Agent-based Modeling and Simulation of Household Electricity Demand Profiles

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Approval

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Acknowledgment

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List of Abbreviation

ABM	Agent-Based Modeling
ABMS	Agent-based Modeling & Simulation
AI	Artificial Intelligence
ANN	Artificial Neural Networks
ARMA	of Auto-Regressive Moving Average
ARMIA	Auto-Regressive Integrated Moving Average
ARMX	Autoregressive Moving Average eXogenous
CDA	Conditional Demand Analysis
CFL	Compact Fluorescent Lamps
CV(RMSE)	Co-efficient of Variance of the Root Mean Square Error
DERA	Distributed Renewables for Energy Access
DSM	Demand Side Management
ES	Evolution Strategy
FTL	Fluorescent Tube Lights
GDP	Gross Domestic Product
GRASP	Greedy Randomized Adaptive Search Procedures
HBS	Household Budget Survey
IAM	Individual Appliance Monitors
IB	Incandescing Bulbs
IDE	Integrated Development Environment
IEA	International Energy Agency
KWh	KiloWatts Hour
LTLF	Long Term Load Forecasting
LV	Low Voltage Network
M&S	Modeling and Simulation
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MTLF	Medium Term Load Forecasting
NILM	Non-Intrusive Appliance Load Monitoring
NS	Neighborhood Structures
NTDC	National Transmission and Dispatch Company
REDD	Reference Energy Disaggregation Dataset
RMSE	Root Mean Square Error
SDGs	Sustainable Development Goals
STLF	Short Term Load Forecasting
ToU	Time of Use
TUS	Time-Use Survey
UN	United Nations

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Abstract

In Pakistan, there is shortage of electricity generation. As per Pakistan National Transmission & Dispatch Company (NTDC); Pakistan will be able to meet the projected demand of peak hours in 2019. In Pakistan, the major consumer class is domestic which constitutes approximately more than 40% of the electricity sale share, therefore the importance of forecasted domestic electricity demand profiles cannot be denied. The forecasting of household's profiles is not only an important factor for the establishment of sustainable energy systems but also helps in the development of demand-side management policies, future energy generation mix, planning of electricity transmission and distribution network and end-user tariff designs. Due to lack of efficient electricity infrastructure in Pakistan, domestic electricity consumption is not being accurately monitored, thus we are unable to predict our future domestic electricity demands and always faces electricity shortage of 10 to 12 hours in summer peak season. Smart Grid Infrastructure deployment and Home Energy Management Solutions currently available are very expensive and require a lot of long-term planning for a developing country like Pakistan. To forecast the household's electricity load profiles, we propose a bottom-up agent-based modeling and simulation framework. Our approach provides households per minute electricity consumption by using the behavioral modeling of electrical appliances uses and suitable for replicating at real-world urban infrastructure scenarios. The proposed ABMS framework will support in: (i) Estimation of the future energy demands; (ii) Analysis of the complex dynamic behavior of the population; (iii) Promote responsible use of energy by incorporating necessary policies; and (iv) Effective production planning using mix strategy electricity generation.

Keywords: *Agent-Based Modeling, Domestic Load Profiles*

Introduction

This chapter provides information about the topic which is being studied. It describes the definitions and concepts of household electricity demand profiles/consumption simulation and some preliminaries to get an understanding of this thesis

As per the United Nations Foundation, about 1.1 billion world's population have no electricity access and 1 billion more have poor access to electricity due to unreliable transmission and distribution networks. The wood and charcoal are used for cooking and heating [1], [2] by 3 billion world's population. The non-availability of the minimum amount of energy necessary to meet day to day living requirements a household leads to energy poverty. The Millennium Development Goals cannot be achieved without elimination of energy poverty therefore "Sustainable Energy for All" was made Goal 7 in 2015 by the UN General Assembly. The World Energy Outlook 2017 report [3] issued by International Energy Agency (IEA) states the residential sector contributes 27% of the total energy use world wise.

1.1 Energy Poverty

Energy Poverty is defined as the non-availability of modern energy services to a large number of people and their well-being is affected by lack of access to these services. As per United Nations (UN) Sustainable Development Goals (SDGs), the lack of access of energy services directly affect the goals of Affordable and Clean Energy (SDG-7) and Responsible Consumption & Production (SDG-12) and indirectly to health (SDG-3), gender equality (SDG5) and energy access for the productive uses (SDGs 1,8,9) [3]. A complex association exists between the income level and household energy consumption and involves many factors. There are many developing countries in which the population is living above the poverty line but has no access to the electricity as shown in figure-1.

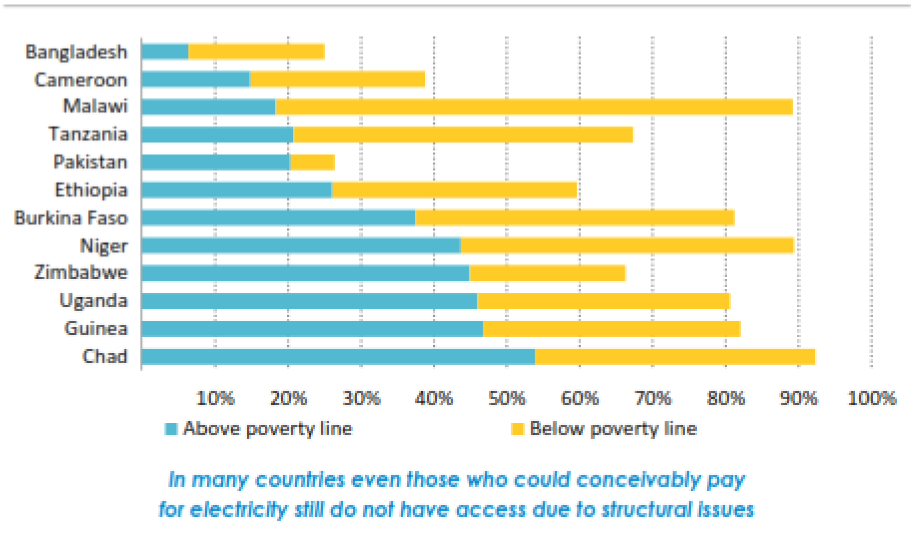

Figure 1: Electricity Access in selected countries, 2016 [3].

1.2 Challenge

In Pakistan, approximately 51 Million of the population has no access to the electricity and 50% of the population has no access to clean cooking [3], 20% of the population is living above the poverty line but have no access to the electricity as shown in figure-1 above. Pakistan is facing shortage of electricity generation, as per Pakistan National Transmission & Dispatch company, Pakistan will be able to meet the projected demand of peak hours in 2019 [4]. During the last five years, the % mean electricity sale of different consumer classes is shown in figure 2. It is quite evident; the major consumer class is domestic which constitutes more than 40% of the total electricity sale and share of the sale of domestic consumer class is increasing yearly.

Following the study carried out by Asian Development Bank in Pakistan in 2009 under the "Pakistan: Sustainable Energy Efficiency Development Program", the residential electricity consumption by end-use was categorized as 36% for space cooling, 35% for Lighting and 29% for general appliances. The Pakistan EEIP Baseline Domestic Lighting Survey [5] was conducted for 3,253 consumers across Pakistan. As per survey results 36% of the light points fittings were with incandescing bulbs (IB), 42 % with Compact Fluorescent Lamps (CFL) and 22% with linear fluorescent tube lights (FTL). [6], [7], [8], [9] studies stated that durable ownership of electric fans in Pakistan is 96% even among the poor with daily per capita consumption under $2 and sale of electronics is growing.

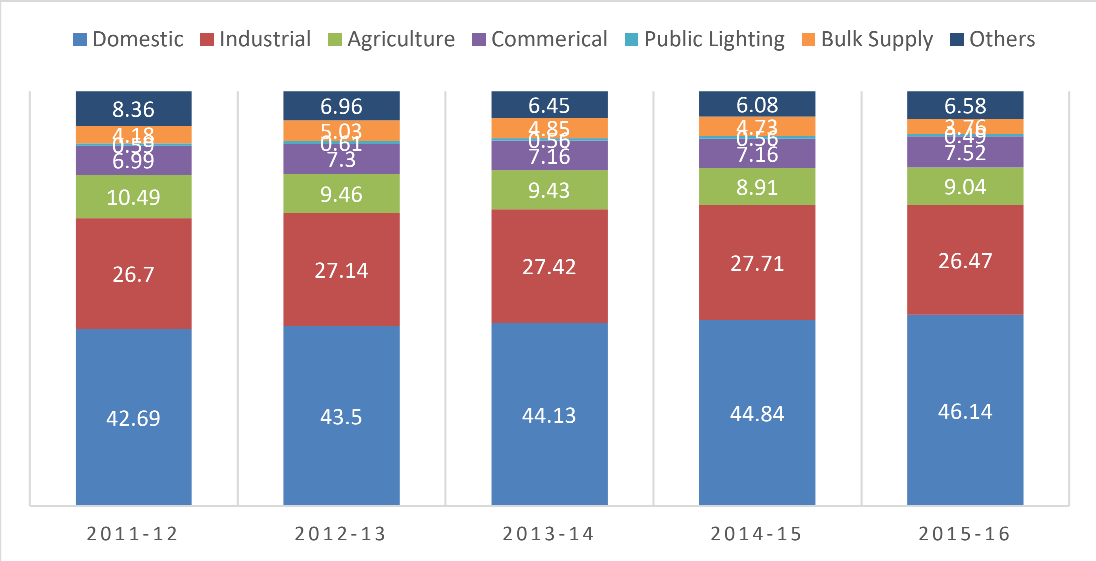

Figure 2: % mean electricity consumption in Pakistan 2015-16 [4]

1.3 Problem Domain

With the technological advancements, new business models in the form of off-grid, Mini-grid and Pico Solar for electricity are evolving as shown in figure 3. During the period of 2012-2016; 6% of new electricity connections were provided by off-grid and mini-grid renewable energy systems worldwide. Off-Grid Solar systems provided the electrical connections to 13% of Bangladesh's population and Distributed Renewables for Energy Access (DERA) systems [10] provided electricity access to 51% of Kenya's population. This trend clearly shows that household's role in future electricity systems is evolving as they are playing the role of power generation capacity and important electricity consumer at the same time. Electricity use by households is influenced by many factors like lifestyle, socio-demographic factors, electric appliances, building characteristics, new residential heating and cooling technologies, penetration of electric vehicles and many others [11].

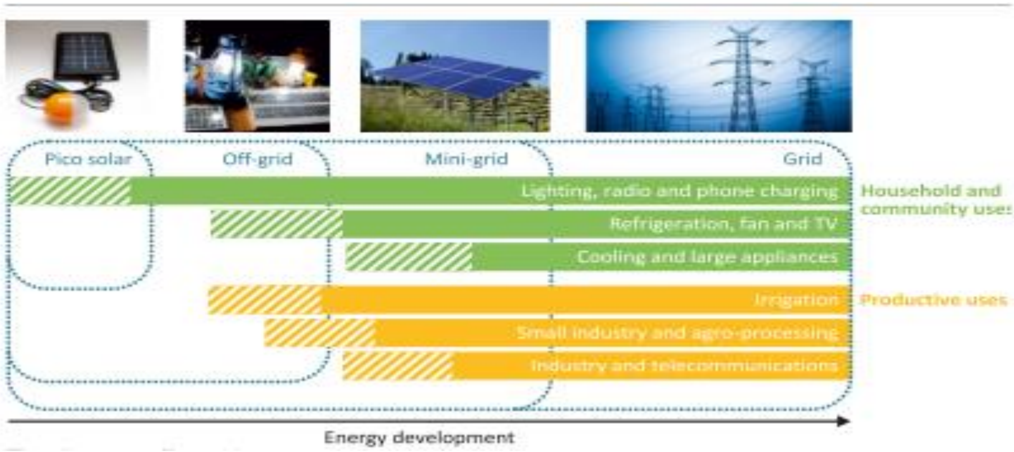

Figure 3: Electricity Access and Technology Options

Forecasting of households' load profiles is a difficult task because it is random in nature. Even two households with the same energy consumption exhibit different load curve. The forecasting of household's load profiles is not only an important factor for the establishment of sustainable energy systems but also helps in the development of demand-side management policies, future energy generation mix, planning of electricity transmission and distribution network and End-user tariff designs (On-Peak, Mid Peak, Off Peak). The most common factors that affect the load profiles are weather, population, economic conditions, electricity price, and power policies. All these factors contribute to the development of short-term, medium-term and long-term forecasting models.

1.4 Problem Statement

With the increased use of renewable energy sources and new electricity business models the domestic electricity consumers role is evolving, which leads us to the formulation of our problem statement which is listed below:

"The simulation of domestic electricity demand profiles is a challenging task due to its randomness in nature. Even two households with the same energy consumption exhibit different load curves ".

1.5 Solution Domain

We give a brief overview of the solution to the above-mentioned problem in our thesis

1.5.1 Modeling and Simulation

Modeling and Simulation (M&S) is a technique for virtual representation of the real-world systems or scenarios. We can model real-world scenarios as we cannot afford to find the right solution by experimenting with real-world objects. It helps us to understand a complex system's behavior without actually testing the system in the real world. Firstly, with the help of computers, a mathematical model which represents the physical parameters of the actual systems and then different conditions are applied to study the different scenarios [12].

1.5.2 Household Electricity Demand Profiles Modeling & Simulation

Household Electricity Demand Profiles modeling & simulation is very important as electricity is consumed in every house. The demand profiles are not only important for the establishment of sustainable energy systems but also helps in demand-side management policies.

1.6 Solution Statement

With the advent of Smart Grid Infrastructure deployment and Home Energy Management Systems, it is possible for us to study electrical appliance level consumption in households. The aggregation of the varying consumption patterns to represent the system as a whole is still a challenging task as there are different family sizes, people belong to different age groups and electricity consumption activities of every individual vary as per different routine of an individual. Modeling and simulation play an essential role in modeling this real-world scenario in a virtual world with some abstractions to analyze the consumption of electricity at the household level and forecast the required amount of electricity that needs to be delivered to the end user in urban infrastructure. An Agent-Based modeling approach is used to develop a framework for analyzing electricity consumption activities in a house.

Anylogic Agent-based framework built-in features and library is used to model and simulate household electricity consumption.

1.6.1 Key Contributions

We propose an agent-based household electricity consumption simulation and analysis framework that encompasses (i) model households on the basis of number of bedrooms (ii) model the occupancy patterns of households (iii) model the household electrical appliances , usage patterns of these electrical appliances (iv) effect of weather variables on the usage of fans and air conditioners (v) per minute , hourly and total electricity consumption and appliance wise electricity consumption for the concerned authorities to best monitor and fulfill the household electricity demand of the end users.

1.7 Research Impact

Our proposed framework will help concerned authorities in understanding the varying patterns of household electricity consumption to meet the On Peak, Mid Peak, Off Peak electricity demand. It will provide better insights for the planning of efficient electricity transmission and distribution network. It will also help in attaining the title of Millennium Development Goal of “Sustainable Energy for All”.

1.8 Thesis Organization

The organization of the thesis is as follows:

1.8.1 Chapter 2: Background

Chapter 2 provides a brief overview of household demand profiles, its importance, factors that affect the demand profiles. Moreover, few electricity demand profiles models' preliminary concepts used in the methodology chapter have also been discussed

1.8.2 Chapter 3: Literature

This chapter explains the work done so far which is related to household demand profiles modeling and simulation. The formulation of the thesis and the novelty of the thesis lie in identifying the research gap from the literature already published

The identification of the direction of research is also one of the sanctions of literature.

1.8.3 Chapter 4: Methodology

Our proposed simulation and analysis framework has been presented in this chapter Moreover, the tool used for the development of the framework and built-in libraries of the tool used for developing the model, are presented here Furthermore, the input parameters required to drive the framework are also presented in this section

1.8.4 Chapter 5: Simulation and Results

The functionality of our proposed framework is described in this section The inputs which the framework requires and the output which our framework provides, the simulation of our framework and the visualizations which our framework provides are all presented in this chapter

1.8.5 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 which is to be carried out is presented in this chapter

Background

This chapter provides information about the topic which is being studied. It describes the definitions and concepts of household electricity demand profiles and some preliminaries to get an understanding of this thesis.

1.9 Household Electricity Demand Profiles

The residential sector contributes 27% of the total energy use worldwide, approximately 27-29% of total energy use in Europe and 40% in Pakistan. As per the Renewables Global Status Report, 2018 [10], 14% of the global population has no access to electricity. The world average electricity consumption per household is increased by 1% and in Asia, the increase in consumption household is 4.1%. This situation clearly indicates that detailed study of household electricity demand profiles and consumption is inevitable for residential sector supply and demand analysis, demand response strategies and. peak load reduction. The study is getting more complex with the increased use of renewables and the evolving role of the domestic consumer as prosumer.

The study of household electricity demand profiles is complex because it involves a lot of socio-demographic and socio-technical aspects. The important socio-demographic factors that affect household electricity consumption are household size, dwelling size, income, employment status, and urban or rural categorization. The second important factor is the ownership of electrical appliances and their efficiency. In non-OECD countries, the demand for residential air conditioners will be increased by 78% and refrigerators by 107% in 2030. The six products which will consume most electricity by 2030 are shown in figure-4 below [13]. The third most important factor is the seasonal demand. The daily load profiles of summer and winter season show different consumption patterns. The domestic consumer class is highly correlated with the weather variables because of cooling and heating appliances installed at home.

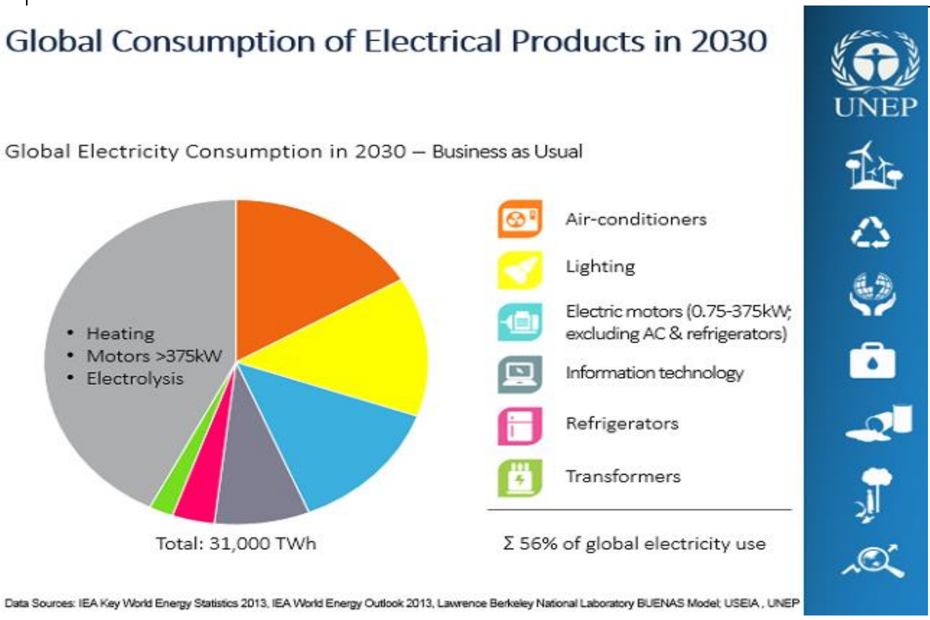

Figure 4: Global consumption of Electrical Products in 2030 [13]

As the electricity demand profiles are the study the consumption of electricity over a period of time, the time resolution of the models is also a very important factor. Generally, the three load forecasting categories are (i) Short Term Load Forecasting (STLF), (ii) Medium Term Load Forecasting (MTLF), and (iii) Long Term Load Forecasting (LTLF) as shown in Figure-5 below.

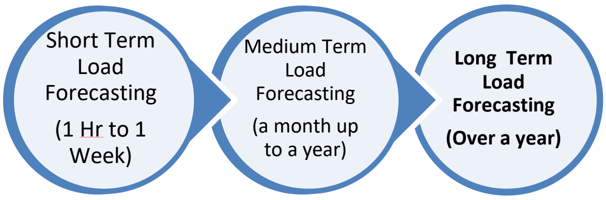

Figure 5: Load Forecasting Types on basis of Time Horizon

1.10 Household Electricity Demand Profiles Modeling & Simulation

The modeling and simulation of household electricity demand profiles are studied by many researchers in detail. Grandjean, Adnot and Binnet [14] reviewed and analyzed twelve domestic load curve models and proposed that an ideal domestic load curve model must exhibit the characteristics like parametric, evolutionary, aggregative, technically explicit and all domestic end uses must be considered. They categorized these models in the three categories (i) Top-Dow Models, (ii) Bottom-up Models and (iii) Hybrid models. With the recent advancements in Information and Communication technologies and Smart Grid Infrastructure deployment; Artificial Intelligence models and agent-based models are also developed. These model categories are described in detail in Chapter -3.

1.10.1 Agent-based modeling & Simulation

An agent-based model is the composition of individual agents and the environment. Each agent individually assesses its situation and makes a decision on the basis of a set of rules. Every agent has its own goals and has some knowledge processing abilities. The emergent behavior resulted from the individual behaviors and interactions between these agents affects the aggregated level of the total system. Agent-based Modeling & Simulation (ABMS) technique is used by many researchers as a suitable approach for complex socio-technical problems; particularly for the study of the wholesale electricity markets [15]. However, recently the framework is used for modeling of smart grid scenarios such as demand response strategies, distributed generation, integration of renewable technologies and energy storage. However, the calibration, verification, and validation of the agent-based models is a challenging task.

1.11 Household Demand Profile Modeling Tools

Different tools have been developed to model and simulate household load profiles. The selection of the tool is dependent upon the methodology used to create these load profiles. [16] implemented the Markov Chain Methodology to build the relationship between occupant activity and appliance usage by using Visual Basic macros and C#. [17] used MATLAB to implement its mathematical model for load profiles of one to five rooms flats for Singapore. [18] uses SQL, Python, Tableau, and SAS for analysis of household electrical appliances usage patterns.

1.11.1 AnyLogic

AnyLogic is a versatile modeling and simulation tool developed by The AnyLogic Company. It allows the modeler to model complex systems with conformity and accuracy because of the built-in libraries provided by Anylogic. It supports agent-based, discrete event, and system dynamics simulation methodologies. Anylogic is used to simulate wide range models such as manufacturing, supply chain and logistics, health care, business processes, aerospace, safety and security and many other real-world scenarios [19]. Its graphical interface that allows the modeler to quickly model complex environments. Anylogic Simulation environment provides both a user-friendly Integrated Development Environment (IDE) as well as an efficient simulation engine. It also facilitates modeler to integrate simulations with external environments.

By using AnyLogic tool [20] developed a hybrid simulation model by combining the Discrete Event and System Dynamics modeling to model country scale electricity demand profiles. [21] used an agent-based modeling approach to model electricity consumption in an office building.

In this research, we are using Anylogic simulation software for the development of our proposed framework. Its rich features help us to build complex simulations robustly. We can design custom agents in Anylogic using agent-based paradigm.

Literature Review

This chapter explains how related is our work with that of others Moreover, it also contributes to the understanding and development of the area of research

Table 1 summarizes different research clusters of the literature reviewed during the course of the literature reviewed.

Table 1: Literature Review

Author (s)	Category	Paper Description	Key Features
[11]	**Electricity Load Profiles**	Explained the importance of household consumers with the increasing use of renewable energy resources.	The authors identify that biggest socio-demographic factors that affect the electricity consumption and load profiles are Household Size, Income Level and Employment Status.
[14]		Reviewed and analyzed the twelve (12) residential load curve models	Described the characteristics of ideal domestic load curve model and evaluated the twelve (12) load curve models on basis of its inputs/outputs, modeled end-use, the diversity of the model and validation method of the model.
[22]	**Statistical / Probabilistic / Time of Use (ToU) Models**	A probabilistic empirical model at 60-minute resolution is developed to generate the load curve. Two types of Demand Side Management (DSM) strategies applied to the model.	At the first step, for every household, the domestic equipment is and general load fluctuation trend is allocated. In the second step, each appliance in each household is simulated with the help of end-use probabilities
[16]		The model is developed using time of use (ToU) approach at 1 (One) minute resolution.	The model generates the daily load curve in four steps. For the first step, the number of residents, a month of the year and day of the week is specified. In the second step, the electrical appliances are allocated to the dwelling. In the third step, occupancy simulation is run to at the 10minute period time. The occupancy information is mapped with the electrical appliance usage probability. In the last step a random no between 0 and 1 is generated to compare with electrical appliance probability in step 2. If the random number is

Author (s)	Category	Paper Description	Key Features
			generated the appliances is set in on status.
[23]		Statistical data of South Africa 1994-2011 is used to develop the Average Load Profile Model and Standard Deviation Profile Model.	The authors collected data about forty (40) different kinds of sociodemographic indicators and measures in terms of their statistical significance and usefulness. The linear regression models are used to generate the mentioned two profiles.
[17]		The load profiles for the residential buildings compromising of One to five rooms public housing are generated.	The author extended the work of [7] by generating the distinct starting probability for every house type (1 to 5 rooms) by defining the distinct mean daily starting frequency and appliance saturation for every house type.
[24]		A stochastic bottom-up model synPRO is developed with a high time resolution of 10 seconds for German Households.	The model generates the daily load curve in six steps. The strength of the model is the fact that stochasticity is covered in detail. The different socio-economic groups can be included easily. The electrical appliances are also categorized in groups for better estimation of duration of their use and start time of the use.
[25]		A Markov Chain based model is developed for load profiles at fifteen (15) minutes resolution. The focus of the model is Distribution Grid Planning and Operation.	For every single household, electrical appliances are allocated on the basis of statistical data and each appliance usage behavior is generated on the basis of season, day and time. The model was simulated for 10000 households and compared with German Standard Load Profile. Furthermore, three different load shifting algorithms based on spot market price are studied.
[26]		A Time of Use (ToU) based model is developed wherein activity patterns of each household members are generated using the Markov-Chain approach.	The model considers the multiple individuals are present in a household and their combined behavior on use of electrical appliances.
[27]		A Hybrid model is developed by combining the engineering methods and statistical methods.	This model requires less data because of the engineering method. The model validation results were improved by more than 50% as compared to the existing methods. However, for some appliances, the method overestimated the electricity consumption.

Author (s)	Category	Paper Description	Key Features
[28]	**Agent-Based Modeling**	For urban areas, a high temporal and spatial resolution bottom-up simulation model is developed which simulates residential energy demand profiles.	The model considered the factors of land use, energy infrastructure, and user behavior. The area under study is divided into different zones by using socio-demographic parameters. A heterogeneous group of agents is generated. An activity schedule is associated with every agent and electricity demand model, heat demand model and heat pump model is developed.
[29]		An agent-based model is developed for electricity consumption of a single representative household of U.S. to study demand response schemes.	The purpose of the research is to study the different residential demand response schemes and effect on the cost of storage technologies and the overall economic viability of the storage technologies and capacities.
[30]		Multi-Agent system framework for the study of household electricity consumption under different pricing schemes.	The researcher developed a multiagent system in which the main three types of agents i.e Occupant Agent, Appliances Agents, and Home Energy Management System Agents are created. The Appliances agents are further divided into four types of agents i. e Shift Able Load Agents, Shed Able Load agents, On Demand load agents and Base Load Agents. The effect of price-based demand response schemes was studied on these loads under different scenarios.
[31]		An agent-based framework is developed to optimize building energy consumption.	The current building performance tools don't include the human-related activities; which is one of the important factors for sustainable building performance. The researcher developed an agent-based model wherein human activities, their movements between buildings and thermal comfort are modeled; and energy saving potential without compromising the thermal comfort in the collection of buildings i.e urban environment is studied.
[21]		An agent-based model is developed to simulate the office building electricity consumption.	The four elements for office energy consumption are considered. These are Energy Management Policies, Energy Management Technologies, Energy User's behaviors, and Office Electric Equipment and Appliances.

Author (s)	Category	Paper Description	Key Features
[32]		An agent-based model is developed to simulate the office building electricity consumption under a tiered price scheme.	The researcher extended the agent-based model developed by [21] and studied the effect on electricity consumption of lights and computers by increasing the price tiers from 10% to 30%. The simulation results showed that daily consumption can be reduced by nearly 20% in third tier price.
[33]		A multi-agent simulation is developed to study electric vehicle penetration and charging patterns.	The researcher simulated three charging patterns for electric vehicles by creating four types of agents. The charging pattern and penetration rates have a high influence on energy demand.
[18]	**Smart Meters/ Home Energy Management Systems / Fuzzy Logic / Genetic Algorithms/ Neural Networks**	Time series analysis of the power consumed by different devices at the circuit level is performed.	MIT's publicly available data for the residential energy consumption profile dataset (REDD) is used for analysis of patterns of household electricity consumption. The analysis found that refrigerator and lightning were the most consistent load.
[34]		The qualitative data collected from surveys are combined with smart meter data to infer energy and time use profile of domestic activities.	Ten (10) households' data is collected for one month to analyze the energy use by examining the activities of households. The ten (10) activities that represent domestic life are identified. Nine (9) individual appliance monitors (IAM) were installed in each house to collect the consumption data and for remaining appliances, Non-Intrusive Appliance Load Monitoring (NILM) technique is used. The activities ontology technique is used to establish a relationship between activities and appliances. Both techniques combinedly helped to infer how much electricity is consumed during each activity.
[35]		A hybrid evolutionary fuzzy model using parameter optimization is proposed. The proposed framework is suitable for short-term forecasting over microgrids and large grids.	A calibration algorithm named GES is proposed by combining the Greedy Randomized Adaptive Search Procedures (GRASP) and Evolution Strategy (ES). During the learning process, real-time parameter optimization is used by using the Neighborhood Structures (NS)
[36]		A fuzzy logic model based on the temperature, humidity, and historical load data is proposed	The fuzzification is achieved by using maximum and minimum values of the temperature and humidity. The triangular membership function is used and fuzzy rule-based is developed. It is observed that

Author (s)	Category	Paper Description	Key Features
		for long-term forecasting.	fewer forecast errors showed when fluctuation between the weather parameters and the load is reasonable.
[37]		A large number of unmonitored residential consumers at the low voltage network (LV) are modeled using a small sample of smart meter data.	The genetic algorithm technique is used to develop a model called "buddying" for residential consumers demand behavior. The proposed model estimated the substation peak demand and daily demand more accurately as compared to the other methods.
[38]		Reviewed and analyzed the Artificial Intelligence-based short term load forecasting techniques.	The (6) Six hybrid training methods for Artificial Neural Networks (ANN) were reviewed. The results of ANN-based forecast models can be improved by addressing the problems of local minima initialization of weight values, poor network generalization, and slow convergence.
[39]		Developed a household short term load forecasting model on the basis of the non-intrusive load monitoring technique.	The researcher used the Non-Intrusive Load Monitoring technique to extract the use pattern of different household appliances. These patterns were used as input for an Artificial Neural Network that forecasts total household power.
[40]	**Effect of Weather on Electricity Consumption**	The relationship between extreme temperature and total electricity demand is studied for Pakistan.	Auto-Regressive Integrated Moving Average (ARMIA) is used to forecast the values of maximum temperature in Pakistan for duration 2011 to 2020. A linear model is used to forecast the electricity consumption on the basis of maximum temperate is for the same period i.e 2011 to 2020.
[41]		The relationship between outdoor temperature and electricity demand is used to forecast the Household Electricity demand.	A hybrid method is used by combining the non-parametric model and time series analysis. The proposed hybrid model outperforms the Autoregressive Moving Average eXogenous (ARMX) model.
[20]		The country scale electricity demand is modeled using the seasonality, the type of day and the daily mean temperature.	A hybrid simulation model is used wherein daily mean temperature is simulated using a stochastic process of Auto-Regressive Moving Average (ARMA) and then modeled using Discrete – Event Simulation and electricity demand is modeled using System-Dynamics framework. The days of the whole year are divided into twenty groups on the basis of the four seasons and days Monday, Wednesday, Friday, Saturday and Sunday.

Author (s)	Category	Paper Description	Key Features
[42]	**Effect of Occupancy on Electricity Consumption**	The smart metering survey of the 4200 domestic Irish Dwelling was studied in detail to find the effect of dwelling and occupant characteristics on domestic electricity consumption.	The data of 345,645 of household consumers were divided into six groups on the basis of the annual household electricity consumption. The following four parameters are used to study the effect i. total electricity consumption, ii. maximum demand, iii. load factor 280 and iv. time of use (ToU) of maximum electricity consumption The multiple linear regression technique was applied by considering approximately 23 variables covering the dwelling type, the age of head of household, type of employment, water is heated by electricity or not, cooking is done by using electricity or not an energy efficiency behavior.
[43]		The electricity consumption is highly correlated with the floor area. The larger floor area will have more lightning requirements and also linked with the high-income group thus leads to more electrical appliance ownership.	The electricity consumption patterns of the 27 dwellings of Northern Ireland were studied in detail with respect to different sociological factors like age, location, number of occupants and their behavior. It was established a strong correlation exists between electricity consumption and floor area.
[44]		Non-homogeneous Markov Chain technique is used to generate activity sequence of individual household members and occupancy states. The electricity demand based on these patterns is calculated.	The proposed Markov Chain model has nine (9) activities or states. These nine activities correspond to different electricity end uses like cooking, dishwashing, washing, TV, Computer, etc. The generalized load patterns for these end users are connected with activities.
[45]		A probabilistic model is developed to generate occupancy status based on three states: (1) at home and awake, (2) sleeping or (3) absent.	The model is calibrated using the Belgian Time-Use Survey (TUS) and Household Budget Survey (HBS). The survey includes 6400 respondents from 3455 households.
[46]		A first-order Markov chain technique is used to develop a four-state occupancy model.	The model generates stochastic occupancy data with occupancy status 1 =”at home” and 0= “not at home” and activity status 1=” active” and 0=” not active”. The model uses different dwellings by the number of residents. Weekdays and weekends are differentiated.

1.12 Household Electricity Demand Profiles

As per the International Energy Agency (IEA), World Energy Outlook report [3], the residential sector contributes to 27% of the total energy worldwide. 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 figure-6 below.

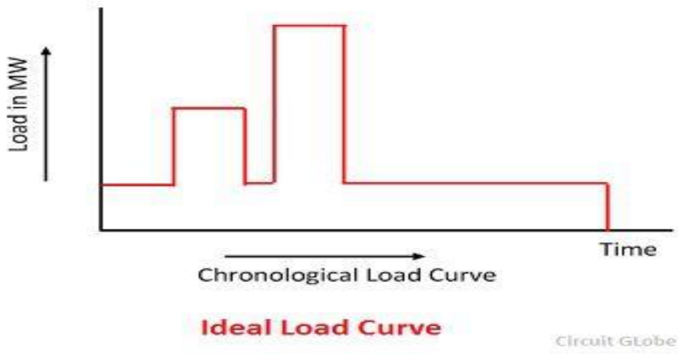

Figure 6: Example of Load Curve

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1.13 Modeling and Simulation of Household Electricity Demand Profiles

The research on the modeling and simulation of the household's electricity demand profiles are studied by many researchers in detail. However, the selection of methodology is greatly dependent upon the purpose of studying. The modeling and simulation of household demand profiles is a difficult task because of its

randomness in nature. Even two households with the same energy consumption exhibit different load curve and the energy consumption can be attributed to the different use of electrical appliances. The models are generally divided into three broad categories: Top-Down Models, Bottom-Up Models and Hybrid Models (figure-7).

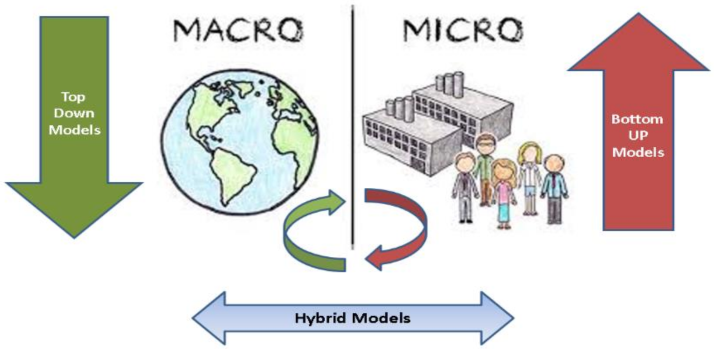


Figure 7: Types of Load Profile Models

1.13.1 Top-Down Models

Top-Down modeling is based on the macroeconomic modeling principles and techniques, the input data for these types of models are generally Gross Domestic Product (GDP), current population and future population growth trends, unemployment rate and many other factors. The main purpose of these types of models is to study the energy taxes; effect of different economic scenarios on energy and environment; macroeconomic consequences of changes in the energy system and general equilibrium effects. [14] discussed two models of Aigner et al. and Bartels et al model called DELMOD in detail. The former model used the technique of Conditional Demand Analysis (CDA) to produce the hourly end-use load curves for a household while in the later model two modules are developed. The purpose of the base module in DELMOD is to calculate the load curve of a given day for the residential sector and weather module uses the daily maximum and minimum temperature to modify the load curves produced by the base module.

1.13.2 Bottom-Up Models

In Bottom-up models, household demand profiles are modeled from individual consumption of electrical appliances installed in homes by combining with other factors like weather, human behavior, dwelling characteristics, and many other factors. Generally Statistical, Probabilistic, Empirical and Time of Use (ToU) approaches are used to simulate the demand profiles. [22] used a probabilistic empirical approach, At the first step, for every household, the domestic equipment is and general load fluctuation trend allocated. In the second step, each appliance in each household is simulated with the help of end-use probabilities. Luo Chuan [17] extended the approach of Paatero and Lund's model [22] for 1-5 rooms flats. However, the load curve for every type of flat is generated and then multiplied by thirty (30) to get the average monthly consumption, however, the effect of weather in [17] is not considered at all. Richardson [16] used the Time of Use (ToU) approach to develop a 1-minute load curve for dwellings. The model output is high spatial and time resolution load curve due to the time of use data. [26] also used the ToU approach for the selected urban area. The activities of each household member are generated by using the Markov-Chain approach. Fisher [24] developed a detailed stochastic bottom-up model by considering the socio-economic factors, type of day, a correlation between duration and start time of an activity, seasonal user patterns and electricity consumption of each device at 10-second level. 100 households for different groups are simulated for one year and results showed 91% accuracy when compared with mean yearly, monthly and daily energy consumption for each group. [25] developed a stochastic bottom-up model by using the time-inhomogeneous Markov chain for distribution grid planning and operation. The Standard Load Profiles of German households is compared with a Monte Carlo Simulation which was run for one year for the average of 10,000 households.

1.13.3 Hybrid Models

In Hybrid models, the approach of the engineering method and Conditional Demand Analysis (CDA) method is combined to develop a hybrid model. In the engineering method, electricity profiles are estimated on the basis of the assumed behaviors of the household members. The basis of assumptions in the engineering method is statistical information, therefore, it requires a large volume of the statistical data for good estimation. The CDA method uses regression analysis to generate load profiles by disaggregating the electricity consumption data and electrical appliance ownership. [14] reviewed the Train et al. model developed by using the hybrid approach. [27] also proposed a hybrid model wherein hourly electricity demand profile is calculated using the engineering method on the basis of the behavior of the household members in the usage of home appliances and appliance power requirement. CDA method was used for the development of regression equations for each hour of the day to produce regression coefficients. To improve the estimation accuracy and overcome the problems of CDA method, the three factors are added externally are electricity consumption of refrigerator, the number of household members at-home and awake and restriction on appliance usage hours.

1.14 Household Electricity Load Profiles in Smart Grid Era

With the advent of Smart Grid and Home Energy Management Systems, there are many open data sources like MIT Reference Energy Disaggregation Data Set (REDD), Electricity Consumption and Occupancy Data Set (ECO, UCI and Dutch Residential Energy Data Sets from which circuit level energy consumption profile can be established. [18] used different tools to analyze the REDD data set collected from six (6) different households for 37 days. The hourly weather data for the same period was also collected and time series analysis of the power drawn showed different patterns as shown in figure-8 for different electrical appliances. [34] collected qualitative data from (10) ten households and combined it with smart meter data to develop a model for energy and time use profile of domestic activities.

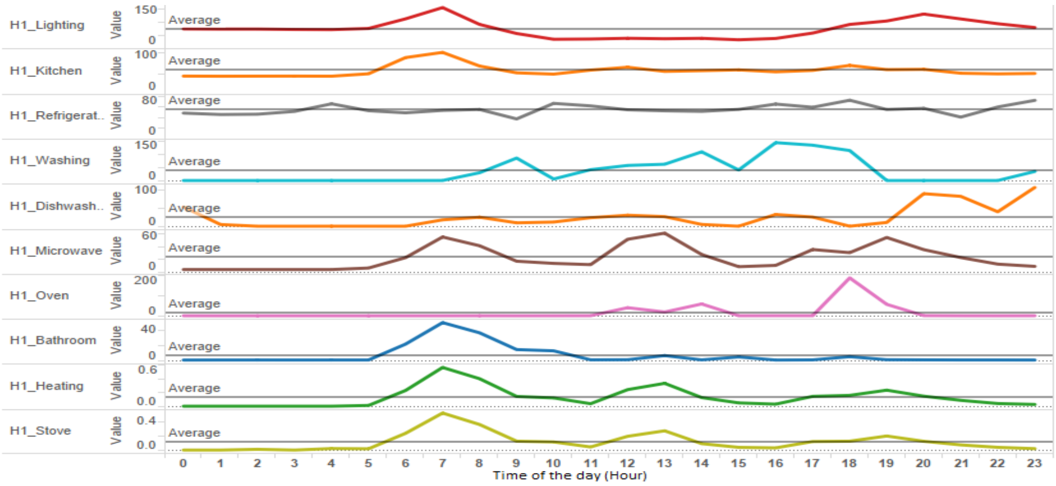


Figure 8: Hourly Devices Power Consumption Patterns For A Day [20].

1.14.1 Artificial Intelligence (AI) Based Models

[35] developed a self-adaptive fuzzy model for microgrids and [36] developed a long-term forecasting model however the focus of both researchers was not domestic use. [37] developed a genetic algorithm "buddying" to model the residential consumers on low voltage networks wherein unmonitored residential consumers the same load curve as the monitored residential consumers. [38] reviewed the Artificial

Intelligence-based load forecasting and hybrid-based Artificial Neural Network (ANN) in combination with fuzzy logic, expert systems, genetic algorithm and support vector machines. However, the accuracy of these models is dependent on the number of parameters.

1.14.2 Agent-Based Models

Agent-based Modeling and Simulation (ABMS) technique is used as a suitable approach by researchers for complex socio-technical problems particularly for the study of the wholesale electricity markets [15]. Recently the framework is used for modeling of smart grid scenarios like demand response strategies, distribution generation, integration of renewable technologies and energy storage. [28] 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. [21] used an agent-based model to study office building electricity consumption.

Various simulators have been proposed to resolve this issue including the US Department of Energy's EnergyPlus [47] to Paatero and Lund's bottom-up model [22]. However, what the authors have observed is that the models, in general, are either structural & environment, as is the case of EnergyPlus or socio-anthropologic as is the case of Paatero model. One of the reasons for this divergence is due to the modeling techniques that are used. 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 systems

Methodology

In this chapter, we propose an Agent-Based Modeling (ABM) and Simulation approach in developing the proposed simulation framework.

The proposed framework is based on the foundational work on the key characteristics for assessing energy usage by Arshad, et al [48]. The proposed framework includes three layers: (i) Neighborhood layer; (ii) Social Layer and (iii) Appliances Layer. Each of these layers is connected in a hierarchical fashion as shown in Figure 9: ABM Based Hierarchical ModelFigure 9. The neighborhood layer is based on the number of houses and parameters such as types of houses (e.g., villas or apartments), areas, size, number of beds. The social layer is based on individuals in a house, their sociological factors such as age groups, family types and living style, occupancy patterns and energy consumption behavior. The appliance layer is based on device types, device usage, power rating and their dependence with respect to the weather.

Our proposed framework incorporates these characteristics using the ABM paradigm where the neighborhoods, houses, individuals and the electrical appliances are represented as agents lined in a hierarchical fashion and their behavioral interactions are modeled using input parameters, state-charts, table functions, stochastic probabilities, and logical reasoning. The emergence of all the households in use, their electrical appliances and their combination with the exogenous variables like weather, seasons and sociological factors provides estimations for the energy consumption of a typical urban neighborhood at a selected time resolution, ranging from minute to year. The proposed framework generates the load curve for a given number of houses on a 24 hours scale, for a period of a year so that the seasonal variations can also be taken into account.

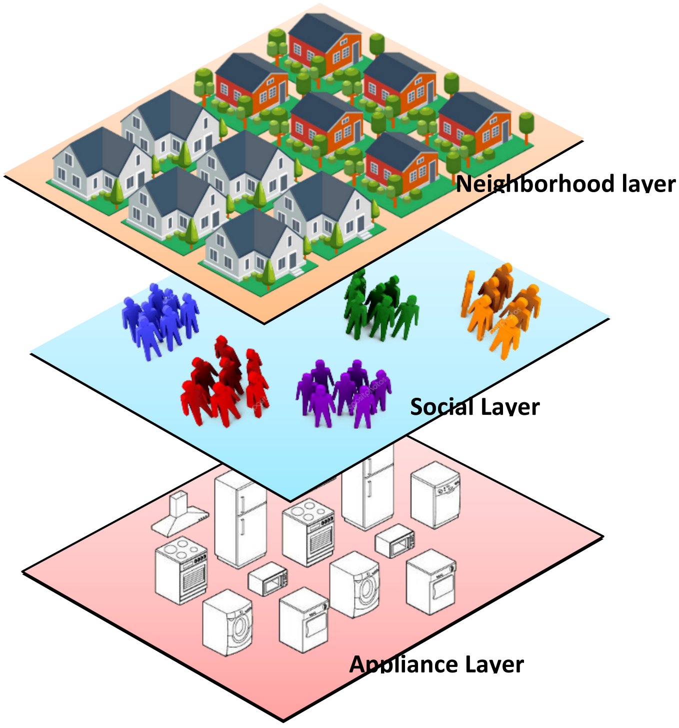


Figure 9: ABM Based Hierarchical Model

The most prominent feature of our framework is its hierarchical, multi-resolution, multi-scale, dynamic, agent-based implementation. It is hierarchical because it is divided into three layers as shown in Figure 9 where agents in different layers are connected with each layer in a hierarchical fashion. It is multi-resolution because it allows the users to model, analyze and forecast the electricity consumption of domestic sector at (a) macro-level, (b) meso-level and (c) micro-level, at the same time. At macro-level our framework allows modeling of a scalable population of households at local, regional or a country scale. At meso-level, our framework allows behavior modeling of different groups of occupants and their sociological features. At micro-level, our framework allows the modeling of individual appliances and their energy consumption. Our framework uses a built-in database to import input data, thus allowing flexibility to the users to model and run the simulation on different datasets, therefore it is dynamic and can easily be used to study any type of population of any region. The block diagram of the proposed framework is shown in Figure 10, which shows different elements and the entities of the ABM model.

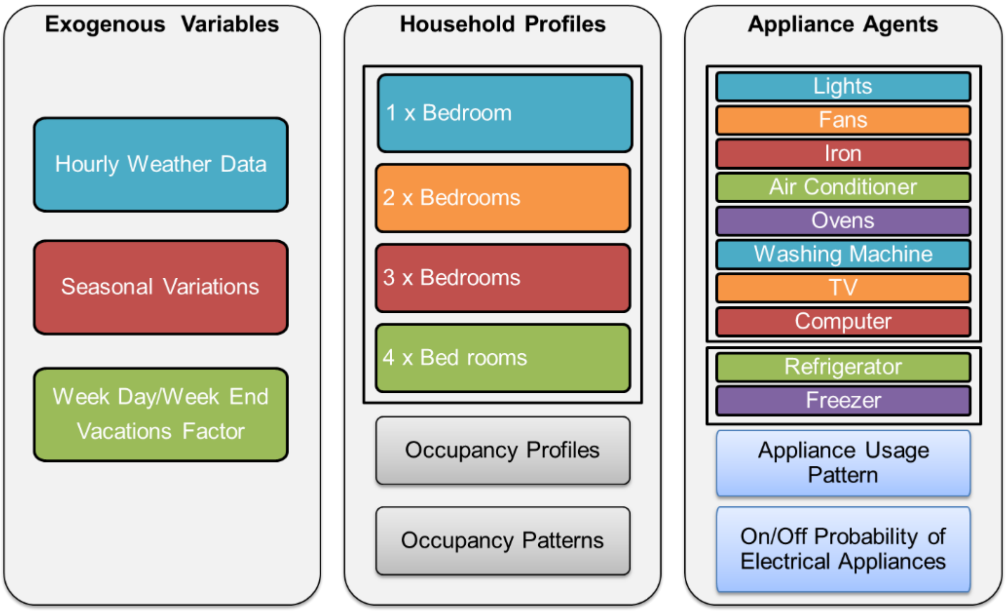


Figure 10: Elements of the proposed framework

1.15 Exogenous Variables

We initially define weather, seasonal variations and vacations factors as exogenous variables as examples to show how they affect different layers of our framework in terms of energy consumption. Due to the strong influence of human behavior on the use of domestic electrical appliances, the consumption pattern of the household electricity consumption is observed to be very dynamic. Even two households with similar configurations will show different load curves. We divide the household electricity consumption into two types: (i) User-independent consumption or base load which constitutes the perpetual use of fridge and freezers; and (ii) User-dependent, which is related to the occupant activities like cooking, washing, and cooling or heating requirements. The occupant activities are further divided into temperature dependent and temperature independent appliances. Users may incorporate more variables to incorporate demographic, econometric and sociologic parameters in order to study their influence, and therefore can benefit from our open-ended implementation.

1.16 Household Profiles

The previous studies and household surveys have identified that household electricity consumption is influenced by socio-economic indicators like household income, dwelling type, appliance holdings, number of occupants and many other factors [42]; while [43] studied that electricity consumption is also highly correlated with floor area. The larger floor area will have more lighting requirements and also linked with the high-income group and more electrical appliances ownership. In the proposed model the houses are divided into four types listed in Table 2. The profiles are used in the initial configuration of the house-agent population. The model can be extended for any number of bedrooms and with any income groups.

Table 2: Household Type Agents

No	House Profile Name	No. of Bed Rooms	Area (sqft)
1.	House Profile 1	1	550 - 750
2.	House Profile 2	2	950 – 1700
3.	House Profile 3	3	2700
4.	House Profile 4	4	3549

1.17 Occupancy Patterns

The other important factor of household electricity consumption is the occupancy patterns of households. The households with no children or where working couple lives consumes less electricity than a household with children and older people living at home. Different occupant behavior models were reviewed on the basis of size, resolution, and complexity [49]. Household occupancy and activity patterns using non-homogeneous Markov-chains were introduced by Richardson, et al. [16], and Widén & Wäckelgård [44]. Aerts, et al. [45] developed a probabilistic three-state occupancy model at 10 mins resolution which consists of absent, at home and awake or asleep states. Similarly, Mckenna, et al. [46] developed a four-state occupancy model which consists of occupancy state (1=”at home” and 0= not at home”) and activity state (1 =” active”, 0 = “not active”). Flett & Kelly [50] developed a domestic occupancy model at a minute resolution and introduced multiple occupant behaviors, type of day (weekday or weekend), related adults as a single entity and higher order Markov-chains for the duration of the activity. Marshalla, et al. [51] used three different occupant classes i.e. Working Family, Working Couple and Daytime-present couple to represent the occupancy patterns in UK Households. University of Southampton (UoS) [52] reviewed 52 documents on the occupancy patterns out of which 16 studies were related to the UK; domestic occupancy patterns identified in these studies were Short Occupancy A, Short Occupancy B, Partial Occupancy, Home Stay A, Home Stay B. In proposed model we implemented a two-state occupancy i.e., '*at-home*' and '*not at home*', and propose four types of occupancy patterns listed in Table 3.

Table 3: Occupancy Patterns

Sr. No	Occupancy Patterns	Description
1.	**WC**	**Working Couple**. This pattern represents the population which remains absent from the house mostly from 8:00 a.m. to 4:00 p.m.
2.	**WCC**	**Working Couple with Children**. This pattern represents the household population which has lower probability of occupancy at home from 8:00 a.m. to 4:00 p.m.
3.	**HS1**	**Home Stay 1**, This pattern represents the household where households remain present in house most of time. Families with school going children and older people.
4.	**HS2**	**Home Stay 2,** This pattern represents the household where households remain present in house most of time. Families with non-school going children and older people. Only one person goes out for work.

1.18 Electrical Appliances Usage Pattern

We consider a set of daily life electrical appliances in our proposed framework as shown in Table 4. The electricity consumption for each electrical appliance, is calculated using a mathematical model, initially proposed by [22].

$$\boldsymbol{P_{start}\left(A\,,\Delta t_{comp},h\right) = P_{hour}\,(A,h) \times f(A\,,d) \times P_{step}\left(\Delta t_{comp}\right) \times P_{sat}(A)}$$

Equation 1: Electrical Appliance Starting Probability Calculation

Table 4: Electricity Appliances with Wattage and Cycle Time

Sr. No	Electricity Device - Agent Name	Nominal Wattage (W)/hr	Time per Cycle (min)
1.	Lights	25	30
2.	Fans	70	30
3.	Iron	1000	30

4.	Refrigerator	110	12
5.	Freezer	200	12
6.	Washing Machine	500	90
7.	TV	100 - 300	90
8.	Computer	80	60
9.	Air Conditioner	1500	120
10.	Ovens	1500	5
11.	Misc. Load	1500	60

Each electrical appliance is assumed to be switched on using a starting probability (P_{start}), during the 24 hours period. In the above mathematical model, (P_{start}) is calculated on the basis of three variables: A is representing the appliance, Δt_{comp} is the computational timestamp, h is an hour of the day. P_{hour} is the hourly probability factor of each appliance, f is the mean daily starting frequency of each appliance, d the day of the week, P_{step} is the step size of the scaling factor that scales the probabilities according to Δt_{comp}, $P_{sat}(A)$ is the saturation probability of appliances. The mathematical model was extended by Chuan & Ukil [17] for the determination of starting probability of different appliances for 1 to 4 rooms. Furthermore, the weekday and weekend starting probabilities for appliances mentioned at sr. no 6-7 and 10 are interpolated. The nominal wattage rating is taken from the local sources. The average time per cycle for each appliance is based on theoretical estimations. A time cycle is a duration for which an appliance remains on. When the appliance cycle time is reached, it will be turned off and the model starts to re-evaluate the on/off status of the appliance for the next cycle. We use the nominal wattage and the time cycle for the appliances listed in Table 4 (1, 6-8 and 10-11). Figure 11 presents the starting probability for each house during the day for type 3 houses. These probability tables are built based on daily life patterns obtained from the observational site, discussed later in this paper.

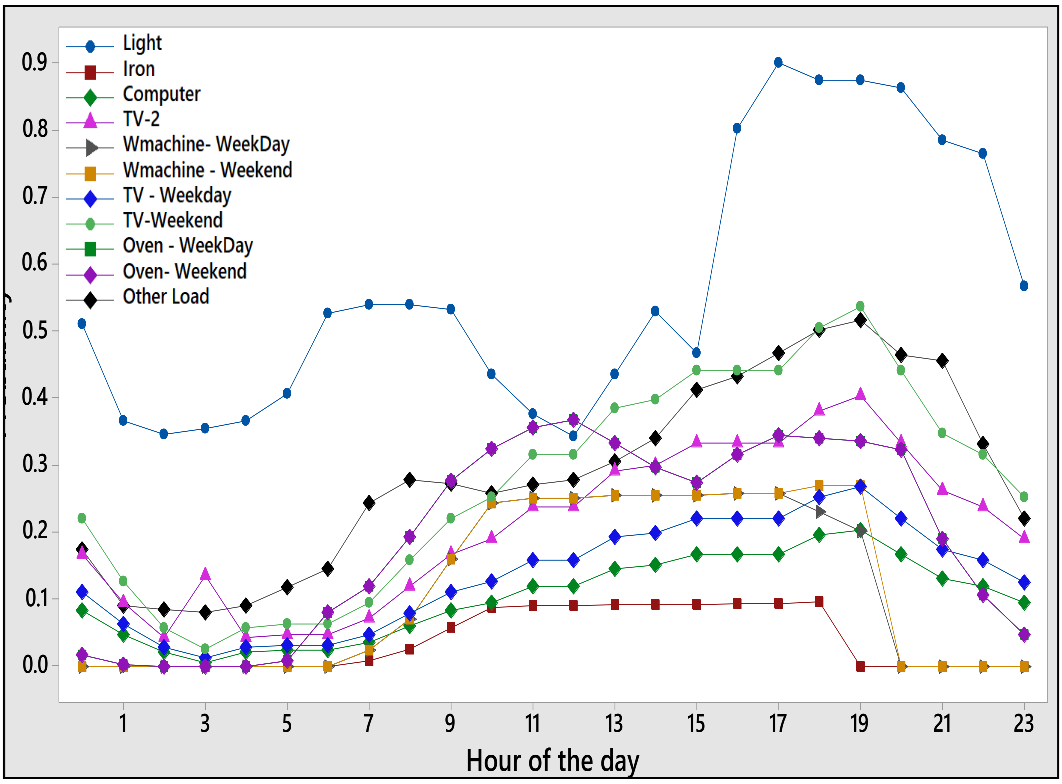


Figure 11: Electrical Appliance Usage for Type 3 House

1.19 Weather Dependent Appliances

In our proposed model we included temperature as an exogenous variable as it directly affects the appliance usage. In this paper, households of countries with extreme temperatures in summer, are considered, which require Air conditioning and other cooling appliances for domestic needs. Similarly, it is assumed that the temperature in winter remains moderate and therefore electricity usage for heating appliances, central heating, or water heating during winter is negligible. In many studies, a high correlation is established between electricity consumption and weather variables like temperature, humidity, rainfall, and solar radiations. In our proposed framework, a simple linear function between the temperature and probability usage of Fans and Air Conditioners are adopted from Tsuji [53] and Shiraki [27]. The appliance usage is 0% at temperature $\mathbf{T_a}$ and 100% at Temperature $\mathbf{T_b}$. The probability of fans usage reaches 0% if the temperature is below 24° C (T_a) and reaches to 100% if the temperature is greater or equal to 28° C (T_b). The probability of Air Conditioner usages reaches 0% if the temperature is below 28° C (Ta) and reaches to 100% if the temperature is greater or equal to 46° C (T_b) as shown in Figure 12. The proposed model can be extended for any type of temperature- dependent appliances. A similar model can be applied for humidity and rainfall.

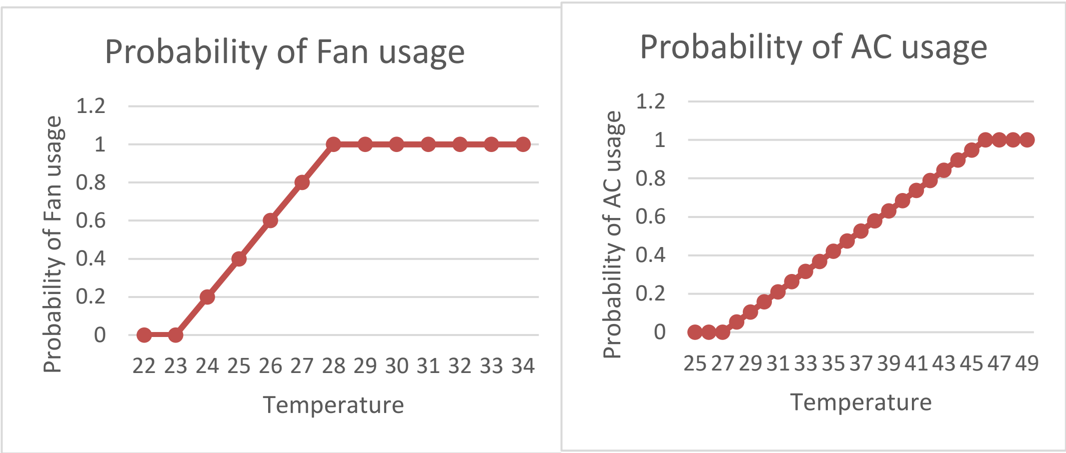


Figure 12: Temperature Dependent Probability of Fan Usage

Simulation and Results

In this chapter, we describe the functionality of our proposed framework. We simulate the scenario of domestic electricity consumption in urban infrastructure, to help regulatory authorities in forecasting total and appliance wise electricity consumption.

1.20 Simulation

The proposed model is implemented in AnyLogic 8.2.4 University Edition, using Agent-based modeling libraries. In order to compute per minute electricity consumption, we created a neighborhood agent consisting of four (4) agents representing the house types as listed in Table 2 and eleven (11) types of electrical appliance agents as listed in Table 4. The number of electrical appliances varies for the different types of houses. An initial population of the house agents is dynamically created as shown in Figure 13. This procedure is configurable through user inputs.

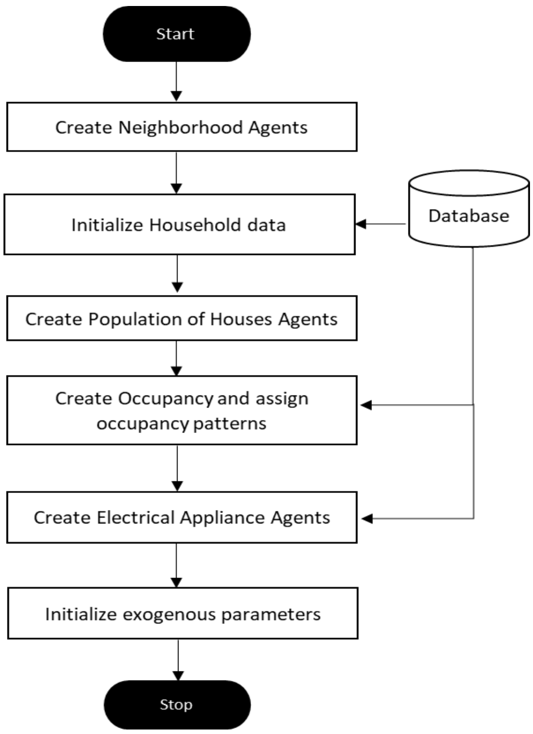


Figure 13: Flow Chart for Model Initialization

1.20.1 The behavior of Neighborhood Agent

Neighborhood agents are modeled to initialize the simulation data and instantiate household population agents. It is also used to perform energy consumption calculations, which are discussed later. Figure 14 shows the structure of the neighborhood agent using the symbols used in Anylogic Simulation Software.

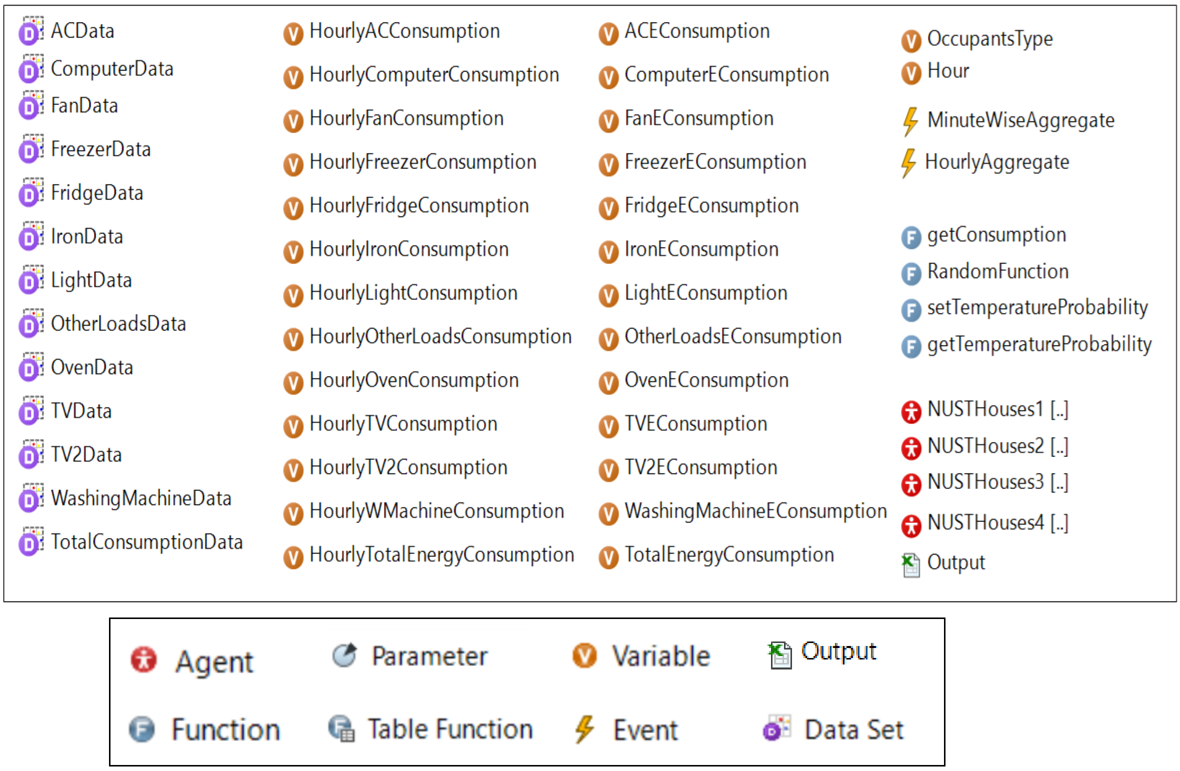


Figure 14: Neighbourhood Agent

1.20.2 Behavior of Household Agent

A household is an agent that is instantiated within a neighborhood agent and is initialized dynamically using the input data obtained from the house table of the database shown in Figure 15. The main purpose of this agent is to manage the occupancy of its occupants using a specified occupancy profile and the occupancy state-chart as shown in Figure 16.

When the simulation starts, the occupants are initialized in the available occupant variable and their number increases or decreases due to the 'recheck' transition that occurs periodically and based on the occupancy profiles, computes the new occupancy. The occupancy behavior of household's agents listed in Table 3 is implemented by using table functions shown in Figure 17.

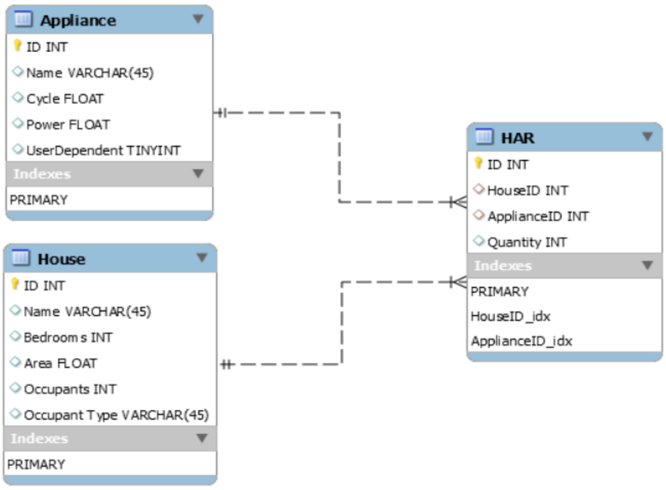


Figure 15: Database Schema

Table functions are elements from the Anylogic toolbox and are used to define complex non-linear relationships which cannot be described in standard functions. The table functions can take discrete values as input and can be made continuous by interpolation and/or extrapolation [54]. The profiles use different variants of these table functions to distinguish between the weekdays, weekends, national holidays and seasonal vacations. In this paper, we consider weekdays and weekends. Our framework allows user inputs for adding or editing the occupancy profiles and allows dynamic analysis of the effects of different occupancy behavior on the energy consumption at runtime. In each household agent, a set of appliance agents are dynamically populated using the input data obtained from the appliance table of the database.

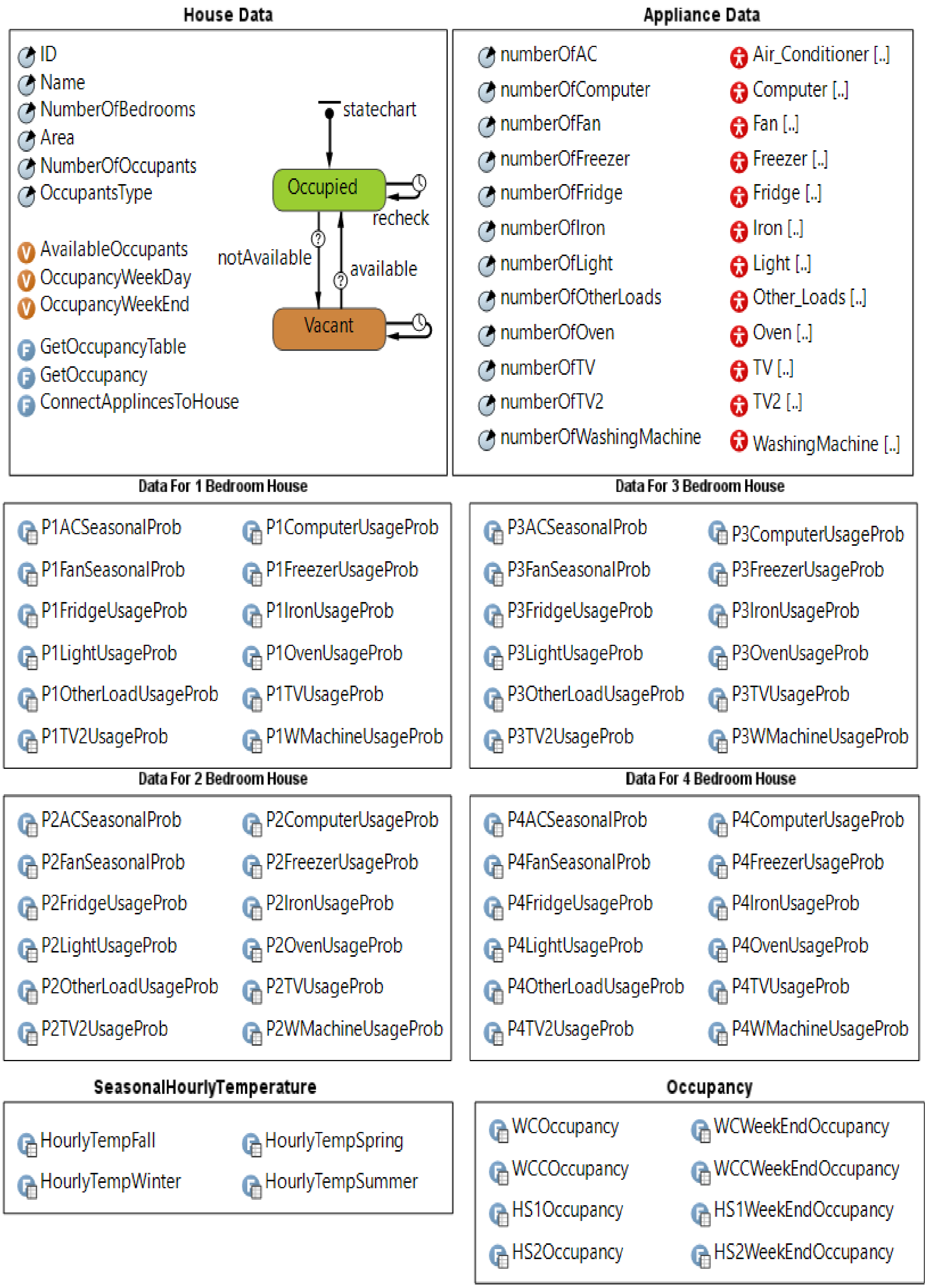
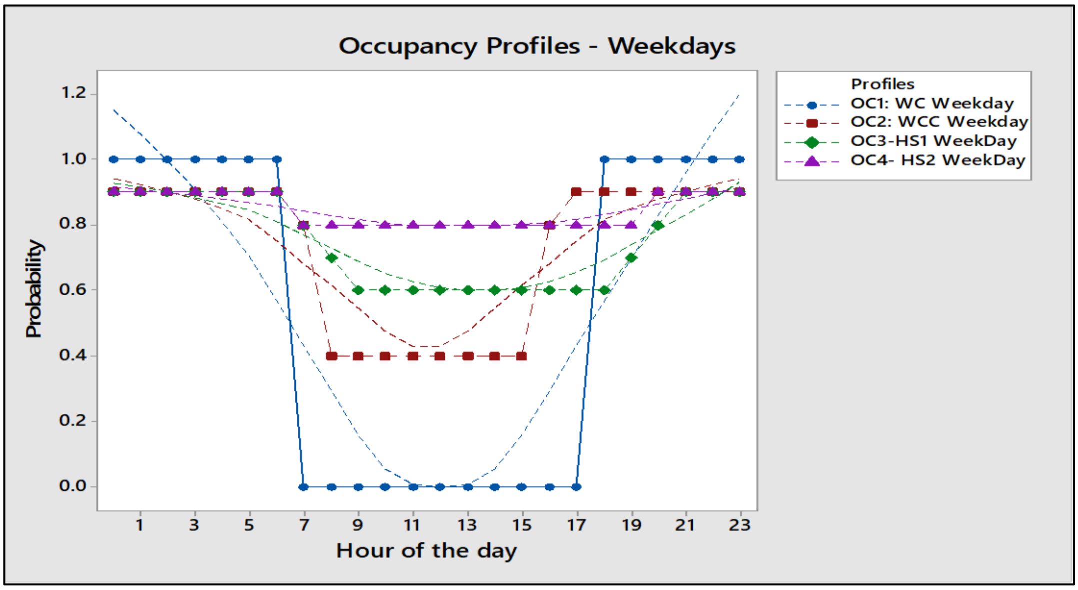


Figure 16: Household Agent



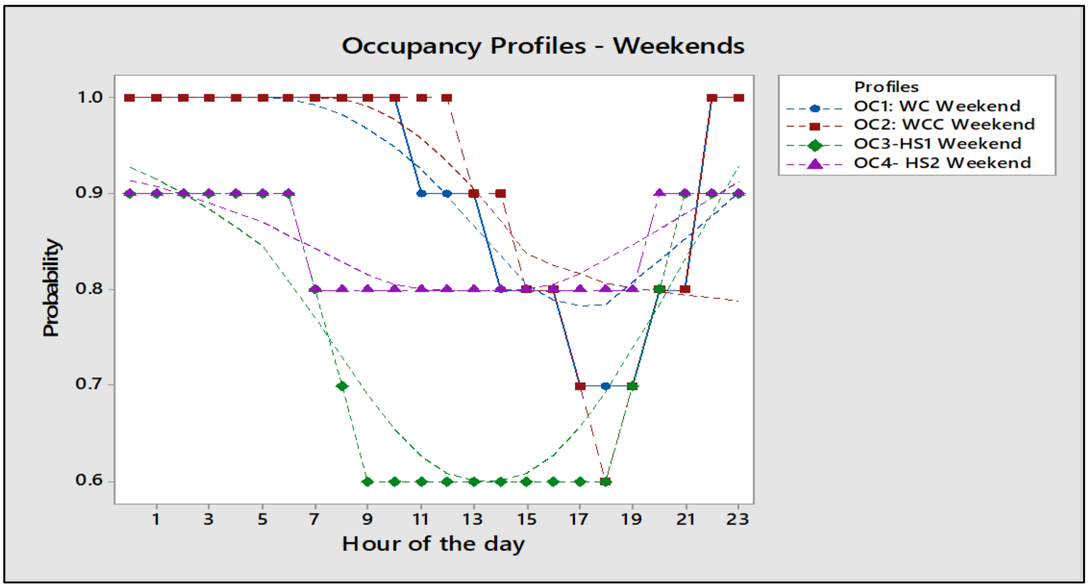


Figure 17: Occupancy Profiles

1.20.3 The behavior of Electrical Appliance Agent

The proposed simulation framework is configured at per minute resolution and control structure of the simulation is implemented using events. All electrical appliance agents respond to time-out triggered events in cyclic fashion. The recurrence time of the events for these appliances is set using time cycles listed in Table 4. A flow chart for the behavior of a device agent is shown in Figure 18. The electrical appliances agents are modeled as passive agents i.e., they possess event-driven reactive behavior. Since the appliance agents are populated under the hierarchy of different house agents. Therefore, a unique behavior pattern for the use of each appliance agent is created using table functions.

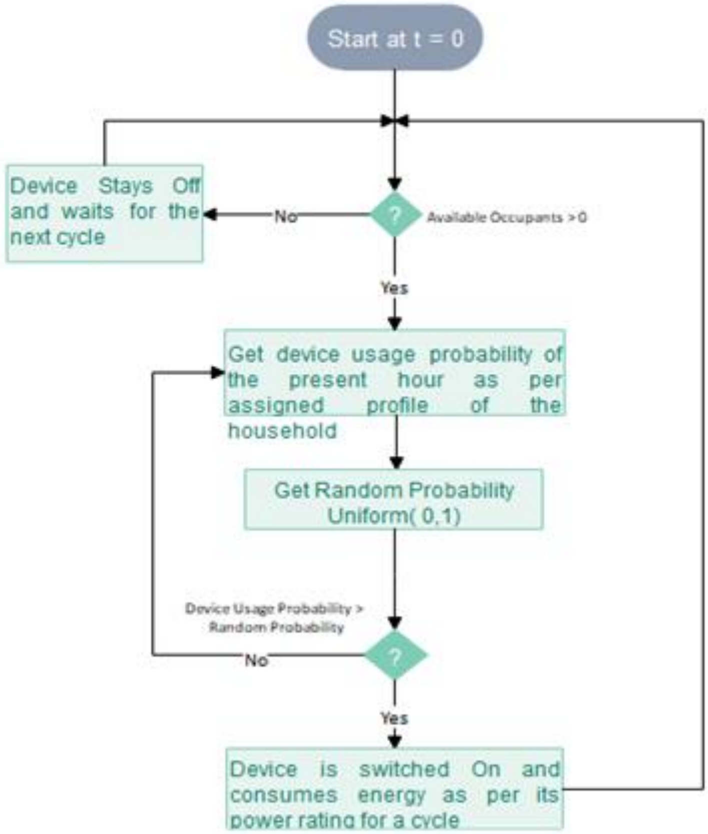


Figure 18: Behaviour of Agent

For every appliance agent, a state chart is created which will indicate the on, and off status and electricity consumption of the appliance according to the states. This behavior can be extended using additional states e.g., 'Stand by' in the case of TV. The transition from 'Off' to 'On' state is initially dependent on the occupancy profile of the household agent. If an occupant is present in the house, a randomly generated number using a *Uniform (0,1)* distribution, is compared with the device usage probability at the corresponding time defined by the table function, shown in Figure 11. If the generated number falls within the probability usage value, the device agent will transit from 'Off' state to 'On' state as shown in Figure 19. And the corresponding wattage will be added in the electricity consumption, i.e., when an agent is switched on, its power will be contributed in the total power of the house agent. The device will remain on until the time cycle of the agent is reached, after which the state-machine will recheck the number of occupants in the house. The higher usage probability will result in a more likely chance for the device to be switched on. Due to the use of *Uniform distribution*, it is possible that not all the agents e.g., all the lights in the house will switch on at once, at a particular time, which makes the model stochastic. The power ratings are instantiated as global constants so that changes in the entire framework can be easily applied. The variability of the power rating is not considered and will be dealt with in future work.

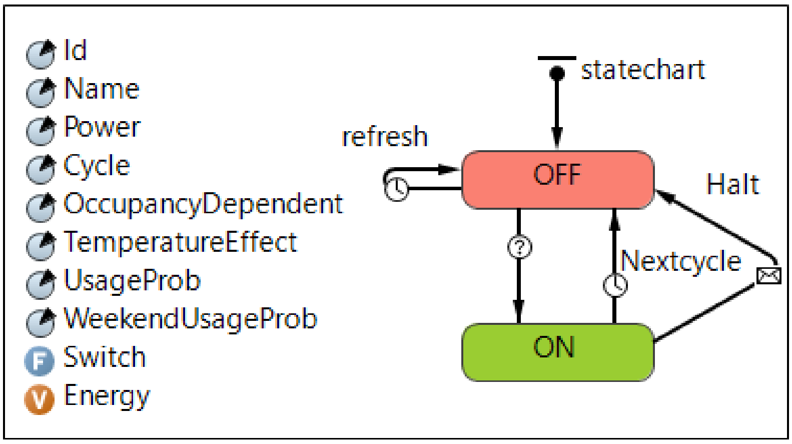


Figure 19: Appliance Agent

1.20.4 Electricity Consumption Calculation

In the proposed framework, the appliance agents are classified into three types: (i) The continuous appliances that run constantly independent of the occupancy profile e.g., refrigerators and freezers; (ii) The appliances that are temperature dependent with on / off states, heavily dependent upon the rise and the fall of the temperature, along with occupancy profile, e.g., fans and air conditioners; and (iii) The appliances that are only dependent upon the occupancy profiles and type of the day i.e., weekday or weekend. The per minute energy consumption for every appliance agent is calculated which is then aggregated for every house and then for all houses using ***Equation 2***

$$E = \sum_{i=1}^{n}\left(\sum_{j=1}^{k}\left(\sum_{t=1}^{24hrs}\begin{cases} N_{rand} < DeviceOnProb_t & Power_A \\ else & 0 \end{cases}\right)\right) \quad (2)$$

Equation 2: *Electricity Consumption Calculations*

Where E_A is the total energy of an appliance during the 24 hours period and is the sum of the electricity consumed by that device during its 'On' state. $Power_A$ is the power rating used for the appliance E_A. N_{rand} is the random number generated using a uniform probability distribution U (0,1) and $DeviceOnProb_t$ is the device usage probability at the time t. k represents the total number of devices in a house and n represents the total number of houses used in the simulation scenario.

1.21 Model Validation and Results

1.21.1 Analysis of Actual Data

We collected actual load data from the Electric Supply Company for 264 domestic consumers, for four different seasons and compared it with the simulation results. The actual load data is for the duration of one year from July 2016 to June 2017 at a resolution of fifteen minutes. The mean season wise load is shown in Figure 20. It can be noticed that consumption in winter is minimum because the fans and ACs are completely switched off. And the thermostats of the fridge and freezers are lowered. In fall there is partial use of fans. In spring there is greater use of fans and partial use of ACs. In summer both fans and ACs are extensively used however the collected data doesn't reflect this, as expected. It was identified that most of the population goes out for vacation in summer.

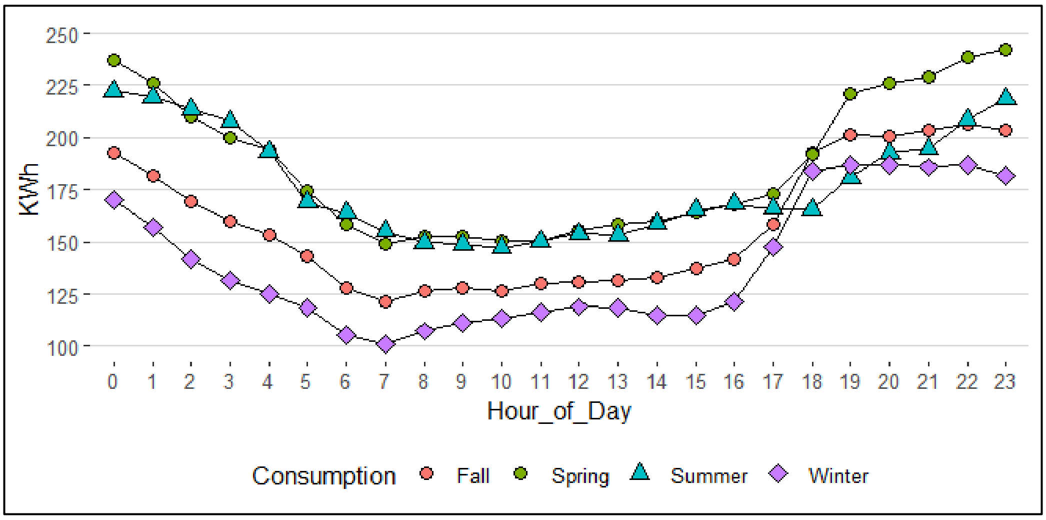


Figure 20: Mean Season Wise Daily Load (KWh)

The box plot of the complete year in Figure 21 is showing a clear trend that consumption at the time from 8:00 a.m. to 3:00 p.m. is lower as compared to other time. The lower consumption at these times can be clearly associated with the working residents. We also examined the correlation between temperature and electricity consumption. Figure 22 shows the scatter plot for the temperature and Load in MW, showing an increase in temperature leads to more electricity consumption. The p-value analysis with co-efficient = 0.37 also confirms the correlation, indicating a positive linear trend.

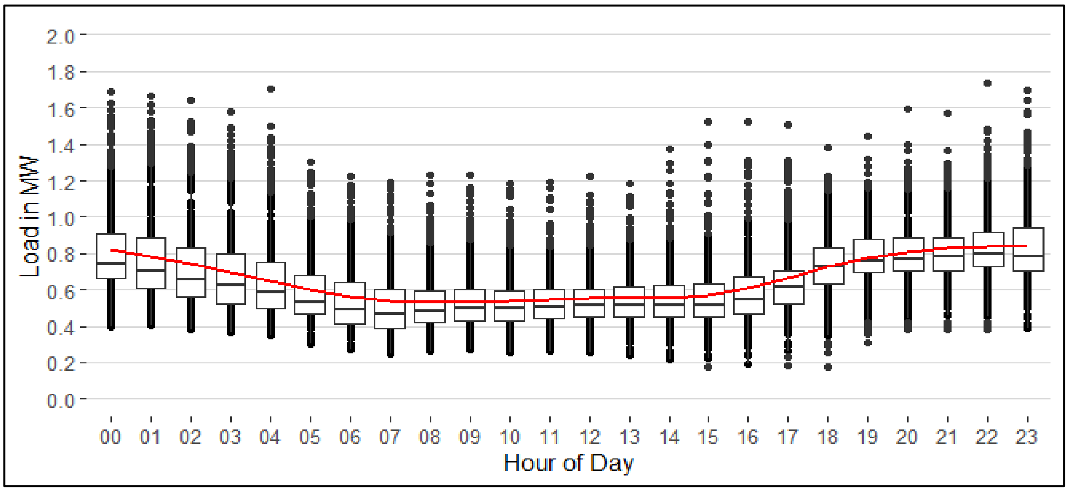


Figure 21: Box Plot of Complete Year Data

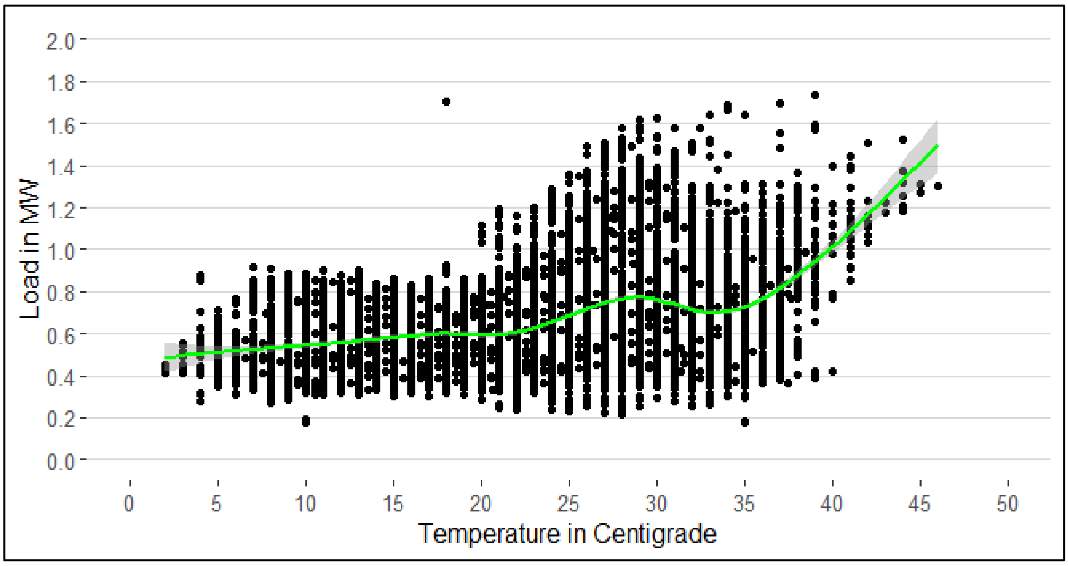
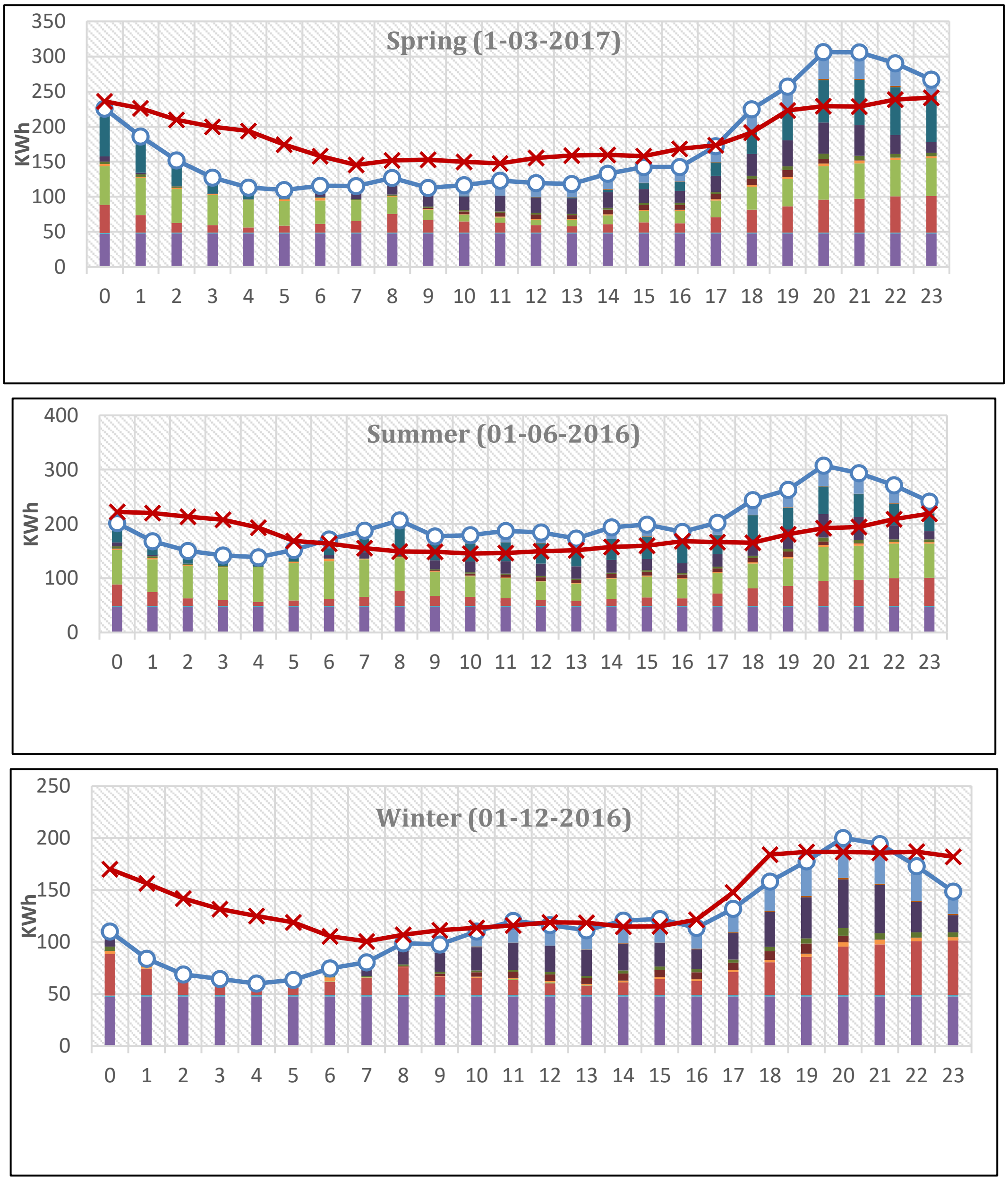


Figure 22: Scatter Plot for Temperature and Load in MW

1.21.2 Simulation Experiment

We ran a simulation experiment of a neighborhood of 264 houses for four different scenarios of four different seasons at per minute resolution. Five iterations of each scenario were run and the average result was compared with the actual consumption. The appliance wise decomposition of electricity consumption for a day of every season is shown in Figure 23.



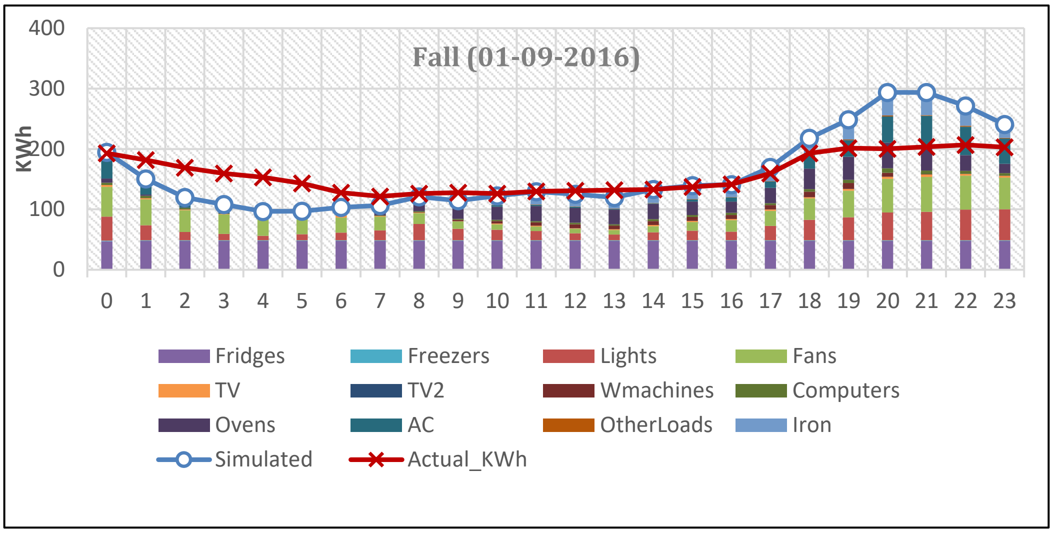
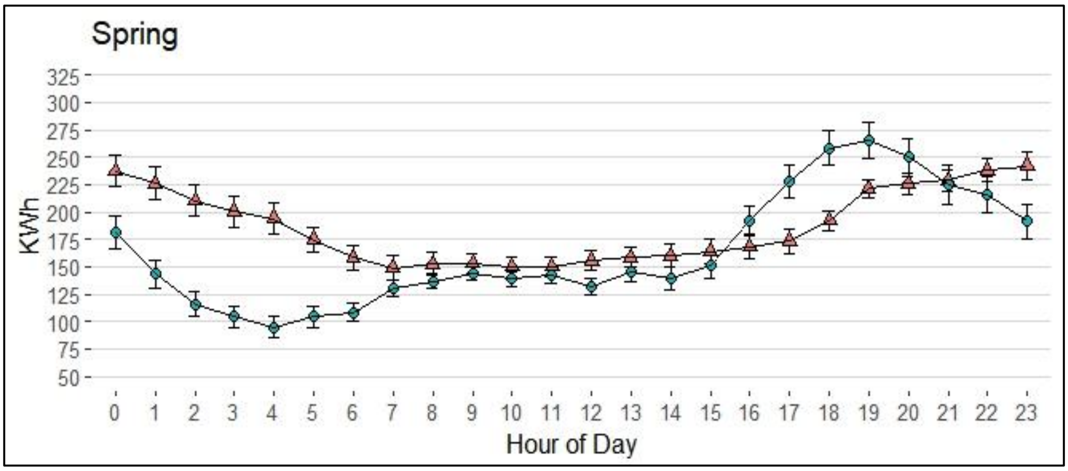
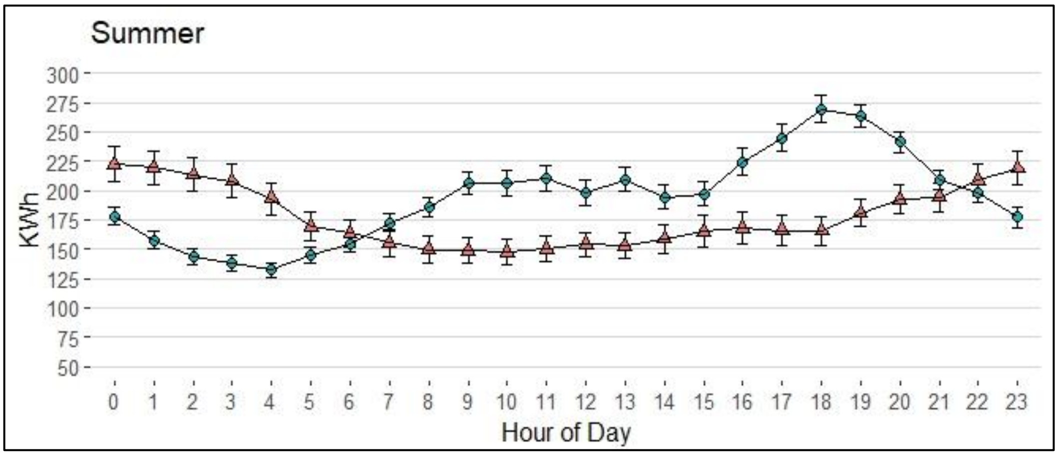


Figure 23: Appliance Wise Electricity Consumption for One Day in each season – 264 Households

The season wise simulations for the whole year was run and comparison of mean simulated load and actual load are shown in Figure 24.





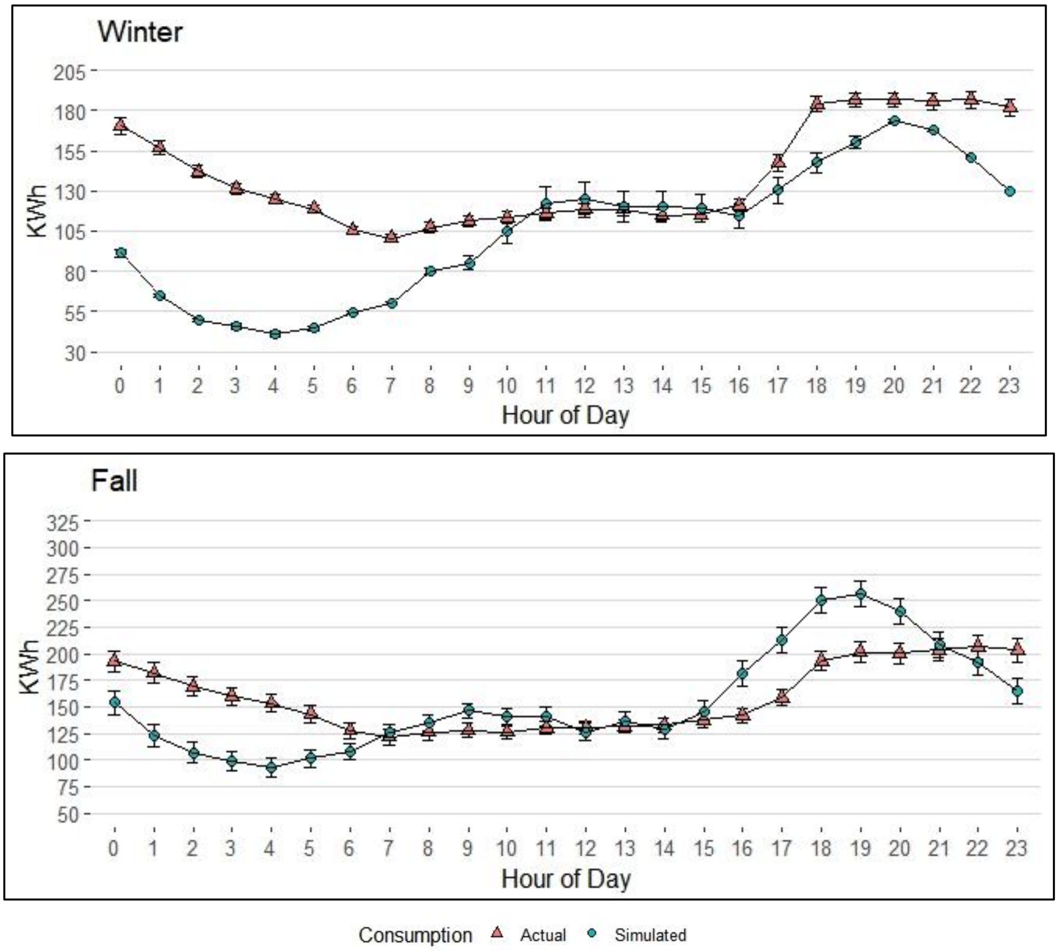
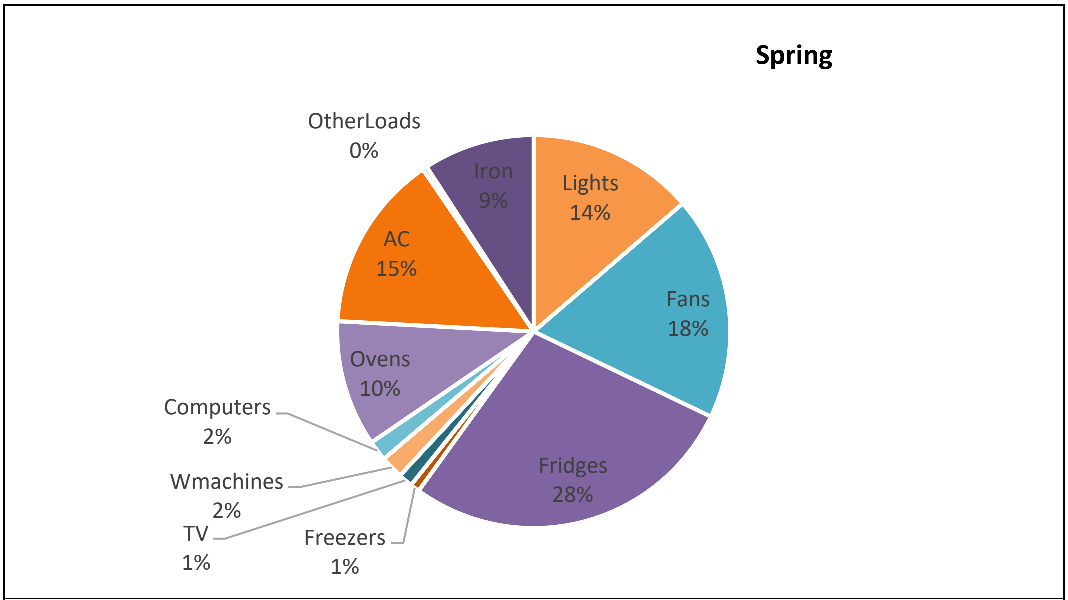
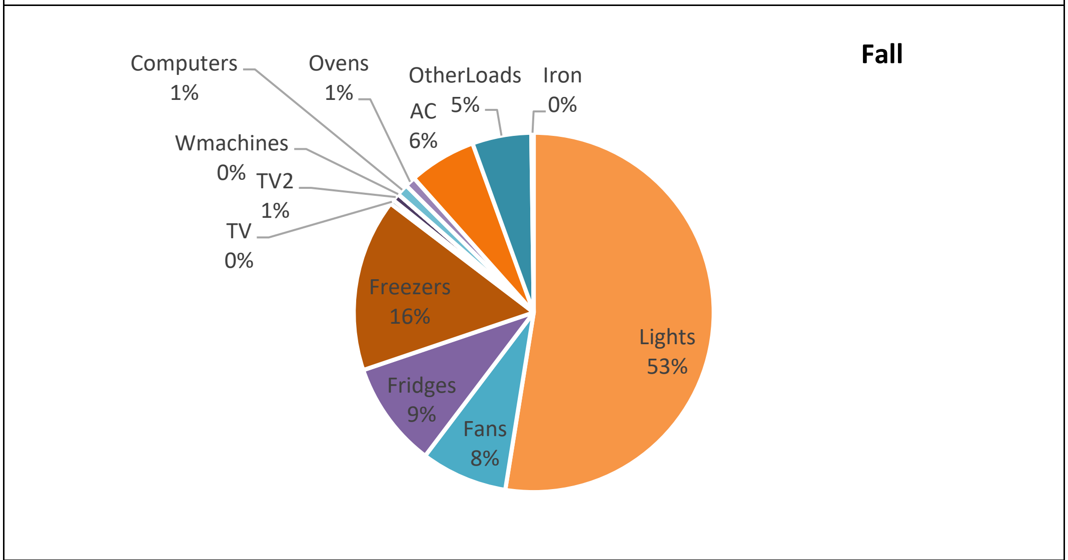
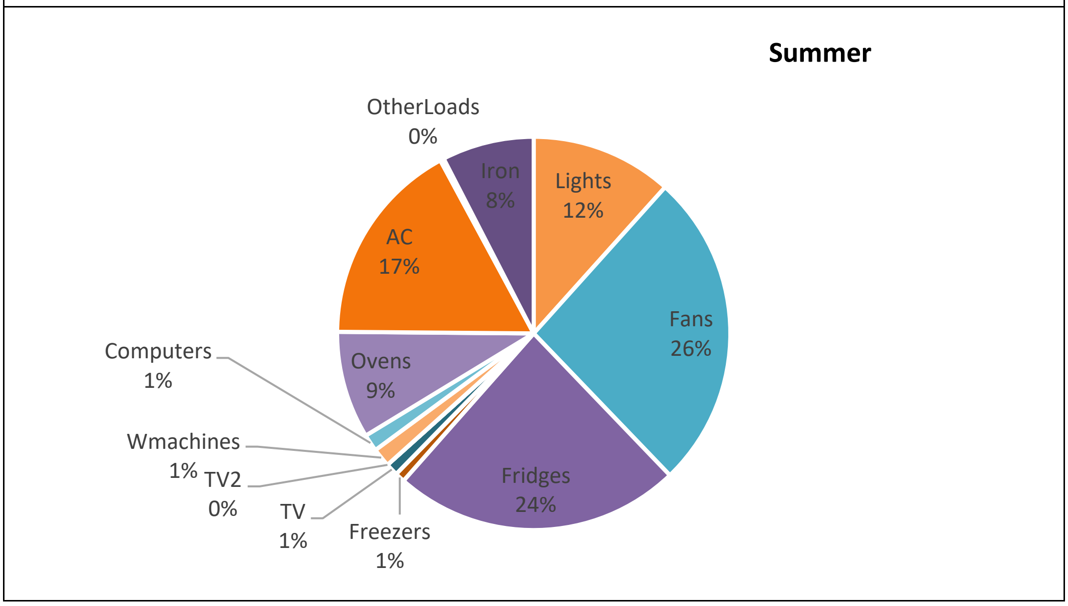


Figure 24: Season Wise Simulated & Actual Consumption – 264 Households

The simulation results for winter season consumption for the duration of 12. a.m. to 5. a.m. is underestimated 50-70KWh by the simulator. For summer season consumption for the duration of 7 a.m. to 7 p.m. is overestimated 17-100 KWh by the simulator. For fall season consumption for the duration of 3 p.m. to 8 p.m. is overestimated 40-60 KWh by the simulator. For spring season duration of 2 a.m. to 5 a.m. underestimated 50-100 KWh and overestimated by 20-67 KWh from 8 p.m. to 11 p.m. The season wise appliance level simulated consumption is shown in **Figure 25** below which clearly showing that for all season, fridges are the electrical appliances that have the share of 9- 41% of total electricity consumption. While for the spring and summer the share of fans and AC constitute 18-26% and 15-17% of total electricity consumption.


Spring
OtherLoads 0%
Iron 9%
Lights 14%
AC 15%
Fans 18%
Ovens 10%
Computers 2%
Fridges 28%
Wmachines 2%
TV 1%
Freezers 1%


Fall
Computers 1%
Ovens 1%
OtherLoads 5%
Iron 0%
AC 6%
Wmachines 0%
TV2 1%
TV 0%
Freezers 16%
Lights 53%
Fridges 9%
Fans 8%


Summer
OtherLoads 0%
Iron 8%
Lights 12%
AC 17%
Fans 26%
Computers 1%
Ovens 9%
Wmachines 1%
TV2 0%
Fridges 24%
TV 1%
Freezers 1%

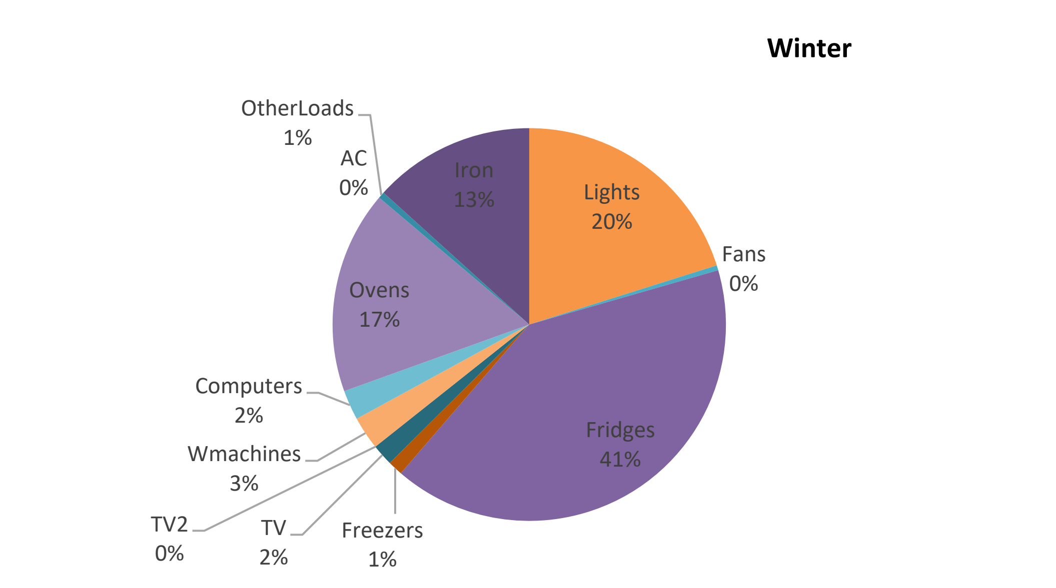


Figure 25: Season Wise Consumption at the appliance

1.21.3 Model Validation and Results

It is quite difficult to perform the validation of Agent-Based Models (ABM), because: (i) ABM are decentralized with no central control; (ii) ABM undergo bottom-up development of the individual entities; and (ii) The behavior in ABM are modeled in different hierarchical layers, e.g., in our case: *Neighborhoods* → *Houses* → *Persons* → *Appliances*. When the ABM is executed, a population of replicated agents is initialized and interact with each other, where we can observe the emergent effect of all the interactions of different entities. Therefore, the aggregated results of the entities, rather than their individual results, are matched with the statistical effect of the whole system [55].

In the domain of electricity consumption, different researches have proposed different measures, to validate the simulated results with the actual load profiles. Fisher et al. [24] used correlation analysis and mean relative error. The correlation analysis is a statistical method used to evaluate the strength of a relationship between two continuous variables, while the Mean Relative Error (MRE) is validation technique, where for each entry a Mean Relative Error (MRE) is computed to calculate the goodness of fit. Shiraki, et al. [27] used root mean square error (RMSE) and mean absolute error (MAE). RMSE is calculated by (i) squaring the residuals, which is the difference between the actual values and the simulated values; (ii) averaging the squares, and (iii) taking the square root. MAE is the average horizontal or vertical distance between two continuous variables of paired observations. Javed, et al. [56] used the three measures of precision, accuracy, and stability. Precision is the measure of closeness of the forecasts with the actual load. Accuracy is the measure of how many correct forecasts are made. Stability is the variance in error. Hong, et al. [57] and Glasgo, et al. [58] referred different worldwide standards such as International Performance Measurement and Verification Protocol (IPMVP), Federal Energy Management Program (FEMP), and American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE). Glasgo, et al. [58] used ASHRAE Guideline 14 for Co-efficient of the variance of the root mean square error CV(RMSE) and relative annual error as a reference value for comparison of Energy Plus Simulation and Actual Pecan Street Home Data collected using energy audit and homeowner survey records. As per ASHRAE Guideline 14; a model is considered calibrated if hourly CV(RMSE) is less than 30% and monthly CV(RMSE) is less than 10%.

Root Mean Square Error (RMSE), Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE%) and Co-efficient of Variance of the Root Mean Square Error CV(RMSE) are calculated by using Equations 3-6 listed in Table 5. The results are showing mean percentage error of all the four seasons lies in the range of 17% to 29 %, however, all the seasons are meeting the ASHRAE's tolerance of 30% CV(RMSE) for hourly values.

$$\boldsymbol{MAD} = \frac{\sum_{t=1}^{n} |A_t - F_t|}{n}$$

Equation 3: *Mean Absolute Deviation (MAD)*

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum_{t=1}^{n} (A_t - F_t)^2}{n}}$$

Equation 4: *Root Mean Square Error (RMSE)*

$$\boldsymbol{MAPE} = \frac{\sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|}{n} \times 100$$

Equation 5: *Mean Absolute Percentage Error (MAPE)*

$$\boldsymbol{CV(RMSE)} = \frac{\sqrt{\frac{\sum_{t=1}^{n} (A_t - F_t)^2}{n-1}}}{\frac{\sum_{t=1}^{n} A_t}{n}} \times 100$$

Equation 6: *Co-efficient of Variance for Root Mean Square Error CV(RMSE)*

Table 5: Validation Results

Season	MAD	RMSE	MAPE %	CV(RMSE) %
Fall	30.11	37.26	18.26	22.55
Winter	24.873	34.763	17.98	24.92
Spring	39.61	50.09	20.56	25.76
Summer	49.13	54.46	28.16	29.37

1.21.4 Analysis

The simulation results show that the model is correctly representing the actual site under observation (i.e., NUST Housing), as the deviation from the actual data in each season is within 30% and is acceptable as per the ASHRAE's criteria. We can observe from Figure 24 that in Fall season simulation has the least deviation. Whereas simulation in summer season is showing highest deviation. It was observed that the simulated consumption is higher in Summer because of the modeled behavior whereas the real data reflects less consumption because most of the families travel during summer vacations. It can also be observed from the simulations of all seasons that there is relatively less consumption during the morning period and higher during evenings and nights, which reflects the behavior commonly observed in working class since the model reflects a typical neighborhood in an urban area of the capital city of Pakistan. The model behavior will vary if we pick a different part in Islamabad, where the saturation of joint families is higher. Moreover, the energy consumption is directly proportional to the increase of temperature, hence Spring and Summer seasons have higher energy consumption as compared to the winter and fall, which is due to the tropical climate of Pakistan. That is why we didn't consider heating devices in colder seasons because the use of electricity for heating in winter is not common. Instead, gas is mostly used. This is also validated as per the results are shown in Figure 24**Error! Reference source not found.**. In the light of the above d iscussion, and our experience in using our framework to simulate electricity consumption of an observing site, we assert that our approach is useful to synthesis household electricity demand profiles. In the absence of smart meters in Pakistan, it provides a low-cost solution to estimate demand and assist in decision support for efficient energy planning.

1.21.5 Models Comparison

In this section we present a feature wise comparison of different ABM frameworks. Pfenninger et al. [59] reviewed different energy systems, optimization models, simulation models and mixed-methods scenarios. They highlighted that the main challenges in these frameworks are the spatio-temporal issues, integration of complex human behavior based on sociologic factors, growing complexity of energy systems, and the balance of uncertainty and transparency. Wiese et al. [60] identified the main challenges for energy system modeling are system complexity, uncertainty quantification, interdisciplinary modeling using appropriate scientific standards. Kriechbaum et al. [61] consider model formulation, spatio-temporal data, stochasticity of the consumers' behaviour and the market stakeholders, as main challenges of the energy system modeling. In our proposed framework, the challenges of spatio-temporal resolution, stochastic nature of consumer's behavior, integration of complex human behavior and sociologic factors, interdisciplinary modeling and scalability are covered, through a hierarchical, multi-scale, multiresolution implementation A comparison of the reviewed models are listed in table below.

Table 6: Model Comparison

Model Type	Source	Model Resolution			Model Scale	Hierarchical	Forecast Range	Exogenous Variables
		Macro Level	Meso Level	Micro Level				
Non-ABM	Paatero and Lund [22]		☒	☑	Large 10,000 households	☑ Two -level Houses-Appliances	Medium Term	social random factor, models the weather and social factors influencing the consumption behavior
	I. Richardson et al [16]	☒	☑	☑	Configurable	☑ Two -level Houses-Appliances	Medium Term	☒
	Chuan and Ukl [17]	☒	☒	☑	Medium 323 houses	☑ Three -level Houses-Type of Houses - Appliances	Medium Term	☒
	Fischer [24]	☒	☑	☑	Small 100	☑ Three -level Houses-Type of Houses - Appliances	Medium Term	Seasonal User patterns is used.
	Wanger [25]	☒	☑	☑	Large 10,000 households	☑ Two -level Houses-Appliances	Medium Term	Season and Weekend/Week Day Consideration
	Bizzozero [26]	☒	☑	☑	Medium 200	☑ Two -level Houses-Appliances	Medium Term	Season and Weekend/Week Day Consideration
	Ahmed. F. Ebrahim [39]	☒	☒	☑	Small 1 Household	☒	Short Term	☒
	Danladi Ali [36]	☑	☒	☒	N/A	☒	Medium Term	Temperature and Humidity Consideration
	Georgios Giasemidis [37]	☒	☑	☒	Small	☒	Medium Term	☒
	Pruckner [20]	☑	☒	☒	N/A Country Level Load Profile	☒	Long Term	Weather and Weekend/Week Day Consideration
	Vitor N. Coelho [35]	☑	☒	☒	N/A	☒	Short Term	Temperature Consideration

ABM	Bustos_Turu [28]	☑	☑	☒	Large	☑	Short Term	Indoor and Outdoor Temperature Consideration
	Zheng [29]	☒	☒	☑	Small 1 Household	☑	Medium Term	Seasonal Effects are considered
	Wang [30]	☒	☒	☑	Small 1 Household	☑ Two -level Houses-Appliances	Short Term	Weather and Building Physical Information Consideration
	Elie Azar [31]	☑	☑	☒	Medium 500 Occupants	☑ Two -level Buildings-Occupants	Short Term	Temperature and Building Physical Information Consideration
	Tao Zhang [21]	☒	☑	☑	Small	☑ Two -level Building-Occupants	Short Term	☒
	Haiyang Lin [32]	☒	☒	☑	Small	☑ Two -level Building-Occupants	Short Term	☒
	Proposed Work	☑	☑	☑	Medium 246 Households	☑ Three levels: Neighborhood - House, Occupants - Appliances	Configurable	Hourly Temperature and Weekday/Weekend Consideration

Conclusion and Future Work

This chapter provides information about the conclusion and future work of the thesis.

1.22 Conclusion

We proposed an agent-based modeling and simulation framework for the estimation of per minute electricity consumption of domestic consumers. We developed a bottom-up model which calculates the per minute electricity consumption of a given number of households, by combining the consumption of major electrical appliances in the household. We currently implemented twelve (12) different types of appliances for four (4) different types of houses, with four (4) types of occupancy patterns. However, the framework is open-ended, and allows the users to (i) add any number of appliances; (ii) modify types of houses with different configurations; and (iii) provides a mechanism to add/modify occupancy patterns. We also incorporated different exogenous variables such as temperature, seasonal variations and the type of days i.e., weekdays, weekends. We presented a case study of 264 domestic consumers using the data of the housing area of the campus, to compare and evaluate the season-wise simulation behavior of our proposed framework with real-world data. The results exhibited a mean absolute percentage error of 17 to 29%, and comply with the ASHRAE's tolerance of 30% CV(RMSE) for hourly values. A correctly implemented and validated, Agent-based simulation framework will support in: (i) Estimation of the future energy demands over a long-range future; (ii) Analysis of the underlying complex dynamic behavior of the population in different conditions; (iii) Behavioral analysis to promote responsible use of energy by incorporating necessary policies; and (iv) Effective planning of the production resources and taking effective decisions for mix strategy electricity generation.

1.23 Future Work

In the future, we planned to extend the model for implementation of demand response strategies to reduce the peak load and analyze critical peak pricing. Furthermore, the model will be validated for appliance level simulation, sensitivity analysis, and application of the optimization techniques to achieve the minimum CV(RMSE) values. Our proposed framework is scale-able and can be configured for a sizeable number of houses to build larger neighborhoods, but requires high performance distributed simulation platforms. 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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