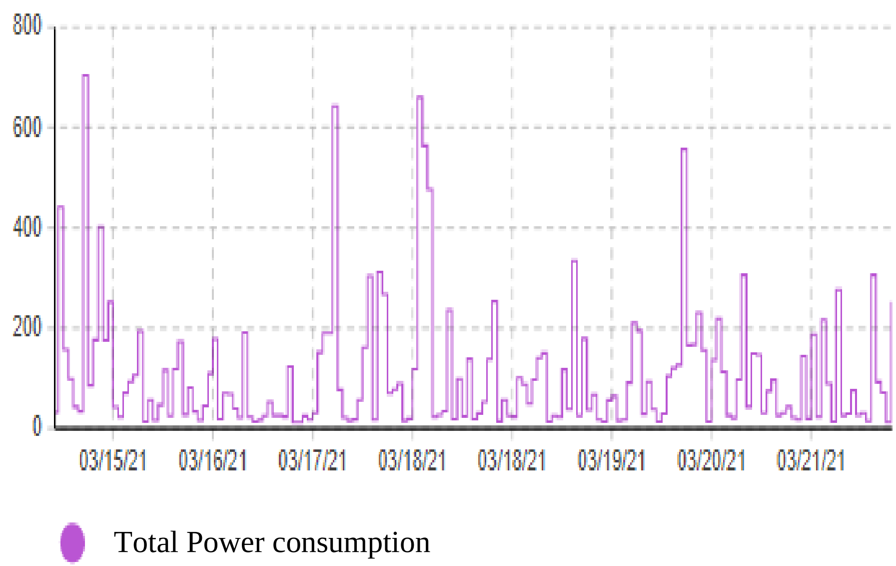


Fig. 5.5: Plot of total loads within a week

The model has been designed to have an automatically updating temperature that corresponds with actual values depending on climatic conditions. Specifically, it simulates temperatures for winter from December to March and summer between June and September. Therefore, when the simulation runs, the values for A/C and heating loads will change depending on corresponding climatic conditions. Moreover, the model allows one to change the temperature, making it possible to simulate different temperature conditions and override the climatic temperature. Fig. 5.6 shows the corresponding result of Air-conditioner (A/C) and heating loads depending on the two main seasons. Air conditioner load gives maximum spike of 50 kWh on one instance in August while average consumption of heating load is 12 kWh. In Fig. 5.6, the bluish (medium turquoise) lines show the consumption of air conditioners, while the purplish (light slate blue) lines show the heating loads.

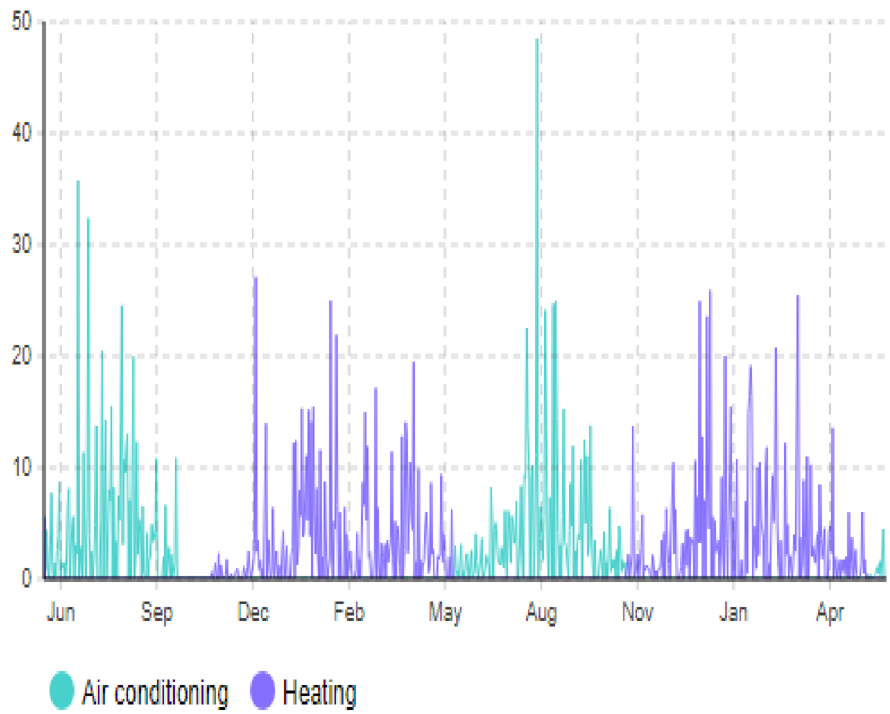
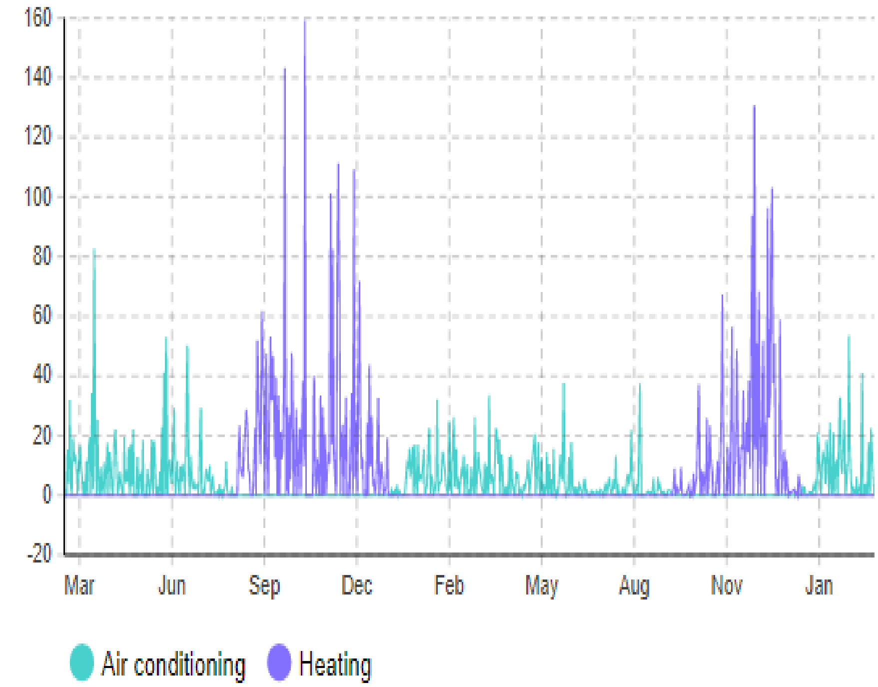


Fig. 5.6: Influence of climate on A/C and heating loads

The climatic condition not only affects the heating and air conditioning loads, it also influences the total power consumed in a household for a given time duration. For instance, considering the case above of two years, the graph in Fig. 5.7 shows the corresponding total power consumed depending on the climatic conditions.



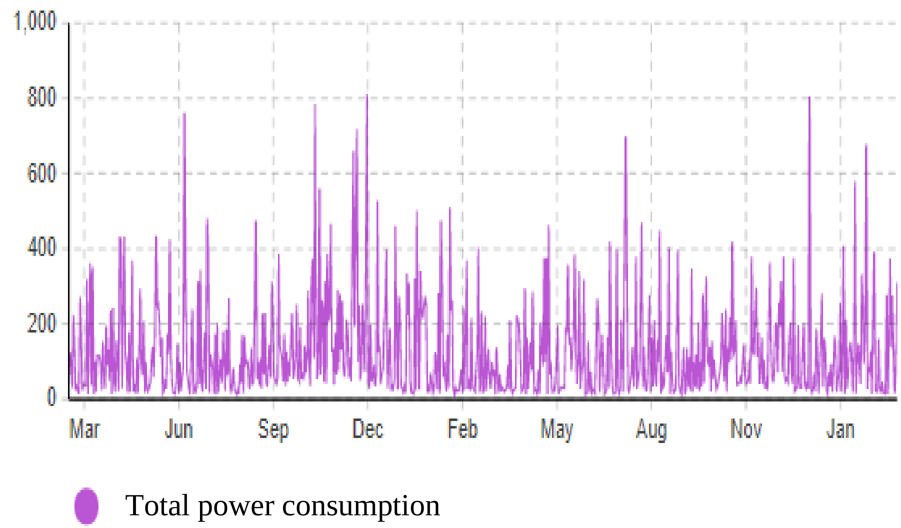


Fig. 5.7: Impact of climate on A/C, heating, and total power consumption

Fig. 5.7 shows that when the heating loads are high, the corresponding total power consumption also goes high and heating loads record more power consumption KWh shown as y-axis compared to Air-conditioner loads. This is due to the fact that heating loads are resistive in nature and energy drop out occurs by converting flow of electrical energy to thermal energy.

Fig. 5.8 shows the power consumption in the second week of June, when it is in summer season.

It is noticeable that there should be no heating loads while air conditioning is high for that period. This results in less value of kWh units consumed as shown on y-axis. Maximum amount of power consumption is 4,250 kWh on a particular day in two week period under consideration. It is evident from the Fig. 5.8 that at weekend days, power consumption is showing slightly upwards trend than week days while most power consumption takes place at days having end of weekday and start of weekend.

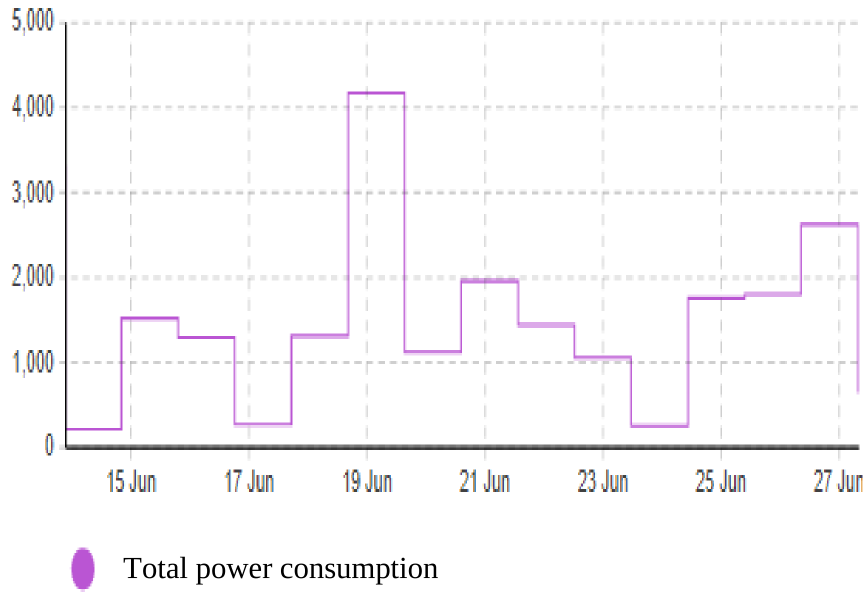


Fig. 5.8: Summer loads two weeks in June

Furthermore, Fig. 5.9 shows the consumption during winter, in the first week of January. At that time, the temperatures are low, and therefore, A/C loads are missing, while heating load is high. Maximum value of consumption on one particular day of corresponding period is 8,750 kWh. Furthermore, the graph shows that electricity consumption is higher in weekends since people are in their homes. This relates to the modelling of occupancy profiles of the occupants. The model simulates weekends by letting all people to stay at home and not go to work. Therefore, their consumption is much higher than during weekdays when they are not at home.

Fig. 5.9: Winter loads two weeks in January

Fig. 5.10 shows the occupants' states in terms of different colours as formulated according to time constraints. Occupants are modelled as agents in the simulation and their occupancy state changes with respect to time. Fig. 5.10 is showing states at a time in simulation model right before agents (people) return to their homes from work. Most of the people are still at work shown as green, while others already at home are shown in golden colour. Occupants in neither of these two states (asleep) are represented in grey colour.

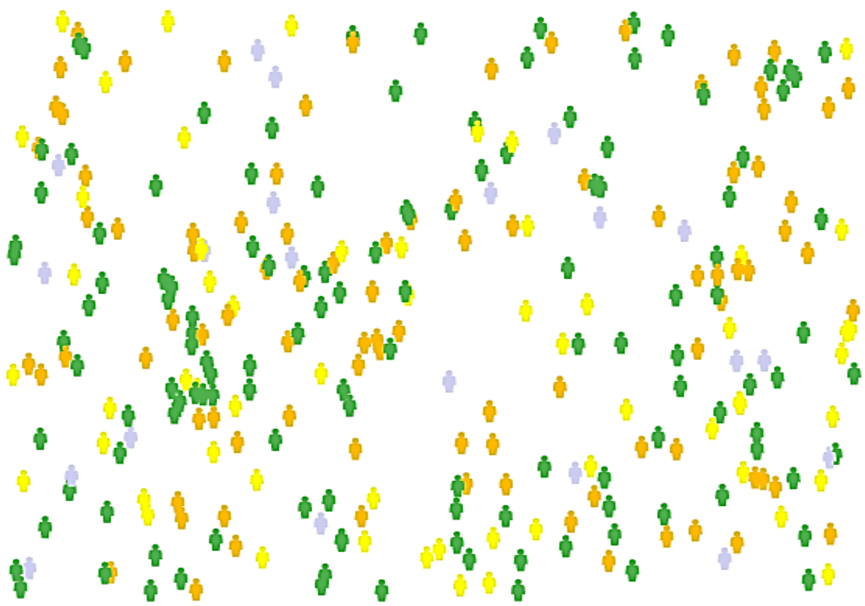


Fig. 5.10: Any-logic graphical representation of the agents in different states

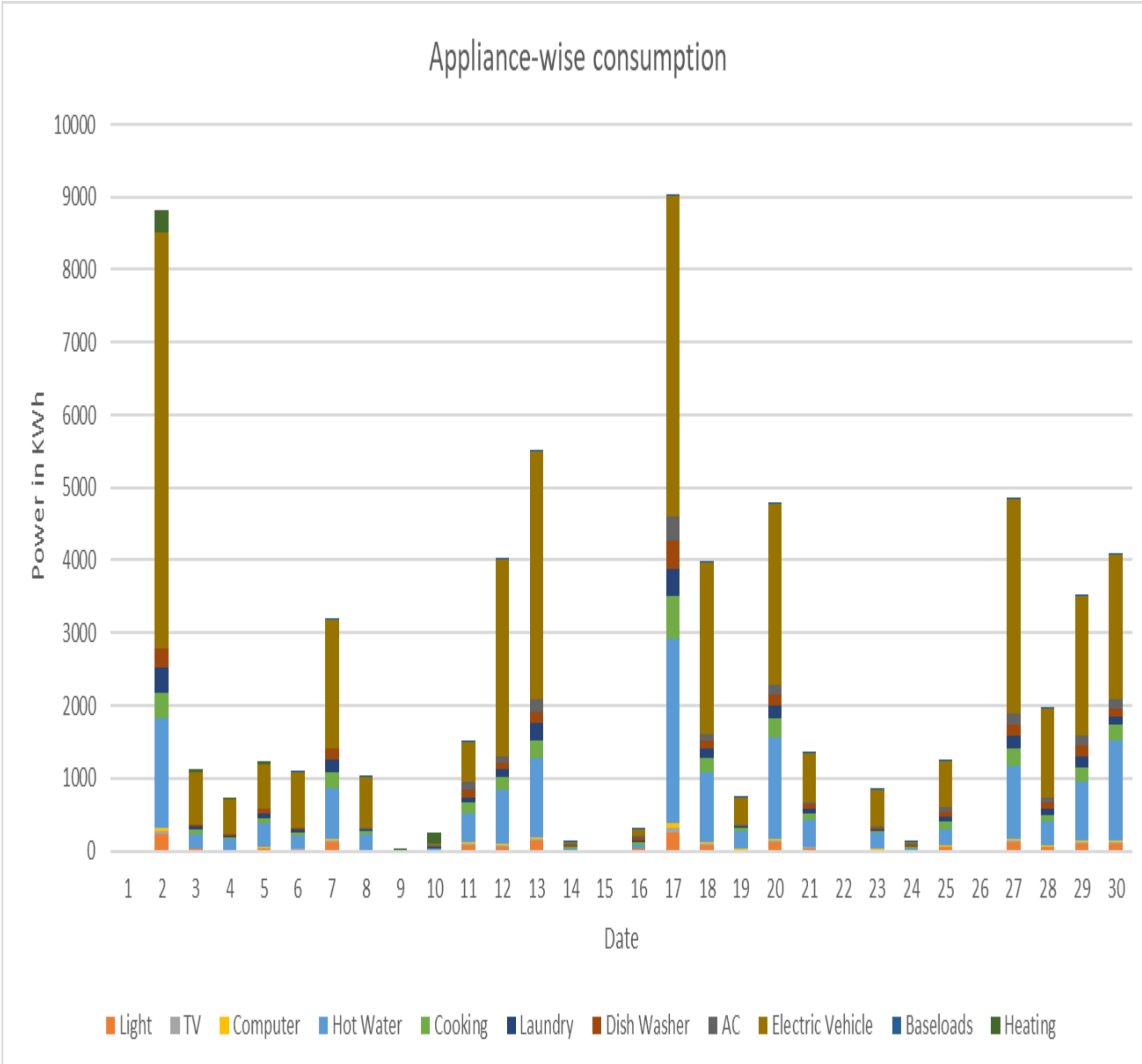


Fig. 5.11: Appliance-wise consumption

Fig. 5.11 shows the appliance-wise consumption data of 300 households for a period of one month. X-axis shows date of a particular month and y-axis shows total energy consumed in KWh. The graph shows important factors worth noting about power consumption for the modelled community. The three largest power consumers are electric vehicles, followed by hot water systems, and air conditioning. One factor that makes electric vehicles to consume large power quantities is the fact that the residents use them daily, and therefore, they have to charge them each day. Moreover, a significant number of households modelled had electric vehicles, which made them to have substantial power consumption. The consumption of hot water systems is high due to the large power rating of these heaters. The case of air conditioners depends on the season under consideration. In hot times, the consumption for these A/C systems will be high. When seasons change, the consumption of A/C reduces to minimum and heating becomes significant as shown in Fig. 5.11. Therefore, the third most significant consumer is heating or air conditioners depending on season of the year.

It can be seen that major power consumption load in simulation environment is Electric vehicle (EV) load. EV load impacts and resultantly cause to modify the electric load curve. The most pronounced effect found is an increase in evening peak loads, as user plug-in their EVs for charging upon returning home from work. The residential designated places and other such marked points of EV charging, such as public Electric vehicle fast-charging stations and other vehicle booths, will see increase in local peak loads. In order to predict changes in the electricity load curve in domestic household areas, a German organization McKinsey conducted a Monte Carlo analysis. For a typical residential feeder circuit of 150 homes at 25 percent local EV penetration, the analysis indicated that the local peak load would increase by approximately 30 percent [42].

Energy sector policy makers have different set of remedial actions to address this situation. They can have an impact on behavioral response: for example, Time of use (ToU) electricity tariffs give motivation to EV owners to recharge after midnight instead of in the early evening. Analysis shows this could result in halve of the increase in peak load. Time-of-use tariffs have been easily implemented for a good amount of time and will demand supervision and further monitoring because it can result in “timer peaks,” or “rebound peaks” which occur when most of the people inadvertently deploy their chargers for the purpose of charging simultaneously. Alternatively, energy sector stakeholders can employ more local solutions to this, such as co-locating an energy-storage unit with the transformer that charges the unit during times of low demand. The storage unit then discharges at times of peak demand, thus reducing the peak load [42].

5.2. Comparison of Results

It is essential to find the validity of this data by comparing with actual results collected. This process helps show if the developed model simulates a practical case of power consumption or not. This paper compares the results with those of a similar case titled *"Agent-based modelling of high-resolution household electricity demand profiles: A novel tool for policy evaluation"* [5]. The results of that study showed a similar response over a day.

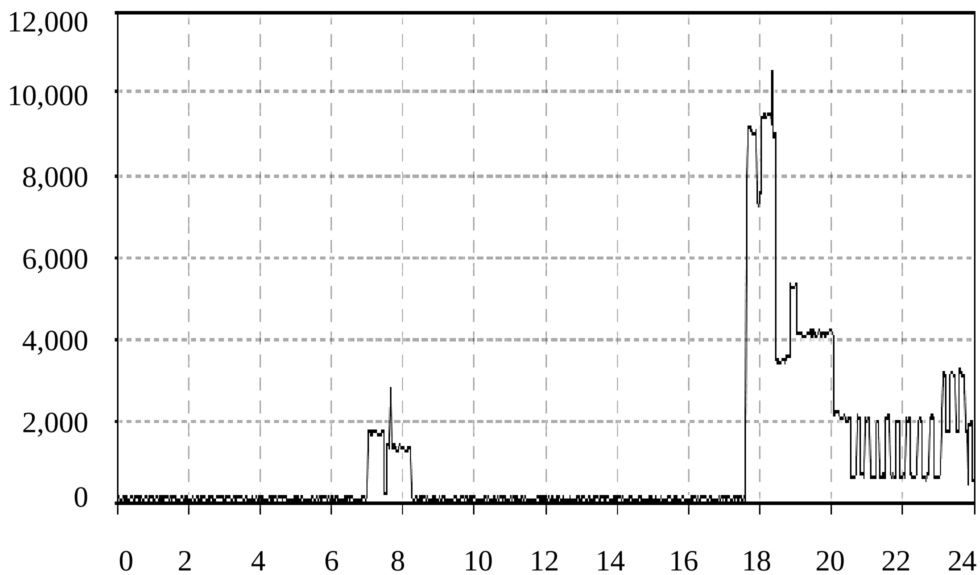


Fig. 5.12: Reference results for evaluation purposes [5]

Fig. 5.12 shows the total load for one day in that study. The obtained results showed a strict adherence to the conditions discussed above. For instance, it showed that the domestic power consumption is not equal for all households. It fluctuates depending on people's usage profile, which depends on the house occupancy patterns. Many models, including the one developed in this project, showed that when users are not at home or are sleeping, the total power load used is much lower than when they return from work [5]. Interestingly, this and many other models show that even when the houses are occupied, their loads are usually not stable, and they show many variations. These changes emerge from the fact that people engage in different activities at different times. For instance, immediately people get home from work in the evening; many models show that their power consumption is usually higher than when they have spent more time at home. A good model should produce such behaviour.

This project performs further validation of its results using actual power consumption data from 300 households. The project collected data for the usage statistics of about 14,000 houses for all the months in 2020. It then selects a sample of 300 households containing specific features from the collected data. The project considered houses in urban areas, since the simulation was for urban dwellers. This data will provide better validation for the accuracy of this project and the simulation. Summary for the selected data for the purpose of validation is shown in Table 5.3. The data in the table shows the total power and average for the values. The average consumption data is also same as the mean power that each person consumed for the month.

Table 5.3: Summary of the validation data

Month	**Total power**	**Average**
Jan	25875	87
Feb	24512	82
Mar	23685	79
Apr	35520	120
May	63082	213
Jun	61293	206
Jul	76365	258
Aug	68140	229
Sep	75687	255
Oct	66950	225
Nov	41943	141
Dec	25214	85

The simulation was set to record total power per day for a whole year. This data was then summed to form monthly consumption and then shown as Table 5.4. Producing this monthly consumption data makes it possible to compare it with the real time data for the purpose of validation. Total power / consumption units are given in kWh in both Table 5.3 and Table 5.4 respectively.

Table 5.4: Summarized simulation data

Month	Total power	Personal
March	28917	96
April	43677	146
May	61593	205
June	68789	229
July	79917	266
August	72076	240
September	77510	258
October	69339	231
November	48287	161
December	31742	106
January	24005	80
February	23675	79

The data in Table 5.3 and Table 5.4 were then plotted on the same axes as shown to produce the bar chart in Fig. 5.13. The graph uses the total power that all the residents consumed for each month. Plotting them in a single graph in this way makes it easy to compare their values and validate the simulation. The graph is shown in Fig. 5.13.

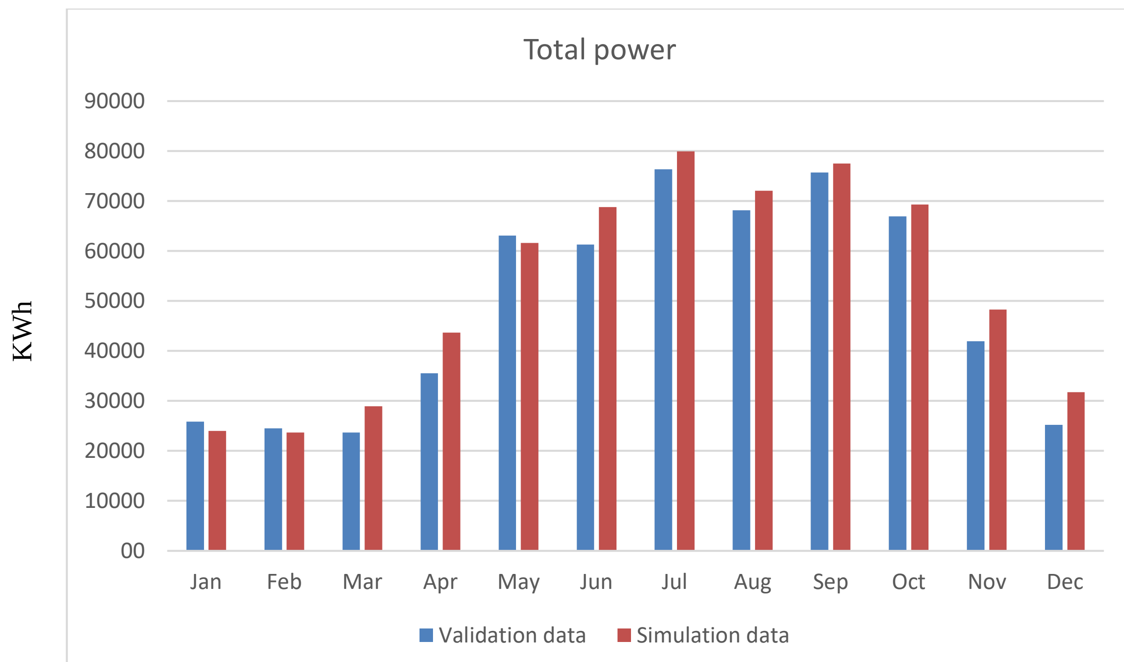


Fig. 5.13: Validation graph

The graph in Fig. 5.13 shows that the developed model closely approximates actual power consumption data. However, the two data sets have some noticeable differences. Specifically, most of the points for the simulated data are higher than the actual power consumption. These differences could have resulted from several causes. The first one could be the fact that the population that the validation data belongs to do not have electric vehicles while the simulation considered it. Electric vehicles have a high power consumption, and therefore, their effect on the consumed power is significant. Another cause of the variation could result from the usage of power for other uses that either the validation or simulation data does not consider. The graph also shows that from May to October, the power consumed is much higher than other months of the year. This high consumption is the result of usage of air conditioners during the hot season.

Another considerable trend appearing from the validation graph is that validation data energy consumption units (kWh) are more than units calculated from simulated model in the months of January, February and May while the opposite stands true for the remaining of the months of year under consideration i.e. 2020. This can be attributed to the fact that there is great degree of varying usage pattern in respect of consumption of heating load used in winter season. Graph also shows that lowest value of units consumed in respect of validated data are in the Month of March and value comes down to 23,685 kWh. Similarly lowest consumption units measured in respect of simulated consumption data is 23,675 kWh for the month of February. Furthermore highest value of units consumed in respect of validated data are in the Month of July and value comes up to 76,365 kWh. Similarly highest consumption units measured in respect of simulated consumption data is 79,917 kWh for the month of February. The greatest difference in percentage between the simulated kWh units and actual kWh consumption units is recorded in the month of December i.e 25.1%. Similarly the months in which simulated data closely approximates the real time data are May and September with value comes out to be 2.4 %. This is most likely because of the mathematical fact that more consumption units in a particular month allows simulated data to be in close proximity with the actual data taken from the power distribution company. Hence heavy usage of A/C load in summer season makes energy consumption go on increasing trend thus enabling simulation model to forecast demand profiles with least error.

Chapter 6

Conclusion and Future Work

6.1. Conclusion

Demand side management is the way forward for efficient utilization of the available energy resources without increasing the supply side energy. The results of this research apply to many situations. They can help power generation and distribution companies to optimize their grids. They can also advise their clients on better ways of using the power to have almost stable power supply patterns. As this paper shows, the agent-based approach leads to developing a realistic model of power usage in domestic settings. This project shows that the total power consumed in a house depends on several factors, and it is never constant. This paper has discussed all the factors that affected the electric load in the domestic setting. Moreover, comparing its data with other similar projects showed that its results are practical since they resemble other studies. Based on the accuracy and validity of this paper's results, it is correct to say that concerned parties can use them in decision making about how to optimize power consumption in people's houses.

This project shows that power loads normally vary for each person and they depend on several factors. The conditions that determine this power consumption profile include the number of rooms present in a house, the number of its occupants, loads in the house and their usage patterns. Moreover, the occupancy patterns of the house are of great concern and they include issues such as when people go to bed, when they wake, and when they go to work. These factors affect the amount of time that they use their devices, which determines the amount of power used in the house. Other than these issues internal to a house, other external conditions, such as temperature can affect the power consumed due to the use of fans and air conditioners. This paper has considered all these factors and modelled them in a population of 300 households to find their contribution to the total power consumption of the population.

6.2. Future Work

Few parameters could be incorporated in the problem formulation of a proposed approach to enhance the viability of results further. In the future, designed model may be extended for implementation of demand response strategies to reduce the peak load and analyze critical peak pricing. Furthermore, the model may be validated for appliance level simulation, sensitivity analysis. Our proposed framework may be equipped with more data driven approach to explicitly model new parameters such as clothing level of occupants and precise temperature monitoring through parameters such as window opening and light switching patterns of the occupants. We also aim to extend our framework for other sectors including commercial, industrial and agricultural and integrate all these sectors to form a country scale energy consumption model.

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COMPLETION CERTIFICATE

"It is certified that that the contents of thesis document titled "Agent base modelling and simulation of Domestic electricity load profiles for effective demand side management" submitted by Mr. Attique Ur Rehman, Registration No. 00000206526 have been found satisfactory for the requirement of degree".

Thesis Advisor ___________________

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