Prediction of an Optimal Energy Usage Pattern Based on Occupant Behavior and Ambient Changes in Academic Buildings: A Case Study

by

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Abstract

The fast economic development and population growth in developing countries is one of the main reasons for the increase in energy consumption worldwide. So, meeting up to the energy demand is becoming strenuous. This study focuses on the energy consumption pattern and prediction of an optimal energy usage pattern of an academic building due to occupant behavior and weather changes. Different energy usage pattern due to occupant behavior and ambient changes is analyzed. An optimal energy usage pattern due to different occupant behavior and weather changes is predicted. Three scenarios (All-on Scenario (current scenario), Random Scenario (proposed scenario) and Sequential Scenario (proposed scenario)) have been considered to analyze different energy usage pattern of appliances in an academic building. Different algorithms such as Exponential Smoothing, Auto-Regressive Moving Average (ARMA) and Auto-Regressive Integrated Moving Average (ARIMA) are used for the prediction. It has been observed that ARIMA has provided relatively better result than the other two. Therefore, ARIMA model is used for prediction of the energy demand for the next six years. The research findings demonstrate that the Sequential Scenario is the optimal energy usage pattern. Simulation result shows that if an academic building uses the Sequential Scenario it can save more than 5 lac taka per year. This study provides a guideline for the university authority as to how they can reduce their power consumption as well as consumption cost.

Chapter 1

Introduction

Bangladesh is a country with huge population. The use of electricity is increasing day by day. Electricity is mostly consumed in the industries, irrigation, households, shopping malls, educational institutions, government and non-government offices etc. To meet the demand of electricity for the huge population, Bangladesh government is trying to increase the capacity to 60,000MW by 2041. Bangladesh government requires US $40 billion investment to increase electricity generation [1]. But nowadays the consumers are using electricity carelessly. As a result, a large amount of energy is wasted. Now it is the top priority to reduce energy consumption and misuse as the demand for energy is ever increasing.

There is evidence in literature that there is a huge difference between predicted and actual energy consumption in buildings. The difference is almost 300% [2]. Reduction in energy consumption means that reduction in operating cost for building owners. It also means reduction in carbon emissions.

1.1 Problem Statement

Buildings (commercial and residential) alone use up to approximately 40% of the total energy consumed annually [3]. Buildings are big energy consumers in modern cities and reducing their energy consumption is essential for sustainable development. If energy pattern of appliances is predicted perfectly the consumption of energy in the building can be reduced [4]. Occupant behavior if considered correctly can also decrease the energy consumption [5].

Summarizing recommendation for policy makers and industry stakeholders are done for developing codes, standards and technologies that can leverage the human dimensions of energy use to reliably predict and achieve energy use reductions in the residential and commercial sectors [6].

1.1.1 Research Gap

Energy is being wasted in buildings (e.g., office buildings, academic buildings, residential buildings, etc.) due to occupant behavior [7]. Besides, analyzing the electrical demand profiles and user activities for a university building can be performed. Identifying gaps in terms of day to day operation of the building certainly has the potential to reduce energy consumption along with installing energy efficient equipment [8] [9].

Analyzing the energy usage patterns due to occupant behavior have not been studied before especially in Bangladesh. Thus this type of study is essential and new in the context of Bangladesh.

1.1.2 Problem Identification

Institutions/academic buildings consume very high energy due to diverse occupancy behavior of the students' movement which can be reflected on the energy consumption datasheet of the institution's electricity substation. To predict this occupant behavior and energy usage pattern this work focuses on how student's occupant behavior can reduce the energy consumption of academic buildings. This energy saving potential of occupant's behavior can be used as a 'tailored advice' for the occupants to help them decide on better energy efficient utilization.

1.1.3 Research Question

For this work two research question is formulated in connection with the problem identification. They are as follows:

Is there any technology to predict optimum energy usage pattern due to occupant behavior?

Is there any analysis for student behavior pattern in the academic building?

1.1.4 Scopes

The research is conducted in buildings, mainly in academic buildings in Bangladesh. The appliances that consume energy in the classrooms of academic buildings are mainly lights, fans, Air-conditioners (ACs), etc. Different occupant behavior lead to different use of appliances and different energy usage pattern can be obtained from the usages of appliances. In this research, some classrooms of Islamic University of Technology are modelled in NetLogo simulation software to obtain the energy usage pattern due to predicted student occupancy (with the help of different class routings) and their usages of appliances.

This study also has some scopes in the energy management of the academic buildings.

1.2 Objective

In line with the research gap, problem identification, research question, and scope the objectives of this study with specific aims are:

- To analyze different energy usage pattern of appliances due to different occupant behavior of students by incorporating students' attendance, class hours, class schedules, ambient changes (winter or summer), etc.
- To predict an optimal energy usage pattern based on occupant behavior and ambient changes in academic buildings for future efficient energy scheduling and energy saving.

1.3 Research Outcome

This work is focused in predicting the proper energy usage pattern in institutional buildings by considering occupant behavior. This study provides two outcome as follows.

- Amount of energy utilization is predicted from the proper energy usage pattern of a building.
- Future monthly/annual bills of energy is predicted and suitable management/scheduling is possible from the proper energy usage pattern of a building.

1.4 Research Significance and Motivation

The study has significance in broadening research and empirical knowledge about the energy consumption in an academic building. The contribution falls into three categories.

First, this study contributes to the literature in developing a new model on the basis of agent-based model by considering, occupant behavior like students attendance, class hours, class schedules, and ambient changes (winter or summer) to examine the proper energy usage pattern of a building.

Second, this study provides some guidelines to the university authority on energy management as to how they can reduce their power consumption in the academic building as well as consumption cost.

Third, this study highlights the crucial role that academic buildings can play in reducing the energy consumption at the academic buildings.

1.5 Research Methodology

The purpose of this study is to find the energy consumption pattern and predict an optimal energy expenditure pattern of an academic building. Due to different occupant behavior energy consumption pattern can differ for the same building. So, this study finds how occupant behavior can lower the energy consumption of academic buildings. Moreover, energy consumption prediction is also important for power plants planning activity. Therefore, a Agent Based Model model is developed to measure the energy consumption due to occupant behavior in academic buildings. Time Series Analysis models (Exponential Smoothing, ARMA and ARIMA) are used for prediction of individual building energy consumption. Islamic University of Technology (IUT) has been selected as the context of this research and the behavior of students of IUT is considered as occupants. Occupancy data is collected from the Department of Electrical and Electronics Engineering (EEE) of IUT.

1.6 Organization of the thesis

This thesis is developed through seven chapters providing details of the theoretical background of the research, data source, analysis and interpretation of the findings, conclusion and implication of the research.

Following this introduction, chapter 2 reviews the literature which covers the study of energy consumption in buildings, such as, why occupant behavior is important, influencing factors of energy prediction and prediction methods.

Chapter 3 provides overviews of the proposed model.

Chapter 4 represents the research methodology for the simulation model of this study and adds the detailed information on agent based simulation model of this research.

Chapter 5 illustrates the data analysis methodology of the research.

Results and discussion are reported in chapter 6 using data analysis methodology described in chapter 5.

Finally, chapter 7 concludes the work with an overview and implications for management. Limitations of the study are also discussed and recommendations for further research are presented in this chapter.

Chapter 2

Literature Review and Related Works

This chapter briefly goes through the background and literature review on the energy consumption in buildings.

2.1 Energy Consumption in Buildings

Energy consumption worldwide is on the increase. This is due to population growth, rising living standards, urbanization and industrialization of the countries. Among the different sectors of energy consumption almost 30% to 40% of global energy use is consumed by buildings (commercial and residential) [10, 11]. During the life cycle of a building, the building consumes 80% of energy when occupants are present and using the building [12]. So almost 20% of energy is consumed when the building is unoccupied.

Buildings use large amounts of energy in modern cities and decreasing their energy use is absolutely necessary for sustainable development. Also decreasing energy consumption means a decrease in operating cost for building owners. It also means a decrease in carbon emissions [7]. As it is evident that carbon emissions lead to global warming which can be a threat to humankind. Increasing number of droughts, flooding of low lying lands, food shortages are some of the consequences of global warming.

Moreover, in commercial buildings, approximately 56% of energy is used during non-working hours while 44% of energy is used during working hours which is regarded as being caused by occupancy related actions [12]. As from the previous literature it can be seen that more energy is being used during the non-working hours of an office building than during the normal working hours. Whereas this should not be the case. A study, studied equipment energy usage at non-working hours in the United States of many commercial buildings and analyzed that the occupants did not turn off almost 50% of the equipment during the unoccupied hours [12]. This trend can be changed in many ways for example, providing campaigns for energy conservation or incentives that inspire occupants to reduce their energy consumption [12].

2.2 Energy Consumption in Academic buildings

Buildings presents a complex socio-technical system that links society, occupants and the environment [13]. Institutions/academic buildings consume very high energy due to diverse occupancy behavior of the students' movement which can be reflected on the energy consumption datasheet of the institution's electricity substation. To predict this occupant behavior and energy usage pattern this study focus on how student's occupant behavior can lower the energy consumption of academic buildings. This energy saving potential of occupant's behavior can be used as a 'tailored advice' for the occupants to help them decide on better energy efficient utilization.

A study [8] analyzed the key trends and patterns in energy use in a multi-purpose academic building. From the analysis it was found that the building was controlled by a building management system (BMS) and the occupants did not have access to the controls which lead the building to consume more energy than required.

2.3 Occupant Behavior

Occupant behavior in the literature is defined in many different ways. It is not well understood due to its vague, varying, compound and multidisciplinary nature [14]. In simple terms occupant behavior imply to how occupants act in a certain environment [7].

To measure and quantify occupant behavior physical sensing and non-physical sensing are used. Physical sensing is obtained by (1) smart metering and building data, (2) Indoor and Outdoor environmental data, (3) Occupant's interaction with the control system [15]. While non-physical sensing is acquired by (1) Occupancy data and (2) Survey questionnaires [16, 17]. There are some drawbacks of physical sensing method as it uses sensing device having high initial installation costs, maintenance cost, operation cost, and it is difficult to install. On the other hand non-physical sensing method is easier to obtain without any associated costs. This paper attain occupant behavior through non-physical sensing method by acquiring occupancy data.

2.3.1 Energy Consumption due to Occupant Behavior

Buildings do not consume energy occupants do because of the behavior to adjust the indoor environment to their comfort level [18]. Occupant profile leads to different energy consumption patterns. In a study of occupancy and behavior patterns in an open-plan office building it is found that occupants with a “wasteful” work style used double the energy than the non-wasteful occupants, and the “austere” work style occupants used half of the energy [19]. So it is important to find the energy-related occupant behavior.

In a previous study it states that human behavior such as age, behavior, and the number of occupants must be taken into account when performing energy simulations. Existing occupancy data if used gives misleading results which creates the gap between actual and simulated consumption rates. The study used DesignBuilder in the EnergyPlus program to build the geometry of the building [20]. This paper uses agent based model to build the classrooms.

In the literature lighting loads was modelled in residential buildings using occupancy and total lighting load demand [21]. The data was obtained from sub-meters in the building and the occupancy data was obtained from a short survey of occupant’s routine. It was found that occupant behavior is the reason for the change in lighting demand. In this paper occupancy data is obtained through class routine.

Two distinct categories of energy-related occupant behavior are: (1) adaptive actions [22], and (2) non-adaptive actions [23]. Adaptive actions refers to the occupants change in behavior to adapt the environment to their needs e.g. turning lighting on/off, opening/closing windows etc. Adaptive behavior also refers to occupant changes to adapt themselves to the environment e.g. clothing adjustment, drinking hot/cold beverage etc. Non-adaptive behaviors is the indirect behavior of occupants to adapt to the environment e.g. occupant presence, and operation of plug-in and equipment. This research have used the non-adaptive behaviors of occupants by collecting the occupant’s presence data. Then Agent Based Model (ABM) is developed for modelling occupant behavior and ultimately finding the energy consumption.

2.4 Importance of Energy Prediction

Energy is an essential element for economic growth and development of a country. In the literature energy prediction is also widely known as load forecasting. Energy forecast is created to predict the future energy demand based on previous energy consumption [24].

Forecasting errors causes an increase in operational cost [25]. International Energy Agency (IEA) [26] shows that developing countries are anticipated to encounter large energy demand between 2017 and 2040. Energy consumption prediction models are therefore gaining rapid importance for power plants planning activity. As many sectors use energy, buildings consume almost 36 percent of total energy consumption worldwide [11]. Load forecasting also provides owners and facility managers targets on the overall building energy consumption rate [27]. For this reason prediction of individual building energy consumption is crucial for achieving sustainability.

Load forecasting is divided into three different categories, based on its forecasting timeframe: short term forecasting, medium term forecasting and long term forecasting. Short-term forecasting is defined as predictions from one hour up to a week [11]. Medium term forecasting ranges from one month up to a year. And long term prediction are more than 1 year. This study focuses on the prediction of an optimum energy usage pattern in academic buildings. In addition, this work will provide medium term prediction of energy consumption up to a year, which will provide suitable management and scheduling of academic building.

2.5 Energy Prediction and Influencing Factors

Energy consumption load data has different patterns classified as horizontal, seasonal, trend and cyclic [27]. Horizontal pattern of a load data is that there is no variation with respect to time which is also called "stationary" data. A seasonal pattern in a load data is viewed as having a change according to week, month or year and is often the result of weather. A load data showing a trend is regarded as being "non-stationary" and has either an increasing or decreasing variation with time. A load having a cyclic pattern is considered as having seasonal trend but the repeating time span is not congruous with time and is not predictable.

Energy forecasting is arduous because the future is complex and is subject to change due to various factors [25]. Factors influencing forecasting are socio-economic factors, environmental factors, and time-index factors.

2.5.1 Socio-economic Factors

Social economic factors are the socio-economic situation of the region [25,28]. Factors include local populations or demographics, different feature of the appliance in use, population activities, and gross domestic products. It is notable that these factors take a long time to have an effect on load. And as this work is focusing on medium term load forecasting these factors does not need to be included in this study.

2.5.2 Environmental Factors

Environmental factors are the factors relating to weather condition. The most important weather condition is temperature to have an influence on load forecasting [25]. In hot summer weather the consumption is much higher due to the use of AC's for cooling. The influence of temperature changes with zone, climate and occupant behavior. Relative humidity is also another part of environmental factor that has an effect on electricity consumption [29]. There are also other indicators such as wind, solar irradiance, and thunderstorm but they are less seen in literature. In this study, weather seasons are taken into account.

2.5.3 Time-Index Factors

As mentioned before, the load consumption data has variations with time. In literature time factors are seasonal, daily, weekly and occasions (holidays) [29]. Day light hours also effect energy consumption. The weekly revolution Monday to Friday shows the working hours of the occupants. This leads power demand to increase on weekdays than on weekends. Special occasions or on holidays power demand changes. Starting of weekday or starting of semester can lead to more power consumption.

2.6 Forecasting Methods

The literature contains different categories of prediction methods for different time horizons. In the related literature for forecasting electricity demand methods used are moving average, regression, time series methods, artificial neural network, support vector regression, grey models etc. Each of the models are unique and none of them outperforms the other [25]. Therefore finding the most appropriate model is meaningless. There are also other models named "hybrid dynamic" models these are beyond the scope of this study

2.6.1 Time Series Analysis

A sequence of values noted over equal periods of time is known as a time series [27]. Among the time series methods autoregressive integrated moving average (ARIMA) is the most commonly employed forecasting method used to forecast future values of load consumption. ARIMA model was first proposed by Box and Jenkins in 1970 [30]. In ARIMA model independent variables are not needed. The data uses its past values to predict the future.

Exponential smoothing was proposed in the late 1950s (Brown, 1959; Holt, 1957;

Winters, 1960) [24], is one of the successful forecasting methods. Exponentially smoothed forecasts are weighted averages of previous observations, with the weights declining exponentially as the measurements get older. In other words, the larger the related weight, the more recent the observation. This framework produces credible predictions fast and for a wide range of time series, which is a significant benefit and critical to applications.

The ARMA model, developed by Box and Jenkins (1970) [36] using the time series analysis method, ignores the role of explanatory variables related to economic or financial theory and instead relies on the estimation mechanism, which is based on the altering law of the time series itself, in the description of the time series. The development of a time series model was motivated by the fact that the time series is stationary. A moving average (MA) model and an autoregressive (AR) model comprise an ARMA process. ARMA models provide the most powerful linear model of time series data when compared to pure AR and MA models since they can model the unknown process with the fewest parameters.

ARIMA is a widely used forecasting method in many domains of work. ARIMA model was used by Sharmin and Khan [31] to forecast the natural gas production in Bangladesh. Ohyver and Pudjihastuti (2018) [32] used ARIMA to forecast the price of medium quality rice in Indonesia. Amini et al. (2015) [33] employed ARIMA model for forecasting electricity demand in EV parking lots'. This paper uses ARIMA model to forecast the power consumption of an academic building.

In the literature there are also several different studies that focus on the prediction for the electricity demand in different regions or countries using time series analysis such as ARIMA method. Some of the related works are given below.

Kandananond (2011) [28] in the paper utilized several forecasting methods, namely autoregressive integrated moving average (ARIMA), artificial neural network (ANN) and multiple linear regression (MLR) to produce model of prediction for the electricity demand in Thailand. The three model performance of the methods was compared. The study used historical energy usage data such as population, gross domestic product (GDP), stock index, revenue from export and electricity consumption from 1986 to 2010. The paired test showed that the methods had no such difference. Both the ARIMA and MLR are more preferred than the ANN because of its uncomplicated form and fast execution.

In 2019, Divina et al. wrote a paper [11] which analyzed and compared different statistical and ML based forecasting strategies of smart buildings. The methods used were linear regression (LR), autoregressive integrated moving average (ARIMA), evolutionary algorithms (EAs) for regression trees (EVTree), generalized algorith regression models (GBM), artificial neural networks (ANN), random forests (RF), ensemble, recursive partitioning and regression trees (RPart), and extreme gradient boosting (XGBoost). The data used was time series data obtained by sensors installed in 13 academic buildings in the South of Spain. The data used in this work enclose daily electric energy consumption in KWh which span from 1 March 2012 to 31 October 2017. The data collected contained missing values which was filled by a way of a linear regression method. ARIMA was found to be the worst performing methods. While the Random Forests (RF) method gave the best result. Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values were used to evaluate the performance of the various strategies used.

Sen et al. (2016) [34] forecasted power consumption and greenhouse gas emission using ARIMA method of a pig iron manufacturing organization. The raw data consisted of 144 data points of monthly energy consumption and greenhouse emission from 2002 to 2013. The paper presented best models for the two data namely power consumption and greenhouse gas emission. However the residual graphs for both the data did not show the precise nature of white noise. Which may be the cause of high unpredictability nature of the original datasets. From the study it was found that ARIMA is best for short term forecasting.

In another paper [24] in 2016, Hussain et al. aimed at forecasting total and portion wise electricity consumption in Pakistan. The paper employed Holt-Winter and ARIMA model on time series data ranging from 1980 to 2011. The forecasting is done in component wise i.e. electricity used in traction, household, commercial, industrial, agriculture, streetlight etc.

Rallapalli and Ghosh (2012) [35] utilized a new version of ARIMA model named Multiplicative Seasonal Autoregressive Integrated Moving Average (MSARIMA) model to forecast the electricity demand in India. The MSARIMA model takes care of the seasonal effect, uncertainty, randomness and non-stationarity. Central Electricity Authority (CEA) performs load forecasting officially in India which is usually condemned for being overestimated. The trend method for forecasting is used in Central Electricity Authority CEA which is regarded as an inferior method. The results of comparing the two methods shows that the MSARIMA model is more efficient.

Erdogdu (2007) [36] estimated electricity demand model in Turkey. They have also provided forecast for 10 years and the results was compared with official projections. The data acquired was quarterly time series data of real electricity prices, real GDP per capita, and net electricity consumption per capita. Cointegration analysis was used to examine the data properties. The forecasting was carried out by using the Box-Jenkins autoregressive integrated moving average (ARIMA) model.

2.7 Summary of the Chapter

The literature reviewed in this section leads to some major conclusions regarding reduction of energy consumption in the academic buildings.

First, buildings use large amounts of energy in modern cities and decreasing their energy use is absolutely necessary for sustainable development. Educational institutes/academic buildings also consume very high energy due to diverse occupancy behavior of the students (occupants) movements. To measure and quantify occupant behavior physical sensing and non-physical sensing methods are usually used in the previous studies. Non-physical sensing method is easier to obtain without any associated costs. In literature, another two distinct categories of energy related occupant behavior are 1. Adaptive actions and 2. Non-adaptive actions. Non-adaptive behavior is the indirect behavior of occupants to adapt to the environment. It is evident from the literature that differences in occupant behavior cause the differences in predicted and actual energy consumption in buildings. So, occupant behavior is a very important component to consider when finding the overall energy usage pattern.

Second, prediction of individual building energy consumption is crucial for achieving sustainability. Energy prediction or load forecasting is created to predict the future energy demand on previous energy consumption. In the literature usually time series analysis Exponential Smoothing, ARMA and ARIMA have been used extensively in many fields. Also it is simple and has an efficient performance.

Therefore, this study has been designed to 1) analyze different energy usage pattern of appliances due to different occupant behavior of students by incorporating students' attendance, class hours, class schedules, ambient changes (winter or summer), etc., and 2) predict an optimal energy usage pattern based on occupant behavior and ambient changes in academic buildings for future efficient energy scheduling and energy saving.

In the next chapters, a model is developed on the basis of agent based model to measure the energy/power consumption due to occupant behavior and Time Series Analysis (ARIMA) is used for prediction of individual building energy consumption.

Chapter 3

Proposed Model

This work is to study the energy usage pattern of academic buildings in Bangladesh. In Bangladesh academic institutions are on the increase and thus finding the energy consumption pattern in these buildings is essential. This chapter will talk about the different attributes of the proposed model.

3.1 Different Attributes of Proposed Model

The different attributes are the conditions for which the model varies. Thus they are important for the model. The next subsections looks into the attributes.

3.1.1 Different Type of Academic Institution

A total of 92 academic institutions are present in Bangladesh. The academic institutions in Bangladesh are of two types: the public institutions and the private institutions. The public institutions are funded by the governments. While private universities are funded by the private sector. Among the universities, 37 are public institutions and the rest is private.

The main buildings in an institution are the admin buildings, the classroom buildings, the cafeteria building, and the library building. All public universities also have dormitories for the students to stay. Many private and public universities have gymnastics. Universities also have an auditorium, boys and girls lounge, mosque, etc.

Universities have different Faculties within which there are different departments. Examples of different faculties are faculty of science, faculty of arts, faculty of business studies, faculty of engineering and technology, etc. The different departments are Economics, Marketing, Chemistry, Biology, Physics, Mathematics, Sociology, and Political Science to name a few.

Academic buildings have different classes such as theory classrooms where theory classes take place. Hardware and software laboratory classrooms are also present. Academic buildings furthermore consist of big examination halls for student assessments. All these rooms and buildings contain energy consuming appliances that consume power.

3.1.2 Different Type of Energy Consuming Appliances

The energy-consuming appliances in the different buildings of a university are lights, fans, air-conditioners (ACs), etc. Almost all the buildings use lights. In the library building, fans or ACs are used for the cooling. Computers are also present. Students also bring their laptops and thus charging sockets are present. In the cafeteria kitchen, there is a fridge to store the foods, in kitchens an electric stove is also used. Blender, oven, coffee, and tea maker is also employed.

The energy-consuming appliances in the classroom are fans and lights. Universities also have Air-Conditioners (ACs), Computers, projectors, etc. Each of these appliances consumes some amount of energy. For example, lights consume about 10 to 25 watts per hour according to the type of light applied. Fans range in size from 36 inches to 56 inches using 55 to 100 Watts, a typical 48-inch ceiling fan uses 75 watts. The power consumption of ACs range from 3000 to 7000 Watt depending on the amount of ton used. The Figure 3.1 shows different energy consumption pattern results from using various energy consuming appliances.

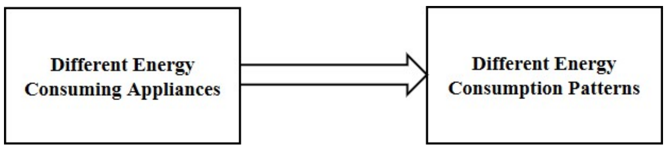

Figure 3.1: Energy consuming appliances lead to different energy consumption patterns.

3.1.3 Occupant Behavior

Human activities and behavior of occupants are the factors that lead to the occupant behavior of a building. Occupant behavior is a very important component to consider when finding the overall energy usage pattern. Differences in occupant behavior cause the differences in predicted and actual energy consumption in buildings.

Occupant behavior is different for different types of buildings e.g. it is different for residential buildings, commercial buildings, and academic buildings. As this work is focused on finding the energy consumption of academic buildings, this work considers the behavior of students and staff.

The officers that are present in the administrative and departmental buildings usually have to stay in their offices during office hours from 9 am to 5 pm. Officers have different behaviors as some of them are very serious about their job and stay in their rooms. While others are less serious and often have a propensity of going out of the office.

Different students behave in different ways. Some students incline to come late in the class while others come on time. Some students sit at the back even though the front seats are empty. Others like to sit alone in one corner without anyone besides them. Thus the various sitting arrangements are crucial to consider as this leads to the change in power consumption as shown in Figure 3.2.

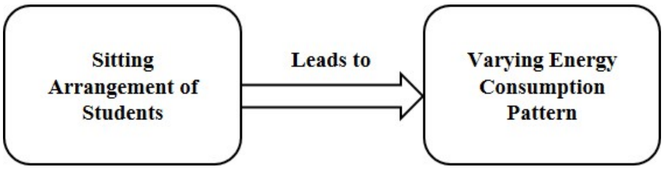

Figure 3.2: Student sitting arrangement resulting varying energy consumption.

3.1.4 Different Type of Weather Seasons

Climate condition is a major aspect to consider when studying the energy consumption pattern of academic buildings. In most regions, the weather is divided into four seasons: Spring, Summer, Fall, and Winter. Different countries have different temperatures in these seasons. For example, spring temperature varies from 21 degree Celsius in Florida to a low of -4.1 degree Celsius in Alaska. Summer usually has the hottest temperature in most regions. Autumn marks the transition from summer to winter. The temperature cools down from the hot summer in autumn. Then the winter comes with the cold air.

In academic buildings, air-conditioners along with fans are usually used in the summer periods when the air temperature is high. In the winter period, air-conditioners and fans are not used. In the fall and spring period, air-conditioners are sometimes used and sometimes not used. In all the seasons the use of light is usually not changed. Figure 3.3 shows varying weather seasons result in different energy expenditure.

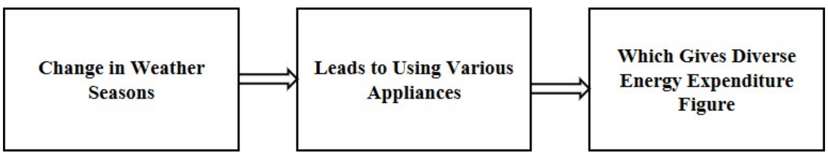

Figure 3.3: Varying weather seasons result in diverse energy expenditure.

3.1.5 Different Type of Class Schedules

The class schedule refers to a list of times on a day a specific class is held. It also shows the classes offered and course description. Room wise class schedules are the most common. The individual class schedule gives an insight of the times the room is busy, leading to the use of electrical appliances during that time.

Different rooms have different schedules. Some rooms have a single class, while others have classes the whole day without any breaks. Also, the class schedule changes for each day. Some days of the week are also off days or weekends when no class is scheduled. Between consecutive classes the amount of break is found. Lunch and prayer break is similarly noted.

In each class the number of students attending is different. Some classes accommodate a lesser number of students than others.

3.2 A Case Study for IUT

The academic institution that is selected for the study is Islamic University of Technology (IUT). Islamic University of Technology (IUT) is an international university located in the outskirts of Dhaka in Bangladesh. Like most universities, IUT has dormitories for student residence. It also has a cafeteria, a library, a mosque, a lounge etc.

Classrooms of Electrical and Electronics Engineering (EEE) department of IUT are considered for this study. The attributes that have been discussed in the previous section have been applied to the classrooms. Each room has different class routines and different energy consuming appliances. Similarly, each academic year has two semesters. In the two semesters there are three weather seasons: summer, monsoon and winter. All of this attributes are incorporated in the model.

Chapter 4

Methodology: Simulation Model

Analyzing different energy usage patterns of appliances in academic buildings is crucial in order to reduce energy consumption in the buildings. To accomplish this, one academic building of Bangladesh is considered to gain an overall view of energy consumption in this sector. This chapter discusses the different characteristics of the model and how data is collected. In the end, what type of scenarios have been considered for the Agent-Based model simulation has been shown.

4.1 Process

The goal in this study is to find the energy usage pattern of academic institutions. The steps involved to achieve the goal are as follows:

- Data Collection
- Simulation
- Energy Prediction

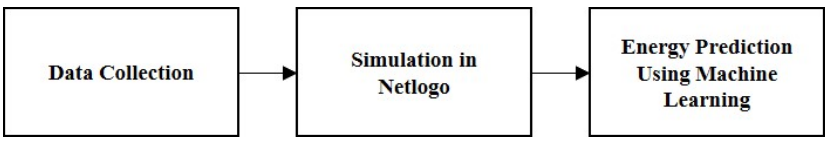

Figure 4.1: Prediction process of energy consumption pattern.

This process is discussed in details in this and next methodology: data analysis chapter.

4.2 Occupant Behavior Characteristics

The occupant behavior considered in this study is the behavior of students in the classroom. In a classroom there are three different occupant behavior patterns these are

1. occupant entry pattern 2. sitting choice pattern and 3. occupant switch ON/OFF pattern.

4.2.1 Occupant Entry Pattern

Occupant entry pattern is how the students enter the classroom or at what times the students enter. Students can enter at random times which is called randomly or they can enter sequentially which is at every minute or every few minutes. But in real world occupant entry time is usually random. So the students actually enter in a random manner.

4.2.2 Sitting Choice Pattern

The sitting choice pattern is the pattern of how the student sit on a seat. There are two type of sitting pattern such as students sit in a random manner or they sit in a sequential manner. Both of the sitting choice pattern has been considered in this study.

4.2.3 Occupant Switching ON/OFF Pattern

The occupant switching pattern is how the occupant turn the appliances on. All the appliances are turned on from the beginning of the class when the first few student enters. This is the real world scenario. The occupants' turn on the appliances when they enter is another occupant switching pattern. The appliances turn on according to the sitting pattern and the switching pattern is automated which is another switching pattern.

4.3 Switching Characteristics

Switching characteristics is explained by the ON/OFF characteristics of the appliances. This characteristics is very important because it is directly connected to the energy consumption pattern. The appliances can be switched on from the morning. The appliances can be switched on when an occupant enters.

4.4 Weather Characteristics

Weather characteristics defines how the outside weather changes and accordingly the appliances that are used are changed. For example if the outside weather is hot, the use of ACs will be high. While, if the outside weather is cold ACs and fans might not be used at all. On the other hand if it rains outside ACs might not be used.

4.5 Data Collection from IUT

Classrooms of the Electrical and Electronics Engineering (EEE) department of the Islamic University of Technology (IUT) are considered for the study. The class schedule per day of the rooms are obtained from the department to study the energy usage pattern. There are a total of 6 classrooms, rooms 201, 202, 203, 509, 511, and 604. In these 6 rooms, the electrical classes take place. The rooms 201,202 and 203 are large rooms with 60 seats each. Whereas the rooms 509, 511, and 604 are smaller rooms with 36 seats each.

4.6 Analysis of Class Routine

The class hour and lunch break time is obtained from the class schedule collected from the department. The time the classes are off is also acquired. The number of students in each class is also determined, along with the class attendance. Figure 4.2 shows the class schedule of IUT of room 201 for the summer 2018-2019 semester. Department class routines from the year 2016 to 2019 are collected. All the other routines are shown in [Appendix A].

It can be seen that the classes of IUT start from 8 am in the morning and closes at 5 pm in the afternoon. There is a lunch break of 1.5 hours from 1 pm to 2:30 pm. Each class time is 1 hour and 15 minutes long. In a day a maximum of 6 classes can take place. While on some days e.g. Wednesday in the Figure 4.2, two class slots are empty with no scheduled class. Therefore from the class schedules, the overall class conductivity hours is found.

In the summer and winter 2018-2019 semesters, rooms 201, 202, 203, 509, 511, and 604 are considered. Therefore, models of these rooms are built and simulated in Netlogo. The total hours of class in a day is calculated and is used in the simulation.

Table 4.1: Total class hours for each day in a week of the summer 2018-2019 semester

Day	Room 201	Room 202	Room 203	Room 509	Room 604	Room 511
Mon	7.50h	7.50h	6.25h	2.50h	3.75h	0.00h
Tues	7.50h	7.50h	6.25h	6.25h	5.00h	7.50h
Wed	6.25h	6.25h	7.50h	6.25h	6.25h	2.50h
Thurs	7.50h	6.25h	7.50h	6.25h	7.50h	0.00h
Fri	7.50h	3.75h	2.50h	3.75h	3.75h	6.25h

Table 4.1 shows the total hours of class in a day for each classroom of the summer 2018-2019 semester obtained from the class routine. The Table 4.2 shows the total

Islamic University of Technology (IUT)

201

	1 08:00 - 09:15	2 09:15 - 10:30	3 10:30 - 11:45	4 11:45 - 13:00	Break 13:00 - 14:30	5 14:30 - 15:45	6 15:45 - 17:00
Monday	EEE 4625 6A QNI	EEE 4641 6A/6B/6C Ce TK	EEE 4651 6A/6B/6C Dt1 KHK	EEE 4651 6B/6A/6C Dt2 KHK	Break	EEE 4603 6A SMA	EEE 4603 6B/BScTE (2yr) 2 SMA
Tuesday	EEE 4625 6C QNI	EEE 4625 6B Ut QNI	Math 4421 4A MRI	Hum 4421 4A TVE X3		Phy 4421 4C SIA	Math 4421 4C MOF
Wednesday		Math 4421 4A MOF	EEE 4403 4A NIBH	Phy 4421 4A SIA		EEE 4605 6B/BScTE (2yr) 2 GS	
Thursday	EEE 4605 6B/BScTE (2yr) 2 GS	EEE 4605 6C GS	EEE 4601 6C MRA	EEE 4625 6C QNI		EEE 4651 6B/6A/6C Dt2 KHK	EEE 4651 6A/6B/6C Dt1 KHK
Friday	EEE 4601 6A RM	Hum 4621 6A TVE X4	Hum 4225 2C TVE X2	Phy 4221 2C MAB		Hum 4222 2C Arabic TVE X1	

Timetable generated:5/27/2019 aSc Timetables

Figure 4.2: Class schedule of room 201 for the summer 2018-2019 Semester.

hours of class in a day for each class room of the winter 2018-2019 semester obtained from the class routine. The Fig 4.3 shows the amount of students attending the class in the Room 201 in the day in summer 2018-2019 Semester. It is evident from the graph that in the 6 classes that take place in a day the average students that attend the classes are about 80% of the total students. Also in the beginning of the day more students attend the class and then decreases as the day goes along.

Table 4.2: Total class hours for each day in a week of the winter 2018-2019 semester

Day	Room 201	Room 202	Room 203	Room 509	Room 604	Room 511
Mon	7.50h	6.25h	6.25h	6.25h	6.25h	6.25h
Tues	5.00h	6.25h	6.25h	5.00h	5.00h	0.00h
Wed	6.25h	7.50h	5.00h	5.00h	6.25h	2.50h
Thurs	6.25h	6.25h	6.25h	6.25h	7.50h	5.00h
Fri	5.00h	2.50h	5.00h	7.50h	5.00h	0.00h

4.7 Simulation Model (NetLogo)

NetLogo is Agent-based modelling (ABM) programming language. NetLogo is a multi-agent programmable modeling environment. Where the agents can interact with each other and with the environment. With this modeling environment, occupant behaviors can easily be incorporated in the simulations. Thus, NetLogo is used in this work to incorporate the occupant behavior.

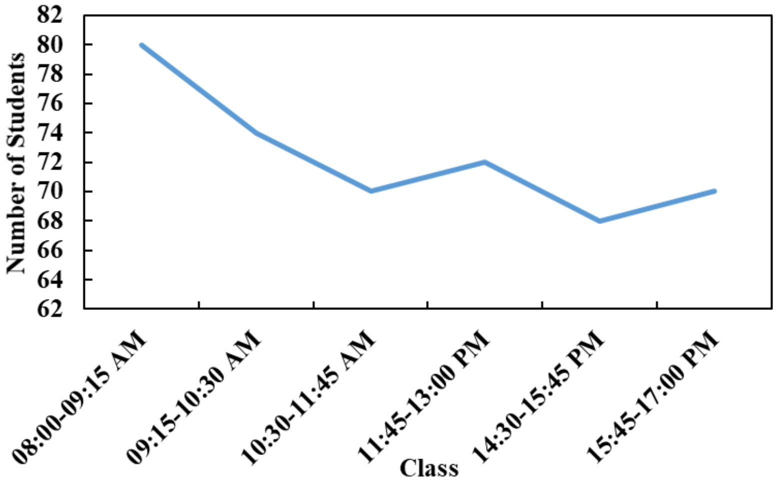

Figure 4.3: Load curve of total number of students attending class of a day in summer 2018-2019 Semester.

4.7.1 Energy Consuming Appliances in IUT

As mentioned earlier the electrical appliances that consume energy in a classroom are fans, lights, and ACs. In IUT these are also the appliances consuming energy in a classroom. But in each room, there are a different number of appliances. For example in rooms 201, 202 and 203 there are 20 lights, 20 fans, and 4 two-ton ACs in each. Whereas in room 509, 511 and 604 there are 8 lights, 8 fans, and 1 two-ton AC. A light consumes about 25 Watt power per hour. One fan consumes 75 Watt of power. And a two-ton AC consumes 3kW power.

4.7.2 Classroom model of IUT in NetLogo

NetLogo simulation is used to model the IUT classrooms. Figure 4.4 shows a single classroom illustration with its tables and appliances. The classrooms are modelled in Netlogo as in 4.5 with its chairs and tables. In the classroom models of 201, 202 and 203 with 90 seats there are 20 lights, 20 fans and 4 ACs in each. Whereas, rooms 509, 604 and 511 have 36 seats, with 8 lights, 8 fans and an AC each. In the model when the appliances are turned on the color of the appliance changes to green. In the simulation, a room is modeled for an entire week of class, which is 5 days a week. From the room wise class routines obtained from IUT the total hours of class in a day is calculated and is used in the simulation.

4.8 Scenarios

Following the above characteristics this study have worked with 3 scenarios of how the students enter, sit and use the appliances. They are students enter randomly, seats ran-

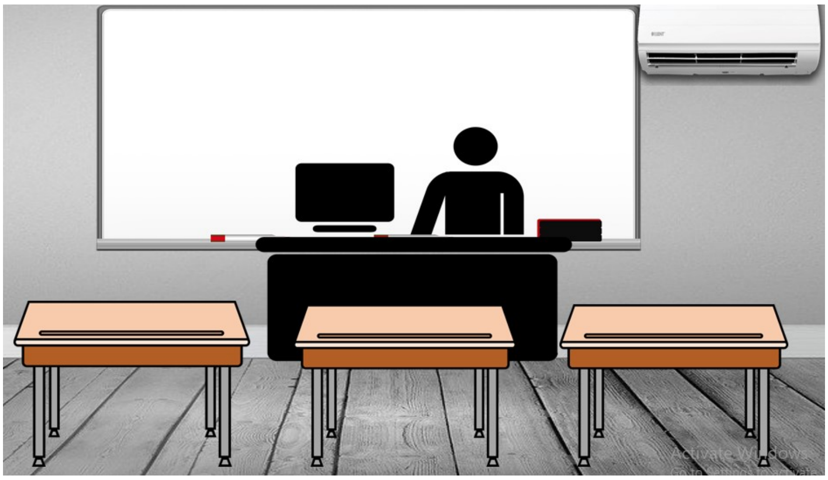

Figure 4.4: Illustration of a classroom in an academic building.

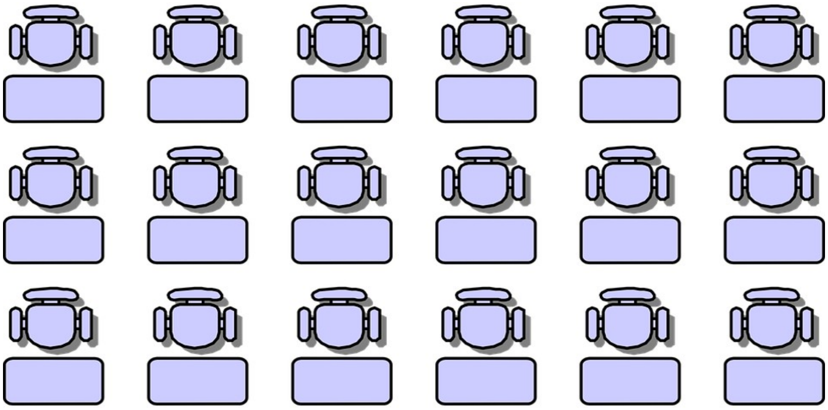

Figure 4.5: Illustration of a classroom model with tables and chairs.

domly and the appliances are switched ON randomly and stays ON (All-on Scenario). Students enter randomly, seats randomly and appliance switched ON randomly (Random Scenario). Students enter randomly, seats sequentially and appliance switched ON sequentially (Sequential Scenario). Table 4.3 shows the difference between the scenarios. With the All-on scenario occupant behavior, weather changes or class schedules are not considered. And with the other 2 scenarios Random and Sequential occupant behavior is incorporated by taking into account the class routine, class hours, students attendance and ambient changes (winter or summer).

Table 4.3: Different characteristics between the three scenarios.

Scenario	Entry Pattern	Sitting Pattern	Switching Pattern
All-on	Random	Random	Random and stays On
Random	Random	Random	Random
Sequential	Random	Random or Sequential	Sequential

4.8.1 All Appliances Switched ON within first 10 to 15 mins of the Class Scenario (All-on Scenario)

The All-on scenario is the current situation in the classrooms. All electrical appliances are turned ON randomly and stays ON the whole class. Most of the students enter the class in the first 10 to 15 minutes of the class start, therefore the first 15 minutes the appliances are switched ON randomly. And after this time all the appliances turn ON. After the class finishes all the appliances are not turned OFF some may stay turned ON until the next class starts. Figure 4.6 shows this procedure. In this case we have not considered any occupant behavior. The total time of the university open hours which is 9 hours a day is inserted. The flowchart of the algorithm for the All-on Scenario is shown in Figure 4.7.

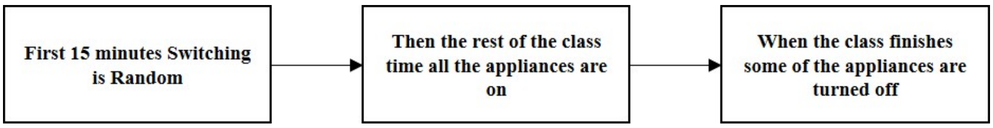

Figure 4.6: All-on Scenario Procedure.

As seen from the flow diagram no matter how or where the students sit, all the appliances will be turned ON within the first 10 to 15 minutes of the class start. The power consumed by the total lights in a day for a room is calculated by multiplying the total number of lights (L_t) with power consumption of one light (L_p) and hours ON $(Hours)$. Equation 4.1 shows the formula. Similarly total power consumption for fans and ACs is shown in Equations 4.2 and 4.3. Then all the appliances power consumption is added to get the total power consumption which is shown in equation 4.4. The power consumption is obtained in Kilo-Watt-hour (KWh).

Total power consumption of Light (KWh):

$$P_l = L_t \times L_p \times \frac{Hours}{1000} \tag{4.1}$$

Total power consumption of Fan (KWh):

$$P_f = F_t \times F_p \times \frac{Hours}{1000} \tag{4.2}$$

Total power consumption of AC (KWh):

$$P_{AC} = AC_t \times AC_p \times \frac{Hours}{1000} \tag{4.3}$$

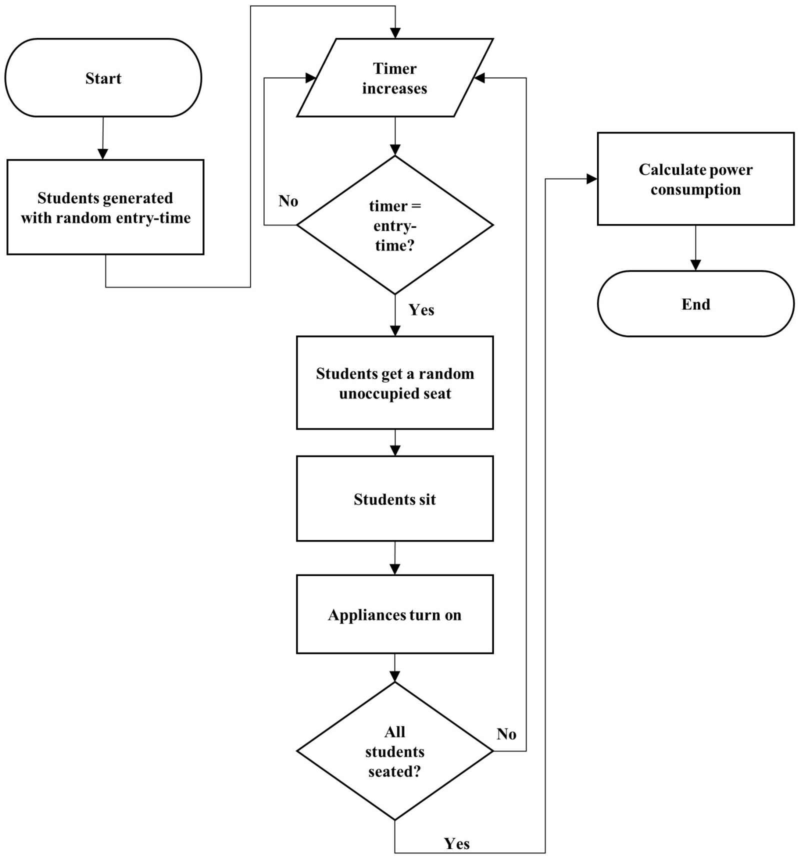

Figure 4.7: Flowchart of All-on Scenario.

Total Power consumed in a room (KWh):

$$P_t = P_l + P_f + P_{AC} \tag{4.4}$$

From NetLogo simulation, the total data from 2016 to 2019 is generated. Table 4.4 shows the main columns of all the three scenarios. The columns of the dataset are Year, Month, Semester, Season, Day, Power of all rooms such as P201, P202, P203, P509, P604 and P511. All-on Scenario data set for the January 2019 can be found in [Appendix B].

Table 4.4: Main columns in all the dataset.

Year	Month	Semester	Season	Day	Power of all Rooms
2016 to 2019	Jan to Oct	Winter or Summer	Winter or Summer or Moonsoon	5 weekdays	In KWh

4.8.2 Random Entry, Random Sitting and Switching Scenario (Random Scenario)

In this Scenario, occupant behavior is considered by taking into account class routines, class hours, students' attendance, and ambient changes (winter or summer).

In the Random Scenario, each student has an entry-time which is randomly chosen from the given time range, and when students enter they sit randomly on the seats. Each of the appliances is turned ON randomly. The ON time for each appliance is stored and the total power consumed is calculated.

The flow diagram of the Random Scenario is shown in Figure 4.8. First students are generated having random entry-time from a range of time. The time in minutes proceeds by a timer. Then the algorithm checks whether the entry-time matches the timer. If it doesn't match, the timer value increases, if it matches the student with that entry-time enters and chooses a seat from a range of unoccupied seats. Next, the student is seated. The occupied seat is then removed from the list of unoccupied seats. Consequently, appliances such as light, fan, and air-conditioner are turned ON randomly and the duration ON time for each appliance is stored. This procedure continues until all the students are seated. Before the simulation ends, the power consumed is calculated.

The ON time of all the appliances are different because that depends on the entry time of the students. Thus for example if a student enters after 10 minutes of class start time and sits on a seat, the light, fan or AC that are near which are off will turn ON and for that light, fan or AC on-time will be 10 mins and the duration-on-time will be $(75mins - 10mins = 65mins)$. Likewise, if a student enters after 15 minutes of class start time and sits on a seat, the light, fan or AC that are near which are OFF will turn ON and for that light, fan or AC on-time will be 15 mins and the duration-on-time will be $(75mins - 15mins = 60mins)$.

Once all the students are seated, the duration-on-time of lights are summed in a variable called light-on-duration (L_{od}), consequently, duration-on-time of fans are summed in a variable called fan-on-duration (F_{od}), and duration-on-time of ACs are summed in a variable called ac-on-duration (AC_{od}). The total power for lights is calculated by multiplying the light-on-duration (L_{od}) (in minutes) with power consumption of one light (L_p). This formula is shown in equation 4.5. Similarly total power consumption for fans and ACs is shown in Equations 4.6 and 4.7. All the times are considered in minutes. One timer tick in the simulation refers to 1 minute. The total power consumed in a room is given by equation 4.8. Random Scenario data set of January 2019 can be found in [Appendix B].

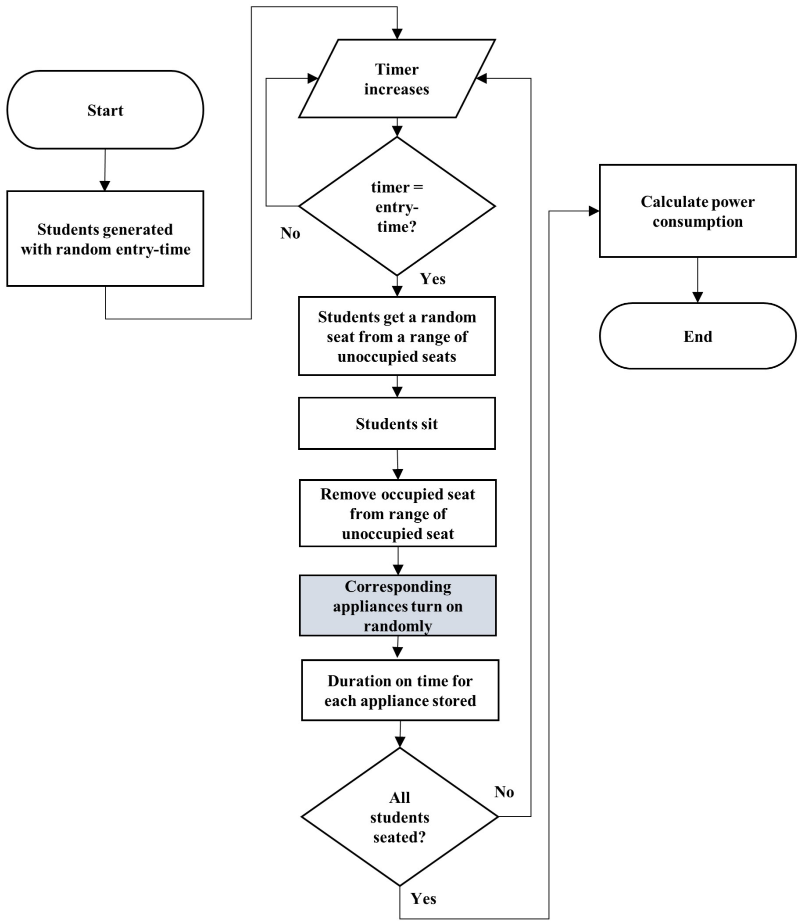

Figure 4.8: Flowchart of Random Scenario.

Total power consumption of Light (KWh):

$$P_l = \frac{L_{od} \times L_p}{1000 \times 60} \tag{4.5}$$

Total power consumption of Fan (KWh):

$$P_f = \frac{F_{od} \times F_p}{1000 \times 60} \tag{4.6}$$

Total power consumption of AC (KWh):

$$P_{AC} = \frac{AC_{od} \times AC_p}{1000 \times 60} \tag{4.7}$$

Total Power consumed in a room (KWh):

$$P_t = P_l + P_f + P_{AC} \tag{4.8}$$

4.8.3 Random Entry, Sequential Sitting and Switching Scenario (Sequential Scenario)

In this Scenario, occupant behavior is considered by taking into account class routines, class hours, students' attendance, and ambient changes (winter or summer).

In the Sequential Scenario, each student has a random entry-time from the given time range and after entering they sit either randomly or sequentially. But the switching of the appliances are sequential from the front one after another. From the ON time of each appliance total power consumed is calculated. The Sequential Scenario flowchart is shown in Figure 4.9. Therefore the appliances in the Sequential Scenario are automated to turn ON from the front.

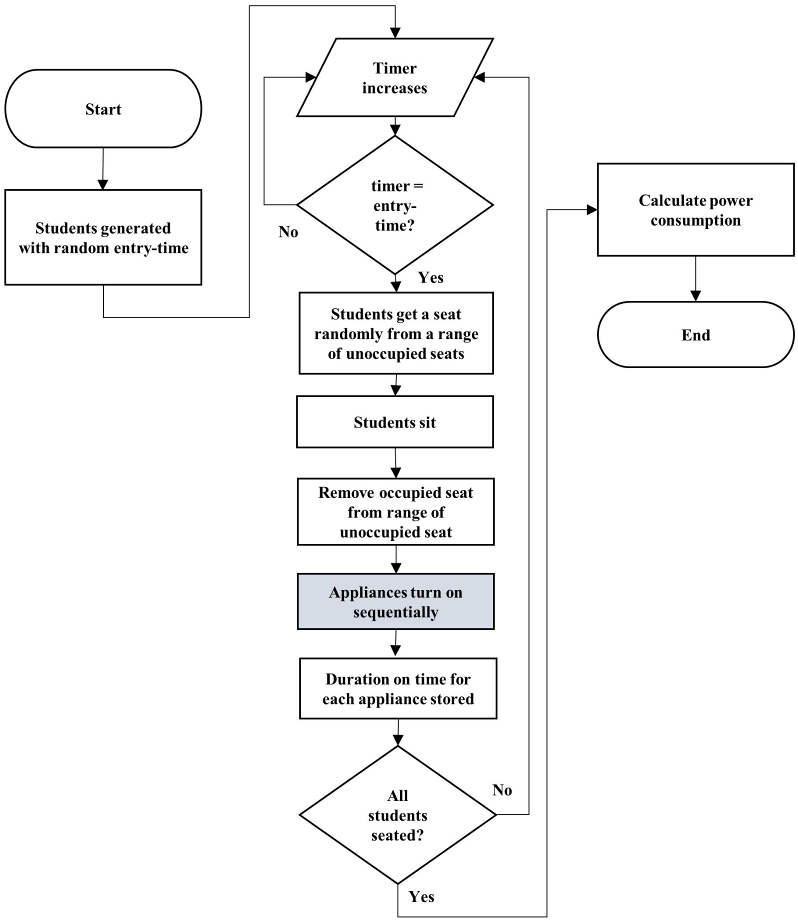

Figure 4.9: Flowchart of Sequential Scenario.

The only difference between the Sequential Scenario from the Random Scenario is the switching arrangement of the appliances. The difference between the Random and Sequential Scenario can be seen in the flowchart of Figure 4.8 and 4.9 with the blocks that are colored. In the Sequential Scenario, the appliances turn ON from the front consecutively without a break. Whereas appliances turn ON randomly in the Random Scenario. The total power consumption of lights, fans and ACs are same as equations 4.5, 4.6 and 4.7. The total power consumed in a room is given in equation 4.8.

From NetLogo simulation, the total data from 2016 to 2019 is generated. January 2019 data set for the Sequential Scenario is in [Appendix B].

4.9 Incorporation of Occupant Behavior in Scenarios

Occupant behavior in a classroom is how the students behave in terms of how late the students enter the classroom. Also how the students take seats. Class attendance is also a part of occupant behavior. The overall class hour can be included as a part of occupant behavior. Thus in this study, occupant behavior is incorporated in Random and Sequential scenarios. In the Random and Sequential cases, the class attendance and the class entry times by obtaining the attendance list from various faculties is taken into account. The class time and hours are obtained from the class schedules. When considering occupant behavior in the Random and Sequential scenarios it is seen that the energy consumption is reduced significantly.

4.10 Incorporation of Weather Seasons in Scenarios

The weather conditions in Bangladesh is considered as this study focuses on the energy consumption pattern of academic buildings in Bangladesh. The weather in Bangladesh is separated into three different seasons. The seasons are hot summer, cool monsoon, and cold winter. In the summer season, the temperature is the highest with around 30 to 40 degrees celsius. The highest temperature is between April to May. In the summer air-conditioners (ACs) are normally used. The monsoon climate has an intermediate temperature. In the cold winter, the temperature varies from 9 to 15 degrees. The coldest month is December. Winter - starts from November to February. Summer - starts from March to June. Monsoon - starts from July to October.

In this work air-conditioners (ACs) along with fans are usually used in the summer periods when the air temperature is high. In the winter periods, air-conditioners (ACs) and fans are not used. In the monsoon period, air-conditioners (ACs) are usually not used. In all the seasons the use of light is not changed.

Chapter 5

Methodology: Data Analysis

To predict energy usage patterns based on occupant behavior and ambient changes in academic buildings, machine learning data analysis tools and algorithms have been used. The steps below are used to predict the energy usage patterns.

- Data Collection from IUT
- Data Collection from Simulation
- Data Preprocessing.
- Data Visualization.
- Energy Prediction.

The first two steps have already been discussed in the previous chapter. The next steps is discussed in the next sections in detail.

5.1 Data Preprocessing

After collecting the data from simulation, preprocessing the data is required. The simulation data contains many values and is a big data set. Thus it is very important to be clear about the data. Data preprocessing is the process of cleaning the data and preparing the data for analysis and future use. For the data, data preprocessing have been performed in the following ways.

- Data Cleaning.
- Data Transformation.
- Data Reduction.

5.1.1 Data Cleaning

Data cleaning is the process of detecting and correcting/deleting missing entries in a data set. It also goes into recognizing incomplete or irrelevant parts of the data and altering or deleting them.

The data obtained from simulation is cleaned with the help of pandas which is a library of python. The function used to detect missing values is $(.isnull())$ and then the missing values are replaced with $(.nan)$ function. The number of missing values is also checked with the $(.isnull.sum())$ function. So for all the 3 scenario dataset Random, Sequential and All-on the above functions are applied and checked.

5.1.2 Data Transformation

Data Transformation is the process of formatting and scaling the data. The data is transformed into a pandas dataframe format. Statistics of the different columns are observed. The function $(describe())$ is used to see the statistics. The data type of each data is checked for integer or float values.

Table 5.1 represents the data statistics values such as total number of data values (count), mean of the data values (mean), standard deviation of the data values (std), minimum of the values (min), 25% of the values (25%), 50% of the values (50%), 25% of the values (25%), 75% of the values (75%) and maximum of the values (max). From Table 5.1 it can be seen that the data count is 1215, the mean of the data values is 15, the standard deviation (std) is 23 and the Maximum (max) is 97.

Table 5.1: Data Statistics.

count	1215
mean	15
std	23
min	0
25%	0
50%	6
75%	15
max	97

5.1.3 Data Reduction

Data Reduction refers to reducing the number of independent variables and filtering the data for the most important parameters. Data in this study is checked for repeated rows and the repeated rows are removed and the most important attributes are kept.

The data also experienced timestamps in other forms. So the data of each scenario is converted to a time-series using Python in Jupyter Notebook. Time-series is the data which has an index as the $(DatetimeIndex)$.

Data filtering is also applied to the different data sets to remove unwanted parts of the data and to keep the or select the different parameters.

5.2 Data Visualization

Data Visualization technique involves plotting graphs and patterns to visualize the relationship between different parameters of the data set. In this section, the data visualization techniques that have been used will be discussed.

5.2.1 Power Consumption and Energy Distribution

The displot function is used which is a function of seaborn library. The function is used to obtain the range of power consumption occurring in the different days of the 3 scenarios. Displot function can be used to show a histogram.

The linear view of the power usage pattern is a great way to see the overall yearly power consumption. The linear view of power consumption is obtained for the scenarios to detect the variations in consumption.

5.2.2 Histogram Representations

Histogram representations is used to discover the power consumption in the two semester of IUT. IUT has two semesters in a year: winter and summer. The winter semester is from January to May, while the summer semester is from June to October. Meanwhile the two months November and December is semester break and no class is scheduled. The data is seen with histogram representation to see the power consumption in the two semesters.

5.2.3 Pairplot Visualization

Pair plot is a great way to see relationships between two variables where one variable in the data row is matched with another variable. Numerical data can be plotted and categorical data can be used for coloring. Pair plots can easily be plotted with seaborn library in Jupyter Notebook.

5.3 Energy Prediction

After visualizing the data with different attributes, the energy prediction is carried out using time series analysis.

A time series is a group of data points composed in a temporal order. The indexed column is the datetime column. The goal of time series analysis is to predict future forecasts. In this study Exponential Smoothing, Auto-Regressive Moving Average (ARMA) and Auto-Regressive Integrated Moving Average(ARIMA) model are used for both the Random and Sequential Scenarios. The models are compared using the error metrics Root Mean Square Error (RMSE) and Akaike Information Criterion (AIC).

5.3.1 Exponential Smoothing Model

Exponential smoothing forecasting methods develop a model where the prediction is a weighted sum of past observations, but the model explicitly uses an exponentially decreasing weight for past observations. Exponential smoothing methods may be considered as peers and an alternative to the popular Box-Jenkins ARIMA class of methods for time series forecasting.

There are three main types of exponential smoothing time series forecasting methods. A simple method that assumes no systematic structure, an extension that explicitly handles trends, and the most advanced approach that add support for seasonality. The advanced approach that support for seasonality is used on both the Random and Sequential Scenario. Figure 5.1 shows the flow diagram of the process. After preprocessing the data, the data is split into train and test sets. Then exponential smoothing is applied to the train set and the predictions are generated. The predictions and the test data is then plotted and the error metrics are found.

5.3.2 ARMA Model

An ARMA model, or Autoregressive Moving Average model, is used to describe weakly stationary stochastic time series in terms of two polynomials. The first of these polynomials is for autoregression, the second for the moving average. Often this model is referred to as the ARMA(p,q) model, where: p is the order of the autoregressive polynomial, q is the order of the moving average polynomial. Equations 5.1 shows the model equation.

$$X_t = c + \epsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} \tag{5.1}$$

Where:

- φ the autoregressive model's parameters,
- θ the moving average model's parameters,

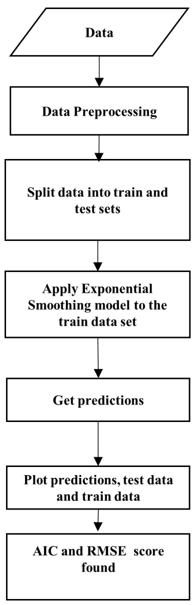

Figure 5.1: Exponential Smoothing Flowchart.

- ϵ error terms (white noise).

ARMA model is applied for both the Random and Sequential Scenarios. Figure 5.2 depicts the ARMA flowchart. First after data preprocessing the data is split into train and test sets. Then the best p and q values are found for the ARMA model by trial and error method. The ARMA model is then applied to the train set and predictions are made. Predictions and the test data are plotted and the error metrics are found.

5.3.3 ARIMA Model

An ARIMA model is a class of statistical models for analyzing and forecasting time series data. ARIMA is an acronym that stands for AutoRegressive Integrated Moving Average. It is a generalization of the simpler AutoRegressive Moving Average and adds the notion of integration. This acronym is descriptive, capturing the key aspects of the model itself. Briefly, they are:

- AR: Autoregression. A model that uses the dependent relationship between an observation and some number of lagged observations.

- I: Integrated. The use of differencing of raw observations (e.g. subtracting an observation from an observation at the previous time step) in order to make the

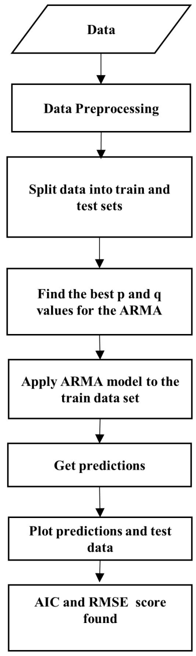

Figure 5.2: ARMA Flowchart.

time series stationary.

- MA: Moving Average. A model that uses the dependency between an observation and a residual error from a moving average model applied to lagged observations.

Each of these components are explicitly specified in the model as a parameter. A standard notation is used of ARIMA(p,d,q) where the parameters are substituted with integer values to quickly indicate the specific ARIMA model being used. The parameters of the ARIMA model are defined as follows:

- p: The number of lag observations included in the model, also called the lag order.
- d: The number of times that the raw observations are differenced, also called the degree of differencing.
- q: The size of the moving average window, also called the order of moving average.

A linear regression model is constructed including the specified number and type of terms, and the data is prepared by a degree of differencing in order to make it stationary, i.e. to remove trend and seasonal structures that negatively affect the regression model.

Figure 5.3 shows the ARIMA flowchart. In order for the ARIMA model to work the data must be stationary. The preprocessed time series data is checked to be stationary by plotting rolling statistics. After checking the data for stationarity the best ARIMA model is found by using the hyperparameter tuning function. This hyperparameter tuning function code can be found in [Appendix C]. The ARIMA model is then applied to the stationary data of the Random and Sequential Scenarios. ARIMA model is not used on the All-on Scenario data because the All-on Scenario is the current scenario that IUT is using. The Akaike Information Criterion (AIC) score and Root Mean Square Error (RMSE) scores are obtained for both the scenarios. Also to get more accurate results the data transformation techniques is used on the data set. At last one year prediction is found for both the Random Scenario and Sequential Scenario respectively.

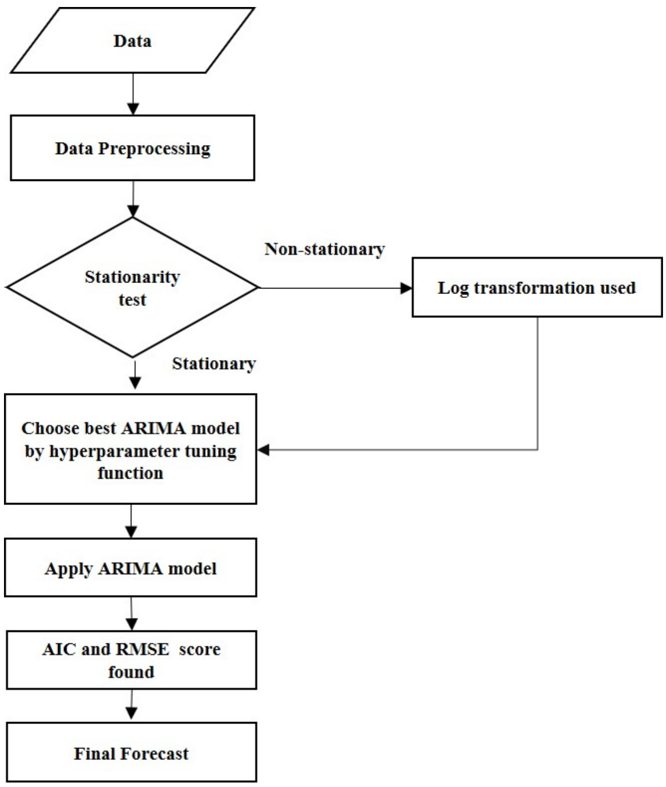

Figure 5.3: ARIMA Flowchart.

The next chapter will discuss the results found for the different scenario data set.

Chapter 6

Results and Discussion

To predict energy usage patterns based on occupant behavior and ambient changes in academic buildings we use machine learning data analysis tools and algorithms. The software tools and library used for the prediction are outlined below. Then the rest of the chapter looks into the results obtained from the methodologies used in chapter 4 and chapter 5.

6.1 Machine Learning Libraries

Different libraries of Python is used in this work. These are listed below.

- Scikit-learn: Scikit-learn is a machine learning library for the Python programming language. It supports machine learning algorithms e.g. Linear Regression, Support Vector Machine, K-means algorithm, ARIMA models etc. It is also used for validation purposes.
- Pandas: Pandas is a Python library for data analysis and manipulation. Data can be easily organized and changed by putting the data in tabular form.
- Numpy: Numpy is a Python based library used for multi-dimensional array and matrix handling. Mathematical operations and formulas can easily be operated in the large matrices.

6.2 All-on Scenario Results

The power consumed by each appliance is different in a day in the rooms 201, 202, 203, 509, 511, and 604 for the All-on Scenario is shown in Table 6.1 and Table 6.2 respectively.

It is seen in Table 6.1 that the total power consumed in a day in room 201 is not constant in the All-on Scenario.

It is also evident from the Table 6.2 that the total power consumed in a day in smaller room of 509 is not constant in the All-on Scenario.

Table 6.1: Power consumed in a day in room 201 of All-on Scenario.

Type of Appliances	Total No.of Appliance	Hours ON	Power Appli-ance(Watt)	Total Power of Appliance (KWh)	Total Power Consumed in a room(KWh)
Light	20	8.5	25	4.5	100
Fan	20	9	75	13.5	
AC	4	8.5	3000	108	

Table 6.2: Power consumed in a day in room 509 of All-on Scenario.

Type of Appliances	Total No.of Appliance	Hours ON	Power Appli-ance(Watt)	Total Power of Appliance (KWh)	Total Power Consumed in a room(KWh)
Light	8	8.75	25	1.8	30
Fan	20	8	75	13.5	
AC	4	8.5	3000	108	

6.3 Random Scenario Results

In the Random Scenario the power consumption is different for different days in each room. An example of the power consumed by each appliance in a day in the larger room 201 and smaller room 509 of the Random Scenario is shown in Table 6.3 and Table 6.4 respectively.

Table 6.3: Power consumed in a day in room 201 of Random Scenario.

Type of Appliances	Total No.of Appliance	Hours ON	No.of Appliances ON	Power per Appli-ance(Watt)	Total Power of Appliance (KWh)	Total Power Consumed in a room(KWh)
Light	20	9	16	25	13.6	84.475
Fan	20	7	15	75	7.875	
AC	4	7	3	3000	63	

It is observed from Table 6.3 that the power consumed in room 201 in a day in Random Scenario can be different depending on the hours ON time of the appliances and also on the number of appliances that are switched ON. Because the appliances turn ON only when a student enters and sits on a seat nearby which results in some of the appliances to stay turned OFF for some time and thus reduces power consumption.

Similarly, it is seen from Table 6.4 that the power consumed in room 509 in a day of Random Scenario can vary depending on the hours ON time of the appliances and also on the number of appliances that are switched ON.

Table 6.4: Power consumed in a day in room 509 of Random Scenario.

Type of Appliances	Total No.of Appliance	Hours ON	No.of Appliances ON	Power per Appliance(Watt)	Total Power of Appliance (KWh)	Total Power Consumed in a room(KWh)
Light	8	9	8	25	1.8	27
Fan	8	8	7	75	4.2	
AC	1	7	1	3000	21	

6.4 Sequential Scenario Results

The power consumed by each appliance in a day of Sequential Scenario in the larger room 201 and smaller room 509 is shown in Table 6.5 and 6.6 respectively.

Table 6.5: Power consumed in room 201 of Sequential Scenario.

Type of Appliances	Total No.of Appliance	Hours ON	No.of Appliances on	Power per Appliance(Watt)	Total Power of Appliance (KWh)	Total Power Consumed in a room(KWh)
Light	20	9	16	25	3.6	74.475
Fan	20	7	15	75	7.875	
AC	4	7	3	3000	63	

It is observed in Table 6.5 that the power consumed for room 201 in a day in Sequential Scenario can vary depending on the hours ON time of the appliances and also on the number of appliances that are switched ON. Because the appliances turn ON only when a student enters and sits on a seat nearby which results in some of the appliances to stay turned OFF for some time and thus reduces power consumption.

Table 6.6: Power consumed in room 509 of Sequential Scenario.

Type of Appliances	Total No.of Appliance	Hours ON	No.of Appliances ON	Power per Appliance(Watt)	Total Power of Appliance (KWh)	Total Power Consumed in a room(KWh)
Light	8	9	8	25	1	26.2
Fan	8	8	7	75	4.2	
AC	1	7	1	3000	21	

It is found from Table 6.6 that the energy consumed for room 509 in a day of Sequential Scenario can differ depending on the hours ON time of the appliances and also on the number of appliances that are switched ON.

6.5 Data Visualization Results

As discussed in Section 5.2 the displot function is used to see the distribution plot for the three scenarios. Figure 6.1 shows the 4 year power distribution in the room 201 of the All-on Scenario. It is a histogram which conveys the number of days a certain range of power is consumed. There are only 5 bars present in the Figure 6.1 where in the smallest bar 75KWh to 88KWh of power is consumed in about 25 days in the 4 years from 2016 to 2019. Similarly, in the larger bar 99KWh to 112KWh of power is consumed in about 450 days in the 4 years from 2016 to 2019. This shows that the power consumption in the All-on Scenario does not have much variation. The highest power consumption is about 126KWh.

Whereas Figure 6.2 and 6.3 show the power distribution of the Random and Sequential Scenario respectively of classroom 201. In Figure 6.2 most of the days around 750 days in the 4 years the power consumption is within the range of 0KWh to 10KWh. Then about 200 days the power consumption is between 10KWh to 20KWh. Higher power consumption occurred in less number of days. The highest power consumption range is between 88KWh to 98KWh occurring in 10 days. Thus it is evident that the highest consumption is 98KWh in the Random Scenario which is less than the highest power consumption of 120KWh occurring in the All-on Scenario.

In Figure 6.3, 0KWh to 8KWh power is consumed in 790 days. Between 8KWh to 18KWh power is consumed in 190 days. The highest power consumption range is between 81KWh to 88KWh occurring in 10 days. The maximum power consumption is 88KWh in the Sequential Scenario which is less than both the maximum consumption of the All-on and Random Scenarios.

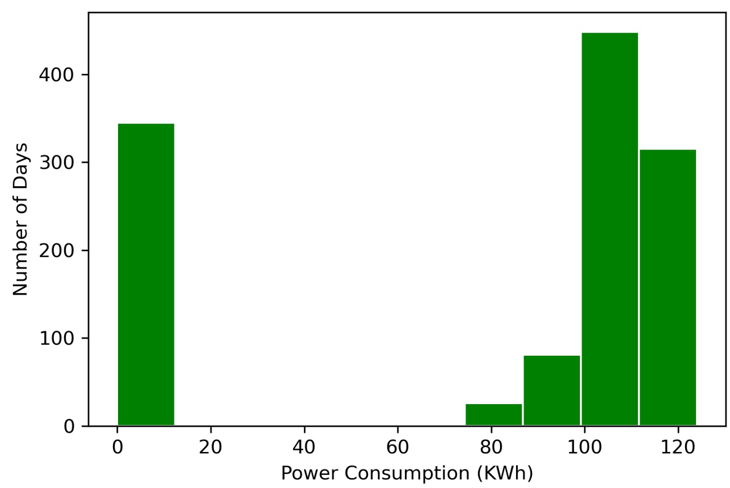

Figure 6.1: 4 year power consumption of room 201 of All-On Scenario.

The linear view of energy usage for Random and Sequential Scenario is shown in Figure 6.4 and 6.5 respectively. As can be observed from both the figures the power consumed in rooms 201, 202, and 203 is more than the power consumed in rooms 509, 604, and 511 due to the difference in the size of rooms, different number of appliances

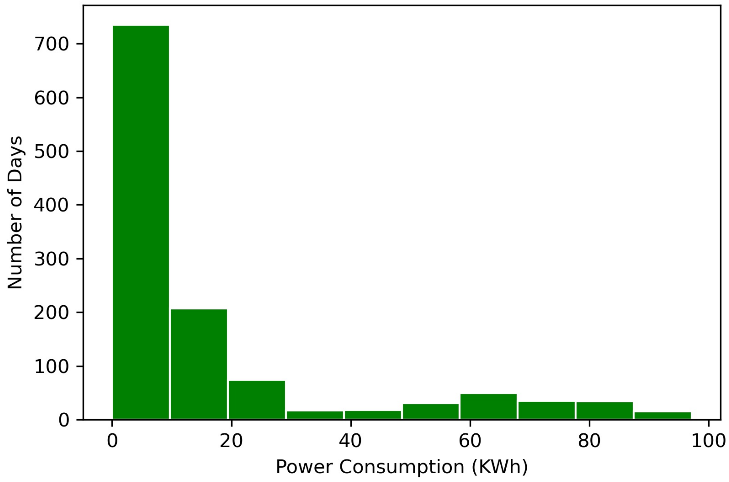

Figure 6.2: 4 year power consumption of room 201 of Random Scenario.

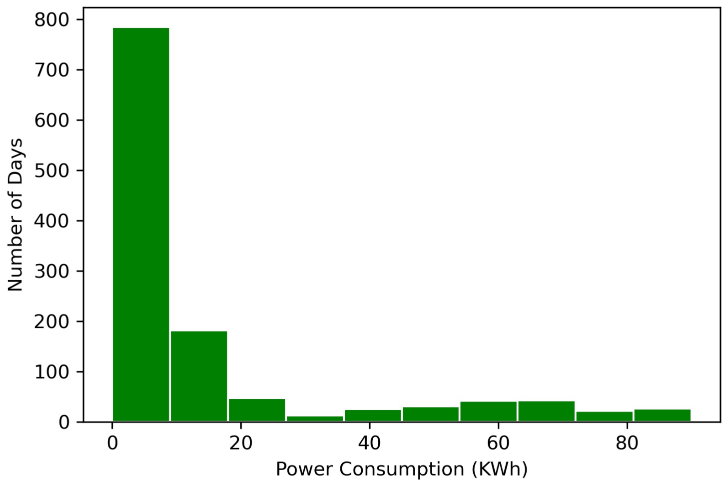

Figure 6.3: 4 year power consumption of room 201 of Sequential Scenario.

and occupant behavior.

Figure 6.4 shows that in the 4 years from 2016 to 2019 there are variations in power consumption. In room 201 power consumption is less in the year 2016 but increases in the year 2017, 2018 and 2019. Power consumption in all of the six rooms show that there is a seasonal trend and there is a part of year when consumption is high and a part when consumption is low. In the three rooms 201, 202 and 203 the highest power consumption is 90KWh occurring in year 2019. Similarly in the rooms 509, 604 and 511 the highest power consumed is 48KWh occurring in year 2019. Room 511 shows 0KWh power consumption in the years 2017 and 2018. This happened because no class are scheduled in those years.

In the Sequential Scenario of Figure 6.5, it is noticed that in the 4 years from 2016 to 2019 there are variations in power consumption. Power consumption in all of the six rooms show that there is a seasonal trend and there is a part of year when consumption is high and a part when consumption is low. The highest power consumption occurred in the three larger rooms 201, 202 and 203 is 48KWh. Whereas in the smaller rooms 509, 604 and 511 highest power consumption is 25KWh. Power consumption is 0KWh in year 2018 for the room 511 due to classes not being scheduled.

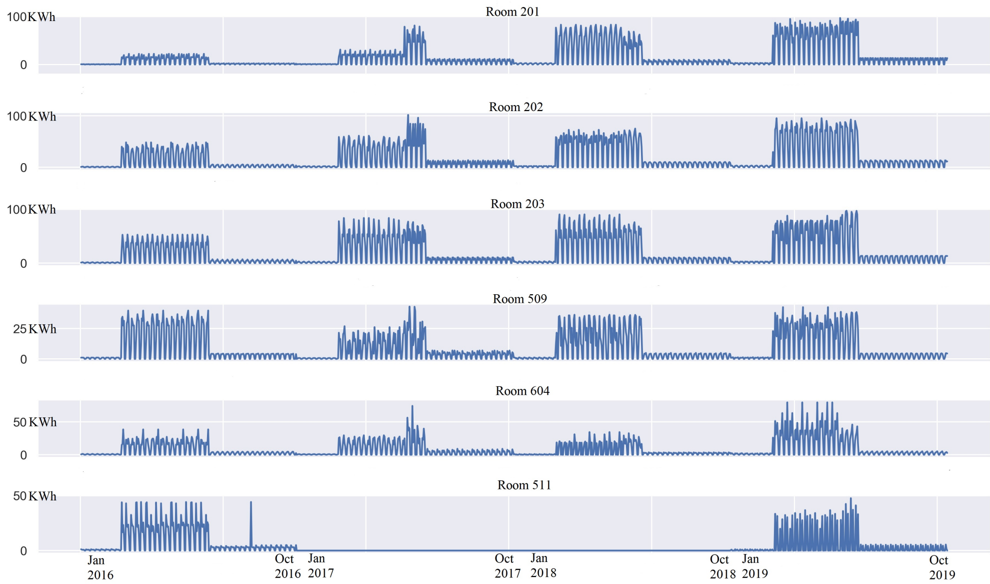

Figure 6.4: Energy usage of each room throughout the 4 years of Random Scenario.

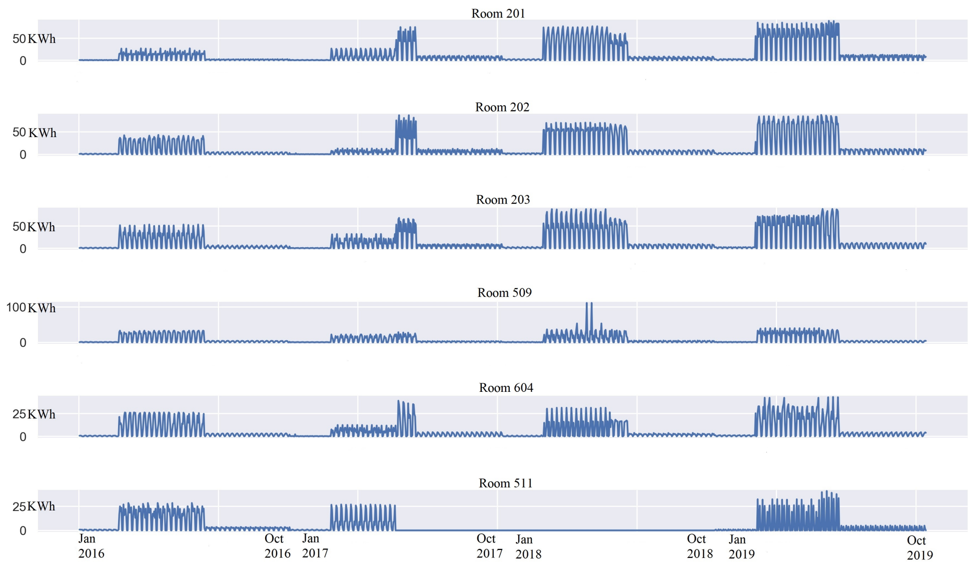

Figure 6.5: Energy usage of each room throughout the 4 years of Sequential Scenario.

6.5.1 Histogram Representation Results

As discussed in chapter 5, IUT has two semesters in an academic year they are winter and summer. Figures 6.6, 6.7 and 6.8 bar graphs are plotted to observe the energy consumption in these two semesters in each of the four years from 2016 to 2019 for the three scenarios All-on, Random and Sequential respectively.

In Figure 6.6 the power consumption in the rooms 201, 202 and 203 are about 80KWh to 70KWh. Power consumption in rooms 509, 604 and 511(except in year 2017 and 2018) is consistent which is about 35KWh. In both the winter and summer semesters power consumption is found to be almost equal.

Both in Figure 6.7 and 6.8 it is seen that power consumption in the winter semester is more than the summer semester each year. This can be the result of the fact that the winter semester of IUT runs through the summer months of March to May and this results in the use higher quantity of air conditioning (AC) and occupant behavior shows their tendency to use power even during winter semester. Likewise, the summer semester runs through the monsoon months of July to October when the use of ACs by the students is less. But there is an exception to this in Figure 6.8 for the rooms 201, 202 and 203 of the year 2017 suggesting change in occupant behavior.

In Figure 6.7 the power consumption in rooms 201, 202 and 203 show an increasing trend from 2016 to 2019. While room 604 show a decreasing trend in power consumption from 2016 up till 2018.

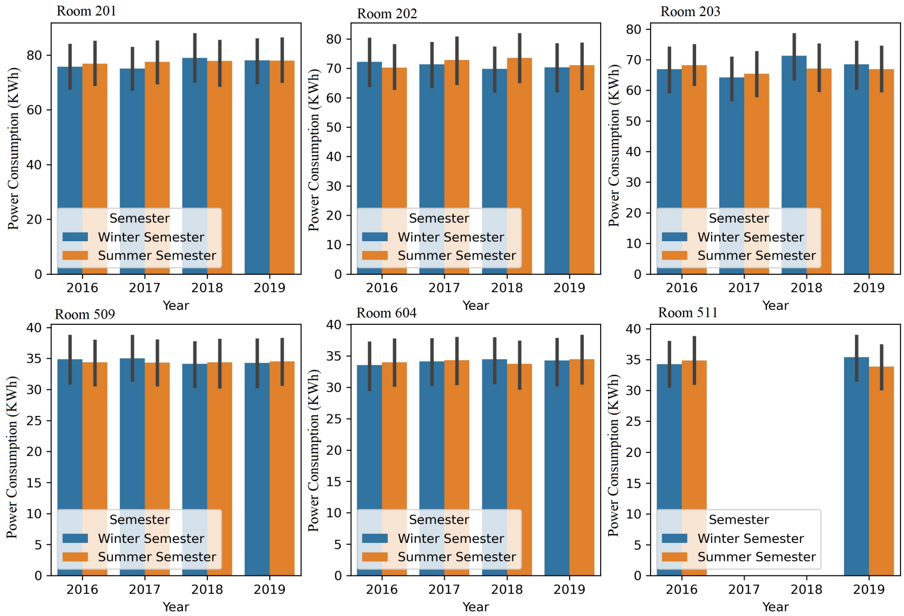

Figure 6.6: Semester wise energy consumption of all rooms of the All-on Scenario.

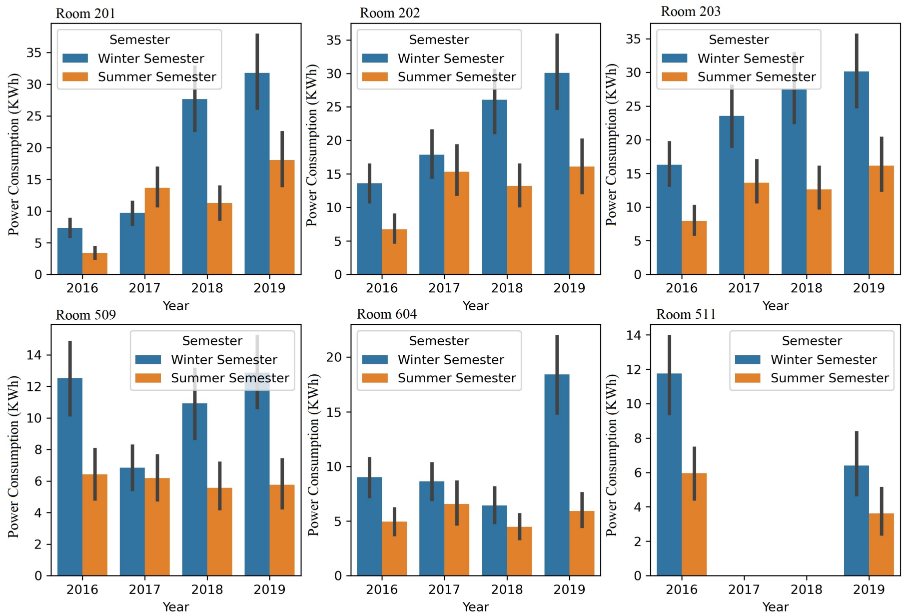

Figure 6.7: Semester wise energy consumption of all rooms of the Random Scenario.

6.5.2 Pairplot Visualization Results

In the pairplot plot power components of each room are matched with the power component of another room. In the pairplot of all rooms in All-on Scenario in Figure 6.9,

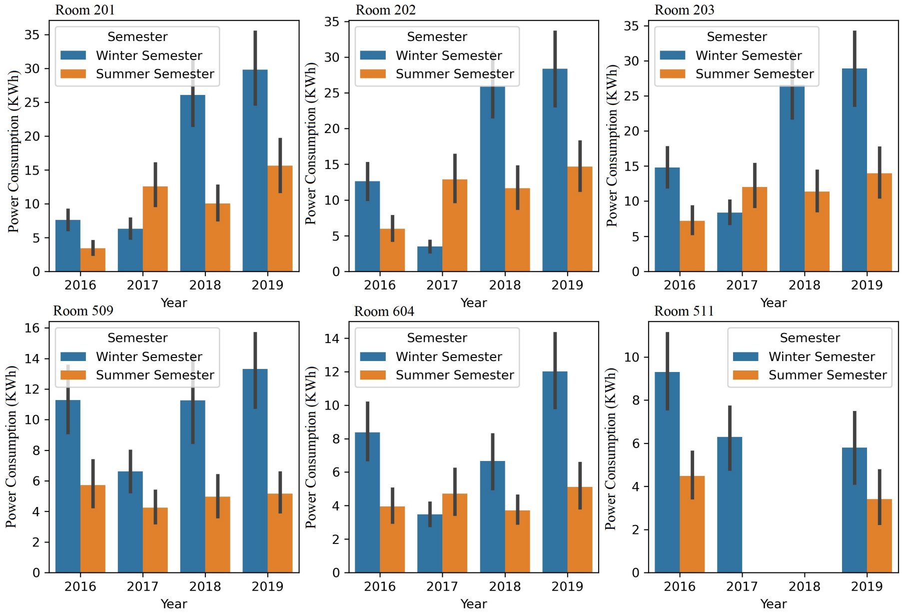

Figure 6.8: Semester wise energy consumption of all rooms of the Sequential Scenario.

there are only a few scattered points. Showing the data is not that much scattered and is consistent.

Both the Random and Sequential Scenario pair plots in Figure 6.10 and 6.11 are scattered. In the Random Scenario pairplot of Figure 6.10, the power consumption data points are more scattered than in the Sequential Scenario pairplot of Figure 6.11. The Random Scenario paiplot in Figure 6.10 shows the power consumption data is very much scattered this is due to variation in the occupant behavior. Whereas, Sequential Scenario paiplot in Figure 6.11 shows the power consumption data is less scattered which is also due to another set of occupant behavior.

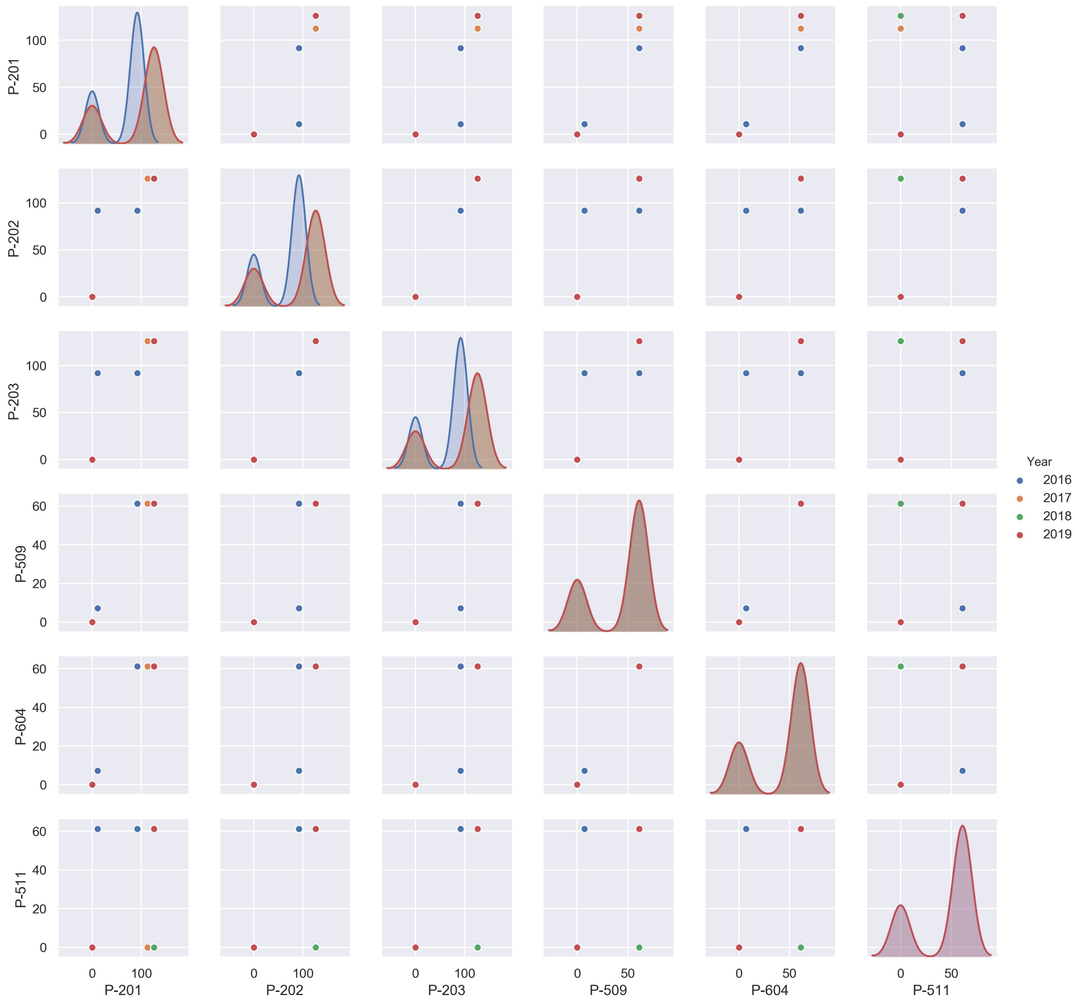

Figure 6.9: Pairplot plot of power consumption of all rooms of All-On Scenario.

6.5.3 Energy Consumption due to number of students and entry time variation

The factors such as the change in the number of students in the class and the change in the entry time of students in the class room vary power consumption pattern. Figure 6.12 and 6.13 shows the power consumption of a single class of room 201 for both the Sequential and Random Scenarios respectively. In the Sequential Scenario, it is seen that as the number of students increases the consumption of power also increases continuously. Whereas in the Random Scenario the power consumption increase but not in a continuous manner.

Figure 6.14 and 6.15 shows the power usage as the time of entry of students increases for both the Sequential and Random Scenario respectively. In both the figures there is a gradual decrease in the power consumption as the entry-time increases.

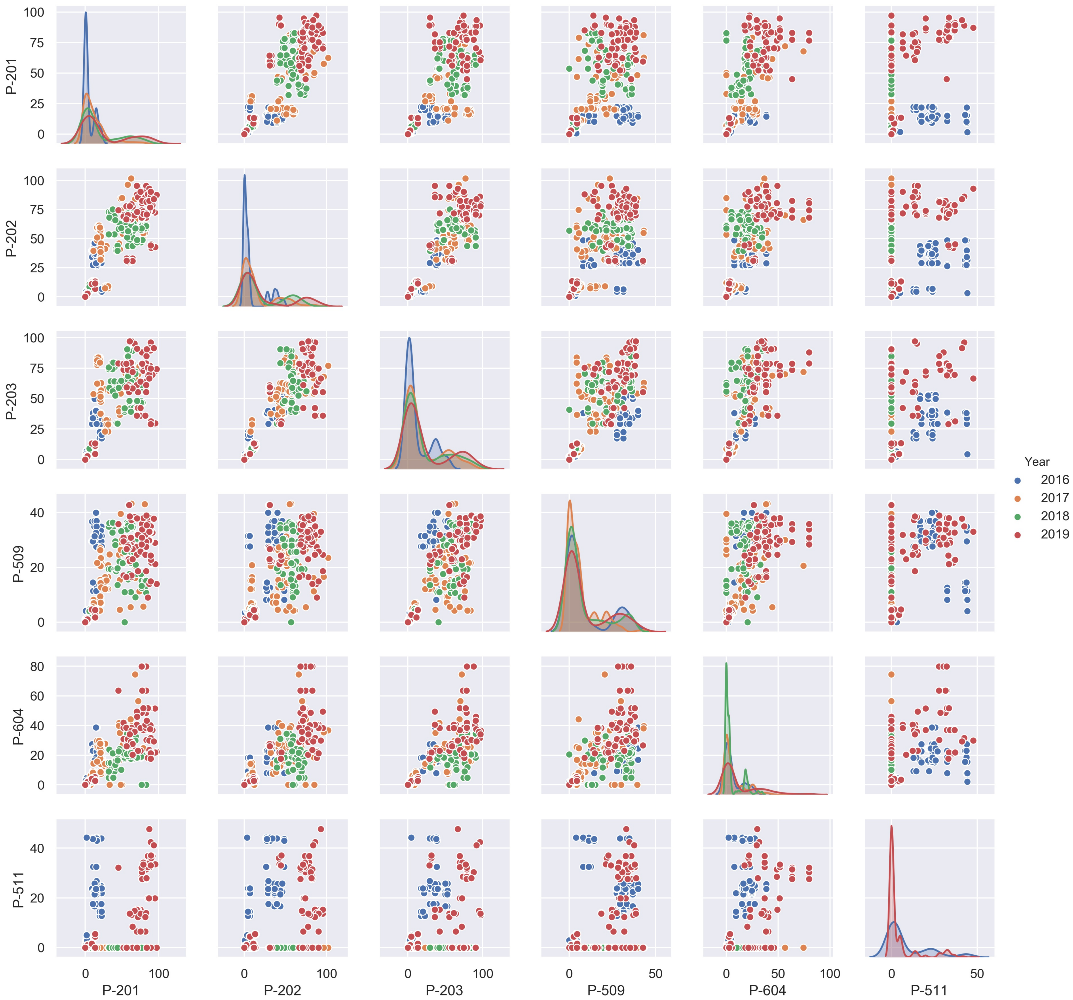

Figure 6.10: Pairplot plot of power consumption of all rooms of Random Scenario.

6.6 Power Consumed in the Three Scenarios

The following Table 6.7 represent the calculated power consumption in the three scenarios. The Table 6.7 shows that among the three scenarios (All-on Scenario, Random Scenario and Sequential Scenario), Sequential Scenario is more energy efficient as less energy is consumed in the Sequential Scenario in the 4 years. So this Sequential Scenario is the optimal energy usage pattern.

Currently IUT uses the "All-on" Scenario as an energy usage pattern of appliances in the classrooms. Since the Sequential Scenario is the best, if IUT used Sequential Scenario in the previous four years then the following amount of energy and cost would have been saved, which is shown in Table 6.8. Thus it is evident from the table that IUT could have saved more than 5 lac taka per year for these classrooms by using Sequential Scenario as a power consumption pattern. But this saving is not an absolute value and

Figure 6.11: Pairplot plot of power consumption of all rooms of Sequential Scenario.

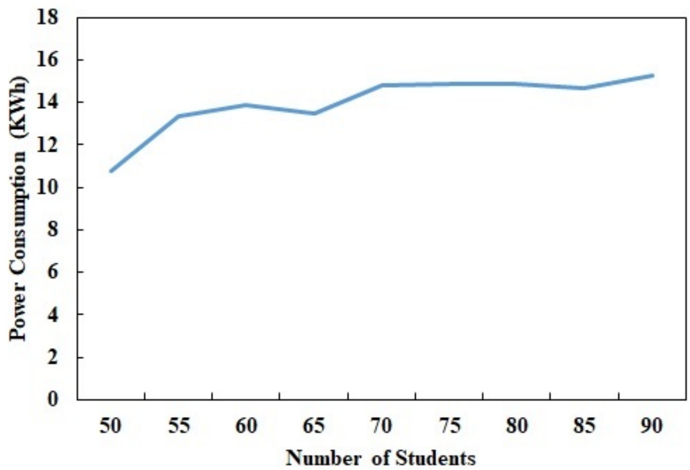

Figure 6.12: Power consumption of a class of room 201 for varying number of students of Sequential Scenario.

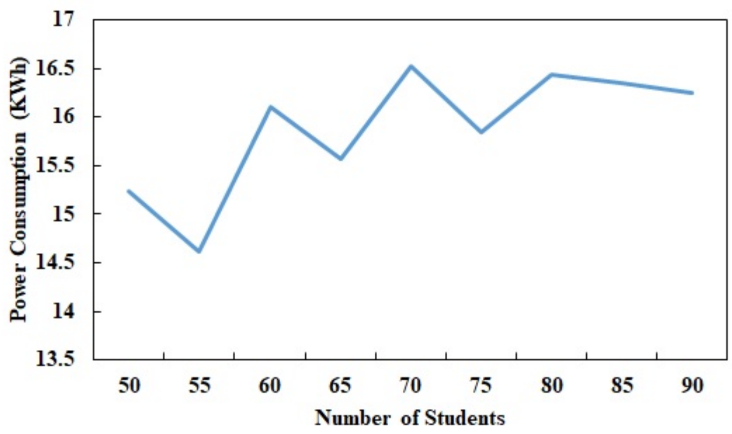

Figure 6.13: Power consumption of a class of room 201 for varying number of students of Random Scenario.

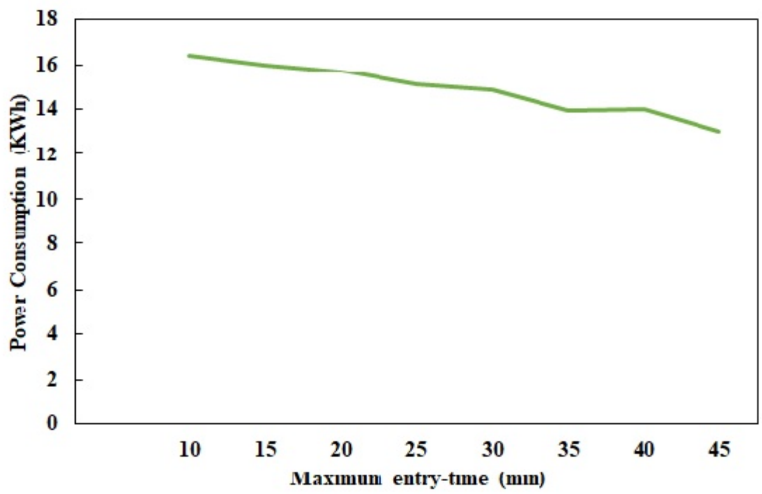

Figure 6.14: Power consumption of a class of room 201 for different maximum entry-time of Sequential Scenario.

this value does not include the costing of the sensors. This is the first outcome of the research.

6.7 Energy Prediction Results

This section provides the results obtained from the energy prediction procedures discussed in chapter 5.

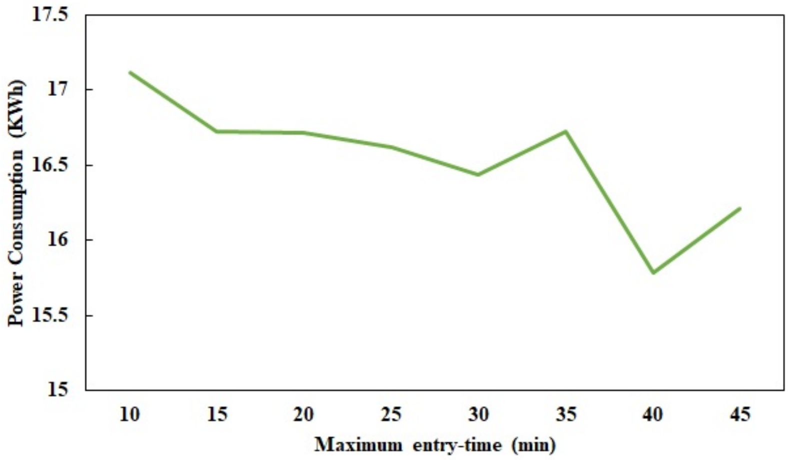

Figure 6.15: Power consumption of a class of room 201 for different maximum entry-time of Random Scenario.

Table 6.7: Comparison of power consumed in the three scenarios.

Year	Power consumed in All-on Scenario (KWh)	Power consumed in Random Scenario (KWh)	Power consumed in Sequential Scenario (KWh)
2016	98955.00	15906.42	14207.40
2017	108531.00	18516.03	12286.13
2018	109087.20	22097.99	20922.60
2019	122367.60	29622.63	26693.13

6.7.1 Exponential Smoothing Analysis of Random Scenario

As has been explained in chapter 5, the Random Scenario dataset is first split into train and test set. For the test set one year of data has been split. Then the exponential model is fitted. To account for the trend and seasonality an additive model is considered. After fitting the model the predictions are plotted. Figure 6.16 show the plot of the predictions with test and train dataset. As can be seen from the plot the predictions are somewhat matching to the test data but the peak of the test data is not being touched by the predictions. The RMSE score is found to be 50 and the AIC score is 992.

6.7.2 Exponential Smoothing Analysis of Sequential Scenario

The Random Scenario dataset is first split into train and test set. For the test set one year of data has been split. Then the exponential model is fitted. To account for the trend and seasonality an additive model is considered. After fitting the model the predictions are plotted. Figure 6.16 show the plot of the predictions with test and train dataset. As can be seen from the plot the predictions are somewhat matching to the test data but the peak of the test data is not being touched by the predictions. The RMSE score is

Table 6.8: Power and electricity cost savings in each year.

Year	Power consumed in All-on Scenario (KWh)	Power consumed in Sequential Scenario (KWh)	Energy Saved (KWh)	Total Electricity Cost Saved (per unit Tk.6)
2016	98955.00	14207.40	84787.00	508482.00
2017	108531.00	12286.13	96244.87	577469.00
2018	109087.20	20922.60	106994.60	641967.60
2019	122367.60	26693.13	95674.47	574046.80

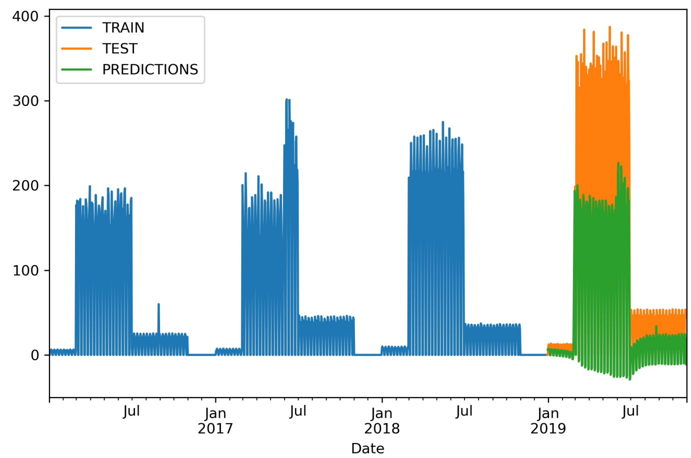

Figure 6.16: predictions, test data and train data plot of Random Scenario.

found to be 45 and the AIC score is 918.

6.7.3 ARMA Analysis of Random Scenario

For the ARMA model the best p and q values is found to be 2 and 1 respectively. The data is split into train and test data. The ARMA model is fitted to the train data and the predictions are plotted. Figure 6.18 shows the test data and predictions plot. From the plot it is evident that the ARMA predictions is a horizontal straight line and the ARMA model does not take into account the trend of the data. The RMSE score is found to be 129 and the AIC score is 800.

6.7.4 ARMA Analysis of Sequential Scenario

The ARMA model p and q values is found to be 2 and 1 respectively. The data is split into train and test data. The ARMA model is fitted to the train data and the predictions are plotted. Figure 6.19 shows the test data and predictions plot. From the plot it is evident that the ARMA predictions is a horizontal straight line and the ARMA model does not take into account the trend of the data. The RMSE score is found to be 117 and the AIC score is 771.

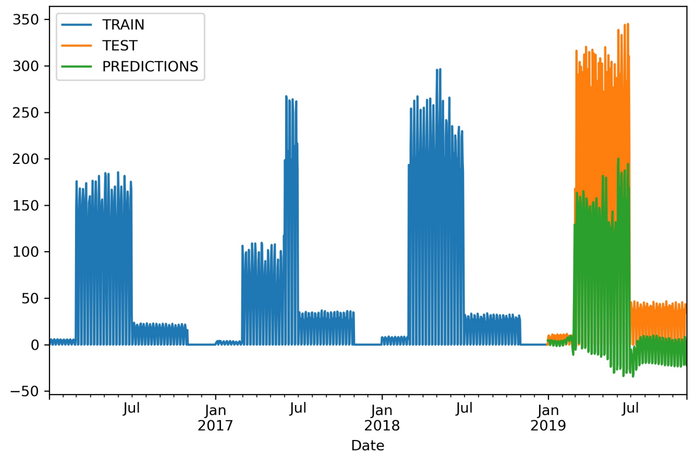

Figure 6.17: predictions, test data and train data plot of Sequential Scenario.

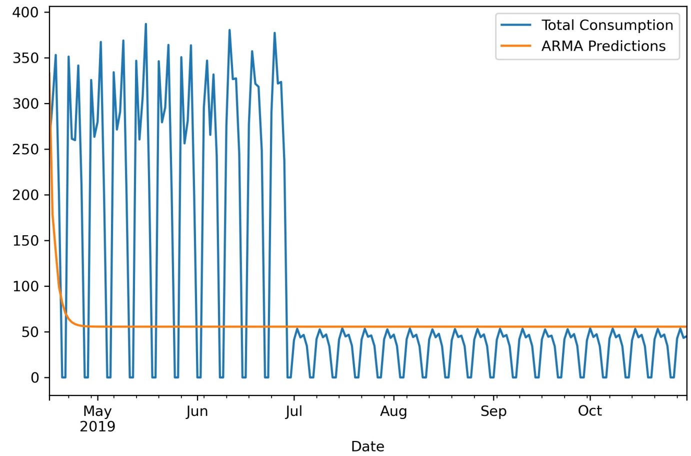

Figure 6.18: predictions and test data plot of Random Scenario.

6.7.5 Time Series Analysis of Random Scenario

Time Series Analysis is applied to the Random Scenario data. The Random Scenario data must be stationary for the analysis to work. The data is checked to be stationary by plotting rolling statistics. The rolling statistics code is shown in [Appendix C]. From the rolling statistics in Figure 6.20, it is seen that both the rolling mean and rolling standard deviation are not constant and thus the data is not stationary. The time series data showed both trend and seasonality.

To eliminate trends, log transformation is used. The constant rolling mean in Figure 6.21 for the Random Scenario represents that the time series is now stationary after the log transformation.

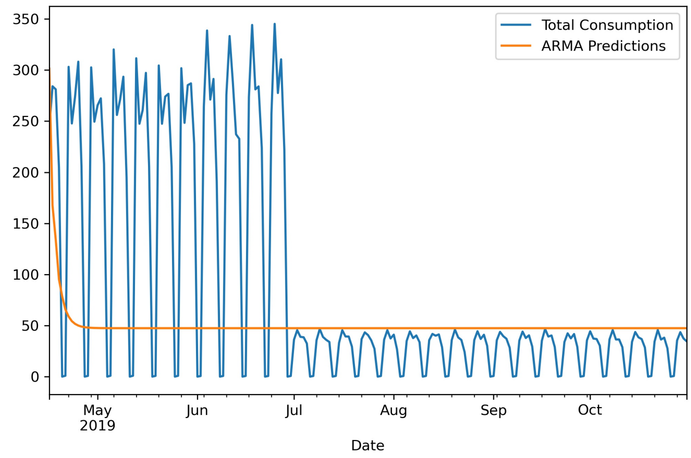

Figure 6.19: predictions and test data plot of Sequential Scenario.

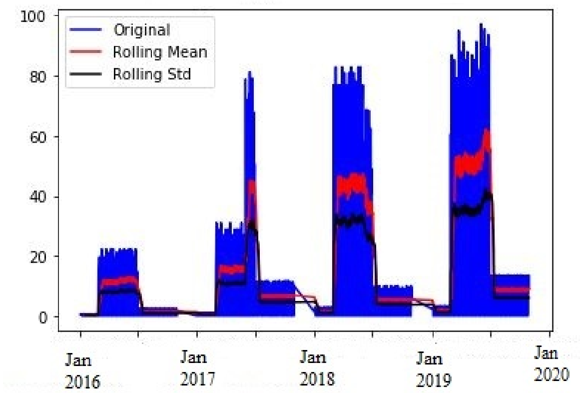

Figure 6.20: Stationarity test of Random Scenario time series dataset.

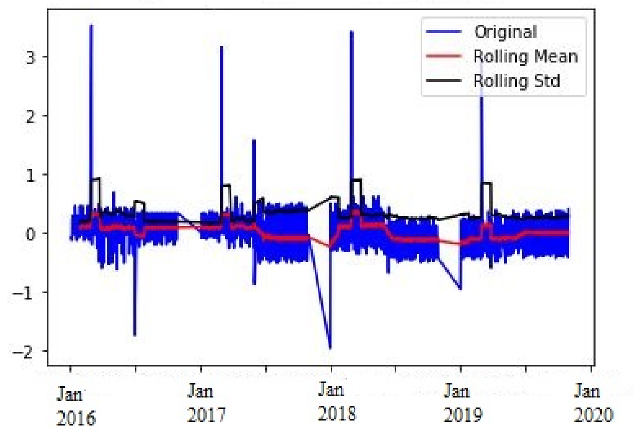

Figure 6.21: Stationarity test of log transformed Random time series data set.

The best ARIMA model is found by changing the order of (p, d, q). Hyperparameter tuning function is used [Appendix C]. The order with the lowest mean squared error (MSE) is taken from the hyperparameter tuning function for the ARIMA model.

From the hyperparameter tuning function the order of (p, d, q) is chosen to be (1,1,2). The Akaike Information Criterion (AIC) score is found to be 1299 while the RMSE is 0.29.

To get more accurate results the Random Scenario data is then transformed using data transformation techniques. The transformation technique used is standardizing the data. The function used is the $(standardscalar())$ function from the scikit-learn library.

The data set was then split into train and test data to be used for the ARIMA algorithm. Then the ARIMA model is applied. The AIC score is then lowered to 792 and the RMSE value is 0.25.

The forecast for the next six years is then found which is shown in Figure 6.22. The forecast for six years for the Random Scenario data shows that there will be a gradual increase in the power consumption in the next years.

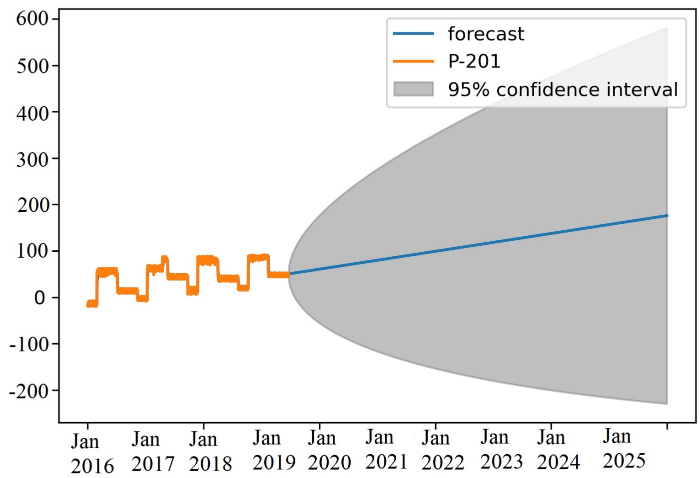

Figure 6.22: Power forecast of six years for Random Scenario.

6.7.6 Time Series Analysis of Sequential Scenario

Sequential Scenario power consumption data is also found to be not stationary. For the Sequential Scenario power consumption data, log transformation is applied to remove the trend and to make it stationary. The stationarity is checked by plotting rolling statistics found in [Appendix C]. From the plot result in Figure 6.23, it is seen that the rolling mean and rolling standard deviation is constant indicates the time series is stationary.

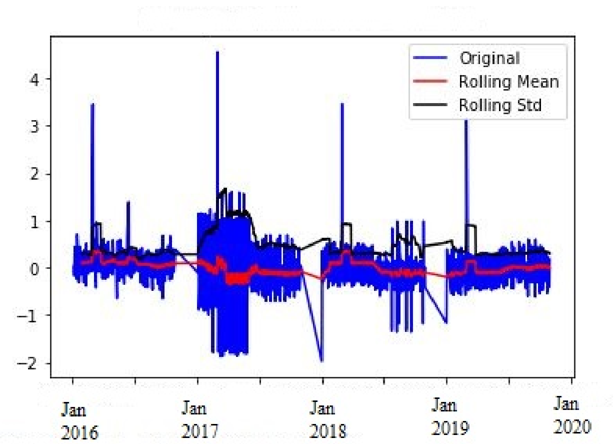

Figure 6.23: Stationarity test of log transformed Sequential time series data set.

The best ARIMA model order is chosen from running the hyperparameter tuning function [Appendix C]. The order of (p,d,q) chosen is (1,1,1).

After log transformation of the data we looked at data transformation techniques that can be applied to our data before supplying to the algorithm to get more accurate or desired results. The Transformation technique that is used is standardizing the data. The function used from scikit-learn is $(StandardScaler())$.

The data set was then split into train and test data to be used for the ARIMA algorithm. Then the ARIMA model is applied. The AIC score is 617 and the RMSE value is 0.18. The forecast for the next one year is then found which is shown in Figure 6.24. The forecast for next six years for the Sequential Scenario data shows that there will be a gradual increase in the power consumption in the next years.

6.8 Discussion of Results

This study is focused on finding the energy consumption pattern of academic buildings of Islamic University of Technology (IUT), Gazipur. The classrooms of Electrical and Electronics Engineering (EEE) department of IUT have been selected for collecting the data. There are a total of six classrooms, rooms 201, 202, 203, 509, 511 and 604. In this six rooms, the electrical engineering classes take place. The rooms, 201, 202 and 203 are larger rooms with 90 seats each. Whereas the rooms 509, 511 and 604 are smaller rooms with 36 seats each. The electric appliances that consume energy in theses classrooms are fans, lights and ACs. In the larger rooms 201, 202 and 203, there

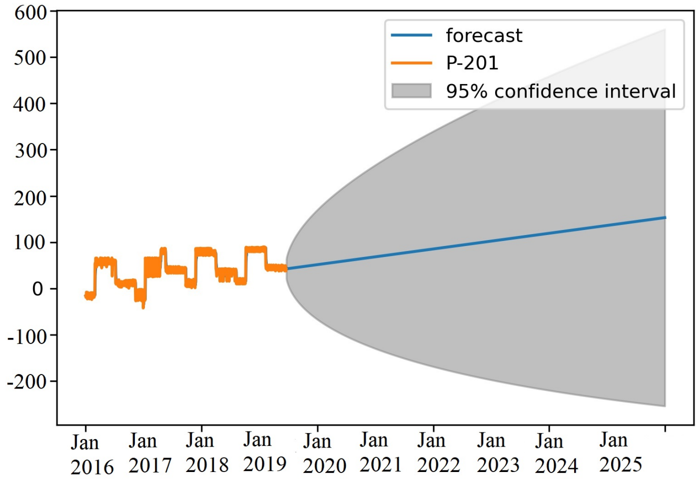

Figure 6.24: Power forecast of six years for Sequential Scenario.

are 20 lights, 20 fans and 4 two-ton ACs in each room. And in the smaller rooms 509, 511 and 604, each room has 8 lights, 8 fans and 1 two-ton AC. 1 light, 1 fan and 1 two-ton AC consume 25 Watt, 75 Watt and 3000 Watt power respectively. The behavior of students of IUT is considered as occupant behavior.

To analyze different energy usage pattern of appliances in the above mentioned rooms, three scenarios (All-on Scenario, Random Scenario and Sequential Scenario) have been considered for the Netlogo simulation. The power consumption data have been calculated for the year 2016, 2017, 2018 and 2019 through the Netlogo simulation. The Table 6.7 represent the calculated power consumption in the three scenarios.

The result shows that among the three scenarios, Sequential Scenario is more energy efficient. So this Sequential Scenario is the optimal energy usage pattern. Currently IUT uses “All-on” Scenario as an energy usage pattern of appliances in the classrooms. Since the Sequential Scenario is the best, if IUT used this scenario in the previous four years then the following amount of energy and cost would have been saved, which is shown in Table 6.8. Thus it is evident from the table that IUT could have saved more than 5 lac taka per year for these classrooms by using Sequential Scenario as a power consumption pattern. But this is an absolute value and this value does not include the cost of sensor. This is the first outcome of the research.

Further this study is also focused on the prediction of an optimum energy usage pattern in the said academic building using the Exponential Smoothing, ARMA and ARIMA method and the error metrics. The forecasting simulations is done in Python library jupyter notebook. Exponential Smoothing, ARMA and ARIMA method is applied to both the Random and Sequential Scenarios. Error metrics such as RMSE and AIC scores are found to find the best model. The Table 6.9 shows the comparison of the error metrics for the Exponential Smoothing, ARMA and ARIMA models for the Ransom Scenario. It is evident that among the three models the RMSE and AIC scores of the ARIMA model is the lowest. Thus the ARIMA model is the best performing model for the Random Scenario.

Table 6.9: Comparison of the models for the Random Scenario.

Methods	RMSE	AIC
Exponential Smoothing	50	992
ARMA	129	800
ARIMA	0.25	792

Table 6.10: Comparison of the models for the Sequential Scenario.

Methods	RMSE	AIC
Exponential Smoothing	45	918
ARMA	117	771
ARIMA	0.18	617

Table 6.10 shows the comparison of the Exponential Smoothing, ARMA and ARIMA models for the Sequential Scenario. It can be seen that the error metrics RMSE and AIC scores are lower for the ARIMA model. Therefore, ARIMA is the best performing model for the Sequential Scenario.

As ARIMA is the best performing model for both the Random and Sequential Scenario it is applied to both the Random and Sequential Scenarios to predict the energy demand for the next six years from 2020 to 2025. The plots of the forecast for both the scenarios is shown in Figure 6.22 and 6.24. From both the plots it is visually evident that the forecast for both the scenario is same. There is not much difference in the scenarios. This is the second outcome of the research. Other than the All-on Scenario which is the current scenario in IUT both the Random and Sequential Scenario forecast show somewhat same result.

The Root Mean Square Error (RMSE) and Akaike Information Criterion (AIC) are used further to measure the performance of the models of Random and Sequential Scenario. Table 6.11 shows the values. It is seen that the RMSE for the Sequential Scenario is 0.18 which is less than the RMSE value of the Random Scenario which is 0.25. The AIC score is 617 for the Sequential Scenario and 792 for the Random Scenario. It is found that Sequential Scenario is more effective and accurate. Such a difference can be explained by the fact that when students are sitting in a random manner in the Random Scenario more of the appliances are getting turned on and energy consumption is increasing. The Sequential Scenario is the optimum scenario because the appliances are automated to turn on from the front. So even though some students have tendencies to sit in the back they will be forced to sit in the front and reduce unnecessary appliances to turn on which eventually reduce power consumption.

Table 6.11: Comparison of the scenarios using ARIMA Methods.

Scenarios	RMSE	AIC
Random Scenario	0.25	792
Sequential Scenario	0.18	617

6.9 Fulfillment of the Objective and Expected Outcome

This study is focused on finding the energy usage pattern of academic buildings of International University of Technology (IUT), Gazipur. The classrooms of Electrical and Electronics Engineering (EEE) department of IUT have been selected for collecting the data.

The first objective is the analysis of different energy usage pattern of applainces due to different occupant behavior which is conducted by adding students' attendance, class hours, class schedules and weather changes when analyzing overall power consumption. From the data visualization results Figures 6.4, 6.5, 6.7, 6.8, 6.10, 6.11, 6.12, 6.13, 6.14 and 6.15 and Table 6.7 it is evident that as the occupant behavior changes the energy usage pattern also differs this proves the first objective.

Three scenarios (All-on, Random and Sequential) is considered and power consumption data is exported from the Netlogo agent based model. The power consumption data have been calculated for the year 2016, 2017, 2018 and 2019 through Netlogo simulation. It is found that the difference in behavior make a large change in consumption data. Among the three scenarios, the Sequential Scenario is the optimal energy usage pattern. This fulfills the second outcome of predicting the optimal energy usage pattern based on occupant behavior and ambient changes.

The first outcome is in line with the second objective. Amount of energy utilization is predicted from the proper energy usage pattern of a building which is evident from Table 6.7. The second outcome is predicting future monthly/annual bills based on occupant behavior and ambient changes in academic buildings for future scheduling and energy saving. From Fig 6.8, 6.22 and 6.24 the second outcome is found.

Chapter 7

Conclusion and Future Work

There is always a big difference between the estimated and current energy consumption in buildings. This is because occupant behavior is not being considered properly when estimating energy consumption. Energy simulation software rely on assumed behavioral patterns from which the predictions obtained are different from current energy usage levels in buildings. Whereas occupants have different energy usage patterns. Therefore, occupant behavior if considered correctly can decrease the energy consumption in buildings [5]. Occupant behavior refers to how occupants behave in certain environment [7].

This work is focused in predicting the proper energy usage pattern in institutional buildings by considering occupant behavior. Educational institutions in developing countries is increasing due to increase in the population. The objective in this work is to analyze the different energy usage patterns of appliances in academic buildings considering different occupancy, occupant behavior and weather condition. Real occupancy data is collected from the department of Electrical and Electronics Engineering of IUT. Three scenarios (All-on, Random and Sequential) are considered and energy consumption data is exported from the agent based model. The power consumption data have been obtained for the years 2016, 2017, 2018 and 2019 through Netlogo simulation. It is found that the difference in behavior make a large change in consumption data. Among the three scenarios, the Sequential Scenario is the optimal energy usage pattern.

At last, the prediction of energy consumption is modelled. The models used are Exponential Smoothing, ARMA and ARIMA. When comparing the three models with Random and Sequential Scenarios, the ARIMA model was found to be more effective. Therefore, the ARIMA model is used for forecasting both the Random Scenario and Sequential Scenario. The plots of the forecast for both the scenarios is same. There is no much difference in the scenarios. However, while Root Mean Square (RMSE) and Akaike Information Criterion (AIC) are used to measure the performance of the models of Random and Sequential Scenario, it is found that Sequential Scenario is more effective and accurate.

7.1 Limitations of the Research

Even though the outcomes of the study are expected to be useful, this research has some limitations which must be taken into consideration in evaluating the results and their implications. First, the most serious of these involves the derivation of a sample of power consumption pattern from a single academic building of IUT, Bangladesh. A study in several academic buildings of other institutes would have been ideal to increase the generalizability of findings. Secondly, the data were collected in the context of Bangladesh. Therefore the findings might not be directly applied to other countries.

7.2 Future Research Direction

Study results and limitations provide the basis for future research. Two general areas of future research are highlighted here for future researches. First, the future research can be directed at the limitations of this study. Second, the present research represents to develop a model to find energy consumption pattern in only the classrooms of an academic building. The energy consumption of the whole campus can be considered and energy prediction can be modeled.

REFERENCES

[1] R. Chowdhury, A. Dhar, and M. A. Ullah, “Study on institutional energy consumption scenario and implement an optimum system,” in *2019 4th International Conference on Electrical Information and Communication Technology (EICT)*, 2019, pp. 1–6.

[2] E. Delzendeh, S. Wu, A. Lee, and Y. Zhou, “The impact of occupants’ behaviours on building energy analysis: A research review,” *Renewable and Sustainable Energy Reviews*, vol. 80, pp. 1061–1071, 2017.

[3] A. M. Omer, “Energy, environment and sustainable development,” *Renewable and sustainable energy reviews*, vol. 12, no. 9, pp. 2265–2300, 2008.

[4] M. A. ul Haq, M. Y. Hassan, H. Abdullah, H. A. Rahman, M. P. Abdullah, F. Hussin, and D. M. Said, “A review on lighting control technologies in commercial buildings, their performance and affecting factors,” *Renewable and Sustainable Energy Reviews*, vol. 33, pp. 268–279, 2014.

[5] K. Schakib-Ekbatan, F. Z. Cakıcı, M. Schweiker, and A. Wagner, “Does the occupant behavior match the energy concept of the building?–analysis of a german naturally ventilated office building,” *Building and Environment*, vol. 84, pp. 142–150, 2015.

[6] S. D’Oca, T. Hong, and J. Langevin, “The human dimensions of energy use in buildings: A review,” *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 731–742, 2018.

[7] S. Pan, X. Wang, S. Wei, C. Xu, X. Zhang, J. Xie, J. Tindall, and P. de Wilde, “Energy waste in buildings due to occupant behaviour,” *Energy Procedia*, vol. 105, pp. 2233–2238, 2017.

[8] M. S. Gul and S. Patidar, “Understanding the energy consumption and occupancy of a multi-purpose academic building,” *Energy and Buildings*, vol. 87, pp. 155–165, 2015.

[9] Z. Yu, B. C. Fung, F. Haghighat, H. Yoshino, and E. Morofsky, “A systematic procedure to study the influence of occupant behavior on building energy consumption,” *Energy and buildings*, vol. 43, no. 6, pp. 1409–1417, 2011.

[10] U. Berardi, “A cross-country comparison of the building energy consumptions and their trends,” *Resources, Conservation and Recycling*, vol. 123, pp. 230–241, 2017.

[11] F. Divina, M. García Torres, F. A. Goméz Vela, and J. L. Vázquez Noguera, “A comparative study of time series forecasting methods for short term electric energy consumption prediction in smart buildings,” *Energies*, vol. 12, no. 10, p. 1934, 2019.

[12] E. Azar and C. C. Menassa, “Agent-based modeling of occupants and their impact on energy use in commercial buildings,” *Journal of Computing in Civil Engineering*, vol. 26, no. 4, pp. 506–518, 2012.

[13] D. Zhao, A. P. McCoy, J. Du, P. Agee, and Y. Lu, “Interaction effects of building technology and resident behavior on energy consumption in residential buildings,” *Energy and Buildings*, vol. 134, pp. 223–233, 2017.

[14] T. Hong, D. Yan, S. D’Oca, and C.-f. Chen, “Ten questions concerning occupant behavior in buildings: The big picture,” *Building and Environment*, vol. 114, pp. 518–530, 2017.

[15] M. Wedel and R. Pieters, *Eye tracking for visual marketing*. Now Publishers Inc, 2008.

[16] X. Feng, D. Yan, C. Wang, and H. Sun, “A preliminary research on the derivation of typical occupant behavior based on large-scale questionnaire surveys,” *Energy and Buildings*, vol. 117, pp. 332–340, 2016.

[17] C. Fu, W. Wang, and J. Tang, “Exploring the sensitivity of residential energy consumption in china: Implications from a micro-demographic analysis,” *Energy Research & Social Science*, vol. 2, pp. 1–11, 2014.

[18] K. B. Janda, “Buildings don’t use energy: people do,” *Architectural science review*, vol. 54, no. 1, pp. 15–22, 2011.

[19] H.-W. Lin and T. Hong, “On variations of space-heating energy use in office buildings,” *Applied Energy*, vol. 111, pp. 515–528, 2013.

[20] V. Motuziene and T. Vilutiene, “Modelling the effect of the domestic occupancy profiles on predicted energy demand of the energy efficient house,” *Procedia Engineering*, vol. 57, pp. 798–807, 2013.

[21] M. N. Iqbal, L. Kütt, and N. Shabbir, "Modeling of lighting load in residential buildings," *International Journal of Engineering and Advanced Technology (IJEAT)*, vol. 8, no. 2S, pp. 232–236, 2018.

[22] R. De Dear and G. S. Brager, "Developing an adaptive model of thermal comfort and preference," 1998.

[23] W. O'Brien and H. B. Gunay, "The contextual factors contributing to occupants' adaptive comfort behaviors in offices–a review and proposed modeling framework," *Building and Environment*, vol. 77, pp. 77–87, 2014.

[24] A. Hussain, M. Rahman, and J. A. Memon, "Forecasting electricity consumption in pakistan: The way forward," *Energy Policy*, vol. 90, pp. 73–80, 2016.

[25] C. Kuster, Y. Rezgui, and M. Mourshed, "Electrical load forecasting models: A critical systematic review," *Sustainable cities and society*, vol. 35, pp. 257–270, 2017.

[26] L. Capuano, "International energy outlook 2018 (ieo2018)," *US Energy Information Administration (EIA): Washington, DC, USA*, vol. 2018, p. 21, 2018.

[27] C. Deb, F. Zhang, J. Yang, S. E. Lee, and K. W. Shah, "A review on time series forecasting techniques for building energy consumption," *Renewable and Sustainable Energy Reviews*, vol. 74, pp. 902–924, 2017.

[28] K. Kandananond, "Forecasting electricity demand in thailand with an artificial neural network approach," *Energies*, vol. 4, no. 8, pp. 1246–1257, 2011.

[29] C. Deb, L. S. Eang, J. Yang, and M. Santamouris, "Forecasting diurnal cooling energy load for institutional buildings using artificial neural networks," *Energy and Buildings*, vol. 121, pp. 284–297, 2016.

[30] V. Ş. Ediger and S. Akar, "Arima forecasting of primary energy demand by fuel in turkey," *Energy policy*, vol. 35, no. 3, pp. 1701–1708, 2007.

[31] S. Sharmin and A. Khan, "Forecasting the production of natural gas and its impact on electricity and gdp in bangladesh," *International Journal of Energy, Environment and Economics*, vol. 23, no. 2, p. 269, 2015.

[32] M. Ohyver and H. Pudjihastuti, "Arima model for forecasting the price of medium quality rice to anticipate price fluctuations," *Procedia Computer Science*, vol. 135, pp. 707–711, 2018.

[33] M. Amini, O. Karabasoglu, M. D. Ilić, K. G. Boroojeni, and S. Iyengar, "Arima-based demand forecasting method considering probabilistic model of electric vehicles' parking lots," in *2015 IEEE Power & Energy Society General Meeting*. IEEE, 2015, pp. 1–5.

[34] P. Sen, M. Roy, and P. Pal, “Application of arima for forecasting energy consumption and ghg emission: A case study of an indian pig iron manufacturing organization,” *Energy*, vol. 116, pp. 1031–1038, 2016.

[35] S. R. Rallapalli and S. Ghosh, “Forecasting monthly peak demand of electricity in india—a critique,” *Energy policy*, vol. 45, pp. 516–520, 2012.

[36] E. Erdogdu, “Electricity demand analysis using cointegration and arima modelling: A case study of turkey,” *Energy policy*, vol. 35, no. 2, pp. 1129–1146, 2007.

APPENDICES

A Classroom Schedules

Islamic University of Technology (IUT)

202

	1 08:00 - 09:15	2 09:15 - 10:30	3 10:30 - 11:45	4 11:45 - 13:00	Break 13:00 - 14:30	5 14:30 - 15:45	6 15:45 - 17:00
Monday	Math 4221 **2A** MO	EEE 4201 **2A** MHR	Math 4421 **4B** MRI	EEE 4401 **4B** M		CSE 4271 **2B** AH	EEE 4201 **2B** MHR
Tuesday	Hum 4225 **2B** TVE X2	EEE 4641 **6A/6B/6C** Ce TK	EEE 4601 **6A** MRA	Phy 4421 **4B** SIA		EEE 4405 **4B** RHS	EEE 4401 **4B** M
Wednesday		EEE 4603 **6A** SMA	EEE 4625 **6A** QNI	EEE 4605 **6A** GS	**Break**	Phy 4421 **4C** SIA	EEE 4403 **4C** NIBH
Thursday	Hum 4621 **6C** TVE X4	Hum 4621 **6B** TVE X4	Hum 4621 **6A** TVE X4	EEE 4605 **6A** GS		EEE 4635 **6A/6B/6C** Pr MFA	
Friday	Hum 4621 **6B** TVE X4	EEE 4601 **6B** RM		Hum 4621 **6C** TVE X4			

Timetable generated:5/27/2019 aSc Timetables

Figure A.1: Class schedule of room 202 for the summer 2018-2019 Semester.

Islamic University of Technology (IUT)

203

	1 08:00 - 09:15	2 09:15 - 10:30	3 10:30 - 11:45	4 11:45 - 13:00	Break 13:00 - 14:30	5 14:30 - 15:45	6 15:45 - 17:00
Monday	Hum 4421 **4C** TVE X3	EEE 4625 **6B** Ut QNI	EEE 4401 **4C** M	EEE 4405 **4C** RHS		Hum 4421 **4A** TVE X3	
Tuesday	Hum 4421 **4B** TVE X3	Math 4421 **4B** MOF	EEE 4603 **6C** SMA	EEE 4605 **6C** GS		EEE 4401 **4A/DTE** M	Phy 4421 **4A** SIA
Wednesday	Math 4221 **2C/BScTE (2yr) 2** MO	EEE 4835 **8A/8B** PS AA	EEE 4601 **6C** RM	EEE 4601 **6B** MRA	**Break**	EEE 4403 **4B** NIBH	Phy 4421 **4B** SIA
Thursday	EEE 4401 **4C** M	EEE 4851 **8A/8B** AC RHK	EEE 4405 **4A/DTE** RHS	EEE 4401 **4A/DTE** M		EEE 4403 **4C** NIBH	EEE 4403 **4A** NIBH
Friday		EEE 4403 **4B** NIBH				Hum 4225 **2B** TVE X2	

Timetable generated:5/27/2019 aSc Timetables

Figure A.2: Class schedule of room 203 for the summer 2018-2019 Semester.

Islamic University of Technology (IUT)

509

	1 08:00 - 09:15	2 09:15 - 10:30	3 10:30 - 11:45	4 11:45 - 13:00	Break 13:00 - 14:30	5 14:30 - 15:45	6 15:45 - 17:00
Monday		Math 4221 **2B** MO	EEE 4405 **4A/DTE** RHS				
Tuesday		EEE 4201 **2A** MHR	Hum 4225 **2A** TVE X2	EEE 4203 **2A** MAH		CSE 4271 **2C** AH	EEE 4201 **2C** MHR
Wednesday		EEE 4851 **8A/8B** AC RHK	Math 4421 **4C** MRI	EEE 4865 **8A/8B** DF TR	**Break**	Hum 4222 **2B** Arabic TVE X1	
Thursday	Phy 4221 **2C** AKMAH	CSE 4271 **2C** AH		EEE 4203 **2C** MAH		EEE 4801 **8B** FI	Phy 4821 **8B** MTF
Friday	Hum 4823 **8B** TVE X5	Hum 4823 **8A** TVE X5		Hum 4225 **2A** TVE X2			

Timetable generated:5/27/2019 aSc Timetables

Figure A.3: Class schedule of room 509 for the summer 2018-2019 Semester.

Islamic University of Technology (IUT)

511

	1 08:00 - 09:15	2 09:15 - 10:30	3 10:30 - 11:45	4 11:45 - 13:00	Break 13:00 - 14:30	5 14:30 - 15:45	6 15:45 - 17:00
Monday							
Tuesday	Hum 4821 **8A** BTM X1	EEE 4203 **2B** MMN	Hum 4823 **8A** TVE X5	EEE 4603 **6B/BScTE (2yr) 2** SMA		EEE **EEE**	EEE **EEE**
Wednesday			EEE 4203 **2C** MMN	EEE 4603 **6C** SMA	**Break**		
Thursday							
Friday	Phy 4221 **2A** MAB	Math 4221 **2A** MO		EEE **EEE**		EEE **EEE**	EEE **EEE**

Timetable generated:5/27/2019 aSc Timetables

Figure A.4: Class schedule of room 511 for the summer 2018-2019 Semester.

Islamic University of Technology (IUT)

604

	1 08:00 - 09:15	2 09:15 - 10:30	3 10:30 - 11:45	4 11:45 - 13:00	Break 13:00 - 14:30	5 14:30 - 15:45	6 15:45 - 17:00
Monday		EEE 4865 **8A/8B** DF TR	Hum 4821 **8B** BTM X1	EEE 4841 **8A/8B** MW TK			
Tuesday		Hum 4225 **2C** TVE X2	Hum 4421 **4C** TVE X3	EEE 4405 **4C** RHS		EEE 4201 **2B** MHR	
Wednesday		EEE 4201 **2C** MHR	Hum 4821 **8A** BTM X1	EEE 4841 **8A/8B** MW TK	**Break**	EEE 4801 **8A** FI	Phy 4821 **8A** MTF
Thursday	CSE 4271 **2A** AH	Phy 4221 **2A** AKMAH	EEE 4203 **2B** MAH	Phy 4221 **2B** AKMAH		Phy 4821 **8A** MTF	EEE 4801 **8A** FI
Friday	Math 4221 **2C/BScTE (2yr) 2** MO	Phy 4221 **2B** MAB		Math 4221 **2B** MO			

Timetable generated:5/27/2019 aSc Timetables

Figure A.5: Class schedule of room 604 for the summer 2018-2019 Semester.

B Dataset of the Different Scenarios

Table B.1: All-on scenario January 2019 dataset

Room	Appliance	Monday				Tuesday				Wednesday				Thursday				Friday			
201	Light	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5
202	Light	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5
203	Light	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5
509	Light	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8
604	Light	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8
511	Light	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8

Table B.2: Random Scenario January 2019 dataset.

Room	Appliance	Monday				Tuesday				Wednesday				Thursday				Friday			
201	Light	3.4	3.36	3.21	3.4	2.24	2.16	2.13	2.24	2.8	2.79	2.71	2.8	2.74	2.86	2.7	2.74	2.3	2.21	2.7	2.3
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	3.4	3.36	3.21	3.4	2.24	2.16	2.13	2.24	2.8	2.79	2.71	2.8	2.74	2.86	2.7	2.74	2.3	2.21	2.7	2.3
202	Light	2.8	2.79	2.62	2.7	2.71	2.66	2.71	2.79	3.4	3.35	3.37	3.1	2.84	2.73	2.84	2.87	1.1	1.1	1.1	1.1
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	2.8	2.79	2.62	2.7	2.71	2.66	2.71	2.79	3.4	3.35	3.37	3.1	2.84	2.73	2.84	2.87	2.8	1.1	1.1	1.1
203	Light	2.9	2.86	2.77	2.8	2.84	2.7	2.81	2.84	2.2	2.23	2.19	2.2	2.7	2.75	2.81	2.7	2.2	2.17	2.2	2.2
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	2.9	2.86	2.77	2.8	2.84	2.7	2.81	2.84	2.2	2.23	2.19	2.2	2.7	2.75	2.81	2.7	2.2	2.17	2.2	2.2
509	Light	1.1	1.07	1.04	1	0.89	0.86	0.86	0.92	0.9	0.89	0.87	0.8	1.13	1.08	1.09	1.08	1.4	1.32	1.3	1.2
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	1.1	1.07	1.04	1	0.89	0.86	0.86	0.92	0.9	0.89	0.87	0.8	1.13	1.08	1.09	1.08	1.4	1.32	1.3	1.2
604	Light	2.2	1.07	1.8	1.8	1.29	0.86	1.27	1.29	0.9	0.89	2.38	2	1.13	1.08	2	2.1	1.4	1.32	0.9	0.9
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	2.2	1.07	1.8	1.8	1.29	0.86	1.27	1.29	0.9	0.89	2.38	2	1.13	1.08	2	2.1	1.4	1.32	0.9	0.9
511	Light	1.1	1.05	1.05	1.1	0	0	0	0	0.4	0.42	0.4	0.4	0.84	0.83	0.84	0.81	0	0	0	0
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	1.1	1.05	1.05	1.1	0	0	0	0	0.4	0.42	0.4	0.4	0.84	0.83	0.84	0.81	0	0	0	0

Table B.3: Sequential Scenario January 2019 dataset.

Room	Appliance	Monday				Tuesday				Wednesday				Thursday				Friday			
201	Light	2.78	2.8	2.92	2.92	1.64	1.64	1.64	1.64	2.42	2.12	2.42	2.5	2.01	2.53	2.01	2.4	1.6	1.88	1.62	1.62
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	2.78	2.8	2.92	2.92	1.64	1.64	1.64	1.64	2.42	2.12	2.42	2.5	2.01	2.53	2.01	2.4	1.6	1.88	1.62	1.62
202	Light	2.56	2.1	2.59	2.5	2.34	2.34	2.29	2.34	2.99	2.41	2.99	3	2.3	3	2.46	2.3	0.8	1	1	1
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	2.56	2.1	2.59	2.5	2.34	2.34	2.29	2.34	2.99	2.41	2.99	3	2.3	3	2.46	2.3	0.8	1	1	1
203	Light	2.2	2.5	2.45	2.2	2.38	2.38	2.38	2.1	2	1.82	1.58	1.8	2.4	2.59	2.4	2.4	2	2	1.93	2.55
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	2.2	2.5	2.45	2.2	2.38	2.38	2.38	2.1	2	1.82	1.58	1.8	2.4	2.59	2.4	2.4	2	2	1.93	2.55
509	Light	1.1	0.9	1.1	0.9	0.8	0.8	0.8	0.8	0.82	0.87	1.1	0.8	1.1	1.1	0.87	1.1	1.3	1.25	1.3	1.25
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	1.1	0.9	1.1	0.9	0.8	0.8	0.8	0.8	0.82	0.87	1.1	0.8	1.1	1.1	0.87	1.1	1.3	1.25	1.3	1.25
604	Light	0.73	0.8	0.81	0.81	1.02	1	1.02	1.02	1	1.1	1.1	1.1	1.33	1.33	1.17	1.2	0.8	0.77	0.84	0.84
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	0.73	0.8	0.81	0.81	1.02	1	1.02	1.02	1	1.1	1.1	1.1	1.33	1.33	1.17	1.2	0.8	0.77	0.84	0.84
511	Light	1.05	1.1	1.1	1.05	0	0	0	0	0.42	0.4	0.39	0.4	0.83	0.84	0.81	0.8	0	0	0	0
	Fan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	1.05	1.1	1.1	1.05	0	0	0	0	0.42	0.4	0.39	0.4	0.83	0.84	0.81	0.8	0	0	0	0

C Codes

```
from statsmodels.tsa.stattools import adfuller  #Performing the stationary test
def test_stationary(timeseries):
    #determining rolling statitics
    movingAverage = timeseries.rolling(window=15).mean()
    movingSTD = timeseries.rolling(window=15).std()

    #Plotting rolling statistics
    orig = plt.plot(timeseries, color='blue', label='Original')
    mean = plt.plot(movingAverage, color='red', label='Rolling Mean')
    std = plt.plot(movingSTD, color='black', label='Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show(block=False)

    #Perform Dickey-Fuller test:
    print('Results of Dickey-Fuller test:')
    dftest = adfuller(timeseries['P-201'], autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistics', 'p-vale','#Lags Used', 'Number of Obse
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print(dfoutput)
```

Figure C.1: function to check stationarity of the time series data.

```
p_values = range(0,5)
d_values = range(0,3)
q_values = range(0,5)
```

```
#MSE value of 0 indicates perfect skill, or no error
for p in p_values:
    for d in d_values:
        for q in q_values:
            order = (p,d,q)
            train, test = f_power_log[0:800], f_power_log[800:869]
            predictions = list()
            for i in range(len(test)):
                try:
                    model = ARIMA(train,order)
                    model_fit = model.fit(disp=0) # displacement = 0
                    pred_y = model_fit.forecast()[0] # first column
                    predictions.append(pred_y)  # Whatever predicted
                    error = mean_squared_error(test, predictions)
                    print('ARIMA%s  MSE = %0.2f' % (order,error))
                except:
                    continue
```

Figure C.2: Hyperparameter tuning function.