12-2021

Forecasting Nigeria's Electricity Demand and Energy Efficiency Potential Under Climate Uncertainty

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I am submitting herewith a dissertation written by Olawale Olabisi entitled "Forecasting Nigeria's Electricity Demand and Energy Efficiency Potential Under Climate Uncertainty." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Industrial Engineering.

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Forecasting Nigeria’s Electricity Demand and Energy Efficiency Potential Under Climate Uncertainty

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Olawale Olabisi

December 2021

ACKNOWLEDGEMENT

My deepest gratitude goes to Dr. Andrew Yu for his guidance and encouragement throughout this research study. I would also like to appreciate the other committee members, Dr. James Simonton, Dr. Zhongshun “Tony” Shi, and Dr. Reza Abedi for their input and direction. Many thanks go to Charlotte Henley for being understanding and helping with registration issues and timely response to all my enquiries as a Ph.D. student.

I also thank Felix Diawuo, whom I met at the Lawrence Berkeley National Lab, CA and was working on electricity demand in Ghana for sharing his knowledge on electricity demand in Africa. Special thanks also go to the International Energy Group of the Lawrence Berkeley National Lab especially Virginie Letschert for providing valuable insights on electricity demand in developing countries. I would also like to thank my former companies, Freeport-McMoRan Oil and Gas and Sentinel Peak Resources, LLC for providing partial tuition reimbursement towards my degree.

Special thanks to my parents, Chief & Mrs. Johnson & Toyin Olabisi who have always believed me in and have always encouraged me to pursue and complete my doctoral studies. I also thank my siblings - Funmilayo, Segun, and Ayomikun; and my wonderful sister in-law, Nafisat Akinola for their love and support all through my academic career.

Finally, many thanks to my loving wife and best friend, Omotola who has always been there for me through thick and thin especially her constant push for me to complete my dissertation on time and graduate. I also like to thank my wonderful kids, Eyitayo, Olamijuwon, and Folakunmi whom I always draw inspiration from to do better, be a good father, and good role model to.

ABSTRACT

The increasing population and socio-economic growth of Nigeria, coupled with the current, unmet electricity demand, requires the need for power supply facilities expansion. Of all Nigeria's electricity consumption by sector, the residential sector is the largest and growing at a very fast rate. To meet this growing demand, an accurate estimation of the demand into the future that will guide policy makers to adequately plan for the expansion of electricity supply and distribution, and energy efficiency standards and labeling must be made. To achieve this, a residential electricity demand forecast model that can correctly predict future demand and guide the construction of power plants including cost optimization of building these power infrastructures is needed.

Modelling electricity demand in developing countries is problematic because of scarcity of data and methodologies that adequately consider detailed disaggregation of household appliances, energy efficiency improvements, and stock uptakes. This dissertation addresses these gaps and presents methodologies that can carry out a detailed disaggregation of household appliances, a more accurate electricity demand projection, peak load reduction, energy savings, economic, and environmental benefits of energy efficiency in the residential sector of Nigeria.

This study adopts a bottom-up and top-down approach (hybrid) supplemented with hourly end-use demand profile to model residential electricity consumption. and project efficiency improvement through the introduction of energy efficiency standards and labelling (EE S&L) under two scenarios (Business As Usual and Best Available Technology). A consumer life-cycle cost analysis was also conducted to determine the cost-effectiveness of introducing EE S& L to consumers.

The results show significant savings in energy and carbon emissions, increased cooling demand due to climate uncertainty, and negative return on investment and increased lifecycle costs to

consumers who purchase more efficient appliances. These results are subject to some level of uncertainties that are mainly caused by the input data. The uncertainties were analyzed based on a Monte Carlo Simulation. The uncertainties that were considered including the type of distributions applied to them were outlined and the result of the outputs were presented.

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ABBREVIATIONS

AEC	Appliance Electricity Consumption
BAU	Business As Usual
BAT	Best Available Technology
BNRCC	Building Nigeria's Response to Climate Change
BUENAS	Bottom-Up Energy Analysis System
CLASP	Collaborative Labelling and Appliance Standards Program
CO2	Carbon Dioxide
DISCOS	Distribution Companies
DSM	Demand Side Management
ECN	Electricity Corporation of Nigeria
EES&L	Energy Efficiency Standards and Labeling
EPS	Electric Power Sub-Sector
EPSR	Enactment of the Electric Power Sector Reform
EU	European Union
FGN	Federal Government of Nigeria
GDP	Gross Domestic Product
GENCOS	Generation Companies
GHG	Green House Gases
HDI	Human Development Index
ICA	International Copper Association
IEA	International Energy Agency
IREC	IEA Residential Electricity Consumption

IPCC	Intergovernmental Panel on Climate Change
LBNL	Lawrence Berkeley National Laboratory
LECB	Low-Emissions Capacity Building
LNG	Liquefied Natural Gas
LOADM	LOAD Curve Model
MEPS	Minimum Energy Efficiency Performance Standards
MREC	Modelled Residential Electricity Consumption
NAMA	Nationally Appropriate Mitigation Actions
NBET	Nigerian Bulk Electricity Trading
NDA	Niger Dam Authority
NDC	Nationally Determined Contributions
NECAL	Nigeria Electricity Calculator
NEPA	National Electric Power Authority
NERC	Nigeria Electricity Regulation Commission
NESC	Nigerian Electricity Supply Company
NESI	Nigerian Electricity Supply Industry
NNPC	Nigerian National Petroleum Corporation
OECD	Organization for Economic and Development
OPEC	Organization of the Petroleum Exporting Countries
PHCN	Power Holding Company of Nigeria
REC	Residential Electricity Consumption
UEC	Unit Energy Consumption
UN	United Nations

UNDP	United Nations Development Program
UNEP	United Nations Environment Program
UNFCCC	U.N. Framework Convention on Climate Change
USDOE	United States Department of Energy
WBDI	World Bank Development Indicators
WMO	World Meteorological Organization

CHAPTER 1: INTRODUCTION

1.1 Background of the Problem

Electricity in today's world is regarded as the most desirable and widely used energy form (Emodi and Yusuf, 2015). An important observation is that there tends to be an increase in the demand for electricity as the population of a country increases. The reason for this is not farfetched as energy is considered a fundamental aspect of human life (Adams, 2010); and a connector that binds increased social equity and economic growth (Ban Ki-moon, 2012). The United Nations Development Programme (UNDP) (2010) describes accessibility and affordability of energy services such as electricity supply as a mitigating necessity for poverty reduction, and an important aspect of economic growth and national development. When nations are unable to provide adequate access to these services, they fall into a state known as the energy poverty, which eventually becomes a vicious cycle that affects other facets of human life.

Inadequate supply of electricity or low levels of electrification, incessant use of alternative electricity generating sets, and the time spent in obtaining fuel wood and charcoal for domestic cooking are some of the issues surrounding the electricity sector at the domestic levels in some developing countries. There are also issues at the legislation and institutional levels (Emordi, 2015). Thus, adequate electricity supply is required to ensure the wellbeing of a person. With constant increases in world population, electricity generation from several energy sources in Africa has been shown to contribute to global warming. Similarly, power supply in many Southeast Asian, African nations, and many other developing countries is often characterized by incessant disruptions, instability, and high billings; this is happening in spite of a high standard of living which generally affects competitiveness and efficiency. It thus implies that electricity issues in these countries are in two dimensions.

First, it appears that the demand for electricity has been on the increase for decades owing to rising needs or otherwise put, inadequate access to electricity. Over 10% of the world's population have no access to electricity (World Bank, 2019). Over 78% of the population with deficient electricity supply resides in the rural areas. Sub-Saharan Africa rural access rates to electricity is 22% (the lowest in the world). The Economist (2007) revealed that South Africa, Egypt, and North African littoral countries generate three-quarters of the electricity Africa generates, even as electricity continues to elude countries around the West African region. Irregular power supply in these countries hinders economic development and other opportunities that can improve the living standards of the people, thereby making them susceptible to all forms of social issues such as poverty.

With a growing population currently standing at over 170 million in Nigeria for example (Figure 1.1), electricity generating plants are being stressed because the plants installed capacity is not enough to meet the needs of the populace. Consequently, electricity supply does not meet the growing demand even after many years of reforms at the industrial and domestic levels. Since the beginning of the democratic governance beginning in 1999, the Federal Government of Nigeria (FGN) under successive democratic governments have paid some attention to the power sector. This has been with the view of revamping the sector especially at the electric power sub-sector (EPS) level after several years of government monopolization and failed attempts to manage the sector. Successive attempts have been made to revitalize the sector through state-owned utilities corporations including, but not limited to the; Nigerian Electricity Supply Company (NESC) in 1929, the Electricity Corporation of Nigeria (ECN) in 1950

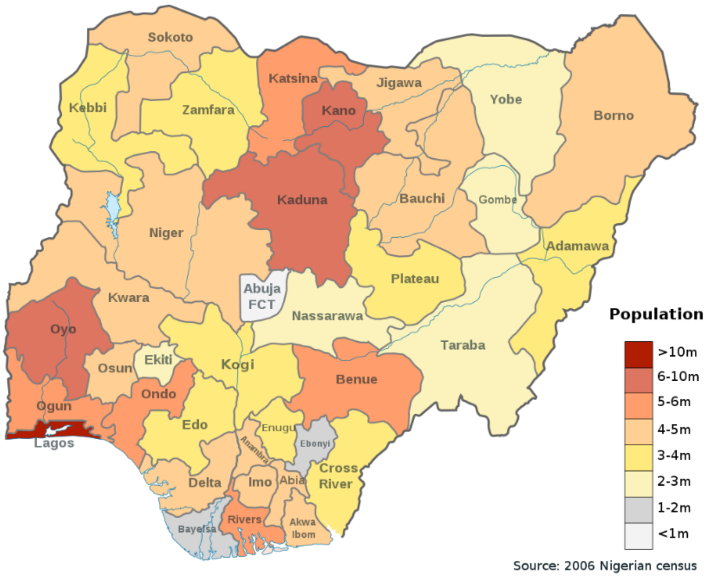

Figure 1.1: Map of Nigeria showing population distribution.

Source: https://commons.wikimedia.org/w/index.php?curid=77656783

Niger Dam Authority (NDA) in 1962 and the National Electric Power Authority (NEPA) in 1973. Towards the end of the ‘90s, a reform programme became necessary to resuscitate the electricity sub-sector and make it more effective, responsive, and efficient to meet the rising demands of the growing population. The reform programme began through the enactment of the Electric Power Sector Reform (EPSR) Act, the establishment of the Nigeria Electricity Regulation Commission (NERC), and the emergence of Power Holding Company of Nigeria (PHCN) between 2005-2006. Attempts by successive governments to address epileptic power generation, distribution, and supply since these reforms began however have not been successful. Huge amounts of money are still being expended on self-generated power by families, individuals, and businesses, adding close to 40% to the cost of doing business (Financial Times, 2014).

A successful reform programme is expected to improve service delivery, enhance electricity sector efficiency, stimulate improved public services, public sector finances, and economic development (Newbery, 2002, Davies et. al., 2003, Kessides, 2012). In addition to that, the poor are supposed to be a major beneficiary of a successful electricity reform programme (Davies et. al., 2003). However, this has not been the case. Instead, there has been apportioning of power within districts with more businesses taking more of the power. The reality is that there is a high reliance on alternative energy and electricity generating sets to meet domestic and industrial electricity needs in Nigeria.

Such problems as technical, socio-economic, and most importantly environmental challenges have been identified as major constraints militating against electricity generation in Nigeria (Egboh, 2011). Nigeria like the rest of the world has over the years had its own share of climate change impact too. The effects of change in climate are evident in desertification and the drying up of lake Chad around the northern region, and incessant flooding and erosion in the Niger Delta and South-eastern region (Dioha, 2017). An assessment of the flood in 2012 in Nigeria showed that the damage caused is over 1% of the country's real GDP for the year, which is about US$17 billion (Dioha, 2017). This is a testament to the prediction that the risk of the coastal areas flooding due to storm surges may double by 2030 (Climate Central, 2012). By 2100, sea level rise is estimated to be between eight inches to 6.6 feet more than the level they were in 1992. (National Oceanic Atmospheric Administration, 2012). This impact is hypothesized to be greater in a developing country like Nigeria where governments, at all levels, still struggle with grid constraints, power generation issues, and policy options. This is why Adeyemi (2014) provided five informative recommendations based on a detailed review of published studies of climatic impacts on energy in Nigeria. The recommendations are: improving the rate of energy efficiency; "*identification of issues which require investigation and providing results through advocacy and research*"; exploring the economic benefits of carbon finance; production of biogas from animal waste; efficient and sustainable charcoal production and utilisation; as well as increasing stakeholder participation in sustainable afforestation programs.

Meanwhile, Harrison (2001) has earlier predicted that the level at which the concentrations of CO_2 are stabilized will partly be dependent on the speed at which nations respond, in addition to the rate of response of developing nations since the effect will *spill-over* from the industrialised nations to the developing world. Therefore, the impact on developing nations will be varied. Unless something is done to tackle climate change impacts especially in the energy sector, the adaptation cost may exceed mitigation cost. This goes to show that an understanding of climate change impacts and electricity needs is becoming necessary for policymakers in charge of electricity supply to the public, and electricity firms that provide such critical services.

Some of the studies reviewed in the literature showed that, through the engagement of past experiences, it is possible to assess the vulnerability rate of electricity to climate change, but is this a sufficient guide for operations and planning in the near future? (Schaeffer et. al., 2012). For any study to have a good grasp on how climate change may affect electricity or how electricity use can contribute to global warming in a multicultural and diverse country like Nigeria, there is a need to put forward a futuristic approach towards understanding what the needs are especially at the household levels where the impact of incessant power outages is mostly felt. Nigeria, like all other developing African countries has experienced ethnic heterogeneity, developmental, governmental, and institutional challenges.

Given rising population growth, uncertain environmental regulation, social unrests, and occurrence of extreme weather events, Nigeria still faces huge pressures in meeting future electricity needs. While commercial usage is likely to be responsive to price, there are probable evidence to suggest that residential energy/or electricity consumers do not perfectly optimize in response to price changes (Ito, 2010). This includes the recent concern as to whether current tariffs are in tandem with economic realities[1].

Since Nigeria has been unable to meet the electricity demand of her growing population, with more people now desiring to acquire automating machines that bring convenience and ultimately, extra consumption of energy; it has become necessary to consider a wide range of variables and scenarios that affect the demand for electricity. Inadequate supply

[1] https://www.olaniwunajayi.net/wp-content/uploads/2018/01/OALP-Power-Infrastructure-Wrap-Up-Report-1.pdf

of electricity in Nigeria coupled with the controversies that surround electricity generation and distribution and the general role electricity plays in Nigeria's economy firmly suggest that, for policies and decisions to be strongly made and implemented, more accurate consumption estimates of electricity needs, or demand must be sought after (Diawuo et. al., 2018). The future holds a lot of climate uncertainty. What we know and factor into most electricity demand forecasts is today's climatic conditions; less or no attention is paid to future climate uncertainties in estimations.

With Nigeria's increasing population and economic growth rate, CO_2 emissions also increases. Nigeria is the 44th largest emitter of CO_2 world-wide and is Africa's 4th largest emitter of CO_2. In 2016, Nigeria contributed over 84 million tons of CO_2 emissions of the world's global share with the power industry contributing 14.8% of it (Figure 1.2). Without doubt, climate change is already a problem faced by Nigeria. Therefore, Nigeria is expected to devise sustainable ways of mitigating CO_2 emissions and climate change. These are issues the country must address as part of her promised "Nationally Determined Contributions" (NDCs). NDCs are the post-2020 climate actions taken by 196 countries including Nigeria under a 2015 international agreement reached in Paris at the U.N. Framework Convention on Climate Change (UNFCCC) Conference of the Parties. In 2017, to indicate Nigeria's commitment to the NDCs, the president of Nigeria, Muhammadu Buhari, committed Nigeria to an unconditional 20% decrease in emissions by 2030, compared to business-as-usual levels. This may also increase to 45%, conditional on international support. The plans include ending gas flaring and installing 13 gigawatts of off-grid solar, as well as 30% improvement in energy efficiency by 2030. Therefore, Nigeria must work on ways of improving energy efficiency as part of her commitment to the NDCs and contributions toward a low carbon economy. Also, improvement in energy

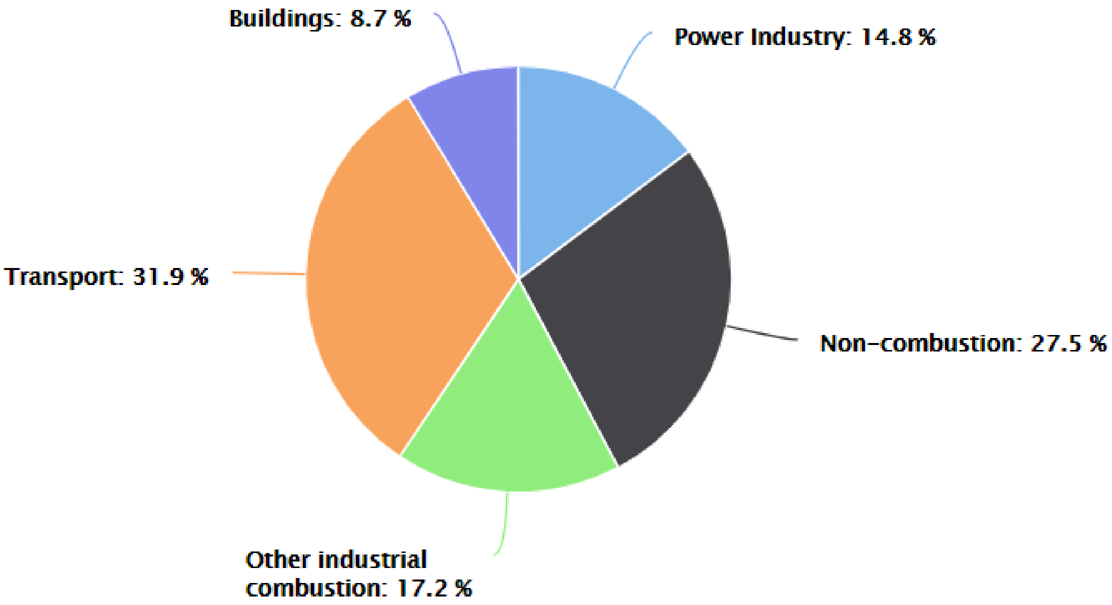

Figure 1.2: Fossil CO_2 emission by sector in Nigeria.

Source: https://www.worldometers.info/co2-emissions/nigeria-co2-emissions/

efficiency is necessary to reduce electricity consumption and wastage, costs of electricity especially for consumers, and for economic development especially in a country like Nigeria where electricity demand exceeds supply. Although, there are many talks on the importance of being energy efficient in Nigeria, there are no in-depth projections for the residential sector that consumes most of the energy including the economic benefits to consumers.

Nigeria's electrification rate currently stands at 56% and the Federal Government of Nigeria has an ambitious plan to reach 100% by 2030. The implication is that more generation plants must be built in order to meet this target. Increasing socioeconomic growth in Nigeria has also caused a high demand for electricity especially in the residential sector where most of the electricity is consumed. Therefore, accurate estimates of residential electricity demand into the future that can guide construction of adequate supply capacities under climate uncertainties must be made. However, Nigeria can reduce electricity demand by becoming more energy efficient. A reduced demand translates to a reduction in the construction of supply capacities including the cost of building them and environmental issues associated with the generation of electricity from power plants.

Modelling electricity demand in developing countries is problematic because of scarcity of data and methodologies that consider detailed disaggregation of household appliances, energy efficiency improvements, and stock uptakes. First, most of the published studies on energy demand forecasts for Nigeria are mostly at the sectorial level. Although, there are very few studies that considered some household appliances (Letschert and McNeil, 2013, Emordi, 2015, ECN, 2015, Olaniyan et. al., 2018, Kotikot et. al., 2018, Dioha et. al., 2019, Dioha and Kumar, 2020), there are currently no published studies that considered detailed disaggregation of the common household appliances used in Nigeria.

A detailed disaggregation can help in determining which appliances consume most of the energy. This study is the first to disaggregate the major or commonly used household appliances (twenty-one) as reported in the literature and national surveys (LSMS, 2012, 2014, 2015, Olaniyan et. al., 2018, Dominguez et. al., 2019).

Second, most existing methodologies used in forecasting electricity demand for Nigeria do not consider the evolution of appliance ownerships (Olaniyan et. al., 2018, Kotikot et. al., 2018) thus assuming a constant ownership of appliances till the end of time. The few studies that forecasted appliance ownership evolution either did not capture the choice of consumer effectively (Letschert and McNeil, 2013) or forecast the ownership evolution of most of the household appliances (Dioha and Kumar, 2020). This dissertation is the first to account for majority (twenty-one), past, and future household appliances ownerships that can capture consumers choice and survival rate functions. Retirement functions will give account of appliances that retire every year thereby providing more accurate demand forecasts.

Third, there are no published studies that supplements residential demand with hourly load profile data from end-use metering campaign. This study is the first to use end metering data thus providing a more accurate peak load demand forecast that can provide the pattern of residential electricity consumption (REC). This can help understand peak load hours which is beneficial for energy conservation and cost savings.

Fourth, there are currently no existing studies that projects future unit electricity consumption (UEC) for household appliances that currently have Energy Efficiency Standard and Labelling (EE S&L) in Nigeria. This study is the first to follow the EU EE S&L framework (a wide range of labelling classifications) to project demand reduction because it accounts for what is technologically achievable. Accurate projections of efficiency can guide policy makers in designing future energy efficiency policy for Nigeria.

To address all these research gaps, this study incorporates both the top-down and bottom-up approaches (a hybrid approach) by using appliance and lighting models to forecast Nigeria's REC. The appliance model calculates electricity demand for household appliances and supplements it with hourly load profiles of appliance use to determine peak load (bottom-up approach). For example, appliance ownership estimations rely on the strength and peculiarity of a top-down approach. In the model for lighting, the floor area is a major driver, and the estimations follow a top-down approach. Energy efficiency projections for the appliances follow a bottom-up approach. The strengths of each of these approaches compensate for the weaknesses of each other.

Consumers demand for energy and energy efficiency are important for any Energy Demand Management program and can ensure the security of the already limited power supply in Nigeria. Energy Demand Management also known as Demand Side Management (DSM) puts less stress on the supply side and focuses more on the demand side through reduced energy consumption. This shift can help save Nigeria a lot of money by not constructing more supply capacity and reduce environmental issues associated with the building and operation of more power plants because DSM also allows for the penetration of renewable energies.

1.2 Research Questions

Issues arising from the study background pose two main research questions. These questions are:

1. What are the projections of Nigeria's residential electricity consumption up till 2050?

2. How do we project efficiency improvement as a way of saving electricity, avoiding wastage, and reducing carbon emissions?
    a. How do we determine the economic and environmental impacts of potential efficiency improvements of household appliances?
    b. What energy policy options provide the best solutions to optimizing Nigeria's electricity supply and balancing future demand without compromising the nation's economic realities?

1.3 Research Objectives

To address the aforementioned questions for the research, the following objectives were raised for in-depth consideration.

1. To determine Nigeria's future residential electricity needs and end-use disaggregation under different technology scenarios and climate uncertainty.
2. To project efficiency improvement as a way of saving electricity, reducing peak demand of household appliances through the introduction of energy efficiency standards and labelling, and ultimately combating climate issues by reducing CO_2 emissions.
    a. To prove the environmental and economic reliabilities of potential energy savings through the implementation of EE S&L.
    b. To recommend sustainable energy policies that will not only help to reduce growing electricity demand and carbon emissions but also improve electricity supply while considering the economic realities of the populace.

1.4 Problem Statement

Although, several workers have made significant contributions toward modelling residential electricity demand in Nigeria, there are currently no published studies that has done a detailed disaggregation of household appliances, detailed stock analysis, supplemented demand with load profile, and projected future UEC for appliances with existing EE S&L. This dissertation reports the use of a hybrid approach that relies on the strengths of econometric (top-down approach) and stock accounting (bottom-up approach) models to forecast Nigeria's residential electricity consumption, peak demand, energy efficiency potential, net savings, environmental, and economic benefits on a detailed disaggregated basis up to 2050. The total residential electricity demand is then supplemented by hourly end-used demand profiles directly from end-use metering to determine consumption pattern and the size of peak load demand.

1.5 Contribution to Knowledge

This dissertation will provide a more accurate and realistic projection of electricity demand and efficiency in Nigeria, broaden the scopes of existing published studies, and provide a large quantitative data support to existing household appliance information that are scarce or currently not available in Nigeria. Most importantly, it will provide the much-needed information on electricity consumption pattern that will guide Nigeria policy makers in electricity policy formulations especially in the areas of electricity generation, distribution, and transmission. It will also provide the technical information needed to construct a road map for energy efficiency including the evaluation of the existing energy efficiency standards and labelling (EES&L) programs as a way of slowing down the rapidly growing peak residential electricity demand in Nigeria. Ultimately, this study will provide the information that can help Nigeria meet her climate and sustainability goals including her commitment to the UNFCCC Nationally Determined Contributions (NDCs) and the United Nations Sustainable Development Target 7 goals of a reliable and sustainable modern energy for all.

1.6 Thesis Outline

This chapter introduces the thesis. It presents a summary of the state of electricity demand and climate change in Nigeria. It closely scrutinizes the trends and problems that surround electricity sector and climate change issues in Nigeria, and other developing countries around the world. The chapter identifies the need for an accurate and realistic projection of residential electricity demand including energy efficiency potentials. It also presents the research objectives, research questions, problem statement, and the contributions of this research to knowledge.

Chapter two reviews extant literature on Nigeria's electricity sector, climate change, energy resources, existing energy efficiency standards and labelling, and various demand forecasting techniques or methodologies.

Chapter three discusses the research methodology and the criteria for the selected methodology. It also discusses the steps taken in developing the model including energy savings, and peak load demand calculations. The environmental and economic impacts of adopting EE S&L through emission mitigations, bill savings, consumer payback period, and life cycle cost (LCC) approaches were evaluated. The data used in this study are also presented in this chapter.

Chapter four analyzes and discusses the research finding in line with the objectives. It also discusses the impact of these finding, the limitations of the study, and the policy implications of the results of this research for Nigeria.

Chapter 5 concludes the study and summarizes the major findings.

The manners in which the contents of each chapter merge to address the research objectives are shown in Figure 1.3.

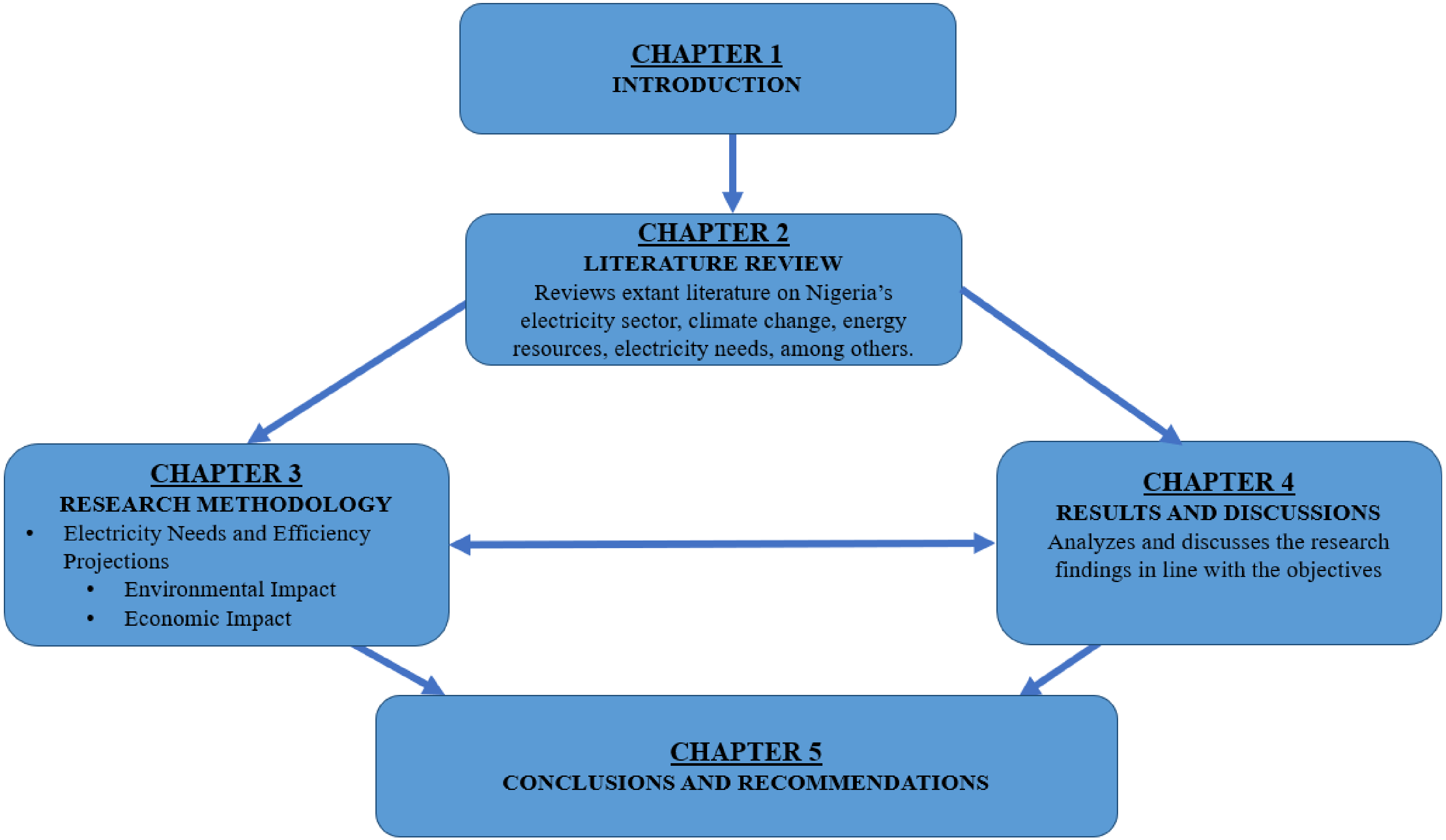

Figure 1.3: Diagram showing a summary of the structure of the thesis.

CHAPTER 2: LITERATURE REVIEW

2.1 Climate Change and Energy Resources

A lot has been said in the media about the influence climate change has on energy resources. Across academic studies, there is an increasing concern on the likely effect of extreme weather and the accompany consequences on critical infrastructure for national development. Climate change is a big threat to the world. As expected, it has sparked a handful of conference papers, debates and policies, especially in the 21st century. Accordingly, the United Nations Environment Programme (UNEP) and the World Meteorological Organisation (WMO) in 1998 jointly established the IPCC to address the increasingly growing climate issues. IPCC, an acronym for 'Intergovernmental Panel on Climate Change' was set aside to assess, among other issues, science-based information about climate change, its impact on the environment and socioeconomics, and come up with strategic management plans for the adaptation and mitigation of accompanying consequences.

Other global efforts include the Kyoto protocol that was signed in 1997 to address climate change issues particularly among the developed nations. Also, in 1992, UNFCC was earmarked to tackle the same issues. Meanwhile, an International Energy Agency (IEA) report has revealed that since 1990, over 1,000 policies have been raised against the challenges of climate change (Akinyemi et. al., 2014). This is an indication that all hands are on deck to see that significant measures are taken; however, as put by the World Energy Council (2007), the effectiveness of such measures is still being doubted, particularly in some developing countries. Major policy responses to climate change impacts around the world are the adaptation and mitigation policy options (Ifeanyi-Obi et. al., 2012; Akinyemi, et. al., 2014). The former emphasizes the adaptive measures to climate change impacts, while the latter calls for a reduction in the negative consequences of climate change. The adaptive strategies as cited in Akinyemi et al (2014, p. 49) is an "*adjustment in practices, processes or structures in response to projected or actual changes in climate with the goal of maintaining the capacity to deal with current and future changes*." In today's world, global climate is dramatically changing so much that measures to tackle emissions will not stop it from further changes; this is why it becomes important that adaptive measures are placed at the forefront of climate related policies.

Climate, although often summarized and manifested as weather, is the average weather in a specific geographical zone over a sustained period. It is determined over historical time spans by certain constant measures that include: the proximity of mountains and seas, altitude, proportion of land to water, and latitudes. Climatic[2] change determinants may comprise but are not limited to thermohaline circulation of the ocean that results to a 9^{o}F warming of the Northern Atlantic Ocean. While this determinant has been described as an internal forcing mechanism, other factors (the external forcing mechanisms) that can shape climate include volcanic eruptions, biotic processes, greenhouse gases, and solar output changes. Whether the mechanism is externally or internally instigated, the climate system's responsiveness can be fast and abrupt. Of concern in this section is that these projections are pointers to the need to understand the vulnerability of the energy sector. A well-thought-out plan is needed to stay abreast on the levels of exposure of energy infrastructure to climate impacts. The sun's output in addition with the output variations, orbit and rotation of the earth are the main drivers of the earth's climate. This is because the sun is predominantly the earth's energy input source. The energy output of the sun has increased largely over an

[2] Climatic change, a term used to describe all kinds of climatic variability on a time period longer than ten years, whether the cause is naturally instigated (e.g. solar output changes) or anthropogenic in nature (greenhouse gases).

approximate period of 4 billion years, and today, the earth receives an average incident solar energy of 342W/m^2, that is about 30 per cent increment in the sun emission. Of the average incident solar energy received by the earth, nearly 31 per cent reflects back to space by the atmosphere. At stake, however, is the remainder that heats the surface of the earth and the atmosphere. To make up for this pitfall, the earth radiates long wave infra-red energy, but the amount of energy is dependent on the body emitting it (Harrison, 2001). According to Harrison (2001), it would take about – 19^0C for an absorbing body to emit 236 W/m^2. Therefore, the earth is continuously being warmed by the atmosphere. This phenomenon as coined by Fourier in 1827 is the 'Greenhouse Effect'. Further scientific studies have also shown that the earth is warming (e.g., Hartmann et. al., 2013).

Since the early 1990s, rises in sea level have continued to attract expert opinions and projections. In a study on 'Nature Climate Change' conducted by Watson et. al, 2015; it was found that an accelerated sea level rise continued from 1995 to 2015, with an average estimate in sea level rise between 2.6 mm and 2.9 mm annually and 0.4mm since 1993. IPCC projections showed that over the 21st century, a 52 – 98 cm global mean sea level may be recorded if the world experience high emissions. Unless the current global mean temperature is addressed, global mean sea level will rise steadily even beyond the year 2100 (Levermann et. al., 2013). Most of the enacted policies by intergovernmental organisations, especially as regard climate and energy are usually aimed at the energy industry to tackle climate change by requiring them to cut CO_2 emissions (one of the main GHGs) drastically. Governments have also taken some steps to see that the magnitudes of GHG emission, including anthropogenic-induced emissions, are reduced to a bearable state. This is in view that the energy sector particularly those of the industrialized economies is the greatest contributor to GHG concentration.

At the Earth Summit in 1992, the UNFCCC was negotiated in Rio de Janeiro, although it did not commence implementation until 1994. Key among the commitments at the convention was to ensure that all parties agree to balance the concentrations of GHG at a level that can curb further damages and other human-induced interferences to the climate. Meanwhile, the basic commitment of the convention was to see that emissions in industrialized countries drop to 1990 levels. At the Kyoto Climate Protocol, the collective commitment was to see a reduced emission by 5% lower than 1990 levels. Like the UNFCCC, industrialized/developed nations that include the US, Japan, UK, and other 81 countries that signed the Kyoto treaty committed themselves to a reduced emission (CO_2, CH_4, N_20, HFC_S, PFCs, and SF_6) by 2010, while the developing nations are expected to maintain theirs. Some of the key points include (Grubb, 1990, Chapman, 2000):

- Joint Implementation
- Removal of subsidies to energy use
- Mandatory commitments for GHGs for each developed nation, with the first period of commitment of 2008 – 2012
- Joint commitment to reduce emission levels by 5% below 1990 levels
- Specific commitments to transfer of technology
- Tradable Emissions Permits

Developing nations (e.g., Argentina) have shown great interest in voluntarily committing themselves to emission limits (Harrison, 2001). One of the reasons for this, according to Grubb et. al., 1999 is the trading mechanism and hard currency earnings benefit. But what will become of other developing nations (e.g., Nigeria) which, although are part of the Kyoto protocol as jointly adopted in December 1997, are yet to implement tangible policies on climate change?

Adeyemi (2014), like other authors who focused on developing nations reiterated the need for nations to emphasize the needs for comprehensive and coordinated approaches to climate change issues. Significant mitigation and/or adaptation efforts are required to ensure that climate change issues are included in the blueprint for sustainable socio-economic developments. As part of Adeyemi's recommendations, he referred to the prioritization and implementation of the Nationally Appropriate Mitigation Actions (NAMA) in developing countries. In Uganda for instance, NAMA was said to have made noteworthy landmarks in reducing GHGs emissions. Technical input and funding have been provided for NAMA initiatives by the European commission, the German government and the government of Austria through the Low-Emissions Capacity Building programme (LECB) of the United Nations Development Programme (UNDP), and the Climate Change Unit. Through these initiatives and other programs on energy efficiency, Uganda, like other East African nations, has made several attempts to mitigate climate change impacts. Several authors have also provided helpful recommendations on how to mitigate climate impacts (Adeyemi, 2004, Harrison, 2011).

Some policy options through which carbon emissions can be mitigated include increased utilization of nuclear and renewable energy, decarbonisation of CO_2 sequestration, fuel switching, increased generation, transmission, and end use efficiencies (Harrison, 2001). The whole essence of these options is to ensure that energy supply moves away from the carbon economy into a more sustainable option. Most talked about of these alternatives is the elimination, storage or sequestration of carbon. In the years to come, Harrison (2001) predicts that the level at which the concentrations of CO_2 are stabilised will partly be dependent on the speed at which nations respond, as well as the rate of response of developing nations since the effect will *spill-over* from the industrialised nations to the developing world. Thus, the impact on developing nations will be varied with most developing countries bearing most of the economy impacts.

2.1.1 A Look at the "IPCC's Special Report (2000) on Emissions Scenarios-SRES"

The scenarios were constructed following the high level of uncertainties of the driving forces - technological change, socio-economic development, and demographic development - of climate change to explore future developments with respect to controlling the emission of greenhouse gases, resulting in various possible GHG emission routes. Four narrative paths (A1, A2, B1, and B2) were defined and they describe linkages between these driving forces and the accompanying evolution, apropos of demographic, socio-economic, technological, and environmental development of that region. These scenarios are designed to create a picture of what GHGs emissions would look like in the future. These scenarios would assist in climate change analysis, such as climate modelling, impact analysis, adaptation, and mitigation, with a high degree of uncertainty of their occurrence. Many studies have adopted these scenarios including those earlier reviewed. The emission scenarios are explained in Table 2.1.

2.2 Climate Change and Energy Use: Demand and Supply Sides

Trends in the foregoing section are pointers to show that indeed climate change is a threat to the energy sector. Generally speaking, both the production and consumption of energy will be affected in most part of the world by an increase in temperatures, extreme weather effects, seasonal patterns, and alterations in precipitation. The energy sector, in many ways, is exposed to these effects arising

Table 2.1: Emission Scenarios. Modified from IPCC Special Report (2000).

Scenarios	Characteristics
A1	A future globalized world that peaks in mid-century and declines afterwards. A future world of quick economic growth and technological development A world with declines in differences in regional per capita income The A1 scenario is further grouped into 3 and describes a different energy system technological change namely: 1. A1FI = fossil intensive energy driven future world 2. A1T = on-fossil energy sources driven future world 3. A1B = a balance of A1F1 & A1B
A2	A regionalized, self-reliant and economic developed future world. A future world with an increasing difference in regional per capita income. A world with slower economic growth and technological changes A globalized future world.
B1	A world with rapidly changing economic structures A clean and resource efficient technology world An environmental and socio-economic sustainable future world. A local and regionalized future world.
B2	An increasing population future world, although at a rate less than the A2 scenario. A world with an intermediate level of economic development A world with locally sourced remedies to environmental sustainability and socio-economic challenges

from changing climate conditions (Schaeffer et. al., 2012); these effects however could manifest either positively or negatively. Although, negative impacts on energy production and consumption or demand and supply have been researched. Evidence from the literature have shown that the supply side has gained more attention (Greenleaf et. al., 2009, Ebinger and Vergara, 2010, Pryor and Barthelmie, 2010, Kopytko and Perkins, 2011, Sathayed, 2013).

Parameters through which climate change or weather events affect the supply and demand of energy may include soil conditions, changes in flow of rivers, wildfires, coastal inundation, temperatures, cloudiness, snowfall, wind speeds, among others. Floods and extreme temperatures can cause supply disruptions and pose a severe risk to infrastructure. Rising sea levels can also be a major constraint to coastal and offshore energy infrastructure because coastal erosions and extreme storm surges pose challenges to infrastructure.

In 2012, almost half of India's population experienced a major blackout following delayed heat waves (and monsoon) in the country that resulted to a reduced hydropower generation. In the same year, about 8 million residents of New York City and environs faced a major blackout following the well-known Hurricane Sandy. Studies have shown that a greater percentage of power outages in the United States are climate-instigated interruptions, and this percentage is, in fact, greater than interruptions caused by cyber-attacks, component and physical attacks on electricity infrastructure combined (IEA, 2015). Also, in 2005, the Gulf of Mexico experienced Hurricane Katrina, which interrupted oil and gas production and processing in the US. These are few among the several incidences of climate change impact on the energy sector in both the developed and developing countries. Since extreme weather conditions can magnify the stress on energy systems, it goes to show that these impacts can *trickle-down* to affect other sectors including the economies of nations, and investments on maintenance and operations of energy infrastructure (Gotham et. al., 2012).

This impact influences both the supply and demand of energy, and even goods and services, particularly in Africa.

Given that extreme weather conditions can disable energy infrastructures temporarily, reduce plant efficiency and transmission line capacity, the supply-side will first be affected, and can hinder affordability and sustainability of the energy sector which is of paramount importance to nation building. This could occur when sea level rises, drought occurs, alterations in precipitation, or increased temperature, which all show impacts on energy infrastructure and its capability to make energy available through thermal, wind, hydropower, and other production sources (Figure 2.1). Governments of nations are being forced into redesigning the energy system structures and consumption patterns, which is central to energy resilient agenda towards improved energy security.

Like Beecher and Kalmbach (2012) rightly posited, energy is an on-demand service, and as such, changes in demand show direct and immediate impact on supply. Aroonruengsawat and Auffhammer (2009) believe that population trends and uncertainty in prices and climate equally have immediate and direct bearing on energy demand, but these impacts have so far not been quantified in many studies. Nevertheless, if climate change continues to affect weather, energy demand by consumers will be affected, and this will shape production. In effect, policies on climate change are already influencing energy supply portfolios and distribution, especially for electricity. In the same manner at which the supply side of energy promotes climate change through GHG, is also the same way climate change (e.g., erosion, wind, floods and rising sea levels) will possibly affect energy infrastructure (Akinyemi et. al., 2012). As part of the key notes of the IEA (2015) on "making the energy sector more resilient to climate change", it was stated that the: (a) energy

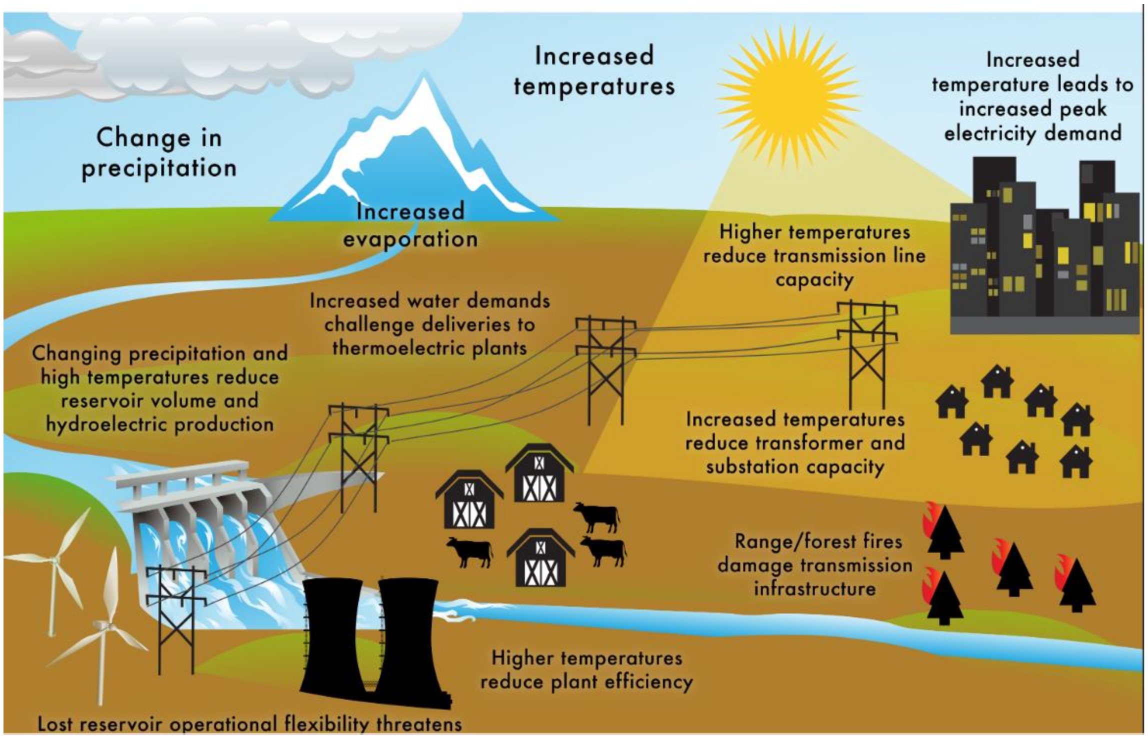

Figure 2.1: Impact of climate induced extreme temperature and precipitation decrease on electricity supply or delivery. Source: Tidewell et. al., 2013.

sector must pinpoint and examine how impacts of climate change can interrupt both supply demand patterns, as well as, infrastructure; (b) fuel supply systems and electricity must become more resilient to rising stress on water resources and extreme changes in weather; (c) Since businesses are the major actors, they must be at the forefront in the design and implementation of resilience-building and adaptive practices; (d) Governments should be up and doing by ensuring that resilience-building plans play significant part in implementation, in emergency response support, and also in managing their own energy assets (IEA, 2015). Table 2.2 shows some climate change impacts on both the demand and supply of energy.

In virtually all households, electricity is used as a lifestyle and mainly for comfort and safety either in the form of cooling or heating. Usage again may vary from household to household, and those who can afford enhanced technologies are likely to adapt to more extreme weather events. In households where these technologies are unavailable, they are prone to climate change consequences. Decreased temperature will cause a need for heating from furnace oil, LNG, etc., and cooling mainly through electricity will be induced by warmer weather (Gotham et. al., 2012). When the demand for cooling rises, summer-peaking electricity loads rises. If the frequency and duration of heat waves rises, then consumer demand pattern on electrical utilities are likely to increase in summer periods. As noted by Beecher and Kalmbach (2012), these demand patterns must routinely adapt management and operations to the variation in weather, and as such, utilize *cooling* and *heating degree days* for modelling and forecasting objectives.

In a response to the question that states: should energy systems be worried about the effects of climate change, an IEA (2015) report declares that the energy sector, in addition to identifying climate change impacts can disrupt supply, must evaluate the impacts on demand patterns and damages on energy infrastructure. But to what extent is the response rate in developing countries

Table 2.2: Climate change impacts and energy resources: Demand vs. Supply side. Source: Beecher and Kalmbach (2012)

Issues	Supply-Side Concerns	Demand-Side Concerns
Climate Change	Renewable energy available (wind, photovoltaic, geothermal, hydroelectric, and bioenergy, etc.)	Changing energy needs of other sectors, including water supply.
	Water availability and shift to power plant thermal cooling alternatives.	Health effects of heat and cold (including death) owing to affordability and accessibility.
	Potential supply disruptions (reliability).	Changes to energy utilization pattern (cooling and heating).
	Stress impact of variable demand on utility revenues and risks.	Rising demand owing to extreme weather
Climate Change Policies	Changes to supply portfolio, including fuel switching from coal to natural gas and investment in alternatives supplies, transmission facilities, energy storage, grid modernization, and back-up capacity.	Increased utility prices and price elasticity effects on demand.
	Higher energy and water utility costs.	Demand management standards.
	Financial incentives, including taxation, rates of return, and carbon tax or trade.	Energy needs of electric vehicles.
	Environmental impacts of renewable energy development (land, aesthetics).	Load management practices.
	Effect of variable resources on reliability complex energy supply markets.	
	Complex energy supply markets.	

where literature on the subject matter is limited, and seeing that albeit in varying degrees, all regions of the world are susceptible to climate change impacts? Worthy of note is that Oricha and Olarinoye (2012) already noted that problems confronting the energy sector in developing nations differ from those militating against the same sector in developed nations.

While interferences on weather, in the US, cost the economy about USD 25-70 billion yearly (IEA, 2015), significant indirect impact especially as regard the supply and demand of food commodities has been recorded in African countries. The study by Chika and Ozor (2010) is a reference point. The authors found that climate change will impact on the profitability of farming and food affordability among African countries. In Nigeria for instance, the demand for fuelwood is on the increase being an alternative method in both the rural and urban centres to meeting energy needs for households given that the government has been unable to mitigate the growing energy need through flared gas. Government spending on firewood and kerosene cumulates to about N222 billion on a monthly basis and this spending is expected to increase with the rapid rate of deforestation. As of 2010, deforestation rate stood at about 300,000-400,000 ha of forest, that is, about 3.5% yearly (Ladipo, 2010). Exploitation of forest for consumption is, hence, not sustainable as most collectors who go to exploit the forest and savannah regions are not interested in sustaining or conserving the vegetation with new trees (Gbadegesin and Olorunfemi, 2011). As majority of the population depend on charcoal and firewood as sources of heat energy, others depend on forest trees for poaching for electric poles and logs which, in fact, pose challenges on the long run for energy infrastructure. Nigeria which hitherto was blessed with a large expanse of vegetation currently boasts of less than 10% forest land area. If the demand on energy particularly the peak demand on fossil fuel increases, an increased GHG emission is expected.

Aside from the aforementioned anthropogenic-induced climate change, a Building Nigeria's Response to Climate Change (BNRCC) report (2011) posits that other weather events arising from climate change such as floods and windstorms can cause more damages to energy transmission and distribution systems. In the following section, the impact of climate change on nonconventional energy resources will be discussed from an empirical point of view.

2.3 Climate Change Impacts on Nonconventional Energy Resources

2.3.1 Solar Power

Solar energy is hypothesized to be affected, though minimally, by climate change through changing atmospheric water vapour content, cloud characteristics and cloudiness, which also have impacts on atmospheric transmissivity (Cutforth and Judiesch, 2007, EIA, 2015). IPCC projection scenarios indicate that the solar radiation will increase in the Middle East and reduce in the sub-Saharan part of Africa (Ebinger and Vergara, 2011).

In 2012, the total installed solar PV capacity in Germany, Italy, Japan, Spain, France, and China represents over 70% of the world's total solar PV according to EIA projections. Solar powered thermal plants need sunshine to produce energy, but Photovoltaic (PV) electricity generation is dependent on the temperature of surface air and surface wind velocity, so PV cells can run in cloudy weather conditions. a reduced output is expected in winter months and an increased output is expected in the summer months. Long-term variability may be caused by changes in the sun's radiation and radiation components, i.e., scattering caused by clouds.

A study by Jerez et.al., (2015) using the regional climate model indicates a change in power output from solar photovoltaic cells in the range of -14% to 2% in the next 100 years in Europe with the largest reduction in the northern part of Europe. Jerez et. al., (2015) explains this latitudinal variation on the variations in wind and cloud conditions of the North compared to the south while other studies indicate a small and a mean positive impact of climate change in Europe.

2.3.2 Biofuel

Biofuel plants are being run in different climatic zones with negligible differences in their efficiency and sensitivity to storms suggesting that biofuels are unlikely not affected by changing climatic conditions. Schaeffer et. al., (2012) however showed a differing view by asserting that liquid biofuels, in particular, are susceptible to certain climate change variables (e.g., rainfall, temperature, CO_2 levels on crops used as raw ingredients in the production of biodiesel and ethanol).

2.3.3 Hydropower

Hydropower is most affected by a changing climate because its generation is dependent on large volume of water. Therefore, an increase in temperature will lead to a drought thereby reducing the flow of water in rivers (IEA 2012, BNRCC, 2011). There is a huge potential for hydropower development in non-OECD countries because most of their hydropower have not been fully developed. This is in contrast with what is obtainable in OECD countries where there is more hydropower development.

For instance, Blackshear et. al., (2011) on the vulnerability of climate change on hydropower, predicted a change in global mean annual precipitation based on IPCC Scenario B1 by region and concluded that New Zealand will be more affected by adverse climate changes due to its relatively higher dependence (70% of total power generated) on it. They also explained that the nature of power plant, small storage reservoirs and run-off- also contributes to its high risk in drought scenarios and that future development should be directed at capacity expansion with larger pump storage reservoirs.

Southeast Asia gets 80% of its rainfall during the summer months, resulting in high variability, during the Monsoon season, and increasing temperatures, may give rise to lengthened periods between rains and increased risks of drought. Attempts by China to regulate their dams as they presently do, may result in flooding in the wet season, and water shortage in the dry season. Deglaciation in the Himalayas may also contribute to very high initial flows of water leading to water variability and unpredictability and more vulnerability of power plants that depend on the Indus and Ganges rivers, which receive 40% of their volume from the Himalayas glaciers. There is a possibility of total dry-up of rivers that are solely dependent on glaciers for water in another 50 years, considering the very high population density of many areas in this region. Immerzeel (2010) concludes that floods, droughts, glacial melt, and erratic monsoon cycle are climate change conditions that are likely to endanger hydropower production in Asia. In the Middle East, Turkey maintains the largest installed capacity of hydropower plants (Yuksel, 2011) at 13,700 and a proposed 7476 South Eastern Anatolia project and 19 hydroelectric dams. The Middle East has majority of its hydro power projects focused on the Tigris-Euphrates River and Run-off River and small-scale reservoir plants are most common. It has its major climatic variations arising from the North Atlantic Oscillation pattern and subsequent decreased precipitation is expected to result from changing climate, but conflicting predictions are for increased precipitation in certain areas of the middle east-Iranian mountains- may translate to increased hydropower potential (Evans, 2010). Turkey is expected to be significantly impacted by climate change, due to its dependence on hydropower resulting from less surface water flow, its topography may allow for exploitation of relatively low flow rates to meet up with its power demand, and its control of the Tigris-Euphrates head waters gives it at an edge over other countries depending on same source for their electric power and has been classified as firm because of her large scale reservoirs. Iraq is badly affected by the disruption of flow because of its location downstream of the Tigris-Euphrates River evidenced in the shutdown of the Mosul Dam in 2011 due to fall in water levels.

Africa is very dependent on hydropower with several nations boasting of over 90% of total installed capacity with most of its generating capacity being dependant on the Nile, Congo, and Zambezi rivers. Hydropower construction activities in Africa have witnessed a 53% increase from 2004-2006 with only 5% use of hydropower potential as at 2009 (Sharife, 2009). Ethiopia was projected to become the second largest electricity generator, behind South Africa, by 2016 with an increase from 745MW-10GW after the development of a set of hydropower stations (Bason, 2004). The Garand Inga dam of Congo is expected to have a capacity of 39GW, making it the largest electricity generating project and a possibility of continent spanning electricity grid (Showers, 2009).

In the developing countries, hydro projects are characterized mainly by large scale projects and a negligible number of pumped storage plants. Currently, the continent is experiencing recurring drought leading to low power (about half their capacity) output and consequent power rationing. The onset of climate change will only make its seasonal and variable rainfall more stochastic (Mukheibir, 2007) and may result in more frequent power outages and a fall in electricity supply, which does not even meet its demand yet.

2.3.4 Wind Power

Pryor and Barthelmie (2010) are some of the authors who have extensively examined the impact of extreme weather events on wind energy in spite the controversies. Wind energy, unlike hydropower, cannot be stored naturally. Wind power stands a risk only during stormy weather, when power is cut-off, and research into technologies that allow for low power production during storms is on. Climate change therefore has a limited impact on wind power production. Several studies (e.g., Cavallo et. al., 1993, Breslow and Sailor, 2002, Sailor et. al., 2008, Lucena et. al., 2010) have all looked into the impacts climate change have on wind power. Table 2.3 summarizes climate parameters and its impact on energy source.

2.4 Climate Change and Challenges to Economic Development

A study of energy demand and supply response to climate change must be approached from the standpoint of economic development because the greatest driver of energy demand is energy policies and not climate change (Damm et. al., 2016). On the issue of climate change, energy policies are generally aimed at mitigating GHG, and attaining energy security and these policies are reflective of a country's susceptibility to climate change. The susceptibility of a country to changes in climate reflects its socio-economic susceptibility to effects of changing climatic conditions and is assessed by a measure of its adaptive capacity, sensitivity and exposure (Füssel and Klein, 2006, Yohe and Tol, 2009).

The vulnerability of a country is determined by the extent of climatic changes projected for a country. Though it is generally assumed that global climate change would bring about increased atmospheric temperatures and precipitation. Global models to determine local and regional climatic changes have been inconsistent. There is an uncertainty about the degree of exposure of a country's economy due to inaccurate prediction of future economic and population growth rate, so most studies on climate change rely on assumptions of economic situations at the time of study.

Table 2.3: Climate parameters and impact on Energy source. Modified from Ebinger, (2011).

Climate Parameter	Energy Uses
Air temperature	Efficiency of turbine production, air source generation output and potential, demand (heating/cooling)
Rainfall	Hydro- generation potential and efficiency
Snowfall and ice	Power line maintenance, and heating demand
Humidity	Demand for drying
River-flow	Hydro-generation potential and modelling (dam control), power station cooling demand
Coastal wave height and frequency	Off-shore infrastructure protection and design
Flood and sea level	Primary energy transportation, coastal infrastructure protection and design. Offshore operations
Drought	Hydro-generation output

The inability to accurately predict future economic growth rates leads to inaccurate prediction of future regional- and consequently, global greenhouse gas emissions which would lead to regional variations in global climate change prediction.

The level of impact (positive or negative) of varying degree of changes of climatic conditions on the socio-economic system of a country tells the sensitivity of a country. A country's sensitivity to climate change depends on its initial socio-economic conditions (economic structure, infrastructural development, natural, and environmental resources) with consideration particularly given to contribution of various economic sectors to its Gross Domestic Product (GDP). It is estimated that by 2100, climate change will result to increases in global GDP by 0.75% as a result of reduced energy demand for heating and will decrease by 0.45% as a result of increased energy demand for cooling depending on the differences in latitude. According to Arndt et. al., (2012), the economy of a country that has agriculture as the largest share of GDP may be most negatively hit by increased temperatures and precipitation. Adaptivity refers to the amount of changes to the country's socio-economic system in order to remain at energy security levels in terms of technology and consumer behaviour. Energy consumption and supply service vary just as economic development levels around the world with OECD countries consuming about 8 times more energy than developing nations in Africa and Asia per capita (IEA, 2004). In the light of the above, an investigation into previous studies on the impact of climate change on electricity in countries at different levels of development (developed, developing, and undeveloped) according to UN classification, will focus on geographic variability, fuel consumption pattern, seasonal variability of supply and demand, and variability in economic conditions- infrastructure and income. Other impacts of climate on the economy are shown in Figure 2.2.

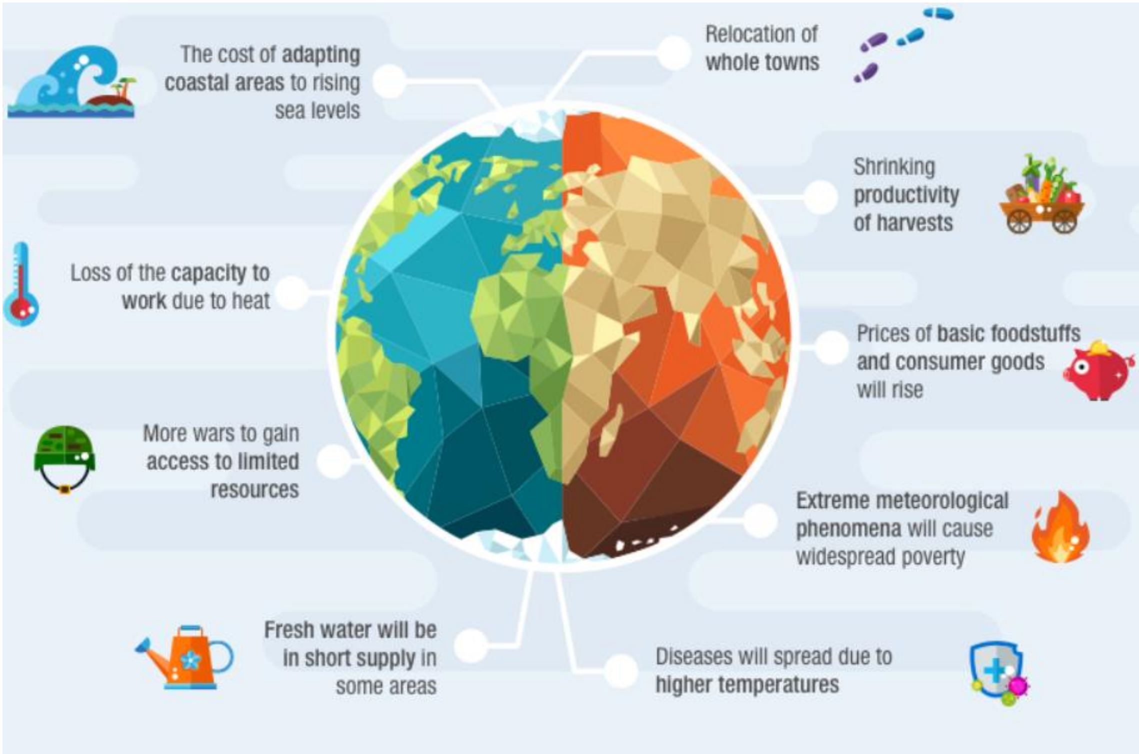

Figure 2.2: Climate change impact on economy.

Source: https://www.iberdrola.com/environment/impacts-of-climate-change)

2.5 Climate Change and Energy Security

The energy demand and supply theory stipulate equilibrium price to be the price where energy demand equals energy supply with the exception of cases of unavailability of energy. This can be implied to mean that energy price is a function of energy demand and not of energy unavailability. Customer behaviour demands the need for stable and predictable prices at a particular time in line with other tangible investments (Helm, 2002). Energy security as defined by Bohi and Toman (1996) is;

"*Economic welfare loss that may result from availability of Energy or a change in price"*.

Accordingly, energy insecurity to the consumer is the socio-economic impact of physical non-availability of energy, or uncompetitive/volatile energy prices (IEA, 2007). This perception of energy can be attributed to costlier total energy expenses, resulting from rises in energy prices which may result in a reduction in quantity of energy consumed. To the supplier, energy insecurity is the temporary loss in energy supply, from extreme weather event related problems in the generation process; increased revenues from higher energy prices; revenue loss due to declining energy consumption and higher production cost of energy.

2.6 Climate Change Impacts on Electricity Supply

Evidence regarding the impacts of climate change on electricity supply have been documented and accounted for in the literature; although not without gaps and limitations (Mideksa and Kallbekken 2010, Van Vliet et. al., 2012). The primary purpose of energy supply is to meet the demand of the end user with respect to quantity and timeliness. This implies that any factor that will distort the pattern of energy demand also affects the supply, climate change inclusive. Cumulatively, climate change has a negative effect on electricity supply, though globally speaking, the risk can be rated as moderate. There is a regional variation to the level of risk facing the different countries mostly depending on the primary energy source (Van Vliet et. al., 2012).

In Europe, climate change implies increased temperatures, and a change in precipitation from summer to winter. More frequent extreme weather events and slight increase in periods of sunshine and average wind speeds with expected 20% reduction in summer precipitation in France and yearlong increase in precipitation in Norway but a much smaller change in Germany and Poland (Bardt et. al., 2013).

A research on climate change impact on four OECD countries (Bardt et. al., 2013) - Poland, France, Norway, and Germany based on the Cologne Institute for Economic Research (IW) climate-risk-indicator and using expert interviews to grade responses on a scale of:

-5 (great risks) $\longrightarrow$ +5 (great potentials)

Risk facing France is expected to be much greater than that facing Germany, Poland, and Norway as these countries are expected to turn to renewable energy. Hence, it is concluded that the greatest impacts were on steam powered plants. In the United States where thermoelectric sources have a 91% share of total electricity production, climate change may result in shortage of power supply as was the case between 2007 and 2008 due to warm temperatures; and restrictions on thermal discharges, and subsequent capacity reduction or total shut down of power plants. Using historical data, a model for hydrological and water temperature framework, a multi-model of daily river flow and water temperature using scenarios A2 and B1 to forecast the susceptibility of thermoelectric power supply to the U.S and Europe were constructed. Bardt et. al., (2013) envisaged a moderate reduction of 10% - 25% power supply, greater impact to thermoelectric plants in southern-, south-eastern Europe, and south-eastern US and a smaller adaptive capacity with scenarios A2 than B1.

In Nigeria, Nnaji et. al., (2013) examined, in a multivariate network, the causal relationships that exist among economic growth, fossil fuel consumption, CO_2 emissions, and electricity supply for the period 1971 – 2009. Their findings showed a positive relationship between CO_2 emissions and electricity supply, while also indicating that economic growth and increased CO_2 emissions are closely associated. Generally, there have been sparse empirical studies justifying climate change effects on electricity supply. Most of the available studies that have broadly investigated the energy sector have shown controversial findings. For instance, Odjugo, 2010 predicted a fall in precipitation by 81mm and a temperature increase of 1.1^0C, desert encroachment, coastal inundations and drying up of surface water. Another study by Akinyemi et. al, 2014 examined the energy supply impact on climate change in Nigeria using the vector error correction procedure for the period 1971 – 2011. In their findings, it was found that there is a positive relationship between energy supply and climate change.

2.7 Climate Change Impacts on Electricity Demand

Electricity is the world's fastest-growing form of all sectors energy consumption. Aside from cooling and heating, the need to look at the impact of climate on electricity consumption is because it has the greatest share of the GHG emitters. The EU Adam research estimated that by 2100, with impacts of climate change scenario A1B (IPCC which assumes rapid economic growth globally and primary energy source will be balanced between fossil and non-fossil fuels) and estimate more than 2^0C increase in temperature, the impact of increased temperatures on electricity consumption was four times the size of equivalent decrease in temperature. This is in line with results from

Petrick et. al., 2010 global study across 157 countries that indicated a net decline in energy demand and consumption due to warmer temperatures; and estimated increased demand in southern states: 10% in Greece, 18% in turkey and fall in demand by northern states, 19.5% in Latvia, 20.8% in Lithuania, and summer temperature increase being equivalent to drop in winter temperatures as the years go by. Although this study did not consider supply changes or local weather variations and socio-economic conditions that may both directly and indirectly influence consumers demand for electricity in Europe. Other studies carried out within Europe, e.g. Dirk and Stefan 2011, in their assessment of changing climatic conditions, used changes in air and water temperature, water availability- conditions in Europe (France, Spain, and Germany) to ascertain changes caused by electricity prices and change in electricity- nuclear and hydro power plants which are the major sources of electricity in Europe- supply pattern resulting from global warming, how they affect wealth distribution, among independent suppliers and consumers. Using the Koch and Vogele approach to analyze energy transformation in electricity generation system, attempts were made by the authors to determine the amount of freshwater needed by an electricity processing plant, and they observed a drop in plant capacity by 6 GW and 12 GW in the nuclear- and hydro power plants respectively and a rise in unavailability by 19GW.

A recent investigation into the impacts of 2^{0}C global temperature increase on electricity demand in Europe for heating and cooling by Damm et. al., 2016 utilized the smooth transition regression model. The study found a greater reduction in electricity demand for heating purpose than the increase demand for cooling purpose. In the 26 countries involved in their study, only Italy was revealed to have an increased demand for electricity for heating., with France having the highest demand decrease in absolute terms in the range of 10TWh to 16TWh per annum and in relative terms, Norway had the highest decrease in relative terms at about 5.2%. In terms of prices, a direct relationship between the price of gas and the level of freshwater availability was found and explained this using other forms of more expensive primary energy source needed to power the plants. Higher supply prices in electricity exporting countries like France and Switzerland would lead to fall in import demand from countries like Germany and increased domestic production of energy. Nuclear power plants in these countries faced cooling problems, resulting from rise in the temperature of rivers, while the hydropower plants are faced with the problems of water scarcity. In this situation, not only should the supplier prepare to adapt to the changes, the complementary efforts of the public are also needed to ensure energy security and curb undesired changes in the pattern of electricity distribution.

Whilst focusing on Australia, Howden and Crimp, 2001 used the IPCC climate scenarios to test the sensitivity of weekly average and peak electricity demand to changing climatic condition for four conurbations in Australia. He estimated a negligible increase in demand (1.5%) for a 7^{o}C rise in temperature for Sydney and Melbourne; substantial demand increase (10% - 28%) for Brisbane and Adelaide, and peak demand responsiveness to temperature changes. Although the impact of long-term socio-economic and structural changes was not considered in their analysis, thereby limiting the analysis to short-term demand sensitivity.

Doshi et. al., 2012 used the hour-by-hour modelling approach to test Electricity demand sensitivities to changing temperatures and finds a significant positive impact of temperature changes on electricity demand, with short-run elasticity ranging from 0.3-0.5 depending on the time of the day and 0.2-0.8 elasticity in the long-run, and larger elasticity in the night than during the day both in the short-run and long-run. They attributed it to a greater share of residential energy demand at night than during the day; it also gives an indication that the effect of future climatic changes on peak demand might be less than on average demand, and higher impacts in the warmer months of the year. The authors also noted light demand increase may result in increased humidity. In a similar study, Ahmed, 2012 employed multiple regression analysis to test the sensitivity of demand to changes in temperature resulting from climate change; however, he included socio-economic variables to predict the future demand for electricity. He used time series analysis to predict future temperature and the degree for heating and cooling in New South Wales, and then estimated per capita electricity demand due to climate change and forecasted an increased demand between 2030-2100 to be 1.36%-6.14% and 2.09%-11.3% during the summer and spring respectively for cooling.

Of all the climatic variables, temperature, humidity, precipitation, and cloud cover were found to be most responsive to changing temperature (Parkpoom and Harrison, 2008). The authors studied the potential impact of climate change on electricity demand in Greece- considering large difference in its local climatic conditions owing to topography and geographical characteristics- using multiple regression analysis used as variables emission scenarios A2 and B2, and IPPC economic development scenarios of both small and large economic development rates. They observed an increase in annual electricity demand resulting from a 3.6%- 5.5% change in climatic conditions, under all scenarios, and attributed this demand increase to increased variability in annual temperatures – an increase in summer temperatures, that exceeded the moderate decrease in winter temperatures. On a concluding note, they posited that in the long run, increased economic development with its accompanying increased demand for heating and cooling should be expected. As way to address these demands, proper adaptation strategies need to be developed to ensure efficient electricity supply. Most noteworthy in this study was the use of regional climate model as opposed to global climate change model; and local economic forecast as opposed to national economic factors which have been previously used in many climate change impact analyses. In a supporting argument for the contrasting methodological approach, electricity consumption patterns in many instances are said to be driven by local socio-economic rather than regional conditions (Parkpoom and Harrison, 2008).

For some developing countries, expanding and upgrading their energy sector to meet modern standards is necessary because there is a correlation between energy consumption and economic growth. The general assumption is that with industrialization comes improved standards of living and energy consumption through dependence on energy consumer goods as is the case with developing nations. The effect of this is a greater sensitivity to climate change than when compared to developed nations. An assessment by the economic commission for Latin America and the Caribbean using the IPCC scenario A2 and B2 and 2011 baseline for per capita electricity consumption to estimate the impact of climate change on electricity consumption has indicated a 1.07% and 1.01% increase using scenarios A2 and B2, respectively. In absolute terms, it is estimated that from 2011-2050, electricity consumption will be valued at US$142.88 million and US$134.83 million under scenario A2 and B2, respectively. In relative terms, these equate to a loss in GDP of 0.737% and 0.695% under scenarios A1 and B2 respectively (ECLACC, 2009).

In Thailand, a large percentage of electricity demand is for cooling due to its low altitude, hence increased temperatures will increase energy demand. A correlation between increased electricity demand and GDP have been established. Darkroom, 2004 confirmed a correlation at 0.77 % for the period 1994-2004 and forecasts an annual demand growth of 5.75% by 2020. However, forecasts have also ignored the impact of climate change effect on economic activities. Parkpoom, 2007 found a correlation between two parameters; electricity consumption and socio-economic growth thus affirming that the magnitude of change in electricity demand due to climate change will be largely dependent on them. His forecast was based on the weather sensitivity model, the sensitivity of demands in the long-term to uniform rises in temperature using three time periods. As part of the consequences of climate change, the study envisaged threats to coastal power stations, and extreme sagging of transmission lines.

Meanwhile, total energy utilization and variability are among the main factors that inform the demand-side of electricity. Because electricity usage varies from household to household, cooler weather events will induce heating, even as cooling mainly through electricity will be induced by warmer weather (Gotham et. al., 2012). When the demand for cooling rises, summer-peaking electricity loads are expected to rise.

In Mansur et. al., 2008, it was also discovered that climate change could cause reductions in electricity consumption on cooling but cause a reduction in the utilization of other fuels for heating. Because the United States is the country in view, their findings imply that the energy expenditures of U.S will likely increase. After all, the study revealed that both at cooler winters and warmer summers, consumption of energy (oil, gas, and electricity) at industrial and household levels will increase. Suggestions from their study revealed that firms in wetter areas prefer oil, while households and residents at warmer areas prefer electricity. So far, there has been no theoretical justification for this finding aside that regional segmentation may show significant relationship with price. Other studies on the impact of climate change on electricity and other energy systems are summarized in Table 2.4.

2.8 Electricity Transmission Issues

The pattern of electricity transmission in a country is largely dependent on several peculiar issues. They include the level of development, distance from supply to end consumer, infrastructural capacity, and the mode of regulation of the sector. Countries with well-developed electricity

Table 2.4: Summary of other studies on climate change impact on electricity and other energy systems.

Author	Country/ Region	Detail	Temp (^{0}C) Change	Change (%) in Energy Consumption/Supply/Generation
Schaeffer et al. (2008)	Commercial/Residential sectors in Brazil	Emphasis on electricity demand (air conditioning)	A2 and B2 IPCC SRES emission scenarios	In worst-case, electricity consumption increased in Brazil in 2030 by 8%
Baxter and Calandri (1992)	California, U. S	Yearly electricity use and peak demand	Increased by 1.9 ^{0}C	Electricity will increase in 2010 by 7500 GWh (2.6%) 2400 MW (i.e., about 3.7%)
Mirasgedi, et al. (2007)	Greece	Emphasis on electricity demand	2100 horizon - A2 and B2 IPCC SRES emission scenarios	Annual electricity demand increased by 3.6-5.5%
Hadley, et al. (2006)	US	Commercial, residential and primary energy	+3.4 ^{0}C by 2025	Heating – 11%, cooling +22%, +2% primary energy
Dolinar, et al. (2010)	Slovenia	Low-energy and standard buildings	Increase in temp. (+1 ^{0}C & +3 ^{0}C)	Cooling: -3 _ +418%
			Rise in solar radiation (+3% & +6%) in next 50 years	Heating: -14 - -32%
Amato et al. (2005)	Massachusetts, US	Electricity demand, demand for heating oil and natural gas for different sectors	1% annual rise in equivalent CO_2 for GHG emissions scenario	2020: 1.2% and 2.1% rise in per capita commercial and residential electricity consumption
Wang, Chen and Ren (2010)	Australia	Emphasis on electricity demand	Average temp. increased by 1 ^{0}C	Peak regional demand changed between -2.1% and +4.6%
Barthendu and Cohhen (1987)	Ontario, USA	Residential sector demand for electricity, heating oil and natural gas	(2 x CO2) is assumed to occur between 2025 and 2065	Cooling energy: +6 to +7% and heating energy: -31 to -45%

Table 2.4 Continued

Author	Country/ Region	Detail	Temp (^{0}C) Change	Change (%) in Energy Consumption/Supply/Generation
Ruth and Lin (2006)	Maryland, USA	Commercial and residential sector demand for heating oil, natural gas and electricity	Mid-range of temp changes (25 years)	Expected larger impacts of regional population and prices on future energy consumption
Christenson, Manz and Gylistras (2006)	Switzerland	Four cities in Switzerland with emphasis on HDD and CDD	A2 and B2 IPCC SRES emission scenarios	HDD: -13 to -87%
Khan (2012)	Developing (Bangladesh) and Developed (Australia) countries	Impact of climate change on power generation over a period of 100 years	2.4^{0}C temperature rise by 2100 in Bangladesh 70C rise by 2100 in Australia	Reduction in power generation efficiency
Ahmed et al (2012)	Australia	Climate change impact on electricity demand	Increases in temperature in summer and spring session	1.36%, 2.72C% and 6.14% rise in per capita electricity demand by 2030, 2050 and 2100
Howden and Crimp (2001)	Four conurbations in Australia	Weekly average and peak electricity demand to changing climatic condition	IPCC climate scenarios	A negligible increase in demand (1.5%) for 7^{0}C in temperature for Sydney and Melbourne; Substantial increase (10% - 28%) for Brisbane and Adelaide
Sathayed (2013)	US	Climate change and energy infrastructure	IPCC Scenario A2	Decreased capacity of existing natural gas fired plants to generate electricity in extremely hot periods by 3% - 6% in California

Table 2.4 Continued

Author	Country/ Region	Detail	Temp (^{0}C) Change	Change (%) in Energy Consumption/Supply/Generation
EU Adam research	European countries	Climate change impacts	A1B emission scenario	Estimates more than 2^0C increase in temperature; Impact of increased temperature on electricity consumption was four times the size of equivalent decrease in temperature
Bye (2008)	Northern Europe	Climate change impact on electricity supply (hydro and wind power)	Increase in river inflow and wind speed by 11% and 1% between 2001 and 2040	Increase in electricity supply by 1.8% relative to 2001 and reductions to the tune of 22% in wholesale electricity price
Cradden, et al (2006)	United Kingdom	Implications of climate change on wind power resource	Increase in wind speeds by 15% in Northern Ireland and 5% in many parts of the UK	Expected increases in the supply of electricity
Eskeland and Mideksa (2009)	31 European countries	Household electricity demand and expected changes in heating and cooling degree days	IPCC emission scenario A1b	1^0C temperature change is estimated to change by 2 kWh/year per capita in heating degree days; and 8 kWh/year per capita on cooling degree days
Parkpoom and Harrison (2008)	Greece	Potential impact of climate change on electricity demand	Emission scenarios A2 and B2 and IPCC economic development	Increased variability in annual temperatures causes increased annual electricity demand resulting from a 3.6% - 5.5% change in climatic conditions under all scenarios

Table 2.4 Continued

Author	Country/ Region	Detail	Temp (^{0}C) Change	Change (%) in Energy Consumption/Supply/Generation
De Cian et al. (2007)	31 warmer and colder countries	Energy consumption and temperature variations	1% temperature increase in summer would raise demand by 1.17% and reduce temperature in colder countries	
Pilli-Sihvola, et al. (2010)	5 European countries	Electricity demand (degree-days and others)	IPCC A1b, A2 and B1 scenarios - 2050 horizon	Increase in electricity demand by 2.5-4% in 2050
Doshi, et al. (2012)		Electricity demand sensitivities to changing temperature	Hour-by-hour modelling approach	A significant positive impact of temperature changes on electricity demand with short-run elasticity in the range of 0.3-0.5
Petrick, et al (2010)	157 countries	Climate change and energy demand and consumption		Warmer temperature caused increased demand in Southern states: Greece (10%), Turkey (18%). Fall in demand in Northern states: Latvia (19.5%); Lithuania (20.8%).
Economic Commission for Latin America and the Caribbean (2011)	Latin America and the Caribbean	Climate change and electricity consumption	IPCC scenario A1 and B2	A 1.07% and 1.01% increase respectively for both scenarios

Table 2.4 Continued

Author	Country/ Region	Detail	Temp (^{0}C) Change	Change (%) in Energy Consumption/Supply/Generation
Scott and Huang (2007)	US energy systems	Energy consumption and climate change	1^{0}C increase in temperature is estimated to change energy consumption in the range of 5%	
Mansur, et al. (2005)	USA	Residential heating	+ 1^{0}C January temperatures	-2.8% electricity, -2% for gas consumers and -5.7% for fuel oil consumers
Bardt, et al (2013)	US and Europe	Forecast of the vulnerability of thermoelectric power supply	IPCC scenarios A2 and B1	A moderate reduction of 10% - 25% power supply,
Thatcher (2007)	Four Australia cities	Electricity demand	1^{0}C increase in average temperature	-2.1% and +4.6% change in peak regional demand

infrastructure, majorly the developed nations, have grids which are run by transmission system operators. In instances where the generating facility is at a distance from the load centre, it is directly conveyed to the distribution systems where power is needed. In transmissions over very long distances, electricity loss due to line resistance occurs and can be reduced by transmitting power in very high voltage. Although the higher the capacity of the transmission lines used (in terms of voltage), the higher the amount of capital requirement to put infrastructures in place. The high voltage generated power is usually stepped down at transformers by the distribution companies for domestic use before it's marketed to the consumers. Commonly, intra-national power transmission grids use alternating current for ease of voltage transformation. In the case of international transmission, as is the latest trend, high voltage direct current links are used to ensure efficient transmission. Efficiency of energy transmission require as much loss minimization as possible.

India has the highest transmission losses in the world (Figure 2.3). Currently, losses due to transmission lines have been recorded to amount over 21% (222 TWh) in India and to 6% (250 TWh) in the United States and worth over $20 billion. Cables carrying and transmitting electricity are expected to be of copper or aluminium with low resistance to minimize transmission losses as heat energy from high resistance cables (Table 2.5). Pakistan has a total of 12436km overhead transmission lines of 500kV (5077km) and 220kV (7359km) direct current with losses – due to transmission and distribution (T&D) -totalling about 30% of total power generated resulting from poor conductance of materials, theft, poor maintenance, and losses due to resistivity.

Some countries like Hong Kong use both the overhead and underground cable transmission systems. In Greece, power generation relies largely on lignite for 77% of its total power generation, and renewables-with an installed electricity generation totalling 15% large hydro-, 61% thermal,

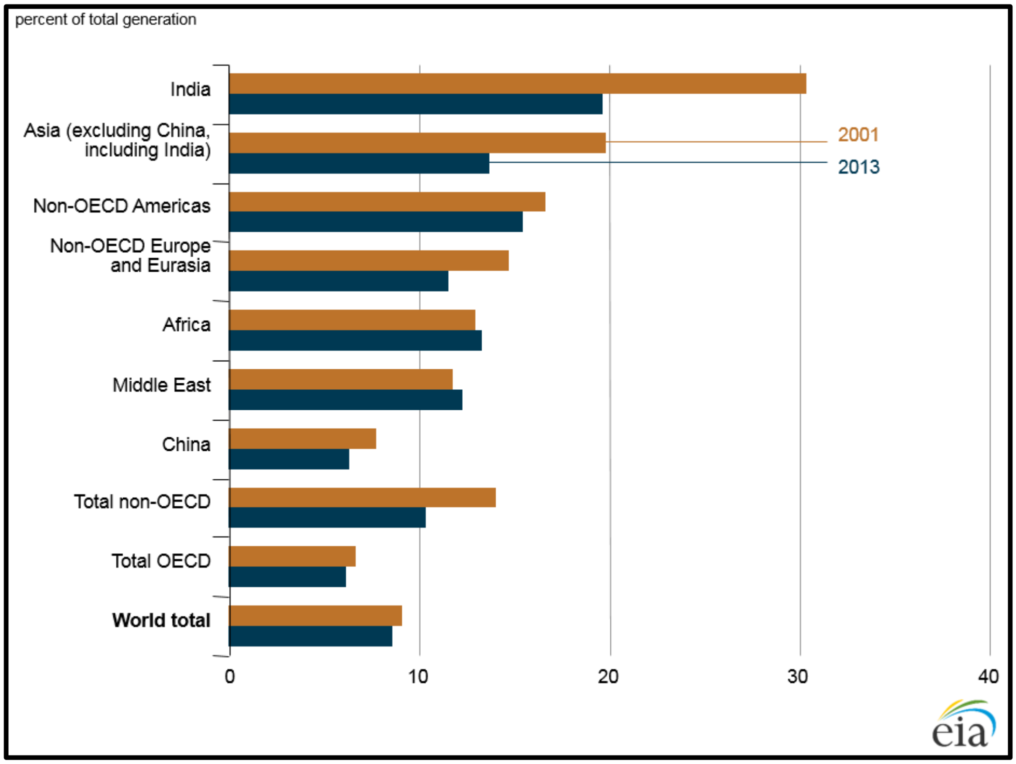

Figure 2.3: World electricity transmission and distribution losses by selected countries and regions, 2001 and 2013. Modified from International Energy Outlook (2016).

Table 2.5: A comparison between overhead lines and underground cables. Modified from http://www.hkphy.org/energy/power/print/transmit_phy_print_e.html

	Overhead Cables	Underground Lines
Installation	Direct, setting up of wires and pylons is relatively simple	Entails trenching, it is complicated, detailed route planning or the utilisation of cable tunnel
Cost/ Configuration	High-voltage electric wires hanging on pylons. Lower per-km cost.	High-voltage cables buried underground. Higher per-km cost
Construction/ Design	No insulation needed on wire surface as the wires are insulated naturally by air. Little or no protection required, natural cooling of wire in air Period of construction is shorter.	Insulation of cables vital as they are directly in contact with soil Protection against thermal stress and mechanical damage required Construction period longer

Table 2.5 Continued

	Overhead Cables	Underground Lines
Protection against inclement weather/ Application	Utilised generally in suburban and rural areas where more space is available for building pylons.	Generally used in urban areas where no space for building pylon is available
	Entails necessary measures against lightning and storms for instance: auto-reclosing scheme, ground wire and surge arrestors.	Less affected by storms and lightning
	Can transmit more power than underground cables of same size.	Lower power carrying capacity than overhead cable of same size owing to severe insulation issues

and 24% of other renewable and interconnected to Albania, Bulgaria, and Italy have a net import of 1.7TWh of power annually. Thailand at 99% electrification relies largely on natural gas for about 45% of total electricity generated, 36% oil, 16% from coal and 3% from hydro. Nigeria at 48% electrification, as of 2010, has electricity as 2% of total energy consumption resulting from her large dependence on biomass for energy and 9% of household's total energy consumption (Shonibare, 2014). With an ever-fluctuating installed capacity of 13,308MW, only 6,158MW was operational as of December 2014 and overhead line transmission network of 12,300 km (330 kV 5650 km; 132 kV 6.687 km) and distribution network of 224,838km (Shonibare, 2014). Some electricity infrastructure, storm surge and sea level rise put low-lying power plants at risk. A good number of electricity infrastructures in the U.S. (including substations and power plants) are sited within four feet of local high tide (Davis and Clemmer, 2014). Therefore, the risks these infrastructures are exposed to through floods and surge increase as seal level continues to increase.

According to Climate Central (2012), coastal flooding may be doubled by 2030 due to climate change. The 1992 sea level rise may be increased by 6'-6.6' by 2100. While historical data informed this estimate on sea level rise, recent data from the National Oceanic and Atmospheric Administration (2012) has shown that the rate of sea level rise has almost increased in double folds implying a rise above 6 feet by 2100.

The risk of coastal flooding from hurricanes or storm surges may be increased following higher sea levels (Stewart et. al., 2005, Tebaldt et. al., 2012). In the western U.S, the average number of huge wildfires on a yearly basis rose to 250 by 2012 from the previous 140 in the '80s (United States Geological Survey, 2013). Higher air temperatures and droughts also pose more intense danger to wildfire. Wildfires also have significant impacts on the electricity sector. As described earlier in this review, poles carrying electricity transmission lines can be destroyed, especially by smokes and particulate matter. As regards smoke, it can ionize the air thereby creating an electrical path away from electricity transmission cables and consequently, a complete shutdown of electricity (Ward, 2013, Sathaye et. al., 2012). An example cited earlier is the wildfire that put 2 high-voltage transmission lines at risk in New Mexico. These impacts are hypothesized to be greater in a developing country like Nigeria where, as of today, governments at all levels still struggle with grid constraints, even power generation issues amidst sparse empirical, and consequently, policy attentions.

2.9 Climate Impacts on Electricity (Financial Cost)

2.9.1 Developed Country - United States

Thermoelectric produces about 91% of electricity (fossil-fuelled and nuclear power plants) in the U.S. (Yearsley, 2012). Although, recently, warm and dry summers resulting in cooling- water scarcity has led to a capacity reduction in the production of many of these thermo-electric power plants in the U.S (Yearsley, 2012). Costs associated with power outage or loss during extreme weather events can be of great significance especially when customers loose power. These costs could be in the form of damaged inventory, wages, or restarting industrial operations. Weather-related power outages for instance in 2012 - when Hurricane Sandy hit the East Coast - cost the country more than $27 billion (EOP, 2013). Effect of adverse weather conditions on electricity supply and demand begins from the power plants, networks for conveyance and the distribution and transmission lines that deliver power to business districts and residential homes, most especially as the present infrastructure was not constructed to withstand a large proportion of occurring extreme weather events (Government Accountability Office, 2014).

A case study from California on the impact climate change has on electricity production and consumption by Sathayed, 2013 showed that very few literatures on climate change impact on energy supply in countries have been limited to UK, Brazil, United States, and that no definite conclusions have been reached about the potential costs to energy supply of rising temperatures. But an estimated global increase in supply side expenditure of $65 billion or 0.08% increase in GDP and $480 billion fall in demand by 2100 was found by the study. Sathayed, 2013 estimated the second- order impact on California Energy Infrastructure: cooling for power plant generation, heat spells to transmission lines and subsequent substation capacity, wildfires near transmission line corridors, sea level encroachment, and resulting flood to approximately 25 power plants, substations, and natural gas facilities situated down the coast of California. The author used IPCC scenario A2 and predicts a decrease in ability of existing natural gas fired plants to generate electricity in extremely hot periods by 3% - 6% in California, and 2% - 4% in San Francisco, and diminished transformer and substations capacity by 2% - 4%, with a small but negligible increase in transmission line capacity and concluded that the real cost of adaptation may be difficult to estimate (Sathayed, 2013).

2.9.2. Developing Countries

In electricity demand growth, economic growth is of utmost importance. Although there is a fall in the world's gross domestic product (GDP) growth when compared with the recent past decades, demand for electricity continues to be on the increase, particularly in the non-OECD developing nations. Electricity generation in 2012 among these countries represented a little above one-half of global demand of electricity. With a continuing economic growth, estimates show that global electricity generation in 2040 from non-OECD nations can rise to 61%, and total non-OECD electricity generation can increase in double folds to 22.3 trillion kWh in 2040 from the 2012's 11.3 trillion kWh (U.S. Energy Information Administration, 2016).

Per capita energy consumption in emerging nations has been growing at a faster rate than that of developed nations while energy conversion efficiency ratio is much lower than that of developed countries (IEA, 2004). With respect to energy security, developing countries need sufficient access to primary energy source required for electricity generation to obtain enough oil for transportation and transition from dependence on conventional fuel sources to non-conventional/renewables or cleaner fuel sources like natural gas, biodiesels etc.

Given that energy shortage hinders both economic and human development, modernization and expansion of the energy sector have become a non-negotiable task to be achieved. Basic human needs that include communication, education, health or sanitation can be prevented when modern energy services are unavailable. Industrial production among nations can also be prevented when power is unreliable and insufficient. Energy consumption per capita increases as nations get wealthier following increases in energy demand at both residential and industrial levels. The general assumption is that with industrialization comes improved standards of living, energy consumption through dependence on energy consumer goods as is the case with developing nations. The effect of this is a greater sensitivity to climate change than when compared to developed nations. An assessment by the economic commission for Latin America and the Caribbean using the IPCC scenario A2 and B2 and 2011 baseline for per capita electricity consumption to predict the effect of climate change on electricity consumption has indicated a 1.07% and 1.01% increase using scenarios A2 and B2 respectively. And in absolute terms, it is estimated that from 2011-2050, electricity consumption will be valued at US$142.88million and US$134.83 million under scenario A2 and B2 respectively. In relative terms, these equate to a loss in GDP of 0.737% and 0.695% under scenarios A1 and B2 respectively (Economic Commission for Latin America and the Caribbean, 2011).

Considering the potential damages that may arise from climate change, it is imperative that preparedness measures be put in place to protect existing equipment and infrastructures otherwise known as ‘hardening’ measures. They are specific to topography and regions and may include, protective sea walls, relocating important equipment from hazard prone areas, use of underground cables as opposed to overhead transmission lines. Evidence from literature point to the fact that to attain energy sufficiency, policies must be put in place. To ensure supplier and consumer adaptability, such policies should be directed at improving infrastructural facilities that may stand adverse weather conditions- extreme heat, rising sea levels, flooding, drought, wildfires- and reducing further emissions to curb changing climatic conditions (Cole et. al., 2013).

The first step to policy planning is to conduct local vulnerability assessments. This is critical to know the status of the country and predict as accurately as possible what changes to be expected. Then, policies should encourage resilience of the electricity sector by investing in infrastructure. Also, climate adaptation and mitigation measures can be put into utility planning. Some adaptive measures include reducing electricity demand through use of energy efficient technologies and appliances. Reduced demand implies less need for new infrastructure and less risk and equipment vulnerability to adverse environmental condition. By making energy more efficient in the homes, the Boston’s Renew Program through annual savings yielded about $2 million (City of Boston, 2013). This in fact, informed the huge investments on more efficient products and appliances by the U.S Environmental Protection Agency’s Energy Star program. Through this initiative, about $26 billion was saved on their electricity bills in the U.S. Noteworthy is that the amount saved is in equal proportion to the average electricity used in 35 million average homes in 2012 (Environmental Protection Agency, 2014).

2.10 Nigeria’s Electricity Sector, Energy Sources, and Climate

Prior to the electricity reform drives that began in 2005, the Federal Government of Nigeria (FGN) was completely in charge of responsibilities regarding the formation of energy regulation and development, and investment in the electricity sector[3]. Like in most OECD (Organisation for Economic and Development) countries, Nigeria witnessed a noticeable deregulation of the electricity sub-sector, which hitherto was a state-run and monopolistic market structure, into a more vibrant oligopolistic enterprise. According to Bacon, 1999, the magnitude and pace of the trend in these countries which began since the end of 1990 has been very commendable. Before the regulation of the sector in Nigeria, the National Electric Power Authority (NEPA) since 1972 conducted operations in the electricity sector through a monopolistic structure while the Federal Ministry of Power (FMP) handled regulatory functions.

After several attempts to manage operations with poor financial performance, NEPA Acts was in 1998 amended from its monopolistic structure into a system that encourages private sector participation[4]. The legal basis for the amendment and formation of successor companies as well as privatization was contained in the EPSR Act (National Mirror, 2014). In 2007, the power sector was reformed and led to the formation of Power Holding Company of Nigeria (PHCN). Meanwhile between 2005 and 2009, PHCN took over NEPA and was unbundled into autonomous transmission, generation, and distribution companies. Given persistent power outages and

[3] www.energypedia.info/wiki/Nigeria_Energy_Situation
[4] www.placng.org/new/laws/E7.pdf

inefficiencies, a power sector reform committee was inaugurated to identify power supply problems and provide workable solutions to the nation 's power supply problems. Between 2010 and 2012, two significant efforts were taken by the FGN as parts of the mitigation efforts to provide solutions to electricity problems. First, a Presidential Action Committee on Power (PACP) and a Presidential Taskforce on Power (PTFP) was constituted by former President Goodluck Jonathan administration. Second, the efforts of these committees brought about the development of a road map for power sector reform.

Towards the end of 2013, PHCN eventually stopped existing[5]. The approaches taken by the FGN through the joint efforts of the PACP and the PTFP was to initiate a 100% privatization of the electricity services industry by selling off its stake (Aladejare, 2014). This was in the view of resuscitating the electricity sub-sector and making it better to meet the teeming demands and allow the FGN focus on transmission. Today, the FGN operates the transmission sub-sector (both the systems operator and market operator divisions) which is now called the Transmission Company of Nigeria (TCN). The distribution companies are referred to as DISCOs, while the generation companies are called GENCOs. The Nigerian Bulk Electricity Trading Plc. (NBET) was also formed with the purpose of buying electricity from the GENCOs, to sell to DISCOs, and from DISCOs to the end-users of electricity.

Highest ever power generation peak, pre- and after the power sector reform exercises, was recorded in December 2007, which was reportedly stated to be 5,222.3 megawatts (MW). There are plans by the FGN to keep up with the global position of shifting away from fossil fuels. The FGN is interested in diversifying Nigeria's energy supply mix and to mitigate issues emanating from gas

[5] www.nigeraelectricityprivatisation.com/

supply shortages which continue to affect generation capacity. Some of the major steps in this direction has been in the form of policy initiatives such as the Renewable Feed-In Tariff Regulation of 2015 and the Renewable Energy Action Plan of 2016. Reasons for the recent interest in renewable energy sources are not farfetched. Nigeria is described as an oil rich nation with an estimated 180 trillion standard cubic feet of gas, making Nigeria 9th on the list of countries with abundant high-quality gas reserves. Several challenges militating against gas supply have however impacted negatively on the nation's economy[6]. The following section addresses some conventional energy resources like gas and available renewable resources in different parts of the country.

2.10.1 Conventional Energy Resources in Nigeria

Nigeria is one of the largest producers of natural gas and oil in the world and a stakeholder in the Organisation of the Petroleum Exporting Countries (OPEC). These oil and gas reserves along with other conventional resources spread across different parts of the country. Before the discovery and concentration on oil and gas resources, coal reserves which stood at about 2.175 billion tons served as the source for electricity generation. Table 2.6 describes the potentials of Nigeria's conventional energy reserves. Historically, coal and natural gas account for over 80% of total electricity production in Nigeria. The rest of this section examines the two main conventional energy resources in Nigeria.

2.10.1.1 Coal

Top on the list of conventional resources based on year of discovery is coal. Nigeria discovered

[6] https://www.olaniwunajayi.net/wp-content/uploads/2018/01/OALP-Power-Infrastructure-Wrap-Up-Report-1.pdf

Table 2.6: Nigeria's major energy reserves and their potentials. n/a – not available Source: National Bureau of Statistics [NBS] (2007)

Resource Form	Reserves (natural units)	Production	Domestic Utilization (natural units)
Coal & Lignite	2.175 billion ton	n/a	n/a
Crude Oil	36.22 billion barrels	2.5 million barrels/day	450,000 barrels /day
Natural Gas	187 trillion SCF	6 billion SCF day	3.4 billion SCF/day
Tar Sands	31 billion barrels of equivalent	Insignificant	Insignificant
Nuclear	n/a	n/a	n/a

coal in the year 1909 in Enugu state of the South-East region. Ogbete drift mine was Nigeria's first coal mine and it was discovered in 1916. As of the period of discovery, its output was 24,500 t. Later in 1950, the Nigerian Coal Corporation (NCC) was formed and some of NCC's responsibilities were to be the sole producer and miner of coal and coke under the management of a polish firm called KOPEX.

In 1956, about 70% of energy generation in Nigeria was from coal production having attained a peak of 790,030 tons. The discovery of oil by Shell-BP in Oloibiri area of Niger Delta however brought about a steady decline in coal production (Nigerian National Petroleum Corporation [NNPC], 2015). By 1982, coal production had dropped to 62,830 tons, after some of the largest consumers of coal such as the Nigerian Railway Corporation switched to diesel and gas (TOPFORGE, 2015). The conversion of coal to oil by the defunct NEPA also contributed to the lack of interest in coal production. Presently, there is no functioning coal plant in Nigeria.

2.10.1.2 Natural Gas

Proven natural gas reserves in Nigeria has increased in the past years and reportedly stated as 180 trillion standard cubic feet, making it world's 9th largest[7]. Nigeria was in the past placed 2nd in the list of gas-flaring nations due to poor infrastructure. However, given the initiatives of FGN to reduce gas flaring via provision of relevant infrastructure and financing, Nigeria rose to 365th on the list (Ibitoye, 2014). Power sector accounted for around 80% of total domestic consumption of previously flared gas, and it generates more than 80% of Nigeria's total electricity supply.

[7] https://www.olaniwunajayi.net/wp-content/uploads/2018/01/OALP-Power-Infrastructure-Wrap-Up-Report-1.pdf

Since its discovery, the production and consumption of natural gas in Nigeria has been on the increase, production however slowed down in 2008 following a disruption caused by the activities of vandals that were siphoning condensate. This caused Shell oil company to stop gas production to fix pipeline damage connected to one of the plants. The plant eventually re-opened after a period of five months. Activities of vandals however persisted in 2009, and coupled with operational challenges at the plant, it was again closed (The Encyclopaedia of Earth, 2015).

Today, safety and security issues, and inadequate pipeline infrastructure are still being named as some of the challenges of gas supply. Given the location of most of the pipeline assets, which are mostly remotely located, they are highly susceptible to the activities of these vandals. Pipeline attacks shut off fuel meant to be supplied by power plants. Since gas is not warehoused, as soon as an affected power plant runs out of fuel required fuel for supplies, they are exposed to risks of forced shut down. In the face of sabotage issues, pipeline infrastructure is also inadequate. It is estimated that Nigeria needs around $1.2m per km of overland pipeline for about 10,000km of gas pipelines. In the face of failing oil prices, the FGN's capacity to meet this target remains very unrealistic. New and emerging challenges such as gas pricing, limited regulatory framework, and forex liquidity issues have also been named[8].

2.10.2 Renewable Energy Resources in Nigeria

Just like the conventional resources, Nigeria is also blessed with diverse nonconventional resources (renewable energy) that have been discovered in time past. Renewable energy resources play a key role in meeting some electricity needs both in the rural and urban centres. Many

[8] https://www.olaniwunajayi.net/wp-content/uploads/2018/01/OALP-Power-Infrastructure-Wrap-Up-Report-1.pdf

developing and developed nations already have adopted renewables as alternatives to conventional resources for curbing issues arising from unsustainable energy resources and climate change (Oyedepo, 2012). More attention must be paid on renewable energy and usage in Nigeria as a way of curbing issues of global warming and contributing more to the electricity mix. This section provides a review of the available renewable energy sources including the extent of use and provides an estimate of their potentials in providing electricity in Nigeria. Table 2.7 showcases some of the Nigeria's available renewable energy sources and domestic utilizations (in natural units).

2.10.2.1 Biomass Energy

Energy derived from organic materials is referred to as biomass. Some of the common biomass peculiar to Nigeria include, but not limited to, animal waste, forage grasses, forestry, municipal solid waste, shrubs, saw dusts, and agro-waste. The most common biomass is fuel wood and usually utilized for domestic purposes such as cooking (Sambo, 2005). Of the total 6.0 x 109 MJ, only 17% are utilized (5% are used for cooking while 12% are used for other domestic purposes) (Lawal, 2007). Table 2.8 specifies some biomass types and their energy value. Although the potentials for energy generation through fuel wood utilization is huge, it however poses some challenges and threats. These threats include desertification, desert encroachment, and soil erosion, just to mention a few. Increasing demand of supplies from construction and furniture companies also poses some threats to the sustainability of biomass resources.

Sambo (2009) estimates that Nigeria loses about 350,000 ha yearly due to the high dependence on fuel woods especially in Nigeria's rural communities. Hence, Shaaban and Petinrin, 2014 suggest that industries in Nigeria could embrace oil palm product, municipal waste, rice husk, and sugar

Table 2.7: Sources of nonconventional energy resources in Nigeria (ECN, 2009)

n/a – not available

Resource Form	Domestic Utilization (natural units)
Large Hydropower	1938 MW
Small Hydropower	30 MW
Wind	n/a
Solar Radiation	6 MWh/day
Biomass Fuel Wood	0.120 m ton/day
Animal Waste	n/a
Energy Crops and Agricultural Residue	n/a

Table 2.8: Biomass resources in Nigeria (Sambo, 2009)

Resource Form	Quantity (million ton)	Energy Value (000 MJ)
Municipal Solid Waste	4.075	n/a
Fuelwood	39.1	531
Agro Waste	11.244	147.7
Saw Dust	1.8	31.433

cane in a responsible manner to produce biogas energy. Consequently, solar energy has been highly recommended in some previous studies as a sustainable alternative to firewood consumption in the rural areas (Sambo, 2009).

2.10.2.2 Solar Energy

Solar energy potential is without bounds and a far-reaching effect. This form of energy has the capacity to produce cost effective and abundant electricity for communities especially those who, because of their geographical location, are unable to connect with the national grid. Hence, solar energy serves as a good alternative for rural communities and small-scale industries, and it has great potentials for rapid development (Emordi, 2017). Nigeria is blessed with abundant sunlight. According to Augustine and Nnabuchi, 2009, available annual solar energy, at the average sunshine of 6.5 h/day is 115,000 times the electricity generated presently. Table 2.9 presents the average daily solar radiation in different states of Nigeria.

2.10.2.3 Hydro Energy

Of all the nonconventional energy resources in Nigeria, hydro energy contributes the most to Nigeria's electricity supply mix. Electricity production from hydro energy currently stands at around 18% (IEA, 2019). Hydro power has the potential of supplying uninterrupted power although problems resulting from relative water levels have been challenging. Nigeria's total Hydropower total potential installed capacity is around 12220 MW and summarized in Table 2.10. Small hydropower potentials in Nigeria are estimated to be around 734.2MW based on some 277 potential sites (see Table 2.10) that were surveyed in the 80s. These numbers are expected to be more if all potential SHP sites in Nigeria are surveyed (e.g., Olaoye et. al., 2016). In many parts of the world however, small hydropower (SHP) has been at the centre of many discussions on

Table 2.9: Max//Min annual solar radiation (kWh/m^2/day)

a – average for April and May, b – average for July and August

Source: Okoro et al. (2007)

Locations	**Altitude**	**Location Long 1E**	**Location Lat. 1N**	**Min^a**	**Max^b**	**Average (monthly)**
Ilorin	307.3	4.58	8.48	4.096	5.544	4.979
Abeokuta	150	3.42	7.25	3.474	4.819	4.258
Abuja	350	7.03	9.27	4.359	5.899	5.337
Akure	295	5.08	7.25	3.811	5.172	4.485
Makurdi	112.85	8.53	7.73	4.41	5.656	5.077
Port Harcourt	19.55	7.02	4.85	3.543	4.576	4.023
Bauchi	666.5	9.8	10.37	4.886	6.134	5.714
Calabar	6.314	8.35	4.97	3.324	4.545	3.925
Gurus	342	10.47	12.9	6.326	8.004	6.966
Kano	472.14	8.53	12.05	5.563	6.391	6.003
Enugu	141.5	7.55	6.47	3.974	5.085	4.539
Ibadan	227.23	3.9	7.43	3.622	5.185	4.616
Jos	1285.58	4.97	9.87	4.539	6.536	5.653
Yola	186.05	12.47	9.23	4.974	6.371	5.774
Kaduna	645.38	7.45	10.6	4.446	6.107	5.672
Benin City	77.52	5.6	6.32	3.616	4.615	4.202
Katsina	517.2	7.68	13.02	3.656	5.855	4.766
Lokoja	151.4	6.74	7.78	4.68	5.639	5.035
Maiduguri	383.8	13.08	11.85	5.426	6.754	6.176
Minna	258.64	6.53	9.62	4.41	5.897	5.427
Owerri	120	7.03	5.48	3.684	4.469	4.146
Sokoto	350.75	5.25	13.02	5.221	6.29	5.92
Warri	6.1	5.73	5.52	3.261	4.237	3.748
Lagos	39.35	3.33	6.58	3.771	5.013	4.256

Table 2.10: Nigeria's potential hydropower site installed capacity (Manohar and Adeyanju, 2009)

Location	River	Install Potential Capacity (MW)
Donka	Niger	225
Zungeru II	Kaduna	450
Zungeru II	Kaduna	500
Zurubu	Kaduna	20
Gwaram	Jamaare	30
Izom	Gurara	10
Gudi	Mada	40
Kafanchan	Kongum	5
Kurra II	Sanga	25
Kurra I	Sanga	15
Richa II	Daffo	25
Richa I	Mosari	35
Mistakuku	Kurra	20
Korubo	Gongola	35
Kiri	Gongola	40
Yola	Benue	360
Karamti	Kam	115
Beli	Taraba	240
Garin Dali	Taraba	135
Sarkin Danko	Suntai	45
Gembu	Dongu	130
Kasimbila	Katsina Ala	30
Katsina Ala	Katsina Ala	260
Makurdi	Benue	1060
Lokoja	Niger	1950
Onitsha	Niger	1050
Ifon	Osse	30
Ikom	Cross	730
Afokpo	Cross	180
Atan	Cross	180
Gurara	Gurara	300
Mambilla	Danga	3960
Total		**12220**

electricity, owing to the capabilities of SHP to mitigate impacts on the environment and offer alternative solutions for flood, and other development benefits in fishery and irrigation.

Like other countries, Nigeria has also tapped into the SHP trend albeit on a small scale. SHP generation represents around 23% of the total installed hydropower capacity as shown in Table 2.11.

2.10.2.4 Biogas Energy

Biogas as an energy form is usable not only in households but in the industrial and agricultural sectors. It constitutes the following raw materials: animal dung from households, farmland and industries. The anaerobic digestion of these wastes in the absence of air produces biogas. It shares some similarities with LPG gas largely because of its odourless and colourless characteristics. In a conventional biogas stove, its efficiency burns at about 55%. Biogas comprises of mixture of carbon IV oxide, nitrogen, methane, water vapour and hydrogen sulphide (Opeh and Okezie, 2011). Because of its capability to reduce GHG, it could be used as alternatives to kerosene, charcoal, and fuel wood. In addition to that, it also poses no health risks or hazard (Akinbami et. al., 2001). Oyedepo (2012) showed that Nigeria produces about 20 kg of solid waste per capita yearly. Ngumah et. al., 2013 estimated potential bioenergy of 610, 350 TJ (equivalent to 169, 541.66 MWh) per annum from organic waste with most contribution from cattle excreta (Table 2.12). At this rate, the potential of biogas to Nigeria's electricity sector cannot be overemphasized since in the past years, this alternative has been vastly underutilized.

2.10.2.5 Geothermal Energy

Geothermal energy is the heat formed in the earth's subsurface. It is a geological process where

Table 2.11: Nigeria's SHP potentials (Sambo, 2009)

Old Nigerian States	River Basin	Total Sites	Hydropower Potential		
			Undeveloped (MW)	Developed (MW)	Total Capacity (MW)
Benue	Lower Benue	19	69.2	--	69.2
Plateau	Lower Benue	32	92.4	18	110.4
Gongola	Upper Benue	38	162.7	--	162.7
Bauchi	Upper Benue	20	42.6	--	42.6
Cross Rivers	Cross Rivers	18	28.1	--	28.1
Katsina	Sokoto-Rima	11	8	--	8
Sokoto	Sokoto-Rima	22	22.6	8	30.6
Kwara	Niger	12	38.8	--	38.8
Niger	Niger	30	117.6	--	117.6
Kaduna	Niger	19	59.2	--	59.2
Kano	Hadeija-Jamaare	28	40.2	6	46.2
Borno	Chad	28	20.8	--	20.8
Total		**277**	**702.2**	**32**	**734.2**

Table 2.12: Biogas Potential in Nigeria (Ngumah et. al., 2013)

Organic Waste	Estimated Biogas Potential (billion m3 year-1)	Biomethane Potential (BMP) of biogas (billion m3 year-1)	Energy Potential of Biogas (TJ) per annum
Cattle Excreta	6.52	3.65	142350
Sheep and Goat Excreta	2.3	1.61	62790
Pig Excreta	0.92	0.55	21450
Poultry Excreta	2.5	1.65	64350
Abbatoir Waste	4.42	2.65	103350
Human Excreta	2.6	1.69	65910
Crop Residue	4.98	3	117000
Municipal Solid Waste (MSW)	1.29	0.85	33150
Total	**25.53**	**15.65**	**610350**

heat from the earth's molten core is passed to the adjacent rocks through conduction after which convection process passes it to subsurface water reservoirs. Under the right conditions, geothermal energy can be used for the generation of electricity and heat production. One way to tap the heat from earth's core is to drill a well into the hot aquifer. A geothermal power plant is then built to tap the hot liquid or steam from this well through a turbine or generators. The hot fluid produced is then used to drive the turbines to generate electricity. Geothermal energy is a reliable source of renewable energy because it is naturally sourced, environmentally friendly, cost effective, and available. It is also not affected by adverse weather conditions. Some geothermal springs available in Nigeria are shown in Figure 2.4.

2.11 Climate Change and Electricity in Nigeria

Climate change is one of the uncertainties that must be put into consideration for effective planning and operations of energy systems (supply and demand). Broadly speaking, these operations are based on decision making and uncertainties (Kopytko and Perkins 2011). A growing number of research findings on climate change impacts on electricity have been published (Amato et. al, 2005, Franco and Sanstad, 2008, Mideska and Kallbekkan, 2010, Seljom et. al, 2011, Schaeffer et. al, 2012, Van Vliet et. al, 2012, Dowling, 2013, Orosz et.al, 2013, Zachariadis and Hadjinicolaou, 2014). Most direct and significant variable (manifestation) of climate change impacts on electricity from the studies reviewed is a direct relationship between temperature and electricity demand. More significant and of concern is the fact that the supply arm of electricity also has a fair share of these seemingly uncontrollable impacts. These happenings are a forewarning on the nature of impacts that should be expected from a changing climate. For instance, Petrick et al.,

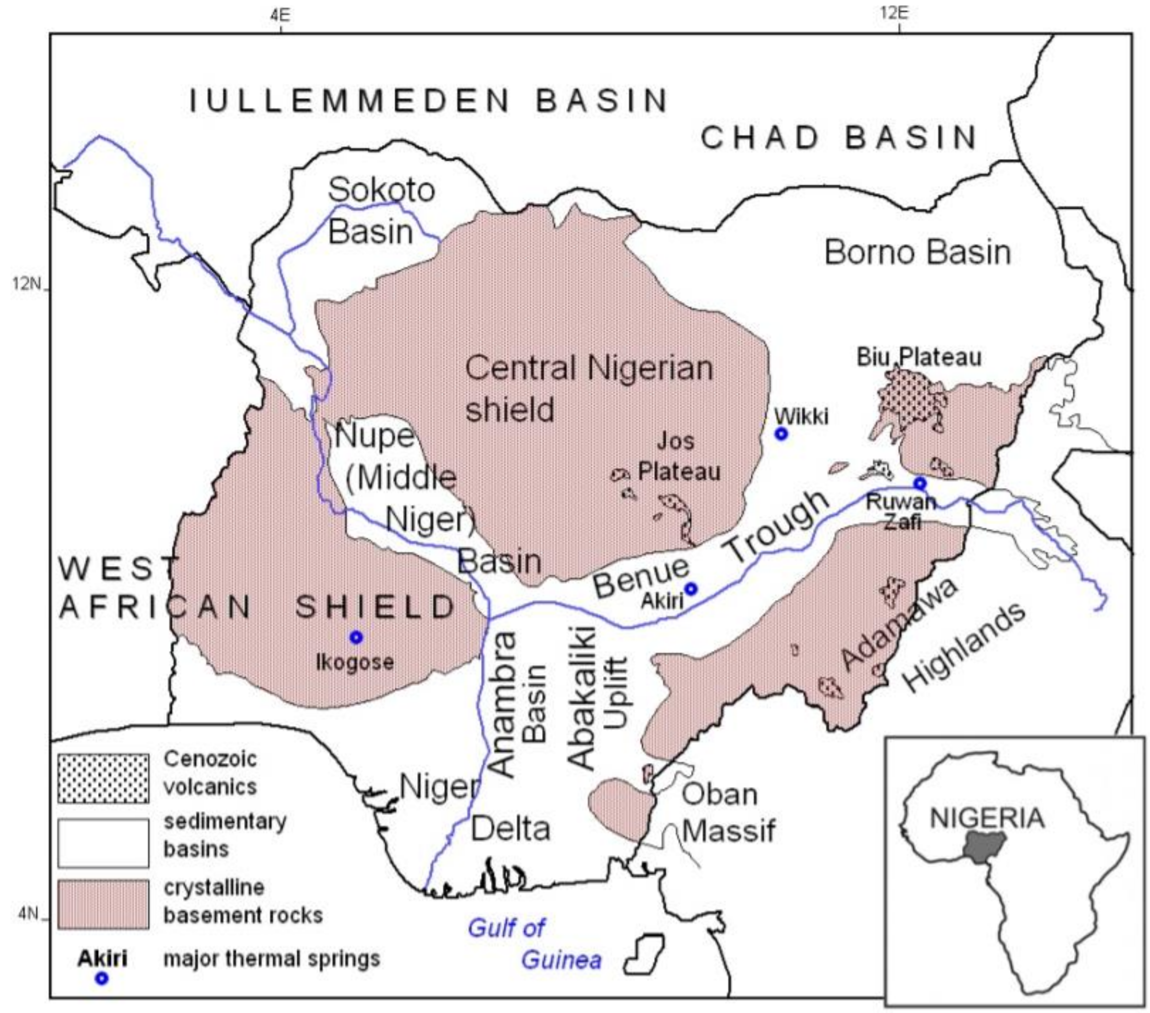

Figure 2.4: Map of Nigeria showing major geothermal springs. Source: Kurowska and Schoeneich, 2010

2010 found that energy utilization over 3 decades in 157 countries declines as a result of rising temperatures, revealing that decreased rate of heating has played major significant roles than the increase in air conditioning loads. While there seems to be a significant level of consistency in the reports across many developed and some developing nations particularly as related with how climate change influences electricity supply and demand, results from other findings have shown that estimated impacts in capacity vary by plant type, climate model, emission scenario, region, and even the methodology.

Because issues pertaining to Nigeria, being the most populous black nation on earth, are critical to the continent and world over, a substantial number of scholars have attempted to investigate how weather events affect several sectors of the Nigerian economy (Morton, 2007, Apata et. al, 2009, Odjugo, 2009, 2010, Onyekuru and Marchant, 2016). Studies focused on the climate impact on energy in Nigeria are not many (Enete and Alabi, 2011, Akinyemi et. al., 2014, 2015). There are very few published studies on how weather events affect the electricity sector in the country, and not without gaps (Enete and Alabi, 2011, Akinyemi et. al, 2014). Nigeria's growing population currently standing at over 170 million puts strenuous impacts on the major electricity generating plants given the role of the sector in initiating and propelling industrial activities and economic growth. The effect is that electricity supply continues to lag behind the growing demand after some years of reforms both at industrial and domestic levels. As a consequence, there has been rationing of electricity in main districts with high business concentration, and dependence on self-generated and alternative electric sets to meet domestic and industrial electricity needs in Nigeria. This is in the face of a new burst of hope and expectation to accelerate economic growth and reform the nation's economy. Eliminating the constraint of unreliable and incessant power will in no doubt improve the microeconomic response of the real sector.

Studies on the determinants of electricity demand have been largely based on industrialized and developed countries. As such, most of the energy and electricity models and forecasting methods available today were raised to cater to the characteristics and uniqueness of the developed countries (Rujiven, 2008, Bhattacharyya and Timilsina, 2010a). Reasons why some energy systems models were primarily built and used in assessing energy systems of developed countries are not farfetched. Developing countries possess peculiar challenges which are quite different from those of the developed world. These challenges include poor performance of power sectors, shortages in supply, low rate of electrification, structural economic change, increased share of traditional biomass, just to mention a few. Other challenges and their implications are described in Table 2. 13.

Peculiar challenges that affect electricity models and forecasting in Table 2.13 explain why there is a paucity of empirical investigation into the demand for electricity in Nigeria, and indeed, some developing countries. It also explains why forecasting models often fail to adequately address energy systems issues in these countries. Meanwhile there are longstanding investigations for India, Australia and Taiwan (Filippini and Pachauri, 2004, Narayan and Smyth, 2005, Holtedahl and Joutz, 2005; UK (Clements and Madlener, 1999, Henley and Peirson, 1999); US (Houthakker, 1980, Silk and Joust, 1997); Middle East (Eltony and Hosque, 1996, Al-Faris, 2002); and Switzerland, Norway, Greece and Cyprus (Fillipini, 1999, Ettestol, 2002). There are also investigations on G7 countries and other Asia-Pacific nations (e.g., McNeil et. al., 2019).

Table 2.13: Challenges and implications of energy systems in developing countries Source: Tait, McCall and Stone (2015)

	Urban Energy Systems Characteristics in Developing Countries	Implications for Modelling Energy Systems and Sustainable Energy Transitions
1	Under-pricing of electricity tariffs (below long-term marginal costs of products	The availability of base loads stations may not be predictable owing to poor maintenance. Difficultly in financing new infrastructure due to low financial viability of utilities. This may affect reliability of assumptions in demand forecasting.
2	Informal markets and economy	Data difficulties following several unregulated transactions that are difficult to capture.
3	Non-technical losses in the electricity sector	Meter data not reflecting consumption.
4	Inequality and poverty	A very wide range of income driven consumer behaviors may exist that requires wide dis-aggregation to achieve a structurally sound model.
5	Usage of many low quality and secondhand end-user technologies with low efficiencies	The assumption of data from other markets, in the absence of survey data, may be highly inaccurate.
6	Households without access to modern and safe energy services	Difficulties in tracking large, suppressed demand and energy use. There is also a large focus on transitioning consumers to modern and safe energy services. Such energy transitions however often are unexplainable with optimizing and rational choice theory. Such transitions in reality often require specific policy interventions are often much more complex.
7	Built environment – informal housing	Impacts on thermal properties of buildings.
8	‘Suppressed demand’	Basing analysis on consumption data only reflects ‘satisfied demand’. Extrapolating consumption patterns into the future might therefore be problematic.

2.12 Review of Electricity Demand Forecasting Techniques

2.12.1 Modelling Approach in the Energy Sector

Policy makers rely on models that can accurately forecast future electricity consumption which can then guide the construction of adequate supply capacities. The high cost of constructing power plant is a reasonable ground to have accurate forecasts for the future. Forecasting can help in reducing the risk in making decisions and cost. Energy demand forecasting models are well discussed in literature. They are categorized based on different views such as sector-based (industry, commercial, residential, and transport), based on renewable energy (e.g., solar and wind), and source-based (e.g., electricity and fuel).

Electricity load forecast can also be categorized into three based on the forecasting time periods. The three categories are (1) Short term load forecast (ST), (2) Medium term load forecast (MT), and (3) Long term load forecasting period (LT). Short term forecasting time period is usually within hours to days to few weeks ahead. Short term forecasting is useful in planning electricity supply a day ahead and in DSM. Medium term forecasting time period is from months to years head. Medium term forecasts are useful in energy trading, assessment of revenues, and scheduling of unit maintenance. In the long-term forecasting, horizons are of years to several decades. Long term forecasting helps policy makers to efficiently manage assets. It also helps guide the construction of adequate supply capacities (Mir et. al., 2020).

Table 2.14 summarizes the application of the different forecasting time periods used in energy studies. Energy demand forecasting models can also be categorized based on the type of approach used. There are two major modelling approaches used in the energy sector namely the simple and sophisticated approaches. These approaches are explained in detail in the following subsections

Table 2.14: Application of different forecasting time periods. (Mir et. al., 2020)

Application	ST	MT	LT
Energy Purchasing	Yes	Yes	Yes
Transmission and Distribution Planning	No	Yes	Yes
Operations	Yes	No	No
DSM	Yes	Yes	Yes
Financial Planning	No	Yes	Yes

(Bhattacharyya and Timilsina, 2009). Energy demand forecasting models can also be categorized based on the type of approach used. There are two major modelling approaches used in the energy sector namely the simple and sophisticated approaches. These approaches are explained in detail in the following subsections (Bhattacharyya and Timilsina, 2009).

2.12.2 Simple Approaches

The simple approaches provide easy answer to energy demand calculation using four simple indicators: growth rate, elasticities, unit consumption, and energy intensity. This approach is less common and not commonly used by researchers. Demand forecasts using this approach rely on any of these indicators and simply predict the future by extrapolation and assumptions. The accuracy for long term projections using this approach is low. Several authors have used this approach to predict electricity demand. Codoni et. al., 1985 used income elasticity for energy assessment of Korea. Grover and Chandra, 2006 used a single indicator, income elasticity to predict India future energy demand. Despite the weakness of the simple approach, its strength lies in the fact that it can form subcomponents of sophisticated approaches. For example, appliance use, or intensity is the basis for predicting appliance energy consumption (AEC) in hybrid models at the disaggregated level. The major weaknesses of this approach are (1) inability to explain demand driver or technology consideration, (2) non-reliance on theoretical foundation, and (3) huge reliance on the value judgement of the modeler (Bhattacharyya and Timilsina, 2009).

2.12.3 Sophisticated Approaches

The sophisticated approach uses advanced and complex methodologies for energy demand calculations. The most common sophisticated modelling types that have been developed and used by researchers are the top-down approach and bottom-up engineering approach. The bottom-up engineering approach modelling techniques is based on disaggregation and focuses more on the detailed technology aspect and future evolution of the energy system. The top-down approach is based on the principles of macroeconomics and does not consider detailed technology but focuses on the whole economy instead and empirically validates economic theories. A third modelling type is the hybrid or combined approach. This approach integrates the bottom-up and top-down approaches. The strength and weaknesses of these approaches compensate for each other. Other types of sophisticated models include the Decomposition, Cointegration, and ARIMA models; Artificial systems – Expert's systems and ANN, Grey prediction, Input–output, Fuzzy logic/Genetic algorithm, Integrated – autoregressive, Support vector regression, and Particle swarm optimization models (Suganthi and Williams, 2000).

2.12.3.1 Top-Down Approach

The top-down approach deals with aggregate values, involving both exogenous and endogenous variables based on historical relationships. Exogenous variables are factors influenced by the external environment of the utility while endogenous variables are the parameters related with the internal environment of the utility. Example of endogenous variables include number of customers, electricity prices, and incentive program levels. Price of competing products, per capita income, population, GDP, temperature, and unemployment rate etc. are examples of exogenous variables.

The Top-Down approach can be divided into six models namely:

1. Time Series
2. Regression
3. Econometric
4. Decomposition
5. Co-integration

6. Input-Output

2.12.3.1.1 Time Series Models

Time series analysis is a modelling technique that emphasizes the ordering or natural ordering of sets of observations. The ordering component in a time series can take the form of time or periods and as such stochastic or variables. Stochastic is a concept that simply explains the disturbance or erratic up and down movements of a variable or phenomenon e.g., measuring extreme volatility of electricity prices. In this instance, we look at determinants like behaviour indices, temporal effects, and non-strategic uncertainties. In time series, the higher the frequency, the more meaning that can be derived from the data; hence, the natural ordering makes time series different from cross-sectional studies, where there exist no natural ordering of the observations. In time series modelling, the basis for analysis is that current and future data is often reflected on past or historical data.

In other words, a variable has a memory which is the tendency to remember it's past. In time series analysis, the consistency of data in a trend is an indication of the past events repeating itself. The consistency of a trend is threatened by values that are extremely far away from the mean, known as the outlier. The use of time series methodology can be applied to the analysis of seasonality, irregularity and major patterns that may affect changes in energy demand consumption. It can also be used to determine the extent of the modelling and application works in the study of signal processing, weather forecasting to determine energy demand levels, and the econometrics of modelling consumption behaviour for residential demand.

There are several published studies that have used the time series method to determine short- and long-term future electricity demand. Amjady, 2001 forecasted short-term hourly load and peak load using the time series modelling approach. Nogales et. al., 2002 also forecasted next day electricity using the time series method. In the medium term, Abdel-Aal and Al-Garni, 1997 used the time series method to forecast monthly electricity consumption in Eastern Saudi Arabia while Brakat, 2001 have used the time series to forecast long-term electricity demand in central Saudi Arabia. Bodger, 1987 used the time series in his analysis of electricity forecast for New Zealand. Electricity demand has also been forecasted in Srilanka using the time series method (Himanshu and Lester, 2008). Gonzalez-Romera et al., 2006 used a trend extraction approach to determine monthly electricity consumption in Spain.

2.12.3.1.2 Regression Models

Regression is a technique that measures the strength of one variable to another. The regression space takes up the econometric functional form of modelling and the effect of a variable (called dependent or predicted) on other variables (called independent variables or predictors). Regression tells us the magnitude of the value of coefficients and the signs of the coefficient. It also tells us the direction of the relationship between the dependent and independent variables(s). Regression is essential, in that it allows us to efficiently determine which factors or determinants affects the predicted variables mostly. Again, aside from the size and magnitude of the coefficient, the probability value for each variable tells us which variable significantly adds weight and value to the dependent variable statistically.

There are different forms of regression models. The specific choice of form depends majorly on which one best fits the data and answers the research objective. The different type of regression models includes linear regression, logistic regression, and quantile regression models. Several researchers have used the regression model to forecast short- and long-term electric load forecast.

Papalexopoulos and Hesterberg, 1990 used a regression-based approach to forecast short term load forecast. Chui et. al., 2008 forecasted electricity demand for Ontario, Canada power system in the long-term using the regression model. Lon-Mu, 1993 forecasted residential electricity consumption in Southeast United States using variables such as weather, price, and income. Bianco et. al., 2009 used the linear regression model to forecast electricity consumption in Italy using economic and demographic variables. Wani and Shiraz, 2020 used the linear regression model to forecast electricity demand in India. Kaytez et. al., 2015 used the regression method to forecast electricity consumption in Turkey and compared the result with other modelling techniques.

2.12.3.1.3 Econometric Models

One simple way to describe econometric models are in its functionality. Econometric models use statistics and mathematics to describe a situation or an economy. In between problem and solution, there are econometric models. In other words, it is a tool for modelling data extracted from a problem. Econometric models allow us to analyze various factors affecting an outcome and use the information to forecast or predict future outcome. Regression and time series models are components of econometric models. In econometric models, the working characteristics are flexibility and form (linearity, polynomial, quadratic, and exponential).

However, the application choice of an econometric model is predicated on the assumptions. For instance, the assumptions of the classical linear regression model (CLRM). A post estimation list of the assumption includes, multicollinearity, heteroskedasticity, and autocorrelation. The central process is the fitting of the regression model to the data by identifying the appropriate tools needed for the analysis.

An instance is the measurement of daily energy consumption on income; a relationship which is linearly dependent on past income. The concept of adjusting for past values of an independent variable is called autoregressive, suggesting that past values of a variable have a complementary effect on consumption and as such provide the basis for predicting current and future consumptions. The major focus and importance of econometric models is in the test of hypothesis. In order to generate forecast, say how CO_2 emission will affect the generation of electricity to meet consumption needs, we estimate the income elasticity of demand for oil, to determine the level of demand per day.

Suganthi and Williams, 2000 used the econometric method to model renewable energy demand for India. Intarapravich et. al., 1996 used the econometric approach to estimate energy supply and demand in the Asia-Pacific. McAvinchey and Yannopoulos, 2003 used econometric method to model the impact of structural change, data stationarity and economic theory on energy modeling and forecasting. Gori and Takanen, 2004 forecasted the consumption of energy in the residential, industrial and services sectors of Italy in order to determine which energy sources could be substituted for each other. Saddler et. al., 2007 used the econometric model to determine how Australia can reduce emissions by 50% or more. Larsen and Nesbakken, 2004 used the econometric and engineering models to estimate household electricity end-use consumption in Norway and recommended regular conduct of surveys for household panels for a more accurate residential electricity consumption prediction. Meng and Niu, 2011 reported an increase in electricity consumption caused by real estate development and industrial growth and predicted a reduction in consumption of electricity due to high cost of real estate.

2.12.3.1.4 Decomposition Models

The central idea in decomposing models is in the breaking down of data into component parts. The model assumes that underlying patterns of the data are needed to create a forecast. The model efficiency is in its ability to combine the separate parts of the data. Decomposition deconstructs a time series into separate components. One example and importance of decomposition model is in its ability to handle seasonality in time series. Cyclical behaviour in weather can affect the level of energy demand adversely without decomposition. The concept also enables better decision making based off its multiplicative characteristics.

Gil-Alana et. al., 2010 used the decomposition model to analyze energy consumption by different energy sources in the United States by fractional integration. Hondroyiannis et. al., 2002 determined the relationship between energy consumption and growth for Greece and found a long-run relationship between energy consumption, real GDP, and price developments. Sari and Soytas, 2004 studied the relationship between energy consumption and economic growth in Turkey and found a relationship between employment, GDP, and energy consumption.

2.12.3.1.5 Unit Root Test and Cointegration Models

The concept of cointegration arises from spurious regression in time series models. In modelling electricity consumption for example, it is important to see if the trend of the predictors of electricity consumption are stable over time, with the intent of ensuring long-run equilibrium. For example, in the absence of stability (presence of volatile predictors), we will not be able to co-integrate, a top-down econometric approach that aims to examine if GDP per capita, electricity consumption per capita, and price electricity are cointegrated in the long-run. That way, we can understand if per capita consumption leads to movement in the prices of electricity.

Odhiambo, 2010 examined the relationship between energy consumption and economic growth in South Africa, Kenya, and Congo using the ARDL-bounds testing procedure and using price as a variable. Economic growth drove energy consumption for Congo but found a one-way flow in the case of South Africa and Kenya. Eltony and Hosque, 1997 studied the cointegrating relationship between energy demand and economic variables in Kuwait. Shahiduzzaman and Alam, 2012 found a cointegration and casual relationship between energy consumption and economic output in Australia over a 50-year period with important variables being energy, capital, and labor. Fouquet et. al., 1997 used the cointegration approach to estimate energy elasticity and forecasts in the United Kingdom. Galindo, 2005 determined the relationship between different energy types and income in Mexico using the Johansen procedure and root tests. A relationship was found between income and relative prices in the study. Abosedra et. al., 2009 investigated the casual relationship between electricity consumption and economic growth using a 10-year monthly data for Lebanon and confirmed the absence of a long-term equilibrium relationship between electricity consumption and economic growth.

2.12.3.1.6 Input– Output Models

The model deals with relationships across industries in an economy, showing the interaction between input from and output to an industry. For example, an analysis that requires the link between the energy sector and the agricultural sector would require an input-output analysis, electricity distribution to agricultural farmland means an output for electricity generating company and input for agricultural sector is a quantitative model. The monetary value of the input-output model is seen in the pricing of the agricultural produce or the sale to consumers. So, the input-output model successfully relates prices and quantities in a system to forecast energy in different economic and geographical scenarios. Arbex and Perobelli, 2010 reported the advantages of using the input-output model to determine the impacts of economic growth on the consumption of energy in Brazil. He et. al., 2011 forecasted energy-saving and power consumption in China using the input-output model. Some of the disadvantages of this model is that it requires a lot of data for analysis. There is also a possibility of these data being inaccurate or inconsistent.

2.12.3.2 Bottom-Up Engineering Approach

Bottom-up models forecast end-uses energy demand at a disaggregated level. It puts into consideration technology penetration and evolution in the market. This approach of estimating future energy demand and planning is widely used in the energy community including notable energy research laboratories (e.g., the Lawrence Berkeley National Laboratory, USA (LBNL), International Institute of Applied Systems Analysis, Austria (IIASA), Brookhaven National Laboratory, USA (BNL), Stockholm Environment Institute, Sweden, International Atomic Energy Agency (IAEA), Austria, and Argonne National Laboratory, USA). The model looks at the present technology and considers future possible technology in its analysis. For example, in the case of residential sector end-use appliances, energy standard and labelling can be considered and future possible technology ratings for each of the appliances are also considered. Most bottom-up models are categorized into end-uses such as cooling, heating, air-conditioning, lighting, audio-visual, cooking, entertainment etc. The bottom-up model methodology generally follows some or all the following steps (Bhattacharyya and Timilsina, 2009):

1. Energy demand disaggregation into end-uses or modules.
2. Analysis of main drivers of electricity demand
    a. Long-term, future evolution and inter-relationship of social, economic, and technological factors.

3. Develop hierarchical structure of electricity demand determinants.
4. Mathematical formalization and relationship of the structure.
5. Development of data and mathematical relationships.
6. Reference year determination
    a. Forecasting exercise foundation
    b. Gathering of all relevant data and develop all mathematical relationships.
    c. Determination of reference year: dependent on most recent year with data.
7. Future scenario(s) development.
8. Forecasting demand quantitatively using mathematical relations and scenarios.

The major types of models that have been developed following this approach are discussed in the following subsections.

2.12.3.2.1 Optimization Models

This model finds the least cost path by optimizing technology alternative choice with respect to the total system costs. The model also balances energy demand and supply and thus can also be categorized as partial equilibrium models. Optimization methodologies work under the assumption that all active agents act optimal and rational under some constraints (Veebeck, 2003). Optimization models are analytical and requires linear and integer programming skills.

2.12.3.2.2 Simulation Models

These are descriptive models that determine the condition at which the complex model can be sustained if replicated in the real world. A simulation model can either be static or dynamic depending on the time period of the system operation. Simulation models require high mathematical knowledge and can be too complex but helpful in in situations where experiments on systems can be costly or impossible (Vanbeeck, 2003).

2.12.3.2.3 Accounting Models

This model is also known as stock accounting or vintage model and is based on the principle of Materials

Flow Analysis (MFA). It accesses a system material flows and stocks in space and time systematically (Muth, 1973 and Heidari, et. al., 2018). MFA methodologies are great decision-support tools in energy analysis and planning because MFA results compare processes inputs, stocks, and outputs (Riedy, 2003 and Heidari, et. al., 2018). The accounting models mainly apply variables determined outside of the model on the technical development (Muth, 1973, Riedy, 2003, Heidari et. al., 2018) and have been used to forecast energy and energy efficiency impacts in different countries and regions (Diawuo et. al., 2018, Heidari et. al., 2018; McNeil et. al., 2018, Diawuo et al, 2019). The model does not optimize or simulate but analyzes the possible effects of different scenarios or technology (energy efficiency) on electricity demand.

Several optimization, simulation, and accounting models have been developed by several researchers and research laboratories following the bottom-up approach. The characteristics of these major bottom-up energy models are highlighted in Table 2.15.

The major differences between the different bottom-up models are in their disaggregation level, technology representation, choice of technology, goal of the model, and macroeconomic integration level (Worrel et. al, 2004). Most of the models discussed here are not available to the public hence the limited number of users. Also, the models are built for specific purposes and requires a lot of training to be used hence its inability to be transferred or transported to other studies. Although, some have more users because they are made public (e.g., LEAP, MAED/MEDEE) but also requires training

Table 2.15: The Major Types of Energy Models. Modified from: Van Beeck (2003)

Energy Model	Purpose	Model Type	Developer
MARKet ALlocation (MARKAL)	Energy supply with constraints. Objective included integrated energy analysis and planning using a least cost approach. Used in over 40 countries	Optimization	Brookhaven National Laboratory (BNL), USA
Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE)	Energy demand and supply, environmental impacts Generation expansion planning, end-use analysis environmental policy analysis, investment policy. Medium to long term.	Optimization	International Institute for Applied Systems Analysis (IIASA), Austria
Price-Induced Market Equilibrium System (PRIMES)	Energy consumption and supply. Focuses on prices to match demand and supply for energy and emissions. Determines market equilibrium volumes. Focus on behaviors and designed for the EU countries.	Optimization	National Technical University of Athens (NTUA), Greece
Energy PLAN (ENERPLAN)	Energy supply and demand. Matching demand and supply. Simulates the operation of national energy systems on an hourly basis.	Optimization	Aalborg University, Denmark.
Energy and Power Evaluation Program (ENPEP)	Energy demand, supply, and environmental impacts. Uses least cost optimization. It is an integrated approach that allows for energy policy analysis, generation expansion planning and environmental policy analysis.	Simulation	Argonne National Laboratory, USA.

Table 2.15 Continued

Energy Model	Purpose	Model Type	Developer
Modular Energy System Analysis and Planning Environment (MESAP PLANET)	A modular package. Demand, supply, environmental throughdifferent modules`	Simulation	University of Stuttgart, Germany.
Prospective Outlook on Long-term Energy Systems (POLES)	Provides quantitative, scenario-based, empirical and objective analysis of the energy sector until 2050. Also accounts for emmissions	Simulation	Enerdata in collaboration with the European Commission's JRC IPTS and University of Grenoble-CNRS (EDDEN laboratory), France.
Long range Energy Alternatives Planning System (LEAP)	Demand, Supply, environmenta impacts integrated approach. Energy Policy, biomass and land-use assessmen, pre-investment project analysis. Integrated energy analysis and fuel cycle analysis. Medium to long term modeling tool. Use in over 169 countries.	Simulation	Stockholm Environment Institute, Sweden.
Model for Analysis of Energy Demand (MAED)	Future energy demand evaluation. Based on long term medium to long term scenarios. Developed for DOS based systems. Used by over 40 countries. Excel based.	Accounting	International Atomic Energy Agency (IAEA), Austria.
MED-PRO	Energy demand accessment and impact of energy efficiency policies at country levels. Been used in over 60 countries.	Accounting	

Table 2.15 Continued

Energy Model	Purpose	Model Type	Developer
Bottom-Up Energy Analysis System (BUENAS)	Energy demand and impacts of efficiency on appliances. Predicts energy consumption for each appliance. Can forecast up to 2030. Used by 11 countries and the European Union.	Accounting	Lawrence Berkeley National Laboratory (LBNL), USA.
NIGERIA 2050 ENERGY CALCULATOR (NECAL)	Integrated Energy demand and supply analysis and emissions. Specially designed for Nigeria.	Simulation	Energy Commission of Nigeria (ECN)
The Integrated MARKAL-EFOM1 System (TIMES)	In-depth energy and environmental analyses. Combines both the technical and economic approaches. Used to project future energy based on scenarios.	Optimization	Energy Technology Systems Analysis Program (ETSAP) in collaboration with the International Energy Agency (IEA).

2.12.4 Hybrid Models

Given the weaknesses or limitations of the top down and bottom-up approaches; researchers believe there is a need for a model that can rely on the strength of the different approaches thereby compensating for the weaknesses of each other. This type of model is called a hybrid model. Several recent studies have been able to combine both the top down and bottom-up approach in their studies (e.g., Diawuo et. al., 2019 and McNeil et. al., 2018). These studies used a hybrid model in projecting future electricity demands. The hybrid model relied on the strength of the technology details of the bottom-up and the microeconomic details of the top-down approaches. The use of the hybrid model is dependent on the objective of the modeler and the questions the model intends to answer. However, some of the challenges of the hybrid model includes the computational complexity, data availability, and policy relevance.

The characteristics of both the top down and bottom-up approaches are summarized in Table 2.16. Table 2.17 summarizes the merits and demerits of both approaches.

2.12.5 Residential Electricity Consumptions Drivers

There are several published studies on the major drivers or determinants of residential electricity consumption (REC). REC is mostly affected by consumers lifestyle, demographic factors (e.g., house occupancy, household size), energy and electricity services saturation effects, fuel mix and its relationship to efficiency and energy services structures (Haas, 1997). Xu and Ang, 2014 classified residential electricity consumption drivers into seven based on extensive review. They quantified the impacts of each using Index Decomposition Analysis (IDA) models and found household income as the most important driver. Other studies have also found household income to be the most important of the household drivers (Greening et. al., 2001 and Zha et. al., 2010).

Table 2.16 Characteristics of Top-Down and Bottom-Up Approaches. Modified from (Van Beeck, 2003).

Top Down	Bottom Up
Based on macroeconomic modelling principles and techniques.	Based on disaggregation and the inclusion of a large number of technical parameters.
Intended to include all important economic interactions of the society	Have a lot of detail and describe a number of specific energy technologies with both technical and economic parameters.
Characterized by behavioral relations at an aggregated level with parameters estimated based on historical relationships.	Both present and future technologies are often included, which means that these models include a description of the change in parameters
The macro econometric approach is based on estimation of historical relations between energy prices and energy demand and assumes that the behavior reflected in the estimated elasticities is constant.	Bottom-up approach can be either optimization or simulation models.
Top-down models include income effects measured by the total consumption	Bottom-up models of household energy demand are typically based on vintage models of a large number of end use technologies
Use aggregated data for prediction.	Penetration rates for each technology, e.g., electric appliances, are described as following a time profile with saturation levels
Endogenize behavioral relationships	Parameters: Stocks, electricity consumption by each unit of appliance, Intensity of use of appliance. Stock input: appliance ownership, average lifetime,

Table 2.17: Merits and demerits of the top-down and bottom-up approaches based on data availability (Mirlatifi, 2016)

Approach	Merit	Demerit
Top-Down Approach (e.g., Regression Based Econometric Method)	It models distinctly nonlinear relationships by linear devices	Models developed in one region may not be adopted in other regions
	It provides detailed information on future levels of electricity demand	Extensive data required for detailed disaggregated model
	Models can be readily estimated	Exogenous determinants are hard to determine, and their accurate data may be inaccessible
Bottom-Up Approach	Ability to obtain clear engineering view on the results.	Wrong assumptions about consumer behavior can result in inaccurate conclusions
	The only feasible method that can estimate the energy for a sector even without having historical time series data.	Relationship between energy demand and end-use can vary by time
	It does not demand high skill	Hard to assess the technological variation
	They are capable to model technological changes	Extensive detailed data requirements about the consumers or their appliances and different sectors.
		Data acquisition is difficult and costly
Integrated Models (Hybrid Approach)	It involves a combination of various approaches	

Jones et. al., 2015 in their review found that sixty-two or more socioeconomic, dwelling, and appliance factors have a potential effect on residential electricity consumption. They found that the number of rooms, dwelling age, and total floor area all have a positive effect on electricity consumption for the dwelling factors. For the appliance factors, the study found out that the number of appliances, appliance usage, and ownership caused an increased REC. For the socioeconomic factors, they found that the household size and household income have a positive effect on residential electricity. Nie et. al., 2017 found climate, increasing household income, and energy cost share to cause an increase in REC.

McLoughlin et. al., 2012 used a multiple linear regression model to determine the main drivers of REC in Ireland. They found a strong relationship between dwelling type, number of bedrooms, household composition, appliance ownerships, and REC. Halvorsen and Larsen, 2001 used microdata to determine the drivers that affect REC growth in Norway and found a positive relationship between REC growth, number of households, appliance ownerships, household income, and floorspace. Wiesmann et. al., 2011 used the econometric method to find the relationship of household and dwelling characteristic on per capita REC in Portugal. They found population, income, and building stock as the main drivers. Baker and Rylatt, 2008 used simple and multiple regression to determine the relationship between REC and key drivers in the United Kingdom. They found a significant relationship between floor area and number of rooms. Ndiaye and Gabriel, 2011 used regression models to analyze the REC of the city of Oshawa in Canada and found nine variables to be the most important in estimating REC. These variables include number of house occupants, presence of air-conditioning, type of fuel used in the heating system etc. Lam, 1998 investigated the relationship between REC, climatic factors, and economic variables for Hongkong using data for the period between 1971-1999. The author found a positive correlation between household size, household income, cooling degree days, and price of electricity. Filippini and Pachauri, 2004 used econometric models to determine household electricity demand elasticities of India and found that dwelling and demographic factors such as household size and age of head of the household all affect household electricity demand. Genjo et. al., 2005 used multivariate analysis to determine the influence of appliance ownership on Japanese households REC and found a positive relationship. Louw et. al., 2008 in their study of the determinants of electricity demand for newly electrified low-income South African households found income to be significant in REC levels. Parker, 2003 found floor area, appliance ownerships etc. to be the major determinants of REC in Florida state of the USA. Taale and Kyeremeh, 2019 in their study of the drivers of Ghana's household electricity expenditure found income, electrical appliance stocks, number of rooms etc. to be major determinants of residential electricity expenditure. Min-Jeong, 2020 used the OLS and quantile regression methods to understand the determinants on REC in Korea and found that the number of households, housing area, number of household appliances and refrigerator usage time to be significant. Table 2.18 lists the major drivers following the detailed review of the major determinants of REC.

2.12.6 Studies on Electricity Consumption Drivers in Nigeria

Owing to the importance of electricity consumption and socioeconomic growth, few studies that have investigated the determinants of electricity consumption in Nigeria exist. Ogundipe and Apata, 2013 in finding a relationship between economic growth and electricity consumption using cointegration techniques found weather variables to be essential in determining the unexpected patterns in consumption of energy or electricity. However, the authors found that the respective coefficients of the variables show that temperature has way more influence on energy

Table 2.18: Major Drivers of Residential Electricity Demand (Xu and Ang, 2014)

Classification	Key Drivers/Indicators
Demographics	Household number Population
Economic factors	Energy prices Household income
Individual factors	Awareness Consuming behavior
Climate	Heating degree days (HDD) Cooling degree days (CDD)
Technology	Energy efficiency
Lifestyle	House size House occupancy Appliance ownership
Structure	Population segment by region, income group, age profile, etc. Housing type segment by number of rooms, number of residents, etc.

consumption when compared to relative humidity. This is consistent with a similar study by Oyedepo et. al., 2013 that points to the positive impact of temperature and relative humidity in driving consumption in the commercial sector. Oyedepo, 2012 determined the major drivers of electricity consumption in the commercial sector in Nigeria. These drivers were then used to predict the demand for electricity in the commercial sector in forecast years 2015 to 2035. The variables analyzed were commercial electricity consumption, temperature, rainfall, total electricity given, total primary energy, and relative humidity.

In forecasting the electricity consumption in Nigeria, Babatunde and Enehe, 2011 made use of the multiple regression technique to predict future demand from the year 1970 to 2007. The independent variables considered were GDP, price of electricity, GDP per capita, and population. These variables were regressed on electricity consumption. Findings from the study suggested a limited price elasticity thereby making pricing policy unusable (in promoting the efficient usage of electricity in Nigeria) as opposed to GDP and GDP per capita.

Ekpo et. al., 2011 found a positive relationship between electricity consumption and real GDP per capita, population, and industrial output in the short and long run using historical data from 1970 – 2008. However, they found that electricity price was not significant in determining electricity consumption in Nigeria. Ubani, 2013 used time series data from 1985 to 2005 to determine the factors that affect electricity consumption in Nigeria using multiple linear regression analysis. The author found that urbanization degree, the density of population, household numbers with electricity, employment rate, number of manufacturing industry and closeness to nearest power generation station and employment rate all affect electricity consumption.

Babatunde and Enehe, 2011 used data from 404 households between March and November 2010, to investigate the relationship between socioeconomic factors and household demand for electricity in Nigeria using ordinary least square regression analysis (OLS). They found the determinants of electricity to be household size, hours of power supply, and number of rooms in a household.

Many of the studies reviewed only focused on the commercial sector. More attention should be paid to the residential sector in order to ascertain the level of permeation of electricity usage among household consumers and the share of the appliances. Thus, there is a need for a more robust multivariate regression analysis that includes drivers not included or adequately captured in previous studies e.g., appliance ownership, technology, household size, number of households, and floor area.

2.12.7 Review of Electricity Demand Forecasting Methodologies in Nigeria

There are several studies focused on the future electricity demand in Nigeria. This section reviews the recent electricity demand studies. Several authors have used different approaches or methodologies in estimating future demand. Dioha and Kumar, 2020 used the TIMES model to determine long term energy consumption up to 2050. The main drivers used in the model are population, household size and numbers, urbanization, income, and electrification rate. These data were obtained from the Central Bank of Nigeria (CBN), Nigeria Bureau of Statistics (NBS), National Population Commission (NPC), and the United Nations (U.N). They found a significant increase in final energy consumption in urban households by 2050 and concluded that cooking consumes most of the energy.

Braide and Diema, 2018 used the top-down approach to project electrical power demand for twenty years using the least-square regression and exponential regression model. Future projections were based on historical consumptions using data from the NBS and CBN. The result of their study showed a difference between available power and forecasted energy demand. The projected electricity demand for twenty years is 455,870.2 MW.

Idoniboyeobu and Ekanem, 2014 used the top-down approach to predict long term future electricity demand in Akwa-Ibom state using the least square method and regression exponential analysis. Historical monthly load allocation and utilization data (from 2006 – 2010) was used in the analysis and projected that electricity load requirements in Akwa-Ibom state is 247.84 MW.

Idoniboyeobu et. al., 2018 adopted the top-down approach and used least square, exponential regression, and modified form of exponential regression model to determine residential, commercial, and industrial sectors long term power load for twenty years (2013 – 2032). Historic load capacity and capacity-utilization data used in this study were sourced from the CBN, NBS, and Power Holding Company of Nigeria (PHCN). They found that projected demand into 2032 is 395.870 MW. They compared the results from the different methods and found similar pattern. However, the modified exponential regression has the lowest percentage error.

Kotikot et. al., 2018 adopted the top-down approach to estimate peak power demand in four African countries of Uganda, Kenya, Nigeria, and South Africa. The major drivers of the demand estimates are appliance ownership, appliance power ratings, household size, and population. Peak demand was calculated under three different scenarios: low, median, and high. For Nigeria, the low, median, and high peak demand estimates are 7,652 MW, 15, 304 MW, 30, 609 MW respectively.

Okakwu et. al., 2018 used the top-down approach to determine the best fit probability distribution functions (PDF) and peak load demand forecast in Nigeria using historic peak load demand data (1998 – 2017) sourced from the National Control Centre (NCC), Oshogbo, Nigeria. The PDFs that were used are Normal, Log-Normal, Gamma, Weibull, and the Logistic distribution. The two peak load demand methods used were the Auto Regression (AR) and Exponential Smoothing (ES) models. They found out that the best PDF function is the Log-normal, then the Normal, Weibull, Gamma and Logistic distribution in that order. The study also found the AR model to be more accurate than the ES in calculating peak load demand in Nigeria.

Olaniyan et. al., 2018 adopted the top-down approach to estimate REC factoring in drivers such as population, appliance ownership, appliance sales, energy expenditure, and weather data. They estimated demand under the universal access scenario to be 85 TWh and the median REC to be between 18-27 KWh per capita. However, these estimates were found to be different for each of the six geopolitical zones of Nigeria.

Briggs and Ugorji, 2017 accessed and projected electricity demand for Rivers state, Nigeria up to 2025 using a top-down approach. Historic electricity allocation and load utilization data from 2011 to 2015 sourced from the Port Harcourt office of the Electricity Distribution Company was used for the analysis. The data was analysed using the regression exponential (RE) and least square methods (LS) to determine future demand. The RE predicted demand to be 2113MW while the LS is 20171 MW in 2025. The study found that the RE model is the best because it captures consumer's elastic demand during peak and off-peak time. The authors also found a positive relationship between electricity consumption and the years.

Ezenugu et. al., 2017 used multiple and quadratic regression models to forecast long term REC up to 2029 using historical annual electricity consumption data (from 2006 – 2014) obtained from the CBN and NBS. The main drivers in this study are population and temperature (a climatic variable). The study found that the quadratic regression model is more accurate than the multiple regression model because it has the least RMSE and highest coefficient of determinant. Therefore, the quadratic regression was adopted by the authors to forecast REC up to 2029. The result of the study is that the population, temperature, and REC in 2029 will be 290.4 million, 33.13 degree Celsius, and 6521.09 MW/h respectively.

Ouedraogo, 2017 used the Long-range Energy Alternative Planning (LEAP) to project long term energy demand in Sub-Saharan Africa up to 2040. The analysis was based on three scenarios that investigated the business-as-usual scenario; assumes an 0.7% annual growth rate, renewable energy mix deployment, energy efficiency measures on both the demand and supply sides. The analysis covered not only the residential sector but the agriculture, industrial, and services sectors. The major drivers in this analysis are GDP, population, number and sizes of households. These data were sourced from the United Nations, Enerdata, World Bank, and ERS International. The result of the study is that total electricity demand for West African countries is 243 TWh with Nigeria contributing to most of the expected demand. The residential sector will account for 3.1% of the total demand by 2040 according to the study.

Adedokun, 2016 used the autoregressive integrated moving average (ARIMA) model to project consumption of electricity in Nigeria. The result of the study is that Nigeria will only be at Italy's electricity consumption level in the year 2671 given the current trend. However, a consistent annual increasing trend of between 10% to 20% would get Nigeria to Italy's 2011 levels by 2050 or 2032. The consumption level could however be expedited and can be achieved if the annual increase is 57% or more.

The Energy Commission of Nigeria in 2015 came up with the Nigeria Energy Calculator 2050 (NECAL 2050). The NECAL 2050 is a simulation model and was used to project future energy demand in Nigeria up to 2050 and it follows the UK 2050 pathways calculator. The calculator models energy, emissions and land use in Nigeria and finds secure pathways for demand and supply up to 2050 based on technological improvement and introduction of renewable energy into the demand and supply mix. The main drivers in this study are population, number of households, household sizes, and GDP. The result of the study is that Nigeria's total electricity demand in 2050 under the no effort and greater effort pathway are 1543 TWh and 814 TWh respectively. A similar study was carried out by Dioha et. al., 2019 and found that the industrial sector will consume most of the projected demand (up to 60%) in 2050.

Emordi, 2015 used the econometric model to project long term per-capita end-use energy consumption up to 2050 in three southwestern states of Nigeria (Oyo, Osun, and Lagos states). The parameters used in estimating per-capita energy in this study are income, household energy expenditure, household demographics, total household energy consumption, appliance ratings and intensity. The data used in this study were sourced from surveys carried out by the author. The minimum poverty energy level in this study is 350W per capita. The author also found no correlation between income, household size, and electricity access.

Iroegbu and Okeke, 2015 used the Artificial Neural Networks (ANNs) to determine short term load forecasting in Umuahia, Abia State of Nigeria. The analysis was based on a one-month historical load data sourced from the Enugu Electricity Distribution Company (EEDC). The author found the Absolute Mean Error (AME) between the actual and predicted load to be 1.73% and concluded that the results from ANNs will be accurate in forecasting electric loads in Nigeria.

Ezennaya et. al., 2014 used the time-series analysis to project electricity demand in the residential, commercial, and industrial sectors up to 2030 using historic electricity consumption data from 2010 – 2012. This data was sourced from the NBS and CBN. The projected total demand in the residential, commercial, and industrial sectors in 2030 is 11494.83 MW, 6421.09 MW, and 1660.13 MW respectively.

Oyelami and Adedoyin, 2014 used the Harvey Logistic Model to project long-term electricity supply and demand up to the year 2026 using historical electricity consumption and generation data sourced from the NBS. The authors extrapolated these data from the year 2005 to 2026 to get an estimate for the future and found a consistent increase in electricity demand up to 2026.

Adepoju et. al., 2007 applied the ANN to forecast short-term electricity load in Nigeria electrical power system. The data used in the analysis are previous hour load, previous day load, previous week load, the day of the week, and hour of the day and were all sourced from the PHCN. They compared the actual and predicted data on a one-week data and found an absolute mean error of 2.54%. The authors concluded that the ANN has the capability of predicting short term load with a high degree of accuracy.

Alawode and Oyedeji, 2013 used two types of ANNs namely the feed-forward back propagation and the Elman recurrent neural networks to forecast a short-term, 24-hour-ahead, one-hour-ahead or next day peak load in order to solve the short-term load forecasting problem of Nigeria. Historical load data gotten from the PHCN was used for this analysis. The authors found that

Elman recurrent neural network gave the best load forecast of the two ANNs because it gave a low forecast error.

Amlabu et. al., 2013 adopted a top-down approach by using least square techniques to forecast load demand in four different regions of Nigeria namely Shiroro, Port-Harcourt, Kaduna and Oshogbo. The authors used a 6-year historical load demand data from 2004 – 2009 for their analysis. They concluded that there will be a continuous growth in demand in the four regions that was studied.

Virginie and McNeil, 2013 adopted a bottom-up approach using the Bottom-Up Energy Analysis System (BUENAS) to project long-term electricity demand in the residential, commercial, and industrial sectors of four Economic Community of West African States (ECOWAS) namely Nigeria, Cote d'Ivoire, Ghana, and Senegal up to the year 2030. The BUENAS is an accounting model developed by scientists at the Lawrence Berkeley National Laboratory and implemented using excel spreadsheet to project peak demand and provide potential energy savings through the implementation of energy efficiency Standards and Labeling programs. The main drivers in this study are income per household, electrification rate, urbanization, cooling degree days, GDP per capita, employment, surface area, and appliance ownership, and technology. The study found that the ECOWAS region will be able to save 63 TWh if they become energy efficient.

Ekpo et. al., 2011 adopted time-series econometrics and used the bounds testing approach to determine the dynamics of electricity demand and consumption between the year 1970 and 2008 using historical time series data. Stability tests confirmed that the main drivers in the long and short run in the analysis were real GDP per capita, population, and output from industrial sector and that they have a strong and positive influence on electricity consumption. Income per capita has the strongest influence on electricity consumption.

Maliki et. al., 2011 used the ANN and regression analysis to forecast long-term electricity generation and future electricity consumption pattern. The data used in the study are historical consumption, generation growth rate, and population growth rate data obtained from the PHCN and the department bureau of census. The ANN outperformed the regression analysis based on MSE, MAE, and RSME values.

Sambo et. al., 2003 used the MAED model to forecast long-term electricity generation and demand up to 2030 based on four different scenarios namely reference, high growth, optimistic 1, and the optimistic 2 scenarios. The key drivers in this study are demography, socio-economy, and technology. In the reference scenario, the total electricity demand is 119,200 MW while the demand is 297,900 MW in the optimistic 2 scenario for the year 2030.

A summary of these methodologies is presented in Table 2.19 and highlights the methods of investigation, activity, and time. Figure 2.5 shows the analysis and categorization of the different forecasting approaches adopted by the different authors. Several types of forecasting techniques were used but were broadly categorized into six main groups based on the techniques followed. Most of the researchers used regression analysis (36% usage) in their forecasts. Bottom-up modelling technique follows as the second (28% usage) most used forecasting technique. Artificial Intelligence has 20% while times series techniques is the least used forecasting technique and has a 16% usage.

Figure 2.6 shows the usage of the different forecasting techniques over different forecasting time periods. Only two forecasting periods (LT and ST) were considered by most authors. All the

Table 2.19: Summary of Recent Studies on Electricity Demand Forecast in Nigeria

Author(s)	Method	Activity	Time	Country/Region	Sector
Dioha and Kumar (2020)	Bottom-Up	Electricity Demand Forecast	Long Term (2010-2050)	Nigeria	Residential, Commercial, and Industrial
Dioha et. Al., 2019	Bottom-Up	Electricity Demand Forecast	Long Term (2010-2050)	Nigeria	Residential, Commercial, and Industrial
Braide and Diema (2018)	Least-square Regression and Exponential Regression Model	Energy Demand Requirement	Long Term (2013 – 2032)	Nigeria	Residential, Commercial, and Industrial
Idoniboyeobu et. Al., (2018)	Modified Exponential Regression Analysis	Electricity Demand Forecast	Long Term (2013 – 2032)	Nigeria	Residential, Commercial, and Industrial
Kotikot et. Al., (2018)	Time Series Analysis	Peak Demand Forecast		South Africa, Nigeria, Kenya, Uganda	Residential
Okakwu et. Al., (2018)	Auto Regression (AR) and Exponential Smoothing (ES)	Peak Load Demand Forecast	Long Term (1998 – 2017)	Nigeria	Residential, Commercial, and Industrial
Olaniyan (2018)	Bottom-Up Method	Peak Demand Forecast	Short term (Daily & Monthly)	Nigeria	Residential
Briggs and Ugorji, (2017)	Regression Exponential & Lease Square Methods	Assessment of Electricity Demand	Long Term (2016 – 2025)	Nigeria/Port Harcourt	Residential, Commercial, and Industrial

Table 2.19 Continued

Author(s)	Method	Activity	Time	Country/Region	Sector
Ezenugu et al (2017)	Multiple & Quadratic Regression Models	Forecasting of Residential Electricity Consumption	Long Term (2015 – 2029)	Nigeria	Residential
Ouedraogo (2017)	Long-Range Energy Alternatives Planning Systems (LEAP)	Long Term Electricity Supply – Demand Forecast	Long Term (2010 – 2040)	Africa/Nigeria	Residential, Commercial, and Industrial
Adedokun (2016)	ARIMA Model	Electricity Consumption Forecast	Long Term (2020)	Nigeria	Residential, Commercial, and Industrial
Ihedioha & Eneh (2016)	Artificial Neural Networks (ANN)	Short Term Load Forecast	Short Term (24 hours)	Nigeria/Enugu	–
ECN (2015)	Bottom-Up	Electricity Demand Forecast	Long Term (2010-2050)	Nigeria	Residential, Commercial, and Industrial
Emordi (2015)	Econometric	Electricity Demand Forecast	Long Term (up to 2050)	Nigeria (Lagos, Oyo, Osun)	Residential
Iroegbu and Okeke (2015)	Artificial Neural Networks (ANN)	Short Term Load Forecast	Short Term (24 hours)	Nigeria/Umuahia	–
Ezennaya et. Al., (2014)	Time Series Analysis	Electricity Demand Forecast	Long Term (2013 – 2030)	Nigeria	Residential, Commercial, and Industrial

Table 2.19 Continued

Author(s)	Method	Activity	Time	Country/Region	Sector
Idoniboyeobu and Ekanem (2014)	Regression	Electric Future Load Demand	Long Term (2011 – 2020)	Nigeria/Akwa-Ibom	–
Oyelami & Adedoyin (2014)	Harvey Logistic Model (Times Series)	Forecasting Electricity Demand and Supply	Long Term (2015 – 2026)	Nigeria	Sector not mentioned. Possibly all sectors
Adepoju et. Al., (2013)	Artificial Neural Networks (ANN)	Short Term Load Forecast	Short Term (24 hours)	Nigeria	–
Alawode and Oyedeji (2013)	Neural Networks	Load Forecasting	Short Term (168 hours)	Nigeria	–
Amlabu et. Al., (2013)	Least Square Regression (LSR)	Electric Load Forecasting	Long Term (2010 – 2020)	Nigeria (Osogbo, Rivers, Shiroro, Kaduna)	–
Virginie and McNeil (2013)	Bottom-Up Energy Analysis System (BUENAS)	Peak Load Demand Forecast	Long Term (2015 – 2030)	ECOWAS (Nigeria, Senegal, Cote d'ivoire, Ghana)	Residential, Commercial, and Industrial
Ekpo, et. Al., (2011)	Bounds Testing Approach – Econometrics	Electricity Demand and Consumption	Long Term	Nigeria	–
Maliki et. Al., (2011)	Regression Model & ANN	Prediction of Electric Power Generation	Long Term (up to 2036)	Nigeria	Residential

Table 2.19 Continued

Author(s)	Method	Activity	Time	Country/Region	Sector
Sambo et al (2003)	MESSAGE Model	Electricity Generation Forecast	Long Term (2005 – 2030)	Nigeria	–

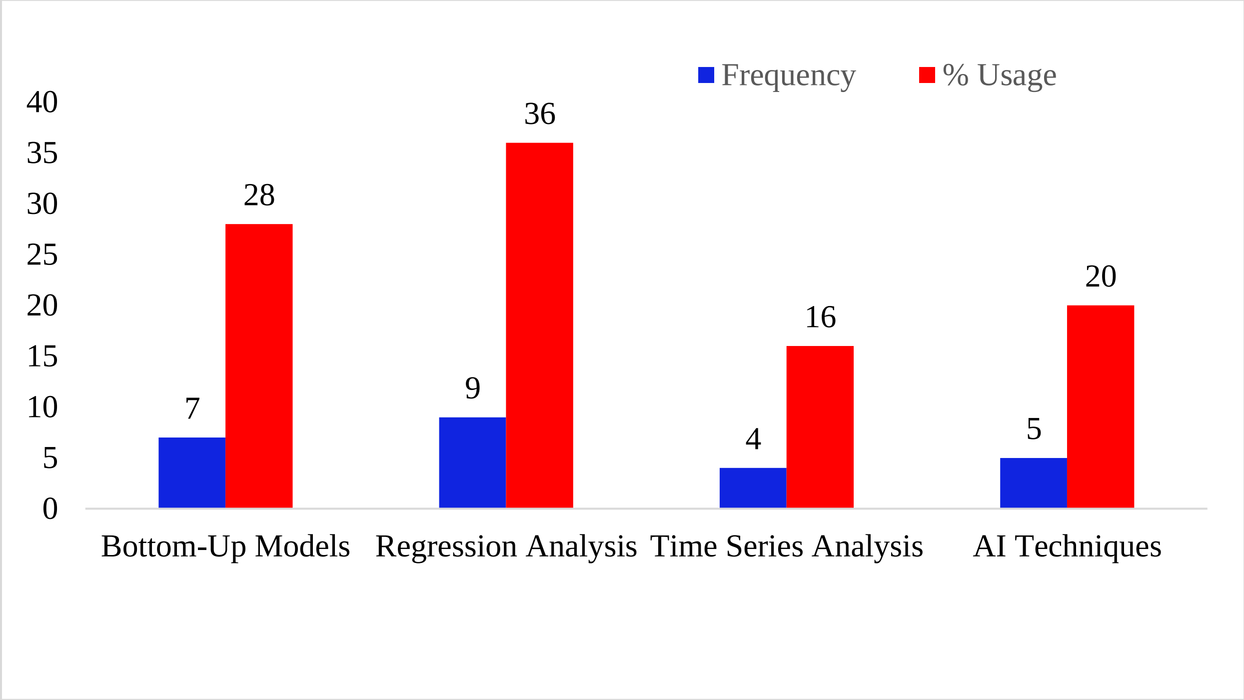

Figure 2.5: Usage of different forecasting methodologies

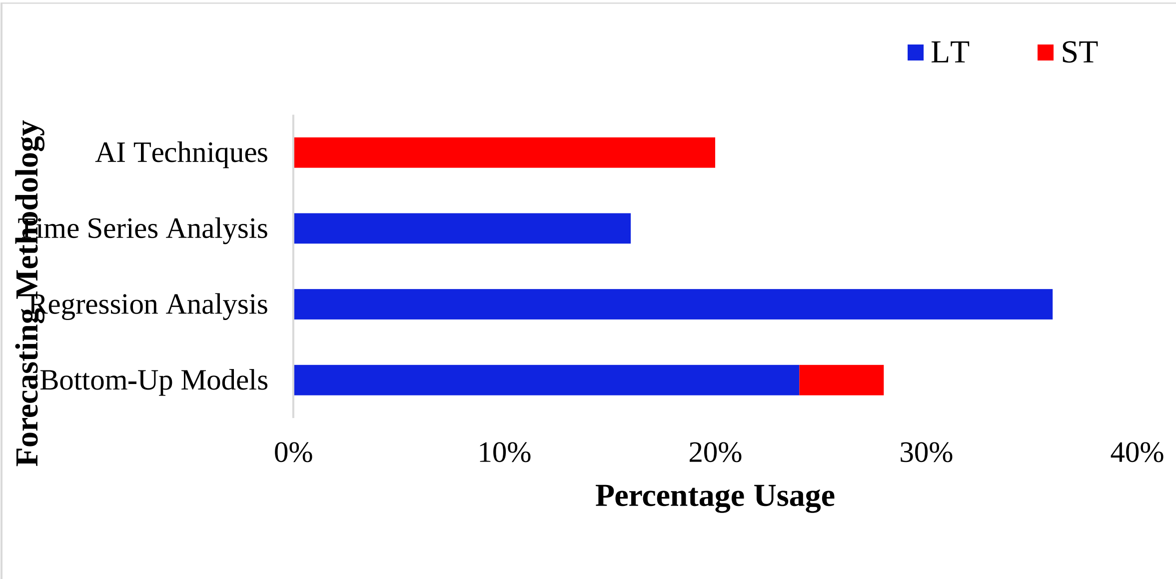

Figure 2.6: Forecasting methodologies over different forecasting time periods.

forecasting techniques except the AI technique was used while forecasting for the long term (80% usage). Regression analysis was mostly used for long term (36% usage) followed by the bottom-up modelling technique at a 24% usage and the time series modelling technique at 16% usage. Artificial intelligence technique was used for only ST at a 20% usage. Bottom-up model was also used for ST but at a very low percentage (less than 0.05%).

Table 2.20 shows all the demand determinants (including their occurrence) used by all the forecasters in the studies reviewed. Figure 2.7 shows the percentage usage of each of these determinants. Population (42%), previous load data (33%), household size (29%), GDP (21%) were used the most in most of the studies. Other determinants such as number of households, GDP per capita, GDP growth rate, load capacity (allocation), capacity utilization, appliance ownership, and electricity consumption all have a 17% usage each. The least used determinants are income, electricity expenses, literacy rate, efficiency improvement, industrial output etc. It is important to note that many of these drivers even though considered were not adequately captured in the studies reviewed.

In summary, the review of different approaches used in projecting electricity demand or consumption found that the econometric methods such as regression and time series analyses – all top-down approaches are the mostly used methods to project future demand in Nigeria. Only few studies adopted the bottom-up approach in their projections. The top-down approach is analyzed at an aggregated level while the bottom-up approach is at disaggregated levels. Most of the econometric methodologies are focused on socioeconomics and demographic factors that have income, GDP, population, household size, and number of households as the main drivers. However, the main concern of this approach is its incapability to include detailed technology and efficiency. In contrast, the few studies that adopted the bottom-up models are mainly focused on

Table 2.20: Electricity demand determinants usage

Determinants of Electricity Demand	Occurrence Frequency	% Use
Population	10	42
Number of Households	4	17
Household Size	7	29
Urbanization	3	13
Income	1	4
Electrification Rate	2	8
GDP	5	21
GDP per Capita	4	17
GDP Growth Rate	4	17
Load Capacity (allocation)	4	17
Capacity Utilization	4	17
Appliance Ownership	4	17
Previous Load Data	8	33
Electricity Price	2	8
Population Density	1	4
Literacy Rate	1	4
Poverty Rate	1	4
Electricity Access/ Electrification Rate	3	13
Temperature	1	4
Electricity Consumption	4	17
Electricity Expenses	1	4
Electricity Generation	2	8
Efficiency Improvement	1	4
Population Growth Rate	2	8
Industrial Output	1	4
Generation Growth Rate	1	4
Population Growth Rate	1	4
Industrial GDP Fraction	1	4

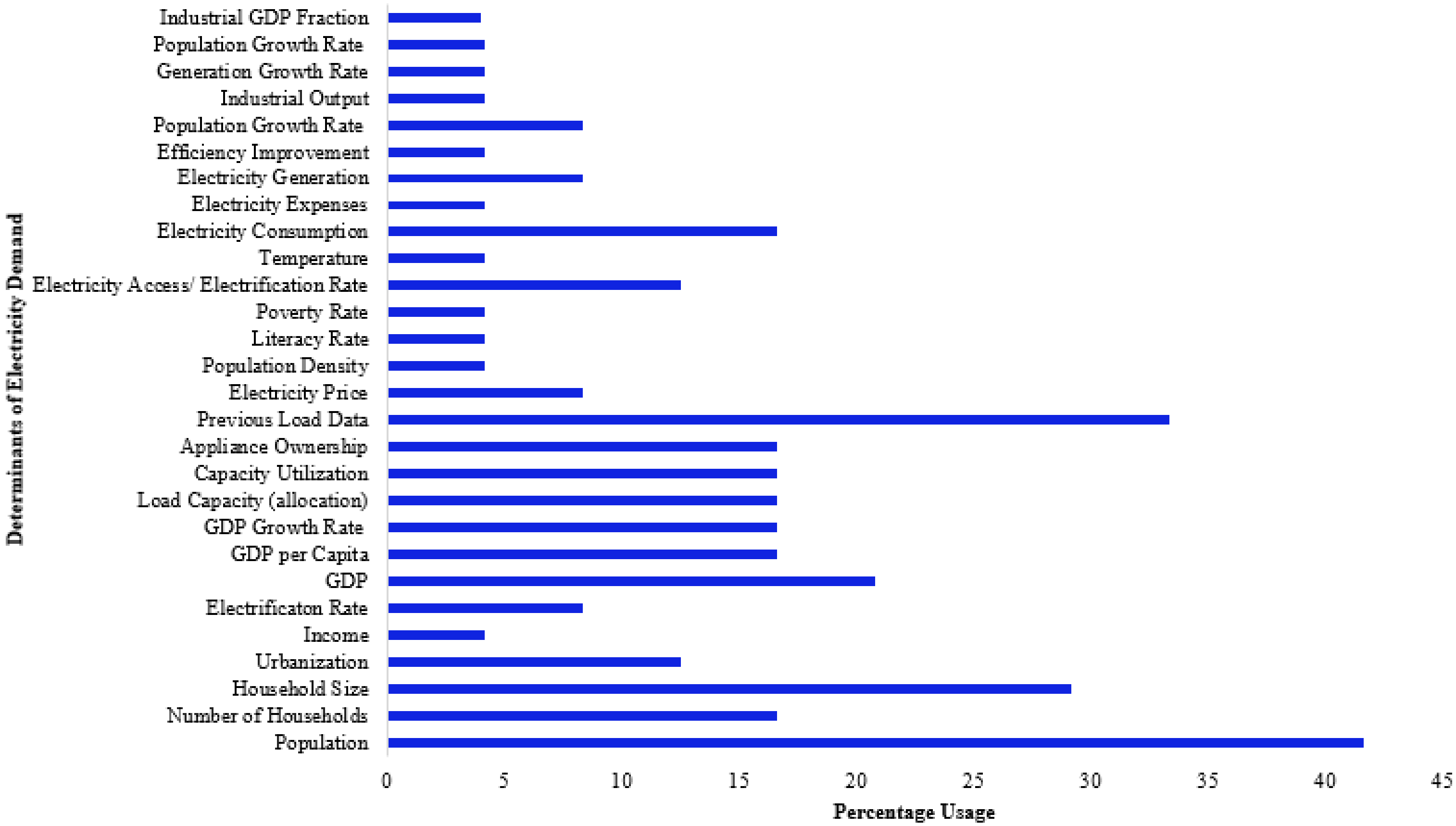

Figure 2.7: Percentage usage of electricty demand determinants

technology. Generally, most bottom-up models are not in the public domain because they cannot be transferred and transported and thus not widely used. Most of the existing models were built to cater for the demands of developed countries. These models are not applicable to developing countries because there are some specific features of developing countries not included in the model. These features as highlighted in Table 2.13 also include low electrification rate, inadequate electricity supply, poor policy implementation, and structural economy change. This is the major reason why there are very few studies that adopted the bottom-up approach in Nigeria (see table 2.19). Although very few studies have used the NECAL, MAED, MESSAGE, TIMES, BUENAS, and LEAP models (Virginie and McNeil, 2013, ECN, 2015, Ouedraogo, 2017, Dioha and Kumar, 2020) but these are also not without gaps.

The limitation to using the NECAL 2050 model is that it does not capture (1) appliance ownership – an important driver in projecting electricity demand and (2) appliance sales and stocks that can provide a more accurate estimate of energy consumptions by appliance. The absence of these important parameters can result in inaccurate estimations or projections of electricity demand. The limitation to using the BUENAS model is that it is not available for public use and cannot disaggregate a lot of appliances.

The Model for Analysis of Energy Demand (MAED) does not calculate emission and takes a very long time to run different scenarios. The MESSAGE is an optimization model that allows for energy investment optimization. The implication of this is that data pertaining to investment and operating cost is important to run the model. However, these data are unavailable or scarce in Nigeria. Also, the model assumes a perfect market and optimal consumers behaviour. Nigeria's imperfect market not captured in the model will result into low energy demand projections.

The TIMES is a bottom-up model that uses an optimization algorithm to forecast future energy demand and provide a least cost energy system. While this model is capable of capturing appliance ownership, it assumes that appliances that were purchased in a particular year will last forever. Therefore, it does not account for survival rate function that can calculate the number of appliances that retire every year. The implication of this is an inaccurate estimation of electricity demand and consumption. The LEAP model requires the expertise of analysts for assumptions and trends. Although the LEAP is popular among energy analysts, a big disadvantage of the LEAP is its inability to do a detailed household analysis including its inability to disaggregate a lot of household appliances.

The econometric models require a lot of data and can be problematic if the data are unavailable, insufficient or unreliable. Most of the energy models reviewed are capable of producing inaccurate results because of scarcity and unavailability of data, non-incorporation of technology (if adopting an econometric approach), absence of socioeconomic demand drivers (if adopting a bottom-up approach). Also, the type of modelling techniques, assumptions, and methodologies of the different studies reviewed failed to provide accurate projections of electricity demand and efficiency improvement into the future. For example, the very few studies such as Kotikot et. al., 2018, Olaniyan et. al., 2018 that included appliance ownership as one of the main drivers in their studies failed to project the future ownership of the appliances analyzed. The study also failed to provide appliance electricity consumption (AEC) estimates for each of the appliances. So, the appliance that consumes the most electricity is unknown. Therefore, vital information about appliances that can help save electricity based on technology improvement or efficiency is also unknown. Other studies such as Ouedogo 2017 did not factor in appliance ownership or disaggregation of appliances into the study thereby giving inaccurate demand projections. The

ECN used the NECAL, 2050 in their study and only used population and GDP as the main drivers. The study did not also consider appliance ownership. Appliances are also not disaggregated in detail to see the contribution of each appliance to the total consumption.

A more recent study (Dioha, 2020) attempted to model appliance ownership but very few household appliances were analysed. UEC data for lighting and all other appliances used in the study were taken from United Nations Development Program (UNDP). These UEC data are inaccurate or lower than expected due to low electricity access in the country. For future technology, assumptions were not based on existing energy standards and labelling; this will cause inaccurate projections. Penetration rates for televisions (TV) was used as a proxy for all other appliances that are not refrigeration or cooling. This is misleading because TV is a common household appliance in Nigeria. This may not be true for other appliances such as washing machines that are much more expensive than TV and not affordable for most Nigerian households. A better approach would be to use ownership data from countries with similar GDP, socioeconomic characteristics, climate, politics as Nigeria where ownership data for Nigeria is not available. This approach will provide a more accurate estimate. The study also assumed that appliances acquired in a certain year will last till the end of time. Survival rate function that can calculate the number of appliances that retire every year should have been factored in for more accurate estimates. The survival rate is also beneficial in calculating appliance sales which is an important parameter in estimating REC. Incorporating these in the model will improve its predictive power. Lighting consumption could also be better captured by adopting a technological approach where the floor space, share of lighting technology, and efficacy are important determinants (Diawuo et. al., 2018).

Virginie and McNeil, 2013 used the BUENAS to model appliance ownership and technology development but based on broad assumptions and very few data. More data of high quality is needed to improve the accuracy of the model. The study did not also supplement demand with daily load profiles to estimate peak demand.

To bridge these identified gaps, there is a need for an energy model that can address the issues below that are lacking in previous studies:

1. Detailed disaggregation of household appliance i.e., project demand at appliance level: Most of the electricity consumption studies are at the sectorial level. For accurate estimations and projections, a model must be able to project into the future the energy consumption of stock of appliances. The benefit of this approach is that the unit energy consumption of each of the appliances can be determined allowing for us to know which appliance consumes the most energy and has the potential for energy savings (Matsui et. al., 2015). The more the appliances analyzed, the more accurate the total demand forecasts. Detailed appliance disaggregation provides more load characteristics, characterize consumption, and can help identify the energy costs of running different appliances (Mayhorn et. al., 2015). A good understanding of the appliance's disaggregation can also help plan on how to avoid peak load that can help avoid electric systems overload (Chavat et. al., 2019). This can also help policy makers identify which appliances to prioritize when planning Energy Efficiency Standards and Labelling (EES&L). Ultimately, it will help to plan on how to reduce the cost of electricity for consumers, an important aspect in policy development and planning. A detailed appliance disaggregation follows a bottom-up approach.

2. Detailed Stock Analysis (appliance sales, survival function, and appliance ownership): Sales of appliances and survival rate are important parameters in calculating appliance electricity consumption (AEC). Unfortunately, yearly appliance sales data are unavailable for Nigeria. However, sales of appliances can be estimated from the stock of appliances. Appliance stock is the number of appliances owned by each household and is calculated as the product of appliance ownership and number of households. The demand for energy has a positive relationship with number of households and appliance ownerships. Historical household data for Nigeria are available and projections into the future is easy but ownership data for most appliances is either incomplete or unavailable. Therefore, a stock model that can calculate the evolution of these appliance ownerships is necessary. The model must also be able to factor in appliance retirement function and average service life of appliances in order to accurately give an estimate of yearly sales and the proportion of the remaining sales in a given year. Most of the previous studies do not account for past and future appliance ownerships. Results from any model that does not account for the ownership of past and future appliances will be wrong and lead to wrong conclusions. In reality, no consumer will use an appliance till the end of time, the survival rate function that accounts for appliances that retire every year must be accounted for in the model for a more accurate result. Estimating and predicting past and future appliance ownerships follows a top-down approach using microeconomic data while sales estimations and predictions follow a bottom-up approach.
3. Calculate demand and supplement it by hourly load profile (electricity load forecast): The importance of hourly load profile is that it helps to determine peak load and what hour(s) of the day this happens thus providing the pattern of residential electricity consumption.

Supplementing electricity demand by hourly load profile can help detect the impacts of climate (weather) on electricity demand. This can also help plant managers to determine the relationship that exists between electricity demand, production schedule, and equipment loads. For consumers, understanding consumption patterns can be beneficial for energy conservation and cost savings. Generally, electricity power companies charge their customers at peak periods leading to higher electricity bills. Electric load forecasts before reaching the peak load can guide consumers in designing a strategy for peak electricity load reduction which is useful for demand response by limiting or avoiding the usage of electricity during the hours of high electricity rates. Ultimately, this can help to strategize in the management of daily load peak and demand response. Studies that supplemented demand with load profiles in Nigeria are very few; the few ones that did relied on surveys (Oluwole, 2018). For accurate forecasts, there is a need to rely on data from metering exercises for available appliances. Surveys should only be used when metering data are not available or when there are no load profiles for some of the appliances. Peak load forecasts generally follow a bottom-up approach.

4. Project efficiency into the future using Energy Efficiency Standards and Labelling (EES&L): There are very few studies on the impact of energy efficiency on peak demand reduction in Nigeria. The very few studies relied on assumptions (Dioha, 2020). There are presently no studies that projected peak demand reduction based on the introduction of existing standards and labelling regimes or best available technology (BAT). Relying on assumptions may not be realistic and can produce wrong forecasts because it does not account for what is technologically achievable. Most appliances imported to Nigeria are from Europe, the United States, and China. Therefore, any efficiency studies in Nigeria

should factor in existing standards and labelling from these countries for more accurate projections because that is the technology currently achievable. Accurate projections of efficiency can guide policy makers in designing future energy efficiency policy for Nigeria. Therefore, there is a need for a scenario-based model that can project efficiency into the future based on existing energy efficiency standards and labelling (EES&L).

Clearly, no one modelling approach can answer the research needs. For a more accurate forecast, a need to incorporate both the bottom-up and end-use approaches in the model is necessary. An advantage of these approach is that the structure of the growth of energy demand in Nigeria will be captured more accurately by an end use level diffusion model where uptake of energy intensity appliances is well predicted rather than assumptions based on relationship between energy demand and economic activity. Another advantage of this approach is that detailed efficiency scenarios can be constructed at the end use levels based on cost-effectiveness and an identified technology (Lestchert and McNeil 2013).

2.13 Overview of Energy Efficiency Standards and Labelling (EES&L) in Nigeria

The benefits of energy efficiency in energy savings and GHG emissions reduction is well discussed in literature (Karali et. al., 2020, Satola et. al., 2020, Favi et. al 2018, Grignon-Masse et. al., 2017, Ruble and Karaki 2013, Mahlia et. al., 2011, Vendrusculo et. al., 2007, Lutz et. al., 2006). The EES&L provides information about the appliance’s energy consumptions and its efficiency. It helps to reduce energy wastage caused by using inefficient appliances thus allowing more people access to electricity. It also helps the government to save money that was to be spent on building more power stations in an inefficient economy. Being energy efficient also help prevent the emission of greenhouse gases that comes with the generation of power.

EES&L is an important component of DSM of electricity and there are regulations on EES&L for major household appliances in most developed countries (IEA, 2017). The appliances that are labelled are usually the ones that consume most of the residential energy. They fall in the air-conditioning, heating, lighting, and refrigeration categories; other appliance categories may also exist. However, there are no or low level of EE S&L implementation in African countries (CLASP, 2017). Few researchers have identified the barriers to the adoption and implementation of EE S&L regulation or policies in most African countries (Agyarko et. al., 2020, Diawuo et. al., 2018, Kenfack et al., 2017). Some of these barriers include financial incapability to purchase efficient appliances, inadequate knowledge on the economic and environmental impact of energy efficiency, weak government policies, and non-implementation of these policies where they exist. Only Ghana and South Africa have fully implemented an EES&L of all the African countries. Senegal, Nigeria, and Kenya are three other African countries that have made attempts at adopting EES&L. These countries are at very early stages of adoptions or implementation (Agyarko et. al., 2020).

There have been talks about the need for energy efficiency in Nigeria's since the late 90s (Gana and Hoppe, 2017) but Nigeria began to take action on the need to be energy efficient in 2009 through the "One Million CFL" project, a joint project between the Energy Commission of Nigeria, ECOWAS and the Republic of Cuba. The project was financed by the governments of Cuba and Nigeria where both countries donated 500,000 CFL's each towards the program. The joint project was aimed at exchanging one million inefficient incandescent light bulbs with CFLs. In 2013, an end user metering study for residential houses was carried out by the United Nations Development

Programme (UNDP) with support from the Global Environment Facility (GEF) and in Collaboration with the Energy Commission of Nigeria, the Nigeria Federal Ministry of Environment (FME) and the National Centre for Energy Efficiency and Conservation (NCEEC). The major aim of the project was to reduce inefficiencies of end use household appliances by understanding their present efficiency levels. The data gathered from the project was to guide the commencement of a minimum energy performance standard (MEPS) and EES&L in Nigeria.

In 2017, the Standard Organisation of Nigeria (SON) in collaboration with the Nigerian Energy Support Programme (NESP) developed the MEPS and EES&L for air conditioners, lamps, and refrigerators. The project was funded by the European Union and the government of Germany. Full commencement of the MEPS was set for early 2019. This was to give room for old stocks to be completely retired and serve to guide the manufactures and importers of these appliances. The label is attached to appliances and will help guide consumers on which appliances have the best efficiency rating. The numbers on the label are 1, 2, 3, 4, and 5 with 1 being the least efficient and 5 most efficient. Appliances with ratings less than 1 are no longer welcome in the country. An example of the energy label is shown in Figure 2.8.

Nigeria stands to benefit a lot from the adoption of energy efficiencies if the barriers earlier discussed are removed. To quantify these benefits, a comparative analysis of the economic impacts of adopting the EES&L is essential. Studies focused on the economic impacts of adopting EES&L for end-use appliances are exhaustive in countries where EES&L policies are strongly implemented. Lutz, et. al., 2006 analyzed the life-cycle cost of energy design options for residential furnaces and boilers in the United States. Vendrusculo et. al., 2007 analyzed the life cycle cost analysis of energy efficiency design options for refrigerators in Brazil. Mahlia et. al., 2011 analyzed the life cycle cost analysis and payback period of lighting retrofit at a Malaysian

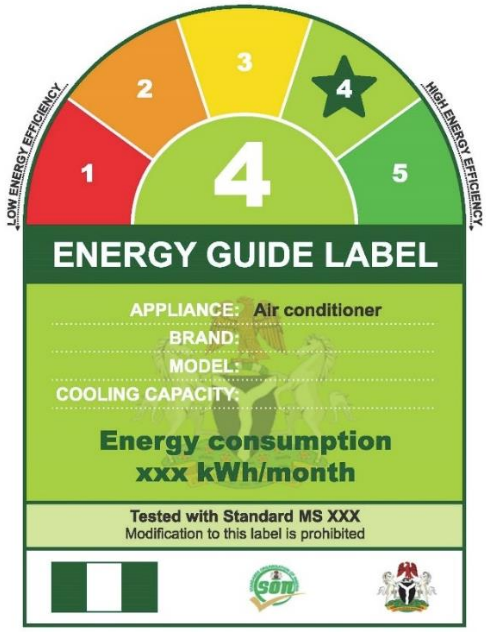

Figure 2.8: An example of energy label in Nigeria. Source (www.son.gov.ng)

university. Ruble and Karaki 2013 performed a cost-benefit analysis on the impact of the introduction of mandatory standards for some selected household appliances in Lebanon. Favi et. al., 2018 performed a comparative life cycle assessment of cooking appliances in Italian kitchens. Grignon-Masse et. al., 2017 used the lifecycle analysis approach to assess the environmental impacts of energy efficient European Acs. Satola et. al., 2020 carried out a comparative lifecycle assessment of various energy efficiency designs of a container-based housing unit in China. Karali et. al., 2020 also accessed the costs and benefits of an improvement in energy efficiency of room air conditioners in China.

Although there are discussions on the economic impacts of adopting EES&L in Africa, there are currently very few published comprehensive analyses of these impacts (Winkler et. al., 2002). To the best of my knowledge, there are currently no comprehensive studies on the economic benefits or impacts of adopting the EES&L in Nigeria. Most of the analyses are focused on the economic impact of renewable energy introduction in the country (Ajao et. al., 2011, Ngala et. al., 2007). Unachukwu, 2011 made an attempt at determining the investment returns if incandescent lamps were to be replaced with compact fluorescent lamps and light-emitting diodes. However, this study is outdated, and the growth of lighting appliances is underestimated in the study. To identify policies that will be beneficial to Nigerian consumers, there is a need to analyze the potential economic impact of EES&L adoption on the consumers.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Basis of Selection of Model for Estimating Electricity Needs and Efficiency in Nigeria

As discussed in previous sections, most developing countries use either the bottom-up or to-down approach for energy modelling. The strength and weaknesses of using either of these approaches have also been discussed and it has been determined that the best approach for this study is a hybrid approach. Generally, the basis for the choice of electricity demand models depends on the model performance, data availability, and the objective of the modeler. The main objective of this research is to determine the future residential electricity consumption (REC) and energy efficiency impact through detailed analysis of a stock of appliances under different scenarios. Hence stock accounting model becomes the method of choice.

The major reasons for selecting the accounting modelling technique include its relative simplicity and ease of use, and ability of the model to combine both the top-down and bottom-up approaches. The modelling technique allows for a detailed appliances disaggregation and stock analysis, allows the modeller to project based on different technology and efficiency scenarios. Most importantly, the model can be implemented in a spreadsheet and requires a short time to run all projections allowing for easy transferability.

Stock accounting models have been used by top research institutions and government agencies to forecast residential future electricity consumption, energy efficiency potential, energy savings, and support detailed policy scenarios. In the United States, the Department of Energy (US DOE) used a stock model developed at the LBNL to forecast future energy savings for household appliances.

In the United Kingdom (UK), the Environmental Change Institute developed a stock model for use in their domestic equipment and carbon-dioxide emissions project to recommend policy scenarios that can reduce residential GHG emissions in the UK, Portugal, and the Netherlands. In Australia, the Australian Greenhouse Office have used the stock model to access the impact of energy, water savings, economy, and GHG, policy scenarios in the household sector.

Several other researchers have also used stock models to forecast peak load and electricity demand in developing West African countries (Letschert and McNeil, 2013), and in a tropical country; Indonesia (McNeil et. al., 2019). The model has also been used in a recent Ghana (Nigeria's neighbouring country) study to estimate future residential electricity consumption and energy efficiency potential (Diawuo et al., 2018 and Diawuo. et. al., 2019). Of note is that these countries have similar socio-economic, socio-political, climate, and political characteristics as Nigeria. Stock models have also been used to analyze energy efficiency of household lighting in Switzerland (Heidari et. al., 2018) and in Kuwait to forecast residential buildings end-use energy consumption (Alajmi and Phelan, 2020).

This study presents a top-down and bottom-up approach (a hybrid approach) that uses the stock accounting model technique to develop a model for appliances to forecast residential electricity consumption up until 2050 in Nigeria. A model for lighting that considers lighting share, efficacy, floor area, and technology share is also adopted for lighting.

The model for appliance calculates electricity demand for household appliances and supplements it with hourly load profiles of appliance use to determine peak load (bottom-up approach). Estimations of appliance ownership, an important parameter in the appliance modelling considers the Gross Domestic Product (GDP), a macroeconomic indicator thereby relying on the strength and peculiarity of a top-down approach. Electricity demand estimates from the lighting model considers the floor area; an important characteristic of the building stock therefore adopting the top-down approach. The combination of the bottom-up and top-down approaches makes this model or methodology different from other methodologies that were presented in Table 2.18 because the strengths of each of the approaches compensates for the weaknesses of each other.

Results from detailed decomposition analysis of household appliances will show the change techniques in electricity consumption in each subsector and how the key electricity demand drivers affect them. In other words, the results will show the growth and evolution of residential electricity consumption and how a reduction in future demand growth can be achieved. The model also projects improvement in efficiency based on specific achievable targets or scenarios. It captures the effect of entrance of new and efficient end-use technologies over time on Nigerian peak load. Simply put, it models electricity demand of different types of electricity consuming end-use appliances including lighting, heating, and cooling. The future holds a lot of climate uncertainty with Nigeria having a tropical climate. What we know and factor into most electricity demand forecasts is today's climatic conditions; less or no attention is paid to future climate uncertainties in estimations. This model captures the potential impact of climate on electricity demand or use thus making it the preferred forecasting model.

Major residential end use drivers are captured in the appliance and lighting models after a detailed analysis of their relationship with electricity consumption. In the model for appliances, population, household size, number of households, GDP/capital, and appliance ownerships are the main drivers of these end uses. In the lighting model, floor space, lighting need, technology share, efficacy, and the lighting time are the major drivers. The model for appliance first calculates the total stock of the appliances from the end use drivers, then the electricity consumption of the appliance stock. The lighting model calculates the total electricity consumption from the major parameters for the lighting model as mentioned earlier. The total electricity demand is then gotten from the combination of the stocks and energy intensity as calculated from both the appliance and lighting models.

Peak load demand is then calculated using a Load Curve Model (LOADM) that combined the calculated REC with sector-specific and appliance daily load profiles in its calculation (McNeil et. al., 2019). In this analysis, daily load profiles were assumed to stay the same during the period of analysis because of Nigeria's tropical climate i.e., no major effect of seasonal changes on consumers behaviour. In summary, the LOADM forecasts the daily progression of load curves and peak demand at the national level from 2020 to 2050 while the appliance and lighting models predict the energy demand of residential appliances and lighting, respectively. Two scenarios were created for the appliance levels: Business as Usual (BAU) and Best Available Technology (BAT). The impact of peak load and electricity consumption was accessed for each of the scenarios and final energy savings was calculated. The final energy demand savings was then converted to carbon dioxide mitigation to access the impact on the environment. Finally, a comprehensive analysis of bill savings, payback periods, and LCC was carried out to accurately quantify the economic impacts of EES&L adoption following the methodologies of the US Department of Energy (DOE) and Mahlia et. al., 2011. The flow chart of the residential consumption model is shown in Figure 3.1.

The steps below are taken to project future REC and develop the model:

Step 1: Detailed energy demand disaggregation into end-uses.

Step 2: Pre-analysis: Statistical analysis of main drivers of residential electricity demand.

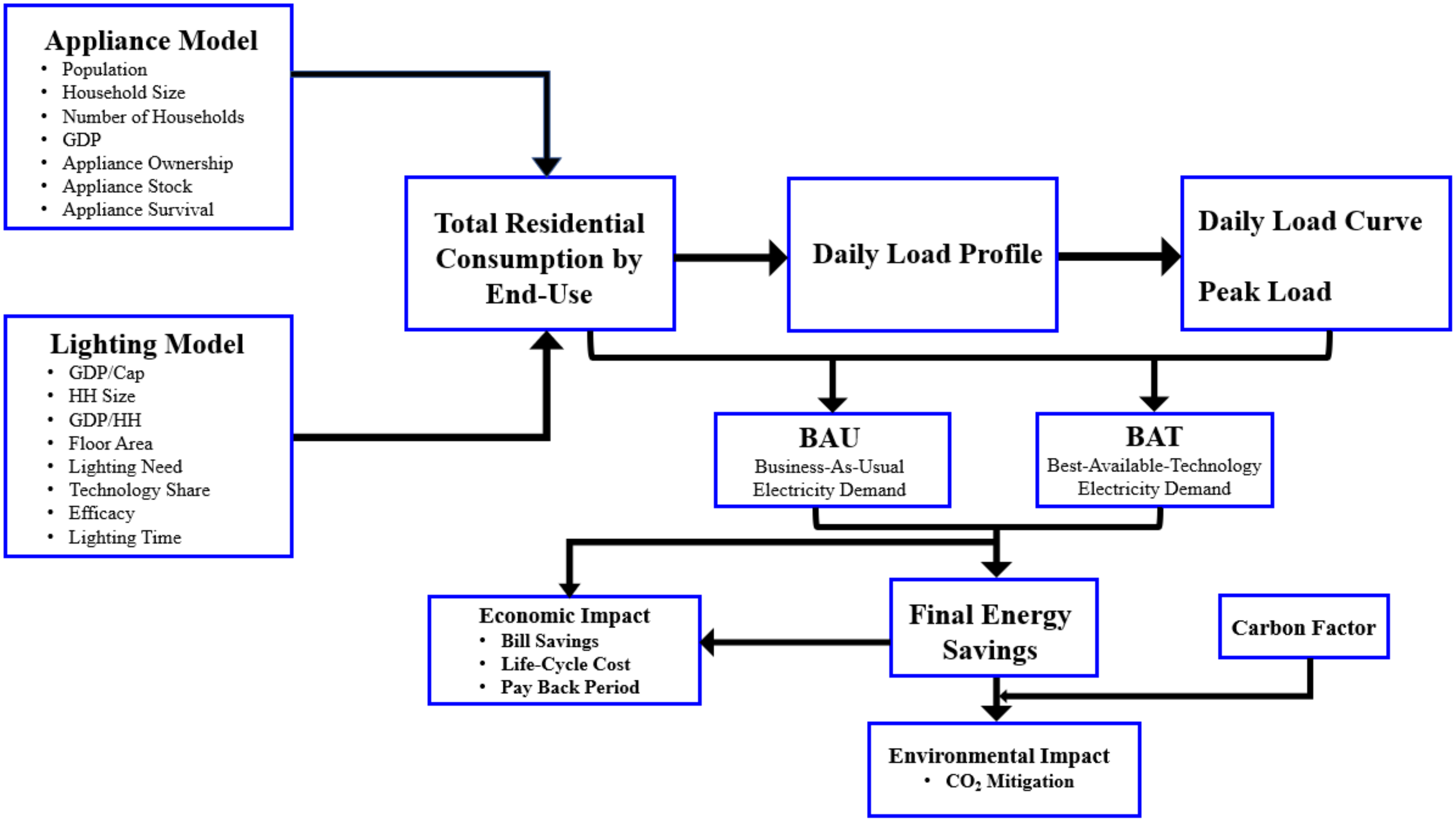

Figure 3.1: Flow Chart of the Residential Electricity Consumption (REC).

Step 3: Model description, development of data and mathematical relationships.

- **a.** Forecasting demand quantitatively using mathematical relations and scenarios.
- **b.** Parameters Estimation
- **c.** Data assumptions.
- **d.** Peak load demand.
- **e.** Final energy savings.
- **f.** Environmental Impact Analysis (emissions mitigation).
- **g.** Economic Impact Analysis (bill savings, payback period, and life-cycle cost)

Details of each step are further elaborated in the sections below.

3.2 Step 1: Detailed Electricity Demand Disaggregation into End Uses

In this study, twenty-one (21) household appliances were modelled. This is because these appliances are the most used in Nigeria and the most reported in literature (LSMS 2012, 2014, 2015, Olaniyan et. al., 2018, Dominguez et. al., 2019). The appliances are categorized as refrigeration (refrigerator and freezer), air conditioning (air conditioning and fan), cooking (microwave, food processor/blender, electric cooker, toaster, electric kettle), lighting (fluorescent lamps, incandescent lamps, compact fluorescent lamps, light emitting diode lamps), entertainment (radio, television, mobile phone, CD/DVD player, PC (desktop computer), PC (laptop)), laundry (washing machine, electric clothes dryer, electric iron), water heating (electric water heater – bathroom) and house cleaning (vacuum cleaner).

3.3 STEP 2: Pre-Analysis: Statistical Analysis of Main Drivers of Residential Electricity Demand in Nigeria

In order to determine future residential electricity demand in Nigeria, a good understanding of the relationship between the main drivers of electricity and electricity consumption is first required. This will help to further understand what determinants play significant roles in the determination of REC including the reasons for the inclusion of these drivers in the model.

The quantitative strategy and objective of the statistical analysis is to ascertain the statistical significance and magnitude of demand drivers on household electrical consumption. An analysis of the components of appliance ownership and their associated impact on the energy demand drivers is carried out. This is determined by using multiple linear regression techniques and applying post-estimation performance modelling to answer the following questions:

1. Which variables (demand drivers) matter most?
2. Which of them can we ignore?
3. What is the interaction of these variables with each other?
4. How sure are we about these variables?

A second analysis is carried out by performing a granger causality test to establish causality between the drivers and energy demand. In causality, the priority is to establish time and precedence and it helps to determine which driver causes consumers to demand energy and by how much. All statistical analyses and computations were done using the R statistical software package.

3.3.1 Data and Stylized Facts

The data set used in the pre-analysis were taken from a sample of twenty-nine years (1990 – 2019) from the International Energy Agency (IEA) (2019), the Central Bank Bulletin (CBN) and Nigeria Bureau of Statistics, NBS (2007, 2010), Nigeria Standard Living Surveys, LSMS (2010,2012, 2014, 2016), and GHS (2019).

The drivers analyzed here are those commonly used in energy demand studies, based on findings from detailed literature review. These determinants are population, number of households, household size, floor area per household, GDP per capita, appliance ownership, and technology. They are all the independent variables in the model. Technology uses education and industrialization as proxies in the model (Brohmann et. al., 2013, Inglesi-Lotz and Morales, 2017, Adom and Bekoe, 2013). Education is measured as primary school enrolment (% gross) while industrialization is measured as industry (including construction) and are both sourced from the World Development Indicator (WDI, 2019).

The dependent variable is electricity consumption (EC) captured as electric power consumption (kWh per capita) and sourced from the IEA (2019). The rationale for using energy by kWh is to majorly identify and estimate the residential segment of consumption which connects to the per capita earnings of households (Keho, 2016).

3.3.2 Causality Test Framework for Estimating the drivers of Energy Demand

We used the pairwise Granger (1969) causality test to identify the direction of causal association among the variables (i.e., electricity drivers and electricity demand), and to find out directional causality between them. The granger causality is based on prediction. The principle of causation is governed by the concept of cause and effect and is deeply rooted in the principles of causal and regression analysis. Before we establish an effect, a cause needs to be identified. Thus, granger causality test is a statistical technique applied to test for the presence of causality. In other words, it helps answer this question: does a particular variable occur before another or influences change in another? In this study, causality inferences in the multivariate framework are made by estimating the parameters of the following vector ECM equations (1-8)

$$\Delta lEC = \alpha + \sum_{i=3}^{m} \beta i \Delta LECt - i + \sum_{j=1}^{n} \gamma j \Delta LPOPt + \varepsilon t \tag{1}$$

$$\Delta lEC = \alpha + \sum_{i=3}^{m} \beta i \Delta LECt - i + \sum_{j=1}^{n} \gamma j \Delta LHHNt + \varepsilon t \tag{2}$$

$$\Delta lEC = \alpha + \sum_{i=3}^{m} \beta i \Delta LECt - i + \sum_{j=1}^{n} \gamma j \Delta LHHSt + \varepsilon t \tag{3}$$

$$\Delta lEC = \alpha + \sum_{i=3}^{m} \beta i \Delta LECt - i + \sum_{j=1}^{n} \gamma j \Delta LFACt + \varepsilon t \tag{4}$$

$$\Delta lEC = \alpha + \sum_{i=3}^{m} \beta i \Delta LECt - i + \sum_{j=1}^{n} \gamma j \Delta LFAHt + \varepsilon t \tag{5}$$

$$\Delta lEC = \alpha + \sum_{i=3}^{m} \beta i \Delta LECt - i + \sum_{j=1}^{n} \gamma j \Delta LGDPCt + \varepsilon t \tag{6}$$

$$\Delta lEC = \alpha + \sum_{i=3}^{m} \beta i \Delta LECt - i + \sum_{j=1}^{n} \gamma j \Delta LEDUt + \varepsilon t \tag{7}$$

$$\Delta lEC = \alpha + \sum_{i=3}^{m} \beta i \Delta LECt - i + \sum_{j=1}^{n} \gamma j \Delta LINDt + \varepsilon t \tag{8}$$

Where:

lpop is the natural logarithm function of population.

Lhhn is the logarithmic function of household number.

Lhhs is the logarithmic function of household size.

Lfac and lfah is the logarithmic function of floor area per household.

Lgpdc is the logarithmic function of GDP per capita.

Lec is the logarithmic function of energy consumption.

Ledu and lind are natural logarithms of education and industrialization, both indicating the efficient transformation of inputs 'technology'.

Lec is the natural logarithms of energy consumption.

βi and γ are the slope coefficients that defines the contribution of electricity demand and the specific electricity driver in each question.

α is the intercept term otherwise known as the autonomous demand which is the demand level assuming there are no drivers of electricity demand.

E_t is the stochastic term or the disturbance that creates a hypothetical space for other variables that were not included in the model but essential in causing changes in energy demand.

Δ symbol represents variable change through time from 1990 to 2019.

3.3.3 Multivariate Regression Model for Electricity Demand Drivers

A multiple linear regression was carried out using the following variables: lamp, blender, electric water heater, fan, vacuum cleaner, laptop computer, freezer, desktop computer, CVD/DVD/MP3/MP4 player, microwave, electric kettle, air conditioner, refrigerator, electric cooker, electric clothes dryer, television, electric iron, mobile phone, toaster, washing machine.

These variables are components that make up appliance ownership and each of them were regressed against the other electricity demand drivers to see their contributory effect on each of the drivers as represented in equation 9.

Energy_Demand_Driver = $\propto_0$ + β_1 *(lamp)* + β_2 *(Refrigerator)* + β_3 *(fan)* + β_4 *(Television)* + β_5 *(Electric.Iron)* + β_6 *(Air.conditioner)* +β_7 *(Washing.Machine)* + β_8 *(Freezer)* + β_9 *(Microwave)* + β_{10} *(Blender.food.processor)* + β_{11} *(Mobile.phone)* + β_{12} *(Desktop.computer)* +β_{13} *(Laptop.Computer)* + β_{14} *(Electric.Clothes.Dryer)* + β_{15} *(VCD/DVD/MP3/MP4player)* + β_{16} *(Radio)* + β_{17} *(Vacuum Cleaner)* + β_{18} *(Electric Cooker)* + β_{19} *(Toaster)* + β_{20} *(Electric.Kettle)* + β_{21} *(Electri.water.heater)* + ε_i ... *(Appliance Ownership Regression Model)*

(9)

Where:

βi = *slope coefficients.*

ε_i = *residual (error).*

Energy Demand Driver = dependent variable

Appliances = independent (explanatory) variable

3.3.4 Forecast Error, Residual Analysis, and Accuracy

The forecast error is determined using the Root Mean Square Error (RMSE). The RMSE is the standard deviation of the residuals (prediction errors). The residuals represent the extent of the length of the data from the regression and tells us the level of concentration of the data around the best fit line (Bianco et. al., 2009). The accuracy of the model can be computed as:

Accuracy = 1.96 * RMSE. ***(10)***

3.3.5 Result and Discussion

3.3.5.1 Descriptive Statistics

Descriptive statistics such as mean, median, and standard deviation values are presented for each driver of energy demand in Table 3.1. The table shows the average or location of data and the dispersion from the location for population, number of households, household size, floor area per household, GDP per capita, technology, and energy consumption. The data suggest that electricity consumption is a reflection of the size of demand. The deviation points show a moderate dispersion in population and number of households as well.

3.3.5.2 Rationale for Setting Hypothesized Value for Comparative Validation

The correlation value is a statistic that shows how one energy consumption driver score relate to energy consumption scores. A value close to +1, suggest a strong direct relationship and values around 0.5 and 0.3 are considered moderate and weak, respectively.

The essence is to examine the response level based on a one-to-one relationship. The effect size or magnitude of this value ranges from a scale of +1 and -1 for measuring the strength of the

Table 3.1: Descriptive Statistics for the Drivers of Energy Demand

Statistics	Population	Household Number	Household Size	Floor Area per HH	GDP capita	Primary School Enrollment	Industrialization	Energy Consumption (kwh)
Mean	141179734	28785580	4.953	51.83	1398.1	91.47	28.35	115.03
Median	137092719	27914695	4.911	50.77	1138.1	90.42	27.79	116.19
Std. Dev.	32010899	7565374	0.2017966	14.28811	949.703	5.727314	5.378174	28.12963

relationship, with values closer to 1 and farther from -1 pointing to a stronger relationship classified from high to moderate to low. Also, the signs of the relationships speak to the direction, with positive (+) and negative (-) as indicated by the range of +1 and -1 on either side of the numbers line. Prior to analysis, a theoretical maximum and minimum of +1 and -1 was set to mark the strength and direction from the bivariate relationship.

Null Hypothesis, H_0: r >0

Alternative Hypothesis, H_a: < 0

If correlation (r >0), in other words correlation is positive, we accept the null hypothesis of positive correlation, otherwise.

3.3.5.3 Responses of Demand Drivers to Electricity Demand

Examining the degree of responsiveness of the drivers on electricity demand, we see that the strength of the relationship among all inter-relationships are high (in terms of magnitude) (Figure 3.2). Figure 3.2 is a correlation chart showing the correlation scores. The *** indicates that all the drivers are statistically significant and thus, validates the presence of a strong relationship, this also implies that all the drivers are important in determining the cycle (up and down) of consumption in the current and projected periods.

3.3.5.4 Pearson's Product-Moment Correlation for Energy Demand Drivers

In order to validate the correlation scores from Figure 3.2, we evaluate the degree of responsiveness of the energy drivers to energy demand using the Pearson's product-moment correlation. The correlation scores show a high degree of correlation between the drivers and the

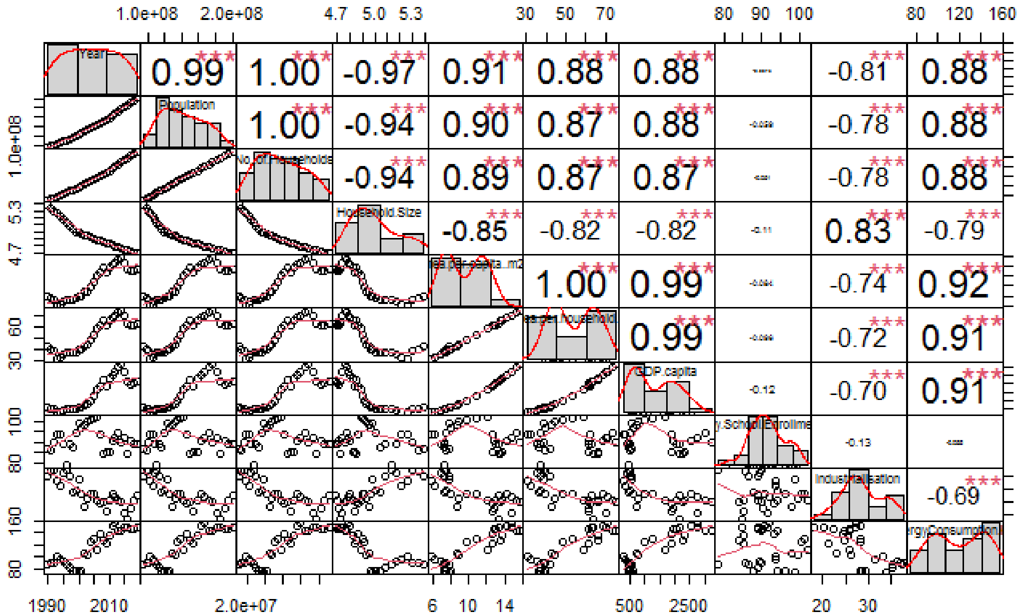

Figure 3.2: Correlation chart of drivers of energy demand and energy demand. The diagonal shows the distribution of each variable. The loess (bivariate scatter plots with a fitted smooth line) is shown below the diagonal. Above the diagonal, the value of the Pearson correlation coefficient plus the significance level as stars are displayed as *p-values (=0, 0.001, =0.01, =0.05, =0.1, =1) ⇔ symbols ("***", "**", "*", ".", " ").*

energy demand variable as well as statistically significant relationship, given by a $\rho < 0.01$ or probability value of less than 1% (99% confidence interval). Table 3.2 presents an interesting fact on the inter-relationship between energy consumption and energy drivers for technology. All other variables were found to be statistically significant and highly correlated to energy consumption, but primary school enrolment was statistically not significant and printed a low correlation to suggest that education response has been quite low with respect to driving consumption. Industrialization is found to be statistically significant but with a moderate correlation value.

The correlation suggests that there is a strong relationship between the variables when paired against each other. This implies that one driver variable can be predicted using another driver variable. This may also suggest the presence of multicollinearity, which demands that we drop one or more of the driver variables or add them together to get a composite variable that reduce the presence of multicollinearity (Tomaschek et. al., 2018). In this study, we ignore multicollinearity since evidence from energy demand literatures validates the selection of the variables and the choice of the model. Table 3.3 displays the effect size and strength of relationship based on the results from Table 3.2. Aside primary school enrolment, the probability values of all the variables are statistically significant suggesting that we have sufficient evidence to reject the null hypothesis and confirm the validity of the strength of the relationship. However, the correlation for primary school enrolment and industrialization were found to be weak compared to the other variables.

3.3.5.5 Multivariate Regression Model for Electricity Demand Drivers

Almost half of the appliance ownership variables (8 out of 21 variables) have a statistically significant relationship with population and household number (Appendix A). A logarithmic transformation was taken across the dependent variables or drivers of energy demand to take care

Table 3.2: Pearson's product-moment correlation table for Energy demand drivers. *The significance levels are noted as: p-values (=0, 0.001, =0.01, =0.05, =0.1, =1) ⇔ symbols ("***", "**", "*", ".", " ")*

Variable	Correlation I	Probability value (ρ)
Population	0.8787079	0.000
Household Number	0.8690353	0.000
Household Size	-0.7933016	0.000
Floor Area per HH	0.9086392	0.000
GDP capita	0.9063008	0.000
Primary School Enrolment	-0.05462962	0.7743
Industrialization	-0.692149	0.000

Table 3.3: Impact Summary. **The larger the effect size^{+}, the stronger the relationship$^{\&}$.*

Demand Drivers	Effect Size^{+}	Strength of Relationship$^{\&}$
Population	+1	Strong
Household Number	+1	Strong
Household Size	-1	Strong
Floor Area per HH	+1	Strong
GDP capita	+1	Strong
Primary School Enrolment	-1	Weak
Industrialization	-1	Moderate

of positive skewness and to normalize the dataset in order to reduce the chances of errors from negative skewed data. Laptop computers recorded a highly statistical significance ($\rho < 0.01$ (1%)) and positive contributory effect to population. Air conditioner and washing machine are found to be statistically significant ($\rho < 0.05$ (5%)) effect to household size and household number. The result further shows that education is significantly influenced by lamp, fan, television, electric iron, and mobile phone. Toaster, electric kettle, and electric water heater all significantly impact on household size at the 95% level ($\rho < 0.05$ (5%)) as shown in Appendix A. All the appliance ownership variables have a positive contributory effect to industrialization.

3.3.5.6 Forecast Error and Accuracy

The accuracy of the model is hinged on the statistical metric of Root Mean Square Error (RMSE) which lays emphasis on providing a forecast error value based – off on RMSE which shows that the inadequacies in the model are low at RMSE of 0.0000087, 0.0002322448, 0.0002337197, 0.175371 and 0.8596972.

3.3.5.7 Causal Analysis

The relationship between the variables shows a probability value of less than 5%. Table 3.4 shows that the variables cause each other. Household number and size have a stronger statistically effect and thus, are more reliable policy actions to drive and improve energy consumption goals.

Table 3.5 shows the results of ordinary least squares regression (OLS) of energy demand against demand drivers. Education positively impacts on energy consumption, but industrialization has a negative contributory effect on energy consumption. Both technology input variables are found to

Table 3.4: Granger Causality Test. * $p < 0.1$. **, $p < 0.05$, *** $p < 0.01$. Reject the statement if probability value is less than the level of significance (10%,5% and 1%)

Coefficient	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-4.52E+03	1.25E+03	-3.626	0.00142**
Lpop	9.24E+02	2.82E+02	3.276	0.00332**
Lhhn	-7.46E+02	2.39E+02	-3.116	0.00486**
Lfah	9.64E-01	9.38E-01	1.028	0.31479
Lgdpc	3.44E-04	1.44E-02	0.024	0.98111
Lpse	5.67E-01	3.77E-01	1.504	0.14627
Lind	-2.11E-01	6.49E-01	-0.325	0.7481

Table 3.5: The effect analysis based off the granger causality test.

Direction of Causality	**F-statistics**
Lpop does not Granger Cause Energy Demand	2.5051*
Lhhn does not Granger Cause Energy Demand	4.2422*
Lhhs does not Granger Cause Energy Demand	6.6696***
Lfah does not Granger Cause Energy Demand	1.4361
Lgdpc does not Granger Cause Energy Demand	0.6466
Lpse does not Granger Cause Energy Demand	0.5348
Lind does not Granger Cause Energy Demand	2.5853*

be not statistically significant. Population and household number were both statistically significant confirming the effect of count and size on the consumption of electricity.

3.3.5.8 Conclusion

Based on the result of the overall significance of the multivariate regression model, the F-test and probability values of the model; $F_{(prob)} < 0.01$ ($\rho < 0.01$), we infer that there is sufficient evidence based on the data to reject the null hypothesis and conclude that the model is valid. The result from the granger causality test shows that the variables cause each other. Household number and size have a stronger statistical effect and thus, are more reliable policy actions to drive and improve energy consumption goals. Overall, all the drivers analyzed here except education and industrialization all have a strong positive relationship with residential electricity consumption (REC) and will all be the main drivers of the REC stock accounting model in this study.

3.4 Step 3: Model Description, Development of Mathematical Relationships, and Data

3.4.1 Model Equations for Appliances

One of the main goals of this research is to determine the yearly electricity consumption of household appliances and lighting up to 2050. The best way to obtain the appliance electricity consumption (AEC) is to source data directly from end users metering campaigns because they directly measure the total electricity consumption of appliances, buildings, and spaces. In 2013, the UNDP with support from the GEF and in collaboration with the ECN, the Nigeria Federal Ministry of Environment (FME) and the National Centre for Energy Efficiency and Conservation (NCEEC) carried out an end use metering campaign for residential houses in Nigeria to monitor the actual consumption of lighting, air conditioners, refrigerators, audio-visuals, computers, and cooking. However, Nigeria's electrification rate at the time the study was carried out was 52% with incessant power outages. Therefore, the average consumption reported would be lower than expected because the incessant power outage will have a great effect on the appliance's consumptions. In the absence of reliable and accurate end users metering estimates; the annual energy consumption (AEC) of an appliance stock over a period of year are usually projected using stock accounting models. Stock, unit energy consumption of appliances sold in a given year, and probability of appliances survival are the three important parameters used in stock modelling to calculate AEC. The appliance electricity consumption and parameters are represented in equation 11:

$$AEC^{a}_{(j)} = \sum_{j=j-l}^{i} S^{a}_{(j)} \times \varphi_a (j - k) \times UEC^{\,a}_{(j)} \qquad \textbf{(11)}$$

Where:

$AEC^{a}_{(j)}$: *Appliance unit electricity consumption in year, j;*

$UEC^{\,a}_{(j)}$: *Appliance unit electricity consumption for appliance a sold in year, j.*

$S^{a}_{(j)}$*: Total number of appliances sold in year j;*

$\varphi_a (j - k)$: *Survival probability of an appliance having age j-k.*

All the appliances are then grouped into end-uses and their consumptions expressed using equation 12.

$$EC^{enduse}_{(j)} = \sum_{a=1,I} AEC^{\,a}_{(j)} \qquad \textbf{(12)}$$

Where: $EC^{enduse}_{(j)}$: *Total electricity consumption in year j for each end-use.*

3.4.2 Model Equation for Lighting

Modelling the lighting follows the methodology of Diawuo et. al., 2018. The result is then multiplied by the electrification rate given that all households with access to electricity use lighting appliances. Thus, the model presented here assumes that the diffusion of lightings is a function of electrification rates as described in equation 13:

$$\mathrm{LEC_j} = \frac{\mathrm{FS_j} \times \sum_{j=1,2I}^{n}\left(\frac{S_{l,j}}{\eta_{l,j}}\right) \times Q_j \times t_j^{*}\, \mathrm{HH_j}}{1000} \times \mathrm{E.R} \qquad \textbf{\textit{(13)}}$$

Where:

$FS = f(GDP/HH)$

LEC_j : *Electricity consumption of lighting in year j;*

FS_j : *Floor space for each household in year j in m²/hh);*

$S_{l,j}$: *Lighting technology l share in year j in %;*

$\eta_{l,j}$: *Lighting technology l efficacy in year j in lm/W;*

Q_j : *Useful lighting need in lm/m²;*

t_j^*: *Lighting time duration average for a household in year j in hrs;*

n: *Lighting technologies cumulative and E.R: Electrification Rate.*

3.4.3 Parameter Estimation

There are no published data for all the parameters in equation 11 for Nigeria. Therefore, these parameters must be estimated in order to calculate the AEC. To accurately estimate the unit electricity consumption (UEC) in the absence of metering estimates, the power ratings and time of operations of the appliances must be considered (Al-ajmi et. al., 2020). It is the product of the appliance power rating, technology improvement factor, and the total operating hours. The technology improvement factor is important because as technology advances, appliances also become more efficient. This will show the advancement in technological efficiency over time. The UEC of the air conditioner is modelled differently because its cooling capacity is an important parameter in the equation. The UEC of air conditioner in this study follows the methodology of Diawuo et. al., 2018. Stock is calculated as a product of the number of households and the appliance ownership at a given year. Probability of appliance survival is estimated as a function of age. For projections into the future, the AEC parameters are developed for the BAU and BAT scenarios. This allows to estimate the impact of efficiency on AEC.

As discussed in previous sections, Nigeria's climate is tropical with very little seasonal difference. Thus, Nigeria has a constant cooling degree day (CDD) and zero heating degree days (HDD) (Baumert and Selman, 2003). To estimate consumption as a result of a warmer climate, baseline projections under the BAU and BAT scenarios were compared to the mid-century projections. Under the mid-century projections, the effect of climate change with respect to a likely reduction in the CDD was factored in.

The electricity consumption for each of the appliances was then derived by multiplying appliance sales by the survival rate, and the UEC. In the lighting model, the total electricity consumption was estimated from the major parameters for the lighting appliances. The final residential electricity demand was then gotten from adding the estimates of the electricity consumption from both the appliance and lighting models. The stock accounting model parameters: UEC, stock, and survival rate and how they combine to estimate the total residential electricity demand are discussed in more detail in the next subsections.

3.4.3.1 Appliance Ownership

The best way to estimate residential consumption in developing countries such as Nigeria is through ownership of individual appliances. The importance of this is its usefulness in estimating the impact of economic growth on the consumption of electricity and to determine which appliance consumes the most energy. However, there are very few household surveys on appliance ownerships in Nigeria. Therefore, the ownership must be modelled through time. A good appliance model must be able to successfully capture the choice of consumers (Li and Just 2018) and evolution of the appliance through time.

As a first step, a pre-analysis was done in order to compare modern methods of analysis, modeling, and forecasting to determine the best modeling approach for appliance ownership. In this study, the naïve, simple exponential smoothing, and Holt's trends (combined with mean imputations) techniques were used to compute a n-step ahead for appliance ownership (see appendix B). The limitation to using these techniques is that it led to biased or inaccurate estimates and gives no room for standard errors estimation. This is because the values that were imputed were determined by the actual data model. Therefore, there is no way to compare actual values with modelling values. Most importantly, the naïve, simple exponential smoothing, and Holt's trend techniques predictions are based on single time series that assumes a linear growth.

Previous researchers have established a non-linear growth (S-Shaped) for appliance ownership, (Farrell, 1954, Gertler et. al., 2011, Letschert and McNeil, 2013, Auffhammer, 2014, McNeil et. al., 2019) especially for developing countries. This is because appliances acquisitions can be delayed for so many reasons thus making the curve non-linear. Income levels and distributions, income inequality, and lower income growth rate are the major reasons in developing countries, and all have negative impacts on the penetration rates of appliances (Li et. al., 2019). For example, due to low poverty line, lower income households may not be able to purchase appliances as they enter the market causing a delay in adoption. Thus, there is a need for a model that can capture the non-linear growth of appliance ownerships for Nigeria.

This study modelled appliance ownership as an S-shaped curve of time; a logistic function (Diawuo et. al., 2018). When the saturation level is reached, the logistic function maximum value equals one by definition. In Nigeria, it is not uncommon for households to have more than one appliance. This model accounts for that, and the curve fitting parameter (saturation) is used to scale the logistic function so that the maximum value may be more than one. Estimates of appliance ownerships in each year was then used to determine the appliance stock. The appliance ownership is expressed in equations 14 and 15. The accuracy of the model is corroborated by predicting the error between the predicted and modelled value in equation 16 (McNeil and Letschert 2010).

$$\gamma_{(j)}^{a} = \frac{S^{a}}{1 + e^{log_e\left(S^{a}/\beta^{a-1}\right)^{-bt}}};\ S = \alpha \times \rho;\ where \begin{cases} \alpha \geq 1 \\ \rho \leq 1 \end{cases}$$

$$\beta = \alpha \times \rho;\ where \begin{cases} \alpha = 1 \\ \rho \leq 1 \end{cases} \qquad \textbf{\textit{(14)}}$$

$$b = \frac{log_e(S^{a}/\beta^{a} - 1)}{\vartheta(t)} \qquad \textbf{\textit{(15)}}$$

Where:

$\gamma_{(j)}^{a}$: *Appliance ownership a at time j*

S^{a}: *Ownership of appliances at saturation*

β^{a}: *first year of appliance ownership*

b: *curve fitting parameter*

t: *Time*

$\vartheta(t)$: *Abscissa inflection point;*

ρ: *penetration of appliance*

a: *level of saturation.*

The RSME is calculated using equation 15.

$$Error = \frac{\sqrt{\sum_{i=1}^{N}[Diff_{\ Model} - Diff_{\ Data}]^2}}{N} \qquad \textbf{(16)}$$

Where:

I *is the country index, and* N *is the number of data points.*

3.4.3.2 Appliance survival

This is the retirement function and predicts the retirement rates of appliances. Generally, the modelling of appliance survival follows a-four-parameter Weibull distribution in countries where there is sufficient or partial data for analysis. These parameters are appliance age, starting age of scrappage, characteristic service life, and the failure steepness. However, data on appliance survival is not available for Nigeria. In such case, survival modelling follows a "modified Weibull distribution" where the Weibull distribution contains three parameters (appliance age, characteristic service life, and failure steepness) (Zachariadis et al., 1995). The appliance retirement rate was then used as an input to determine the sales of appliance. The equation for the appliance survival is presented in equation 17 (Zachariadis et al., 1995).

$$\varphi_i(l) = exp - \left[\left(\frac{l + b^i}{T^i}\right)^{b^i}\right] and\ \varphi_i(0) \cong 1 \qquad \textbf{(17)}$$

Where:

$\varphi_i(l)$: *the presence probability of appliance I having age l;*

l: *the age of appliances in years*

b^i: *the failure steepness for appliance type I (b^i > 1, i.e., failure rate increases with age);*

T^i: *service life for appliance type i. at the 90th percentile.*

3.4.3.3 Stock modelling

In the absence of sales data, the stock of an appliance is modelled to get the sales. The stock is the total number of household appliances that are consistently in use. For a given year, appliance stock is the product of the number of households and appliance ownership (i.e., appliances per household). The number of households in a particular year is obtained by dividing the population by the household size. The equations for the stock modelling are shown in equations 18, 19, and 20.

$$Stock^a_{(j)} = HH_{(j)} \times \gamma^a_{(j)} \qquad \textbf{(18)}$$

Where:

$Stock^a_{(j)}$: Total number of appliances sold in year *j*;

$HH_{(j)}$: Total number of households in year *j*.

Estimates of appliances sold each year is determined using equation 18 and was then inputted in the electricity consumption calculation.

$$S^a_{(j)} = stock^a_{(j)} - stock^a_{(j-1)} + Ret_{(j)} \qquad \textbf{(19)}$$

Where:

$S^{a}_{(j)}$*: Total number of appliances sold in year j;*

$stock^{a}_{(j-1)}$*: Total number of appliances sold in year j-1;*

$Ret_{(j)}$*: Total number of appliances retired from the stock in year j*

$$Ret_{(j)} = S^{a}_{(j)} \times \left(1 - \varphi_i\,(0)\right) + \sum_{j=j-l}^{j-1} S^{a}_{(k)} \times \left(\varphi_i\,(j - k + 1) - \varphi_i\,(j - k)\right) \tag{20}$$

Where:

$S^{a}_{(k)}$ *: Number of appliances with age l sold in sales year j;*

$\varphi_a\,(j - k + 1) - \varphi_a\,(j - k)$: *Survival probability of an appliance having ages j-k+1 and j-k.*

The unit electricity consumption of appliances excluding air conditioner is determined using equation 21.

$$UEC_{(j)} = \frac{P(_{j-1}) \times \left(1 - \eta^{a}_{t.f}\right) \times t_{(j)}}{1000} \tag{21}$$

Where:

$UEC_{(j)}$ *: Appliance Unit Electricity Consumption in year j;*

$P(_{j-1})$*: Appliance Power rating in year, j-1;*

$\eta_{t.f}$*: Technology improvement factor of an appliance*

$t_{(j)}$ *: Appliance total operating hours*

The unit electricity consumption of air conditioner is expressed using equation 22.

$$AC\left(UEC_{(j)}\right) = \frac{CC_{(j)} \times t_{(j)}}{EER_{(j)}} \tag{22}$$

Where:

$AC(UEC)_{(j)}$: *Air conditioner (AC) unit electricity consumption in year j;*

$t(_{j)}$*: AC total operating hours in year, j;*

$CC_{(j)}$*: AC average cooling capacity in year, j;*

$EER_{(J)}$*: AC energy efficiency ratio in year, j,*

3.4.4 Peak Load Demand

The peak load is that time of the day with the peak REC. Steps to determine this are highlighted below:

- Normalize the load curve profiles gotten from literature by following the following steps:
    - Determine Average Load: i.e., average of all hourly load for each appliance category.
    - Determine Maximum Demand: This is the maximum of the hourly load for each appliance category.
    - Load Factor: Load Factor is the ratio of the calculated maximum demand to average load. It is gotten by dividing the maximum demand by average load.
    - Load Curve Profile: This is a chart showing the pattern of consumption over a 24-hr period. This is determined by dividing the inputted hourly load gotten from the literature for each category by their corresponding average load calculations.
- The next step is to determine average load:
    - The average load is the estimates of residential consumption from modelling calculations converted from GWh to MW.

- Third, demand load curves are defined: This is a chart showing the differences in consumption over a 24-hr period. This is determined by multiplying the average load (MW) by hourly load curve profile for each category.
- Account for Transmission and Distribution loss (T&D): Because Nigeria does not enjoy constant electricity, T&D loss is then factored into the load curves.
    - Multiply the load curves by T&D number.
- Peak Load: The peak load is the maximum REC for all the appliances in a 24-hour period.
    - This is the hourly summation of each appliance category demand load.

3.4.5 Final Energy Savings

This analysis creates a realistic scenario of possible energy efficiency achievements assuming Nigeria adopts the minimum energy performance standard (**MEPS**) program. The MEPS program mandates the use of the most efficient available technology or product for all end-uses appliances that are readily available. Two scenarios are created for the appliance levels up to the year 2050: Business as Usual (BAU) and Best Available Technology (BAT). The impact of peak load and electricity consumption was accessed for each of the scenarios.

1. Business as Usual (BAU): This scenario assumes that between now and 2050, appliance efficiency will continue to improve based on historical path.
2. Best Available Technology (BAT): This is the efficient future scenario. It is assumed that all new appliances between 2020 and 2050 are replaced by the globally best available technology. The BAT scenario results give estimates of technical potential energy efficiency, or the potential energy savings potentials that would result from implementation of MEPS in Nigeria.

The final energy savings from electricity is determined using equation 22 (Letschert et. al., 2013):

$$\Delta E(y)=E_{BAU}(y)-E_{BAT}(y) \qquad \textbf{(22)}$$

Where:

E_{BAT} = *Efficiency Best Available Technology Demand (BAT)*

E_{BAU} = *Efficiency Business as Usual Energy Demand (BAU)*

E = Final Energy Demand

3.4.6 Environmental Impact

The impact of EES&L on the environment is the potential reduction in GHG that can negatively impact the environment. Carbon dioxide is the most common or primary anthropogenic GHG and its potential reduction is determined in the form of emissions mitigation as described in subsection 3.4.6.1

3.4.6.1 Emissions Mitigation

The environmental impact is a function of the final energy demand savings. The final energy demand savings is converted to carbon dioxide mitigation and is determined using equation 23 (Letschert et. al., 2013). The mitigated carbon dioxide is tradable in the global carbon credit market.

$$\Delta CO_2(y)=\Delta E(y) \times f_c(y) \qquad \textbf{(23)}$$

Where:

$\Delta CO_2(y)$ = CO_2 *mitigation in year y*

$\Delta E(y)$ = *Final Energy Savings in year y*

f_c = *carbon conversion factor (kg/kWh or kg/GJ) in year y*

3.4.7 Economic Impact

This analysis determines the methodology for determining the benefits of EE S& L in terms of economic costs and benefits to the consumers who purchase energy efficient appliances. The economic impact is a function of energy savings, bill savings, payback period, and life cycle costing (LCC). A comprehensive analysis of each of the variables is described in the following subsections.

3.4.7.1 Life-Cycle Cost (LCC)

LCC is an engineering economic approach that chooses between alternative products that provide equal service to the consumers (U.S DOE, 2016, Ruble and Karaki 2013). In EES&L studies, LCC is important in determining cost savings whereby there is a reduction to the consumers total cost while making sure that the cost savings does not have any adverse impact on the manufacturers of the appliances. LCC is the first cost or the purchase price in addition to the operating and maintenance costs (including the electricity prices) over the lifetime of the appliance. Generally, the first cost of acquiring an appliance may either be through cash payment or through credit whereby the consumer borrow money to pay for the cost and pay interest on the money borrowed after the purchase has been made. There is no change to the cost of maintenance of an appliance over its lifetime whether there is a decrease in the efficiency of a model or not (Favi et. al 2018). Thus, the maintenance cost is ignored in this study because of this ineffectiveness. The LCC is expressed in equation 24 (U.S DOE, 2006) where future operating costs is being discounted to the purchase. These are then summed up over the appliance lifetime. The calculations are implemented using Microsoft Excel.

$$LCC = IC + \sum_{t=0}^{n} \left(\frac{OC_t}{(1+r)^t} \right) \tag{24}$$

Where:

LCC = life-cycle cost

IC = total installed or purchase cost of appliance

OC = yearly operating cost

r = discount rate

t = operating costs summed over the appliance lifetime

Several inputs go into the LCC analysis as expressed in equation 24. These inputs are:

1. Inputs used for establishing the total purchasing costs (PC).

2. Inputs used for establishing the total operating costs (OC).

Figure 3.3 is a flow diagram that shows the relationship between the inputs of the PC and OC used in the LCC calculations. These inputs are further described in detail in the following subsections.

3.4.7.1.1 Operating Cost (OC)

This is the cost to the consumers to operating the appliance. The operating costs equal the annual energy consumption of each appliance multiplied by the electricity tariff and can be calculated following equation 25.

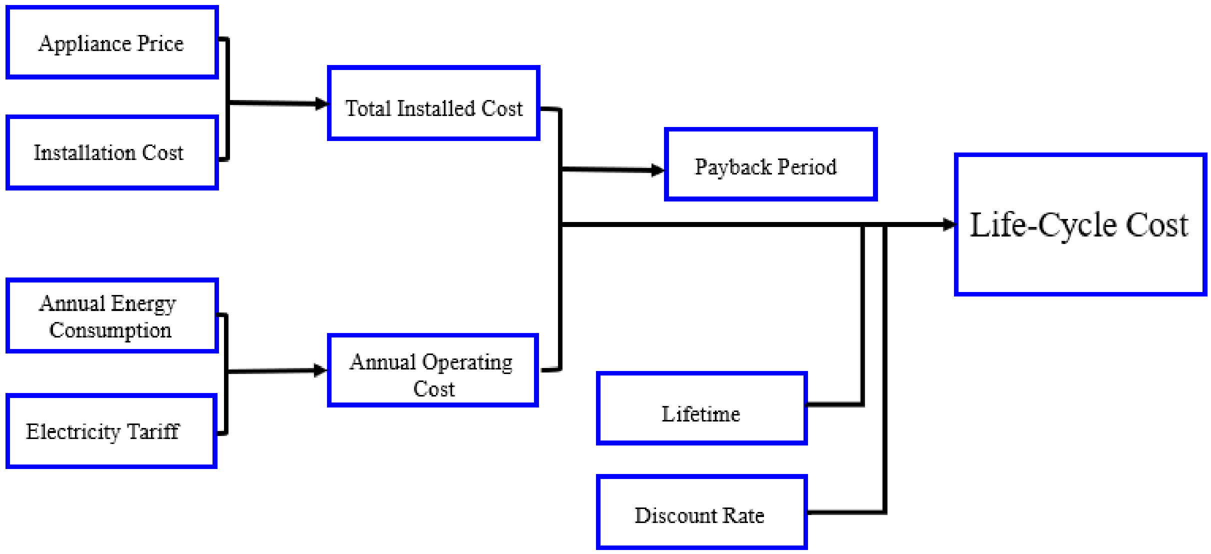

Figure 3.3: Flowchart for life-cycle cost inputs.

$$OC = AEC \times ET \quad \textbf{\textit{(25)}}$$

Where:

AEC = Annual Energy Consumption for appliance i

ET = Electricity Tariff.

The inputs for AEC have been described earlier in subsection 3.4.1.

3.4.7.1.2 Installed Cost (IC)

This is the cost to the consumers for purchasing and installing the appliance. The installed cost equals the appliance price and the installation cost as expressed in equation 26.

$$IC = APP + INST \quad \textbf{\textit{(26)}}$$

Where:

APP = Appliance price (i.e., customer price for the appliance only), expressed in dollars

INST = Installation cost or the customer price to install the appliance (i.e., the cost for labor and materials), also in dollars.

3.4.7.2 Bill Savings (BS)

Bill savings is the money consumers would save on energy and utility bills if EES&L is adopted. Mathematically, it is expressed by multiplying electricity savings by electric tariff as shown in equation 27.

$$BS = ES \times ET \quad \textbf{\textit{(27)}}$$

Where:

BS = Bill savings

ES = Electricity savings

ET = Electricity Tariff

3.4.7.3 Payback Period (PBP)

The PBP is the recovery time of the purchase of additional energy efficient appliance due to lower operating costs. The PBP calculation is similar to the LCC analysis. The only difference is that future electricity price and discount rates are not needed for PBP calculations. The price of electricity is only needed for the year where the MEPS is expected to start. Mathematically, the PBP is the ratio of the change in purchase expense to the annual operating costs as represented in equation 28.

$$PBP = \Delta IC / \Delta OC \qquad \textbf{(28)}$$

Where:

ΔIC = Difference in the total installed cost between the more efficient standard level and the baseline design

ΔOC = difference in annual operating expenses.

The unit of PBP is years. A PBP of 15 years simply means that the increased cost of purchasing the appliances is recovered in 15 years due to lower cost of operating the appliances. If the PBP of an appliance is greater than the average lifetime of the appliance, it then means that purchase price increase is not recovered even with a lower cost of operating the appliances.

3.4.8 Data and Assumptions

This section details the assumptions that go into the appliances and lighting models including the load profiles. It also discusses the assumptions that go into the environmental and economic impact analyses of adopting EES&L. Like most developing countries, data availability poses a great problem in Nigeria. This study relies on limited data or data from countries with similar weather and socioeconomic characteristics to estimate electricity consumption. Majority of the data were sourced from the National Bureau of Statistics, Energy Commission of Nigeria, World Bank, International Energy Agency, and other published studies. The appliances considered in this study are summarized in Table 3.6.

3.4.8.1 Macroeconomic and Demographic Assumptions

Population and GDP per capita data for previous years were gotten from the World Bank (2020), 2050 population projection was sourced from the United Nations (2019). Household numbers and sizes were sourced from CBN and NBS (2007, 2010), LSMS (2010,2012, 2014, 2016), and GHS (2019). Future projections for up to 2050 for population, GDP per capita and household sizes followed the single compound amount methodology.

The population of Nigeria was approximately 196 million in 2018, making it the largest country in Africa and the world's most populous black nation. Nigeria's population growth rate from 2018 to 2050 is estimated to be 2.27% and future projection up to 2050 is estimated to be 401 million. Household size declines by 0.2% per year from 2018 to 2050 and electrification rates is estimated to increase to 100 % by 2050. GDP per capita growth rate from 2018 to 2050 is estimated at 6.41%. The baselines data assumptions for population, GDP per capita, household size, electrification rates and other key drivers used are presented in Table 3.7.

Table 3.6: Residential Sector Appliances

Category	Appliances
Refrigeration	Refrigerator
	Freezer
Air Conditioning	Air conditioner
	Fan
Lighting	Incandescent lamp
	Fluorescent lamp
	Compact Fluorescent lamp
	LED lamp
Cooking	Microwave
	Food processor/blender
	Electric cooker
	Toaster
	Electric kettle
Entertainment	Radio
	VCD/DVD/mp3/mp4 player
	Desktop computer
	Laptop computer
	Television
	Mobile Phone - Chargers
Laundry	Washing machine
	Electric Clothes Dryer
	Electric Iron
House Cleaning	Vacuum Cleaner
Hot Water Heating	Electric Water heater (bathroom)

Table 3.7: Macroeconomics assumption

Residential	Unit	2010	2050
Population	Million	158503197	401315000
GDP per capita	(US$)	2292.44516	14,804
Number of Households	Million	32856823.9	91207955
Household Size	NA	4.82	4.40
Electrification Rate	%	48	100

3.4.8.2 Appliance Unit Energy Consumption

Power rating data and time were sourced from (Olaniyan et. al., 2018 and Diawuo et. al., 2019) and presented in Tables 3.8 and 3.9. Based on technological advancement, technological improvement factors were factored into the UEC calculations to give room for evolution of energy efficient appliances. Data for the technological improvement for the appliances were sourced from (Diawuo et. al., 2018). To project future UEC, appliances that currently have EE S&L were given baseline assumptions as defined in the EU commission delegated regulations no 1059/2010 (EU, 2010) while those without an existing EE S&L were forecasted by historical trend projection. The inputs for the EE S&L and baseline assumptions are shown in Table 3.10 – Table 3.17.

3.4.8.3 Appliance ownership

Ownership of appliances is directly affected by income (Dominguez et. al., 2019, Olaniyan et. al., 2018, McNeil and Letschert, 2010). Thus, this study uses GDP per capita as a proxy for income for each household in Nigeria. There are very few historic appliance ownership data for Nigeria. Where they exist, all the mostly used appliances were not covered. For appliances with no historical ownership data, data from Ghana and India were adapted (Diawuo et. al., 2018, Walia et. al., 2020) because they have similar socioeconomic characteristics, climatic condition, and electrification rates as Nigeria. Appliance ownership data for the end year, 2050 was also adopted from a recent Ghana study (Diawuo et. al., 2019). Table 3.18 shows the parametric data used in predicting the future ownership evolution up to 2050 and the model metric RMSE. The lower the RMSE value, the better the modelled result matches the raw data. Figure 3.4 showed the modelled appliance ownership profile up to 2050.

Table 3.8: Parameters and data for estimating the historical appliance unit annual electricity consumption

Annual Electricity Consumption (kWh)							
Appliance Description	**Average Rated Consumption (Watts)**	**Estimated Average Use (Frequency)**	**Estimated Weekly Average Use (Hours/Week)**	**Estimated Average Annual Use (Weeks/Year)**	**Estimated Average Annual Use (Hours/Year)**	**Estimated Average Annual Consumption (kWh)**	**Technology Improvement Factor**
Radio	60	4hours/day, all year	28	52	1456	87	1.50
Television	205	4hours/day, all year	28	52	1456	298	1.50
Mobile Phone (Charging)	3	2hour/day, all year	14	52	728	2	1.50
CD/DVD Player	17	2hours/day, all year	14	52	728	12	1.50
PC(Desktop Computer)	100	2hours/day, all year	14	52	728	73	0.50
PC (Laptop) (Charging)	65	2hours/day, all year	14	52	728	47	1.00
Fan	80	6hours/day, 9months/year	42	40	1680	134	1.50
Electric Cooker/Oven	1215	2hour/day, all year	14	52	728	885	1.00
Refrigerator	225	24hours/day, 7days/week	168	52	8736	1966	1.50
Freezer	286	24hours/day, 7days/week	168	52	8736	2498	1.30
Microwave Oven	814	15minutes/day, all year	1.75	52	91	74	1.50
Blender	323	3times/week, 3min per use	0.15	52	7.8	3	1.50
Toaster	754	5times/week, 2min. per use	0.17	52	8.84	7	1.00

Table 3.8 Continued

Annual Electricity Consumption (kWh)							
Appliance Description	**Average Rated Consumption (Watts)**	**Estimated Average Use (Frequency)**	**Estimated Weekly Average Use (Hours/Week)**	**Estimated Average Annual Use (Weeks/Year)**	**Estimated Average Annual Use (Hours/Year)**	**Estimated Average Annual Consumption (kWh)**	**Technology Improvement Factor**
Electric Kettle	1832	5times/week, 5min. per use	0.42	52	21.84	40	1.00
Electric Water Heater	1916	4times/week, 15mins per use	1	52	52	100	1.50
Electric iron	1254	3times/week, 30mins per use	1.5	52	78	98	1.50
Vaccum	1709	3times/week, 20min per use	1	52	52	89	1.50
Electric Clothes Dryer	2790	3times/week, 60mins per use	3	52	156	435	1.00
Washing Machine	2500	3times/week, 60mins per use	3	52	156	390	1.00

Table 3.9: Parameters and data for estimating the unit energy consumption of an air conditioner (Diawuo, et. al., 2019)

Year	Cooling Capacity (kW)	EER (W/W)	Input power (kW)	Number of Hrs/yr	UEC(kWh/yr)
2000	4.4	2.50	1.76	1120	1971.20
2001	4.4	2.52	1.75	1120	1957.50
2002	4.4	2.54	1.74	1120	1943.89
2003	4.4	2.55	1.72	1120	1930.38
2004	4.4	2.57	1.71	1120	1916.96
2005	4.4	2.59	1.70	1120	1903.63
2006	4.4	3	1.47	1120	1642.67
2007	4.4	3	1.47	1120	1642.67
2008	4.4	3	1.47	1120	1642.67
2009	4.4	3	1.47	1120	1642.67
2010	4.4	3	1.47	1120	1642.67
2011	4.4	3	1.47	1120	1642.67
2012	4.4	3	1.47	1120	1642.67
2013	4.4	3	1.47	1120	1642.67
2014	4.4	3	1.47	1120	1642.67

Table 3.10: Energy Efficiency Class for Refrigerator (kWh/year). Note: Norminal Temp (Tc) = ºC, Fresh-food storage compartment = 5, FF = 1, CC = 1.2, BI = 1, M = 0.77, N = 303, CH = 50

EE Class	A+++	A++	A+	A	B	C	D
EEI	21	28	38	49	65	85	103
Category (Table 1)	7	7	7	7	7	7	7
Climate Classes (Table 3)	T						
Storage volume of compartment (Vc) [l]	500	500	500	500	500	500	500
Equivalent volume (Veq)[l]	600	600	600	600	600	600	600
Standard annual energy consumption (SAEc) [kWh/yr]	819.2	819.2	819.2	819.2	819.2	819.2	819.2
Annual energy consumption (Aec) [kWh/yr]	172.03	229.38	311.30	401.41	532.48	696.32	843.78

Table 3.11: Energy Efficiency Class for Freezer (kWh/year). Note: Norminal Temp (Tc) = ºC, Food freezer compartment (four-star compartment) = -18, FF = 1, CC = 1.2, BI = 1, CH = 0, Category = 9, M = 0.472, N = 286.

EE Class	A+++	A++	A+	A	B	C	D
EEI	21	28	38	49	65	85	103
Category (Table 1)	9	9	9	9	9	9	9
Climate Classes (Table 3)	T						
Storage volume of compartment (Vc) [l]	420	420	420	420	420	420	420
Equivalent volume (Veq)[l]	1083.6	1083.6	1083.6	1083.6	1083.6	1083.6	1083.6
Standard annual energy consumption (SAEc) [kWh/yr]	797.459	797.459	797.459	797.459	797.459	797.459	797.459
Annual energy consumption (Aec) [kWh/yr]	167.47	223.29	303.03	390.76	518.35	677.84	821.38

Table 3.12: Energy Efficiency Class for Washing Machine (kWh/year)

EE Class	A+++	A++	A+	A	B	C	D
EEI	45	48	55	63	72	81	87
Rated Capacity (Kg)	6	6	6	6	6	6	6
Standard annual energy consumption (SAEc) [kWh/yr]	333.7	333.7	333.7	333.7	333.7	333.7	333.7
Annual energy consumption (Aec) [kWh/yr]	150.17	160.18	183.54	210.23	240.26	270.30	290.32

Table 3.13: Energy Efficiency Class for Television (kWh/year)

EE Class	A+++	A++	A+	A	B	C	D
EEI	0.09	0.13	0.2	0.28	0.36	0.49	0.68
P_{basic} [W]	24	24	24	24	24	24	24
Visible Screen area, A (dm2)	31	31	31	31	31	31	31
P_{ref}(A) [W]	157.994	157.994	157.994	157.994	157.994	157.994	157.994
P=(Pref*EEI)	14.2195	20.5393	31.5989	44.2384	56.878	77.4173	107.436
Annual on-mode energy consumptionI [kWh/yr]	20.76	29.99	46.13	64.59	83.04	113.03	156.86

Table 3.14: Energy Efficiency Class for Vacuum Cleaner (kWh/year)

EE Class	A+++	A++	A+	A	B	C	D
EEI	9	12	19	26	32	38	44
Annual energy consumptionI [kWh/yr]	9	12	19	26	32	38	44

Table 3.15: Energy Efficiency Class for Desktop Computer (kWh/year)

EE Class	A+++	A++	A+	A	B	C	D
EEI	0	0	0	28.7	33.4	63.5	75.8
Annual energy consumptionI [kWh/yr]	0	0	0	29	33	64	76

Table 3.16: Energy Efficiency Class for Laptop Computer (kWh/year)

EE Class	A+++	A++	A+	A	B	C	D
EEI	0	0	0	10.9	18.1	26.3	0
Annual energy consumptionI [kWh/yr]	0	0	0	10.9	18.1	26.3	0.0

Table 3.17: Appliances UEC and class baseline for projection between 2020 and 2050

Appliances	2020	2030		2040		2050	
Refrigerator	843.776	696.32	C	696.32	C	532.48	(B)
Freezer	821.382976	677.84032	C	677.84032	C	518.34848	(B)
Air Conditioner	1642.67	1449.41	(A+)	1449.41	(A+)	1232	(A++)
Washing machine	290.319	270.297	C	270.297	C	240.264	(B)
Vacuum cleaner	44	38	C	38	C	32	(B)
Television	156.86	113.03	C	113.03	C	83.04	(B)
Desktop computer	64	33	(B)	29	(A)	29	(A)
Laptop computer	30.1	26.3	C	18.1	(B)	18.1	(B)

Table 3.18: Appliance ownership parameters

Appliance	S^a	b	$\vartheta(t)$	RMSE
Refrigerator	0.8938	0.129079754	33.1872823	2.644719881
Fan	0.815	0.085782211	18.5407341	1.985466904
Television	0.808	0.135242352	20.08354678	2.373034847
Electric Iron	0.9064	0.102267853	25.07747715	3.013661392
Air conditioner	0.197	0.15897063	35.60235537	0.576148177
Washing Machine	0.338	0.234931097	40.36684232	0.38965877
Freezer	0.206	0.133579766	24.45774579	0.367513128
Microwave	0.55	0.215855737	37.57145192	0.725938822
Blender/food processor	0.7	0.430303744	26.77816539	0.001058154
Mobile phone	0.85	0.759654204	16.92421172	2.66961653
Desktop computer	0.203	0.15411809	30.93533238	1.078620044
Laptop computer	0.3	0.382967837	29.00173104	0.002927059
Electric Clothes Dryer	0.338	0.267036402	39.65875693	0.260779464
VCD/DVD/MP3/MP4 player	0.56	0.135035793	18.34674486	1.44850127
Radio	1	0.080615166	17.31178136	2.711716413
Vacuum cleaner	0.134	0.317568478	30.6351388	0.001403273
Electric cooker	0.5322	0.207942564	36.99975596	0.75744323
Toaster	0.3	0.331551076	31.093125	0.003591
Electric kettle	0.393	0.310998545	33.92205827	0.008703156
Electric Water heater	0.064	0.296345901	29.55145308	0.002120284

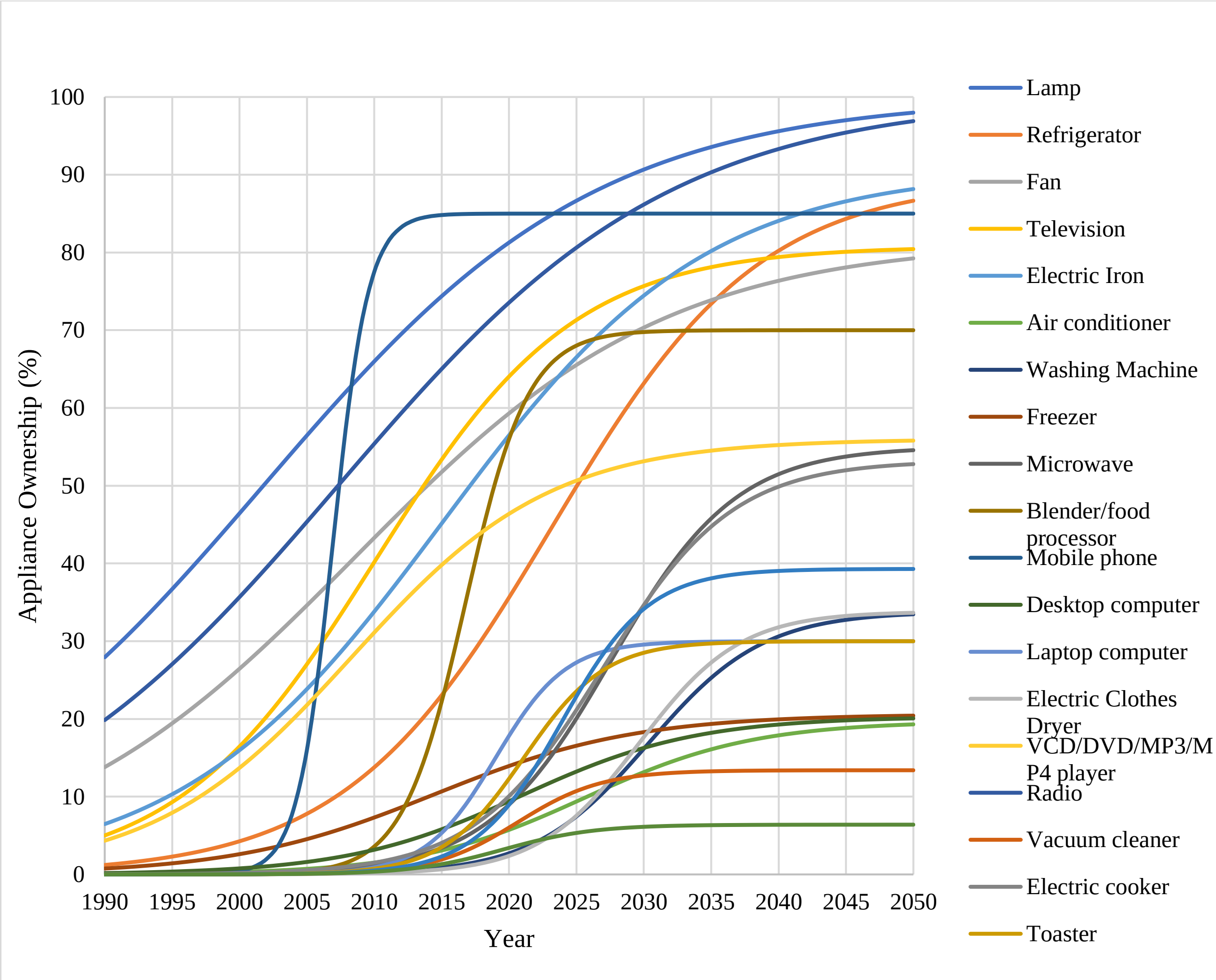

Figure 3.4: Modelled appliance ownership evolution profile.

3.4.8.4 Appliance Survival

This study adopts appliance usage data from existing published studies because most appliances have same lifetime and similar survival curve (McNeil and Letschert 2010, Diawuo et. al., 2019). A 90th and 50th percentile of the appliances average lifetime is considered as the failure steepness and service life (Zachariadis et. al., 1995). Table 3.19 and Figure 3.5 show the data used for calculating survival and the curves respectively.

3.4.8.5 Lighting Parameters

Table 3.20 show the lighting technologies efficacy adopted for this study (Shen, 2006). There is a positive correlation between floor space area and GDP/capita for Ghana as determined by Diawuo et. al., 2018. This study adopts that relationship (Figure 3.6), and the correlation is used to forecast floor space for lighting up till 2050 for Nigeria. Future projections lighting technologies share up to 2050 is presented in Table 3.21.

3.4.8.6 End-use load profiles (LOADM)

The residential load profile data and their sources are presented in Table 3.22. This study assumes that refrigerator power demand is constant in tropical environments even though the demand is related to temperature (McNeil et. al., 2019). The LOADM make up for loss in transmission and distribution (totalled 16% in 2014) (World Bank, 2019). The raw load profile data for all the end uses are presented in Table 3.23 while the average load, maximum demand, and load factor parameters for all end uses are presented in Table 3.24. The assumed normalized load profiles used in this study for all end use are shown in Figures 3.7 and 3.8.

Table 3.19: Appliance survival parameters.

Appliance	Average age (l)	T^i	b^i
Refrigerator	15	14.85	5.463009816
Fan	10	9.9	3.642006414
Television	10	9.9	3.64200647
Electric Iron	10	9.9	3.642006414
Air conditioner	12	11.88	4.370407739
Washing Machine	15	14.85	5.46300979
Freezer	12	11.88	4.370407699
Microwave	9	8.91	3.27780573
Blender/food processor	10	9.9	3.642006414
Mobile phone	4	3.96	1.456802577
Desktop computer	8	7.92	2.913605146
Laptop computer	6	5.94	2.185203881
Radio	10	9.9	3.642006414
Electric Clothes Dryer	13	12.87	4.734608204
VCD/DVD/MP3/MP4 player	5	4.95	1.82100323
CD player	5	4.95	1.82100323
Vacuum cleaner	10	9.9	3.642006414
Rice cooker	6	5.94	2.185203881
Toaster	7	6.93	2.54940452
Electric kettle	6	5.94	2.185203881
Water heater	11	10.89	4.006207118

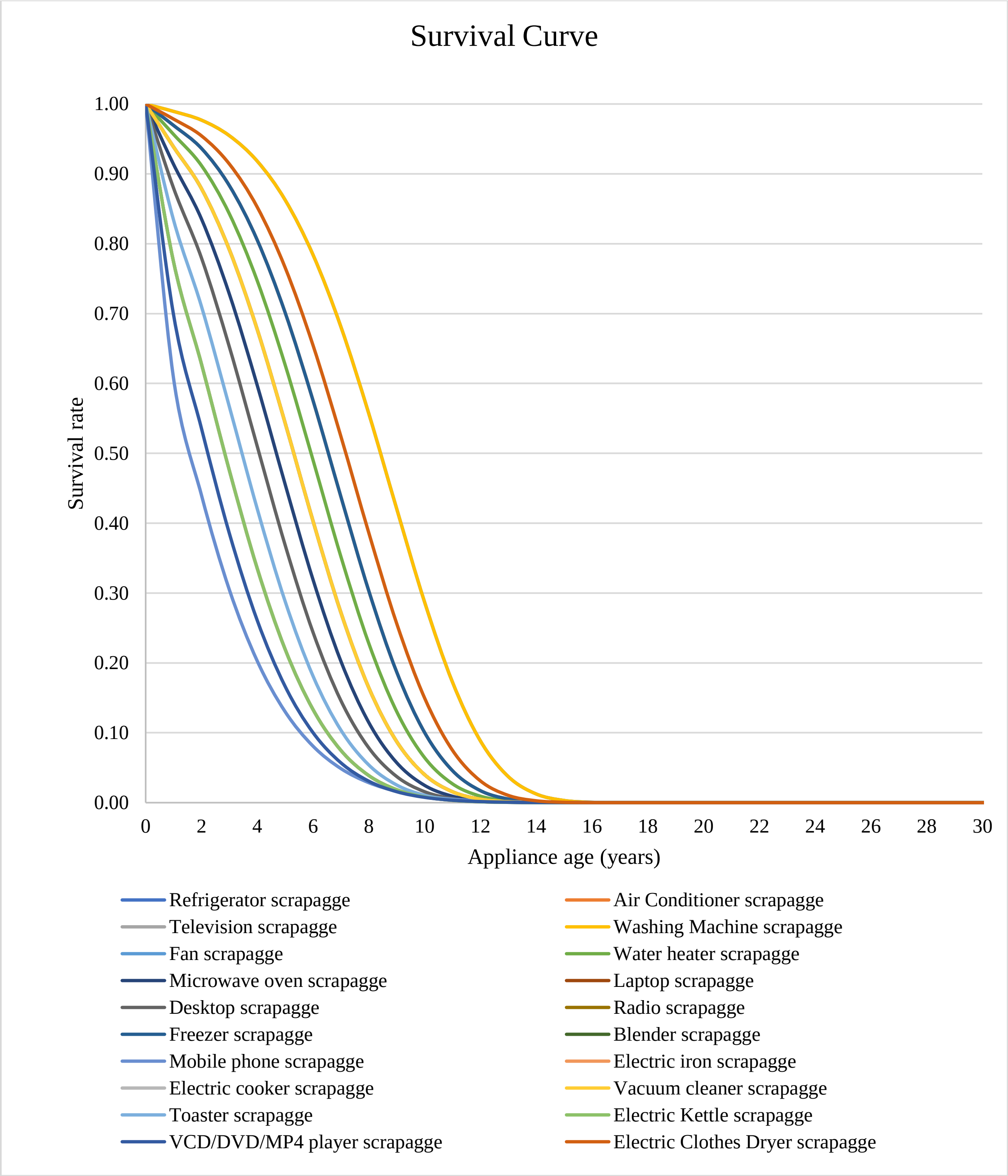

Figure 3.5: Appliances Survival Curve.

Table 3.20: **Lighting technology efficacy data.** Note: Average lighting requirement = 80 lm/w, lighting duration = 2.5 hours. Source: Shen (2006)

Lighting technology	Efficacy (lm/W)
Incandescent lamp (IL)	12
Fluorescent lamp (FL)	70
Compact fluorescent lamp (CFL)	75
Light emitting diode (LED)	94

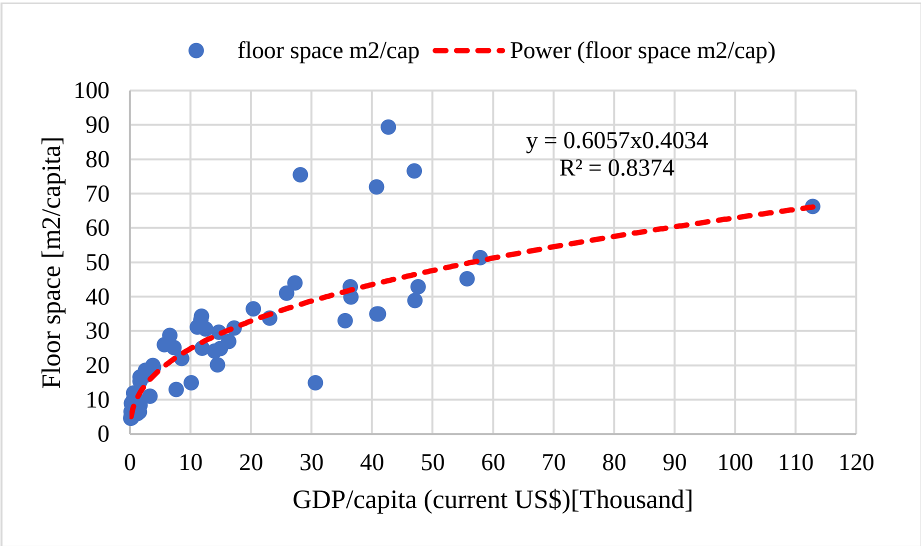

Figure 3.6: Floor space (m^2 /cap) vs. GDP per capita (reproduced from Diawuo et. al., 2018).

Table 3.21: Lighting technology shares baseline (2010-2050)

Lighting technology	2010	2020	2030	2040	2050
Incandescent lamp (IL)	65%	26%	0%	0%	0%
Fluorescent lamp (FL)	15%	5%	5%	3%	3%
Compact fluorescent lamp (CFL)	20%	65%	85%	87%	85%
Light emitting diode (LED)	0%	4%	10%	10%	12%

Table 3.22: Sources of load profile data

End Use	Source	Country
Lighting	ECN, GEF, & UNDP (2014)	Nigeria
Air conditioning	ECN, GEF, & UNDP (2014)	Nigeria
Entertainment	ECN, GEF, & UNDP (2014)	Nigeria
Refrigeration	ECN, GEF, & UNDP (2014)	Nigeria
Laundry	Diawuo et. al., 2020	Ghana
Cooking	Diawuo et. al., 2020	Ghana
Heating	Diawuo et. al., 2020	Ghana
Cleaning	ECN, GEF, & UNDP (2014)	Nigeria

Table 3.23: Load profile data for all end uses.

	Lighting (W - hourly)	Air conditioner (W - hourly)	Entertainment (W - hourly)	Laundry (% Frequency)	Cooking (W - hourly)	Heating (% Frequency)	Cleaning (% Frequency)
1:00	44.44	97.89	7.11	0	1.15	0	0
2:00	42.30	91.59	5.41	0	0.99	0	0
3:00	42.38	86.71	4.64	0	1.08	0	0
4:00	40.98	81.09	4.91	0	1.17	0	0
5:00	44.13	75.77	5.60	0	1.83	30	0
6:00	50.43	62.83	7.71	0	4.09	100	0
7:00	54.90	45.79	11.94	0	1.35	0	0
8:00	47.01	36.32	16.63	27	2.76	0	27

Table 3.23 Continued

	Lighting (W - hourly)	Air conditioner (W - hourly)	Entertainment (W - hourly)	Laundry (% Frequency)	Cooking (W - hourly)	Heating (% Frequency)	Cleaning (% Frequency)
9:00	40.71	33.07	16.88	75	3.01	0	75
10:00	36.99	34.61	16.03	100	3.20	0	100
11:00	33.22	42.15	15.28	75	3.10	0	75
12:00	30.48	46.10	15.08	50	2.39	0	50
13:00	34.32	52.54	15.91	28	3.87	0	28
14:00	36.36	54.83	16.38	28	3.40	0	28
15:00	39.52	63.52	17.53	18	4.22	0	18
16:00	39.82	67.06	18.43	0	3.87	0	0
17:00	44.82	77.39	20.69	0	4.25	0	0
18:00	51.37	74.93	23.67	0	3.23	0	0
19:00	75.52	69.64	27.74	0	3.28	0	0
20:00	95.57	92.84	34.54	61	4.05	49	61
21:00	102.38	105.88	37.03	90	3.46	49	90
22:00	93.26	107.11	31.61	77	3.49	0	77
23:00	68.35	110.35	18.21	0	1.81	0	0
24:00	53.13	111.04	11.10	0	1.44	0	0

Table 3.24: Average Load, Maximum Demand, & Load Factor Parameters for all end uses

	Lighting (W – hourly)	Air conditioning (W – hourly)	Entertainment (W – hourly)	Laundry (%)	Cooking (W – hourly)	Heating (% Frequency)	Cleaning (% Frequency)
Average load	51.77	71.71	16.67	26.21	2.77	9.50	26.21
Maximum demand	102.38	111.04	37.03	100.00	4.25	100.00	100.00
Load factor	0.51	0.65	0.45	0.26	0.65	0.10	0.26

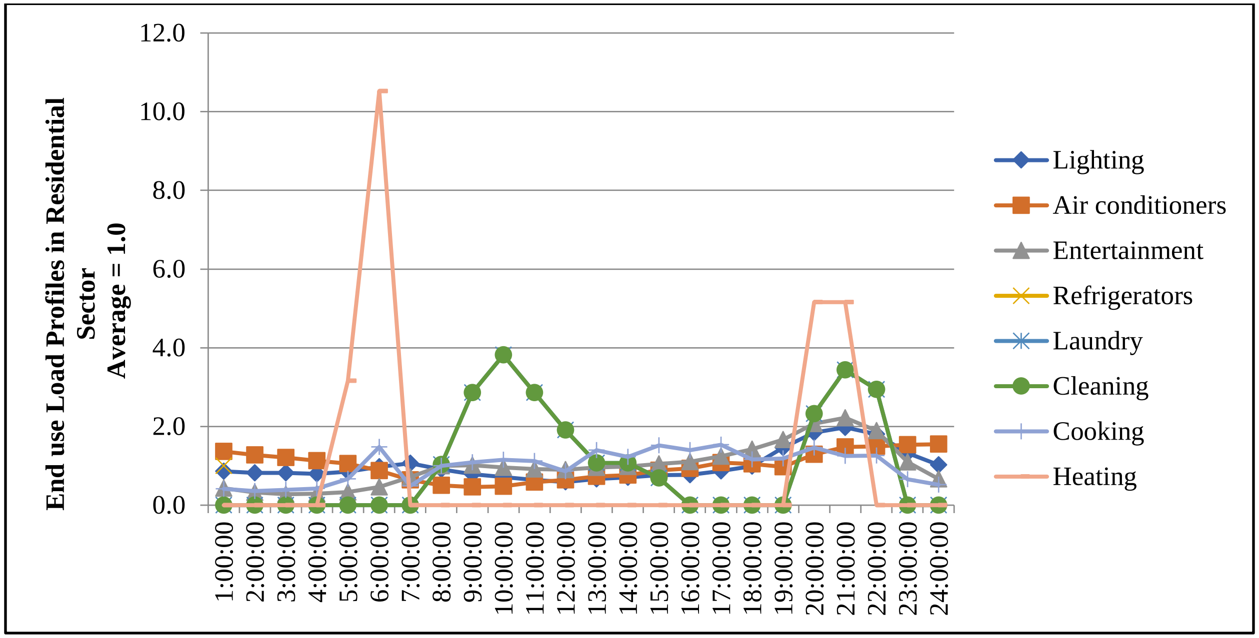

Figure 3.7: Load Curve Profile for all end uses.

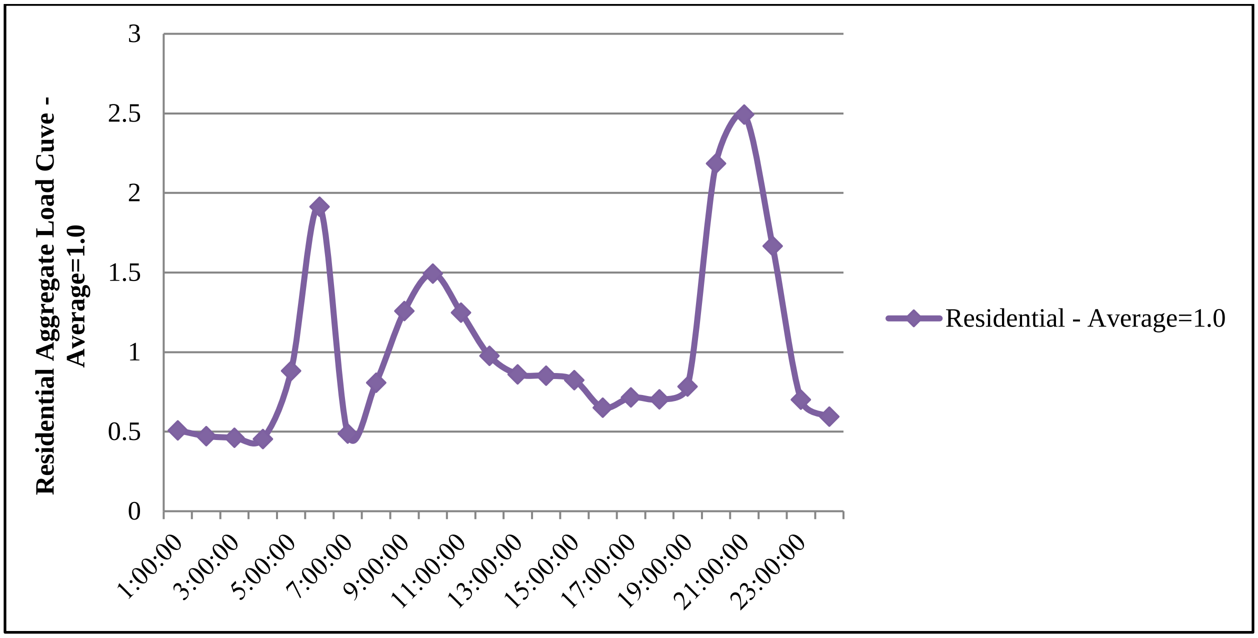

Figure 3.8: Average Load Curve Profiles for all end uses.

3.4.8.7 Emissions Mitigation

Electricity specific carbon factor of 0.439 was used based on the work of Ecometrica, 2011 where the consumed electricity emission factors factored in the emissions/kWh of consumed electricity and losses from transmission and distribution (T&D).

3.4.8.8 Bill savings, Payback Period, and Life-Cycle Cost:

Electricity tariff was sourced from the Nigerian Electricity Regulatory Commission (NERC) for the four distribution companies in Nigeria (Benin, Ibadan, Ikeja, and Eko). The tariffs were reported in Naira (Nigeria local currency) and then converted to dollars in this study. For conversion, an official exchange rate of 440/$ (the exchange rate at the time of writing this dissertation) was assumed. After converting to dollars, the averages for all the zones for the years 2014 – 2018 were averaged and then forecasted up to 2049 using the single compound amount methodology. An electricity tariff of 0.064 USD/kWh for Africa was assumed for 2050 (Pappis, 2016).

The price of appliances was gotten online from Nigeria's most popular e-commerce website, www.jumia.com.ng. Future purchase price is assumed to be dependent on previous trends of prices of appliances in the market adjusted for inflation. It is assumed that price and cost move in same direction. As such, the causal factor is the rising rate of inflation as a macroeconomic policy variable that determines all the appliance prices under the BAU and BAT scenarios. A discount rate of zero was also assumed because purchases in Nigeria are paid in cash. Consumers can install most of the appliances themselves, so cost of installation for most of the appliances is assumed to be $0. For appliances that requires technical expertise, e.g. A.C, an installation price of 20% of the purchase price is assumed.

LCC, PBP, Energy Savings, and Bill Savings were only calculated for appliances with existing standards and labeling in Nigeria. This is because there are already MEPS for these appliances. Both LCC and PBP can be calculated across a wide range of labeling. As earlier discussed, standards for Nigeria were announced in 2019. This study assumes that the standard will be effective three years after the announcement. Thus, an effective standard date of 2022 was assumed. Therefore, LCC and PBP was calculated assuming that consumers will each purchase new appliances in 2022. Eight appliances have existing standards as shown in tables 3.12 – 3.19. These appliances are refrigerator, freezer, air conditioners, washing machines, vacuum cleaners, desktop computer, and laptop computers and televisions.

CHAPTER 4: RESULT AND DISCUSSION

This section discusses the total residential electricity consumption (REC), peak load demand, and energy savings in both the Business As Usual (BAU) and the Best Available Technology (BAT) scenarios from 2020 – 2050. The result of the comprehensive analysis of the environmental and economic impacts of efficient energy appliances are also discussed. These analyses were performed following the equations, assumptions, and data presented in Chapter 3.

4.1 End Use Electricity Consumption Evolution under the BAU and BAT scenarios

4.1.1 Evolution of end use energy consumption

The end use consumption under the BAT and BAU scenarios are shown in Figures 4.1 and 4.2. Electricity consumption in 2050 is highest under the BAU scenario (160540 GWh) compared to the BAT scenario (127902 GWh). The percentage difference between the BAT and BAU scenarios between 2020 – 2050 is presented in Table 4.1. The percentage share of each of the end use in 2020 and 2050 is also shown in Figures 4.3 – 4.6. Consumption of electricity increases in the BAU and BAT scenarios prior to when the saturation level has been reached and introduction of efficient lightings and other efficient appliances. Refrigeration, entertainment, and cleaning contribute to the reduction in consumption in 2050. Each of the end uses are explained further in the next sections.

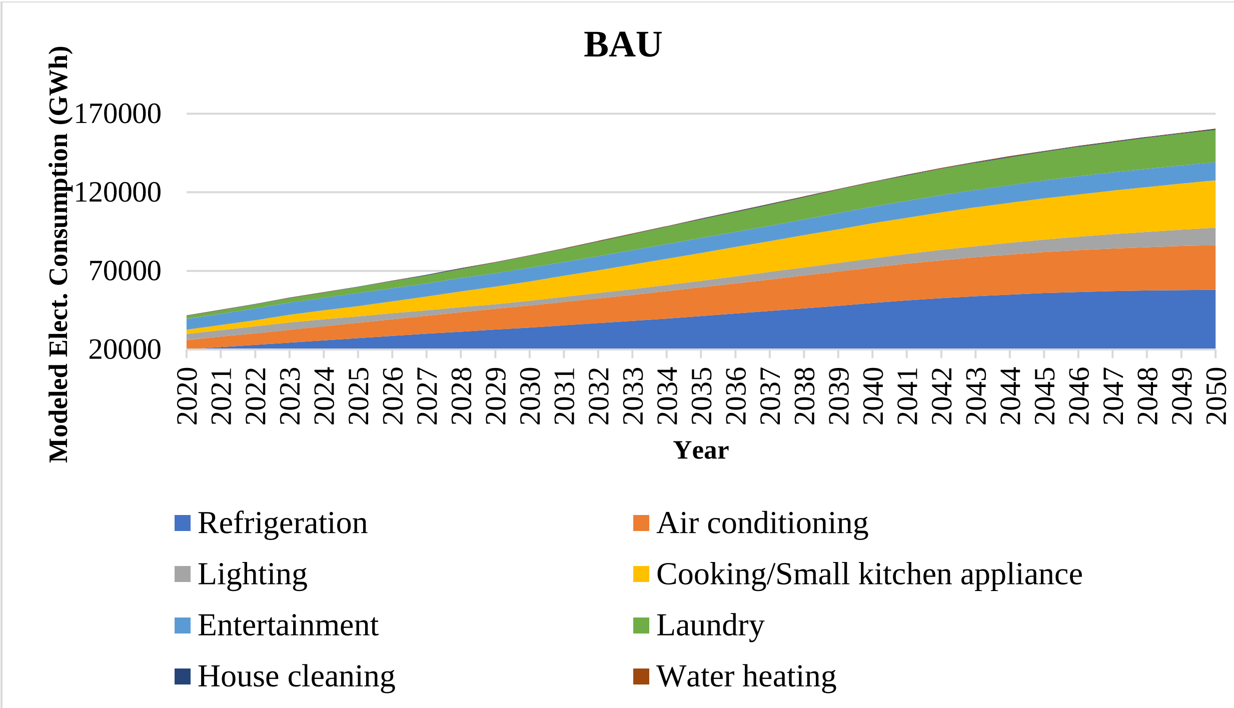

Figure 4.1: Future evolution of end use under the BAU scenario

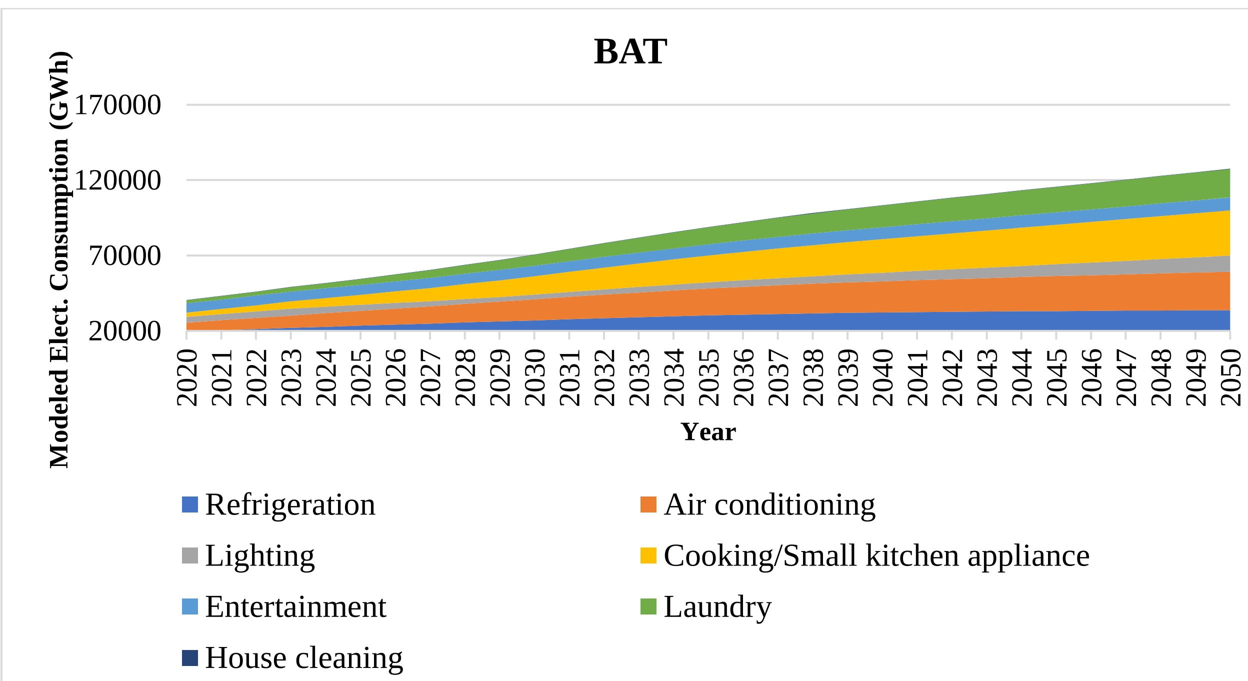

Figure 4.2: Future evolution of end use under the BAT scenario

Table 4.1: Differences in REC under the BAU and BAT scenarios

	2020	2030	2040	2050
Scenarios	**REC (GWh)**	**REC (GWh)**	**REC (GWh)**	**REC (GWh)**
BAU	41657.84	79945.67	126863.82	160540.20
BAT	40507.26	70872.56	103658.50	127902.44
% decrease	-2.76	-11.35	-18.29	-20.33

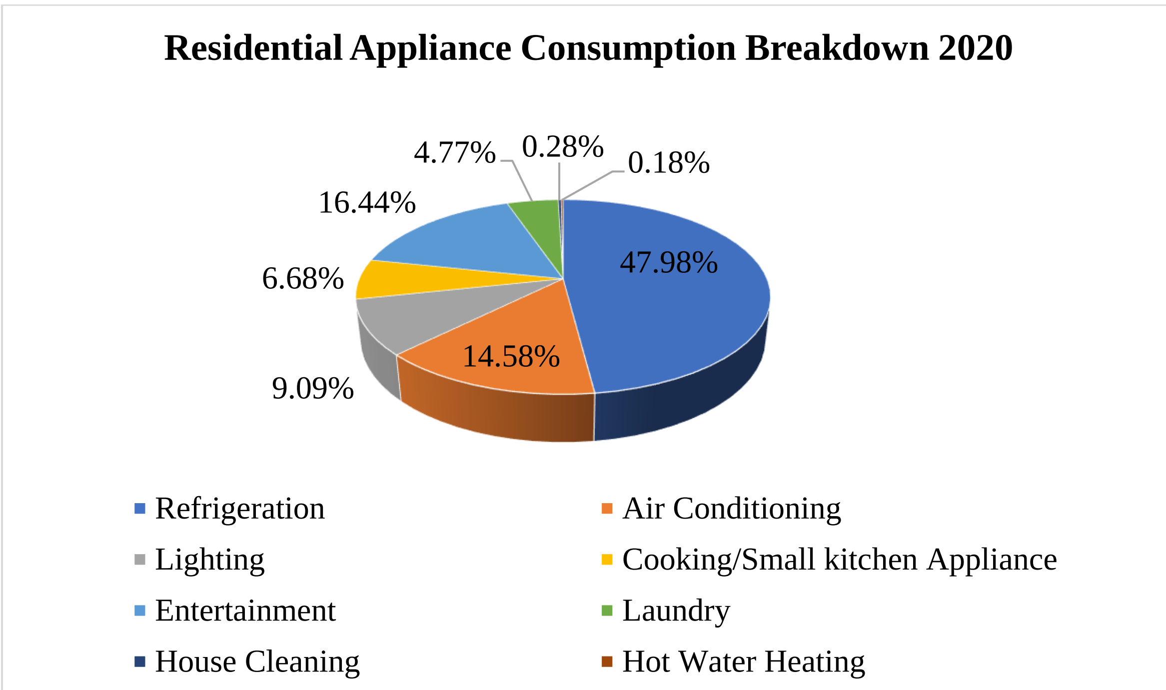

Figure 4.3: Percentage end use share in 2020 under the BAU scenario

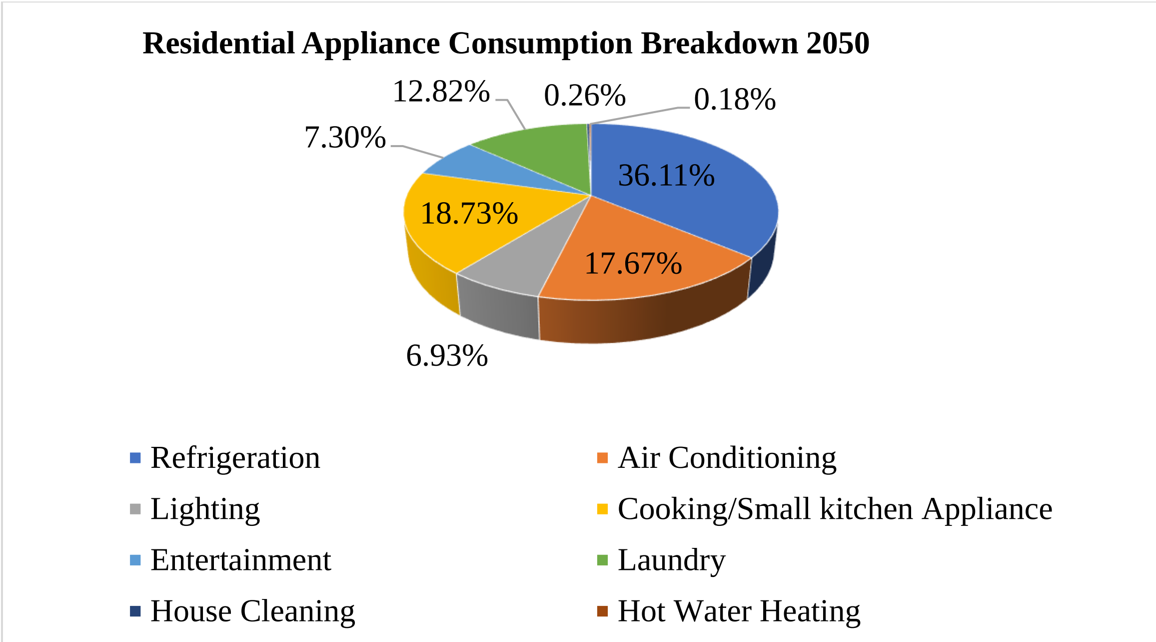

Figure 4.4: Percentage end use share in 2050 under the BAU scenario

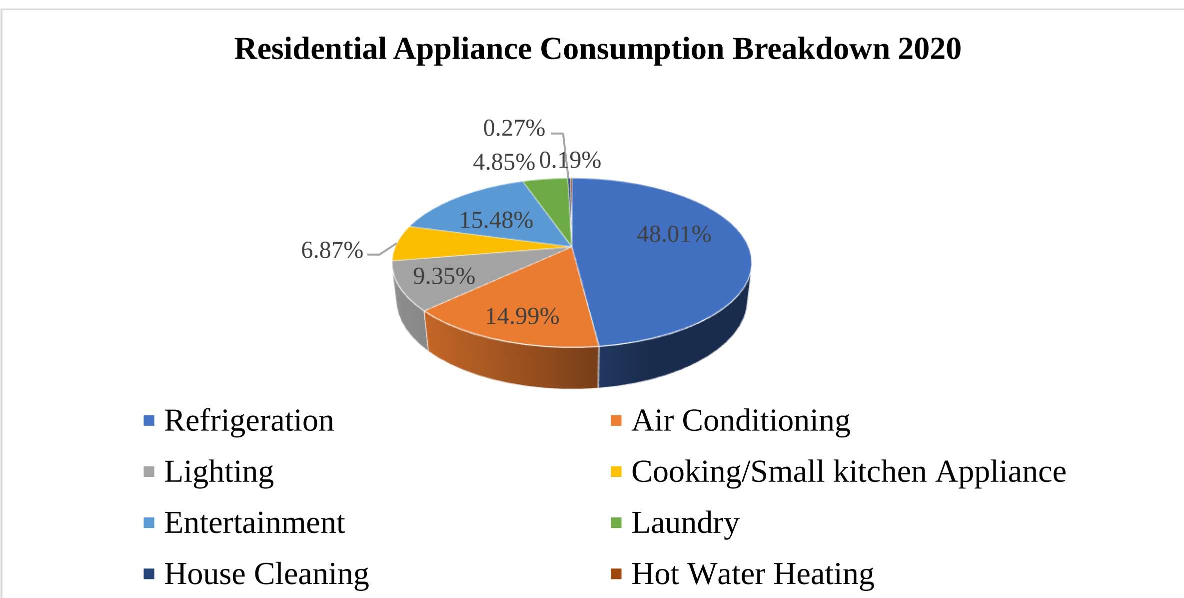

Figure 4.5: Percentage end use share in 2020 under the BAT scenario

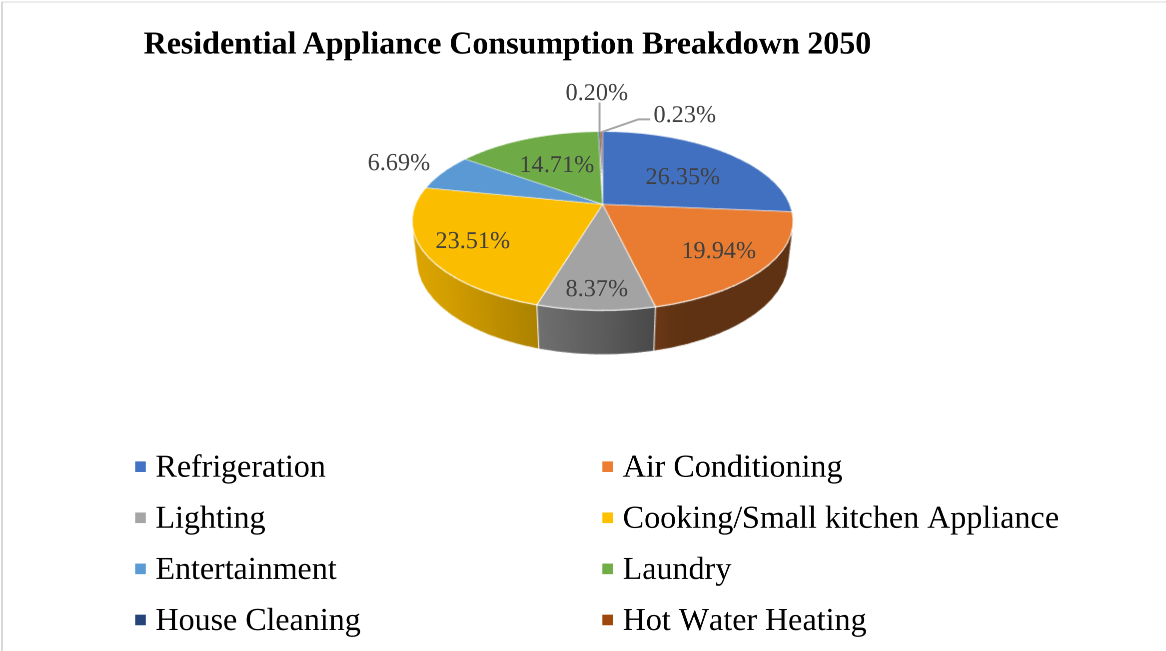

Figure 4.6: Percentage end use share in 2050 under the BAT scenario

4.1.2 Refrigeration services

Refrigeration services consumed 48% (19986 GWh) of the total household electricity in 2020 and is projected to decrease to 36% (57967 GWh) in 2050 under the BAU scenario. In the BAT scenarios, the contribution is 48% (19445 GWh) in 2020 and projected to decrease to 26% (33699 GWh) in 2050. Refrigeration services take the largest share of residential electricity consumption under both scenarios caused by an increasing refrigeration services ownership.

4.1.3 Air conditioning services

Air condition services consumed 15% (6073 GWh) of the total household electricity in 2020 and is projected to increase to 18% (28370 GWh) in 2050 under the BAU scenario. In the BAT scenario, the contribution is 15% (6074 GWh) in 2020 and projected to increase to 20% (25502 GWh) in 2050. Although efficient air conditioners are introduced into the market, more Nigerians are expected to own and use the appliances for longer hours because of the tropical nature of the country making air conditioners the 3rd largest contributor to the total REC in both the BAU and BAT scenarios in 2050.

4.1.4 Entertainment services

Entertainment services consumption percentage of the REC is 16% (6846 GWh) in 2020 while its 2050 projection is 7% (11711 GWh) under the BAU scenario. Its percentage share under the BAT scenario is 15% (6269 GWh) and 7% (8557 GWh) in the year 2020 and 2050 respectfully. Entertainment services is the 4th and 5th largest contributor to REC under the BAU and BAT scenarios respectively. Although there is a steady increase of entertainment services ownership in Nigeria, its lower consumption share can be ascribed to the introduction of highly efficient entertainment appliances into the market.

4.1.5 Laundry services

Laundry services contributed 5% (1988 GWh) and 13% (20585) in 2020 and 2050 respectively under the BAU scenarios. It contributed 5% (1964 GWh) in 2020 and expected to contribute 14% (18817 GWh) in 2050 under the BAT scenario. The increase in the contribution of this service can be ascribed to an increase in appliance ownerships. Washing machines are becoming popular in Nigeria and many households due to its comfortability. More so, as GDP improves, more Nigerians can afford the appliance thus making it the 4th largest contributor to the total REC in 2050 under the BAU and BAT scenarios.

4.1.6 Lighting services

Prior to the introduction of efficient CFLs into the Nigeria market in 2009, lighting took a chunk of the total REC because every household need light regardless of the affordability. Lighting contribution to the total REC in 2020 is 9% (3788 GWh) and 7% (11133 GWh) respectively under the BAU scenarios. Under the BAT scenarios, lighting constitutes 9% (3788 GWh) and 8% (10711 GWh) of the total REC in 2020 and 2050 respectfully. Although, lighting ownerships increase over the years, the continuous introduction of efficient lighting into the market slowed than the REC increase making it the 5th largest contributor to the total REC.in 2050 under the BAU and BAT scenarios.

4.1.7 Cooking services

Cooking services contribution to the REC under the BAU scenario in 2020 and 2050 is 6% (2782 GWh) and 19% (30065 GWh) respectively. Under the BAT scenario, its contribution is 7% (2782 GWh) and expected to increase to 24% (30065 GWh) in 2050. This makes these services the 2nd contributor to the total REC under both scenarios. The reason for this continuous growth can be ascribed to the fact that more Nigerians will continue to use these appliances in meeting their cooking needs. Although the numbers presented here may reduce if energy labelling and standards become available for them in Nigeria.

4.1.8 House cleaning and water heating services

Both cleaning and water heating services contribute less than 1% of the total REC in Nigeria. Under the BAT scenario, house cleaning services contribute 0.27% (110.57 GWh) in 2020 and 0.20% (256.79 GWh) in 2050 to the total REC. Under the BAU scenario, house cleaning services contribute 0.28% (117.05 GWh) and 0.26% (412 GWh) in 2020 and 2050 respectively. Water heating contribute 0.19% (75.54%) in 2020 and 0.23% (2955 GWh) in 2050 under the BAT scenario. It contributed 0.18% (75.54 GWh) in 2020 and 0.18% (294.57 GWh) in 2050. The low contribution can be ascribed to the fact that many Nigerians use fuels and biomass for heating and do not own vacuum cleaner and electric heater.

The appliance share of each of the end-uses is summarized in Table 4.2

4.2 Load Curves under the BAU Scenarios

The hourly load curves under the BAU scenario between 2010 and 2050 is shown in Figure 4.7 while Table 4.3 shows the peak demand numbers. With 2020 as the base year, Nigerian residential peak demand is projected to increase by 96% (14036 MWh) in 2030, then by 220% (22970MWh) in 2040, and by 313% (29575.24MWh) in 2050. In 2010, the evening peak between 7pm to 9pm is largely caused by lighting and refrigeration with both consuming 56% of peak demand at 9pm and entertainment consuming 25%. The two end uses alone consume more than 80% of the evening peak demand. In 2050, laundry and refrigeration consume 27% and 22% of the evening peak demand respectively. Air condition and cooking consumes 16% and 14% of the peak demand

Table 4.2: Percentage share of end-use for 2020 and 2050 under the BAU and BAT scenarios. Note: All numbers are in %

	Appliances	BAU 2020	BAU 2050	BAT 2020	BAT 2050
Refrigeration	Refrigerator	74.81	81.63	74.91	81.62
	Freezer	25.19	18.37	25.09	18.38
Air Conditioning	Air conditioner	67.86	80.92	67.86	78.78
	Fan	32.14	19.08	32.14	21.22
Lighting	Incandescent lamp	68.84	0.00	68.84	0.00
	Fluorescent lamp	2.27	3.29	2.27	2.28
	Compact Fluorescent lamp	27.54	86.92	27.54	72.28
	LED lamp	1.35	9.79	1.35	25.44
Cooking	Microwave	5.31	6.21	5.31	6.21
	Food processor/blender	1.13	0.27	1.13	0.27
	Rice cooker	89.16	90.10	89.16	90.10
	Toaster	0.82	0.39	0.82	0.39
	Electric kettle	3.59	3.03	3.59	3.03
Entertainment	Radio	25.55	30.37	27.91	41.57
	VCD/DVD/mp3/mp4 player	1.86	2.72	2.03	3.73
	Desktop computer	3.86	4.53	3.35	6.14
	Laptop computer	3.43	4.23	3.12	3.49
	Television	64.69	57.41	62.93	44.07
	Mobile Chargers	0.60	0.73	0.66	1.00
Laundry	Washing machine	17.43	37.42	16.38	31.54
	Electric Clothes Dryer	14.54	41.29	14.73	45.17
	Electric Iron	68.03	21.29	68.89	23.29
House Cleaning	Hoover (Vacuum Cleaning)	100.00	100.00	100.00	100.00
Hot Water Heating	Water heater (bathroom)	100.00	100.00	100.00	100.00

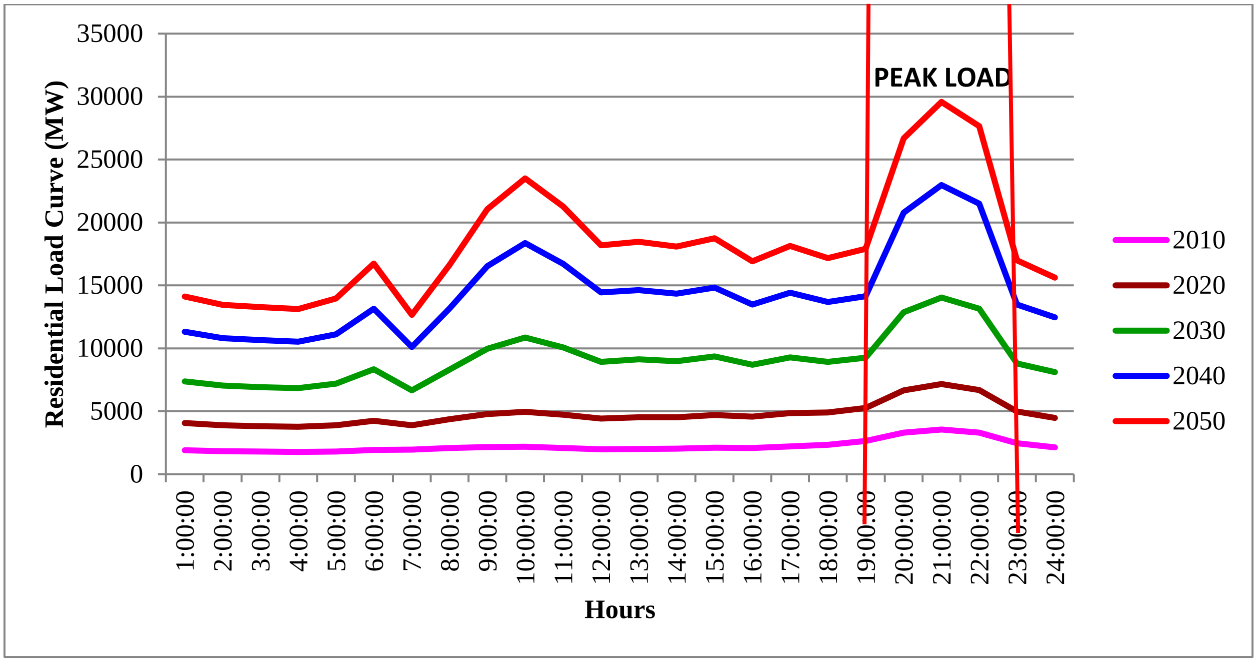

Figure 4.7: Evolution of Nigerian hourly load curve in the BAU scenario between 2010 and 2050

Table 4.3: Nigeria's Peak demand projections in the BAU scenario between 2010 and 2050

	21:00:00	*21:00:00*	*21:00:00*	*21:00:00*	*21:00:00*
	2010	**2020**	**2030**	**2040**	**2050**
Lighting	1015.63	855.11	684.52	1313.46	2513.53
Air conditioning	344.28	1023.74	2364.29	3809.04	4782.16
Entertainment	888.99	1736.10	2211.80	2668.66	2969.68
Refrigeration	966.44	2281.58	3878.97	5659.51	6617.24
Laundry	283.20	779.61	2940.31	6063.58	8069.61
Cooking	45.79	396.77	1744.08	3178.44	4288.02
Heating	3.85	44.48	101.72	135.49	173.44
Cleaning	2.83	45.89	110.80	142.24	161.56
Residential Peak Load (MWh)	3551.02	7163.28	14036.49	22970.42	29575.24

respectively. When compared to 2010, laundry evening peak demand has grown by 147% in 2050. This is due to the replacement of inefficient incandescent with CFL that started in Nigeria in 2009. Table 4.4, Table 4.5, Figures 4.8, and 4.9 show the hourly average load profiles for all end uses in 2010 and 2050 for the BAU scenario. The peak load demand projection for 2050 increases from 29575MW to 34339W when account is made for transmission and distribution loss (T&D) (Figure 4.10).

4.3 Load Reduction under the BAT Scenarios

Load curves in the BAU and BAT scenarios are compared between 2030 – 2050. A slow increase in the peak load up to 2050 is noticed because of the introduction of more efficient lightings in Nigeria starting in 2009 and other efficient appliances. In 2030, peak load in the BAT scenario is 12675 MW compared to 14037 MW (-11%) in the BAU scenario. In 2040, peak load in the BAT scenario is 19514 MW compared to 22970 MW (-15%) in the BAU scenario. In 2050, peak load in the BAT scenario is 24672 MW compared to 29575 MW (-17%) in the BAU scenario. Power savings in the BAT and BAU scenarios are compared in Figures 4.11, 4.12, and 4.13 for forecast years 2030, 2040, and 2050 respectively. The largest reduction in peak load under the BAT scenario comes from refrigeration and entertainment. Air-conditioner has a lower savings because tropical countries like Nigeria requires a high cooling capacity for air conditioners. The reductions are summarized in Tables 4.6 – 4.8.

4.4 Climatic Impact on Electricity Demand

As the world faces global warming, cooling degree days are expected to reduce in the tropical regions. This is because temperature increases will affect the demand for cooling and the operating

Table 4.4: Nigeria's hourly average load (MW) in 2010 under the BAU Scenario.

Hour	Lighting	Air conditioner	Entertainment	Refrigerator	Laundry	Cooking	Heating	Cleaning
1:00:00	440.855923	318.2815408	170.7901152	966.4424847	0	15.21467758	0	0
2:00:00	419.666614	297.804009	129.7975775	966.4424847	0	13.15138477	0	0
3:00:00	420.466173	281.9312243	111.3917279	966.4424847	0	14.23793968	0	0
4:00:00	406.572462	263.6443791	117.797049	966.4424847	0	15.45628697	0	0
5:00:00	437.742974	246.3746715	134.4705043	966.4424847	0	24.2630061	2.359288261	0
6:00:00	500.290195	204.2871366	185.026901	966.4424847	0	54.08922489	7.864294203	0
7:00:00	544.590057	148.8752317	286.7153048	966.4424847	0	17.80715056	0	0
8:00:00	466.363143	118.0871596	399.2642562	966.4424847	84.96116	36.49612277	0	0.84956428
9:00:00	403.858345	107.5180801	405.2850098	966.4424847	236.0032	39.82424881	0	2.35990078
10:00:00	366.986193	112.5161091	384.9279724	966.4424847	314.671	42.3974775	0	3.14653438
11:00:00	329.55804	137.0431867	366.8570616	966.4424847	236.0032	40.99434852	0	2.35990078
12:00:00	302.420493	149.9026845	362.1635105	966.4424847	157.3355	31.59425331	0	1.57326719
13:00:00	340.464126	170.8261032	382.0941661	966.4424847	88.10787	51.26634725	0	0.88102963
14:00:00	360.748624	178.2840324	393.2499442	966.4424847	88.10787	44.98841299	0	0.88102963
15:00:00	392.029823	206.5168488	420.9016094	966.4424847	56.64077	55.80813862	0	0.56637619
16:00:00	395.026955	218.0440977	442.4064165	966.4424847	0	51.23635776	0	0
17:00:00	444.668499	251.6325529	496.7996402	966.4424847	0	56.25640702	0	0
18:00:00	509.589819	243.6295554	568.3362914	966.4424847	0	42.6737185	0	0
19:00:00	749.187481	226.4123528	666.0274908	966.4424847	0	43.37794603	0	0
20:00:00	948.130739	301.8718158	829.3766582	966.4424847	191.9493	53.5323	3.853504159	1.91938597
21:00:00	1015.62879	344.2750966	888.9929868	966.4424847	283.2039	45.78702408	3.853504159	2.83188094
22:00:00	925.148911	348.242877	758.9560393	966.4424847	242.2966	46.14545823	0	2.42283147
23:00:00	678.015819	358.7808557	437.2692233	966.4424847	0	23.95658005	0	0
24:00:00	527.024412	361.021642	266.5510444	966.4424847	0	18.98880078	0	0

Table 4.5: Nigeria's hourly average load (MW) in 2050 under the BAU Scenario

Hour	Lighting	Air conditioner	Entertainment	Refrigerator	Laundry	Cooking	Heating	Cleaning
1:00:00	1091.05125	4421.095703	570.5249229	6617.24145	0	1424.876629	0	0
2:00:00	1038.610938	4136.652163	433.5892203	6617.24145	0	1231.646264	0	0
3:00:00	1040.589725	3916.17095	372.1044213	6617.24145	0	1333.403708	0	0
4:00:00	1006.204905	3662.157185	393.5014166	6617.24145	0	1447.503699	0	0
5:00:00	1083.347174	3422.271988	449.1991472	6617.24145	0	2272.265722	106.1898716	0
6:00:00	1238.142019	2837.654297	618.082951	6617.24145	0	5065.534383	353.9662387	0
7:00:00	1347.777427	2067.954194	957.7733872	6617.24145	0	1667.665485	0	0
8:00:00	1154.177732	1640.291901	1333.743517	6617.24145	2420.882728	3417.914846	0	48.46673365
9:00:00	999.4878791	1493.481905	1353.855864	6617.24145	6724.674246	3729.598678	0	134.6298157
10:00:00	908.2349198	1562.907121	1285.853116	6617.24145	8966.232327	3970.585278	0	179.5064209
11:00:00	815.6059428	1903.600952	1225.487181	6617.24145	6724.674246	3839.180213	0	134.6298157
12:00:00	748.4446487	2082.226046	1209.808358	6617.24145	4483.116164	2958.84766	0	89.75321047
13:00:00	842.5968455	2372.863185	1276.386777	6617.24145	2510.545052	4801.167797	0	50.26179786
14:00:00	892.7978879	2476.45769	1313.652689	6617.24145	2510.545052	4213.230145	0	50.26179786
15:00:00	970.2140893	2868.626156	1406.023165	6617.24145	1613.921819	5226.513148	0	32.31115577
16:00:00	977.6315362	3028.745622	1477.860041	6617.24145	0	4798.359238	0	0
17:00:00	1100.486794	3495.306688	1659.560778	6617.24145	0	5268.494134	0	0
18:00:00	1261.157172	3384.140901	1898.529189	6617.24145	0	3996.455649	0	0
19:00:00	1854.124883	3144.985027	2224.866951	6617.24145	0	4062.407578	0	0
20:00:00	2346.47914	4193.15611	2770.535364	6617.24145	5469.40172	5013.377559	173.4434569	109.4989168
21:00:00	2513.526535	4782.159677	2969.683899	6617.24145	8069.609095	4288.021233	173.4434569	161.5557788
22:00:00	2289.602617	4837.274204	2535.295063	6617.24145	6903.998892	4321.589111	0	138.2199441
23:00:00	1677.985864	4983.652195	1460.699231	6617.24145	0	2243.568478	0	0
24:00:00	1304.305132	5014.777879	890.4146113	6617.24145	0	1778.328742	0	0

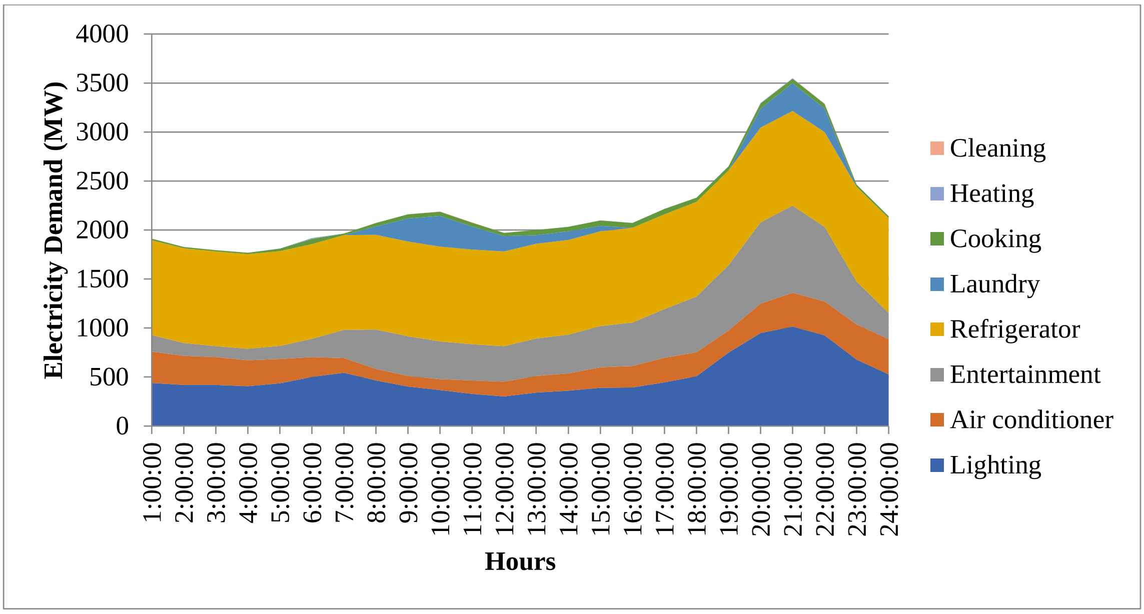

Figure 4.8: Evolution of Nigerian hourly load in the BAU scenario (2010)

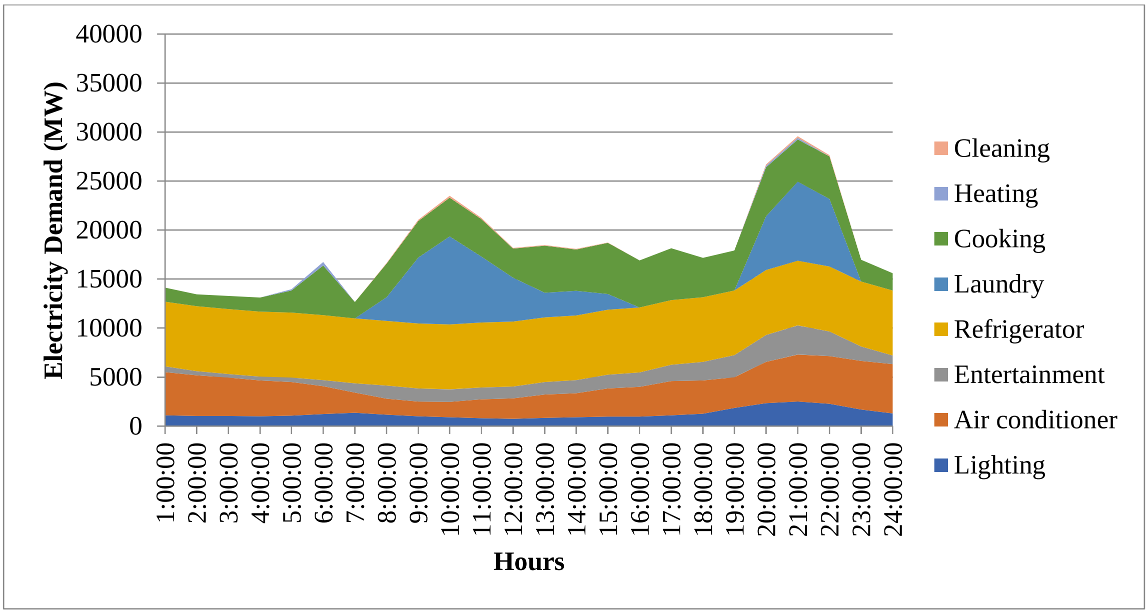

Figure 4.9: Evolution of Nigerian hourly load in the BAU scenario (2050)

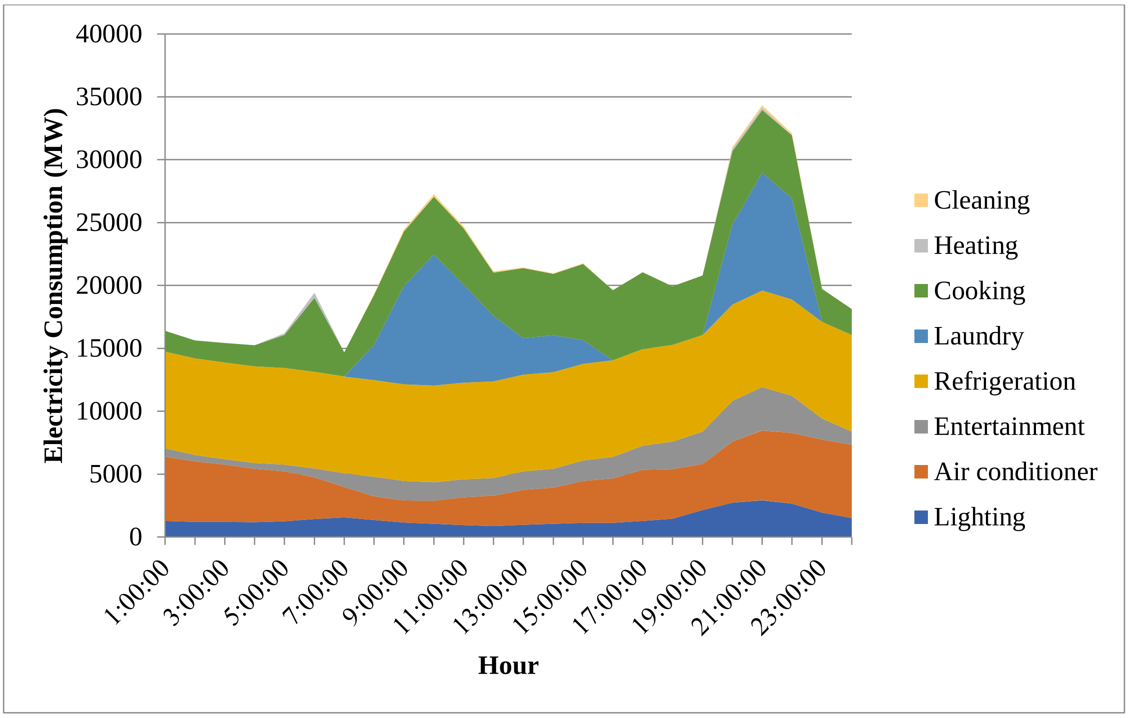

Figure 4.10: Evolution of Nigerian hourly load in the BAU scenario (2050). Account made for T&D

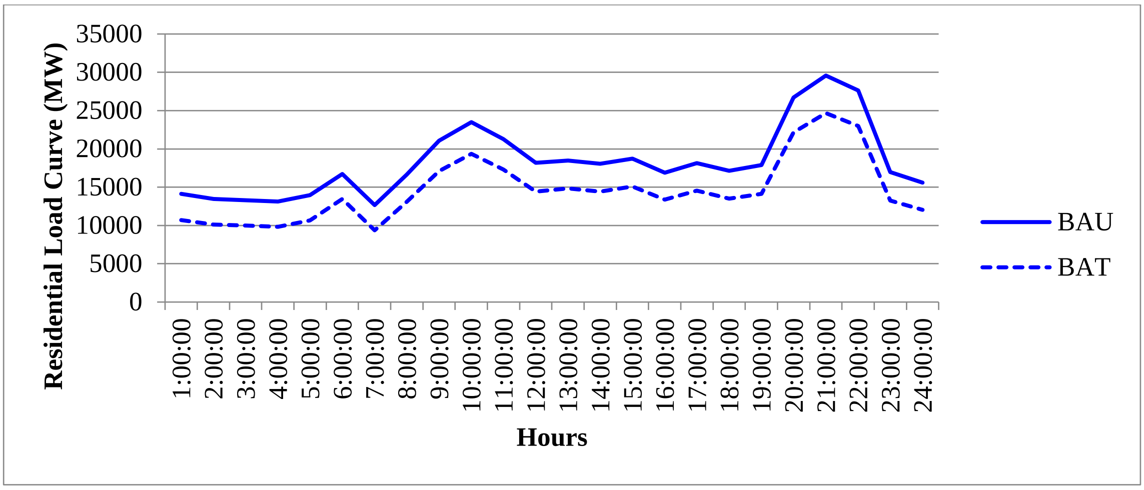

Figure 4.11: Nigeria average hourly load curves in the BAU and BAT scenarios in 2050

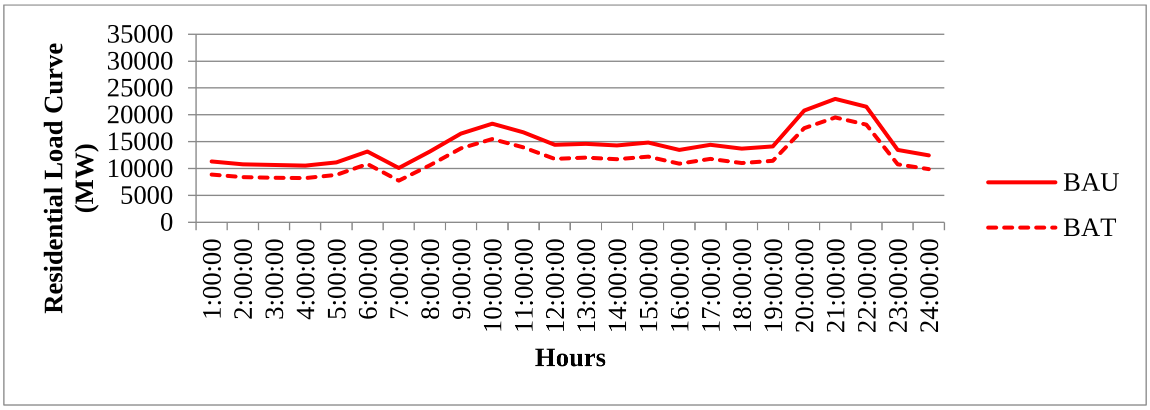

Figure 4.12: Nigeria average hourly load curves in the BAU and BAT scenarios in 2040

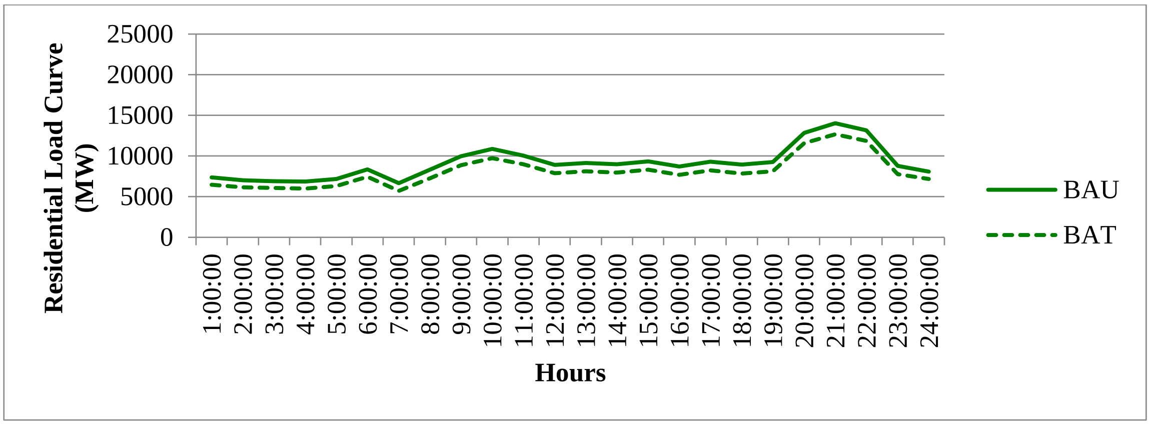

Figure 4.13: Nigeria average daily load curves in the BAU and BAT scenarios in 2030

Table 4.6: Contribution of end uses to reduced peak demand in 2030 in the BAT scenario compared with the BAU scenario.

End Uses	Peak Load (MWh)	% Reduction
Lighting	0	0
Air conditioning	0	0
Entertainment	448	20
Refrigeration	801	21
Laundry	96	3
Cooking	0	0
Heating	0	0
Cleaning	17	15
Total	1362	59

Table 4.7: Contribution of end uses to reduced peak demand in 2040 in the BAT scenario compared with the BAU scenario.

End Uses	Peak Load (MWh)	% Reduction
Lighting	27.04	2.05
Air conditioning	316.09	8.29
Entertainment	673.08	25.20
Refrigeration	1986.07	35.09
Laundry	415.43	6.84
Cooking	0.00	0.00
Heating	0.00	0.00
Cleaning	38.48	27.00
Total	3456.18	104.47

Table 4.8: Contribution of end uses to reduced peak demand in 2050 in the BAT scenario compared with the BAU scenario.

End Uses	Peak Load (MWh)	% Reduction
Lighting	95.35	3.70
Air conditioning	483.62	10.12
Entertainment	799.94	26.94
Refrigeration	2770.34	41.86
Laundry	693.09	8.58
Cooking	0.00	0.00
Heating	0.00	0.00
Cleaning	60.89	37.68
Total	4903.23	128.88

hours for cooling appliances. This study modelled the possible impact of climate uncertainty on cooling demand in 2050. The result shows a 23.8% and 24.2% increase in cooling demand under the BAU and BAT scenarios due to climate change (Table 4.9). Figures 4.14 and 4.15 show the details of the hourly cooling demand increase in the BAT scenario and BAU scenario under climate change in 2050. Overall, in a warmer climate, the total REC for Nigeria will increase by 5469 GWh (3.41%) under the BAU scenario and by 4861 GWh (3.80%) under the BAT scenario. The differences in air-conditioning hourly demand are presented in Tables 4.10, 4.11, and 4.12.

4.5 Environmental Impact

The impacts of emissions from CO_2 on the environment as a result of energy savings from BAU and BAT was evaluated. Total energy savings from 2021 – 2050 was converted to emissions reduction by applying a specific electricity specific factor of 0.439 kg CO_2/KWh. The emissions that were avoided through energy savings can be traded in the carbon credit market. This is also called carbon pricing and is one of the climate change approaches used by several cities, states, and countries around the world to reduce global warming. Carbon emitters take responsibility by being charged for the carbon they emit through a cap-and-trade program. The program sets a limit for carbon emissions and emissions allowances are issued by the government. Each of these allowances gives the holder the right or permission to emit a ton of CO_2. The allowances are usually limited, and the supply controlled by the government thereby capping the total amount of CO_2 emissions. The allowances are tradable by businesses or in the international markets and the basic economic concept of supply and demand determines its market price. At a carbon trade price of 68.53/tCO_2, Nigeria can earn \$15.44 billion in the carbon market in the 29-year period of becoming more energy efficient from 225 million metric tons (Mt) CO_2

Table 4.9: Effect of a warmer climate on AC consumption in 2050 (BAU vs BAT). Note air conditioner excludes fan in this assumption.

	Static Temperature	Increased Temperature	
Scenarios	**AC AEC (GWh)**	**AC AEC (GWh)**	**% Increase**
BAU	22958.52	28427.07	23.8
BAT	20089.38	24950.32	24.2

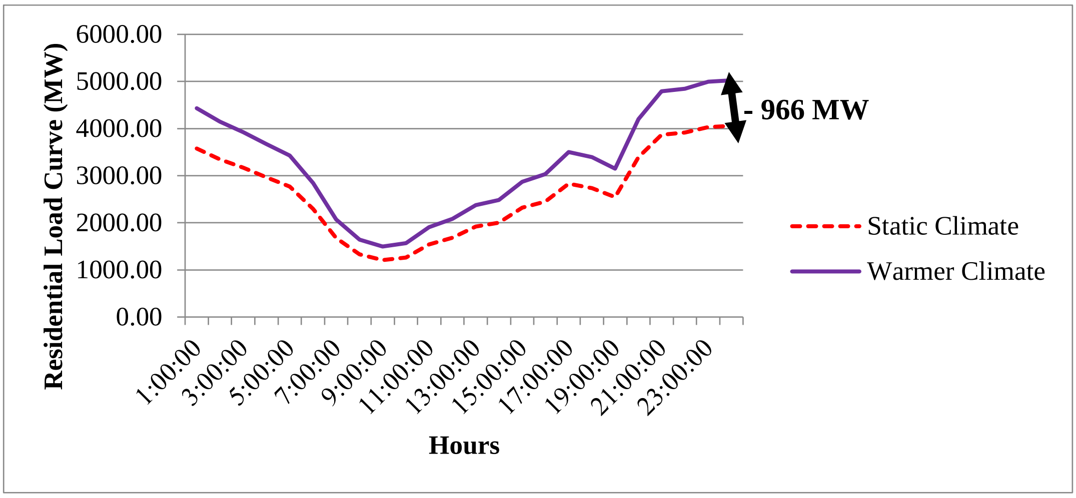

Figure 4.14: Air conditioner average hourly load curves under the BAU scenario in 2050 (Static Climate vs Warming Climate. Note air conditioner excludes fan in this assumption.

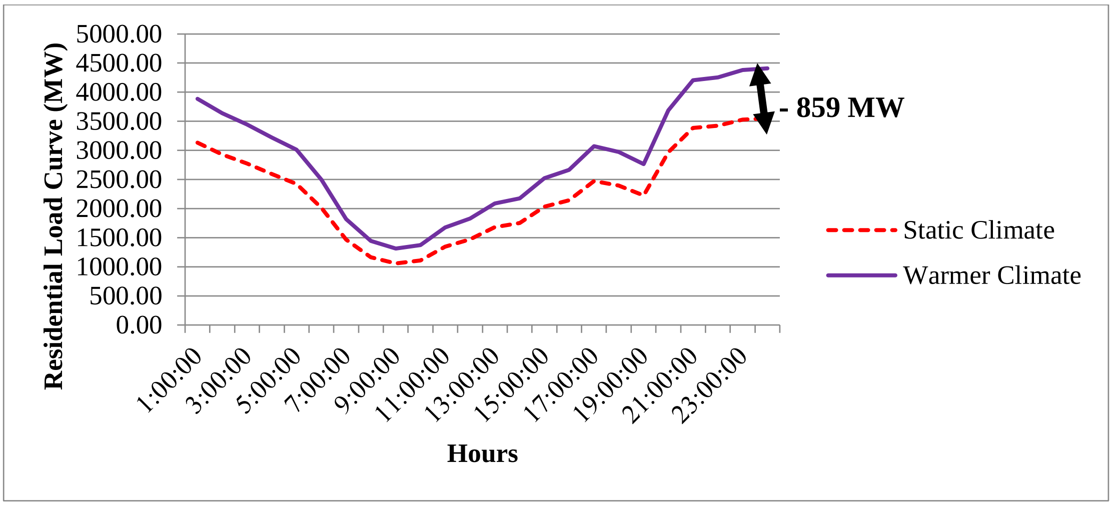

Figure 4.15: Air conditioner average hourly load curves under the BAT scenario in 2050 (Static Climate vs Warming Climate. Note air conditioner excludes fan in this assumption.

Table 4.10: Nigeria's average hourly daily load in 2050 under the BAU scenario comparing, Static climate vs Warmer Climate. Note air conditioner excludes fan in this assumption

Hour	Static Climate Demand (MW)	Warmer Climate Demand (MW)	Difference (MW)
1:00:00	3577.67	4429.84	852.17
2:00:00	3347.49	4144.84	797.35
3:00:00	3169.07	3923.92	754.85
4:00:00	2963.51	3669.40	705.89
5:00:00	2769.39	3429.04	659.65
6:00:00	2296.31	2843.27	546.96
7:00:00	1673.44	2072.05	398.60
8:00:00	1327.37	1643.54	316.17
9:00:00	1208.57	1496.44	287.87
10:00:00	1264.75	1566.00	301.25
11:00:00	1540.44	1907.37	366.92
12:00:00	1684.99	2086.35	401.35
13:00:00	1920.18	2377.56	457.37
14:00:00	2004.02	2481.36	477.34
15:00:00	2321.37	2874.30	552.93
16:00:00	2450.94	3034.74	583.80
17:00:00	2828.49	3502.22	673.73
18:00:00	2738.54	3390.84	652.30
19:00:00	2545.01	3151.21	606.20
20:00:00	3393.21	4201.45	808.24
21:00:00	3869.85	4791.62	921.77
22:00:00	3914.45	4846.84	932.39
23:00:00	4032.90	4993.51	960.61
24:00:00	4058.09	5024.70	966.61

Table 4.11: Nigeria's average hourly daily load in 2050 under the BAT scenario comparing, Static climate vs Warmer Climate. Note air conditioner excludes fan in this assumption.

Hour	Static Climate Demand (MW)	Warmer Climate Demand (MW)	Difference (MW)
1:00:00	3130.57	3888.05	757.49
2:00:00	2929.15	3637.91	708.75
3:00:00	2773.03	3444.01	670.98
4:00:00	2593.16	3220.62	627.46
5:00:00	2423.30	3009.66	586.36
6:00:00	2009.33	2495.53	486.19
7:00:00	1464.31	1818.63	354.31
8:00:00	1161.49	1442.53	281.04
9:00:00	1057.53	1313.42	255.89
10:00:00	1106.69	1374.47	267.78
11:00:00	1347.93	1674.09	326.15
12:00:00	1474.42	1831.18	356.76
13:00:00	1680.22	2086.77	406.55
14:00:00	1753.57	2177.88	424.30
15:00:00	2031.27	2522.76	491.50
16:00:00	2144.65	2663.58	518.93
17:00:00	2475.02	3073.89	598.87
18:00:00	2396.30	2976.12	579.82
19:00:00	2226.95	2765.80	538.85
20:00:00	2969.16	3687.60	718.44
21:00:00	3386.23	4205.59	819.35
22:00:00	3425.26	4254.06	828.80
23:00:00	3528.91	4382.78	853.88
24:00:00	3550.95	4410.16	859.21

Table 4.12: Differences in REC in 2050 under the BAU and BAT scenarios (static climate vs warm climate)

	Static Temperature	Increased Temperature	
Scenarios	**REC (GWh)**	**REC UEC (GWh)**	**% Increase**
BAU	160540.20	166009.20	3.41
BAT	127902.44	132763.44	3.80

avoided emissions (Table 4.13). A trade price of 59.02/tCO_2 was assumed based on the May 2021 European Union carbon price (CNBC, 2021).

4.6 Comparison to Historical Data and ECN estimates

Two comparisons were drawn between the results from this study, historical data and published studies: (1) Modelled REC (MREC) with historic Nigerian IEA REC (IREC) starting from 2000-2017 (IEA, 2020), (2) MREC with Energy Commission of Nigeria (EREC) (ECN, 2015). Percentage difference from IREC and MREC ranges from 9.9% to 116.5% with a mean of 61.5% (Table 4.14). The difference between IREC and MREC can be attributed to population and stocks growth. As population and appliance ownerships increase, load demand continues to increase while electricity generation in Nigeria remains static and, in most cases decreasing causing a suppressed demand. Suppressed demand can be defined as the desire to consume electricity but the desire cannot be met due to electricity supply constraints. Another cause of the suppressed demand is the transmission constraints on the part of the electricity distribution companies. The capability of transmission grids was not increased with increasing load demand. Nigeria's available capacity is roughly 6000 MW while the transmission grid can only take a supply of 4000MW. What this means is that transmission capability is limited and cannot take the increasing load and all the available capacity. Figure 4.16 compares the actual IREC data with the MREC, the shaded area between the desired consumption and the actual consumption is the suppressed demand. Although, some of the suppressed demand may have been met by other alternatives such as renewables or electric generator sets, the estimates of that are beyond the scope of this study.

Table 4.15 shows the percentage difference between the EREC and MREC estimates. The EREC estimates are higher than the MREC estimates. For example, the MREC is 71% and 90% lower than the EREC's estimates in 2010 and 2050, respectively. The difference could be

Table 4.13: Environmental Impacts as a result of energy savings from 2021 – 2050

Year	BAU (TWh)	BAT (TWh)	Energy Savings (TWh)	Emissions Reduction (Mt) CO2	Carbon Credit Market (Million $)
2021	45.24	43.24	2.00	0.88	60.22
2022	49.02	46.14	2.87	1.26	86.47
2023	52.97	49.21	3.75	1.65	112.97
2024	56.53	51.90	4.63	2.03	139.27
2025	60.06	54.58	5.48	2.41	164.92
2026	63.87	57.57	6.30	2.77	189.52
2027	67.58	60.51	7.07	3.10	212.72
2028	71.71	63.92	7.79	3.42	234.33
2029	75.70	67.24	8.45	3.71	254.33
2030	79.95	70.87	9.07	3.98	272.96
2031	84.48	74.67	9.81	4.31	295.03
2032	89.11	78.45	10.65	4.68	320.54
2033	93.80	82.15	11.65	5.11	350.49
2034	98.52	85.71	12.81	5.62	385.32
2035	103.26	89.10	14.16	6.22	425.97
2036	108.00	92.35	15.65	6.87	470.94
2037	112.74	95.43	17.31	7.60	520.76
2038	117.46	98.34	19.12	8.39	575.13
2039	122.17	101.11	21.06	9.25	633.72
2040	126.86	103.66	23.21	10.19	698.12
2041	131.27	106.20	25.08	11.01	754.47
2042	135.44	108.68	26.76	11.75	805.19
2043	139.34	111.09	28.25	12.40	849.95
2044	142.99	113.51	29.48	12.94	886.80
2045	146.38	115.92	30.47	13.37	916.55
2046	149.55	118.27	31.28	13.73	941.07
2047	152.52	120.69	31.84	13.98	957.80
2048	155.32	123.11	32.21	14.14	968.99
2049	157.98	125.44	32.54	14.29	979.00
2050	160.54	127.90	32.64	14.33	981.90
Total				**225.38**	**15445.45**

Table 4.14: Percentage Difference between MREC and IREC Data (GWh/year)

Year	Real	Model	% Difference
2000	4431.03	6772.22	-52.84
2001	4605.48	7504.94	-62.96
2002	7710.69	8474.51	-9.91
2003	7664.17	9752.86	-27.25
2004	9559.86	10618.03	-11.07
2005	10304.18	11964.49	-16.11
2006	7826.99	13510.32	-72.61
2007	10094.84	15142.56	-50.00
2008	10234.4	16852.73	-64.67
2009	10164.62	18085.56	-77.93
2010	11967.27	19570.37	-63.53
2011	13572.21	22030.96	-62.32
2012	14549.13	22000.10	-51.21
2013	13455.91	24142.26	-79.42
2014	14002.52	26237.02	-87.37
2015	14374.68	27970.20	-94.58
2016	14758.47	30595.00	-107.30
2017	15153.89	32811.23	-116.52
Sum	194430.3	324035.4	-1107.6071
Count (n)	18	18	18
Average (mean)	10801.69	18001.97	-61.533728
Median	10269.29	17469.14	
Standard Deviation	3412.557	8164.589	

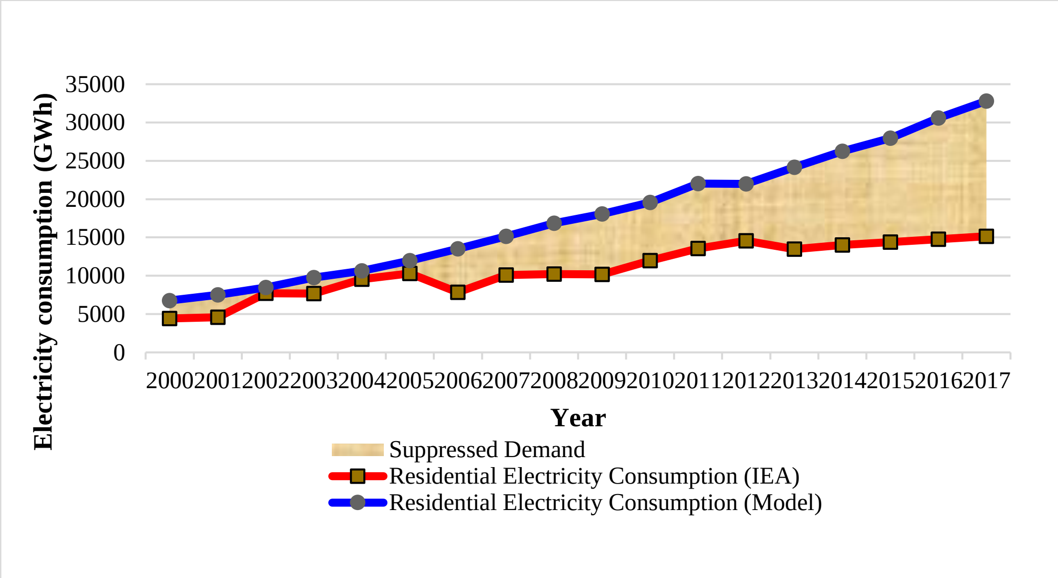

Figure 4.16: REC comparison from 2000-2017 (MREC vs IREC).

Table 4.15: Percentage Difference between EREC and MREC Data (GWh/year)

Year	ECN	MEC	% Difference
2010	67000	19570.37	-70.79
2015	110000	27970.20	-74.57
2020	194000	41657.84	-78.53
2025	358000	60057.44	-83.22
2030	531000	79945.67	-84.94
2035	769000	103260.30	-86.57
2040	1001000	126863.82	-87.33
2045	1258000	146382.98	-88.36
2050	1543000	160540.25	-89.60
Sum	194430.3	324035.371	-743.916256
Count (n)	9	9	9
Average (mean)	602543	109028.42	-82.6573618
Median	531000	79945.67206	
Standard Deviation	3412.557	8164.589336	

attributed to the difference in modelling approaches used in both studies. The EREC uses the Nigeria 2050 Energy Calculator (NECAL 2050) in its forecast and only assumed a relationship between economic growth and electricity demand. Appliance ownership evolution, stocks, and sales were not factored into the calculation. In agreement with previous studies, this study believes a good estimate of appliance stocks uptake will better determine the growth of electricity demand (Letschert and McNeil, 2013, Diawuo, et. al., 2018, McNeil et. al., 2019).

Additionally, GDP and population growth rate in this study (6.4% and 2.54% respectively) is lower than ECN's (7% and 3.1% respectively). The MREC also assumes a gradual electrification rate up till 2050 while the EREC assumed 100% rate starting from 2030. For instance, the MREC assumed a 70% electrification rate in 2030 while the EREC assumed 100%. However, both projections saw a decrease in electricity consumption when appliance technology improves or when more efficient appliances are introduced.

4.7 Model Validation

The best way to validate the model is to compare the results of the output from the model with historical actual residential electricity consumption for Nigeria. However, actual demand for Nigeria is suppressed as explained in section 4.6 thereby causing an underestimation of historical consumption data. Because of this limitation, historical REC data for Brazil sourced from IEA, 2021 was used to validate the REC for Nigeria for year range 2000 – 2019. Brazil was deemed most suitable for comparison because it has similar demography and economy (for example, it is a tropical country, has similar population, GDP, household size, and lifestyles) as Nigeria. An analysis of GDP versus REC per population was carried out for both Brazil and Nigeria. The resulting consumption per person for Brazil was subtracted from that of Nigeria and the result was divided by the consumption per person for Brazil. The average of the difference between the two countries was then calculated. This analysis was carried out to allow for a normalized comparison of consumption per person for both countries as shown in equations 29 – 32.

$$\text{Consumption Per Person}_{\textit{Brazil}} = \frac{(\text{Historical residential consumption } \boldsymbol{Brazil})}{(\text{GDP per Capita } \boldsymbol{Brazil})} \tag{29}$$

$$\text{Consumption Per Person}_{\textit{Nigeria}} = \frac{(\text{Historic residential consumption } \boldsymbol{Nigeria})}{(\text{GDP per Capita } \boldsymbol{Nigeria})} \tag{30}$$

$$\text{Difference}_{\textit{Brazil,Nigeria}} = \frac{\text{Consumption Per Person } \boldsymbol{Brazil} - \text{Consumption Per Person } \boldsymbol{Nigeria}}{\text{Consumption Per Person } \boldsymbol{Brazil}} \tag{31}$$

$$\text{Average}_{\textit{Brazil,Nigeria}} = \text{Average } (\text{Difference}_{\textit{Brazil,Nigeria}}) \tag{32}$$

Prior to analysis, a theoretical maximum and minimum of 1 and 0 was set to mark the strength of the fit of the model to the data. Values close to 0 (between 0 and 0.5) suggest a strong to moderate fit and the capability of the model to accurately predict the data. Table 4.16 shows the descriptive statistics of the analysis. The average of the difference between Brazil and Nigeria is 0.29 suggesting a strong relationship and the ability of the model to be able to accurately forecast residential electricity consumption for Nigeria. The disparity is reasonable and possibly caused by Brazil's higher population, GDP, appliance ownerships, and power ratings.

4.8 Risk and Uncertainty

There is always some level of uncertainties with every forecasting model and this study is not an exemption. This study acknowledges some level of uncertainties in the historical input data and forecast parameters used. In the appliance survival calculation, data for average age were sourced from existing literature. The accuracy of the appliance ages will impact the result of the stock modelling. In the UEC calculation, the hours of usage of appliances may differ from one end user to the other, a significant difference in the usage time from the assumption made

Table 4.16: Descriptive statistics of the difference between consumption per person for both Nigeria and Brazil

Mean	0.29
Standard Error	0.04
Median	0.27
Mode	#N/A
Standard Deviation	0.17
Sample Variance	0.03
Kurtosis	-1.42
Skewness	0.13
Range	0.51
Minimum	0.05
Maximum	0.56
Sum	5.80
Count	20.00
Confidence Level(95.0%)	0.08

will have a significant impact on the electricity consumption. Macroeconomic parameters such as population and household size are subject to some level of uncertainty. Their future projections assumed a continuous increase up till 2050 from the base year. These parameters will affect the correctness of the stock modelling and the final electricity consumption. Nigeria has a low electrification rate, projection up to 2050 assumed that electrification rate will continue to increase and will get to 100% by 2050. Floor area, time, and household sizes are important variables in the lighting model. There is a level of uncertainty for these variables over the projected years if they do not grow as predicted. Because of insufficient data, this study also relied on proxy data from other countries for appliance ownership forecasts. The data has an influence on the results of this study and subject to a reasonable uncertainty.

In order to determine how these uncertainties, affect and influence the modelled Residential Electricity Consumption (REC) including the soundness of the conclusions, a Monte Carlo Analysis (MCA) was carried out. MCA is a technique that uses the probabilistic distribution functions (PDF) of the input parameters combined with simulations from computers to get a probabilistic distribution of the output variable. There are several types of probabilistic distributions, they include the Normal, Log-normal, Weibull, Beta, Triangular etc. The description, parameters, and conditions underlying these distributions, and uses including MCA are well discussed in literature (e.g., Kroese, et. Al., 2014, Martinez-Soto and Jentsch, 2015, Martinez-Soto and Jentsch, 2019). For this study, a triangular distribution was assumed because the model already provided "most likely" values for each forecast years. Recognizing that the modeled electricity consumptions have many possible outcomes, we can then assume a "minimum" and "maximum" values (based on percentage increase and decrease) around the "most likely" values.

For all appliances except lighting, a triangular distribution was assumed for population, household size, appliance ownership, retired stocks, previous years stocks, and UEC in order to capture the variability of these inputs. A minimum and maximum of 25% was assumed around the averages for each of the input parameters. A triangular distribution was also assumed for lighting appliances input such as time, floor area, and household sizes. A minimum and maximum of 15% was assumed around the averages for each of the input parameters. A Monte Carlo simulation was then conducted by randomly selecting values from the probability distributions of the input parameters. For each year, REC is conducted 1,000 times per each Monte Carlo simulation. The simulation allows to determine the uncertainty of the REC for each forecast year as a probability distribution. The Monte Carlo Analysis (MCA) was carried out using Crystal Ball – an add-in software to Microsoft Excel spreadsheet.

The uncertainty analysis outputs are distributions of the total residential electricity consumption. The frequency charts showing the distributions, ranges, and means for each of the inputs for the appliances are plotted. As an example, and for brevity's sake, the frequency charts for Television in the forecast year 2030 are shown in Figures 4.17 – 4.22. Figure 4.23 also shows the distribution of the final electricity consumption output for Television in the forecast year 2030. The green box shows the base line estimate, mean, standard deviation and percentiles for these distributions. As earlier mentioned, these results are based on a sample of 1,000 runs.

Figure 4.24 shows the results of the characterization of the uncertainties of the REC forecast for all the appliances and the total REC thereby providing the probability of exceedance. It shows the confidence intervals around the forecasts peak demand over a 30-year period (2020 – 2050) and determines the probabilities of exceeding the 10^{th} and 90^{th} percentiles of the distribution. In each year, there is an 80% chance that the peak demand value will be within the 10^{th} and 90^{th} percentiles. The 90^{th} percentile is the value at which 90% of the time, peak demand value is below the 90^{th} percentile line and the other 10%, it exceeds the peak demand value.

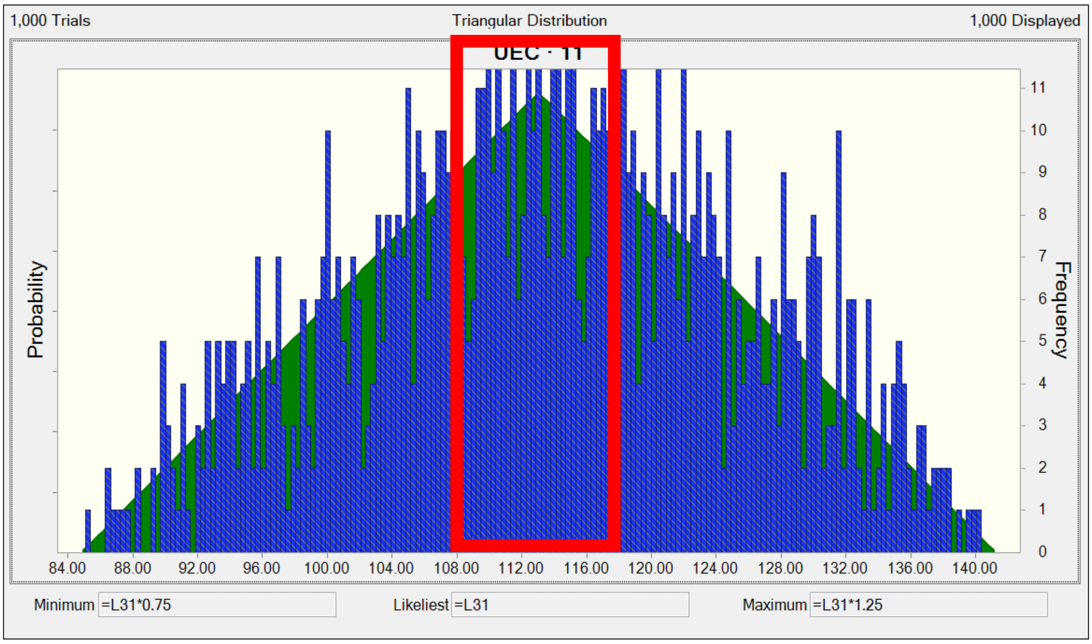

Figure 4.17: Triangular distribution of Unit Energy Consumption (UEC) in the year 2030 for Television. The minimum value is the lower limit of the triangle (left side of the triangle) and the upper limit (right side of the triangle). The red box shows the expected mean values range.

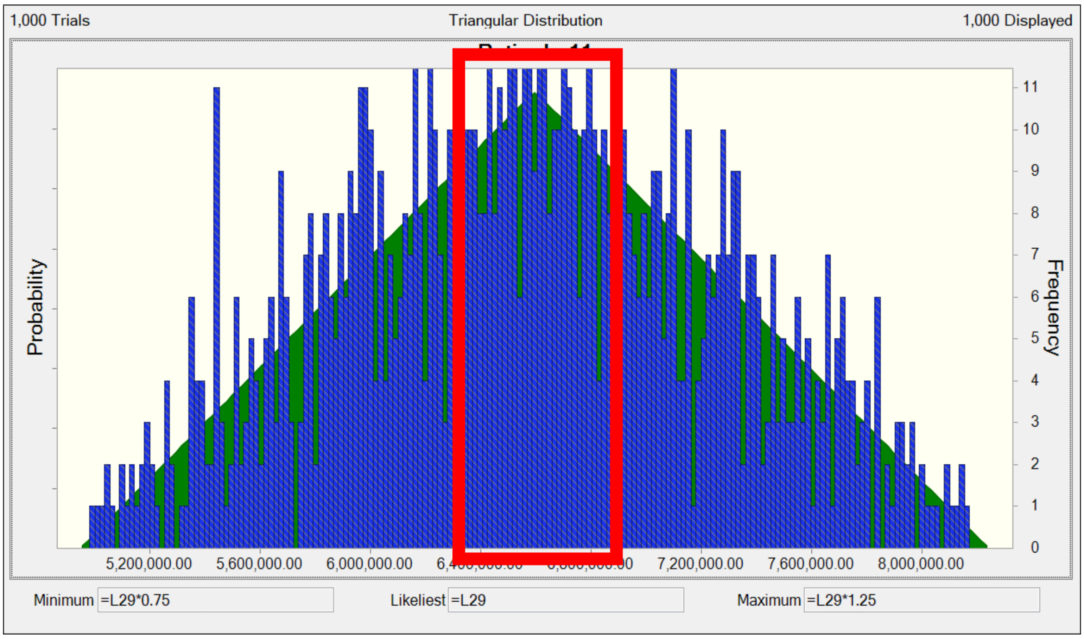

Figure 4.18: Triangular distribution of retired stocks in the year 2030 for Television. The minimum value is the lower limit of the triangle (left side of the triangle) and the upper limit (right side of the triangle). The red box shows the expected mean values range.

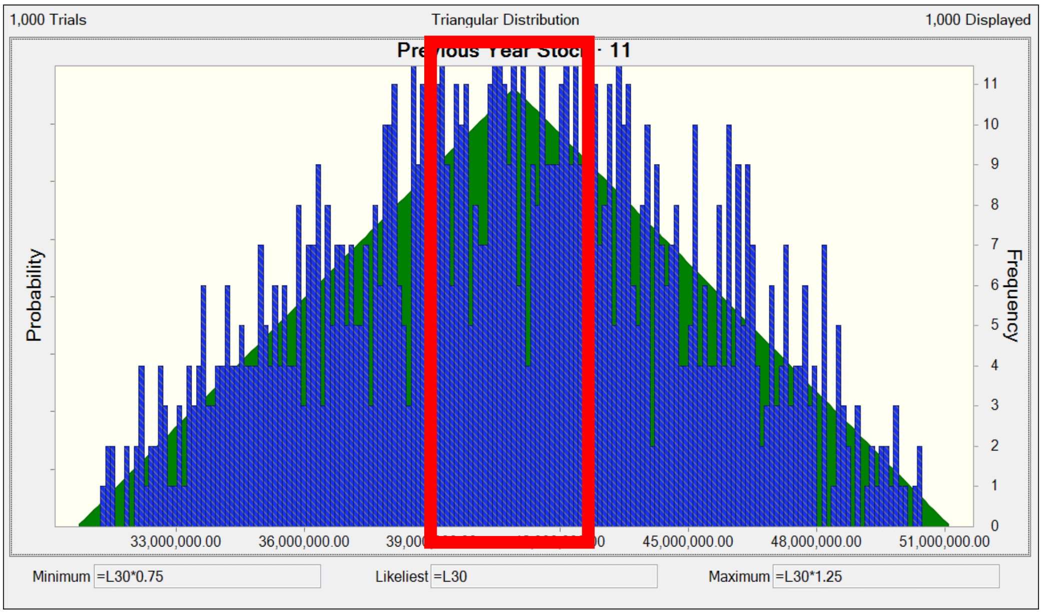

Figure 4.19: Triangular distribution of previous year stock in the year 2030 for Television. The minimum value is the lower limit of the triangle (left side of the triangle) and the upper limit (right side of the triangle). The red box shows the expected mean values range.

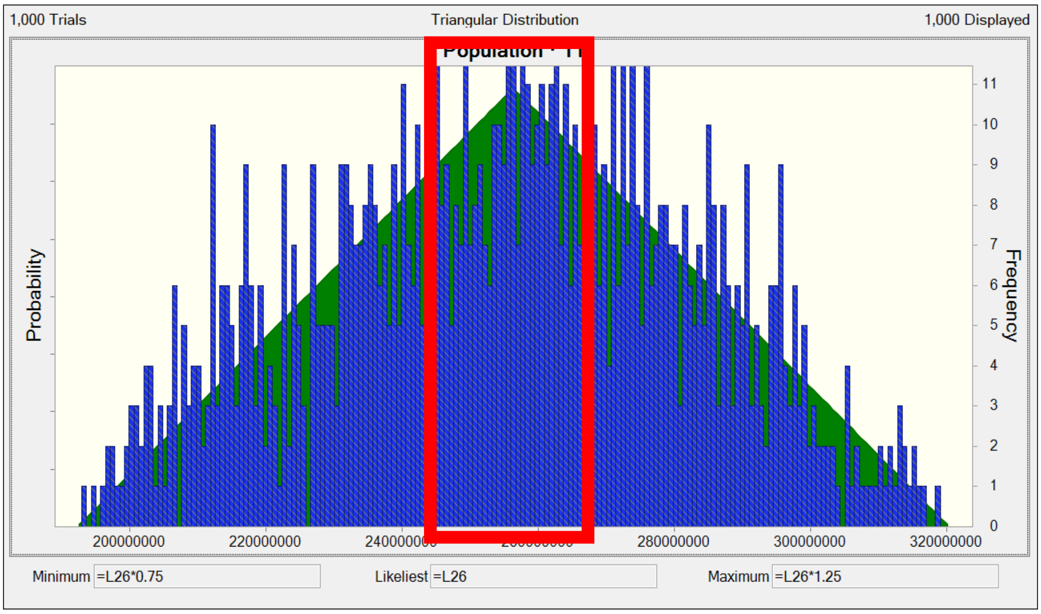

Figure 4.20: Triangular distribution of population in the year 2030 for Television. The minimum value is the lower limit of the triangle (left side of the triangle) and the upper limit (right side of the triangle). The red box shows the expected mean values range.

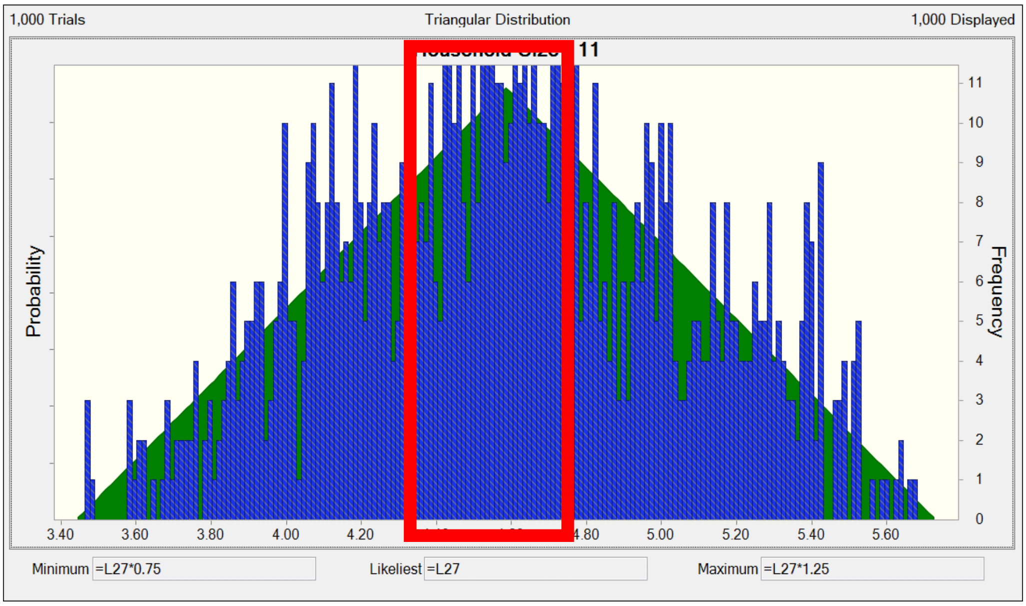

Figure 4.21: Triangular distribution of household size in the year 2030 for Television. The minimum value is the lower limit of the triangle (left side of the triangle) and the upper limit (right side of the triangle). The red box shows the expected mean values range.

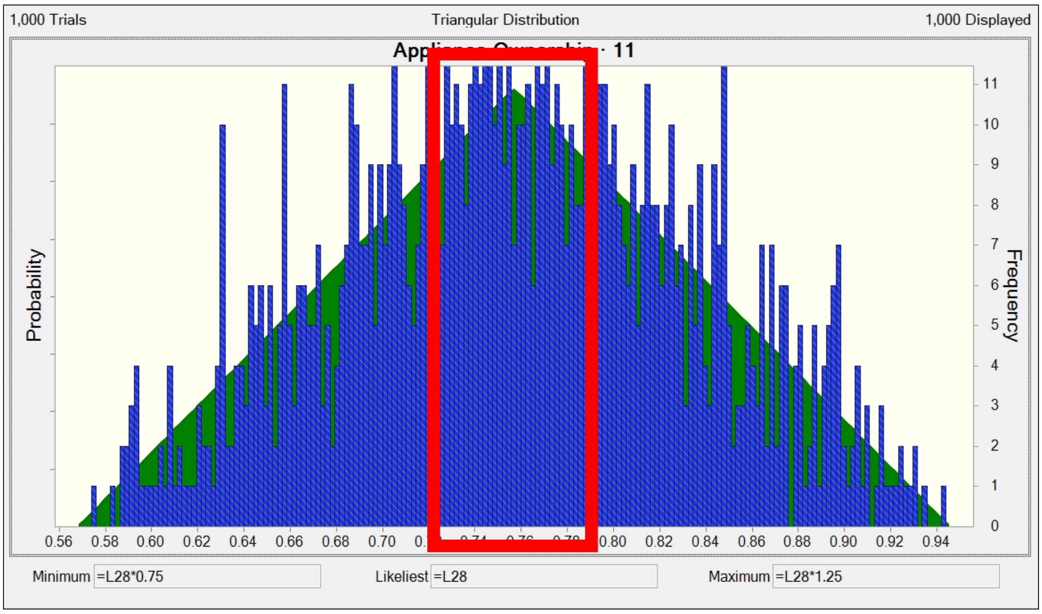

Figure 4.22: Triangular distribution of appliance ownership in the year 2030 for Television. The minimum value is the lower limit of the triangle (left side of the triangle) and the upper limit (right side of the triangle). The red box shows the expected mean values range.

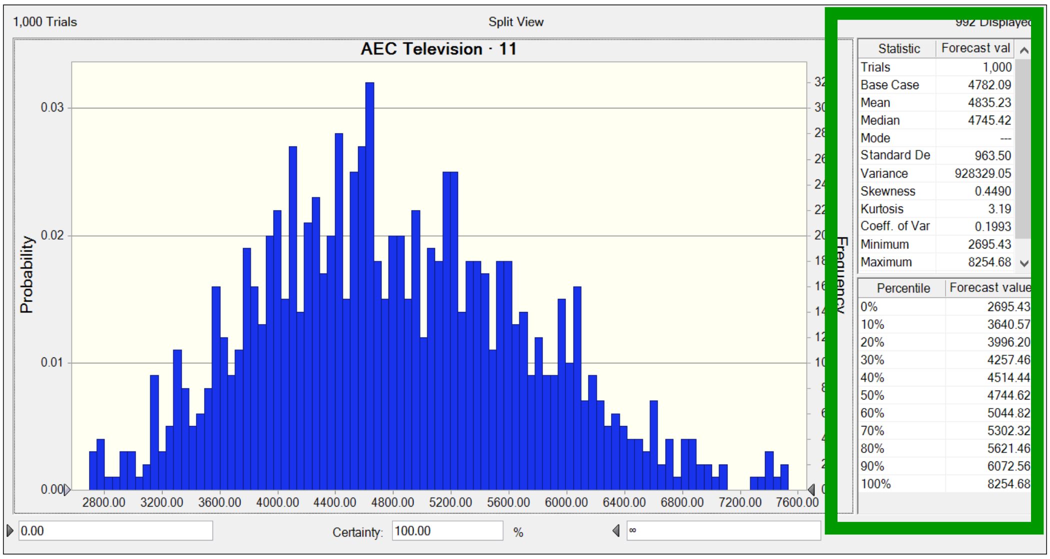

Figure 4.23: Triangular distribution of annual electricity consumption (AEC) in the year 2030 for Television. The green box shows the mean, median values and percentiles.

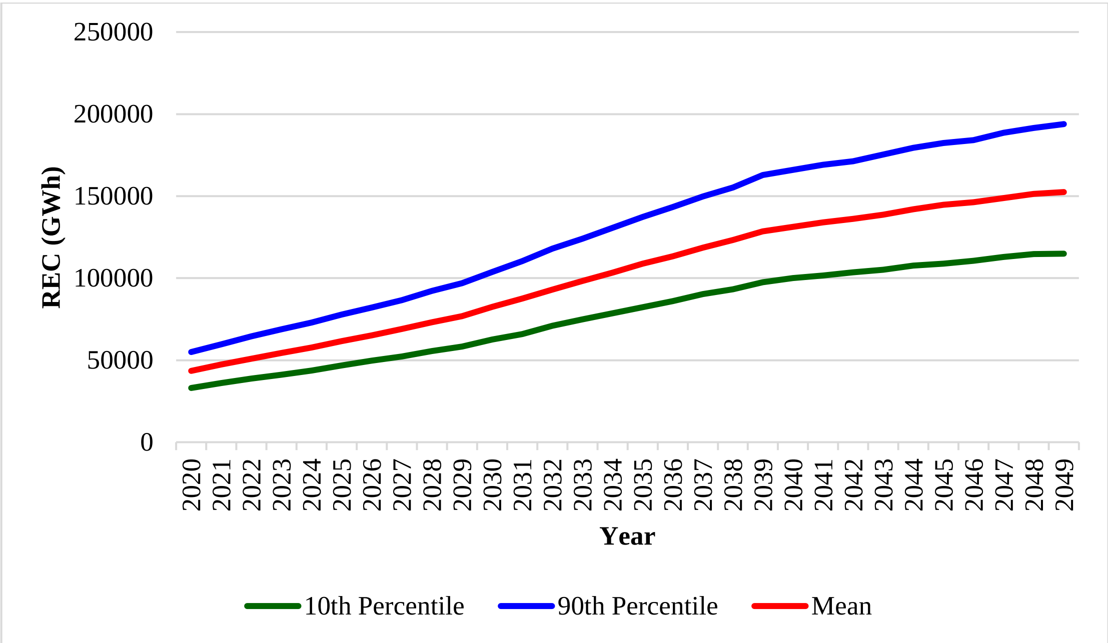

Figure 4.24: REC Uncertainty over Time

Tables 4.17 and 4.18 show the difference of the 10th and 90th percentiles of the final REC with respect to the model mean value for forecast years 2025, 2030, 2035, 2040, 2045, and 2050. These differences are due to the uncertainties surrounding the input parameters.

4.9 Results of Bill Savings, Payback Period and LCC

Bill savings, PBP, and LCC for the eight appliances with existing EE S&L have been calculated using equations 24, 25, 26, 27, and 28. The results for each of the appliances are discussed in subsections 4.9.1 – 4.9.8.

4.9.1 Refrigerator

Table 4.19 shows the result for refrigerator. For all the seven classes of refrigerator, the most efficient model (A+++) has the highest LCC and PBP. There is a general increase in LCC and PBP with increasing efficiency level. The shortest payback period is less than 15 years for a class C refrigerator. Given an average lifetime of 15 years for a refrigerator, the average consumer will only achieve a return on investment if she chooses to purchase a class C refrigerator rather than the other classes. However, consumers will be able to save more energy and spend less on electricity bills by using a higher efficient model. In absolute terms, LCC reductions from the Class D model (baseline) ranges from $323. 13 (Class A+++) to $14.73 (Class C). The PBP ranges from 14.5 years for a class C to 29.17 years for a class A+++ while the bill savings range from $5.6 for class C to $ 25.6 class A+++. Energy savings range from 147.45 kWh for a class C to 671.74 kWh for a class A+++.

4.9.2 Freezer

LCC and PBP for a freezer increases with an increase in the efficiency level (Table 4.20). LCC reductions from the Class D model (baseline) range from $323. 18 (Class A+++) to $50.10 (Class C). The PBP ranges from 22.4 years for a class C to 45.9 years for a class A+++ while

Table 4.17: Difference of the 10th percentile of the final REC with respect to the model mean value. All values are in GWh

	2025	2030	2035	2040	2045	2050
AC	-1699.4	-2695.1	-3592.7	-4673.2	-5060.2	-5497.8
Blender	-10.481	-12.502	-14.422	-16.197	-18.369	-21.274
CFL Light	-428.76	-671.48	-912.11	-1327.7	-1730.9	-2397.5
Fluorescent	-30.223	-42.32	-33.699	-49.052	-65.454	-90.663
Incand Light	-528.9	0	0	0	0	0
LED	-18.005	-63.03	-83.649	-121.76	-194.97	-270.06
Desktop	-79.182	-76.495	-91.932	-105.74	-114.6	-140.04
EClothes Dryer	-266.46	-667	-1216.4	-1561.3	-1829.2	-2170.7
ECooker	-1544.6	-2624.6	-4098	-5259.6	-6286.3	-6917
Ekettle	-72.2	-125.91	-157.29	-182.95	-199.68	-235.99
EWater Heater	-32.838	-45.426	-51.251	-63.129	-65	-77.489
Fan	-614.33	-740.19	-865.44	-1015.8	-1194.5	-1363.5
Freezer	-1575.4	-1729.7	-2036.8	-2514.5	-2503.2	-2359.5
Iron	-449.15	-570.63	-700.25	-828.27	-941.59	-1107.3
Laptop	-98.349	-108	-108.57	-99.041	-111.09	-125.47
Microwave	-91.272	-176.78	-265.15	-345.68	-424.14	-486.93
MPhone	-12.677	-13.725	-14.403	-17.562	-19.004	-22.221
Radio	-519.89	-577.65	-669.14	-700.06	-786.99	-914.29
Refrigerator	-4340.5	-5571.1	-7111.4	-8857.7	-9422.1	-9627.6
Television	-1201.6	-1232.7	-1426.8	-1601.8	-1571.6	-1501.9
Toaster	-13.309	-16.896	-21.064	-22.474	-26.822	-27.652
Vaccum	-56.066	-67.885	-86.143	-101.31	-98.618	-102.15
VCD	-39.937	-47.555	-56.889	-60.642	-70.554	-83.877
Washine Machine	-270.96	-601.84	-1090.3	-1483.8	-1737.1	-2030.1

Table 4.18: Difference of the 90th percentile of the final REC with respect to the model mean value. All values are in GWh.

	2025	2030	2035	2040	2045	2050
AC	1967.09	2849.98	4171.26	5395.04	5733.57	6149.49
Blender	12.1296	13.8484	15.158	17.9863	19.9945	22.6635
CFL Light	481.802	734.98	1041.52	1390.74	1972.76	2611.93
Fluorescent	33.9616	46.3223	38.4799	51.382	74.6004	98.7705
Incand Light	594.328	0	0	0	0	0
LED	20.2324	68.9906	95.5174	127.544	222.214	294.21
Desktop	90.2135	82.4699	104.575	114.252	124.667	151.883
Eclothes Dryer	294.159	725.78	1321.91	1757.25	2125.45	2420.6
Ecooker	1642.18	2829.1	4343	5872.11	6548.91	7303.41
Ekettle	74.5679	135.535	174.167	191.502	218.153	254.283
Ewater Heater	37.1674	49.3735	55.6285	67.4261	70.0544	81.6207
Fan	681.041	821.49	945.76	1174.09	1310.27	1474.73
Freezer	1735.95	2120.04	2307.57	2836.25	2787.62	2583.72
Iron	519.546	586.659	748.276	928.587	1103.12	1264.35
Laptop	110.526	108.16	121.292	110.089	128.559	146.086
Microwave	105.353	196.268	317.184	377.416	463.746	543.787
Mphone	13.6616	14.8277	16.1087	19.965	20.9847	24.2117
Radio	576.49	659.761	727.417	726.739	837.804	907.455
Refrigerator	4586.4	5955.97	7787.96	9603.74	9879.58	11008.3
Television	1305.6	1317.63	1581.51	1761.42	1735.09	1695.57
Toaster	14.0768	20.2625	23.3119	24.2153	27.9733	32.6291
Vaccum	57.4464	74.2366	90.648	108.639	105.367	113.982
VCD	42.592	53.4867	61.8217	66.2217	82.7134	89.7297
Washine Machine	319.792	644.651	1216.23	1651.12	1856.01	2149.73

Table 4.19: LCC, Bill Savings, and PBP results for Refrigerator

Efficiency Level	UEC (KWh)	Average IC ($)	Average OC ($)	Average LCC ($)	Energy Savings (KWh)	Bill Savings ($)	OC for PBP Calc. ($)	PBP (Years)
Class D – Baseline	843.78	428.45	551.67	980.12			32.22	
C	696.32	510.12	455.26	965.38	147.46	5.63	26.59	14.50
B	532.48	646.25	348.14	994.39	311.30	11.89	20.33	18.32
A	401.41	782.39	262.45	1044.84	442.37	16.89	15.33	20.95
A+	311.30	918.52	203.53	1122.05	532.48	20.33	11.89	24.10
A++	229.38	1054.65	149.97	1204.62	614.40	23.46	8.76	26.69
A+++	172.03	1190.78	112.48	1303.26	671.74	25.65	6.57	29.72

Table 4.20: LCC, Bill Savings, and PBP results for Freezer

Efficiency Level	UEC (KWh)	Average IC ($)	Average OC ($)	Average LCC ($)	Energy Savings (KWh)	Bill Savings ($)	OC for PBP Calc. ($)	PBP (Years)
Class D – Baseline	821.38	645.49	417.42	1062.91			31.37	
C	677.84	768.54	344.47	1113.01	143.54	5.48	25.88	22.45
B	518.35	973.63	263.42	1237.05	303.03	11.57	19.79	28.36
A	390.76	1178.72	198.58	1377.30	430.63	16.44	14.92	32.43
A+	303.03	1383.81	154.00	1537.81	518.35	19.79	11.57	37.30
A++	223.29	1588.90	113.47	1702.37	598.09	22.84	8.53	41.31
A+++	167.47	1793.99	85.11	1879.10	653.92	24.97	6.40	45.99

the bill savings range from $5.4 for class C to $ 24.9 for class A+++. Energy savings range from 143.54 kWh for a class C to 653.92 kWh for a class A+++. In terms of energy and bill savings, a more efficient model is beneficial. However, a freezer has an average lifetime of 12 years, consumers will not be achieving a ROI by purchasing any classes of the freezer.

4.9.3 Washing Machine

Table 4.21 shows the result for washing machine. The most efficient washing machine (A+++) has the highest LCC. The LCC for a consumer that purchases a freezer with an A+++ label is $621.70 higher than a washing machine with a label D. This amounts to approximately 105% increase in LCC. Energy savings range from 20.02 KWh for a class C to 140.15 kWh for a class A+++ and bills savings range from $0.76 (class C) to $5.35. Payback period for all classes of washing machine is high with a range of 99.6 years (class C) to 133.2 years (class A+++). A washing machine has an average lifetime of 15 years thus making the investment on more efficient models not profitable to consumers.

4.9.4 Air Conditioner

Five classes of air conditioners have been evaluated for LCC, PBP, energy savings, and bill savings (Table 4.22). The class A+++ has the highest PBP, energy savings, and bill savings. The LCC ranges from $1964.66 for class B to $2362 for class A+++. There is a general increase in energy and bill savings with an increase in efficiency level. Energy savings range from 294.59 KWh for class A to 842.15 KWh for class A+++. Bill savings range from $11.2 for class B to $32.15 for class A+++. Air conditioners have average lifetimes of 12 years. Consumers who purchase any of the five classes of air conditioners will have no ROI because the PBPs range from 18.35 years for class B to 25.68 years for a class A+++.

Table 4.21: LCC, Bill Savings, and PBP results for Washing Machine

Efficiency Level	UEC (KWh)	Average IC ($)	Average OC ($)	Average LCC ($)	Energy Savings (KWh)	Bill Savings ($)	OC for PBP Calc. ($)	PBP (Years)
Class D – Baseline	290.32	400.92	189.81	590.73			11.09	
C	270.30	477.35	176.72	654.07	20.02	0.76	10.32	99.96
B	240.26	604.73	157.09	761.82	50.06	1.91	9.18	106.63
A	210.23	732.11	137.45	869.56	80.09	3.06	8.03	108.29
A+	183.54	859.49	120.00	979.49	106.78	4.08	7.01	112.46
A++	160.18	986.88	104.72	1091.60	130.14	4.97	6.12	117.90
A+++	150.17	1114.26	98.18	1212.44	140.15	5.35	5.73	133.28

Table 4.22: LCC, Bill Savings, and PBP results for Air Conditioner

Efficiency Level	UEC (KWh)	Average IC ($)	Average OC ($)	Average LCC ($)	Energy Savings (KWh)	Bill Savings ($)	OC for PBP Calc. ($)	PBP (Years)
Class B – Baseline	1937.26	980.16	984.51	1964.67			73.98	
A	1642.67	1186.63	834.80	2021.43	294.59	11.25	62.73	18.35
A+	1449.41	1393.10	736.58	2129.68	487.85	18.63	55.35	22.17
A++	1232.00	1599.56	626.10	2225.66	705.26	26.93	47.05	23.00
A+++	1095.11	1806.03	556.53	2362.56	842.15	32.16	41.82	25.68

4.9.5 Television

The LCC, PBP, energy, and bill savings have been evaluated for seven classes of television (Table 4.23). The A+++ has the highest LCC of $600.44 while the Class D has the lowest of $278.11. Like the other appliances, there is a general trend of increasing LCC, PBP, energy and bill savings with the most efficient class having the highest. The energy savings range from 48.3 KWh for class C to 136.1 KWh for class A+++. Consumers that purchase class A+++ will save more on bills ($5.19) compared to clasee C ($1.67). Payback periods range from 24.2 years for class C compared to 72.8 years for class A+++ thus giving a negative ROI for consumers because televisions have an average life time of 10 years.

4.9.6 Desktop Computer

Four classes of desktop computers have been evaluated for LCC, PBP, energy, and bill savings (Table 4.24). There is a general trend of increasing LCC, PDP, energy and bill savings with increased efficiency. Class A desktop computer has the highest LCC, energy savings, bill savings and pay back period of $1366.07, 47.1 KWh, $1.75, and 341.7 years, respectively. A desktop computer has a PBP of eight years thereby making the purchase of any of its classes not profitable to consumers because of the PBP that ranges from 303.57 years to 341.7 years.

4.9.7 Laptop Computer

Three classes of laptop computers were evaluated for LCC, PBP, energy and bill savings (Table 4.25). Class A has the highest LCC of $876.66 , energy savings of 15.4 KWh, bill savings of $0.58, and PBP of 517.256 years. Laptop computers have average life time of 6 years thereby making the purchase of classes A and B not beneficial to the consumers because the total costs of owing them are far greater than the returns.

Table 4.23: LCC, Bill Savings, and PBP results for Television

Efficiency Level	UEC (KWh)	Average IC ($)	Average OC ($)	Average LCC ($)	Energy Savings (KWh)	Bill Savings ($)	OC for PBP Calc. ($)	PBP (Years)
Class D – Baseline	156.86	212.94	65.18	278.12			5.99	
C	113.03	253.53	46.96	300.49	43.83	1.67	4.32	24.25
B	83.04	321.19	34.50	355.69	73.82	2.82	3.17	38.40
A	64.59	388.85	26.84	415.69	92.27	3.52	2.47	49.92
A+	46.13	456.51	19.17	475.68	110.73	4.23	1.76	57.60
A++	29.99	524.16	12.46	536.62	126.87	4.84	1.15	64.24
A+++	20.76	591.82	8.63	600.45	136.10	5.20	0.79	72.90

Table 4.24: LCC, Bill Savings, and PBP results for Desktop Computer

Efficiency Level	UEC (KWh)	Average IC ($)	Average OC ($)	Average LCC ($)	Energy Savings (KWh)	Bill Savings ($)	OC for PBP Calc. ($)	PBP (Years)
Class D – Baseline	75.80	742.00	24.72	766.72			2.89	
C	63.50	884.59	20.71	905.30	12.30	0.47	2.42	303.57
B	33.40	1120.65	10.89	1131.54	42.40	1.62	1.28	233.86
A	28.70	1356.71	9.36	1366.07	47.10	1.80	1.10	341.77

Table 4.25: LCC, Bill Savings, and PBP results for Laptop Computer

Efficiency Level	UEC (KWh)	Average IC ($)	Average OC ($)	Average LCC ($)	Energy Savings (KWh)	Bill Savings ($)	OC for PBP Calc. ($)	PBP (Years)
Class C – Baseline	26.30	569.96	6.31	576.27			1.00	
B	18.10	722.05	4.34	726.39	8.20	0.31	0.69	485.70
A	10.90	874.15	2.62	876.77	15.40	0.59	0.42	517.26

4.9.8 Vacuum Cleaner

For all the six classes of vaccum cleaners, the class B has the lowest LCC. When compared to other classes, the LCC range from 49.7 for class D to $91 for a class A+++. The energy savings range from 6 KWh for a class C to 35 KWh for a class A+++. Consumers electricity bill savings range from $0.22 for a class C to $1.33 for a class A+++. The PBP ranges from 26.1 years for a class C to 41.8 years for a class A+++. Vaccum cleaners have an average life time of 10 years thereby making the purchase of the classes of vaccum cleaner not beneficial to consumers in terms of cost. Table 4.26 summarizes the results.

4.10 Uncertainty Analysis

The result of the LCC and PBP is dependent on several parameters or inputs such as installation cost, electric tariffs, and UEC. There is always some level of uncertainties in the projections of these inputs. To address this, a probability distribution was applied to all the inputs and a Monte Carlo simulation or analysis (MCA) was used to perform the calculations. A triangular distribution was assumed for installation costs, electricity tariff or price, and UEC in order to capture the variability of these inputs. A minimum and maximum of 15% was assumed around the averages for each of the input parameters. For each of the appliances, LCC and PBP was calculated for each labeling class based on Monte Carlo simulations run based on 1,000 samples. Tables 4.27 – 4.34 show the LCC and PBP results for all the eight appliances with existing labeling. The 90th percentile is the value at which 90% of the time, LCC and PBP values are below the 90th percentile line and the other 10%, it exceeds the LCC and PBP values.

4.11 Renewable Energy Potential

Table 4.35 presents the installed capacity and the annual electricity production from each of the renewable sources in Nigeria (see Appendix C for calculation). The total installed capacity

Table 4.26: LCC, Bill Savings, and PBP results for Vacuum Cleaner

Efficiency Level	UEC (KWh)	Average IC ($)	Average OC ($)	Average LCC ($)	Energy Savings (KWh)	Bill Savings ($)	OC for PBP Calc. ($)	PBP (Years)
Class D – Baseline	44.00	31.43	18.28	49.71			1.68	
C	38.00	37.42	15.79	53.21	6.00	0.23	1.45	26.14
B	32.00	47.41	13.30	60.71	12.00	0.46	1.22	34.87
A	26.00	57.39	10.80	68.19	18.00	0.69	0.99	37.77
A+	19.00	67.38	7.89	75.27	25.00	0.95	0.73	37.66
A++	12.00	77.37	4.99	82.36	32.00	1.22	0.46	37.59
A+++	9.00	87.35	3.74	91.09	35.00	1.34	0.34	41.84

Table 4.27: LCC and PBP MCA results for Freezer

Efficiency Level	LCC Mean	LCC 10%	LCC 90%	PBP Mean	PBP 10%	PBP 90%
Class D – Baseline	1,057.14	994.72	1,118.21			
C	1,109.59	1,038.61	1,179.95	29.99	6.59	1.00
B	1,238.43	1,156.87	1,320.42	30.57	19.09	43.66
A	1,378.51	1,286.20	1,475.51	33.68	25.28	43.53
A+	1,538.51	1,425.86	1,650.13	38.32	30.16	47.67
A++	1,697.84	1,570.51	1,830.17	42.01	33.99	50.75
A+++	1,876.81	1,727.61	2,027.67	46.78	38.55	55.35

Table 4.28: LCC and PBP MCA results for Laptop Computer

Efficiency Level	LCC Mean	LCC 10%	LCC 90%	PBP Mean	PBP 10%	PBP 90%
C	576.43	527.31	626.77			
B	726.80	668.53	784.78	516.88	239.61	815.45
A	877.45	805.58	948.02	526.91	358.99	700.05

Table 4.29: LCC and PBP MCA results for Desktop Computer

Efficiency Level	LCC Mean	LCC 10%	LCC 90%	PBP Mean	PBP 10%	PBP 90%
Class D – Baseline	768.49	706.68	831.71			
C	904.70	825.82	983.69	463.90	73.12	847.89
B	1,129.40	1,042.01	1,216.84	234.47	161.38	312.27
A	1,368.43	1,258.89	1,474.55	344.99	263.60	434.48

Table 4.30: LCC and PBP MCA results for Air Conditioner

Efficiency Level	LCC Mean	LCC 10%	LCC 90%	PBP Mean	PBP 10%	PBP 90%
B – Baseline	1,953.19	1,840.70	2,070.30			
A	2,015.22	1,893.38	2,132.69	18.97	5.45	53.43
A+	2,128.74	1,999.32	2,252.68	26.45	13.32	40.60
A++	2,221.04	2,082.66	2,360.38	24.42	15.97	33.89
A+++	2,358.67	2,200.37	2,512.52	26.77	19.00	35.05

Table 4.31: LCC and PBP MCA results for Washing Machine

Efficiency Level	LCC Mean	LCC 10%	LCC 90%	PBP Mean	PBP 10%	PBP 90%
Class D – Baseline	591.06	555.22	628.31			
C	654.04	610.89	696.64	94.19	23.82	266.98
B	761.77	708.92	814.74	104.7	57.64	240.26
A	866.95	805.92	929.58	116.45	72.61	167.57
A+	980.61	906.86	1,052.52	117.33	82.71	155.04
A++	1094.22	1,014.47	1,173.51	121.49	92.00	155.37
A+++	1211.97	1,123.11	1,303.71	135.69	104.62	172.76

Table 4.32: LCC and PBP MCA results for Television

Efficiency Level	LCC Mean	LCC 10%	LCC 90%	PBP Mean	PBP 10%	PBP 90%
Class D – Baseline	277.74	258.72	296.28			
C	300.02	278.61	321.16	26.27	8.03	46.84
B	355.5	328.95	383.08	39.39	26.09	54.32
A	415.6	382.96	449.25	50.6	37.97	64.45
A+	472.83	436.16	511.89	57.43	45.64	71.02
A++	535.64	492.55	578.02	64.52	52.47	76.82
A+++	601.72	551.12	651.14	73.68	60.20	87.75

Table 4.33: LCC and PBP MCA results for Vacuum Cleaner

Efficiency Level	LCC Mean	LCC 10%	LCC 90%	PBP Mean	PBP 10%	PBP 90%
Class D – Baseline	49.44	46.46	52.43			
C	53.1	49.88	56.39	21.11	3.60	82.40
B	60.78	56.60	64.79	40.11	22.66	59.21
A	67.89	63.27	72.47	39.55	28.18	53.16
A+	75.39	69.66	81.20	39.17	29.85	49.08
A++	82.48	76.21	89.00	38.67	31.31	46.62
A+++	91.08	83.63	98.05	42.76	35.02	50.76

Table 4.34: LCC and PBP MCA results for Refrigerator

Efficiency Level	LCC Mean	LCC 10%	LCC 90%	PBP Mean	PBP 10%	PBP 90%
Class D – Baseline	981.01	923.13	1,037.19			
C	962.5	910.07	1,017.86	7.28	3.76	34.36
B	992.75	931.51	1,053.57	19.06	11.91	27.22
A	1044.59	975.41	1,114.66	21.38	15.67	27.75
A+	1122.19	1,047.59	1,202.32	24.46	19.10	29.98
A++	1209.96	1,119.63	1,305.03	27.26	21.75	33.18
A+++	1301.59	1,205.50	1,400.17	29.97	24.42	35.70

Table 4.35: Nigeria's Renewable Energy Potential

Energy Source	Total Installed Capacity (MW)	Annual Plant Capacity Factor	Annual Electricity Production (MWh)	Annual Electricity Production (GWh)	% of Total
On shore Wind	1600.00	0.37	5185920.00	5185.92	1.93
Offshore Wind	800.00	0.37	2592960.00	2592.96	0.97
Solar PV Panels	7000.00	0.26	15943200.00	15943.20	5.94
Geothermal	500.00	0.77	3372600.00	3372.60	1.26
Biomass	50.00	0.49	214620.00	214.62	0.08
Small and Large Hydro	64000.00	0.43	241075200.00	241075.20	89.82
Total	**73950.00**		**268384500.00**	**268384.50**	

is 73, 950 MW while the possible annual production is 26, 834.50 GWh. Large and small hydro account for the largest share of renewable energy source contributing up to 90% with annual production of 24,1075 GWh while solar energy contributes 6% with annual production of 15943 GWh. In 2017, hydropower contributed 5527 GWh to Nigeria's electricity generation while solar PV contributed 26 GWh (IEA, 2020). What this means is that up to 80% of hydropower and 99% solar PV are yet to be developed in Nigeria. If this is fully exploited, Nigeria may be able to meet its electricity needs in 2050 if at least 50% of annual electricity production from renewable sources is added to the current electricity mix. CO_2 emissions will also be reduced drastically if renewable is fully harnessed in 2050 thus contributing to sustainability.

4.12 Policy Implications

Findings from this study have shown that policy makers have a lot of work to do if Nigeria wants to reduce peak demand, carbon emissions, and meet her ambitious goal of 100% electrification by 2030. The following policies are advised:

Awareness Campaign: A nationwide campaign on the beneficial usage of efficient appliance in saving electricity is encouraged. The government is also encouraged to continue the free replacements of incandescent lamps with a more efficient CFL. Most energy appliances can also be subsidized in the form of tax or rebates to encourage consumers and save them money. This study shows that Nigeria's peak load demand is between 7pm – 10pm. This puts a lot of pressure on the national grid and leads to constant load shedding. The government can encourage people to change their consumption behaviour by billing people who consume energy at peak times the more.

MEPS for more Appliances and Enforcement: Although there are existing MEPS for refrigerators, lightings, and air-conditioners in Nigeria; implementation has been a problem.

There should be a coordination between the SON and the Nigerian customs on the need to not allow appliances with no energy labels into the country. The necessary government agencies should be educated on the importance of energy efficiency and why the need for an enforcement will save Nigeria a lot of energy – all hands must be on deck. The government should also consider MEPS for other appliances aside refrigerator and air-conditioning that were identified in this study to consume the largest amount of residential sector electricity.

Integration of Renewable Energy: This study has shown that Nigeria's electricity needs can be met by renewable energy. The government should encourage heavy investment in renewable energy in order to meet the needs of the people. Households that get electricity from renewable sources can get tax breaks, low or no interest loans, or have the cost of switching to renewable source subsidized.

Investment in the Electricity Sector: Total REC up to 2050 has been estimated in this study. The estimates can guide the government in the aspect of supply capacity. Electricity generation, transmission, and distribution require a lot of capital. Therefore, cost of building power plants must be optimized based on demand estimates. Nigeria as a country does not have the financial strength to build electricity supplies that can provide the demand estimated in this study. Genuine investors can be encouraged by providing investment incentives to attract them to the energy sector. The government should also consider regular funding of the electricity transmission companies so that transmission lines and assets can be regularly maintained or repaired. This will reduce the transmission loss and the country can at least enjoy all the electricity generated.

Electricity Demand Research*:* Existing energy research centres in Nigeria are mostly focused on renewable energy potentials. Data pertaining to electricity consumption is scarce or not available in Nigeria. The Energy Commission of Nigeria (ECN) and other research agencies should conduct more studies on energy demand to determine the electricity behaviours of its customers. This will help guide in EE awareness campaigns. The availability of data will reduce the uncertainties associated with this study and all other relevant studies in Nigeria. It will also encourage researchers to conduct independent studies that can guide the country in policy formulations.

Implementation of Existing Policies: Existing energy policies in Nigeria include the National Energy Policy, Electricity Power Sector Reform 2005, the Rural Electrification Strategy and Implementation Plan (RESIP), and the Nigerian Electricity Regulatory Commission (NERC) Mini Grid Regulation. These policies are focused on sustainability, alternative energy resources, and mini-grid development in Nigeria. However, there has been lack of interest by stakeholders especially the enforcing agencies, legislative, and judiciary arms of government. For example, existing policies such as the EE S&L not backed by an act of the national assembly should be passed into law while the government must be ready to sanction any defaulters. Such sanctions can include prosecution in the court of law and revocation of licenses. Many Nigerians are also unaware of existing policies; the government through the National Orientation Agency (NOA) must be ready to publicize these policies so that the people can be aware of them. This study has shown that strict implementation and enforcement of the EE S&L will cause a reduction in Nigerian households' peak demand and cost.

Provision of Incentives for Manufacturers: Companies that manufacture household appliances are very few in Nigeria. Majority of household appliances are imported from the USA, European countries, and China. The government is encouraged to support local manufacturing of appliances in Nigeria by providing soft loans to manufacturing companies that exist or willing to do business in the country in order to manufacture appliances that are affordable to local consumers. More attention should be focused on the research and development sections of these companies by providing funds that will assist in research and development of efficient appliances. This approach is cost-effective and will save Nigeria more money that would have been used to build more power plants.

Provision of Incentives for Consumers: Efficient appliances are expensive and not affordable for most consumers. The federal government of Nigeria can encourage consumers to buy efficient appliances by providing soft loans to purchase them. Providing financial incentives will increase appliances availability and sales, providing the foundation needed for effective implementation of EES&L in Nigeria. Ultimately, it will reduce the payback period of most appliances thereby providing a positive ROI on the purchase of efficient appliances.

CHAPTER 5: CONCLUSION

This study estimates Nigeria's electricity consumption and savings on a disaggregated basis and forecasts to mid-century under the BAU and BAT scenarios. The economic and environmental impacts of using energy efficient appliances was also analyzed. Electricity consumption in 2020 under the BAU scenario is 41657 GWh and 40507 GWh under the BAT scenario. Electricity consumption in 2050, under the BAU scenario is 160540 GWh and 127902 GWh under the BAT scenario. The BAU scenarios has the highest consumption. This study finds that the introduction of MEPS can help save 2.76% of final energy in 2020 and 20.33% in 2050. The end-uses with the largest consumptions are refrigeration, air-conditioners, cooking, entertainment, and lighting. This study envisaged that electricity consumption increase will be from the entrance of appliances like refrigerators, washing machines, dryers, and air-conditioners in the market. These appliances currently have a low ownership percentage but are expected to grow over the years. The most reasonable way to reduce the consumption of these appliances is to aggressively implement the MEPS now before the predicted growth. As addressed in the policy section, strict enforcements of the MEPS and awareness campaigns will be the way forward for a possible reduction in REC.

Load curves in the BAU and BAT scenarios between 2030 – 2050 show a slow increase in the peak load up to 2050. This is because of the introduction of more efficient appliances particularly lightings that started in 2009. In 2030, peak load in the BAT scenario is 12675 MW compared to 14037 MW (-11%) in the BAU scenario. In 2040, peak load in the BAT scenario is 19514 MW compared to 22970 MW (-15%) in the BAU scenario. In 2050, peak load in the BAT scenario is 24672 MW compared to 29575 MW (-17%) in the BAU scenario. Total energy savings in 2030, 2040, and 2050 are 1036 MW, 2649 MW, and 3726 MW respectively. The largest reduction in peak load under the BAT scenario comes from refrigeration and entertainment.

The result of a possible impact of climate uncertainty on electricity demand in 2050 is a 23.8% and 24.2% increase in cooling demand under the BAU and BAT scenarios. In a warmer climate, the total REC for Nigeria will increase by 5469 GWh (3.41%) under the BAU scenario and by 4861 GWh (3.80%) under the BAT scenario. This study shows that emission savings for 2030, 2040, and 2050 are 3.98 million metric tons (Mt) CO_2, 10.19 million metric tons (Mt) CO_2, and 14.33 million metric tons (Mt) CO_2, respectively. Nigeria's Intended Nationally Determined Contribution (INDC) total emission projection for 2030 is 900 (Mt) CO_2. Therefore, approximately 0.44% of carbon can be reduced in Nigeria if residential appliances and lighting become more efficient. In 2017, as Nigeria's commitment to the NDCs, the president of Nigeria, Muhammadu Buhari committed Nigeria to an unconditional 20% reduction in emissions by 2030, compared to business-as-usual levels. Thus, Nigeria is expected to reduce her 2030 emission projection by 180 million (Mt) CO_2. This means that the residential sector with a 10.19 million metric tons (Mt) CO_2 savings can contribute 5.5% of this reduction.

Monte Carlo Analysis results show the uncertainty surrounding the modeled REC including the variation over time. The modeled REC varies considerably. For example, in prediction year 2050, the 10th percentile is approximately 37571 GWh less of the modeled mean value while it is 41423 GWh more at the 90th percentile. LCC and PBP analyses show a general increase in LCC and PBP with increasing efficiency levels for the eight appliances with existing standards. Specifically, all the appliances have a long PBPs that exceed their average lifetimes thereby making the investment on more efficient models not profitable to consumers.

Renewable energy total installed capacity is 73,950 MW while the possible annual production is 26, 834.50 GWh. Large and small hydro account for the largest share of renewable energy source contributing up to 90% with annual production of 24,1075 GWh while solar energy contributes 6% with annual production of 15943 GWh. This study concludes that Nigeria can meet its electricity needs through renewable energy source. These estimates may increase in the future if more renewable energy sources are discovered.

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APPENDICES

Appendix A

Table A1: Regression Analysis of the appliance ownerships and the energy demand drivers

Variables	Population		Household Number	
Parameters	***Coef.***	***Std.Error***	***Coef.***	***Std.Error***
(Intercept)	18.04***	0.06256	21.94***	1.657
Lamp	281***	49.44	902.4	1310
Refrigerator	-5790**	1414	61570	37460
Fan	-1253***	229.3	-2645	6075
Television	-436.4***	86.09	-126.5	2281
Electric.Iron	2298***	454.1	-2836	12030
Air.conditioner	26730**	8165	-549100*	216300
Washing.Machine	1853	2726	-251100**	72230
Freezer	2739**	645.6	-15650	17110
Microwave	-4882	3320	307400**	87960
Blender.food.processor	0.1636	0.7208	15.22	19.1
Mobile.phone	-0.000476	0.0008347	-0.01442	0.02211
Desktop.computer	NA	NA	NA	NA
Laptop.computer	61.16*	20.59	-998.3	545.5
Electric.Clothes.Dryer	538.8	617	-71170***	16350
VCD.DVD.MP3.MP4.player	NA	NA	NA	NA
Radio	NA	NA	NA	NA
Vacuum.cleaner	-785.7	739.6	60900**	19590
Electric.cooker	NA	NA	NA	NA
Toaster	-1.675	211	-19110**	5590
Electric.kettle	703.5	521.5	-42410**	13820
Electric.water.heater	-160.5	715.4	-64050**	18950

Table A2: Regression Analysis of the appliance ownerships and the energy demand drivers

Variables	Household.Size		Floor Area per HH	
Parameters	***Coef.***	***Std.Error***	***Coef.***	***Std.Error***
(Intercept)	-3.9*	1.668	14200*	6135
Lamp	-621.4	1318	1524000	4849000
Refrigerator	-67360	37690	-104500000	138700000
Fan	1392	6113	-9468000	22490000
Television	-309.9	2295	-7116000	8443000
Electric.Iron	5133	12110	2.38E+07	44530000
Air.conditioner	575800*	217700	1.57E+08	800700000
Washing.Machine	253000**	72690	-428200000	267400000
Freezer	18390	17210	1.06E+08	63320000
Microwave	-312300	88520	3.36E+08	325600000
Blender.food.processor	-15.06	19.22	195000*	70690
Mobile.phone	0.01394	0.02225	75.55	81.86
Desktop.computer	NA	NA	NA	NA
Laptop.computer	1059	549	-1237000	2019000
Electric.Clothes.Dryer	71700***	16450	31410000	60510000
VCD.DVD.MP3.MP4.player	NA	NA	NA	NA
Radio	NA	NA	NA	NA
Vacuum.cleaner	-61680**	19720	2.79E+07	72530000
Electric.cooker	NA	NA	NA	NA
Toaster	19110**	5625	7669000	20690000
Electric.kettle	43120**	13910	-91230000	51150000
Electric.water.heater	63890**	19070	-136200000	70160000

Table A3: Regression Analysis of the appliance ownerships and the energy demand

Variables	**GDP.capita**		**Primary School Enrolment**		**Industrialization**	
Parameters	***Coef.***	***Std.Error***	***Coef.***	***Std.Error***	***Coef.***	***Std.Error***
(Intercept)	602200	468600	33810**	9839	14310	11770
Lamp	74440000	370300000	25590000**	7776000	7500000	9306000
Refrigerator	-1559000000	1.06E+10	-2.23E+08	2.22E+08	-2.15E+08	2.66E+08
Fan	-376200000	1717000000	-109600000*	3.61E+07	-35780000	4.32E+07
Television	-229900000	644800000	-3.33E+07*	1.35E+07	-1.50E+07	1.62E+07
Electric.Iron	674700000	3401000000	173100000*	7.14E+07	71450000	8.55E+07
Air.conditioner	-1.04E+10	6.12E+10	5.08E+08	1.28E+09	9.07E+08	1.54E+09
Washing.Machine	-1.98E+10	2.04E+10	-88710000	428800000	-92460000	513100000
Freezer	2893000000	4836000000	9.80E+07	1.02E+08	1.26E+08	1.22E+08
Microwave	1.89E+10	2.49E+10	1.76E+08	5.22E+08	-5.56E+07	6.25E+08
Blender.food.processor	6107000	5399000	-73290	113400	99400	135700
Mobile.phone	4064	6252	-447.5**	131.3	-129.7	157.1
Desktop.computer	NA	NA	NA	NA	NA	NA
Laptop.computer	-76910000	154200000	3846000	3238000	836200	3875000
Electric.Clothes.Dryer	-734400000	4621000000	-135300000	97040000	89380000	116100000
VCD.DVD.MP3.MP4.player	NA	NA	NA	NA	NA	NA
Radio	NA	NA	NA	NA	NA	NA
Vacuum.cleaner	2087000000	5539000000	-1.70E+08	1.16E+08	-5.82E+07	1.39E+08
Electric.cooker	NA	NA	NA	NA	NA	NA
Toaster	-24160000	1580000000	47040000	33180000	26900000	39710000
Electric.kettle	-4236000000	3906000000	-4.16E+07	82030000	-2.64E+07	98160000
Electric.water.heater	-5718000000	5358000000	54920000	1.13E+08	-31440000	1.35E+08

APPENDIX B: Imputation and forecasting of appliance ownership missing data

Three different time-series forecasting models also based on the estimation of missing values were used to forecast appliance ownership in order to determine their usability in the REC model. These approach follows two steps. First, the mean imputation method was to estimate the missing values from 1990 – 2020. This works by using the average of the actual values to determine the next mean value. Second, the results from the mean imputation were then used to forecast for future years (2021 – 2050) using the Naïve, Simple Exponential Smoothing, and Holt's Trend techniques. These techniques are briefly described below.

1. **The Naïve Method**

Naïve dictates that we use the previous period energy consumption data to forecast for the next period. In this study, one-year-ahead consumption data is forecasted for different appliances. Forecasts have been made for the year beyond 2020.

$Y_{T+h|T} = Y_T$ … (Naïve Forecast Model)

2. **Simple Exponential Smoothing**

The exponential smoothing is an extension of the naïve method where the forecast is derived from using the weighted averages of the past observations. The weights decay exponentially as the observations get older (tends to older historical appliance ownership points, say 1991 is older than 2011 refrigerator ownership percentage, as the data memorizes it's past).

3. Holt’s Trend Method

Holt winter is an extension of the simple exponential smoothing method. Holt’s trend introduces the trend component while generating the forecast values. The smoothing equations are level and trend.

The results of the mean imputations and forecasting models are presented in Tables B1-B11. For the mean imputation results, the bolded values are the actual values while those that are not bolded are imputation values. For the forecasting model results, the bolded values are the actual or given values for forecast end year while those that are not bolded are forecast values.

Table B1: Mean Imputation Results

Year	Refrigerator	Fan	Television	Electric Iron	Air Conditioner	Washing Machine	Freezer
1990	17.68	46.94	38.82	37.76	2.51	0.86	8.91
1991	17.69	46.94	38.81	37.76	2.51	0.86	8.92
1992	17.69	46.94	38.76	37.76	2.51	0.86	8.92
1993	17.69	46.93	38.76	37.75	2.51	0.86	8.91
1994	17.68	46.93	38.8	37.75	2.51	0.86	8.91
1995	17.67	46.94	38.92	37.75	2.51	0.85	8.91
1996	17.68	46.95	39.13	37.79	2.51	0.86	8.92
1997	17.68	46.96	39.37	37.78	2.52	0.86	8.94
1998	17.69	46.92	38.02	37.77	2.51	0.86	8.91
1999	17.72	46.91	38.73	37.76	2.51	0.85	8.89
2000	17.74	46.93	38.3	37.75	2.51	0.84	8.89
2001	17.66	46.97	38.77	37.64	2.52	0.85	8.92
2002	17.59	46.99	39.18	37.81	2.52	0.87	8.97
2003	17.61	47.06	39.87	37.7	2.52	0.89	9.03
2004	17.72	46.63	40.81	38.11	2.49	0.85	8.74
2005	17.72	46.87	41.27	37.68	2.51	0.82	8.81
2006	17.78	47.08	27.2	37.68	2.52	0.79	8.86
2007	17.94	47.17	44.46	37.68	2.53	0.89	9.08
2008	17.94	47.16	34.85	37.68	2.54	0.98	9.27
2009	17	47.43	42.5	36.8	2.55	1.05	9.43
2010	17	44.1	42.5	39.2	2.3	0.6	7
2011	17.8	48.3	45.4	36.8	2.6	0.6	9.2
2012	18.6	48.3	48.3	41.4	2.6	0.6	9.2
2013	17.69	47.72	44.97	36.8	2.6	1.5	10.4
2014	18.27	47.13	47	39.42	2.6	1.5	10.4
2015	19.2	49	50.2	41.8	2.6	1.5	10.4
2016	17.58	46.87	39.49	37.64	2.51	0.82	8.81
2017	17.71	47.08	43	38.26	2.52	0.79	8.86
2018	17.67	47.17	43.09	38.11	2.53	0.89	9.08
2019	17.73	47.16	45.11	38.4	2.54	1.8	9.27
2020	18.09	47.43	46.39	39.24	2.55	1.05	9.43

Table B2: Mean Imputation Results

Year	Microwave	Blender	Mobile Phone	Desktop computer	Laptop computer	Electric Clothes Dryer	VCD/DVD/ MP3/MP4 player
1990	8.31	57.4	18.94	2.23	17.5	0.87	36.04
1991	8.31	57.4	19.49	2.23	17.5	0.87	36.05
1992	8.31	57.4	19.06	2.23	17.5	0.87	36.07
1993	8.31	57.4	18.03	2.24	17.5	0.87	36.11
1994	8.32	57.4	19.19	2.23	17.5	0.87	36.14
1995	8.32	57.4	21.67	2.23	17.5	0.87	36.16
1996	8.29	57.4	17.35	2.24	17.5	0.87	36.17
1997	8.29	57.4	13.93	2.26	17.5	0.87	36.17
1998	8.31	57.4	23.79	2.2	17.5	0.87	36.16
1999	8.34	57.4	31.63	2.21	17.5	0.87	35.63
2000	8.38	57.4	0.03	2.29	17.5	0.87	35.82
2001	8.3	57.4	0.27	2.32	17.5	0.87	35.92
2002	8.13	57.4	63.23	1.98	17.5	0.87	36.16
2003	8.28	57.4	63	2.27	17.5	0.87	36.37
2004	8.41	57.41	62.65	2.58	17.5	0.86	36.56
2005	8.53	57.4	64.24	2.46	17.5	0.88	36.45
2006	8.62	57.38	63.03	0.6	17.5	0.85	36.34
2007	7.81	57.4	62.06	3.43	17.5	0.9	36.25
2008	7.12	57.43	61.28	3.83	17.5	0.8	36.16
2009	9.2	57.39	70.6	2	17.5	1	36.08
2010	9.2	57.31	58.18	4.6	17.5	0.6	29.8
2011	9.2	57.49	58.18	3.3	17.49	1.4	37.9
2012	9.2	57.54	58.18	5.4	17.52	1.4	37.1
2013	2.96	57.23	58.18	4.8	17.46	1.41	38.7
2014	2.96	56.98	58.18	4.8	17.58	1.39	38.7
2015	2.96	58.19	78.9	4.8	17.34	1.43	38.7
2016	8.53	57.75	37.45	4.8	17.81	1.35	35.2
2017	8.62	56	58.18	4.31	16.88	1.5	35.2
2018	7.81	56	58.18	4.6	18.75	1.2	35.2
2019	7.12	63	58.18	4.6	15	1.8	35.2
2020	6.08	56	52.99	4.76	22.5	1.8	35.2

Table B3: Mean Imputation Results

Year	Radio	Vacuum cleaner	Electric Cooker	Toaster	Electric Kettle	Electric Water heater-Bathroom
1990	59.95	7.31	3.37	13.45	12.38	1.03
1991	59.94	7.31	3.37	13.45	12.38	1.03
1992	59.95	7.31	3.37	13.45	12.38	1.03
1993	59.96	7.31	3.37	13.45	12.38	1.03
1994	59.97	7.31	3.37	13.45	12.38	1.03
1995	59.99	7.31	3.37	13.45	12.38	1.03
1996	60.01	7.31	3.37	13.45	12.38	1.04
1997	60.04	7.31	3.37	13.45	12.38	1.04
1998	60.06	7.31	3.37	13.44	12.38	1.04
1999	59.83	7.31	3.37	13.45	12.38	1.03
2000	59.79	7.31	3.37	13.45	12.38	1.03
2001	59.85	7.31	3.37	13.45	12.38	1.02
2002	59.92	7.31	3.37	13.45	12.38	1.01
2003	59.97	7.31	3.36	13.44	12.38	1.04
2004	60.07	7.31	3.37	13.45	12.38	1.09
2005	60.17	7.31	3.37	13.41	12.38	1.06
2006	60.2	7.32	3.37	13.48	12.38	1.03
2007	60.24	7.31	3.37	13.48	12.38	1
2008	60.29	7.3	3.37	13.43	12.39	0.98
2009	60.37	7.29	3.37	13.47	12.38	0.96
2010	57.3	7.36	3.37	13.35	12.39	0.94
2011	59.25	7.31	3.37	13.56	12.36	1.24
2012	60.6	7.26	3.3	13.11	12.43	1.5
2013	60.6	7.23	3.4	13.97	12.3	0.8
2014	60.6	7.63	3.4	13.44	12.55	0.8
2015	61.2	7.1	3.4	13.13	12.05	0.8
2016	61.2	7.1	3.35	13.75	13.06	0.8
2017	60.6	7.1	3.37	12.5	11.04	0.8
2018	60.6	9.2	3.38	15	15.08	0.8
2019	60.9	5	3.37	10	7	3.6
2020	61.2	7.1	3.38	20	23.15	3.6

Table B4: Naïve Method Forecast Results

Year	Refrigerator	Fan	Television	Electric Iron	Air Conditioner	Washing Machine	Freezer
2021	19.04	49.63	56.68	42.56	2.69	1.66	10.82
2022	19.43	50.55	60.94	43.93	2.75	1.91	11.39
2023	19.73	51.25	64.21	44.99	2.80	2.11	11.83
2024	19.99	51.84	66.96	45.88	2.84	2.27	12.21
2025	20.21	52.36	69.39	46.66	2.87	2.41	12.53
2026	20.41	52.83	71.59	47.37	2.90	2.54	12.83
2027	20.60	53.26	73.61	48.02	2.93	2.66	13.10
2028	20.77	53.66	75.48	48.63	2.96	2.77	13.35
2029	20.94	54.04	77.25	49.20	2.98	2.88	13.59
2030	21.09	54.40	78.92	49.74	3.01	2.98	13.82
2031	21.24	54.74	80.51	50.25	3.03	3.07	14.03
2032	21.38	55.07	82.02	50.74	3.05	3.16	14.24
2033	21.51	55.38	83.48	51.21	3.07	3.25	14.43
2034	21.64	55.68	84.88	51.66	3.09	3.33	14.62
2035	21.76	55.97	86.23	52.10	3.11	3.41	14.80
2036	21.88	56.25	87.54	52.52	3.13	3.49	14.98
2037	22.00	56.52	88.80	52.93	3.15	3.56	15.15
2038	22.11	56.78	90.03	53.32	3.16	3.64	15.32
2039	22.22	57.04	91.23	53.71	3.18	3.71	15.48
2040	22.33	57.29	92.39	54.09	3.20	3.78	15.64
2041	22.44	57.53	93.53	54.45	3.21	3.84	15.79
2042	22.54	57.77	94.64	54.81	3.23	3.91	15.94
2043	22.64	58.00	95.72	55.16	3.24	3.97	16.08
2044	22.74	58.23	96.78	55.50	3.26	4.04	16.23
2045	22.83	58.45	97.82	55.84	3.27	4.10	16.37
2046	22.93	58.67	98.84	56.17	3.29	4.16	16.51
2047	23.02	58.88	99.84	56.49	3.30	4.22	16.64
2048	23.11	59.09	100.82	56.81	3.31	4.28	16.77
2049	23.20	59.30	101.79	57.12	3.33	4.33	16.90
2050	**89.38**	**81.50**	**80.80**	**90.64**	**19.70**	**33.80**	**20.60**

Table B5: Naïve Method Forecast Results

Year	Microwave	Blender	Mobile Phone	Desktop computer	Laptop computer	Electric Clothes Dryer	VCD/DVD/MP3/ MP4 player
2021	9.24	59.63	85.02	6.68	25.60	2.21	39.14
2022	10.54	61.13	98.29	7.48	26.88	2.38	40.77
2023	11.54	62.29	108.47	8.09	27.87	2.52	42.02
2024	12.39	63.26	117.05	8.61	28.70	2.63	43.07
2025	13.14	64.12	124.61	9.06	29.43	2.72	44.00
2026	13.81	64.89	131.45	9.47	30.09	2.81	44.84
2027	14.43	65.60	137.73	9.85	30.70	2.89	45.61
2028	15.00	66.27	143.58	10.20	31.26	2.97	46.33
2029	15.55	66.89	149.08	10.53	31.80	3.04	47.01
2030	16.06	67.48	154.28	10.84	32.30	3.11	47.65
2031	16.54	68.04	159.22	11.14	32.78	3.17	48.26
2032	17.01	68.58	163.94	11.42	33.23	3.23	48.84
2033	17.46	69.09	168.47	11.69	33.67	3.29	49.39
2034	17.89	69.58	172.83	11.95	34.09	3.35	49.93
2035	18.30	70.06	177.04	12.21	34.50	3.40	50.45
2036	18.70	70.52	181.11	12.45	34.89	3.45	50.95
2037	19.09	70.97	185.05	12.69	35.27	3.50	51.43
2038	19.47	71.40	188.88	12.92	35.65	3.55	51.90
2039	19.83	71.82	192.60	13.14	36.01	3.60	52.36
2040	20.19	72.24	196.23	13.36	36.36	3.65	52.80
2041	20.54	72.64	199.77	13.57	36.70	3.69	53.24
2042	20.88	73.03	203.22	13.78	37.03	3.74	53.66
2043	21.21	73.41	206.60	13.98	37.36	3.78	54.08
2044	21.54	73.78	209.90	14.18	37.68	3.83	54.48
2045	21.86	74.15	213.14	14.37	37.99	3.87	54.88
2046	22.17	74.51	216.31	14.56	38.30	3.91	55.27
2047	22.47	74.86	219.42	14.75	38.60	3.95	55.65
2048	22.78	75.21	222.47	14.93	38.90	3.99	56.03
2049	23.07	75.55	225.47	15.11	39.19	4.03	56.40
2050	**55.00**	**70.00**	**85.00**	**20.30**	**30.00**	**33.80**	**56.00**

Table B6: Naïve Method Forecast Results

Year	Radio	Vacuum cleaner	Electric Cooker	Toaster	Electric Kettle	Electric Water heater
2021	62.63	8.96	3.43	24.15	29.82	4.64
2022	63.23	9.73	3.45	25.87	32.59	5.07
2023	63.68	10.32	3.46	27.19	34.71	5.41
2024	64.07	10.81	3.48	28.30	36.50	5.69
2025	64.41	11.25	3.49	29.28	38.07	5.93
2026	64.71	11.65	3.50	30.17	39.50	6.15
2027	64.99	12.01	3.51	30.98	40.81	6.36
2028	65.25	12.35	3.52	31.74	42.03	6.55
2029	65.50	12.67	3.53	32.45	43.17	6.73
2030	65.73	12.97	3.53	33.13	44.26	6.90
2031	65.95	13.26	3.54	33.77	45.29	7.06
2032	66.17	13.53	3.55	34.38	46.27	7.21
2033	66.37	13.79	3.55	34.97	47.21	7.36
2034	66.56	14.05	3.56	35.53	48.12	7.50
2035	66.75	14.29	3.57	36.08	49.00	7.64
2036	66.93	14.53	3.57	36.61	49.85	7.77
2037	67.11	14.75	3.58	37.12	50.67	7.90
2038	67.28	14.98	3.59	37.61	51.47	8.02
2039	67.45	15.19	3.59	38.10	52.24	8.15
2040	67.61	15.40	3.60	38.57	53.00	8.26
2041	67.77	15.61	3.60	39.02	53.73	8.38
2042	67.92	15.81	3.61	39.47	54.45	8.49
2043	68.08	16.00	3.61	39.91	55.16	8.60
2044	68.22	16.19	3.62	40.34	55.85	8.71
2045	68.37	16.38	3.62	40.76	56.52	8.81
2046	68.51	16.57	3.63	41.17	57.18	8.92
2047	68.65	16.75	3.63	41.57	57.83	9.02
2048	68.79	16.92	3.64	41.97	58.47	9.12
2049	68.92	17.10	3.64	42.36	59.09	9.22
2050	**100.00**	**13.40**	**53.22**	**30.00**	**39.30**	**6.40**

Table B7: Simple Exponential Smoothing Forecast Results

Year	Refrigerator	Fan	Television	Electric Iron	Air Conditioner	Washing Machine	Freezer
2021	18.54	48.58	52.52	40.66	2.63	1.63	10.26
2022	18.54	48.58	52.79	40.67	2.63	1.63	10.26
2023	18.54	48.58	53.05	40.68	2.63	1.64	10.26
2024	18.54	48.58	53.29	40.70	2.63	1.64	10.26
2025	18.54	48.58	53.54	40.71	2.63	1.65	10.26
2026	18.54	48.58	53.77	40.72	2.63	1.65	10.26
2027	18.54	48.58	54.00	40.73	2.63	1.66	10.26
2028	18.54	48.58	54.23	40.74	2.63	1.67	10.26
2029	18.54	48.58	54.45	40.75	2.63	1.67	10.26
2030	18.54	48.58	54.66	40.76	2.63	1.68	10.26
2031	18.54	48.58	54.87	40.77	2.63	1.68	10.26
2032	18.54	48.58	55.08	40.78	2.63	1.69	10.26
2033	18.54	48.58	55.28	40.79	2.63	1.69	10.26
2034	18.54	48.58	55.47	40.80	2.63	1.70	10.26
2035	18.54	48.58	55.67	40.81	2.63	1.70	10.26
2036	18.54	48.58	55.86	40.82	2.63	1.71	10.26
2037	18.54	48.58	56.05	40.83	2.63	1.71	10.26
2038	18.54	48.58	56.23	40.84	2.63	1.72	10.26
2039	18.54	48.58	56.41	40.85	2.63	1.72	10.26
2040	18.54	48.58	56.59	40.86	2.63	1.73	10.26
2041	18.54	48.58	56.77	40.87	2.63	1.73	10.26
2042	18.54	48.58	56.94	40.88	2.63	1.73	10.26
2043	18.54	48.58	57.11	40.89	2.63	1.74	10.26
2044	18.54	48.58	57.28	40.90	2.63	1.74	10.26
2045	18.54	48.58	57.45	40.91	2.63	1.75	10.26
2046	18.54	48.58	57.61	40.92	2.63	1.75	10.26
2047	18.54	48.58	57.78	40.93	2.63	1.76	10.26
2048	18.54	48.58	57.94	40.94	2.63	1.76	10.26
2049	18.54	48.58	58.09	40.95	2.63	1.77	10.26
2050	**89.38**	**81.50**	**80.80**	**90.64**	**19.70**	**33.80**	**20.60**

Table B8: Simple Exponential Smoothing Forecast Results

Year	Microwave	Blender	Mobile Phone	Desktop computer	Laptop computer	Electric Clothes Dryer	VCD/DVD/ MP3/ MP4 player
2021	9.29	59.71	85.45	6.23	19.71	2.07	39.19
2022	10.62	59.71	89.41	6.37	19.71	2.12	39.19
2023	11.64	59.71	92.96	6.50	19.71	2.17	39.19
2024	12.50	59.71	96.20	6.62	19.71	2.21	39.19
2025	13.26	59.71	99.21	6.73	19.71	2.25	39.19
2026	13.94	59.71	102.02	6.83	19.71	2.29	39.19
2027	14.57	59.71	104.67	6.93	19.71	2.32	39.19
2028	15.16	59.71	107.19	7.03	19.71	2.35	39.19
2029	15.71	59.71	109.59	7.12	19.71	2.38	39.19
2030	16.23	59.71	111.89	7.21	19.71	2.41	39.19
2031	16.72	59.71	114.11	7.30	19.71	2.44	39.19
2032	17.20	59.71	116.24	7.38	19.71	2.47	39.19
2033	17.65	59.71	118.29	7.47	19.71	2.49	39.19
2034	18.09	59.71	120.29	7.54	19.71	2.52	39.19
2035	18.51	59.71	122.22	7.62	19.71	2.54	39.19
2036	18.92	59.71	124.10	7.70	19.71	2.57	39.19
2037	19.31	59.71	125.93	7.77	19.71	2.59	39.19
2038	19.69	59.71	127.72	7.84	19.71	2.61	39.19
2039	20.07	59.71	129.46	7.91	19.71	2.64	39.19
2040	20.43	59.71	131.16	7.98	19.71	2.66	39.19
2041	20.78	59.71	132.82	8.05	19.71	2.68	39.19
2042	21.13	59.71	134.45	8.11	19.71	2.70	39.19
2043	21.47	59.71	136.05	8.18	19.71	2.72	39.19
2044	21.80	59.71	137.61	8.24	19.71	2.74	39.19
2045	22.12	59.71	139.15	8.30	19.71	2.76	39.19
2046	22.44	59.71	140.66	8.36	19.71	2.78	39.19
2047	22.75	59.71	142.14	8.42	19.71	2.80	39.19
2048	23.06	59.71	143.60	8.48	19.71	2.82	39.19
2049	23.36	59.71	145.03	8.54	19.71	2.83	39.19
2050	**55.00**	**70.00**	**85.00**	**20.30**	**30.00**	**33.80**	**56.00**

Table B8: Simple Exponential Smoothing Forecast Results

Year	Radio	Vacuum cleaner	Electric Cooker	Toaster	Electric Kettle	Electric Water heater
2021	62.22	8.38	3.40	16.35	17.11	4.66
2022	62.28	8.38	3.40	16.35	17.11	5.09
2023	62.35	8.38	3.40	16.35	17.11	5.42
2024	62.40	8.38	3.40	16.35	17.11	5.70
2025	62.46	8.38	3.40	16.35	17.11	5.95
2026	62.52	8.38	3.40	16.35	17.11	6.17
2027	62.57	8.38	3.40	16.35	17.11	6.37
2028	62.62	8.38	3.40	16.35	17.11	6.56
2029	62.67	8.38	3.40	16.35	17.11	6.74
2030	62.72	8.38	3.40	16.35	17.11	6.91
2031	62.76	8.38	3.40	16.35	17.11	7.07
2032	62.81	8.38	3.40	16.35	17.11	7.23
2033	62.86	8.38	3.40	16.35	17.11	7.38
2034	62.90	8.38	3.40	16.35	17.11	7.52
2035	62.94	8.38	3.40	16.35	17.11	7.66
2036	62.98	8.38	3.40	16.35	17.11	7.79
2037	63.03	8.38	3.40	16.35	17.11	7.92
2038	63.07	8.38	3.40	16.35	17.11	8.04
2039	63.11	8.38	3.40	16.35	17.11	8.16
2040	63.15	8.38	3.40	16.35	17.11	8.28
2041	63.18	8.38	3.40	16.35	17.11	8.40
2042	63.22	8.38	3.40	16.35	17.11	8.51
2043	63.26	8.38	3.40	16.35	17.11	8.62
2044	63.30	8.38	3.40	16.35	17.11	8.73
2045	63.33	8.38	3.40	16.35	17.11	8.84
2046	63.37	8.38	3.40	16.35	17.11	8.94
2047	63.40	8.38	3.40	16.35	17.11	9.04
2048	63.44	8.38	3.40	16.35	17.11	9.14
2049	63.47	8.38	3.40	16.35	17.11	9.24
2050	**100.00**	**13.40**	**53.22**	**30.00**	**39.30**	**6.40**

Table B9: Holts Trend Forecast Results

Year	Refrigerator	Fan	Television	Electric Iron	Air Conditioner	Washing Machine	Freezer
2021	18.72	48.92	53.09	40.97	2.66	1.62	10.44
2022	18.73	48.94	53.36	41.01	2.66	1.63	10.44
2023	18.74	48.96	53.64	41.06	2.66	1.65	10.45
2024	18.75	48.98	53.91	41.11	2.66	1.67	10.45
2025	18.77	49.00	54.19	41.15	2.66	1.68	10.46
2026	18.78	49.02	54.46	41.20	2.66	1.70	10.46
2027	18.79	49.04	54.73	41.25	2.67	1.71	10.46
2028	18.80	49.06	55.01	41.29	2.67	1.73	10.47
2029	18.81	49.08	55.28	41.34	2.67	1.75	10.47
2030	18.82	49.10	55.55	41.38	2.67	1.77	10.48
2031	18.84	49.12	55.83	41.43	2.67	1.78	10.48
2032	18.85	49.14	56.10	41.48	2.68	1.80	10.49
2033	18.86	49.16	56.37	41.52	2.68	1.82	10.49
2034	18.87	49.18	56.65	41.57	2.68	1.84	10.50
2035	18.88	49.20	56.92	41.62	2.68	1.86	10.50
2036	18.89	49.22	57.19	41.66	2.68	1.88	10.50
2037	18.91	49.24	57.46	41.71	2.68	1.90	10.51
2038	18.92	49.26	57.73	41.75	2.69	1.92	10.51
2039	18.93	49.28	58.01	41.80	2.69	1.94	10.52
2040	18.94	49.30	58.28	41.85	2.69	1.97	10.52
2041	18.95	49.32	58.55	41.89	2.69	1.99	10.53
2042	18.96	49.35	58.82	41.94	2.69	2.01	10.53
2043	18.98	49.37	59.09	41.99	2.69	2.04	10.54
2044	18.99	49.39	59.36	42.03	2.70	2.06	10.54
2045	19.00	49.41	59.63	42.08	2.70	2.09	10.54
2046	19.01	49.43	59.91	42.12	2.70	2.12	10.55
2047	19.02	49.45	60.18	42.17	2.70	2.14	10.55
2048	19.03	49.47	60.45	42.22	2.70	2.17	10.56
2049	19.05	49.49	60.72	42.26	2.70	2.20	10.56
2050	**89.38**	**81.50**	**80.80**	**90.64**	**19.70**	**33.80**	**20.60**

Table B10: Holts Trend Forecast Results

Year	Microwave	Blender	Mobile Phone	Desktop computer	Laptop computer	Electric Clothes Dryer	VCD/DVD/ MP3/MP4 player
2021	10.10	60.05	89.13	6.46	20.00	2.13	39.27
2022	10.04	60.07	93.69	6.64	20.01	2.22	39.28
2023	9.99	60.09	97.97	6.81	20.03	2.32	39.29
2024	9.94	60.11	102.03	6.97	20.04	2.43	39.30
2025	9.88	60.13	105.91	7.14	20.06	2.54	39.31
2026	9.83	60.14	109.64	7.30	20.07	2.66	39.32
2027	9.78	60.16	113.25	7.46	20.08	2.78	39.34
2028	9.72	60.18	116.76	7.61	20.10	2.90	39.35
2029	9.67	60.20	120.17	7.77	20.11	3.03	39.36
2030	9.62	60.22	123.50	7.92	20.13	3.16	39.37
2031	9.56	60.24	126.76	8.07	20.14	3.30	39.38
2032	9.51	60.25	129.95	8.22	20.15	3.43	39.39
2033	9.46	60.27	133.08	8.37	20.17	3.58	39.40
2034	9.40	60.29	136.16	8.51	20.18	3.72	39.41
2035	9.35	60.31	139.18	8.66	20.20	3.86	39.42
2036	9.30	60.33	142.17	8.80	20.21	4.01	39.43
2037	9.24	60.34	145.11	8.94	20.22	4.16	39.44
2038	9.19	60.36	148.01	9.08	20.24	4.32	39.45
2039	9.14	60.38	150.88	9.22	20.25	4.47	39.46
2040	9.08	60.40	153.71	9.36	20.26	4.63	39.47
2041	9.03	60.42	156.51	9.50	20.28	4.79	39.48
2042	8.98	60.44	159.28	9.64	20.29	4.95	39.49
2043	8.92	60.45	162.02	9.78	20.31	5.11	39.50
2044	8.87	60.47	164.74	9.91	20.32	5.28	39.51
2045	8.82	60.49	167.43	10.05	20.33	5.44	39.52
2046	8.76	60.51	170.10	10.18	20.35	5.61	39.53
2047	8.71	60.53	172.74	10.32	20.36	5.78	39.54
2048	8.66	60.55	175.37	10.45	20.38	5.95	39.55
2049	8.60	60.56	177.97	10.59	20.39	6.13	39.56
2050	**55.00**	**70.00**	**85.00**	**20.30**	**30.00**	**33.80**	**56.00**

Table B11: Holts Trend Forecast Results

Year	Radio	Vacuum cleaner	Electric Cooker	Toaster	Electric Kettle	Electric Water heater
2021	62.21	8.31	3.41	16.71	18.13	4.75
2022	62.26	8.30	3.41	16.73	18.60	5.24
2023	62.32	8.29	3.41	16.75	19.09	5.63
2024	62.37	8.28	3.41	16.76	19.63	5.98
2025	62.42	8.27	3.41	16.78	20.23	6.29
2026	62.48	8.27	3.41	16.80	20.89	6.58
2027	62.53	8.26	3.41	16.82	21.62	6.85
2028	62.58	8.25	3.41	16.83	22.41	7.11
2029	62.63	8.24	3.41	16.85	23.27	7.35
2030	62.68	8.24	3.41	16.87	24.20	7.59
2031	62.74	8.23	3.41	16.89	25.18	7.82
2032	62.79	8.22	3.41	16.90	26.22	8.04
2033	62.84	8.21	3.41	16.92	27.31	8.25
2034	62.89	8.20	3.41	16.94	28.46	8.46
2035	62.94	8.20	3.41	16.96	29.64	8.67
2036	62.99	8.19	3.41	16.97	30.87	8.87
2037	63.04	8.18	3.41	16.99	32.14	9.07
2038	63.09	8.17	3.41	17.01	33.44	9.26
2039	63.14	8.17	3.41	17.03	34.77	9.45
2040	63.19	8.16	3.41	17.04	36.14	9.63
2041	63.24	8.15	3.41	17.06	37.54	9.82
2042	63.29	8.14	3.41	17.08	38.97	10.00
2043	63.34	8.13	3.41	17.10	40.43	10.18
2044	63.39	8.13	3.41	17.11	41.91	10.35
2045	63.44	8.12	3.41	17.13	43.42	10.53
2046	63.49	8.11	3.41	17.15	44.96	10.70
2047	63.54	8.10	3.41	17.17	46.52	10.87
2048	63.59	8.10	3.41	17.18	48.10	11.04
2049	63.64	8.09	3.41	17.20	49.71	11.20
2050	**100.00**	**13.40**	**53.22**	**30.00**	**39.30**	**6.40**

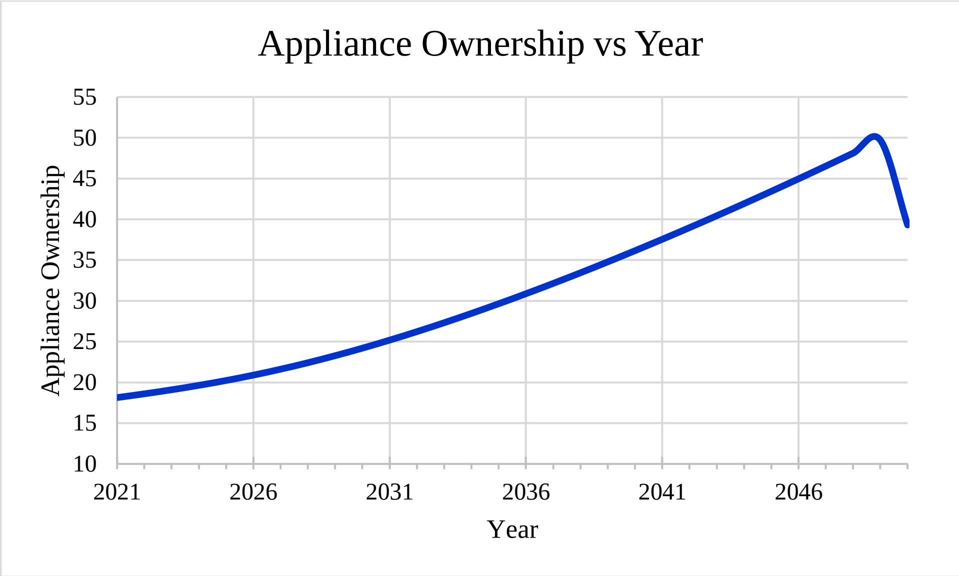

Figure B1: Example of the linear growth of appliance ownerships. Here, electric kettle ownership using the Holts trend forecasting technique shows a linear relationship with forecast year. The sharp drop in appliance ownership in forecast year 2050 is due to the Holt's trend forecasting technique inability to incorporate the end year assumption into the forecast.

APPENDIX C: Calculation of Total Potentials of Renewable Sources

Going by the discussion of the available renewable energy sources and the extent of use in Nigeria; this study estimates the potential of each of the sources to provide the electrical energy needed by power stations or plants using available quantitative data from the literature.

This study builds on these data and factors in the operational capability of each of the renewable energy power plants in determining the final annual electricity production from all the renewable energy sources. Power plants do not operate round the clock and at optimal levels. Thus, plant capacity factor for each renewable energy plant is a very important variable in the final electricity production calculation. Plant capacity factor is the measure of the total produced energy by a plant during a given period of time compared with its maximum installed capacity or output and represented in the following equations.

$$Cf = \frac{AEp}{Pm \times T}$$

Where:

Cf = Capacity factor

AEp = actual energy produced or supplied in time T

Pm = maximum plant rating

T = time, number of hours in a year

The annual plant capacity factor is then calculated as:

$$aCf = \frac{AEg}{Pm \times 8760}$$

Where:

aCf = annual capacity factor

AEg = actual annual energy generation

Pm = maximum plant rating

8760 = time, number of hours in a year

The annual electric production from each of the sources is then calculated by multiplying the total generation capacity by the calculated annual capacity factor and time (T) as represented in the equation below.

$$AEp = tGc \times aCf \times T$$

Where:

AEpf = annual electric production in MWh

tGc = total generation capacity

aCf = annual capacity factor

T = time, no of hours in a year

Findings from this systematic analysis is thereafter matched against calculated appliance electricity consumption (AEC) up to the year 2050 to determine the extent to which Nigeria's renewable resources can meet the needs over these periods.

Renewable Energy

Data for installed capacity and annual plant capacity factor for each of the energy sources were sourced from Olaoye et. al., 2016 and EIA, 2020. They are presented in Table C1.

Table C1: Installed capacity and plant capacity factor for energy sources.

Energy Source	Total Installed Capacity (MW)	Annual Plant Capacity Factor
On shore Wind	1600	0.37
Offshore Wind	800	0.37
Solar PV Panels	7000	0.26
Geothermal	500	0.77
Biomass	50	0.49
Small and Large Hydro	64,000	0.43

VITA

Olawale Olabisi (Wale) was born in Ondo city, Nigeria and graduated in 2006 with a bachelor's degree in Geology from Adekunle Ajasin University, Akungba-Akoko, Ondo State, Nigeria. Wale relocated to Bakersfield, California for graduate studies and obtained a master's degree in Geology (Petroleum Concentration) from California State University, Bakersfield (CSUB). Upon graduation, Wale worked for Plains Exploration and Production (PXP), Freeport McMoRan Oil and Gas (FMOG) and later Sentinel Peak Resources (SPR) as a Petroleum Geologist where he helped the companies to develop heavy oil fields in a manner that met the California state energy needs. He presently works for the California Geologic Energy Management agency (CalGEM) – a division under the California State Department of Conservation where he is part of the team helping California achieve its climate change and clean energy goals. Wale began his PhD in in the department of Industrial Engineering (Engineering Management concentration) at the University of Tennessee, Knoxville in 2015. His research interests are in energy and climate. His hope is that his research study will increase our understanding of electricity demand and energy efficiency under climate uncertainties in Nigeria and other developing countries.