MODELLING OF ENERGY DEMAND AND SUPPLY PATTERNS IN TANZANIA

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A Dissertation Submitted in Partial Fulfilment of the Requirements for the Degree of Doctor of Philosophy in Sustainable Energy Science and Engineering of the Nelson Mandela African Institution of Science and Technology

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ABSTRACT

Energy is an important element in realizing the interrelated socio-economic development of countries. In an attempt to develop long term energy demand and supply patterns that would enable the country meet her growing energy demand sustainably using the current and future available energy resources, a study of its own kind was carried out. The analysis of the influential indicators in the determination of energy demand based on the selected socio-economic and environment indicators preceded the study. Artificial neural network-multilayer perceptron (ANN-MLP), multiple linear regression (MLR), and support vector machine for regression (SVR) techniques were employed in the analysis. The findings depicts a strong relationship between energy indicators and energy demand for Tanzania. The energy indicators model showed greater accuracy in the prediction of energy demand as compared to economic and environment indicators models. ANN-MLP, MLR and SVR techniques reached satisfactory prediction results though ANN-MLP produced the most accurate predictions.

The long-term energy demand simulation for a study period 2010-2040 was done using the Model for Analysis of Energy Demand (MAED). The simulation involved case study scenarios to mimic possible future long-term energy demand based on socio-economic and technological development. Simulated results suggest an exponential growth of the total final energy demand with electricity demand shift from household dominance towards industry and service sectors describing changes in the lifestyles. Nevertheless, the electricity demand growth rate has been shown to be greater than that of energy demand describing more mechanisation in the industry and service sectors. Final energy demands per capita shows an increasing tendency while there is a decrease in energy intensity suggesting energy efficient measures.

Long-term energisation plan was achieved through a bottom-up modelling approach using Model for Energy Supply Strategy Alternatives and their General Environmental Impacts (MESSAGE). Least-cost results showed dominance of hydro, coal, geothermal and natural gas as possible supply options for future electricity generation. Though these energy resources are locally available and give least-cost advantages, their combinations is heavily skewed to the non-environmental friendly resources. Optimised results indicate, without interventions in promoting renewable energy, its influence in power generation will remain insignificant and therefore recommends policies

formulations to ensure significant contribution. Finally, the results have established that it is feasible to have a sustainable and economical supply of energy for Tanzania that will meet her energy demand and ensure an optimized option for short, medium and long term energisation plans using currently available energy resources.

DECLARATION

I, BARAKA KICHONGE do hereby declare to the Senate of Nelson Mandela African Institution of Science and Technology that this dissertation is my own original work and that it has neither been submitted nor being concurrently submitted for degree award in any other institution.

Baraka Kichonge

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Name and signature of candidate **Date**

The above declaration is confirmed

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Name and signature of supervisor 1 **Date**

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Name and signature of supervisor 2 **Date**

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CERTIFICATION

The undersigned certify that, he has read and hereby recommends for acceptance by the **Nelson Mandela African Institution of Science and Technology** a dissertation titled ***"Modelling of Energy Demand and Supply Patterns in Tanzania"*** in partial fulfilment of the requirements for the degree of Doctor of Philosophy (PhD) in Sustainable Energy Science and Engineering of the **Nelson Mandela African Institution of Science and Technology**.

Name and signature of supervisor 1	**Date**
Name and signature of supervisor 2	**Date**

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DEDICATION

In loving memory of my revered father **Stephen Nyangi Kichonge** (1947-1995) – The fountain of my inspirations and influence. I will always cherish you Dad!

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBREVIATIONS AND SYMBOLS

ACM	Agriculture, Construction and Mining
APE	Absolute Percentage Error
ARDL	Autoregressive Distributed Lag
ANN	Artificial Neural Network
BAU	Business as Usual Scenario
BCS	Base Case Scenario
BY	Base Year
CC	Correlation Coefficient
CCGT	Combined Cycle Gas Turbine
ED	Energy Demand
EED	Electricity Energy Demand
FY	Future Year
FYD	Five-Year Development
COSTECH	Commission for Science and Technology
GHG	Greenhouse Gas
GDP	Gross Domestic Product
GNI	Gross National Income
GT	Gas Turbine
HEC	High Economic Consumption Scenario
HFO	Heavy Fuel Oil
IAEA	International Atomic Energy Agency
ibid	Latin, short for ibidem, meaning "in the same place"
IEA	International Energy Agency
kTOE	Thousands Tonnes of Oil Equivalent
LEC	Low Economic Consumption Scenario
MAE	Mean Absolute Error
MAED	Model for Analysis of Energy Demand
MAPE	Mean Absolute Percentage Error
MESSAGE	Model for Energy Supply Strategy Alternatives and their General Environmental Impacts

MEM (T)	Ministry of Energy and Mineral – Tanzania
MLP	Multilayer Perceptron
MLR	Multiple Linear Regression
MTOE	Million Tonnes of Oil Equivalent
NBS	National Bureau of Statistics Tanzania
NG	Natural Gas
NM-AIST	Nelson Mandela African Institution of Science and Technology
PUKF	Pearson VII Universal Kernel Function
PSMP	Power System Master Plan
PV	Photovoltaic
RAE	Relative Absolute Error
RBF	Radial Basis Function kernel
REFiTs	Renewable Energy Feed-in Tariff
REPP	Renewable Energy Penetration Policy
RES	Renewable Energy Scenario
RMSE	Root Mean Squared Error
RRSE	Root Relative Squared Error
SD	System Dynamic Model
SVR	Support Vector Machine for Regression
SVM	Support Vector Machine
TAEC	Tanzania Atomic Energy Commission
TANESCO	Tanzania Electric Supply Company Limited
UN	United Nations
WB	World Bank

CHAPTER ONE

INTRODUCTION

1.1 Background Information

Energy is an essential input for sustainable development of nations. Exponential increases in energy demand has been witnessed in the past decades following the start of industrial development and globalization (Suganthi and Samuel, 2012). In developed and developing countries, energy plays an important role in socio-economic advances despite its subsequent impacts on global sustainability (Seow and Rahimifard, 2011; Van Ruijven *et al.*, 2008). Significant number of studies have established the existence of the relationship between energy and economic development such as that of Akinlo (2008), Ozturk (2010) and Sadorsky (2010). Linkage between energy and economic growth has been equaled to other factors of production such as land and capital in Chontanawat *et al.* (2008) and Ikeme and Ebohon (2005). Energy unlocks access to improved social services and thus boosts expansion of economic sectors such as industries, service, transport, households and agriculture. Van Beeck (1999) Describes economic growth as a reason for a rise in activities requiring energy; whereas any society growth path is determined by energy accessibility (Martin, 1992). The expansion of economic sectors as a result of energy accessibility describes a strong feed-back between energy and economy as stated by Iwayemi (1998). In most cases, insufficient energy tends to hold back economic growth and development, thus leading to negative changes in consumption pattern (Blum and Legey, 2012).

Energy models main purposes are to predict the future of energy demand and/or supply of a particular nation or a region. Energy models work by assuming a certain number of boundary conditions, for instance the growth in the demographic and economic activities, or projected increases in energy prices on the international markets among many others (Herbst et al., 2012). The models are in the same way applicable to simulate policy and technology options that may possibly influence future energy demand and supply, and henceforth investments in energy systems as well as energy policies. Since their inception in the early 1950s, models have been in use as tools to improve and optimize energy systems and energy infrastructure across industrialized countries. Energy modeling is considered useful because it is an efficient, feasible and necessary means of understanding complex energy systems. It also provides a basis for the discussion of the nature of the problem, and if the model assumptions are expressed in an understandable form, comparisons between different approaches can be made (Luukkanen, 1994). The rise of macroeconomic energy models in the 1950s, was largely influenced by the needs and ambitions to develop the industrial economy in industrialized countries (Karjalainen et al., 2014). However, detailed techno-economic models sometimes referred as end-use models, were first developed as an alternate approach to explain and predict energy demand/supply following the first oil crisis in the early 1970s (Akins, 1973; Herbst et al., 2012). Acceptably, energy models have conventionally modeled the technical features of the energy systems in relation to the world economy. Neo-classical economics and the modernization theory dominated energy modeling assumptions in the 20th century (Luukkanen, 1994).

A review of energy models suggests existence of a large variety of classification approaches since its development back in 1950’s. A widely held classification is as suggested in Grubb *et al.* (1993) and Hourcade *et al.* (1996) for which energy models are distinguished by the use of analytical approach top-down against bottom-up (end-use). Grubb et al. (1993) Describes a bottom-up analytical approach as associated with an “optimistic” engineering paradigm. Bottom-up approach provides an explanation of needs at a localized level such as household and more detailed analysis from an engineering perspective (*ibid.*). On the contrary, top-down analytical approach is associated with a pessimistic economic paradigm. Hourcade et al. (1996) describes top-down analytical approach as useful “if historical development patterns and relationships among key undelaying variables hold constant for the projection period”. Top-down models surpass in providing an aggregate perspective and an economic-oriented view. Hybrid energy models mix the bottom-up and the top-down approaches, and could improve understanding about and attempt to overcome limitations of both approaches (Karjalainen et al., 2014). Another un-popular form of energy model classification is that proposed by Hourcade et al. (1996) in which three dimensions namely model’s purpose (i.e. prediction, scenario analysis, back-casting), structure and input assumptions are used to distinguish the models. A summarized general distinction between top-down and bottom-up analytical approaches as derived from various studies including Van Beeck (1999), Herbst et al. (2012), Catenazzi (2009), Grubb et al. (1993), Bhattacharyya and Timilsina (2009), McFarland *et al.* (2004) and Hourcade *et al.* (1996) is depicted in Table 1.1.

Table 1.1: Bottom-Up models vs. Top-Down models

Bottom-Up Models	Top-down Models
Engineering approach	Economic approach
Incorporate high degree of technological details	Lacks technological details
Deliver detailed information of energy demand/supply	Deliver generalized information of energy demand/supply
Independent of observed market behavior	Based on observed market behavior
Does not tend to favor monetary related policies only	Tend to favor monetary related policies
Use disaggregated data for exploring purposes	Use aggregated data for forecasting purposes
Considers discontinuities in historical trends	No discontinuities in historical trends
Considers potential for efficiency improvement (regards technically most efficient technologies)	Underestimate potential for efficiency improvement (dis-regards technically most efficient technologies)

A further review of energy models based on top-down and bottom-up classification suggests the existence of a large variety of approaches in use. Figure 1.1 shows a summarized distinction of energy models based on a simple approach as derived from Craig et al. (2002), Armstrong (2001), Brown et al. (2001) and Bhattacharyya and Timilsina (2009). A summarized distinction of energy models based on sophisticated approach as derived from Catenazzi (2009), Nathani *et al.* (2006), Tintner (1953), de Vries *et al.* (1999), Kemp-Benedict *et al.* (2002), (Mundaca and Neij, 2009) and Herbst et al. (2012) and Merven *et al.* (2013) is shown in Figure 1.2.

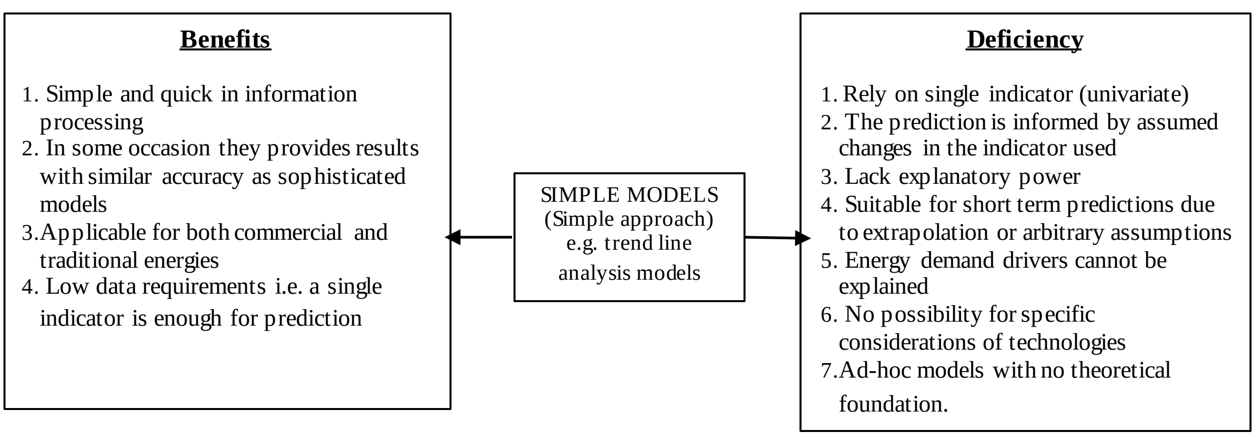

Figure 1.1: Distinction of energy demand models based on simple approach

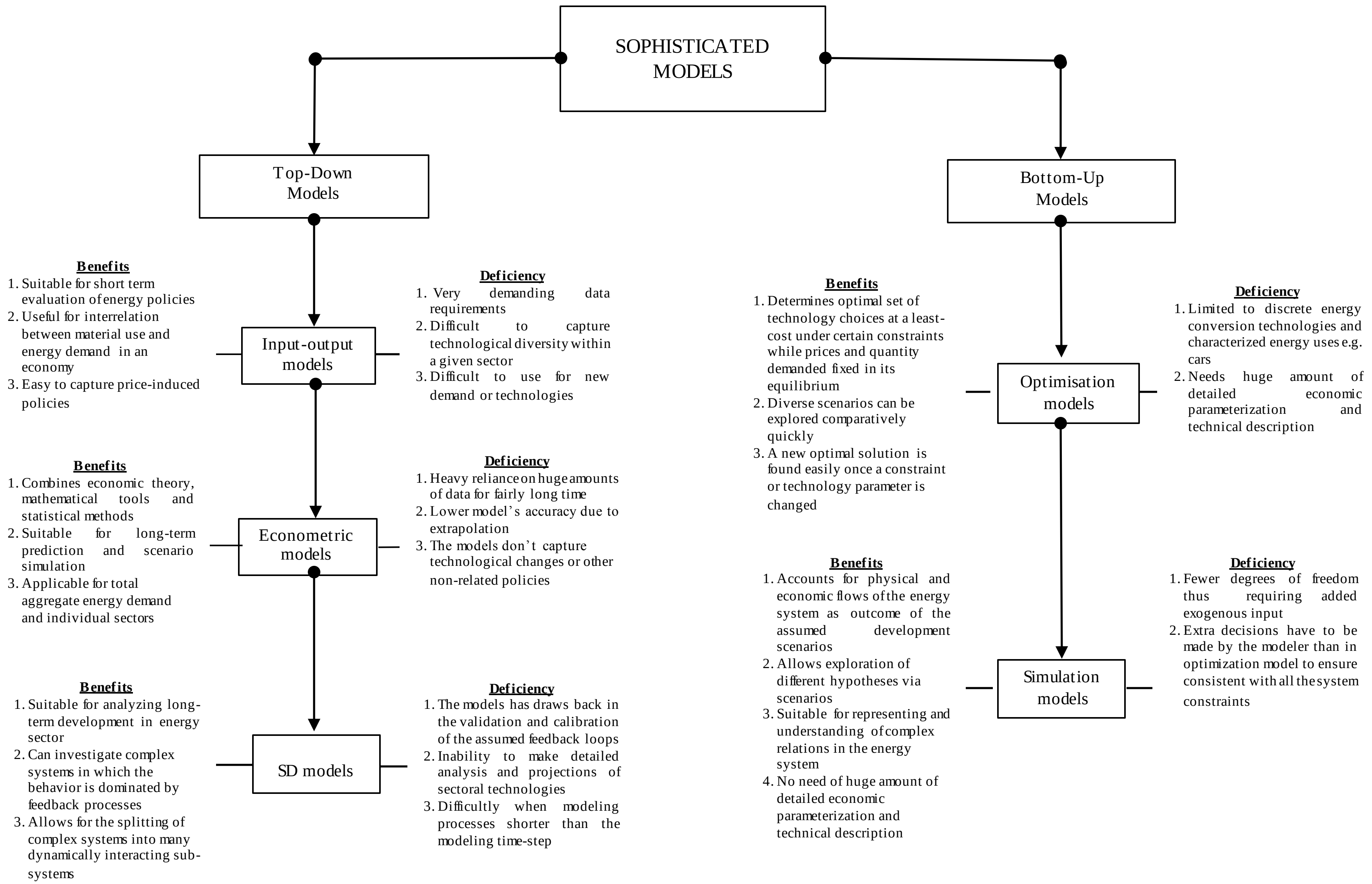

Figure 1.2: Distinction of energy models based on sophisticated approach

Energy demand growth depends much on economic development, which in turn influences factors such as industrial development, demographic and life-style changes, technology advances and others. Figure 1.3 portrays the relationship between economic development and energy demand in consuming sectors. Population growth and other demographic issues, for instance employment level and income growth, influences energy demand and thus have an impact on energy intensity. When the population becomes well-off, energy demand and therefore energy intensity may well rise due to the increased energy-consuming equipment and appliances. Advances in technology also influence energy demand and therefore energy intensity as new technologies improve efficiency attracting more penetration thus increasing energy demand.

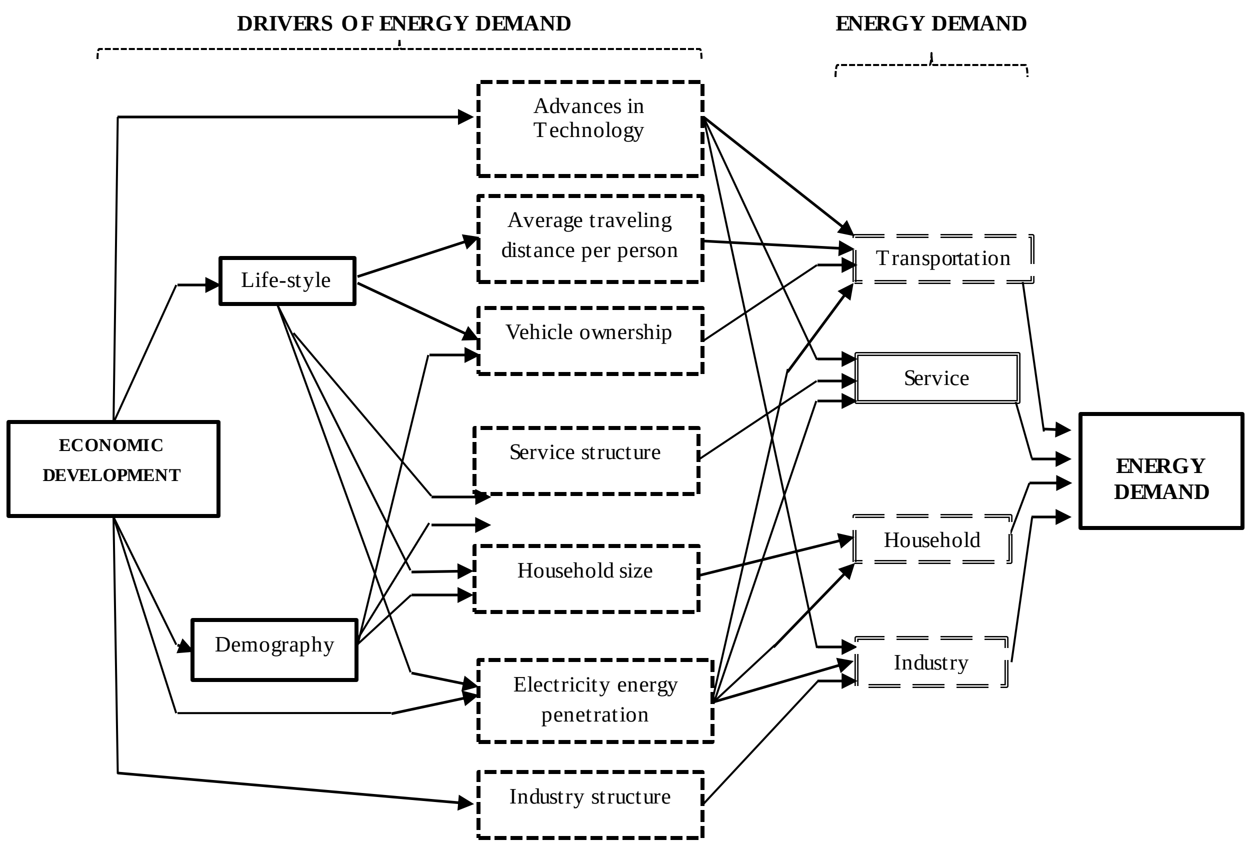

Figure 1.3: Economic development and energy demand relationship

The relationship between energy and socio-economic development indicators has been the subject of interest to energy analysts. The energy-indicators relationship and their varied levels of influences in determination of future energy demand have been shown to exist in a number of studies. The results from these studies have shown varied results across methodologies as detailed in Soytas and Sari (2003) and Mozumder and Marathe (2007) studies. The relationship between energy and influential indicators were used to determine the accurate predictions tools using different approaches including machine learning such as in Yu et al. (2012) and AbuAl-Foul (2012). Likewise, a number of studies have applied different modeling approaches in understanding of future energy demand and supply modeling. Modelling approaches have previously successfully assisted in the design of enhanced sustainable utilization of limited energy resources with the considerations of the possible effects to environmental quality in a number of countries. These approaches have been adopted by many countries spurred by its previously success in realizing the expected output such as in Hainoun et al. (2010) and Ryabchenko et al. (2013).

Long-term energy demand customarily has an upward trend owing to the economic and demographic growth as shown in a number of studies including Ekonomou (2010); IEA (2013b) to name a few. The expected energy demand increase in Tanzania is also attributed to population growth mostly in urban areas and economic expansion (UN, 2013; UNDP-WHO, 2009) as a result of investments coming into the economic sectors such as oil and gas, service, agriculture, and mining. Volatile energy markets and supply challenges makes modeling of energy demand and supply patterns in Tanzania a very important issue in meeting expected increases. Meeting energy needs is essential in sustaining population growth and economic expansion with the competing demand over energy resources considerations. Presently, the country's energy status is in an unbalanced state accompanied by recurrent energy shortages such as electricity (MEM, 2013b; Mwampamba, 2007). Other forms of energy services such as biomass are constrained (Malimbwi and Zahabu, 2005). Previous experience in meeting energy needs for accelerating economic growth through the use of biomass have caused climatic challenges such as deforestation (Felix and Gheewala, 2011; Mwampamba, 2007). It is a well-known fact that deforestation reduces the amount of evapotranspiration (Costa and Foley, 2000; Li et al., 2007) which is the recycling of moisture back into the atmosphere through plantation leaves. Evapotranspiration causes the air that normally travels over deforested areas to be less humid leading to lower rainfall such as that observed in Loisulie (2010) resulting in rivalry over resources such as water for agricultural activities (Casmiri, 2009).

Tanzania, being a Sub-Saharan African country, has enough energy resources to sustainably meet its total needs but remains with the challenge of unequal dissemination and under-development (IEA, 2014b). The challenge is resolvable and the benefits of success are huge through efficient energy planning and management. Analysis and modeling of energy demand and supply patterns is an approach towards energy planning and management. Effective energy planning and management is vital for providing a stage for optimal energy supply with guaranteed reduction of environmental impacts. The need to identify the relationship between energy demand and its influential indicators coupled with the application of a bottom-up modeling approach in understanding future energy demand and supply is overwhelming in the quest to achieve sustainable development.

1.2 Research problem and justification

The expected worldwide increases in energy demand with the rising competing demand over energy resources makes it necessary for Tanzania to address short to long term energy demand and supply patterns for sustainable exploitation of resources. Inappropriate supplies policies and investment decisions as is the case in most developing countries (Bhattacharyya and Timilsina, 2009) contributes to the lack of balance between energy demand and supply (Mohamed and Yashiro, 2013). As suggested in Suganthi and Samuel (2012), energy planning through understanding of the possible future trends is essential for economic prosperity and environment security. In lieu of that, understanding of future energy demand and supply pattern in Tanzanian economic sectors is essential because of multi-dimensional necessities. First, the sustainable economic development of the country depends on adequate, affordable and secure energy services for its quest to become a middle income country through implementation of Vision 2025 goals (URT, 1999). Second, the country endowed with natural gas and coal potential and other energy resources that could be harnessed to solve energy challenges resulting from experience with limited energy resources dependence.

The review of relevant literature about energy in Tanzania resulted in observed gap in studies that examined and used the relationship between energy and the corresponding influential indicators to determine the prediction tools. Previous studies which tried to link energy and influential indicators in the economy of Tanzania were the Granger causality test and Autoregressive Distributed Lag (ARDL) bounds testing (Ebohon, 1996; Odhiambo, 2009). In Ebohon (1996) causal directions between energy consumption and economic growth proxied by GDP and GNP was established. In a similar study, Odhiambo (2009) used ARDL bounds testing to examine the linkage between energy consumption and economic growth. Likewise, Nyoni (2013) adopted the Cobb-Douglas function to analyse the correlation between economic growth and energy consumption. The Granger- causality test in Nyoni (2013), showed the more energy consumption the more the economy develops. Generally, these studies established the relationship between economic growth and energy, which was shown to exist. The limitation with these studies is that they did not attempt to determine prediction tools for energy demand out of the relationship they established.

Further review of relevant literature showed non-existence of studies that applied bottom-up or top-down modeling approaches to examine and propose possible future energy demand and supply patterns for Tanzania. The existing literatures on energy issues such as Msaki (2006), attempted to demonstrate the need for nuclear energy inclusion into electricity generation. The study was limited to electricity specifically installed capacity and did not consider thorough analysis in diversification of energy resources coupled with economic growth trend for electricity generation. Moreover, enormous discoveries of natural gas and coal were unknown by then and were not incorporated into the study as alternative energy sources. Mohamed and Yashiro (2013) used a combination of land-use characteristics, satellite image and household energy surveys to give a generic overview of trends behind energy demand at household level.

The Power System Master Plan (PSMP) which was first released in 2008 (the latest update is the 2012 version) is another source of energy information with regards to Tanzania (MEM, 2012). PSMP preparations used a combination of econometric and trend line approaches and is the only Tanzanian official energy plan addressing the issues of electricity. PSMP has been in use to re-assesses the short-term, mid-term and long-term generation and transmission plan requirements. PSMP energy mix is composed of an enormous application of hydro and thermal generation using predominantly heavy fuel oil (HFO), coal and natural gas. The limitation with PSMP is first, it does not fully utilize several alternatives that are becoming progressively attractive to energy planners worldwide (IRENA, 2012). Amongst these alternatives are the greater usage of non-hydro renewable energy such as solar thermal, wind, solar PV, geothermal and biomass, which have been increasing in significance worldwide. Second, PSMP does not show clearly how its demand are met through modelling against assumptions such as environmental constraints, life styles changes, technological options and how it curbs hydropower uncertainties. A similar case is also observed in the Msaki (2006) study in which the largest composition is thermal generation without consideration of non-hydro renewable energies.

In the pursuit to conduct this study, two important conclusions were drawn from the review of relevant literature about energy in Tanzania. First, previous analysis of energy and influential indicators to the economy of the country have been limited to the use of traditional statistical methods without any indication of extension to the use of machine learning approaches such as ANN, MLR and SVR. In lieu of that, it is therefore significant to carry out an extended analysis using machine learning to find the level of influence of selected indicators that are closely linked in the determination of energy demand. The level of influence of the selected indicators will enable the determination of an accurate energy demand prediction tool.

Second, there is no substantiation of the use of bottom-up modelling approach for the management and planning of energy demand and supply pattern in Tanzania specifically IAEA tools (MAED and MESSAGE). MAED and MESSAGE are simulation and optimisation energy systems modelling platforms categorized as bottom-up models. These models have successfully been applied in the planning and management of energy demand and supply patterns. Following the literature review, it is therefore important to take on studies with the use of bottom-up models as the succeeding part of the dissertation objectives is to determine energy demand and its supply pattern for successful medium to long-term energisation plan of the country. The choice of a bottom-up modelling approach is based on the fact that the country is experiencing a rapid economic growth with constantly changing circumstances. Bottom-up models are suitable as they allow for scenarios and sensitivity analyses to cover-up such circumstances. Besides, the bottom-up modelling approach allows for detailed description of the available energy conversion technologies for both renewable and non-renewable resources. Moreover, the choice of MAED and MESSAGE was spurred by their ability to allow for environmental impact assessment, and the incorporation of a high degree of technologies details, among many other advantages, to give a clear overview of different options and their consequences.

1.3 Objectives

1.3.1 General objective

The general objective of this research is to develop long-term energy demand and supply patterns for Tanzania that would enable the country to meet her growing energy demand sustainably using the current and future available energy resources.

1.3.2 Specific objective

In the course of the research, for the accomplishment of the general objective, fulfillment of the following set of specific objectives were required:

i) To perform analysis of the influence of social, economic and environment indicators in the energy demand of Tanzania;
ii) To compare the performances of machine learning approaches in the analysis and prediction of energy demand using social, economic and environment indicators;
iii) To simulate future energy demands under various scenarios and analyze the influence of each scenario to energy demand;
iv) To model the energy resource mix to meet short, medium and long-term energisation plans for Tanzania.

1.4 Research questions

To meet the objectives of the study, the following were the questions this research sought to answer:

i) What are the likely influences of social, economic and environment indicators to energy demand for Tanzania?
ii) What are the possible future energy demands trends under various scenarios?
iii) Is it feasible to have a sustainable and economical supply of energy to Tanzania that will meet her energy demand and ensure for short, medium and long-term energisation plans using currently available energy resources?

1.5 Scope of the study

The study examines and compares the relationship between energy demand and influential indicators in the prediction of futuristic demand using machine learning approach specifically ANN, MLR and SVR. It further compares the performances of ANN, MLR and SVR for predictions of energy demand. The study finally applies MAED to predict future energy demand and then applies MESSAGE to model supply options for electricity generation.

1.6 Significance of the research

From the aforementioned background information, it is obvious that significance of the research benefits a number of interested parties in the field of energy. This study is expected to bring the following positive outcomes:

(i) The research findings add a body of knowledge to researcher and scholars that exists in the analysis of the influence of socio-economic and environment indicators in the energy demand of Tanzania. The research findings will further provide effective and accurate tools that can be applied to predict long-term energy demand of the country using machine learning approach. From a policy perspective, the use of machine learning approach will enable the relationship between energy demand and the economic development to be identified so that energy conservation measures may be taken appropriately.

(ii) The research findings provide a platform for more comparative studies with similar or different algorithms in determining the level of influence of socio-economic indicators and energy usage in Tanzania.

(iii) The research finding provides vital information to policy analysts and decision makers on possible future energy demand trends under various scenarios representing economic development paths and the influence of each. The outputs from this research are anticipated to provide more understanding of the relationship between energy and economic growth coherent with sustainable development goals and objectives. Besides, the research finding provides a platform for the re-assessment of energy systems in the country with a view toward planning energy programmes and policies in the Tanzanian and global contexts.

(iv) The research finding provides vital information to policy analysts and decision makers into energy resource utilization options that ensure access to adequate, affordable and secure energy services considering vulnerability that may cause energy insecurity. Furthermore, the research finding provides a platform for environmentalists to advocate the effective use of environmentally friendly energy resources in reducing the impact of greenhouse gas (GHG) emissions and other associated challenges in energy use.

1.7 Dissertation Organization

The organisation of this PhD dissertation is built on the papers which constitute the main modelling parts. The dissertation modelling of energy demand and supply patterns in Tanzania follows a framework as illustrated in Figure 1.4 and organized into seven chapters as follows.

i) **Chapter One:** The chapter covers the introduction of the study, which includes the background information, research problem and justification of the study, the objectives of the study, research questions and scope of study and significance of the research.

ii) **Chapter Two:** The analysis of the relationship of economic, energy and environmental indicators on the prediction of energy demand by the use of machine learning is the primary focus of this Chapter. The content of this chapter forms a paper that uses artificial neural network (ANN) and multiple linear regression (MLR) techniques to analyse and determine the relationship of economic, energy and environmental indicators on the prediction of energy demand.

iii) **Chapter Three:** The chapter analyses the relationship upon which economic, energy and environmental indicators have on the prediction of energy demand. The content of this chapter forms a paper that uses support vector machine for regression (SVR) technique to analyse and determine the relationship of economic, energy and environmental indicators on the prediction of energy demand.

iv) **Chapter Four:** The content of this chapter forms a paper that uses bottom-up modeling approach to model medium to long-term energy demand in the main economic activities sectors using the Model for Analysis of Energy Demand (MAED).

v) **Chapter Five:** The chapter presents analysis through bottom-up modeling, energy supply options for electricity generation using MESSAGE model.

vi) **Chapter Six:** The chapter analyses through bottom-up modeling approach the prediction of the contribution of renewable energy sources into electricity generation in Tanzania.

vii) **Chapter Seven:** The chapter covers discussions of the main findings resulting from papers as presented in chapters two, three, four, five and six.

viii) **Chapter Eight:** The chapter covers general conclusion and recommendations.

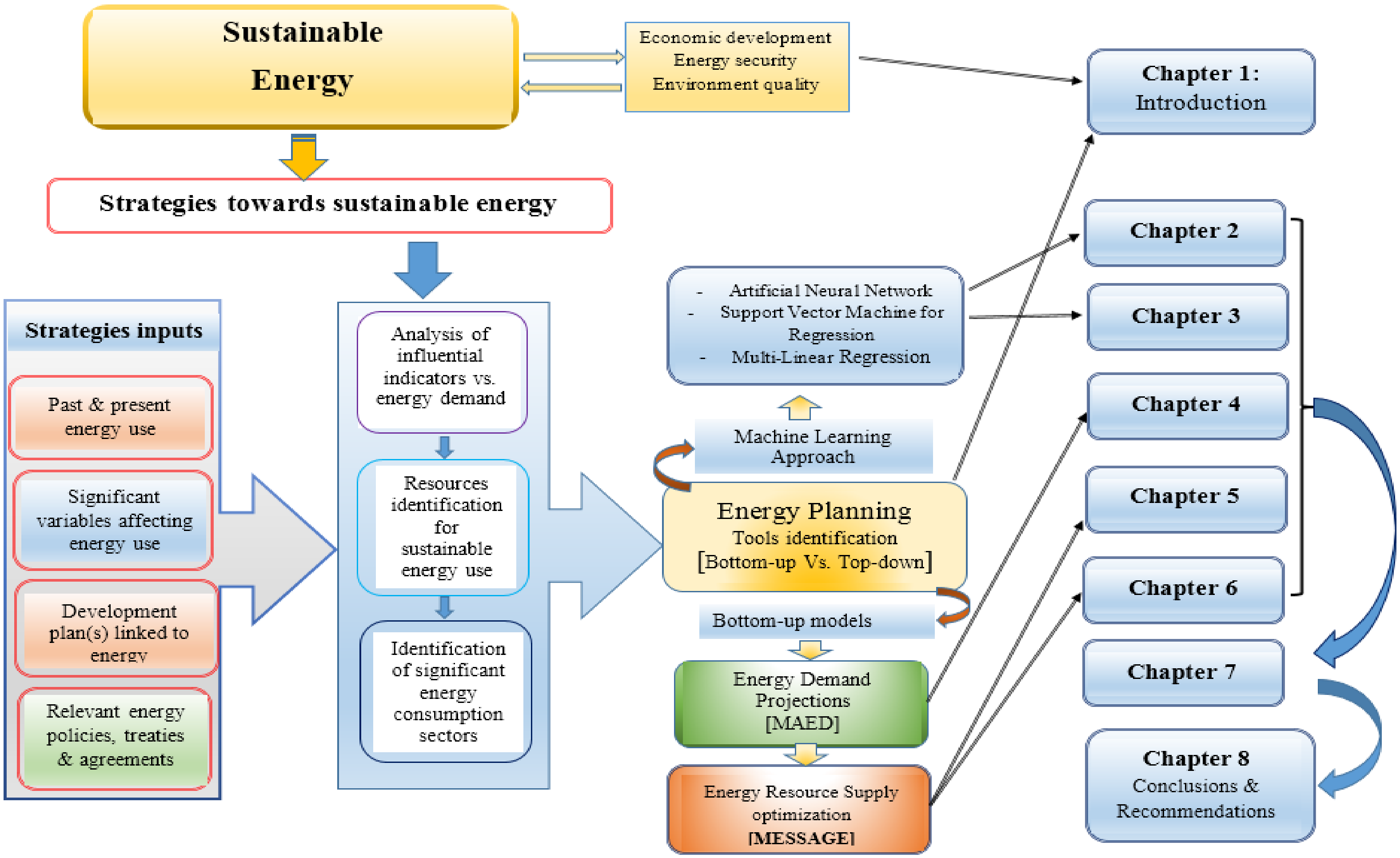

Figure 1.4: Dissertation framework

CHAPTER TWO

ANALYSIS OF TANZANIAN ENERGY DEMAND USING ARTIFICIAL NEURAL NETWORK AND MULTIPLE LINEAR REGRESSION[1]

2.1 Abstract

Analysis of energy demand is of a vital concern to energy systems analysts and planners in any nation. This paper presents artificial neural network-multilayer perceptron (ANN-MLP) and multiple linear regression (MLR) techniques for the analysis of energy demand in Tanzania. The techniques were employed to analyze the influence of economic, energy and environment indicators models in predicting the energy demand in Tanzania. Statistical performance indices were used to evaluate the prediction ability of economic, energy and environment indicators models using ANN-MLP and MLR techniques. Predicted response values of ANN-MLP and MLR techniques were then compared to determine their closeness with actual data values for determining the best performing technique. The results from ANN-MLP and MLR techniques showed the best model for predicting the energy demand in Tanzania were from energy indicators as opposed to economic and environmental indicators. The ANN-MLP prediction values had a correlation coefficient (CC) of 0.9995 and mean absolute percentage error (MAPE) of 0.67%; outperforming the MLR technique whose CC and MAPE values were 0.9993 and 0.83% respectively. ANN-MLP technique graphical presentation of actual against predicted values showed close relationship between actual and predicted values as opposed to the MLR technique whose predicted values deviated much from actual values. Analyses of results from both techniques conclude that ANN-MLP outperforms the MLR technique in predicting energy demand in Tanzania.

2.2 Introduction

Analysis and prediction of energy demand is a subject of present extensive interest among analysts of challenges in energy production and consumption. Studies have shown energy demand to be influenced by a number of indicators such as population growth, economic performance and

[1] International Journal of Computer Applications (IJCA), Volume 108 – Issue No. 2 (2014), pp. 13-20

technological developments (Apergis and Payne, 2009; Reister, 1987). Indicator relationships to energy and their effects on future energy demand have shown varied and conflicting results not only across countries but also across methodologies for the same country and have been detailed in Soytas and Sari (2003) and Mozumder and Marathe (2007) studies. The conflicting results calls for scholars to analytically determine the influence of key energy indicators in the future energy demand of their countries. There exist few studies for Tanzania, which attempted to examine the relationship between energy indicators (variables) and energy demand. These studies were limited to the Granger causality test and autoregressive distributed lag (ARDL)-bounds testing approaches (Ebohon, 1996; Odhiambo, 2009). The inter-temporal causal relationship between energy consumption and economic growth were examined by Odhiambo (2009) and found economic growth is being spurred by energy consumption. Ebohon (1996) investigated energy consumption and economic growth causal directions proxied by GDP and GNP in which a simultaneous causal relationship was shown to exist. Not all these studies attempted to predict energy demand but rather the link between energy consumption and economic growth.

Developing countries such as Tanzania are in the stage of improving economically where various economic policy reformations and formulations are implemented. Economic improvement will unquestionably require a proper energy demand prediction tool as energy is an important aspect in realizing sustainable development (Vera and Langlois, 2007). The goal of this study is based on the absence of sufficient studies for the energy prediction and analysis tools to the influence of the energy key indicators in Tanzania. The objective was to analyze the influence of economic, energy and environmental indicators on the prediction of energy demand by the use of artificial neural network (ANN) and multiple linear regression (MLR) techniques. This is because the ANN and MLR demonstrated strong computational abilities to handle complex non-linear functions which are the characteristics possessed by energy demand indicators (Mellit et al., 2009; Mubiru and Banda, 2008). In the last few years, many studies have applied ANNs to energy and to mention a few are solar resource potential forecasting (Sözen et al., 2005), predicting global radiation (Azadeh et al., 2009) predictive and adaptive heating control system (Morel et al., 2001), modeling and control of combustion processes (Kalogirou, 2003) and mapping of wind speed profile for energy (Fadare, 2010). The study results will present policy makers with an effective and accurate tool that can predict long-term energy demand.

2.3 Predictors

2.3.1 Artificial Neural Networks (ANNs)

Over the past three decades, much advancement has been made in developing intelligent systems that can solve problems that cannot be programmed by conventional programming approaches. This includes the artificial neural network (ANN). In fact many researchers from different scientific disciplines designed ANNs to solve a variety of problems (Jain *et al.*, 1996). This approach has been widely applied in solving a variety of problems in pattern recognition, prediction, optimization, associative memory, and control (Jain et al., 1996). It provides an ideal environment in which the smart world can benefit by solving unpredictable and uncontrollable problems with a subtle range of influencing parameters.

In fact ANN can be defined as a highly connected array of elementary processors called neurons (Park *et al.*, 1991). They are a network of simple processing neurons operating on their local data and communicate with other neurons (Svozil *et al.*, 1997). The term 'neural network' has its origins in attempts to find the mathematical representations of information processing in biological systems (McCulloch and Pitts, 1943; Rosenblatt, 1961). Indeed, the plausibility models resemblance to biological system is true with regard to the mechanism of interconnectivity of the units and their firing when a predefined threshold limit is reached; more often termed as synaptic strength in physiology. Each neuron in the network is able to receive input signals from its preceding unit, to process them and to send an output signal to the neurons after it. There are many types of neural network but this study is confined to a specific type titled multilayer perceptron feed-forward network (MLP).

An MLP feed-forward neural network is the most widely studied type of neural network (Bishop, 2006) and comprises of neurons (the processing units) that are ordered into layers. The layers can be put in three different types, namely input layers which receives a signal from the input variables, hidden layers which process the input fed from the predecessor layers or the input variable and the output layer which provides the desired or target output signal. Its output layer of neurons are successively connected (fully or locally) in a feed-forward fashion with no connections between units in the same layer and no feedback connections between layers (Jain et al., 1996). Each neuron in a particular layer is connected with all neurons in the succeeding layer (Figure 1 depicts this).

Figure 2.2 shows the connection between the i_{th} and j_{th} neuron as characterized by the weight coefficient w_{ij} and the i_{th} neuron by the threshold coefficient ϑi. The weight coefficient reflects the degree of importance of the given connection in the neural network. The output value of the i_{th} neuron x_i is determined by equations (2.1) and (2.2).

$$X_i = f(\tau_i) \tag{2.1}$$

$$\tau_i = \vartheta_i + \sum_j \omega_{ij} x_j \tag{2.2}$$

Where j consists of all predecessors of the given neuron i and $f(\tau_i)$ is a transfer (activation) function which may be sigmoid, tangent or step function.

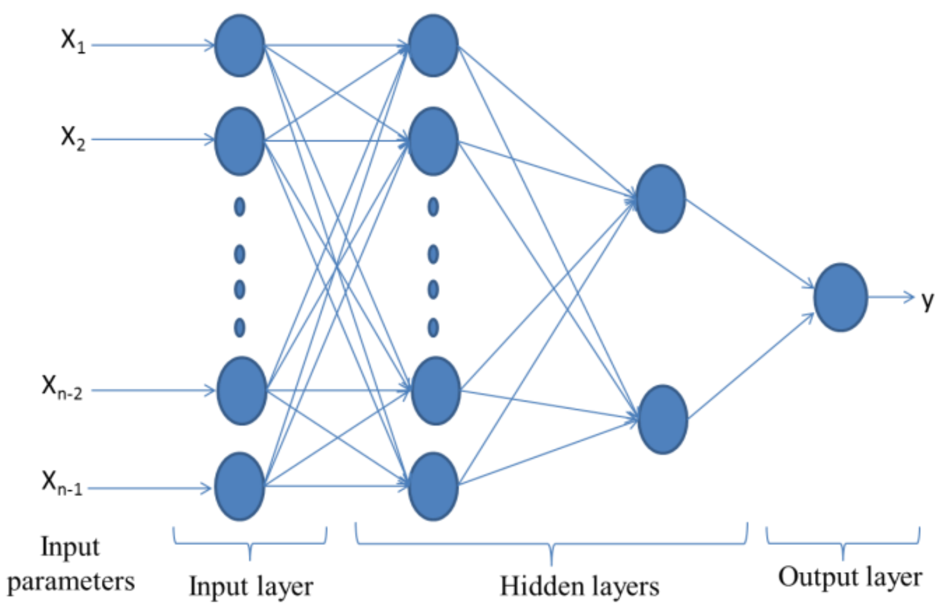

Figure 2.1: A multilayer feed forward neural network consisting of four layers

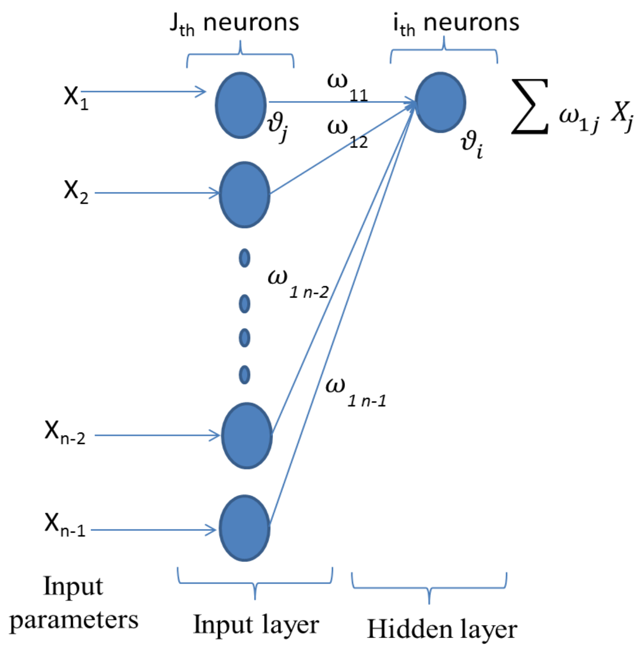

Figure 2.2: Connection between neurons

For the case of this research the sigmoid function of the form given in equation (2.3) was adopted and the summation in equation (2.2) is carried out over all the neurons j of the preceding layer connected to the neuron i of the current layer.

$$f(\tau) = \frac{1}{1+\exp(-\tau)} \tag{2.3}$$

With the supervised learning process, the threshold coefficients also known as bias ϑ_i in equation (2.2) and weight coefficients ω_{ij} are changed to minimize the sum of the squared error between the computed and desired output values. This is done using the training data fed into the system on every neuron as information passes. The equation (2.4a) shows the actual minimization where x and y are the computed and desired vector for the output neurons and the summation runs over all output neurons.

$$E = \frac{1}{2}(x - y)^2 \tag{2.4a}$$

$$J(E) = \frac{1}{2}\sum_{i=1}^{n}(h_E(x_i) - y_i)^2 \tag{2.4b}$$

The widely used training algorithm for the MLP is the back propagation algorithm using the gradient descent applied to a sum-of-squares error function (Bishop, 2006). The intuition is to find how close is estimation x to the required or target y as shown in equation (2.4a) and update all other neurons. This can be reformulated into a cost function in equation (2.4b) and the network is initialized with randomly chosen weights, which is the initial guess value of E. The gradient of the error function is computed and used to correct the initial weights, this is repeatedly changed to minimize $J(E)$ until it converges to the value that minimizes the Error E so that the input and output are as close as possible. With the back propagation, the information update when the weight value is changed is propagated backward.

2.3.2 Multi Linear Regression (MLR)

Multiple linear regression (MLR) is a multivariate statistical technique that examines the relationship between a dependent variable and two or more independent variables by fitting a linear equation to observed data (Campbell, 2001; Tranmer and Elliot, 2008). MLR is an extension of simple linear regression analysis capable of predicting the single dependent variable using a set of known independent variables. In MLR there are p independent variables whereas the relationship amongst dependent and independent variables is given in equation (2.5) (Tranmer and Elliot, 2008).

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots \beta_p x_{pi} + e_i \qquad (2.5)$$

where β_0 is a constant term and β_1 to β_p represents the coefficient that relates the p independent variables. If the value of p is equaled to 1, then the equation 2.5 will represent a simple linear regression. MLR models have been effectively employed in the forecasting of the consumption of various commodities like electricity, coal, gas and petroleum products (Bianco *et al.*, 2009; Sharma *et al.*, 2002). Regression analysis according to Yee (1998) has been and still is the most popular modeling technique in predicting energy demand.

2.4 Methodology

2.4.1 Data collection and preprocessing

The data collection included historical data over the period from 1990 to 2011. The data sources were from the National Bureau of Statistics (NBS), World Development Indicators, International Energy Agency (IEA), Bank of Tanzania (BoT) and Tanzania Electric Supply Company Limited (TANESCO). The annual dataset used in this study for all variables included population, GDP, per capita energy use, total primary energy supply, gross national income per capita, electricity generation and greenhouse gas emissions (CHG). Pre-processing of the data to fit in the proposed models was done. The three proposed models based on the indicators of study were economic, energy and environment indicator models. The models were proposed with the objective of determining the influence of indicators in the prediction of energy demand.

2.4.2 Experimental setup

In the experiment, two predictors were used for the study. They included the artificial neural networks (ANN) with the multilayer perceptron (MLP) architecture and the multiple linear regression (MLR). The artificial neural networks (ANN) with the multilayer perceptron (MLP) architecture are as abbreviated as ANN-MLP throughout the study. The cross-validation with k-folds was also adopted for training. The training set was thus split into k chunks with $k-1$ chunks used for training and the remaining chunk for the validation process aimed at evaluating the model performance. In fact each of the chunk in the k splits was eventually used as a validation against the rest. The performance measure reported by k-fold cross-validation was then the average of the values computed in the loop.

The software used for this study was Weka which is a suite of machine learning software written in Java applicable for data mining tasks (Hall et al., 2009). Weka is composed of tools for pre-processing of data, classification, regression, clustering, association rules, and visualization (Hall et al., 2009; Witten et al., 1999). Weka is designed to bring a range of machine learning techniques under a common interface due to the fact that the various implementations in existence requires the data to be presented in their own format, and their own way of specifying parameters and output (Garner, 1995). In fact Weka has smoothed the differences of the implementations and offers a consistent method for input format, simulations and results analysis. Weka interface has made it easy enough that users need only to concern themselves with the selection of features in the data for analysis and what the output means, rather than how to use a machine learning scheme (package).

2.4.3 Performance evaluation

The models' performances in both approaches were evaluated by using the following statistical parameters: correlation coefficient (CC), root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) (Azadeh et al., 2007), root relative squared error (RRSE) and relative absolute error (RAE) (Chattefuee and Hadi, 2006; Lee and Nicewander, 1988). The values of statistical indices were derived from the statistical calculation of observation in the models output predictions and are given in equations 2.6, 2.7, 2.8 and 2.9 (Armstrong and Collopy, 1992; Makridakis and Hibon, 1995). Selection of the best model for estimating energy demand was done considering higher correlation coefficient with the lowest root mean square error, mean absolute error and relative absolute error.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - a_i)^2} \qquad (2.6)$$

$$\mathrm{RAE} = \sum_{i=1}^{n}|P_i - a_i| \Big/ \sum_{i=1}^{n}|\bar{a} - a_i| \qquad (2.7)$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|P_i - a_i| \qquad (2.8)$$

$$\mathrm{MAPE}\ (\%) = \frac{100}{n}\sum_{t=1}^{n}\frac{P_i - a_i}{P_i} \qquad (2.9)$$

Where P_i is the actual values of P_{t+1} with $i = 1, 2, 3, 4, \ldots, n$ years observations; $P_i{}'$ is the average of P_{t+1} ; a_i is the predicted P_{t+1} values and n is the total observations.

2.5 Results and discussions

2.5.1 Training and validation

A cross-validation technique with 10 folds was experimentally chosen for the analysis of energy demand. The data set was broken into 10 different sets of size n/10 also known as chunks and the training was carried out on 9 sets and testing was done on the remaining one. For each 10 experiments carried out, 9 folds were used for the training and the remaining fold for evaluation. The rotation was kept changing the evaluation fold for each iteration until each of the folds has been used for evaluation against the rest. For this case, the true error was estimated by taking a mean accuracy.

2.5.2 Architecture identification

The most appropriate ANN-MLP architecture was selected by considering performance indices to represent the best generalizing ability among the architectures. The first ranking experimental results for the economic indicators model were from the architecture with two neurons in hidden layer (3-2-1) and CC value of 0.9983. The second and third ranking architectures for economic indicators model had CC values of 0.9983 and 0.9982 but were characterized with the highest MAE, RMSE, RAE and RRSE values as compared to the best architecture. ANN-MLP experimental results for the energy indicators model with architectures (4-4-1) showed the best accuracy as compared to other architectures that were examined. The CC values of the second and third ranking architectures had the same values as the first ranking architecture but their MAE, RMSE, RAE and RRSE values were the highest. The best results for the environment indicators model were from the architecture that doubled the number of hidden neurons relative to the number of input neurons (3-6-1). The second and third ranking architectures for the environment indicators model had both CC value of 0.9986 which was less than the first ranking architecture value accompanied with the highest MAE, RMSE, RAE and RRSE. Results for the first ranking architecture involving economic, energy and environment indicators model are summarized in Table 2.1.

Table 2.1: ANN-MLP models performance comparison

	Economic indicators model	Energy indicators model	Environment indicators model
CC	0.9983	0.9995	0.9987
MAE	0.1331	0.0873	0.1586
RMSE	0.2108	0.1155	0.2009
RAE	3.92%	2.57%	4.67%
RRSE	5.56%	3.04%	5.29%
Architecture	4 – 2 - 1	4 – 4 – 1	3 – 6 - 1

2.5.3 ANN-MLP results

The economic, energy and environment indicators models' results are presented in this section to show the comparison of the predicted values against actual values for the purpose of determining the best indicators for the prediction of energy demand in Tanzania based on the ANN-MLP technique. The results as presented in Table 2.1 are the statistical parameters for performance evaluation of the models. As illustrated in Table 2.1, the CC based on the energy indicators model is 0.9995 whereas the economic and environment indicators models had 0.9983 and 0.9987 respectively. The CC value of the energy indicators model depicts a higher degree of correlation to energy demand as compared to the economic and environment indicators model using ANN-MLP technique.

The magnitude of differences between the CC values among the models is very small to determine the supremacy of the energy indicators model. Statistical performance evaluation parameters are further compared to determine the first ranking model among the three. In terms of RMSE, RAE, MAE and RRSE values, the energy indicators model values were less in comparison to the economic and environment indicators model respectively. Though the results of ANN-MLP techniques are numerically close in terms of CC values, the statistical performance evaluation parameters on energy indicators model ranks the first in prediction accuracy as compared to its counterparts.

The graphical presentation of absolute errors deviations for economic, energy and environment indicators models using ANN-MLP technique are illustrated in Figure 2.3. The upper absolute errors deviation of predicted against actual values for energy indicators model is 0.214 while in economic and environment indicators models are 0.455 and 0.536 respectively. These values again confirm the energy indicators model as the best as compared to environment and economic indicators. The patterns exhibited by economic and environment indicators models have high deviations values between actual and predicted values. The absolute error deviations of predicted values against actual values in the energy indicators model are minimal as compared to the other models. Concerning absolute error deviation curves, a conclusion is drawn that for better prediction, the energy indicators model is better in comparison to its counterparts.

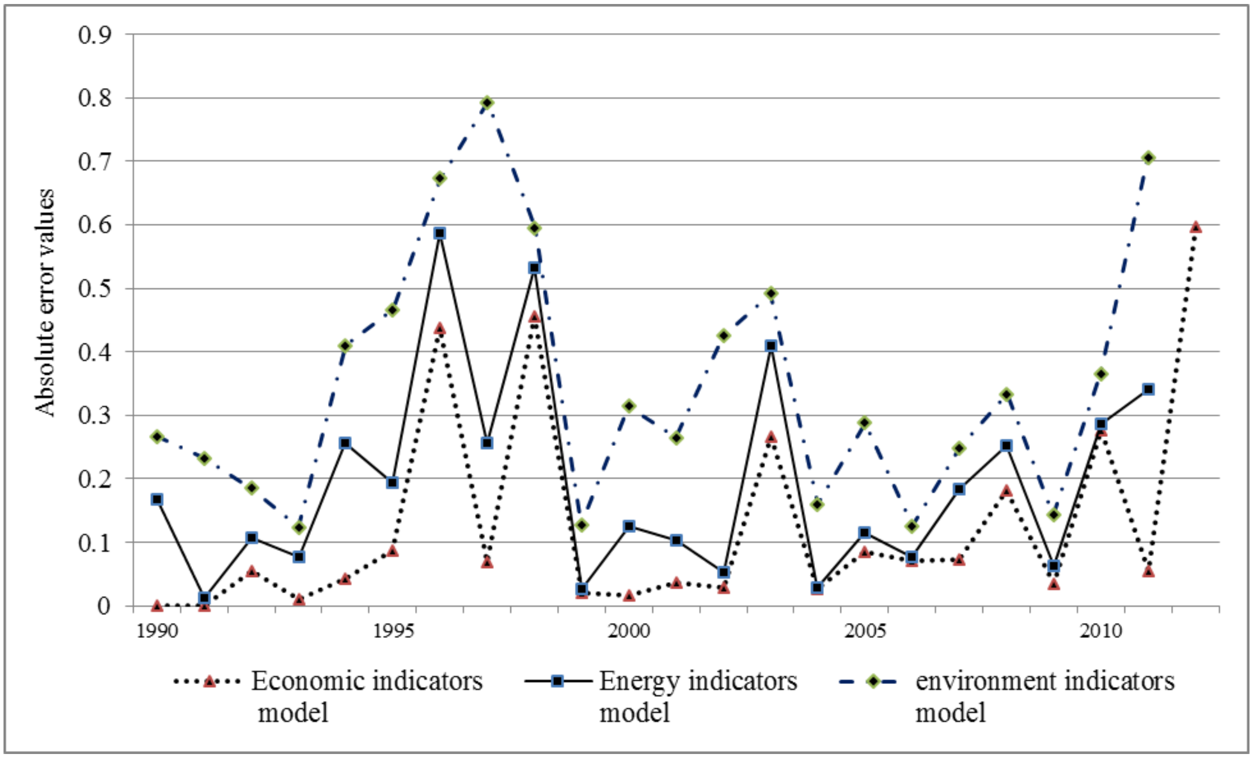

Figure 2.3: Absolute error values comparison among models - ANN-MLP technique

The computation of absolute percentage error (APE) values using data in Table 2.2 and equation (2.10) for the energy indicators model show fluctuations between 0.01% and 2.03% while in the economic indicators and environment indicators model they fluctuate between 0% and 4.04% and 0.27% and 4.75% respectively. The computed mean absolute percentage error (MAPE) using equation (2.9) for economic and environment indicators models are 0.93% and 1.19% respectively whereas in the energy indicators model it is 0.67%. As can be observed, the MAPE between actual and predicted values for energy indicators model are within acceptable accuracy outpacing the economic and environment indicators models. The statistical performance evaluation parameters are in favor of the energy indicators model. This is because the energy indicators perform better in comparison to its counterparts when using the ANN-MLP technique.

$$\text{APE}\ (\%) = \left|\frac{\text{Actual Values} - \text{Predicted Values}}{\text{Actual Values}}\right| * 100 \qquad (2.10)$$

Table 2.2: ANN-MLP technique models output comparison

YEAR	ACTUAL VALUES (MTOE)	PREDICTED VALUES (MTOE)			YEAR	ACTUAL VALUES (MTOE)	PREDICTED VALUES (MTOE)		
		Economic Indicators model	Energy Indicators model	Environment Indicators model			Economic Indicators model	Energy Indicators model	Environment Indicators model
1990	9.73	9.73	9.898	9.631	2001	14.2	14.171	14.267	14.039
1991	9.93	9.875	9.918	9.709	2002	14.92	14.653	14.944	14.548
1992	10.06	10.05	10.112	10.138	2003	15.49	15.464	15.347	15.408
1993	10.33	10.372	10.397	10.377	2004	16.2	16.286	16.202	16.332
1994	10.52	10.432	10.306	10.366	2005	17.14	17.069	17.17	16.968
1995	11.02	10.582	10.914	10.748	2006	17.81	17.883	17.803	17.858
1996	11.16	11.229	11.308	11.247	2007	18.31	18.491	18.42	18.376
1997	11.27	11.725	11.458	11.806	2008	19.1	19.134	19.029	19.019
1998	11.93	11.909	12.007	11.993	2009	19.35	19.627	19.378	19.269
1999	12.75	12.733	12.756	12.649	2010	20.04	20.095	20.05	19.961
2000	13.39	13.353	13.282	13.201	2011	20.75	20.154	20.465	20.384

2.5.4 Multiple Linear Regression (MLR) results

A summary of the MLR statistical performance results is shown in Table 2.3 for economic, energy and environment indicators models. The results show that the CC value for the energy indicators model has a higher value as compared to economic and environment indicators models. The greater CC for energy indicators model indicates a higher correlation in predicting energy demand as opposed to the economic and environment indicators using the MLR technique. This implies that the prediction of energy demand using energy indicators model is more accurate than that of its counterparts. The second and third are as shown in Table 2.3.

Table 2.3: Performance evaluation of models – MLR technique

	Economic indicators model	Energy indicators model	Environment indicators model
CC	0.9942	0.9993	0.9901
MAE	0.3412	0.1102	0.4431
RMSE	0.3904	0.1329	0.5123
RAE	10.06%	3.25%	13.06%
RRSE	10.29%	3.51%	13.51%

It is further shown in Table 2.3 that RMSE, RAE, MAE and RRSE for the energy indicators model are correspondingly less valued as compared to the economic and environment indicators models. The lower RMSE, RAE, MAE and RRSE values as depicted by the energy indicators model represent a higher accuracy in the prediction of energy demand. Using equation (2.10), the APE values computed from Table 2.4 for energy indicators model depicts fluctuations between 0.09% and 2.19% while the economic and environment indicators model fluctuates between 011% and 7.18% and 0.06% and 8.62% respectively. The MAPE values for economic and environment indicators models computed using equation (2.9) are 2.5% and 3.27% respectively while in the energy indicators model it is 0.83%. MAPE further shows that the energy indicators model outperforms its counterparts.

Table 2.4: MLR technique models output comparison

YEAR	ACTUAL VALUES (MTOE)	PREDICTED VALUES (MTOE)			YEAR	ACTUAL VALUES (MTOE)	PREDICTED VALUES (MTOE)		
		Economic Indicators model	Energy Indicators model	Environment Indicators model			Economic Indicators model	Energy Indicators model	Environment Indicators model
1990	9.73	9.163	9.88	9.013	2001	14.2	13.957	14.486	14.117
1991	9.93	9.605	10	9.387	2002	14.92	14.625	15.117	15.552
1992	10.06	10.023	9.992	9.864	2003	15.49	15.118	15.402	14.846
1993	10.33	10.397	10.194	10.278	2004	16.2	15.842	16.006	15.815
1994	10.52	10.722	10.29	10.569	2005	17.14	16.752	17.101	16.524
1995	11.02	11.163	10.945	11.409	2006	17.81	17.319	17.778	17.821
1996	11.16	11.652	11.127	11.845	2007	18.31	18.082	18.358	18.027
1997	11.27	12.079	11.23	12.241	2008	19.1	18.739	18.885	18.461
1998	11.93	12.571	12.065	12.601	2009	19.35	19.626	19.31	18.937
1999	12.75	13.059	12.901	13.009	2010	20.04	20.481	20.152	20.507
2000	13.39	13.375	13.455	13.055	2011	20.75	21.195	20.73	21.462

The graphical presentation of absolute errors deviations between actual and predicted values for all models is illustrated in Figure 2.4. The absolute errors values for predicted against actual values for energy indicators model are lower than the other models. The upper absolute error values deviations for the energy indicators model is 0.286 while for economic and environment are 0.809 and 0.971 respectively. Looking at the three absolute errors deviations curves, the economic and environment indicators models curves exhibits the higher fluctuations over the entire dataset. It is thus drawn from the absolute errors deviations curves that for better energy prediction, the energy indicators model leads its counterparts.

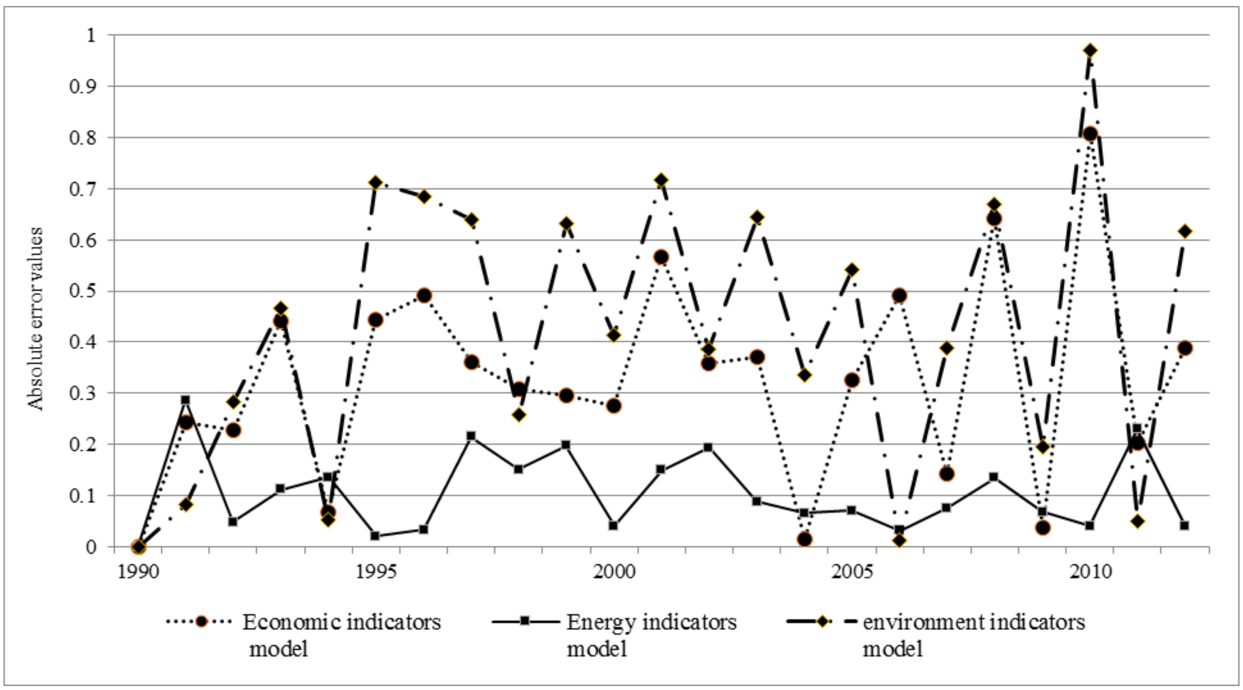

Figure 2.4: Absolute error values comparison among models – MLR technique

2.5.5 ANN-MLP and MLR performance comparison

The energy indicators model is shown to have a strong influence in the prediction of energy demand by outperforming the economic and environmental indicators models. Table 2.5 shows performance evaluation indices for energy the indicators model. It is shown that the CC has greater values and MAE, RMSE, RAE, RRSE and MAPE have lesser values in the ANN-MLP in comparison to the MLR values. Figure 2.5 presents the comparison between predicted values against actual values for the energy indicators model in both ANN-MLP and MLR cases. The observations on the curve produced by the ANN-MLP approach show that the predicted values are close to the actual values as compared to the curve produced by the MLR approach. This was noted in the experimental results where RMSE, MAE, RAE, RRSE and MAPE had lower values and higher CC values. These observations show that the ANN-MLP provides better results than the MLR technique for energy demand prediction.

Table 2.5: ANN-MLP and MLR performance comparison

	ANN-MLP Technique	MLR-Technique
CC	0.9995	0.9993
MAE	0.0972	0.1102
RMSE	0.1229	0.1329
RAE	2.82%	3.25%
RRSE	3.25%	3.51%
MAPE	0.67%	0.83%

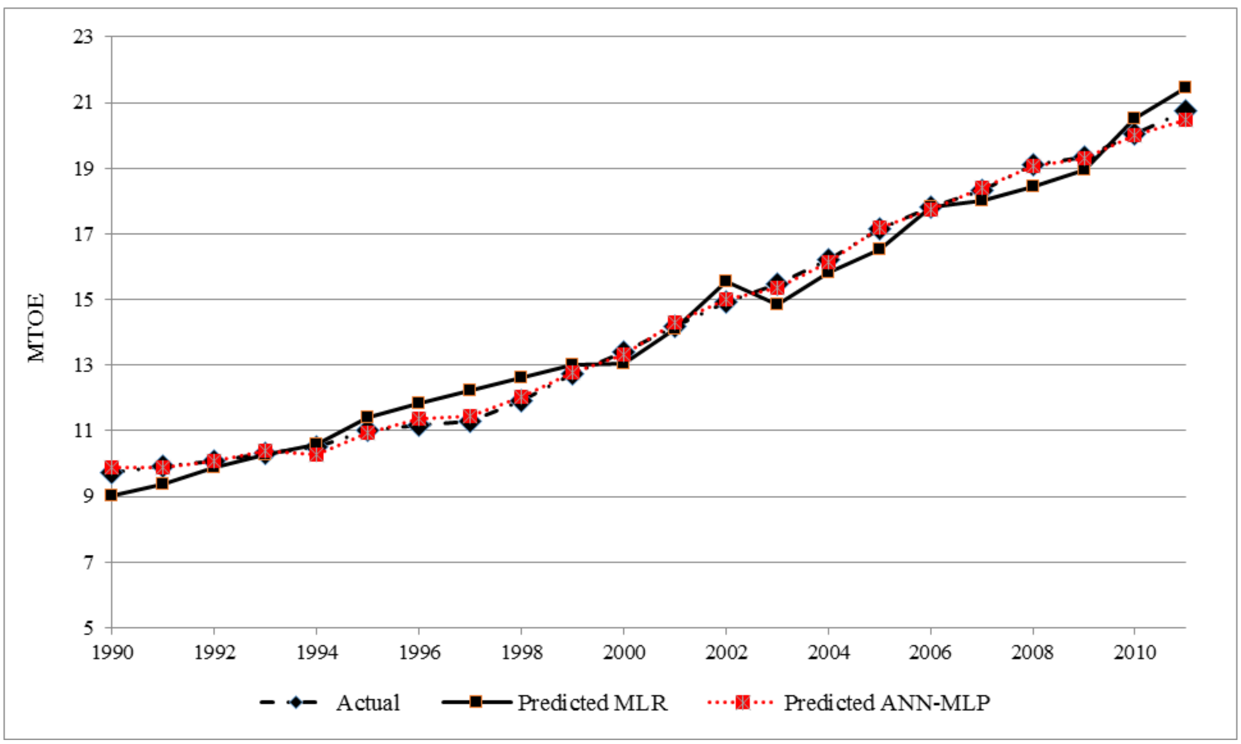

Figure 2.5: Comparison of actual and predicted values for ANN-MLP and MLR techniques

2.6 Conclusion

This paper presented ANN-MLP and MLR techniques for determining an accurate prediction tool for energy demand in Tanzania using economic, energy and environment indicators models. The ANN-MLP and MLR techniques were first used to analyze separately the influence of economic, energy and environment indicators models in the energy demand of Tanzania. Then statistical performance indices were applied to evaluate the estimating ability of economic, energy and environment indicators in predicting energy demand using ANN-MLP and MLR techniques. The best performing indicators model from each techniques were then compared to determine the best energy demand prediction technique for Tanzania. Results from both ANN-MLP and MLR techniques unanimously determined the energy indicators model as the first ranking followed by economic and environment indicators models. Results for the energy indicators model under ANN-MLP technique had a CC value of 0.9995 against 0.9993 for the MLR technique.

Comparison of the statistical performance indices showed that MAPE value of the energy indicators model under ANN-MLP technique is 0.67% better than that of MLR technique valued at 0.83%. The RMSE, MAE, RAE and RRSE values of the energy indicators model under ANN-MLP technique had less numerical values as opposed to MLR technique. Additionally, the ANN-MLP technique had a predicted values curve close to the actual values as compared to the curve produced by MLR technique whose results deviated more from the actual values. Based on the results of this study it is concluded that ANN-MLP technique outperform MLR approach in estimating energy demand for Tanzania. The study results therefore suggests energy indicators model as an accurate model in estimating energy demand of Tanzania and the ANN-MLP as the best technique in such analyses. The use of the ANN-MLP technique in estimating future energy demand will assist government in decision-making on expected energy demand for long-term sustainable development. Further studies are recommended to compare the ANN-MLP results with other algorithms for analysis of energy demand in Tanzania.

CHAPTER THREE

PREDICTION OF TANZANIAN ENERGY DEMAND USING SUPPORT VECTOR MACHINE FOR REGRESSION (SVR)[2]

3.1 Abstract

This study discusses the influences of economic, energy and environment indicators in the prediction of energy demand for Tanzania applying support vector machine for regression (SVR). Economic, energy and environment indicators were applied to formulate models based on time series data. The experimental results showed the supremacy of the polynomial-SVR kernel function and the energy indicators model in providing the transformation, which achieved more accurate prediction values. The energy indicators model had a correlation coefficient (CC) of 0.999 as equated to 0.9975 and 0.9952 with PUKF-SVR kernels for the economic and environment indicators model. The energy indicators model more closely predicted values as compared to actual values when compared to the economic and environment indicators models. Furthermore, root mean squared error (RMSE), mean absolute error (MAE), root relative squared error (RRSE) and relative absolute error (RAE) of the energy indicators model were the lowest. Long-term sustainable development of the energy sector can be achieved with the use of the SVR-algorithm as a prediction tool for future energy demand.

3.2 Introduction

Notwithstanding its extremely vivacious importance to all human activities and life in general, energy prediction studies using the machine learning approach in the developing countries like Tanzania has not been done deeply. In addition, energy availability and concerns as to its scarcity due to the depletion of fossil fuel resources, has made the analysis of energy demand to be of great interest to researchers. In fact, energy is important to all human activities and thus a socio-economic development catalytic agent for individuals and nations in general. The energy analysis using various approaches for different applications has assisted individuals and countries to plan

[2] International Journal of Computer Applications (IJCA), Volume 109 – Issue No.3 (2015), 34-39

for their energy demands ahead of time. Tanzania is among the developing countries where intensive investments are being made in all sectors of the economy. The country energy demand is expected to grow (Kichonge *et al.*, 2014a) as new investments floods in due to economic sectors expansions and liberalization especially in gas, minerals and agriculture. To facilitate and assist energy policy makers in decision-making, this study adopts support vector machine for regression (SVR) to analyze the influence of economic, energy and environment indicators in the prediction of energy demand of Tanzania. The choice of SVR is due to its strong computational capabilities. SVR has previously used for a number of applications such as electricity load forecasting (Pai and Hong, 2005a, b); predicting crude oil price (Xie et al., 2006); wind speed estimation (Mohandes et al., 2004); classification (Maji et al., 2008; Xue et al., 2005); among many others. Expectations are that the study results will present an effective tool for the prediction of long-term energy demand based on time series data.

3.3 Support Vector Machine

The support vector machines (SVMs) in machine learning are supervised learning models with associated learning algorithms that analyze data and recognize patterns (Olson and Delen, 2008). SVMs are applicable for classification and regression analysis. When SVMs are used for classification they involve identifying to which of a set of categories a new observation belongs, on the basis of a training set of data containing observations whose category membership is known (Goel, 2009). SVM for regression applies a loss function to solve various regression problems; and it has contributed to a broad range of problems arising in various fields. It is a training algorithm for learning regression rules from data which can be used to learn linear-SVR, polynomial-SVR, RBF-SVR and PUKF-SVR (Üstün *et al.*, 2006). PUKF-SVR has been demonstrated to work well with approximation of the linear, polynomial-SVR or RBF-SVR feature space. It has further been shown to really act like linear, polynomial-SVR or RBF-SVR (Üstün et al., 2006). The detailed theory of SVM is well given in (Burges, 1998; Cristianini and Shawe-Taylor, 2000; Olson and Delen, 2008; Schölkopf *et al.*, 1998; Smola and Schölkopf, 2004) and the theory of kernels in (Bishop, 2006). An overview concept of SVR and PUKF-SVR function is as presented in this study.

3.3.1 Support vector machine for regression (SVR)

Support vector regression (SVR) is an SVM version for regression (Drucker *et al.*, 1997; Olson and Delen, 2008). The scholars Schölkopf et al. (1998) and Üstün et al. (2006) approach SVR by considering a data set $[(x_1, y_1), \ldots\ldots, (x_n, y_n)]$ (d-dimensional input space) and y in R space, basically arguing that, SVR tries to find the function f(x), which relates the measured input object (say, for this case energy indicators) to the desired output property of this object (say, predicted energy demand value in MTOE as represented in equation 3.1. The variables W and b represent the slope and offset of the regression function. The solution for this regression problem is solved by minimizing equation 3.2.

$$f(x) - WX + b \qquad (W, X \in R^d) \tag{3.1}$$

$$\frac{1}{2}||W||^2 + C\sum_{i=1}^{n} L_\varepsilon(f(x_i), y_i) \tag{3.2}$$

$$\text{Where} \quad C > 0 \text{ and } L_\varepsilon(f(x_i), y_i) = 0$$

$$\text{if } |y_i - f(x_i)| \le \varepsilon \text{ and } L_\varepsilon(f(x_i), y_i) = |y_i - f(x_i)| - \varepsilon \text{ otherwise} \tag{3.3}$$

$\frac{1}{2}||W||^2$ as given in equation 3.2, is the term characterizing the model complexity (flatness) whereas C is the regularization constant which determines the trade-off between the model complexity f(x) and the amount up to which deviations larger than ε are tolerated (Burges, 1998; Cristianini and Shawe-Taylor, 2000; Schölkopf et al., 1998; Smola and Schölkopf, 2004). Large values of C favor solutions with few errors and small values denote preference towards low-complexity. The reformulation of equation 3.2 by introduction of the slack variable ξ_i and ξ_i^* gives the primal equation 3.4 which refers to the formulation of the regression problem in the original data space (Cortes and Vapnik, 1995).

The primal formulation of the problem is suitable in case the number of objects is (much) larger than the number of involved variables; otherwise, the so-called dual is used. The slack variables ξ_i and ξ_i^* are introduced in the situation that the target value (property of the input object) exceeds the numerical limits of the ϵ tube. The points outside the ϵ tube are named support vectors and in fact are the vectors supporting the actual regression model (Üstün et al., 2006). The support vectors machine contribute only to building the regression function whereas the rest of the input data in the space are not important and can be rejected after the regression model is built. This is termed as sparsely of the solution where only a few data from the input space are actually taken into account in building the regression function. Therefore we get at the formulation of the approximation function as stated in (Vapnik, 2000).

Minimize

$\frac{1}{2}||W||^2 + C\sum_{i=1}^{n} (\xi_i + \xi_i^*)$ subject to $y_i - \langle w, x_i \rangle - b \leq \varepsilon + \xi_i \;\; \langle w, x_i \rangle + b - y_i \leq \varepsilon + \xi_i^*$ and $\varepsilon,\ \xi_i, \xi_i^* \geq 0$ (3.4)

Finally, intuitively taking into consideration of the non-linear regression by including the mapping to the feature space, equation 1 can be re-constructed into equation 3.5 by introducing the Lagrange multipliers.

$$f(x) - \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\langle \emptyset(x_i), \emptyset(x)\rangle\, b \tag{3.5}$$

In equation 5, the model parameters α_i and α_i^* that represent the Lagrange multipliers satisfying the constraint $0 < \alpha_i, \alpha_i^* < C$. These parameters can be obtained by maximizing the dual formulation, which can be derived from equation 3.4.

Maximize $-\frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)\langle \emptyset(x_i).\emptyset(x)\rangle + \sum_i^n(\alpha_i - \alpha_i^*)y_i - \ \varepsilon\sum_i^n(\alpha_i - \alpha_i^*)$

(3.6)

Subject to $\sum_i^n(\alpha_i - \alpha_i^*) = 0$ and $\alpha_i - \alpha_i^* \in [0, C]$ (3.7)

According to Cristianini and Shawe-Taylor (2000), with the Karush–Kuhn–Tucker conditions, it is only a small number of coefficients α_i and α_i^* will be non-zero, and the data points associated with these parameters are mentioned to the support vectors of the model. The vector inner product $\langle \emptyset(x_i).\emptyset(x)\rangle$ in equations 3.5 and 3.6 represent the mapping function from the input space to feature space. These can be replaced by the generic kernel function $K(x_i, x)$. The kernel function represents the underlying relationship between the input data and desired output to be modeled. Therefore, changing equation 3.6 by introducing the kernel function it develops into equation 8.

$$f(x) - \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\, K(x_i, x) + b \tag{3.8}$$

As a result, the kernel function transforms the nonlinear input space into a high dimensional feature space in which the solution of the problem can be represented as being a straight linear problem.

3.3.2 Kernel idea

Kernel-based algorithms action idea is to change the data in the input space into a high dimensional Hilbert space (Muller *et al.*, 2001; Schölkopf and Smola, 2002; Üstün et al., 2006).That is to say, a space spanned by inner-product based functions of real-valued vectors representing physical entities which is referred to as the corresponding feature space (Üstün et al., 2006). In this way, it becomes possible to solve the problem as if the feature space was linear separable. Kernels based methods for SVR have been studied, proposed and the field is now in its development point (Cortes and Vapnik, 1995; Vapnik and Vapnik, 1998). The linear, polynomial-SVR and RBF-SVR represented in equations 3.9 to 3.11 respectively, are well implemented and tested in the SVR. Furthermore, the kernel based on PUKF-SVR has been effected and tested. A detailed explanation of the PUKF-SVR is well covered in (Üstün et al., 2006) and the following section gives a brief discussion.

$$K(x_i, x_j) = (\langle x_i, x_j \rangle + 1) \tag{3.9}$$

$$K(x_i, x_j) = (\langle x_i, x_j \rangle + 1)^d, \qquad d = 2 \text{ Poly}_1 \tag{3.10}$$

$$K(x_i, x_j) = e^{\left(\frac{-||x_i, x_j||^2}{2\delta}\right)} \tag{3.11}$$

when $\delta = 3$ the equation is polynomial $-$ SVR 2 (Poly_2)

$\delta = 8$ Poly_3 $\delta = 0.5$ RBF-SVR_1 $\delta = 2$ RBF-SVR_2

3.3.3 Pearson VII universal kernel (PUKF-SVR)

PUKF-SVR was proposed by Karl Pearson in 1895 and it is a special case of Type IV (symmetrical) of the families of distribution he proposed after noting that not all distribution had distributions that resembled the normal distribution (Lahcene, 2013). The general form of the Pearson VII function for curve fitting purposes is as given in equation 3.12.

$$f(x) = \frac{H}{\left[1+\left(\frac{2(x-x_0)\sqrt{2^{1/w}-1}}{\delta}\right)^2\right]^w} \tag{3.12}$$

From equation 3.12, H is the peak height at the centre x_0, and x characterizes the independent variable. The parameters δ and w regulates the half-width and the tailing factor of the peak. The main reason to use the Pearson VII function for curve fitting is its flexibility to change, by varying the parameter w, from a Gaussian shape (when w approximates infinity) towards a Lorentzian shape (w equal to 1) as depicted in Figure 3.1 (Üstün et al., 2006). The function was selected to be used as the kernel because of its suppleness to vary between a Gaussian and a Lorentzian shape and out there. This property makes it able to serve as a kind of universal kernel, which can substitute the set of commonly applied kernel functions, such as the linear, polynomial-SVR and RBF-SVR kernels (Üstün et al., 2006). The PUKF-SVR function is tested to be a valid kernel functions because its matrices belongs to the class of the symmetric and positive semi-definite matrix, which is a requirement for any function to be a kernel. The Pearson function in equation 3.12 is modified to suit the kernel in equation 3.13 (Üstün et al., 2006).

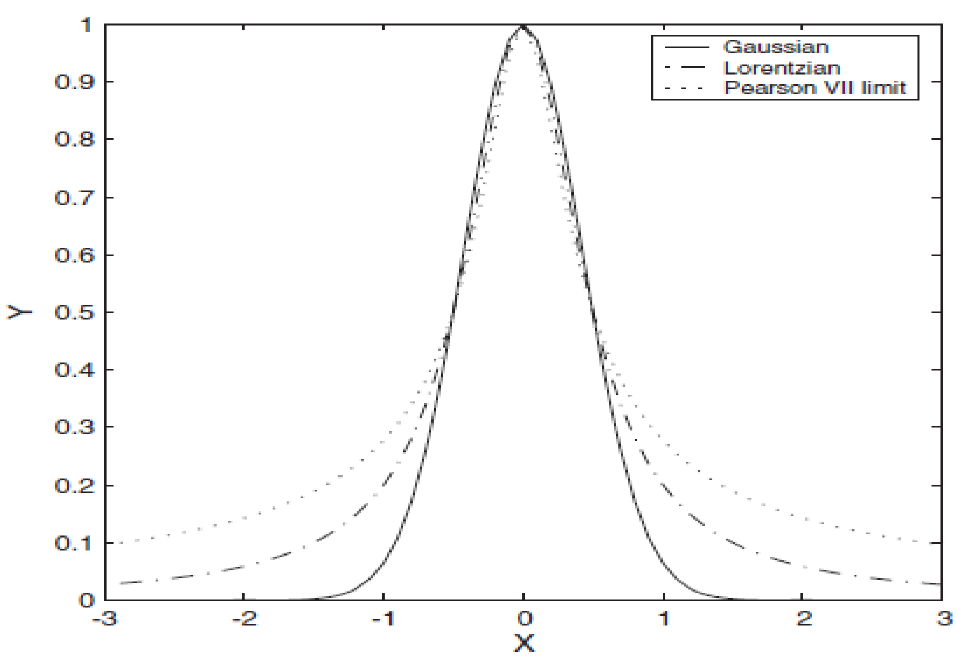

Figure 3.1: Pearson VII peak shapes

As the Pearson width x =1, it resembles a Lorentzian and as it approaches infinity, it becomes equal to a Gaussian peak shape. Moreover, a Pearson peak with x =0.5 (Üstün et al., 2006) is shown in Figure 3.1. Note: the region close to zero can be imagined to compare to RBF-SVR and higher order polynomial-SVR function shapes. The region between 0.25 – 0.75 represents a linear function. Extremely, the full range between 0 – 3 becomes more or less comparable to a sigmoid function, which is widely used in neural network modeling.

$$K(x_i, x_j) = \frac{1}{\left[1 + \left(\frac{2(||x_i - x_{j||}{}^2)\sqrt{2^{1/w} - 1}}{\delta}\right)^2\right]^w} \tag{3.13}$$

As can be envisaged, the single variable x in equation 3.12 is replaced by two vector arguments and the Euclidean distance measure between these vectors has been introduced. The peak offset term x_0 is removed and the peak height H is simply replaced by 1, this without loss of generality.

3.4 Methodology

3.4.1 Data collection and pre-processing

Data used were from National Bureau of Statistics (NBS), World Development Indicators, International Energy Agency (IEA), Bank of Tanzania (BoT) and Tanzania Electric Supply Company Limited (TANESCO). The dataset had the historical annual data over the period from 1990 to 2011. The dataset included population, gross domestic product (GDP), per capita energy use, total primary energy supply, gross national income per capita, electricity generation and CO_2 emissions. The pre-processing of the data to fit in the models was done. The three models based on the indicators of study were economic, energy and environment. The models were developed with the objectives of determining the influence of indicators in the prediction of energy demand.

3.4.2 Experimental setup

In the experiment, SVR was used for the study. The training to build the regression model used for evaluation involved the polynomial-SVR, normalized polynomial-SVR, RBF-SVR and the PUKF-SVR kernels. Data for all the experiments were cross-validated using k-folds cross-validation (CV). The idea was to split the data into k disjoint and equally sized subsets. The validation was done on a single subset and training was done using the union of the remaining k−1 subsets. This procedure was repeated k times, each time with a different subset for validation. The intention was to allow for the large data in the dataset to be used for training and all cases appear for the validation cases (testing). For this case, the true errors were estimated as the average error rate.

3.4.3 Performance evaluation

The models' performances in both approaches were compared and evaluated using an appropriate choice of the following statistical parameters: correlation coefficient (CC) (Lee and Nicewander, 1988), root mean squared error (RMSE), mean absolute error (MAE), root relative squared error (RRSE) and relative absolute error (RAE). The values of statistical indices were derived from statistical calculation of observation in the models output predictions and are given in Armstrong and Collopy (1992) and Chattefuee and Hadi (2006). Selection of the appropriate kernel and the accurate model for prediction of energy demand was done by considering the combination of higher CC and the lowest RRSE, RMSE; MAE and RAE values.

3.5 Result and discussion

To demonstrate the SVR capability on energy prediction, three experiments were conducted using the cross-validation with 10 folds for the training data. The first experiment involved the economic, the second energy and the last one environmental indicators. The value for k was experimentally chosen to be 10 folds; and thus the union of 9 folds were used for the training and the remaining subset for validation set (testing) in each cycle of one experiment.

3.5.1 Analysis of the kernels performance

The results of the kernels performance analysis regarding the economic indicators model as shown in Table 3.1 and Figure 3.2 suggests the PUKF-SVR kernel performed excellently in comparison to its counterparts. It had the highest CC value of 0.9975 while the RBF-SVR kernel had the lowest CC value in that case. The PUKF-SVR kernel had the lowest MAE and RMSE values of 0.1934 and 0.2589 respectively. Furthermore, the lowest RAE and RRSE characterize PUKF-SVR kernel in relation to the other kernels. The error value findings as depicted in Figure 3.2 provide the comparison of errors for the various kernels involved. The two algorithm maps achieved by the

Polynomial-SVR and PUKF-SVR appeared to be slightly close in most of the years with the PUKF-SVR attaining the lower value in most cases.

Table 3.1: Kernels statistical performance comparison-economic indicators model

	Normalized Polynomial SVR	Polynomial SVR	RBF-SVR	PUKF-SVR
CC	0.9904	0.9912	0.4383	0.9975
MAE	0.461	0.406	2.9243	0.1934
RMSE	0.5989	0.4941	3.3271	02589
RAE	13.59%	11.97%	86.20%	5.70%
RRSE	15.79%	13.03%	87.73%	6.83%

The results of the kernels performance analysis on the energy indicators model for the prediction of energy demand using the normalized polynomial-SVR, polynomial-SVR, RBF-SVR and the PUKF-SVR are depicted in Table 3.2. The polynomial-SVR kernel had the greatest predictive ability with the correlation coefficient of 0.999. The RBF-SVR and the normalized polynomial-SVR kernels had the least CC value with the RBF-SVR having the smallest CC value of 0.4961. The MAE and RMSE values of polynomial-SVR are shown to be 0.1448 and 0.1629 respectively outperforming the other kernels. The polynomial-SVR further exhibits the lowest RAE and root relative square error vindicating it to be the better estimating or predictor of energy demand under energy indicators model. These can as well be spotted in Figure 3.3. Even though PUKF-SVR and Polynomial-SVR appears to have similar values over the considerable range, the predictive capability went down beyond the year 2010 making the polynomial-SVR a better approach for the prediction of energy demand for this case.

Table 3.2: Kernels statistical performance comparison-energy indicators model

	Normalized Polynomial SVR	Polynomial SVR	RBF-SVR	PUKF-SVR
CC	0.6411	0.999	0.4961	0.9977
MAE	2.544	0.1448	2.7927	0.1465
RMSE	2.8269	0.1629	3.1987	0.2552
RAE	74.99%	4.27%	82.32%	4.32%
RRSE	74.54%	4.30%	84.34%	6.73%

The last experiment was evaluating the effect of the kernels in the use of environment indicators model for the energy demand prediction. Table 3.3 shows that the greatest predictive validity algorithm was PUKF-SVR, which had the CC value of 0.9952. It is as well noted to have the lowest values for MAE and RMSE of 0.2331 and 0.3686 respectively. The RAE was 6.872% and the RRSE is 9.72. The RBF-SVR kernel had again the least CC value. The absolute errors comparison between predicted and actual values for both algorithms is illustrated in Figure 3.4. The PUKF-SVR and the polynomial-SVR had slightly closer results although in most cases again PUKF- SVR values were the lowest. This puts the PUKF-SVR to be a better kernel for energy prediction using the environment indicators model.

Table 3.3: Kernels statistical performance comparison-environment indicators model

	Normalized Polynomial SVR	Polynomial SVR	RBF-SVR	PUKF-SVR
CC	0.8120	0.9934	0.4375	0.9952
MAE	1.5012	0.3323	2.8991	0.2331
RMSE	2.1296	0.4282	3.3048	0.3686
RAE	44.25%	9.79%	85.46%	6.87%
RRSE	56.15%	11.29%	87.14%	9.72%

3.5.2 Models performance comparison

Two visible plausible conclusions can be drawn here. The first one involves the best performing indicators model on energy demand prediction based on time series data and the second the overall better performing kernel regardless of the models. This section begins with the best performing indicators model for energy prediction. Although it is noted, the PUKF-SVR kernel had a better performance over its counterparts in both the economic and environment indicators models, thorough analysis of the energy indicators model results shows the polynomial-SVR kernel had the greatest performance over the PUKF-SVR kernel. Comparison of kernels in Table 3.4 shows that the polynomial-SVR has the highest correlation coefficient of 0.999 with the energy indicators model while in the economic and environment indicators models, the correlation coefficients are 0.9975 and 0.9952 respectively. Polynomial-SVR kernel for energy indicators model achieved the least values in terms of MAE as compared to the PUKF-SVR kernel in the economic and environment indicators model. The PUKF-SVR kernel had MAE values of 0.1934 and 0.2331 respectively for economic and environment indicators models. These statistical values are greater in comparison to the MAE values of 0.1448 for the energy indicators model making it the best.

Table 3.4: Statistical values performance comparison

	Economic Indicators model	Energy indicators model	Environment indicators model
SVR Kernel	PUKF-SVR	Polynomial SVR	PUKF-SVR
CC	0.9975	0.999	0.9952
MAE	0.1934	0.1448	0.2331
RMSE	0.2589	0.1629	0.3686
RAE	5.7%	4.27%	6.87%
RRSE	0.07%	4.30%	0.09%

Similarly, in terms of the RMSE values, the polynomial-SVR kernel in the energy indicators model had a lower value of 0.1629 while the PUKF-SVR kernel for both economic and environment indicators model had a higher value of 0.2589 and 0.3686 respectively. Not only these, but also RAE value and RRSE values for economic and environment indicators models are similarly higher valued as compared to the energy indicators model. Furthermore, the absolute errors deviations values between actual and predicted energy demand is relatively very small for the polynomial-SVR kernel as illustrated in Figure 3.3. It is further as suggested earlier that the polynomial-SVR kernels works well with the energy indicators model than is the PUKF-SVR kernel although it had shown better results with the economic and environment indicators model. These comparisons concludes that the energy indicators model were more accurate for the prediction of energy demand with the use of polynomial-SVR kernel in comparison to the economic and environment indicators models using PUKF-SVR kernel.

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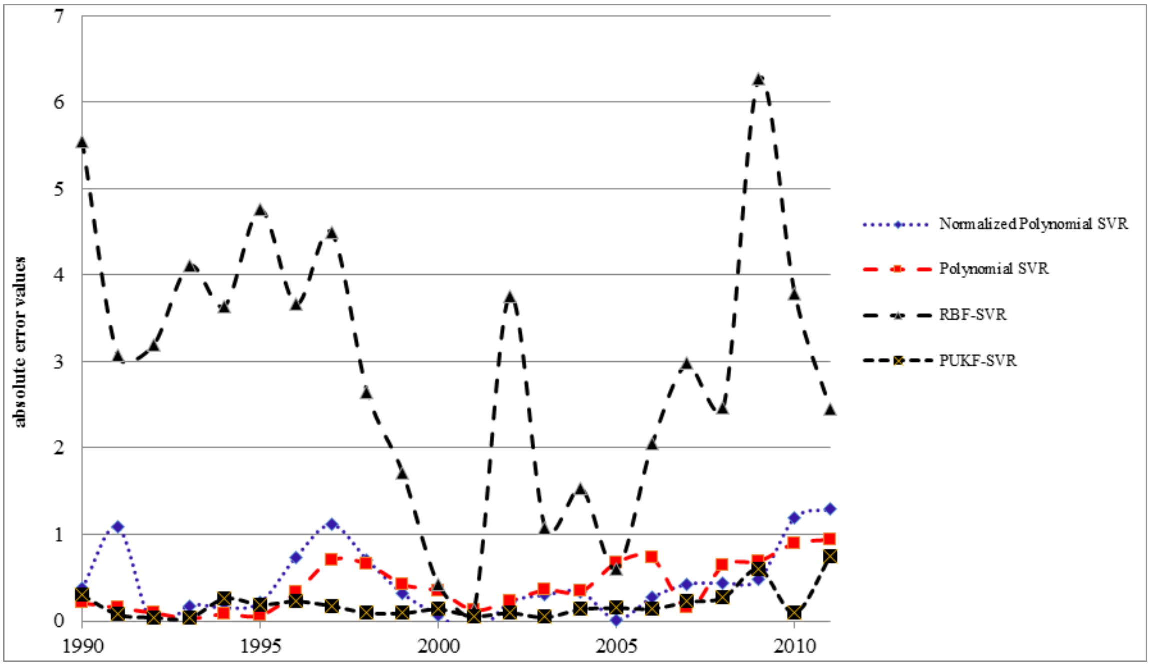


Figure 3.2: Absolute errors comparison between kernels – Economic indicators model

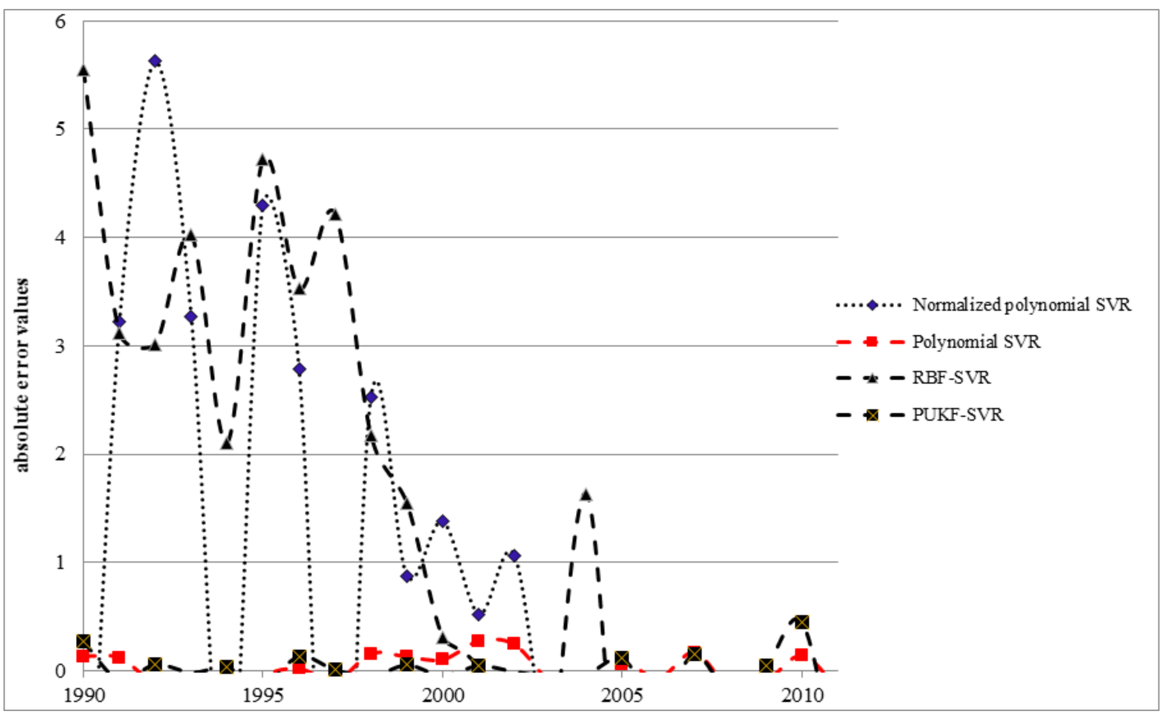


Figure 3.3: Absolute errors comparison between kernels – Energy indicators model

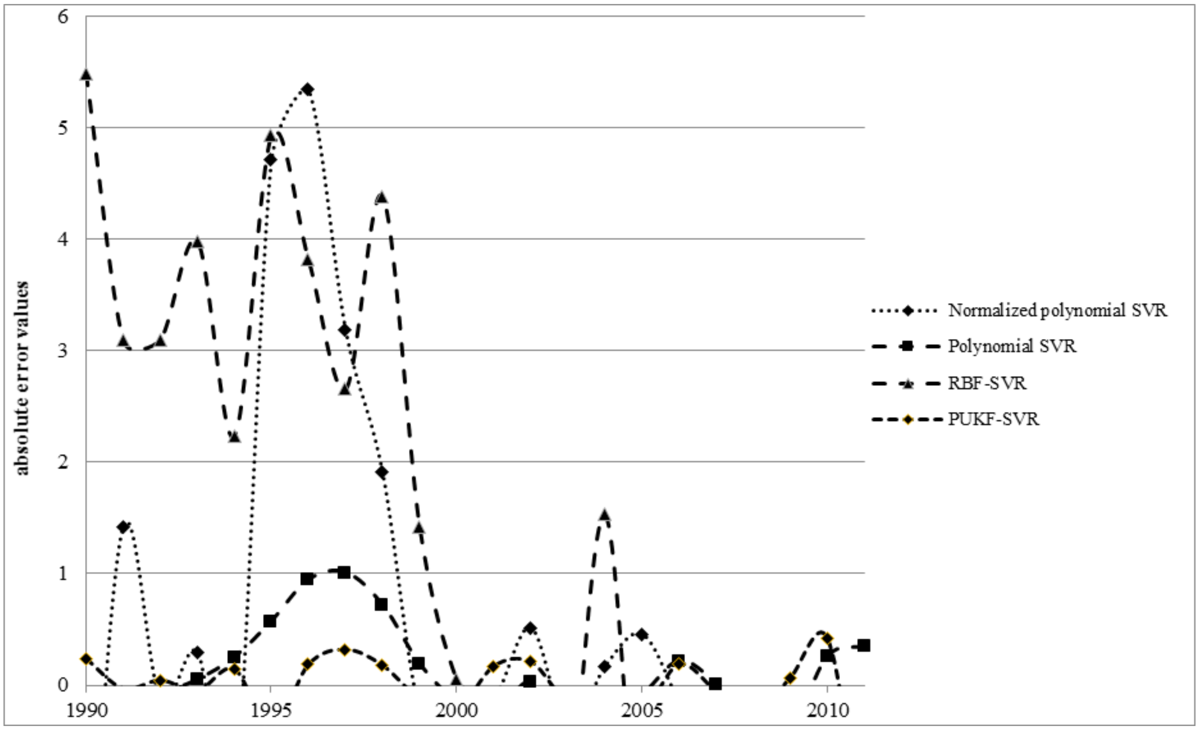


Figure 3.4: Absolute errors comparison between kernels – Environment indicators model

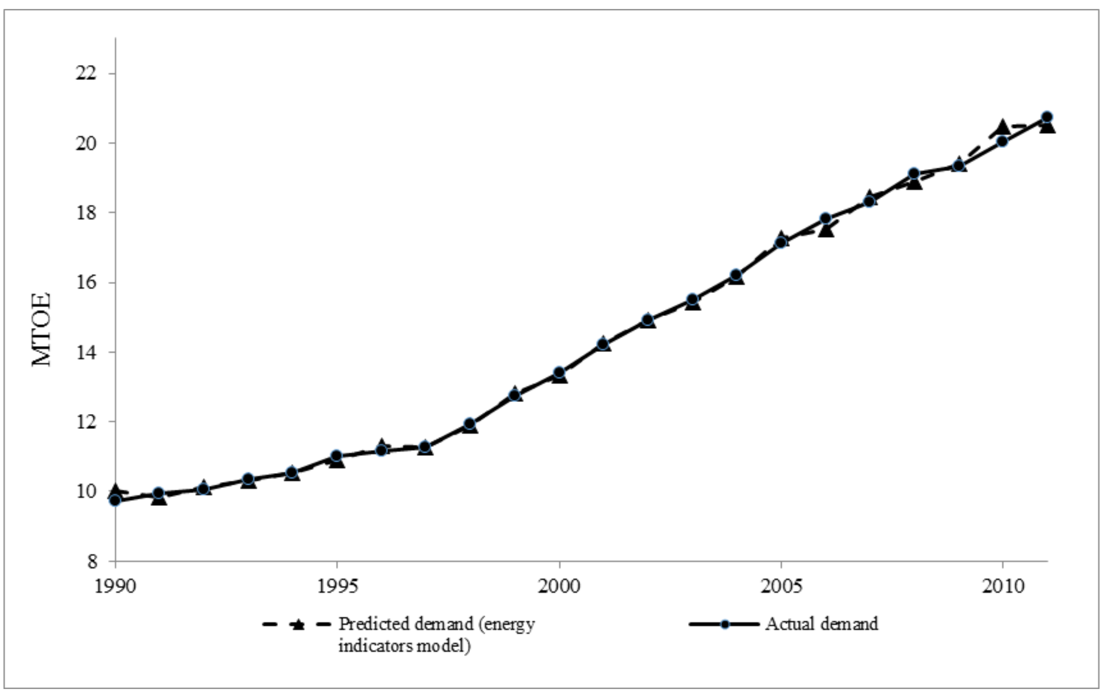


Figure 3.5: Energy demand prediction curve comparison using polynomial-SVR kernel

3.5.3 Energy prediction curve

Figure 3.5 depicts the prediction of the energy demand for the period between 1990 and 2011 using the energy indicators model which emerged as a better predictor with polynomial-SVR kernel. It can be noted that the curve approximates well the energy demand over the period of interest. This curve demonstrate the practicability of the support vector machine for regression (SVR) in the real time energy demand prediction for both short and long term.

3.6 Conclusion

The application of the support vector machine for regression (SVR) with normalized polynomial-SVR, polynomial-SVR, RBF-SVR and PUKF-SVR kernels functions in the analysis of energy demand was discussed in this paper. The economic, energy and environment indicators derived from time series data were used to build the energy models. The statistical performance indices applied to evaluate the estimating ability of these techniques within SVR were correlation coefficient (CC), root mean squared error (RMSE), mean absolute error (MAE), root relative squared error (RRSE) and relative absolute error (RAE). The comparison of the experimental results to the kernel functions reveals the possibility of the use of the SVR for the analysis and prediction of the energy demand in Tanzania. The analysis of the kernels show that the polynomial-SVR kernel function with the energy indicators model provided the transformation, which achieved more accurate prediction values with the SVR. The use of SVR algorithm in estimating future energy demand will assist government in decision making on expected energy demand for the long-term sustainable development of the country. Although SVR has shown good results in the prediction of energy demand, intensive study of its comparison with other learning algorithms is of future interest. The idea is to unveil the best possible algorithm that can be implemented for the analysis and prediction of energy demand with the consideration of accuracy.

CHAPTER FOUR

MODELLING OF FUTURE ENERGY DEMAND FOR TANZANIA[3]

4.1 Abstract

This paper present modelling of long-term energy demand forecast in the main economic sectors of Tanzania. The forecast of energy demand for all economic sectors is analysed by using the Model for Analysis of Energy Demand (MAED) for a study period from 2010-2040. In the study three scenarios namely business as usual (BAU), low economic consumption (LEC) and high economic consumption scenario (HEC) were formulated to simulate possible future long-term energy demand based on socio-economic and technological development with the base year of 2010. Results from all scenarios suggests an increased energy demand in consuming sectors with biomass being a dominant energy form in service and household sectors in a study period. Predicted energy demand is projected to increase at a growth rate of 4.1% and reach 74 MTOE in 2040 under the BAU scenario. The growth rates for LEC and HEC are projected at 3.5% and 5.1% reaching 62 MTOE and 91 MTOE in 2040 respectively. Electricity demand increases at a rate of 8.5% to reach 4236 kTOE in 2040 under BAU scenario while electricity demand under LEC and HEC increases to 3693 kTOE and 5534 kTOE in 2040 respectively. Sectorial predicted demand results under both scenarios determine high demand of biomass for service and household sectors with decreasing demand of biomass in industry sector. Transport sector predicted energy demand pattern suggests a greater increase in demand in passenger transport than freight transport in both scenarios. Final energy demand per capita in both scenarios shows an increased trend with lower growth rate in LEC scenario while there is a decrease in energy intensity throughout the study period.

4.2 Introduction

Energy is essential in achieving economic prosperity and advances in social and overall human development. Energy has evolved to match modern human development and requirements. As

[3] Journal of Energy Technologies and Policy, Vol. 4, Issue No. 7 (2014), pp. 16-31

countries develop and the economy grows there is always an associated increase in energy use (Reister, 1987). Tanzania being among developing countries, its energy demand is expected to increase as its economy and population grows (Tiris, 2005). Energy demand in the country has been shown to be spurred by the population growth and economic activities development that has occurred in the past decades (Odhiambo, 2009). A growth in energy consumption has been shown to increase economic diversity which is measured by a number of economic sectors consuming energy (Templet, 1999).

Global energy status is currently steered by fossil fuels which play a crucial role in the world energy market (Goldemberg, 2006; Shafiee and Topal, 2009). Global rate of energy consumption with addition of volatile energy markets and the production challenges faced by many producers has resulted in worries on energy availability, management, security and environmental concerns (Asif and Muneer, 2007; Hughes and Shupe, 2010). Attention to these concerns is serious due to the uneven distribution of the fossil fuel resources on which most countries currently rely on. The growing competition for energy resources, the need for economic development, energy availability at an affordable price and energy supply challenges are making energy security a key issue all over the world (Costantini et al., 2007; Grubb et al., 2006; Hughes, 2009). Without knowing future energy demand it is difficult to plan for energy supply that will ensure energy security, availability and economic development.

The main objective of this study is to forecast the energy demand of Tanzania. The forecast will focus on simulations of future demand based on social, economic and technological development. The demand forecast is essential to assess and plan for supply through the use of the energy resources for a given set of demands. The study output will present the connection between energy demand and development while facilitating policy and decision makers to plan for sustainable, reliable and affordable energy.

4.2.1 Socio-economic Status

4.2.1.1 Demography

Tanzania had a population of 44.9 million persons in 2012 as compared to 12.3 million persons in 1967 (NBS, 2013). From 2002 to 2012 the population has increased by 30% from 34.4 million to 44.9 million (NBS, 2013). The population growth rate has fallen slightly from an average of 3.3%

in the period of 1967-1978 to 2.8%, 2.9% and 2.7% in the periods of 1978-1988, 1988-2002, and 2002-2012 respectively (NBS, 2012; UN, 2013). Figure 4.1 describes predictions of annual population change for Tanzania in a period from 2010–2100 under high, medium and low variants scenarios (UN, 2013). The trend line equation on annual population change for high variant follows polynomial equation of order 2 given as equation 4.1. Low and medium variant population change are also following similar polynomial trend line equation of order 2. Country's lifestyle shows a constant household size of 4.9 between 2002 and 2012 censuses whereas an average of 4.8 was reported in 2012 census (NBS, 2013).

$$\Delta \mathrm{P} = -0.008\ (\mathrm{FY})^2 - 0.107(\mathrm{FY}) + 3.3462 \qquad (4.1)$$

Where ΔP and FY represents population change and corresponding year.

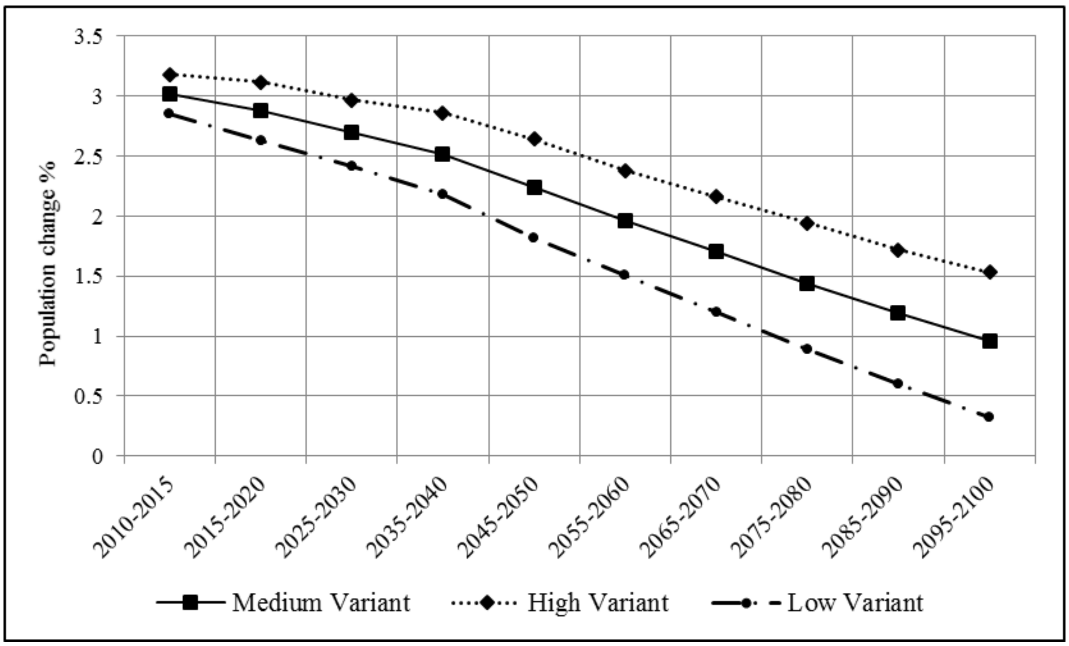


Figure 4.1: Projected population change (2010 – 2100)

4.2.1.2 Economic

Tanzania's gross domestic product (GDP) has been growing steadily since 2000 at a rate of 7% annually. Highest and lowest growth rates of 7.8% and 6% were recorded in 2004 and 2009 respectively (BOT, 2012; NBS, 2012). The GDP per capita at current prices shows an increase trend from US$ 306 in the year 2001 to US$ 608 in 2012 (UN-data, 2014). Figure 4.2 illustrates

GDP growth rate from 2001 to 2012 at 2001 constant prices with projection for 2013 – 2016. GDP growth rates for 2014-2016 are projected figures (NBS, 2012).

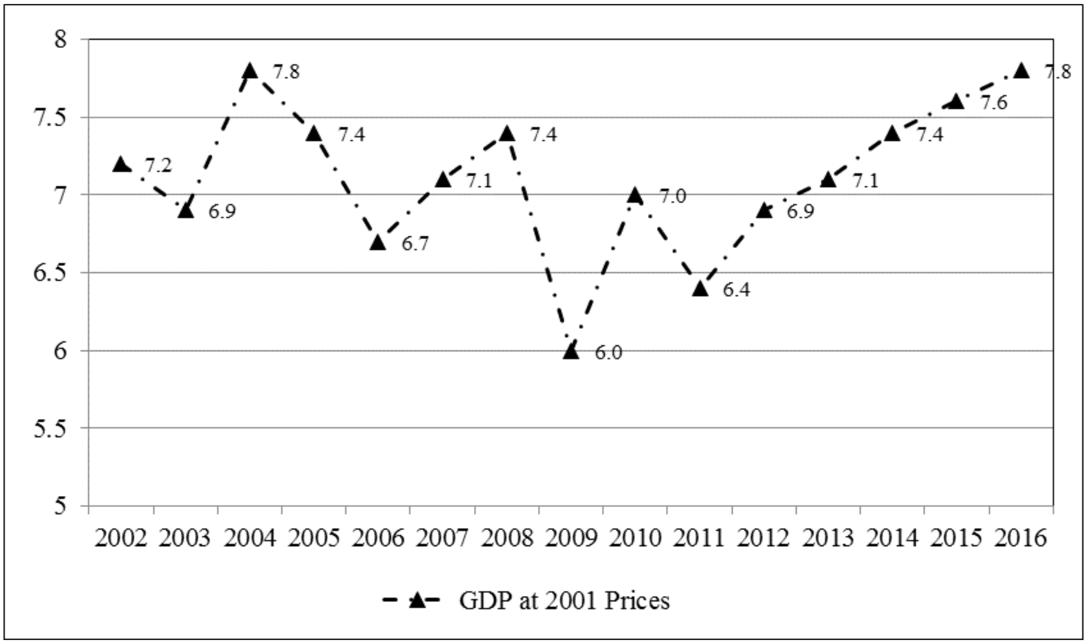


Figure 4.2: GDP at 2001 constant price

4.2.2 Country's Energy Status

4.2.2.1 Primary energy supply

Tanzania has been endowed with numerous energy resources ranging from renewable to non-renewable. The country produces natural gas and coal for domestic consumption mostly in electricity generations and industrial applications and does not produce crude oil. Total primary energy supply of Tanzania is estimated to be more than 22 million tonnes of oil equivalent (MTOE) (Bauner *et al.*, 2012; Wilson, 2010). Primary energy supply is composed of biomass at approximately 90% of the total supply (MEM, 2013c). The rest of primary energy supply is represented by 7– 8% from oil products and 1– 2% from electricity (MEM, 2013b; Mwakapugi *et al.*, 2010). High consumption of biomass is attributed to the low per capita income and limited investment in alternative energy supplies (Monela *et al.*, 1999). The country's dependence on biomass has reached an annual yield of 40 million m^3 while annual sustainable yield is estimated at 24.3 million m^3 (Mwihava, 2010). Biomass in Tanzania is consumed un-sustainably contributing to a deforestation rate which is estimated to be between 130,000 and 500,000 hectares per year

(Lema, 2009; Songela, 2009). Population that relied on biomass in the form of wood fuel for the year 2010 was approximated at 79% while that for charcoal was nearly 14% (Mwihava, 2010).

Tanzania imports all its petroleum based products requirements. Imports of petroleum based products was 1,482 thousand tonnes of oil equivalent (kTOE) representing 7.14% of total primary energy supplies in 2011 which is 66.8% of total fossil fuel consumption and about 23% of the total imports (IRENA, 2014). Transport sector was estimated to consume 40% of all imported energy in the form of motor oils for the year 2010 followed by industry (25%), household (10%) while the balance were accounted by agriculture and commerce sectors (Wilson, 2010). Total energy use per capita in 2011 was equivalent to 0.45 tons of oil equivalent. The energy self sufficiency of Tanzania was estimated at 92% in 2010 (IRENA, 2014). Historical energy production and imports of Tanzania from 1995 to 2011 are shown in Figure 5.3 (IEA, 2013a). The country has a potential of using municipal solid waste (MSW) as renewable energy source as addressed in (Omari *et al.*, 2014a) and Omari *et al.* (2014b).

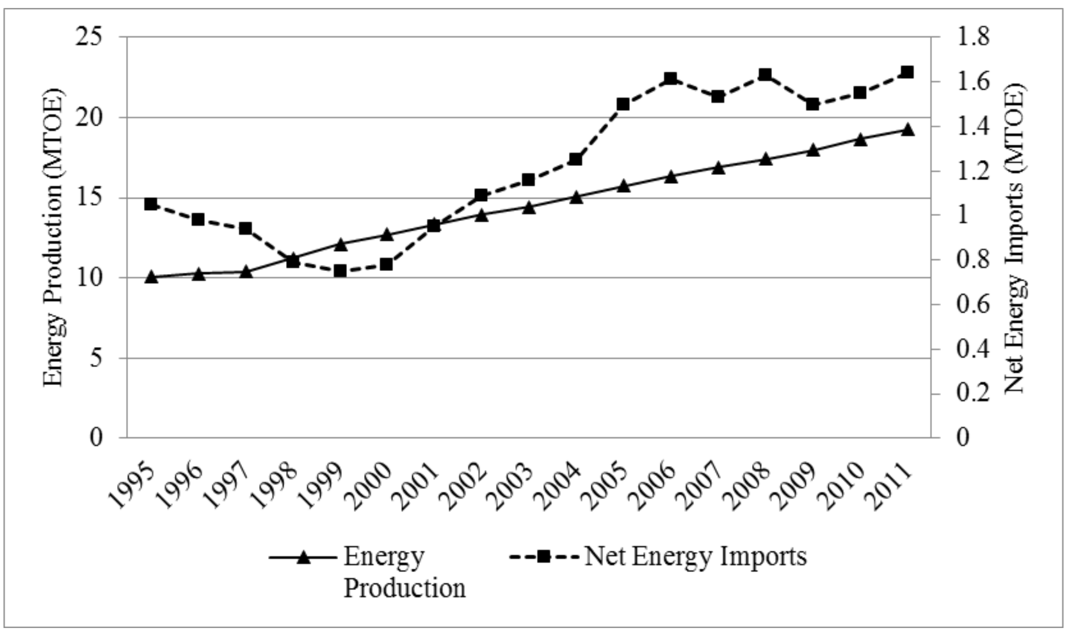


Figure 4.3: Energy production and energy imports

4.2.2.2 Electricity

Electricity generation using various energy sources from 2003 to 2013 is illustrated in Figure 4.4 (MEM, 2013b). The share of hydropower in 2003 was 79% of the total generation whereas the rest were covered by thermal generation using heavy fuel oil (HFO), diesel, JET-A and imports. The share of hydropower decreased to 34% in 2013 followed by natural gas 41% and the rest covered by others thermal generation using HFO, diesel, JET-A and imports (MEM, 2013a). Total installed capacity in 2013 was 1,509.85 MW of which 1,438.24 MW was available on the national grid (MEM, 2013c). Out of the total installed capacity available for the grid, 553 MW is hydropower representing 35%. Capacity utilization shows decreasing utilisation of hydro power at 65%, 48% and 43% in 2011, 2012 and 2013 respectively depending on the availability of water (MEM, 2013a).

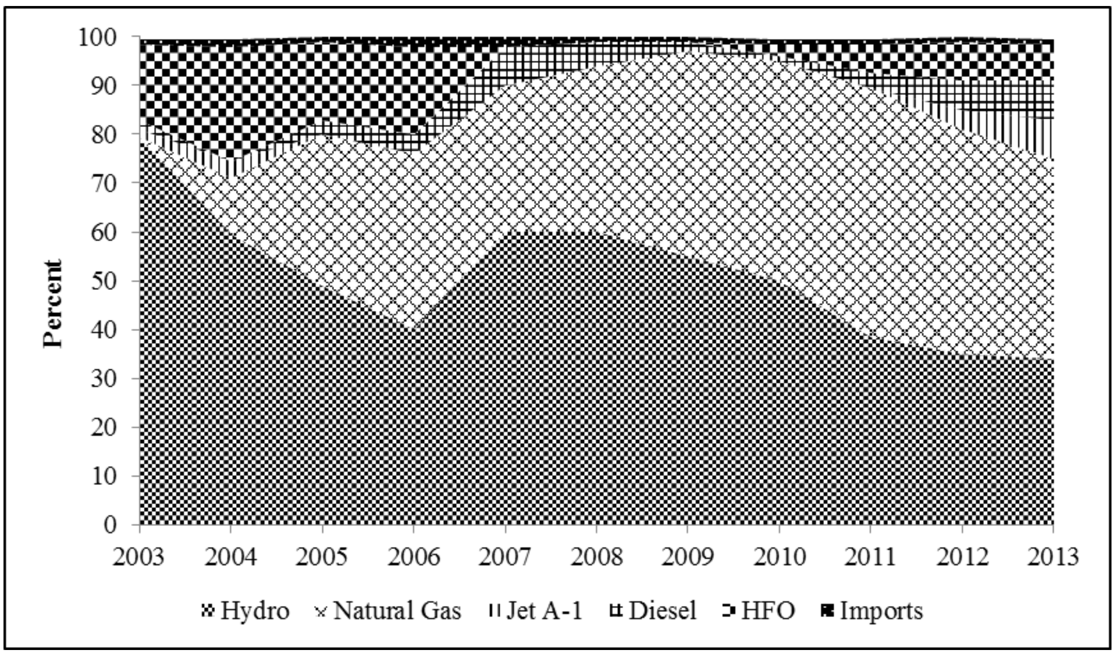


Figure 4.4: Electricity generations by source

4.2.3 Energy models and factors influencing energy demand

The following section reviews in brief, factors influencing energy demand and the modelling scheme that has been used in this study. A bottom-up modelling approach evaluates future energy demand centred on medium to long-term scenarios of socio-economic, technological and demographic developments.

4.2.3.1 Factors influencing energy demand

Population, imports, exports, GDP and sectorial changes in the economic profile of a country characterize paths of energy development (Apergis and Payne, 2009; Csereklyei and Humer, 2012). Population is a major driver of energy demand although its most weighty determinant is the level of economic activity and its structure as measured by the total GDP together with a number of sectors and sub-sectors of the economy (Oyedepo, 2012; Sahu, 2008). Population and economic growth have been discussed in a number of studies as the major factors that influence energy (Bhattacharyya, 2012; O'Keefe et al., 1984).

4.2.3.2 Energy models

A common and accepted classification of energy models is through the use of the distinction between two general groups of energy models namely top-down and bottom-up approach (Fleiter *et al.*, 2011; McFarland et al., 2004). Interactions amongst energy systems and the economy are represented by two modelling paradigms known as top-down and bottom-up (Böhringer and Rutherford, 2008). Top-down and bottom-up terms are shorthand for aggregate and disaggregated models. Bottom-up models are characterized as being built on engineering philosophy while top-down models are characterized to represent the view of economists (Böhringer and Rutherford, 2008; Fleiter et al., 2011). Top-down models examine the broader economy but they don’t feature technological details of energy production or conversion. Additionally bottom-up models are characterized as those using an engineering approach, reflecting technical potential, and being able to use disaggregated data for exploring purposes (Van Beeck, 1999). Bottom-up models are viewed as being made with detailed considerations of technologies which allow modelling the impact of distinct and well-defined technologies on the long-term development of energy consumption (Rivers and Jaccard, 2006). Bottom-up models have the potential to model the effects of technology-oriented policies due to technology explicitness.

MAED is a bottom-up approach model widely used for forecasting medium and long-term energy demands. MAED interrelates energy demand with the population, gross domestic product (GDP), technological development, among many other factors (Hainoun et al., 2006; Nakarmi et al., 2013). MAED, being a bottom-up model is built with detailed considerations of technologies which allow modelling the impact of distinct and well-defined technologies on the long-term development of energy consumption (Rivers and Jaccard, 2006). MAED relates systematically specific energy demands to the corresponding socio-economic and technological factors that affect the demand (IAEA, 2009, 2006).

Future energy demands are disaggregated into end-use categories as a function of several determining factors including population growth, transportation modes, and national priorities for the development of certain industries or economic sectors, energy forms, among others. Key consumption sectors that are considered in MAED comprises of industry, household, transport, and service. The industry is further divided into sub-sectors that comprise of agriculture, construction, mining (ACM) and manufacturing while the transport sector is sub-divided into passenger and freight transport. MAED final consumption fuel types and energy forms comprise of fossil fuel for thermal use (mainly industry), motor fuel and electricity (Hainoun et al., 2006). MAED's important demographic and economic data are labour force, rural and urban populations, potential labour force, and sectorial distribution of GDP (Ediger and Tatlıdil, 2002).

Reconstruction of the base year energy consumption pattern is the process that requires compiling and reconciling necessary data to help calibrate the model to the specific situation of the country. The second stage is development of future scenarios that suits the country's possible future energy demands. The MAED framework of analysis is given by breaking down of the economy by sector through scenario assumptions up to final energy demand. The energy demand is calculated by MAED as a function of a scenario of possible development (IAEA, 2006).

The MAED generic equation, in which energy demand in future year is determined, is given in Equation 5.2.

$$(\mathrm{ED})_{\mathrm{FY}} = \left(\frac{ED}{DP}\right)_{\mathrm{BY}} \times (\mathrm{CH})_{\mathrm{FY}} \times (\mathrm{DP})_{\mathrm{FY}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (4.2)$$

Where:

FY - Represent "Future Year"

BY - Represent "Base Year"

$(\mathrm{ED})_{\mathrm{FY}}$ - Represents energy demand in future year;

$\left(\frac{ED}{DP}\right)_{\mathrm{BY}}$ - Specific energy demand per unit of driving parameter in base year;

$(\mathrm{CH})_{\mathrm{FY}}$ - Coefficient to reflect evolution of specific energy demand per unit of driving parameter in future year;

$(\mathrm{DP})_{\mathrm{FY}}$ - Specific energy demand per unit of driving parameter in future year

4.3 Methodology

The following sections detail the methodology that was applied in the study. The study period considered in this analysis is from 2010-2040.

4.3.1 Division of the main economic sectors

The main Tanzanian economic consumption sectors disaggregated were industry, service, household and transport sectors. The energy consumption in the industrial sector was further subdivided into consumption by agriculture, construction and mining (ACM) and manufacturing while that for transport was subdivided into freight and passenger transport.

4.3.2 Elements influencing energy demand

The following are important factors influencing energy demand that were used in the study. These factors are GDP growth rates and their structural changes, population growth and its distribution in the country (urban and rural) changes in life style, population mobility growth, passenger and freight transportation, and market penetration of competing energy forms.

4.3.3 Modelling Scenarios

Three different scenarios were proposed to represent possible future energy demand for Tanzania. In the analysis of the long-term energy demand, three possible future development scenarios were proposed as Business as usual scenario (BAU), low economy consumption scenario (LEC) and high economic growth scenario (HEC).

4.3.3.1 Business as usual scenario (BAU)

Business as usual scenario (BAU) being the reference economic growth scenario was developed to assume normal economic growth rate and expected development of other factors influencing energy consumption. Tanzanian economic structure has experienced a significant changes during the last two decades. The country historical and projected GDP growth rates from 2002 to 2016 are shown in Figure 4.2 in which the average growth is approximately 7% over the last 10 years.

BAU scenario presumed that GDP average growth rate trend of 7% will continue in the future until the end of study period in 2040. The population growth rate characterizes the most significant factor. BAU scenario presumed population growth rate, would decline moderately from base year value to 2.52% at the end of study period according to the official estimations for Tanzania under medium variant prospects of United Nations (UN, 2013). The additional factors describing the future population distribution development show moderate change to a more urbanization scene resulting from the fact that villages around the cities will develop to form towns and small cities. With that regards, BAU scenario assumed the current moderate trends will continue and lead to an urbanization rate of 37% towards the end of study period as compared to 27% in the base year. The increase of the share in urbanizations, signifies an increase of population in cities and towns reducing the rural population share. Furthermore, the expected life styles improvement will be moderate leading to decrease in children per family, the number of persons per household and other socio-economic parameters.

4.3.3.2 Low Economic Consumption scenario (LEC)

The slow economic growth scenario named as low economy consumption scenario (LEC) was developed to assume a slower economic growth rate. LEC scenario defines a lower bound for economic development, which could be expected in the number of assumptions. These include high population growth rate (high variant as per Figure 4.1) which aggravates the difficult economic situation (URT, 1992) associated with considerable increase in current level of urbanization. Others are economic situation and development related to unstable socio-economic and political environments, low level of internal and foreign investment, low GDP growth rate for the entire study period and decrease of growth in income per capita. On international environment the scenario assumed un-favourable investment backgrounds due to un-stable political situation in the region, and unexpected climatic, political and economic crises. In life style the scenario assumed no improvement in household size whereas car per family ownership and public transport follows past trends. The scenario does not favour the growth on the use of renewable energies.

The slow economic scenario in LEC was represented by a GDP growth rate of 5% which has never been experienced by Tanzanian economy for over a decade ago as shown in Figure 4.2. The lowest GDP growth rate so far reached was 6% in 2009. Therefore, the selection of 5% GDP growth rate is a good representative of slower economic growth of Tanzania as far as historical GDP growth rate is concerned. LEC scenario presumed population growth rate would decline slowly from base year value to 2.86% at the end of study period according to the official estimations for Tanzania under high variant prospects of United Nations (UN, 2013). The added factors describing the future population distribution development in LEC scenario features high shift towards more urbanization scene resulting from the slow economic situation. In LEC scenario, it is presumed that availability and quality of services at rural level such as hospital, schools and other social services will be limited causing migrations to towns and cities. The migration is presumed to cause a decreasing share of rural population and increases of urban population share. With that regards, LEC scenario assumed the current moderate trends will shift towards high urbanisation rate of 40% towards the end of study period as compared to 27% in the base year. Furthermore, the expected life styles improvement will be slow leading to slow decrease in children per family, the number of persons per household and other socio-economic parameters.

4.3.3.3 High Economic Consumption scenario (HEC)

The high economic growth scenario (HEC) is developed to assume high economic growth rate and expected development of other factors influencing energy consumption. HEC scenario is presumed from an optimistic perspective based on the assumption that the country’s economy will grow at a higher constant GDP growth rate of 8 % for the entire study period. As shown in Figure 4.2, the GDP growth rate of Tanzania has never crossed an 8% growth rate line. The selection of this value is based on that fact and it is assumed as a good representative of higher economic growth rate for the country. The growth in HEC scenario is linked to decrease in current population growth rate from base year value to 2.18% in 2040, no considerable increase in current level of urbanization and negligible net migration value as in BAU scenario. Economic situation and development under HEC is presumed to be stable with increase in service and industry sectors shares, exploration of more natural gas, minerals and new discoveries in oil resources resulting in positive growth in income per capita.

Population growth rate in HEC follows low variant trend to favours economic development. Life style in HEC scenario is a result of low variant growth rate that favours improvements in household size. HEC scenario is presumed to have increases in car per family ownership, cooking and thermal applications in household shifting to service sector and more population travel within the country and abroad. Furthermore, HEC assumes technological improvement in the use of non-commercial energy sources with improved efficiency leading to mechanisation/automation. Transportation policies in HEC scenario, favours upgrading of existing and construction of modern roads with the introduction of railroads in intracity and intercity transport. HEC scenario on international environment favours investment due to stable political situation in the region.

4.3.4 Base Year Reconstruction

The selection of a base year for the study was from among the recent past years to represent the economic and energy background of the country. The year 2010 was chosen as the base year to present the economic and energy background of Tanzania. The main reason for the choice is the stable energy consumption, which represents the best pattern for the country. Furthermore the year 2010 is well-matched with Tanzanian Vision 2025 which is to be implemented by a series of three five year development plans (FYD) (URT, 1999, 2012). The first series of FYD aims at unleashing the growth potential 2011/12 - 2015/16; the second one nurturing an industrial economy 2016/17 – 2020/21 while the third series aims at realizing competitiveness–export led growth 2021/22 – 2025/26. In 2010 shares of GDP at 2001 prices for the service sector was 48.8% of which the transport sector constituted 5.1% of the service sector. Agriculture and fishing constituted 24.1% whereas industry and construction was 21.6% (NBS, 2011). The total population for 2010 was estimated at 43.2 million persons with an average household size of 4.8 and the share of urban population being 27%.

4.4 Results and discussions

Modelling results for three scenarios formulated to represent possible developments trends in energy demand of Tanzania based on social, economic and technological development are presented in the following sub-sections.

4.5.1 Final energy demand forecast

The projected final energy demand for the three scenarios from 2010 – 2040 are presented in Figure 4.5. The average annual growth rate will amount to 4.08%, 3.45% and 5.07% for BAU, LEC and HEC respectively. The final energy demand will grow from 22 MTOE in 2010 to 74 MTOE in 2040 for BAU scenario. A similar trend is observed for LEC and HEC scenarios in which energy demand will increase to 62 MTOE and 91 MTOE in the year 2040 respectively. The growth in final energy demand for all three scenarios follows an increasing exponential trend due to exponential growth of population as is the case of global energy demand (Demirbas et al., 2004). The trend line equation representing exponential growth for BAU is given as equation 4.3 while the corresponding trend line equations for LEC and HEC are given as equations 4.4 and 4.5 respectively.

$$\mathrm{ED} = 17.719\mathrm{e}^{0.2\mathrm{FY}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.3)$$

$$\mathrm{ED} = 18.25\mathrm{e}^{0.17\mathrm{FY}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.4)$$

$$\mathrm{ED} = 17.127\mathrm{e}^{0.23\mathrm{FY}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.5)$$

Where ED and FY denote energy demand and future year forecast respectively

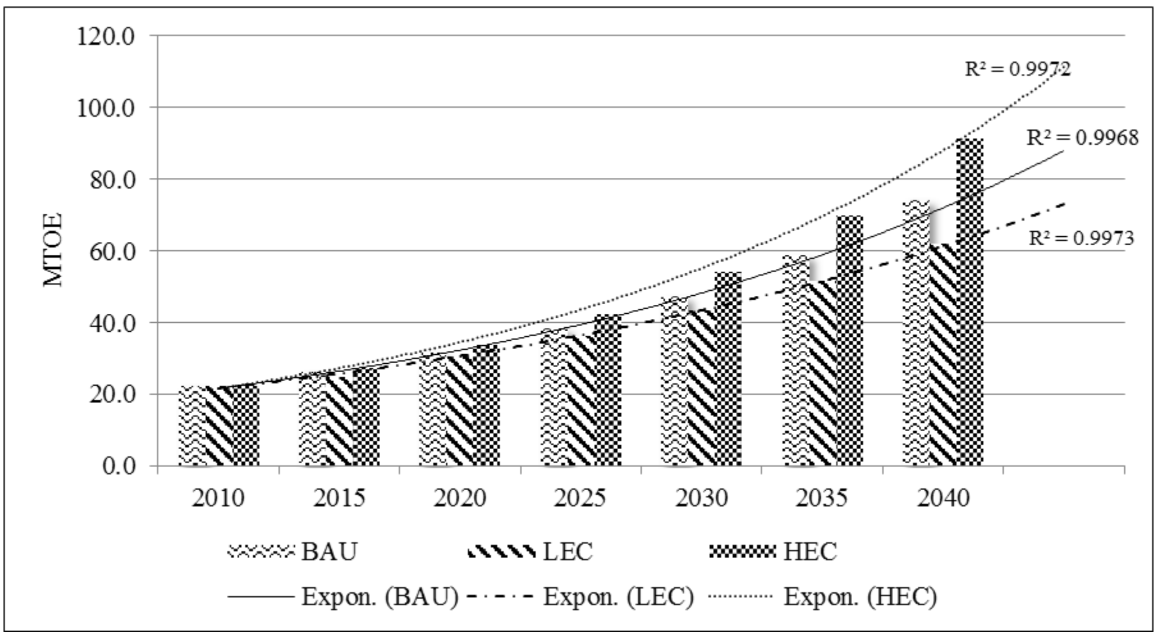


Figure 4.5: Final energy demand forecast 2010-2040

The energy balances for both scenarios has been dominated by biomass followed by imported energy (fossil and motor fuels) and electricity. Biomass dominates both scenarios by having an average share of 76.5 % of total final energy demand for BAU, LEC and HEC scenarios in 2040. Moreover, results indicate that imported energy has an average share of 17% in 2040 for both scenarios. Electricity will command a share of 5.7%, 5.9% and 6.1 % of final energy demand in BAU, LEC and HEC scenarios respectively in 2040.

4.5.2 Projected demand by energy form

Table 4.1 depicts projected demand by energy form for the BAU, LEC and HEC scenarios. In comparing the three scenarios, the LEC scenario shows less projected energy demand growth rate as compared to BAU and HEC scenarios. The final energy demand in LEC scenario is less by 12 MTOE as compared to BAU scenario whereas HEC scenario is higher by 17 MTOE both in 2040. The annual growth rate of biomass demand is projected to amount to 3.44%, 2.79% and 4.15% for BAU, LEC and HEC scenario respectively. Electricity demand annual growth rate is projected to increase at a rate of 8.51%, 8.01% and 9.48% for BAU, LEC and HEC scenario respectively. Fossil fuel for thermal applications projected demand is expected to increase at 9.97% for BAU scenario, 8.01% for LEC scenario and 10.39% for HEC scenario.

Motor fuels demand projected growth rate is above 6% in all scenarios as depicted in Table 4.1 reaching a maximum of 6.8 MTOE in HEC scenario while that of LEC and BAU scenarios are 5.1 and 6.2 MTOE respectively. Solar energy demand annual growth rate is projected to increase at a rate of 11.3%, 9.9% and 12.1% for BAU, LEC and HEC scenario respectively. The unsatisfactory growth rate in LEC scenario is attributed to poor performance in the economy that hinders its ability to promote renewable energy.

Table 4.1: Energy demand by energy form

Energy Form	GROWTH RATE (%)			BASE YEAR (MTOE)	2040 (MTOE)		
	BAU	LEC	HEC	BASE YEAR	BAU	LEC	HEC
Biomass	3.4	2.8	4.1	20.7	57.1	47.5	70.4
Electricity	8.5	8.0	9.5	0.4	4.2	3.7	5.5
Fossil fuels	10.0	9.0	10.9	0.4	6.8	5.1	8.6
Motor fuels	6.4	6.5	7.1	1.0	6.2	5.7	6.8
Solar	11.3	9.9	12.1	0.000	0.006	0.004	0.008

4.5.3 Energy consumption by sectors

The results of final energy demand by sector are illustrated in Figure 4.6, 4.7 and 4.8 for BAU, LEC and HEC scenarios respectively. The results of the projected sectorial energy demand show the service sector commanding an average share of 41% of the final energy demand while household; industry and transport sectors account for 31%, 21% and 7% respectively in all scenarios. The service sector will have a total final energy demand of 31.9 MTOE in 2040 for the BAU scenario whereas the LEC and HEC will have 20.9 MTOE and 42 MTOE respectively. The transport sector depicts higher final energy demand in passenger transport as compared to freight transport in all scenarios. Final energy demand in the transport sector in BAU scenarios for 2040 will be 4.64 MTOE for passenger transport as compared to 0.49 MTOE for freight transport. In the industry sector manufacturing is the leading sub-sector in consumption of final energy demand as compared to agriculture, construction and mining (ACM) combined together. The same trend is observed for LEC and HEC, which depicts higher consumption in manufacturing as compared to ACM. The final energy demand for the three scenarios concludes that the service sector would have the highest shares in the projected final energy demand followed by the household sector for BAU and HEC while the highest share holder for LEC would be the household sector. This is explained by slow economic growth that does not favour growth in the service sector and higher population growth.

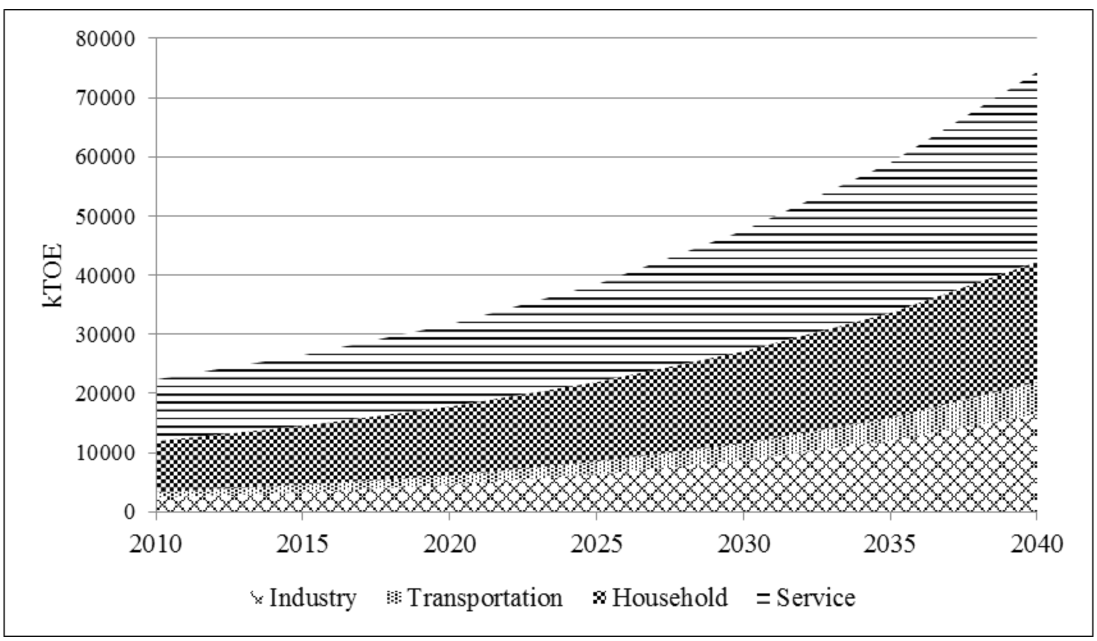


Figure 4.6: Final energy demand by sector (BAU)

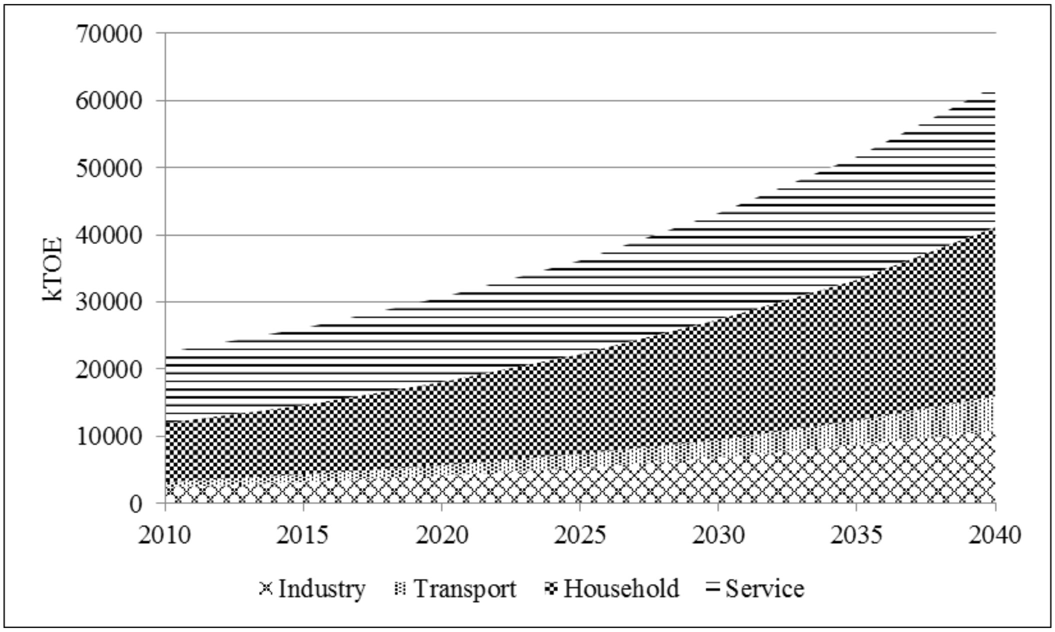


Figure 4.7: Final energy demand by sector (LEC)

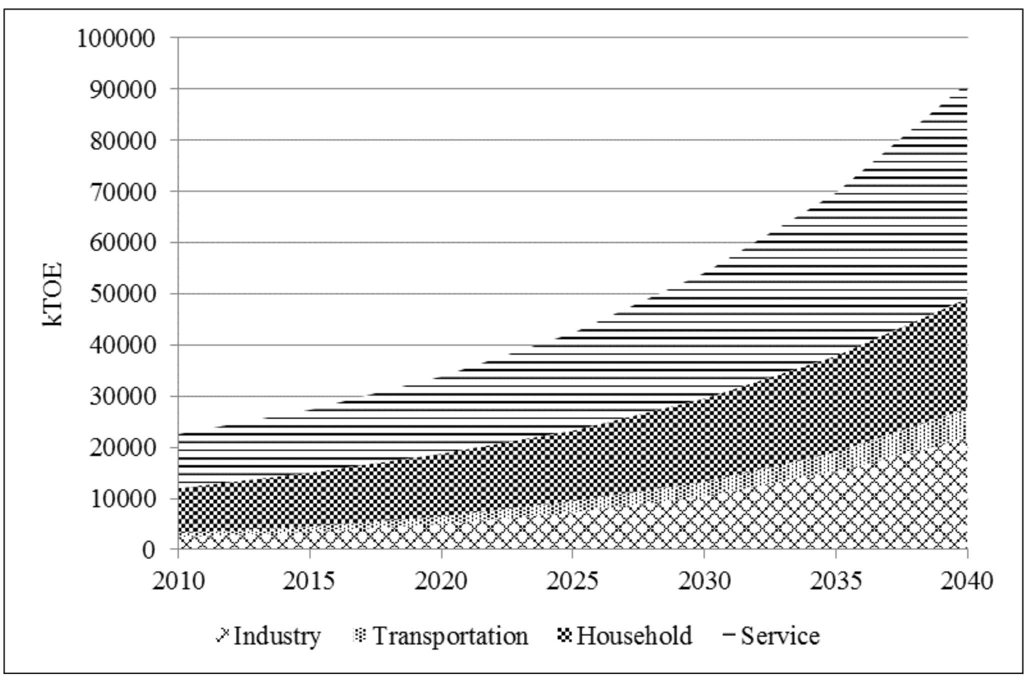


Figure 4.8: Final energy demand by sector (HEC)

4.5.4 Sectorial biomass consumption

Sectorial biomass demand projections for the BAU, LEC and HEC scenarios are illustrated in Table 4.2. The annual growth rate of biomass for BAU, LEC and HEC are projected to be 3.4%, 2.7 % and 4.1 % respectively. The highest consumer of biomass is the service sector followed by household and industry sectors respectively. Service and household sectors in the BAU scenario are projected to demand 26 MTOE and 17.6 MTOE respectively in 2040. Service sector demand for biomass in the HEC scenario is higher by 8.3 MTOE as compared to BAU. In the industry sector, biomass projected demand is increasing at a higher rate in the manufacturing sub-sector as related to agriculture, construction and mining (ACM). Manufacturing sub-sector biomass demand is projected to increase annually at an average of 6.5% as compared to 4.7% of ACM. The highest growth rate in biomass demand is observed in the industry sector at an average value of 6% followed by the service sector at 3% and household 2.7%. In the LEC scenario the population growth rate has been presumed to be higher as compared to other scenarios resulting into high biomass demand.

Table 4.2: Sectorial biomass consumption

Energy Form	GROWTH RATE (%)			BASE YEAR (MTOE)	2040 (MTOE)		
	BAU	LEC	HEC	BASE YEAR	BAU	LEC	HEC
Industry	6.1	4.6	7.1	2.1	12.4	8.1	16.4
- Manuf.	6.7	5.2	7.7	1.3	8.9	5.8	11.8
- ACM	4.9	3.4	5.9	0.8	3.5	2.3	4.6
Household	2.6	3.2	2.7	8.4	18.1	22.0	18.236
Service	3.2	1.8	4.2	10.204	26.6	17.4	35.8

4.5.5 Sectorial electricity demand

The electricity demand under BAU, LEC and HEC scenarios are projected to increase as depicted in Figure 4.9. Electricity demand for the BAU scenario will increase to 4,236.4 kTOE in 2040 which is equivalent to an average annual increase of 8.5 % against 365.7 kTOE in the base year. LEC and HEC scenarios will observe an increase in electricity demand of 3,693 kTOE and 5,535 kTOE respectively in 2040, which is equivalent to an increase of 8.0% and 9.5% from base year value. As a country's population grows and its economy expands, electricity demand multiplies.

Projected electricity demand growth follows an exponential trend with the trend line equation representing the growth for the BAU scenario given as equation 4.6 whereas the corresponding trend lines for LEC and HEC scenarios are given by equations 4.7 and 4.8 respectively.

$$\mathrm{EED} = 250.44\mathrm{e}^{0.407\mathrm{FY}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4.6)$$

$$\mathrm{EED} = 259.6\mathrm{e}^{0.384\mathrm{FY}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4.7)$$

$$\mathrm{EED} = 239.84\mathrm{e}^{0.451\mathrm{FY}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4.8)$$

Where EED and FY denote electricity demand and future year forecast respectively

The peak growth rate in electricity demand is observed in the industry sector. The industry sector will command 39.7% share of electricity demand in the period 2035-2040 followed closely by service and household sectors at 35.6 % and 24.7 % respectively in BAU scenario. This is attributed to presumed industrial development in 2040 as compared to the period prior to 2025. The trend before 2025 shows the service sector as the highest consumer of electricity. Similar trends are observed for the LEC and HEC scenarios with different magnitude in the consumption. Table 4.3 depicts the comparison in electricity demand growth for the BAU, LEC and HEC scenarios. Sectorial consumption of electricity shows the growth rate of electricity demand for industry to be 9.3 %, 7.8 % and 10.3 % for BAU, LEC and HEC scenarios. Average growth rate for households is 7.6 %, 9 % and 8.5 % respectively for BAU, LEC and HEC scenarios. Household higher electricity demand in LEC scenario as compared to BAU and HEC is due to higher population growth rate as presumed in the scenario.

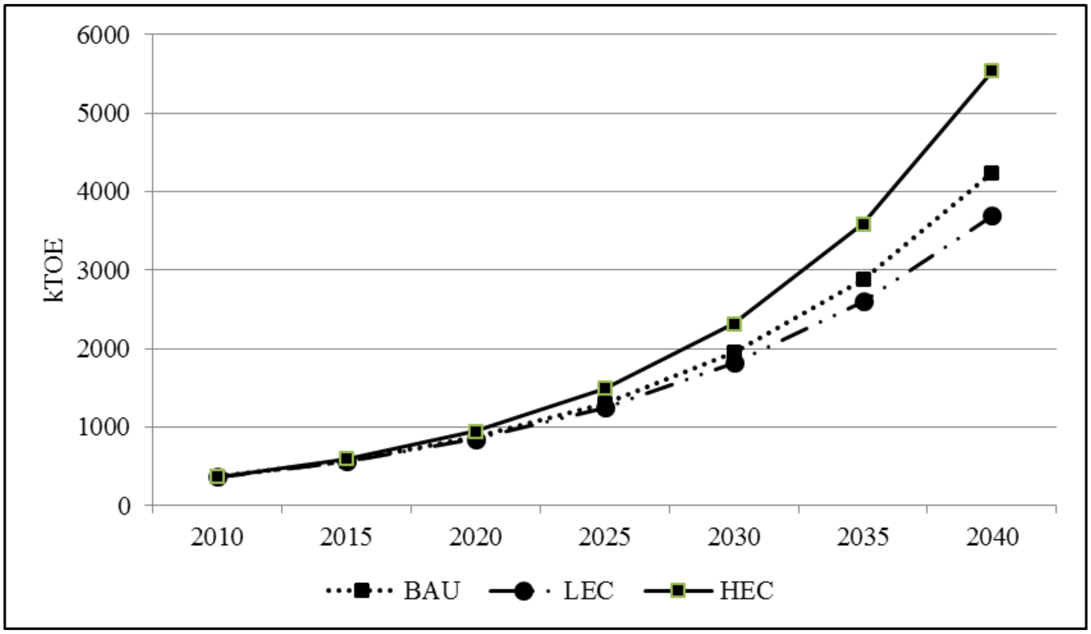


Figure 4.9: Projected electricity demand

Table 4.3: Sectorial projected electricity demand

CONSUMING SECTOR	GROWTH RATE (%)			BASE YEAR (kTOE)	2040 (kTOE)		
	BAU	LEC	HEC	BASE YEAR	BAU	LEC	HEC
Industry	9.3	7.8	10.3	116.7	1681.7	1100.9	2223.1
- Manuf.	10.1	8.6	11.1	75.3	1350.1	883.8	1784.8
- ACM	7.2	5.7	8.2	41.4	331.6	217.1	438.3
Household	7.6	9.0	8.5	117.5	1046.8	1570.2	1347.8
Service	8.5	7.1	9.4	131.6	1507.8	1022.3	1963.4

4.5.6 Fossil and motor fuel consumption by sector

Fossil fuel consumption projected trends into 2040 with the exclusion of aviation and marine bunkers is illustrated in Figure 4.10. Fossil fuel demand for thermal applications is observed to increase exponentially in both scenarios with the projected demand in 2040 amounting to 6,754 kTOE. The share of the service sector in fossil fuel consumption is 55.9% followed by industry at 25 % and households at 19 % in 2040 for BAU scenario. Figure 4.11 depicts the projected shares in fossil fuel demand by consuming sectors for the BAU scenario. There is an observed increase in demand for fossil fuel by the service sector while the households and industry share decreases. The trend is a result of the presumed economy in the BAU scenario that is mainly service oriented. An average of 21.4 %, 30.4 % and 48 % will be commanded by industry, household and service sectors respectively for the LEC scenario. However the share for HEC will be 26%, 15.7 % and 58.2 % for industry, household and service sectors respectively. The annual growth rate of fossil fuel for each scenario is projected at 9.8 % for BAU scenario, 9 % for LEC scenario and 10.9 % for HEC scenario.

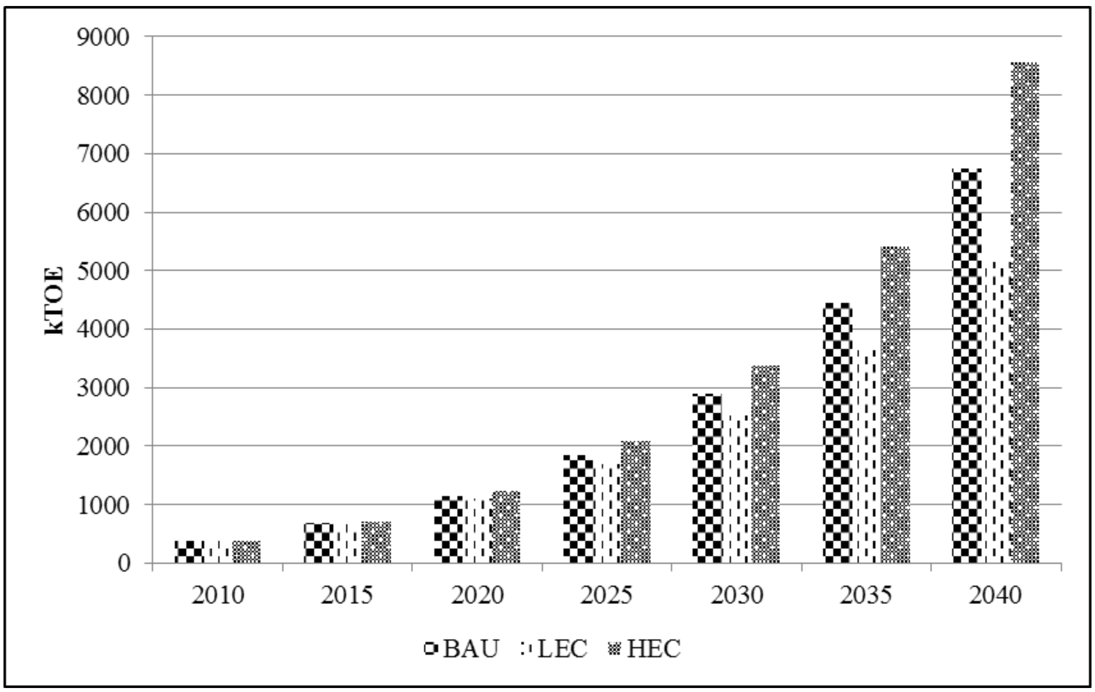


Figure 4.10: Projected fossil fuel consumptions

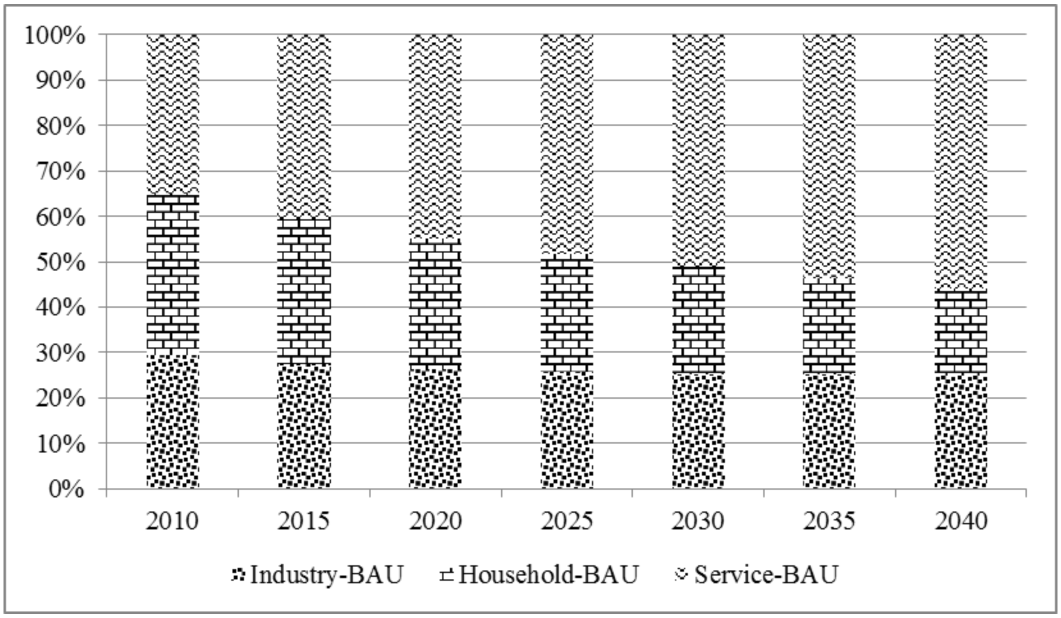


Figure 4.11: Projected fossil fuel consumptions - BAU

Motor fuel predicted demand in all scenarios is illustrated in Figure 4.12. BAU, LEC and HEC are projected to consume 6754 kTOE, 5146.7 kTOE and 8570.9 kTOE respectively in 2040 compared to base year demand of 956.2 kTOE. The projected demand is equivalent to an annual growth rate of 6.4%, 6.5% and 7.1% for BAU, LEC and HEC respectively. Motor fuel growth rate in the LEC scenario is higher as compared to the BAU scenario due to the high population growth presumed in the scenario resulting in the higher demand in passenger transport. Motor fuel shares for the base year were transport 87%, industry 11% and service 1.8%. The distribution of shares in 2040 for the projected motor fuel demand show transport to command a higher share of 85.6% followed by industry at 12.7% and service at 1.7% respectively for the BAU scenario. For the LEC scenario the shares are predicted to be distributed at 89.8% for transport followed by 9% and 1.2% for industry and service sectors respectively. A similar trend is also observed for the HEC scenario in which the transport sector will command a higher share of 82.6% followed by industry at 15% and service at 2.1%. The share of transport in the HEC scenario is much lower as compared to LEC and BAU scenarios due to low variant population growth and increased activities in industry and service sectors.

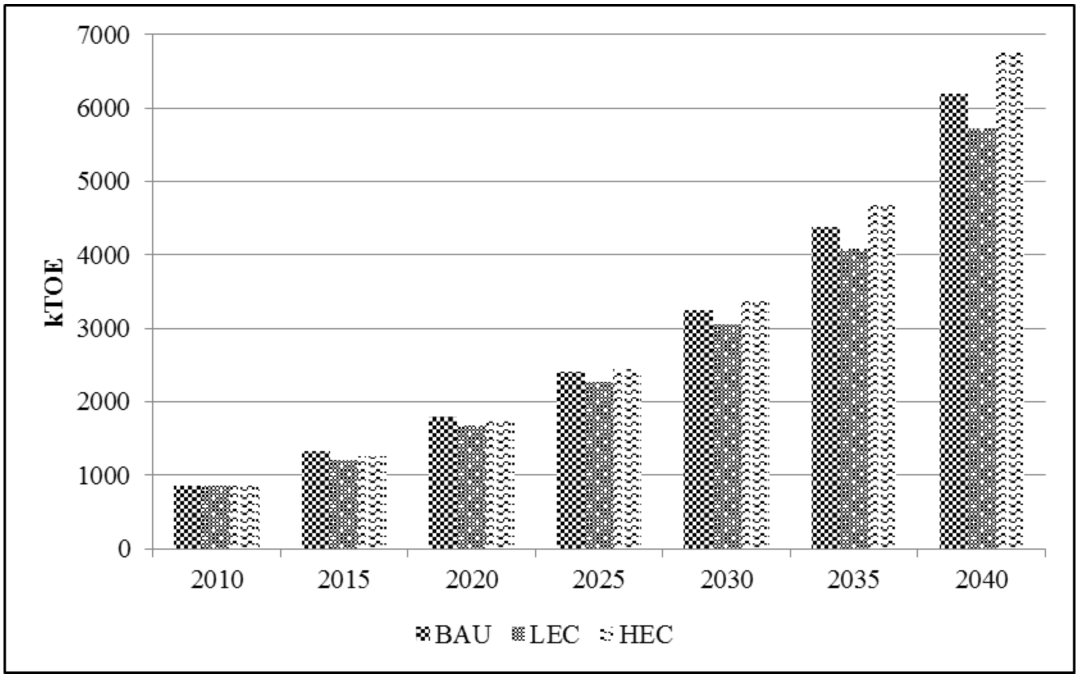


Figure 4.12: Projected motor fuel consumptions

Table 4.4 represents fossil and motor fuel demand for sectors and sub-sector growth rates in scenarios. It is predicted there will be an average fossil fuel growth rate of 9.2%, 11.5% and 8.1% for industry, the service sector and households respectively. There is a higher growth rate in fossil fuel demand in the LEC scenario as compared to the BAU and HEC scenarios due to presumed high variant population growth rate in the scenario resulting in higher demand. The predicted motor fuel demand growth rate averages at 7.1%, 6.6% and 6.5% for industry, transport and service sectors respectively. Higher growth rate in motor fuel is observed in the service sector followed by industry and household sectors for BAU, LEC and HEC scenarios respectively.

Table 4.4: Fossil and motor fuel consumption growth rate (%)

Consuming Sectors	FOSSIL FUEL				MOTOR FUEL			
	BASE YEAR (kTOE)	BAU Growth Rate (%)	LEC Growth Rate (%)	HEC Growth Rate (%)	BASE YEAR (kTOE)	BAU Growth Rate (%)	LEC Growth Rate (%)	HEC Growth Rate (%)
Industry	114.6	9.4	7.8	10.4	94.8	7.3	5.8	8.3
- Manufacturing	58.0	9.8	8.2	10.8	18.8	8.9	7.4	9.9
- ACM	56.6	8.9	7.4	10.0	76.0	6.8	5.3	7.8
Transport	-	-	-	-	846.2	6.3	6.6	6.9
-Freight	-	-	-	-	107.7	6.7	5.2	7.7
-Passengers	-	-	-	-	738.5	6.2	6.8	6.8
Household	139.3	7.7	8.6	8.0	-	-	-	-
Service	136.3	11.7	10.1	12.8	15.1	6.7	5.2	7.7

4.5.7 Final energy demand per capita

Modelling results depicts an increasing trend in energy demand per capita in all three scenarios. An energy demand per capita of 12.2 MWh for BAU scenario will be realized in 2040 against a base year value of 8.2 MWh. Contrariwise energy demand per capita of 9.3 and 15.9 MWh will be realized under LEC and HEC scenarios in 2040 against 8.2 MWh in the base year. Annual growth rate of energy demand per capita of 1.3%, 0.38% and 2.18% is observed for BAU, LEC and HEC scenarios respectively. Development of final energy demand per capita comparisons for BAU, LEC and HEC scenarios is shown in Figure 4.13.

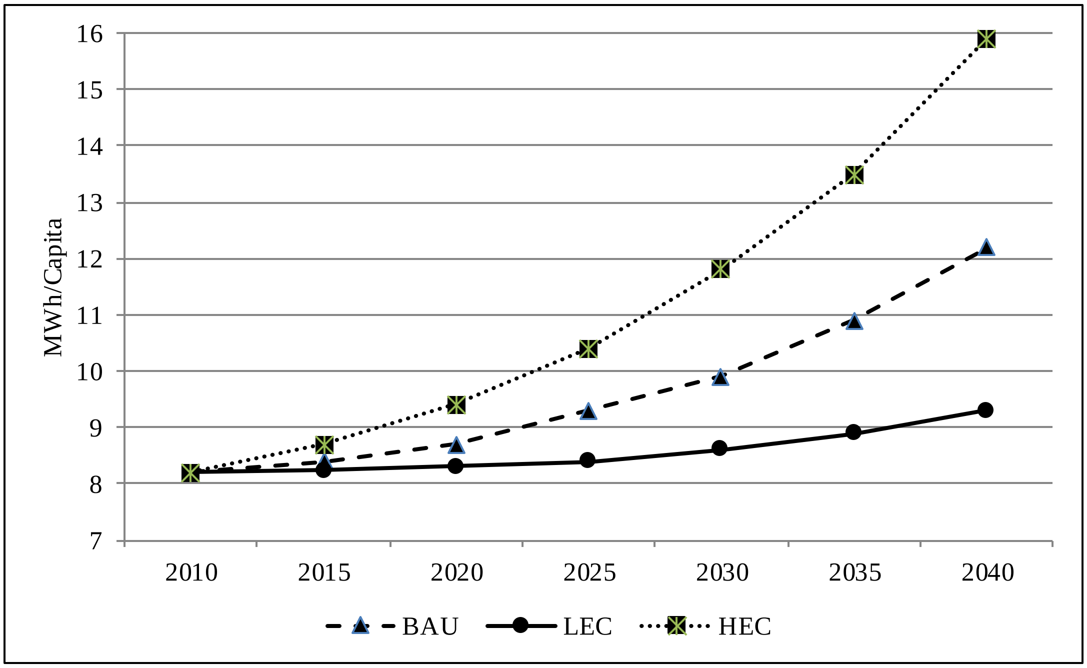


Figure 4.13: Final energy demand per capita

4.5.8 Energy intensity

Energy intensity shows an annual decreasing rate of 2.7% reaching 7.9 kWh/US$ in the BAU scenario by 2040 against the base year value of 18 kWh /US$. Energy intensity on the other hand will decrease at an annual rate of 1.9% and 2.9% under LEC and HEC scenarios respectively in 2040 against the base year value. Comparison of final energy demand per GDP in all scenarios is shown in Figure 4.14. Energy intensity in the BAU and HEC scenarios is projected to improve by approximately 50% from base year up to 2040 while that for LEC the improvement will be less than that. By these values it means it will take the country approximately half the energy to produce a dollar of GDP in 2040 as it was in the base year. The projected decrease in energy intensity is brought about mainly by improvements in technological energy efficiency in industry, service, household and transport. The high decrease rate in HEC scenario is due to these changes while the low decrease rate in the LEC scenario is due to less improvement.

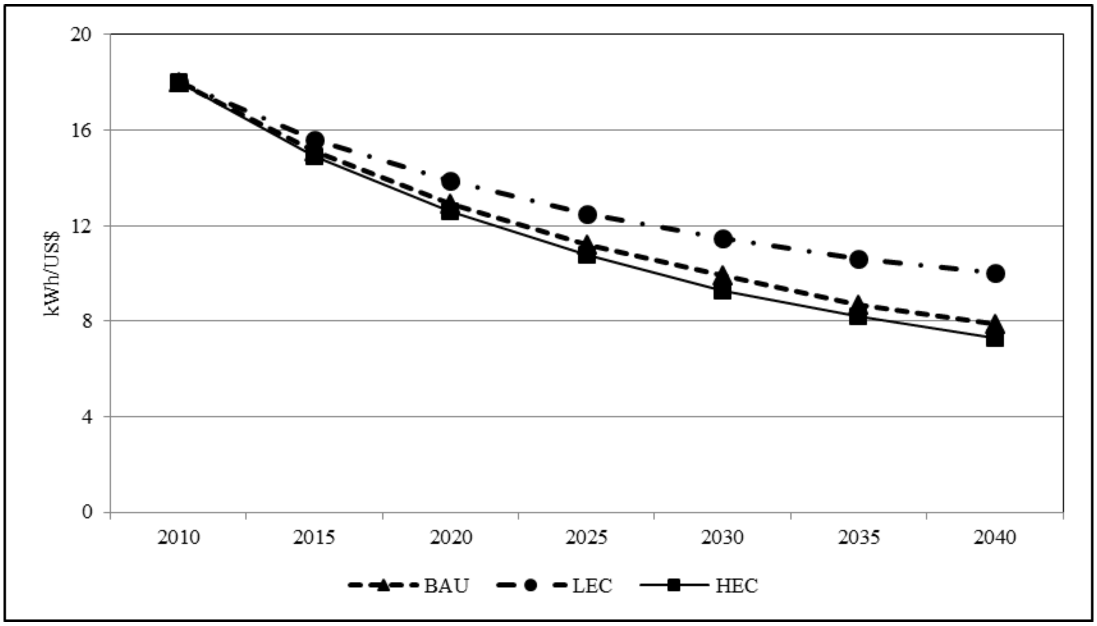


Figure 4.14: Energy intensity projections

4.6 Conclusion

It has been shown from the modelling results that energy demand of Tanzania is increasing exponentially. It has been determined that there is an increase of energy demand in all sectors of the economy with total demand more than tripled towards the end of study period 2010-2040. Based on the obtained results presented in this study, the following important conclusions are drawn:

i) Projected energy demand by energy form shows biomass to dominate the energy balance in the study period by commanding the highest share followed by fossil and motor fuels combined and electricity. The average share of biomass in both scenarios is more than 75 % of total final energy demand.
ii) Projected sectorial energy demand shows the service sector to command the highest share of the total final energy demand in the study period. The share of the service sector averages 41% of the total energy demand followed by households 31%, industry 21% and the transport sector 7%.
iii) Biomass demand in the study period is projected to grow annually at an average of 3.5 % for all three scenarios combined whereas the highest growth observed in HEC scenario. Biomass

demand will be highly dominated by the service sector followed by households and industry sectors.

iv) The study results show the highest growth rate of electricity demand is in the industry sector followed closely by the service and household sectors.

v) Fossil fuel demand for thermal applications is increasing exponentially in all three scenarios with the highest share being in the service sector. Much of the fossil fuel consumption increases is observed in the service sector followed by industry and household sectors.

vi) Modelling results predict motor fuel demand to grow at an average of 6.7% with higher demand being in the transport sector followed by industry and service sectors.

vii) A further detailed analysis of the supply side is recommended to optimize the use of energy resources available locally to lessen dependence on biomass and imported energy for environmental conservation.

CHAPTER FIVE

MODELLING ENERGY SUPPLY OPTIONS FOR ELECTRICITY GENERATIONS IN TANZANIA[4]

5.1 Abstract

The current study applies an energy-system model to explore energy supply options in meeting Tanzania's electricity demands projection from 2010 to 2040. Three economic scenarios namely; business as usual (BAU), low economic consumption scenario (LEC) and high economic growth scenario (HEC) were developed for modelling purposes. Moreover, the study develops a dry weather scenario to explore how the country's electricity system would behave under dry weather conditions. The model results suggests: If projected final electricity demand increases as anticipated in BAU, LEC and HEC scenarios, the total installed capacity will expand at 9.05%, 8.46% and 9.8% respectively from the base value of 804.2MW. Correspondingly, the model results depict dominance of hydro, coal, natural gas and geothermal as least-cost energy supply options for electricity generation in all scenarios. The alternative dry weather scenario formulated to study electricity system behaviour under uncertain weather conditions suggested a shift of energy supply option to coal and natural gas (NG) dominance replacing hydro energy. The least cost optimization results further depict an insignificant contribution of renewable energy technologies in terms of solar thermal, wind and solar PV into the total generation shares. With that regard, the renewable energy penetration policy option (REPP), as an alternative scenario suggests the importance of policy options that favour renewable energy technologies inclusion in electricity generation. Sensitivity analysis on the discount rate to approximate the influence of discount rate on the future pattern of electricity generation capacity demonstrated that lower values favour wind and coal fired power plants, while higher values favour the NG technologies. Finally, the modelling results conclude the self-sufficiency of the country in generating future electricity using its own energy resources.

[4] Journal of Energy in Southern Africa (JESA), Vol. 26, Issue No. 3 (2015), pp. 41-57

5.2 Introduction

Energy is an important element in accomplishing the interrelated socio-economic development of any country. Tanzania's energy supply relies mainly on biomass which accounts for nearly 90% of the total primary energy supply (IEA, 2013a; Wawa, 2012). The remaining energy supply is accounted from petroleum products at approximately 8%, grid electricity 1% and renewable energy sources such solar and wind which account for nearly 1% (Kabaka and Gwang'ombe, 2007; MEM, 2012). Total electricity generation shares in 2012 were mainly from natural gas 50.7%, hydro 28.6%, oil products 20.1%, biofuels 0.3% and solar PV 0.2% (IEA, 2014a). Projections are approximating electricity demand to reach 47.7 TWh in the year 2035 equivalent to an annual growth of approximately 8% (MEM, 2012). Energy resources are enormous and are available in various forms, including biomass, hydro, geothermal, biogas, wind, solar, natural gas and coal (Kihwele et al., 2012; MEM, 2013a). There is an estimated coal proven reserve of 304 million tonnes whereas that of natural gas is 45 billion cubic meters (Kusekwa, 2013; MEM, 2012). Geothermal has an estimated potential of 650 MW (Kihwele et al., 2012; Mnjokava, 2008) while hydro estimated potential is 4700 MW (MEM, 2012). Biomass estimated sustainable potential is 12 million TOE from agriculture wastes, plantation forests and natural forests (Wilson, 2010). The country experience annual sunshine hours of 2800 to 3500 and solar irradiation ranging from 4-7 kWh/m2 across the country (Casmiri, 2009; Kihwele et al., 2012). The renewable energy potential in the country is substantial but largely untapped for electricity and other thermal applications (Bauner et al., 2012; Kichonge *et al.*, 2014b). The country's renewable energy potential from municipal solid wastes currently disposed in dump sites is considerable as shown in studies by Omari et al. (2014a) and Omari et al. (2014b).

Tanzanian energy demand specifically electricity has been growing over years because of socio-economic transformations that opened up the country's economy. Statistics on the country's GDP growth since the year 2000 show annual average increase of 7% (BOT, 2012). However, substantial challenges faces the electricity sector owing to constrained generation capacity and distribution network (Kapinga, 2013; Wangwe et al., 2014) which previously resulted into outages and rationing (Loisulie, 2010; MEM, 2013c). Despite the electricity sector challenges, the demand is expected to grow as the country targets a middle income economy status as detailed in Development Vision 2025 (URT, 1999) and its implementation through Big Results Now (BRN) initiatives (Kahyoza, 2013). Realizing Tanzania Development Vision 2025 goals implies that the country needs adequate, reliable, affordable and environmentally friendly electricity supply options. Achieving these require optimal generation capacity additions, which consider diversifications of power plants systems. Finding optimal generation capacity addition based on least cost plan is important in formulating supply options considering the high investments costs associated with it. It is therefore the objective of this study to apply MESSAGE (Model for Alternative Energy Supply Strategies and their General Environmental Impacts) to find least-cost optimal energy supply options. MESSAGE is an appropriate framework for this study as it is capable to deal with long-term planning horizons based on high-resolution short-term system dynamics. Using MESSAGE, optimization of electricity supply options in each scenario will help describes possible future final electricity supply options availability. Study results will benefit policy and decision makers to arrive at a relevant solution interactively in national electricity system expansion planning.

5.3 Methodology

5.3.1 MESSAGE Model

Model for Energy Supply Strategy Alternatives and their General Environmental Impacts (MESSAGE) is an optimization modelling tool (Messner and Strubegger, 1995) which calculates the least-cost energy supply system. Connolly *et al.* (2010), describes MESSAGE as a bottom-up model capable of optimizing operation and investment of technologies in a medium to long term energy systems. MESSAGE modelling approach allows the realistic evaluation of the long-term role of an energy supply option under competitive conditions (Hainoun et al., 2010; IAEA, 2008). The least-cost determination in MESSAGE is through minimization of the total discounted energy system cost subject to the constraints representing demands, resource deficiency and capacity limits. Discounted energy system cost minimization includes investments, fixed and variable operation costs, maintenance costs, fuel and any additional penalty costs, which defines the limits and constraints relation. With MESSAGE, alternative energy supply strategies in agreement with user-defined constraints are assessed (IAEA, 2006; Tait *et al.*, 2014).

Mathematical techniques tied up with MESSAGE comprises of linear and mixed-integer programming. The purpose for linear programming (LP) applications is that all the limits and the objective function (optimization target) are linear functions of the decision variables. Mixed-integer use in MESSAGE is due to integer values at the optimal solution requirements by some of the decision variables. Objective function in MESSAGE modelling approach is as shown in Equation 1. The variable $X_{i,j,t}$ denotes a flow variable (input) of fuel form i in technology j in the time step t. Flow variable describes amount produced in which technology and the type of fuel. The investment variable denoted by $Y_{i,t}$ represents new installation of technology j in time step t.

$$\mathrm{Min} \sum \mathrm{Cost} * \left(X_{i,j,t} + Y_{i,t}\right) \tag{5.1}$$

The MESSAGE model computes the objective function to satisfy the condition that ensures a balance between demand and supply as illustrated in equation 5.2. The parameter D denotes energy demand, j represents energy demand of j while t represents time step. In addition, η represents technology efficiency, X denotes production decision of the technology, i is the number of technologies and n total number of technologies.

$$\sum_{i=1}^{i=n} \eta_{i,t} X_{it} \geq D_{j,t} \tag{5.2}$$

MESSAGE has been used to model power supply sector by means of the principle of reference energy system (RES) which allows representation of the entire energy network including possible development paths (Rečka, 2011; Selvakkumaran and Limmeechokchai, 2011). RES is composed of energy resources and sources, energy carriers (form) and technologies. RES captures network flow of energy carrier from one process to the other starting in the resource to the consumer delivery. The explanation of energy forms includes each level of energy chains, technologies using or producing these energy forms, and the energy resources. MESSAGE defines energy forms and technologies in all steps of energy chains. This includes identification of energy chain levels beginning from the demand to the resources, the energy forms to energy services. MESSAGE computes energy demand from the first level of each energy chain up to the energy resource level. Final demand level is distributed according to the types of consumption (Pinthong and Wongsapai, 2009; Van Beeck, 1999).

The MESSAGE modelling approach has previously applied to formulate an optimal energy supply strategy for Syria (Hainoun et al., 2010); policy options study for power sector in Zambia (Tembo, 2012); strengthening of renewable energy applications (IAEA, 2006, 2007); Optimal electricity system planning in a large hydro jurisdiction: Will British Columbia soon become a major importer of electricity? (Kiani *et al.*, 2013) alternate electricity supply model (Roque, 2014); climate change policy analysis (Nakicenovic N *et al.*, 2000): nuclear energy in mitigating CO2 emissions (AlFarra and Abu-Hijleh, 2012) among many others. Further information on MESSAGE as LP optimization tool is as found at the IAEA organization web site.

5.3.2 Electricity Demand Projections

The final electricity demand projections were done using Model for Analysis of Energy Demand (MAED) (Kichonge et al., 2014a) and have been summarized in Figure 5.1. MAED is a bottom-up modelling approach (Bhattacharyya and Timilsina, 2009) chosen because of its suitability to model the final electricity demand projections based on time and data availability. Suitability of MAED to relates systematically the corresponding social, technological and economic factors which affect the demand was also considered in the selection of the model (IAEA, 2009, 2006). Literatures such as Hainoun et al. (2006), IAEA (2006), Nakarmi et al. (2013) and IAEA organization website IAEA (2009) gives detailed account of MAED.

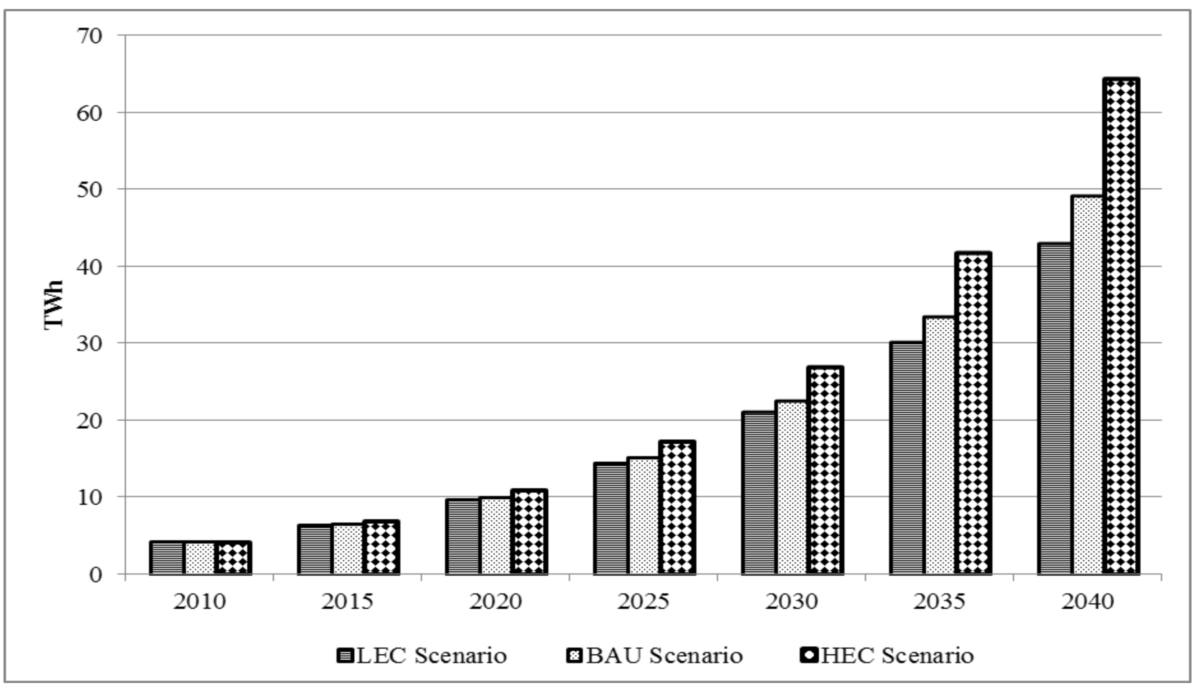


Figure 5.1: Electricity demands forecasts

5.3.3 Modelling framework

5.3.3.1 Electricity conversion technologies

Conversion technologies candidates considered includes coal, solar PV, hydro, solar thermal, biomass, conventional gas turbine (GT), heavy fuel oil (HFO) and combined cycle gas turbine (CCGT) power plants.

5.3.3.2 Reference energy system (RES)

The proposed Tanzanian RES accommodates resources, primary, secondary and final demand energy levels. Simplified schematic flow of the energy chains, levels and conversion technologies in RES are as described in Figure 5.2. Rectangles in the RES represents the technologies, which contains the techno-economic data. A single technology as used in the proposed RES denotes all conversion technologies, which uses the same type of fuel. The energy resource level is characterized by coal and natural gas, which are locally available resources. Energy carriers in the form of natural gas (NG), coal and HFO defines primary energy level in the energy chain. The secondary energy level is composed of electricity as the only form of energy echoed in this study.

Intermediary of primary and secondary energy levels, there are electricity conversion technologies whose main inputs are energy carriers from the primary energy level. Electricity transmission and distribution network connects secondary and final energy levels. The final electricity demand developed from model's external factors (Kichonge et al., 2014a) is given at the first level of each energy chain. The model calculates the equivalent productions of each technologies at the succeeding levels of the chain up to the energy resource level which then gives the optimal technical choice by minimizing the total system cost while meeting the given final electricity demand.

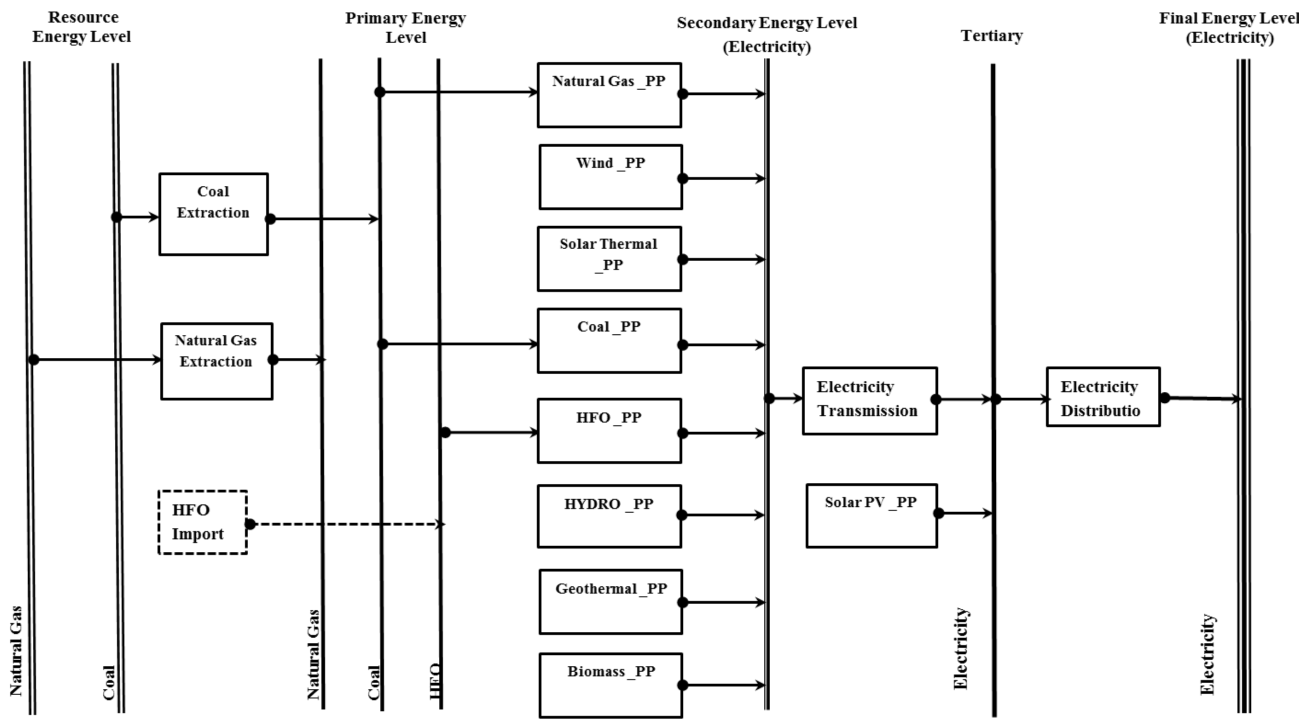


Figure 5.2: Energy chain levels and conversions technologies schematic flow diagram

5.3.4 Modelling basic assumptions

The general assumptions considered in modeling energy supply options for electricity generation for Tanzania are as follows:

~All model scenarios span from 2010, which is the base year to 2040 as the last year. A time step of five years has been adopted throughout the study period as more steps slows down the solver and also for easy results reporting;

~Each model year in all scenarios is divided into four seasons to capture seasonal variations in reservoir inflows and load for hydro, solar PV and wind turbines. The seasons includes Season 1 which encompasses January to February (dry season); Season 2 - March to May (wet/rainy season); Season 3 - June to September (dry/sunny weather season) and Season 4 - October to December (short rainy season);

~The expected load profile for defining the mix in power generation plants follows an annual hourly and monthly load curve characteristics as shown in Figure 5.3 and Figure 5.4. An annual hourly load curve characteristics was produced from hourly generation data collected for the years 2009 to 2012. Generation of annual hourly load curves was done by taking average values in load demands for a particular hour throughout a year. Daily base load patterns together with energy resources variations are taken into account by describing two types of days which are workdays (Monday to Saturday) and weekends (Sunday and holidays). The daily base load patterns for a 24 hours day has been divided as nine parts for Season 1, ten parts for Season 2, eight parts for Season 3 and twelve parts for Season 4;

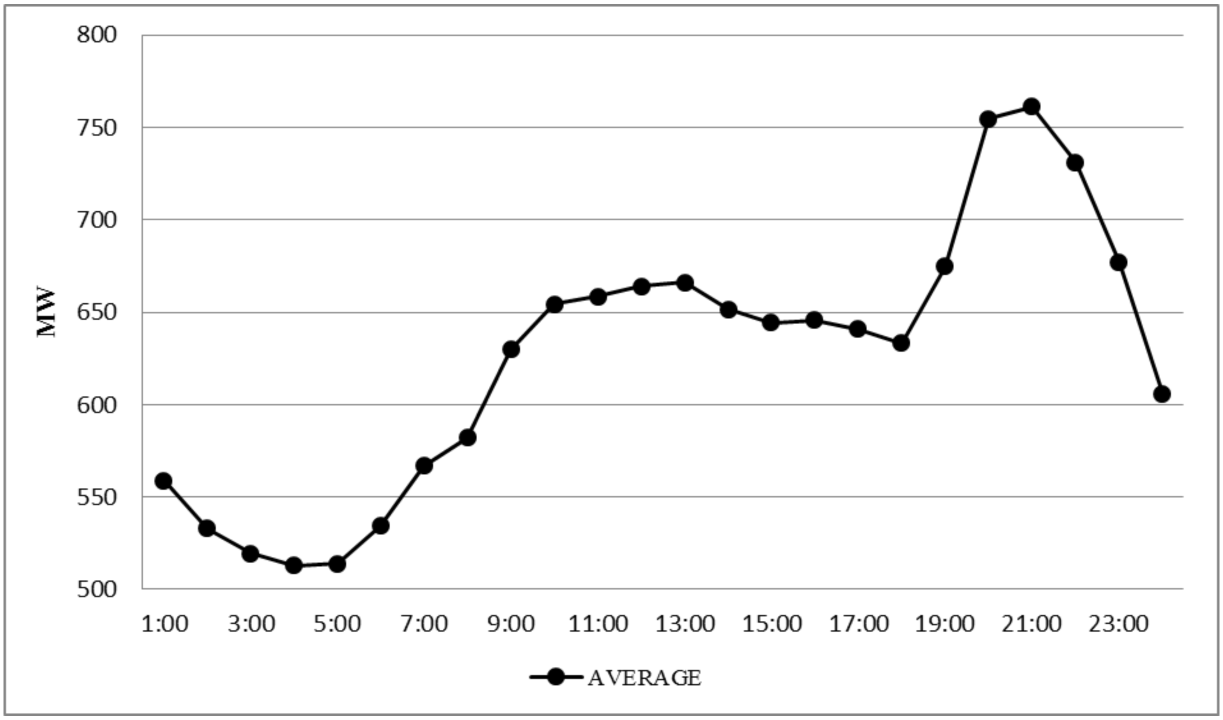


Figure 5.3: Annual hourly load curve characteristics

~ Final electricity demand differences under business as usual (BAU), low economic consumption (LEC) and high economic growth (HEC) scenarios as projected in MAED are as depicted in Figure 5.1. Other parameters such as energy forms, seasonal and daily power demand variability, constraints, technologies and resources remained the same for BAU, LEC and HEC scenarios;

~Air emissions control measures have not been included in the model;

~The operation time thus electricity output for solar PV, solar thermal and wind power plants follows the proposed seasonal and daily sunshine/wind variation;

~Geothermal power plants begin operation in 2025 with an initial installed capacity of 100 MW and increasingly to 650 MW in 2040 (MEM, 2012; Mnzava and Mayo, 2010);

~Discount rate parameter for economic evaluation of the future investment project was set to 10% in each scenario. The value of discount rate is the official one used in the investment of most of the projects concerned with electricity;

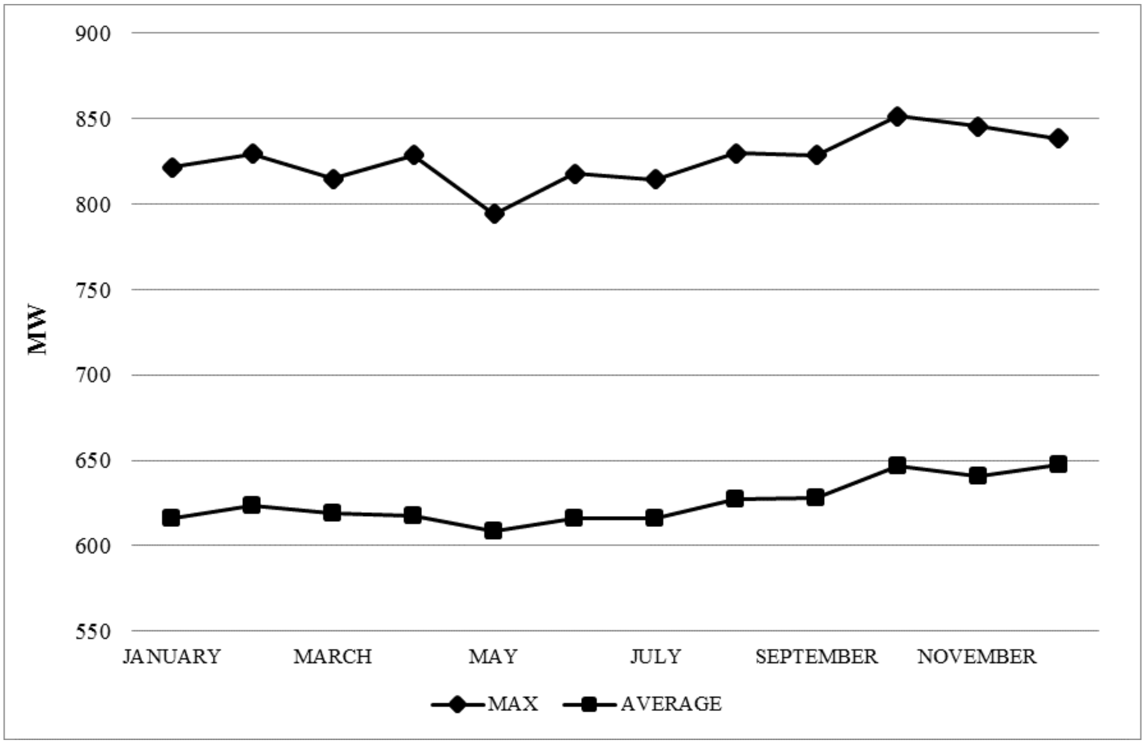


Figure 5.4: Annual monthly load curve characteristics

~The entire national electricity system has been simplified and modeled as a single grid system;

~Existing and future expansion projects, transmission and distribution losses and reserve margins as specified in the power system master plan (MEM, 2012) has been adopted for optimization purposes;

~Summary of the crucial parameters for modeling electricity supply options in terms of specific technical and economic characteristics adopted for conversion technologies are as depicted in Table 5.1.

~The investment costs for renewable energy technologies (wind, solar PV and thermal) assumed a decreasing trend as the industry develops and thus became cost competitive in future (Philibert, 2014). The investment cost for wind technology in the base year as shown in Figure 5.5 was approximated at 2438 US$/kW and then decreased steadily to 1800 US$/kW in 2025 where it assumed this constant value to 2040. The assumed constant value is due to uncertainties towards the future though with current trend, the value is likely to decrease. Solar PV technology investment costs assumed a base year value of 4000 US$/kW and decreased in steps to 3500 US$/kW and 2500 US$/kW in 2025 and 2030 respectively where it presumed a constant value of 2500 US$/kW towards the year 2040. Similarly, the investment cost for solar thermal technology towards the end of the study period presumed a decreasing trend from the base year value of 4500 US$/kW to 3500 US$/kW.

Table 5.1: Summary of technical and economic characteristics of conversions technologies

	CONVERSION TECHNOLOGY								
	CCGT_PP	GT_PP	HYDRO_PP	SOLAR PV_PP	SOLAR TH_PP	BIOMASS_PP	HFO_PP	Wind_PP	COAL_PP
Investment Costs (US$'00/kW)	1808.5	1220	2227	4000*	4500*	3860	800	2438*	1900
Variable O & M Costs (US$'00/kWyr)	26.5	39.5	4.5	0	40	26.5	105	4.5	52.56
Fixed Costs (US$'00/kW/yr)	9.5	9.5	8.5	40	149	40	20	40	50
Plant life (years)	25	25	50	30	30	30	40	25	30
Plant factor (share)	0.95	0.95	0.95	0	-	0.95	0.75	0.9	0.95
Efficiency (%)	0.52	33		-	-	28	30	-	40
Operation time (share)	0.94	0.75	0.85	0.26	0.26	0.9	0.7	0.35	0.85
Input	NG	NG	-	-	-	Biomass	HFO	-	Coal
Output	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity

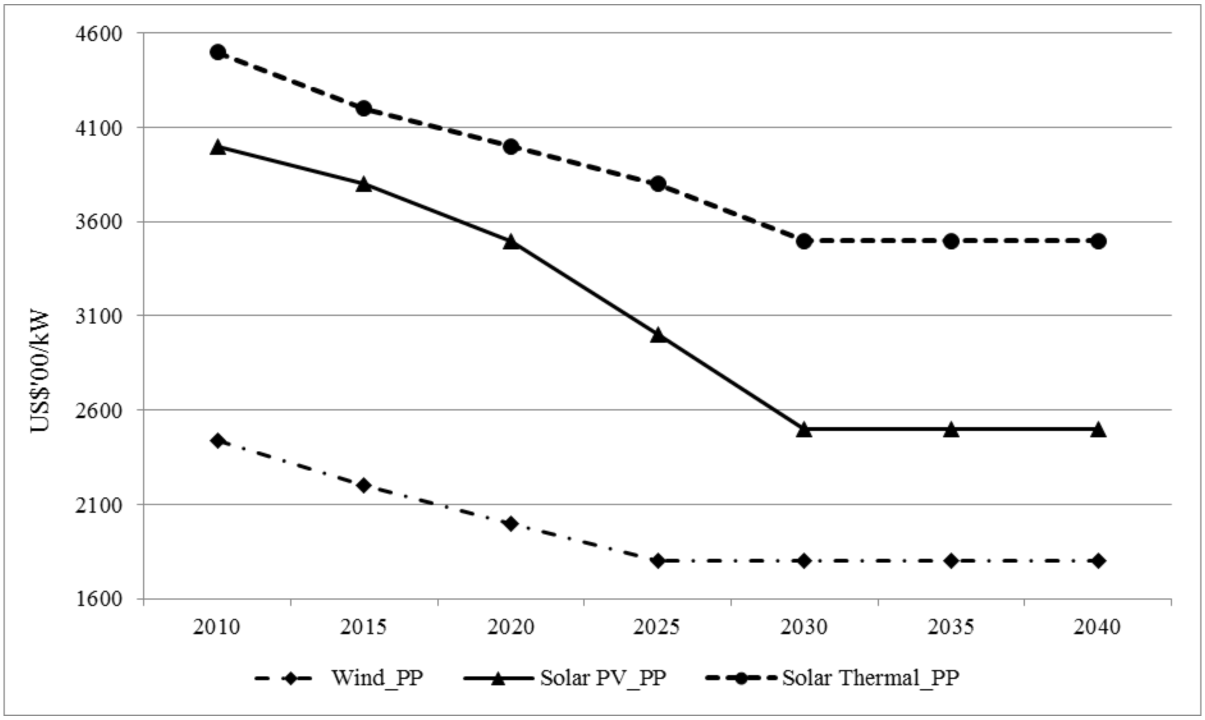


Figure 5.5: The investment costs for wind, solar thermal and solar PV power plants

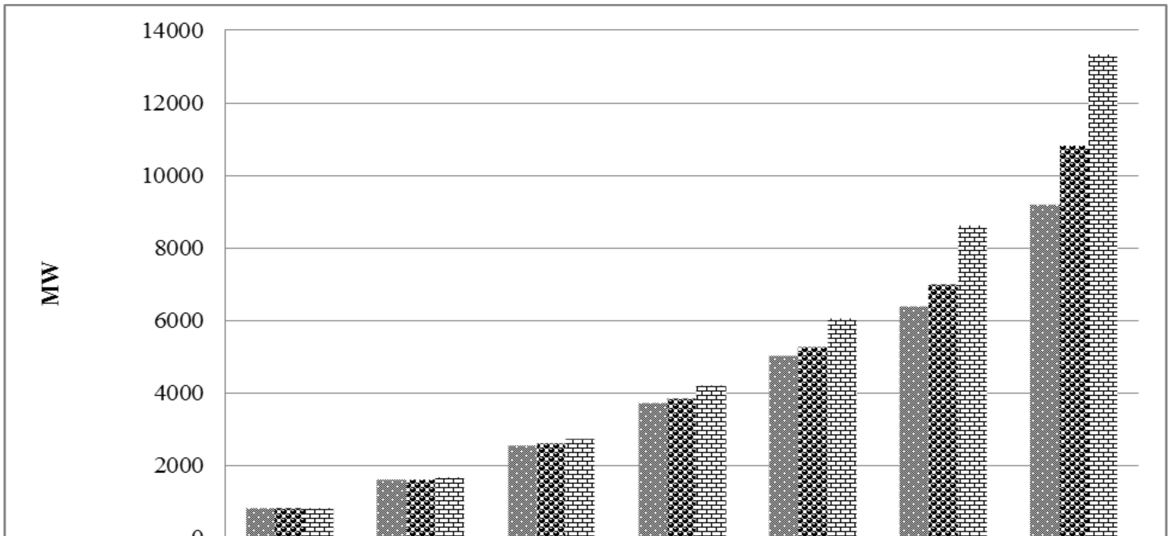
5.4 Results and Discussions

Final electricity demands have been optimized in order to determine the optimal energy supply options for Tanzanian electricity sector. This section presents MESSAGE modeling results calculated based on the least-cost energy supply options for electricity generation for the period 2010-2040. Based on the total system costs of the electricity system discounted over the study period 2010-2040, three different energy supply options have been optimized in lieu of BAU, LEC and HEC scenarios as detailed in Kichonge et al. (2014a).

5.4.1 Installed capacity

The total installed capacity increases gradually from 804.2 MW in the base year to 10811.5 MW, 9190.6 MW and 13325.6 MW in 2040 for BAU, LEC and HEC scenarios respectively as illustrated in Figure 5.6. The least-cost optimal results show HEC scenario has the highest total capacity additions at 12,521.4 MW in 2040 as compared to the BAU scenario 10,007.3 MW and LEC scenario 8,386.65 MW. Annual increase of installed capacity in HEC scenario is equivalent to 9.81% while BAU and LEC scenarios projection increases are 9.05% and 8.46% respectively. Hydro, NG, coal and geothermal power plants dominate the total installed capacity additions in all scenarios. Wind and biomass represents a small proportion in the total installed capacity whereas solar PV and thermal were not able to compete.

There is a corresponding increase of thermal installed capacity addition (coal and NG power plants) in both scenarios. NG power plants (CCGT and GT) increase their shares in the total installed capacity from 202 MW in 2010 to 2546.55 MW in 2040 for BAU scenario. LEC scenario observes similar increasing trend to 2090.67 MW in 2040 while HEC scenario is 4794.47 MW. The shares of hydro power plants witnesses an opposite decreasing trend in the period 2015-2030 where it pick-ups the dominance to 2035. Hydro power plants shares decreases from 69.8% in 2010 to 35.8%, 42.1% and 29% in 2040 for BAU, LEC and HEC scenarios respectively. The main reason attributed to the decreasing trend is the potential constraints despite the fact that it is the cheapest in operating costs (MEM, 2013c).



	2010	2015	2020	2025	2030	2035	2040
LEC Scenario	804.2	1586.14	2525.5	3708.36	5019.73	6362.58	9190.85
BAU Scenario	804.2	1595.42	2579.36	3823.93	5258.02	6994.48	10811.47
HEC Scenario	804.2	1656.2	2728.07	4206.07	6046.88	8625.97	13325.6

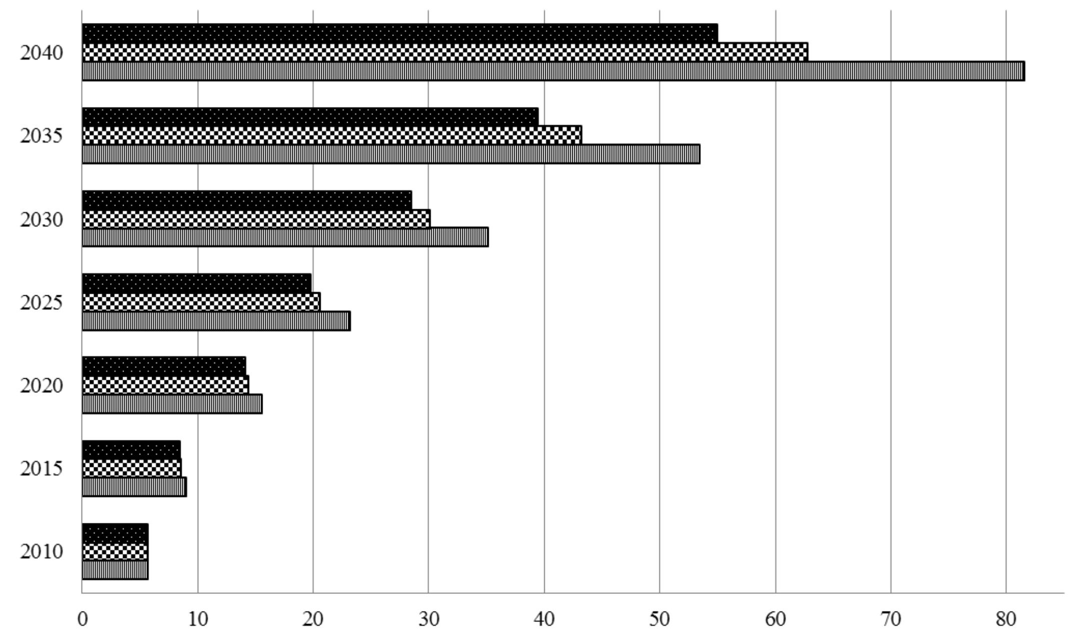
Figure 5.6: Total installed capacity (2010 - 2040)

Table 5.2: Installed capacity shares by technology

	2010	2015			2020			2025			2030			2035			2040		
	Base Year	BAU	LEC	HEC	BAU	LEC	HEC	BAU	LEC	HEC	BAU	LEC	HEC	BAU	LEC	HEC	BAU	LEC	HEC
Coal_PP	-	-	-	-	9.3	7.4	14.2	10.1	5.0	9.2	7.3	3.7	13.2	27.0	18.3	26.7	29.1	27.0	25.6
HFO_PP	5.1	10.8	10.9	10.5	6.4	6.6	6.1	4.34	4.48	3.95	3.16	3.31	2.75	2.37	2.61	1.92	0.96	1.13	0.78
CCGT_PP	-	30.6	30.2	33.2	36.8	37.6	34.8	24.8	27.9	31.6	9.8	11.1	12.9	2.4	5.2	15.9	18.4	16.7	31.8
GT_PP	25.1	21.9	22.0	21.1	13.8	13.8	12.8	9.1	9.4	8.3	6.8	5.6	7.7	7.8	7.3	6.5	5.2	6.1	4.2
Hydro_PP	69.8	35.4	35.6	34.1	25.4	25.9	24.0	43.3	44.6	39.3	56.4	59.1	49.0	51.0	56.0	41.3	35.8	42.1	29.0
Wind_PP	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	4.6	-	3.8
Biomass_PP	-	1.2	1.2	1.2	0.8	0.8	0.7	0.5	0.5	0.5	0.4	0.4	0.3	0.2	0.2	0.2	-	-	-
GeoTh_PP	-	-	-	-	-	-	-	2.6	2.7	2.4	12.4	12.9	10.7	9.3	10.2	7.5	6.0	7.1	4.9
Solar_PV	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Solar_Th	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Electricity Import	-	-	-	-	7.8	7.9	7.3	5.2	5.4	4.8	3.8	4.0	3.3	-	.	-	-	-	-
Total (%)	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

5.4.2 Electricity generation mix

Summarized least cost total electricity generation for each scenario are as shown in Figure 5.7 and the least-cost electricity generation supply options results by technology in Table 3. BAU scenario least cost electricity generation expanded from 5,632 GWh in 2010 to 62,770 GWh in 2040. The expansion is equivalent to an annual growth rate of 8.4 % as compared to 7.9% and 9.3% for the LEC and HEC scenarios respectively. The base year proportions in the generation mix include hydro (66.7%), NG (28.9%), biomass (2.5%) and HFO (2 %). Results describe general dominance of hydro power plants in generation mix with NG, biomass and HFO power plants compensating the balance. The optimized results show the proportion of hydropower plants generation increasing gradually to 41.2 %, 47.1 % and 31.7 % in 2040 for BAU, LEC and HEC scenarios respectively.



	2010	2015	2020	2025	2030	2035	2040
LEC (TWh)	5.6	8.5	14.1	19.7	28.4	39.4	54.9
BAU (TWh)	5.6	8.5	14.4	20.5	30.1	43.2	62.8
HEC (TWh)	5.6	9.0	15.6	23.2	35.1	53.4	81.5

Figure 5.7: Electricity generation projections (2010-2040)

Table 5.3: Electricity generation shares by technology (2010-2040)

	2010	2015			2020			2025			2030			2035			2040		
	Base Year	BAU	LEC	HEC	BAU	LEC	HEC	BAU	LEC	HEC	BAU	LEC	HEC	BAU	LEC	HEC	BAU	LEC	HEC
Coal_PP	-	-	-	-	11.8	9.3	17.7	13.3	6.7	11.9	6.6	3.3	15.0	25.9	17.2	30.4	38.1	33.5	33.0
HFO_PP	2.0	0.2	0.2	0.2	-	-	-	0.03	0.02	0.06	0.05	0.03	0.04	0.03	0.03	0.02	0.01	0.01	0.01
NG Power Plants	28.9	54.3	53.8	56.5	57.1	58.8	53.4	28.9	33.1	36.9	11.8	11.8	14.5	7.5	9.8	15.8	10.7	10.6	27.6
CCGT_PP	-	76.5	76.2	78.8	86.9	86.6	86.8	88.6	89.4	92.6	88.3	92.2	90.5	88.3	91.2	96.3	96.9	95.7	99.3
GT_PP	100.0	23.5	23.8	21.2	13.1	13.4	13.2	11.4	10.6	7.4	11.7	7.8	9.5	11.7	8.8	3.7	3.1	4.3	0.7
Hydro_PP	66.7	44.3	44.7	42.2	30.4	31.2	28.2	53.9	56.1	47.8	66.0	69.8	56.5	55.2	60.5	44.6	41.2	47.1	31.7
Wind_PP	-	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.2	0.0	1.7
Biomass_PP	2.5	1.2	1.2	1.0	0.6	0.6	0.6	0.3	0.3	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0
GeoTh_PP	-	-	-	-	-	-	-	3.6	3.8	3.2	15.2	14.8	13.8	11.2	12.3	9.1	7.7	8.8	5.9
Solar_PV	-	-	-	-	-	-	-	0.0	-	-	-	-	-	-	-	-	-	-	-
Solar_Th	-	-	-	-	-	-	-	0.0	-	-	-	-	-	-	-	-	-	-	-
Electricity Import	-	-	-	-	0.1	0.1	0.2	-	-	-	0.1	0.1	0.1	0.1	0.1	0.1	0.05	0.1	0.03
Total (%)	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

The proportion of coal power plants in the total generation rises gradually from 11.8 % in 2020 to 38.1% in 2040 for BAU scenario while for LEC scenario is 9.3% in 2020 and rises to 33.5% in 2040. HEC scenario witness higher proportion at 17.7% in 2020 and grows to 33% in 2040. The higher proportion of hydro, NG and coal power plants in generation mix is imminent due to lower investment and fuel costs as compared to other candidates technologies considered. Unlike the increases in hydro and coal power plants generation shares, the proportions of NG power plants increasingly dominate more than 50% of the generation from 2015-2020 and thereafter declines in 2040. The decline in NG power plants proportions after 2020 is due to presumed new investments in hydro power plant. NG power plants technologies proportion in 2040 for BAU scenario split into CCGT (96.9%) and GT (3.1%). However, similar trend follows in LEC and HEC scenarios in which the share of CCGT will be as high as 95.7% and 99.3% respectively in 2040. The choice of CCGT in least-cost optimized results attributes to higher availability and efficiency up to 60% in comparison to that of GT 40% (Sharman, 2005; Sims et al., 2003).

Combined thermal generation contributes 48.8% of the total in 2040 for BAU scenario as shown at the top-left plate of Figure 5.6. The contribution of thermal generation for LEC scenario is 44.1 % top-right plate while for HEC scenario is 60.6% bottom-left plate. Higher electricity demands in HEC scenario drives the use of thermal generations. The use of more thermal generations instead of hydro and geothermal attributes to energy resource potential constraints. On the contrary, renewable energy with the exclusion of hydro makes up small proportion in the contribution of the total electricity generation mix.

The contribution of renewables technologies into electricity generation for BAU, LEC and HEC scenarios extends to 6.2 TWh, 4.8 TWh and 6.2 GWh respectively in the year 2040. The share of renewable energy generation in BAU scenario accounted for an average of 2.1% in the period from 2010 to 2025 and thereafter grows to 15.4% in 2030 and then retreat to 9.9% in 2040. The rise of renewable energy in 2030 attributes to utilization of full geothermal energy potential presumed in the year. HEC scenario shares of renewable energy from 2025 – 2040 averaged at 1.9 % in the total electricity generation. Comparable trends are also as observed in LEC scenario. Moreover, within renewable energy technologies geothermal dominates the generation mix followed by biomass and wind with insignificant shares from solar thermal and solar PV power plants. Geothermal and wind power plants by the end of study period in 2040 generated 7.7 % and 2.2 % respectively of all electricity in BAU scenario. Similarly, geothermal power plants generation for LEC and HEC scenarios was approximately 8.8 % and 5.9 % respectively. The constraints on geothermal energy resources potential and the rise in electricity demand reduced the share of geothermal technologies in 2040 for HEC scenario.

The least-cost electricity generation results in the BAU, LEC and HEC scenarios draws four most important conclusions. The first one is the key role played by hydro, coal and NG technologies in the final electricity generations. These technologies have shown least-cost competitiveness in electricity generation, which describes their importance in sustainable development of the electricity sector. The second is insignificant contribution from solar thermal and solar PV technologies in the entire study period. The high investment costs associated with the technologies discourages the penetration in generations mix despite their least operations and maintenance costs. The last conclusion is the country self-sufficiency in generating electricity using its own local energy resources thus ensuring security of supply for sustainable development.

5.4.3 Primary energy supply

Primary energy supply composition for electricity generation is as shown in Table 5.4. Coal, NG, HFO and biomass are the main primary energy supply for electricity generation. Conversion technologies for geothermal, hydro, wind, solar PV and solar thermal do not consume primary energy for electricity generation. Primary energy supply in BAU scenario will grow from 6203 GWh in 2010 to 73083 GWh in 2040. Similarly, the growth in LEC scenario amounts to 57529 GWh against 110,700 GWh in HEC scenario. Generally, all scenarios projects increased coal consumptions as compared to NG with small proportions from biomass and HFO towards 2040. The least-cost supply option, show electricity generation will depend on coal and NG to cover primary energy supply. It further depicts gradually decrease in HFO to less than 0.1% in 2040. Figure 5.8 depicts primary energy supply in BAU scenario that is the representative trend for other scenarios.

Table 5.4: Primary energy production (2010-2040)

	Coal			Natural Gas			HFO			Biomass		
	BAU	LEC	HEC	BAU	LEC	HEC	BAU	LEC	HEC	BAU	LEC	HEC
2010	-	-	-	5326.4	5326.4	5326.4	380.8	380.8	380.8	495.5	495.5	495.5
2015	-	-	-	10469.6	10310.4	11278.5	66.7	63.4	72.5	369.9	367.6	326.9
2020	4235.5	3283.0	6865.4	17314.4	17465.6	17524.9	0.0	-	0.0	313.0	315.7	312.7
2025	6809.8	3283.0	6865.4	12356.9	13519.5	17351.5	21.5	14.3	42.6	242.2	237.6	154.7
2030	4995.2	2366.6	13130.6	7430.1	6801.0	10467.1	52.6	25.4	48.0	126.4	117.4	123.8
2035	27982.2	16905.6	40673.7	6787.2	7933.7	16647.6	41.0	44.4	38.5	91.2	91.2	50.3
2040	59862.6	45949.3	67200.2	13196.3	11555.5	43475.7	24.2	24.2	24.2	-	-	-
Total	**103885**	**71787**	**134735**	**72881**	**72912**	**122072**	**587**	**552**	**607**	**1638**	**1625**	**1464**

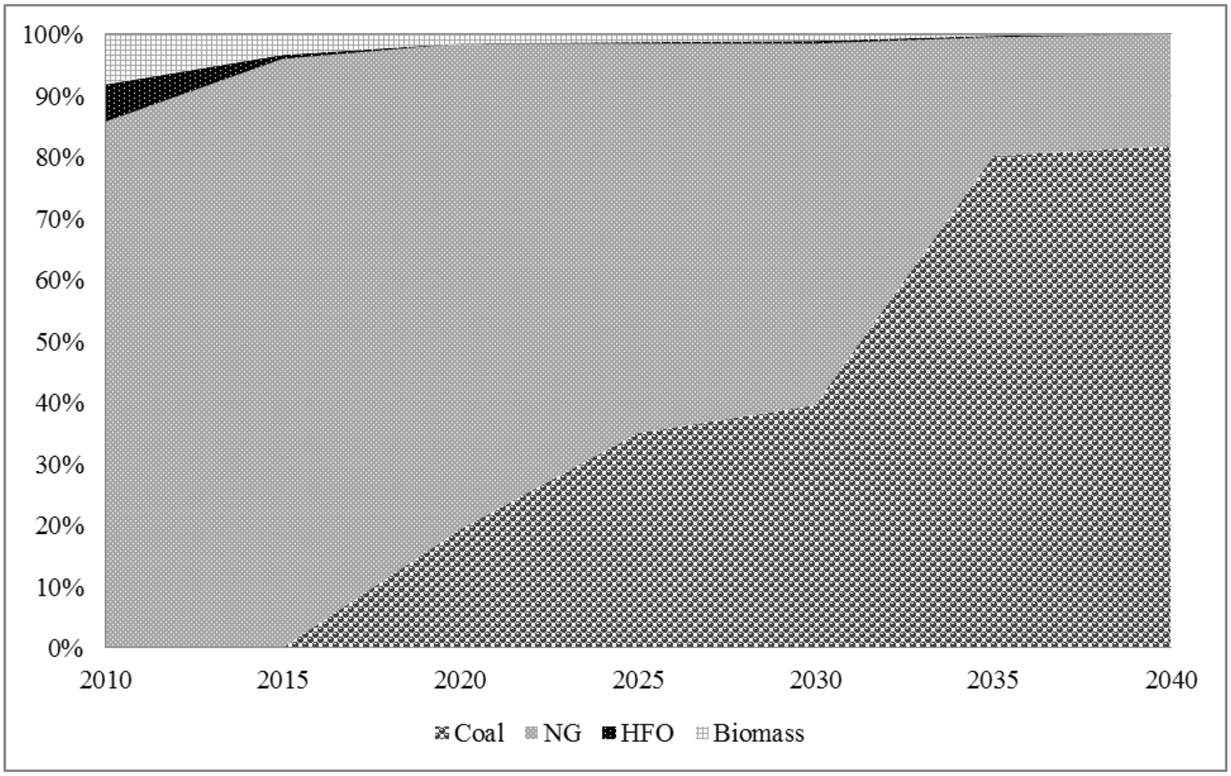


Figure 5.8: Primary energy supply – BAU scenario

5.4.4 CO_2 emissions

The total CO_2 emission depicted in Figure 5.9 rises from 1182-kilo tonnes of CO2 in 2010 to 23652.3-kilo tonnes of CO_2 in 2040 for BAU scenario. The rise in CO_2 emission in BAU scenario represents an annual growth of 10.5 %. Similarly, the increases for LEC and HEC scenarios represent annual growth of 9.5% and 11.7 % respectively. The growth rate in CO_2 emission in LEC scenario is much lower than that of HEC and BAU scenarios due to slow economic growth presumed in the scenario representing less energy consumption. Similarly, the higher CO_2 emission in HEC scenario is highly contributed by higher electricity demands, which resulted in optimal capacity additions of coal and NG power plants. The emission of CO_2 in all scenarios is higher due to insignificant renewable energy conversion technologies applications.

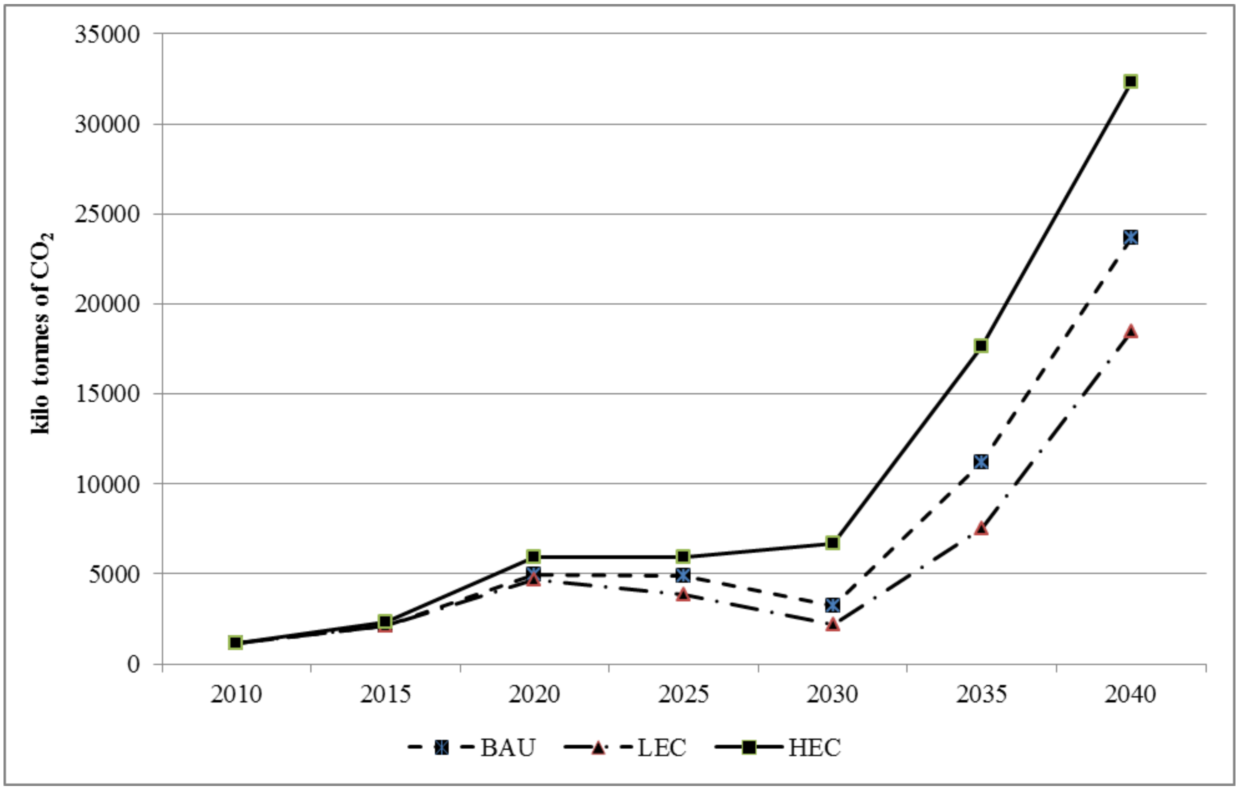


Figure 5.9: Projected CO_2 emissions (2010-2040)

5.5 Economics of scenarios

The capital investment cost required for the entire period of study is as based on MESSAGE least cost modelling results. The sharing of capital investments for the period of 2010 – 2045 is as shown in Figure 5.10. In meeting final electricity demand under BAU, LEC and HEC scenarios, the total capital investment cost of 4488 million US$, 3903 million US$ and 5573 million US$ respectively would be required. The main share of the capital investments for the entire period in BAU, LEC and HEC scenarios falls into the period of 2015 to 2035 in which most of the capacity addition is taking place. The capital investment needed to develop a BAU scenario final electricity demand in the entire study period would be about 584 million US$ more than LEC scenario, while 1086 million US$ increase would be needed for a HEC scenario. The higher capital investment costs is observed in 2035 for HEC and BAU scenarios while for LEC scenario is in 2030.

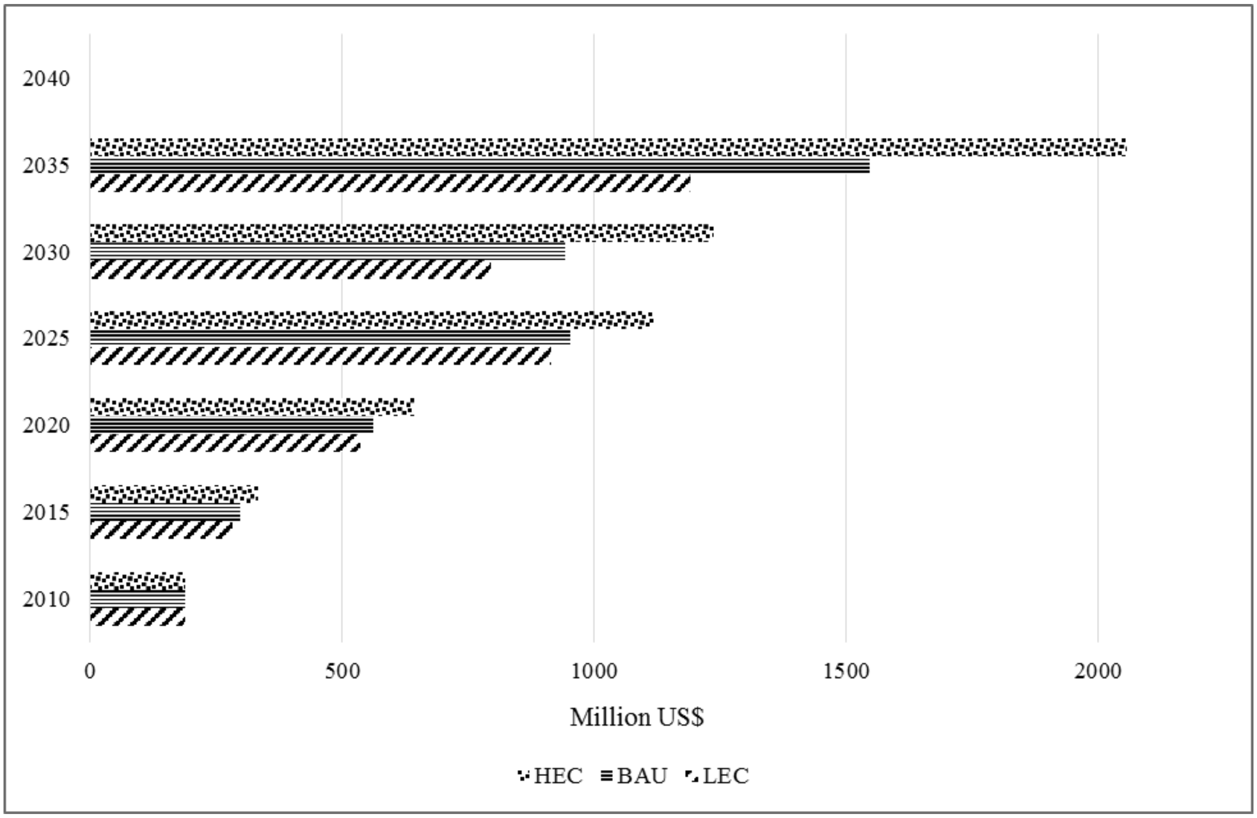


Figure 5.10: Capital investment costs for the entire study period (2010-2040)

Least cost modelling results as presented in Table 5.5 shows the main differences among BAU, LEC and HEC scenarios in terms of the investment costs and variable and fixed O&M costs. Variable O&M costs for HEC scenario are 335.1 and 529.4 million US$ higher than those for the BAU and LEC scenarios. Moreover, the LEC scenario entail lower fixed O&M costs at 1013.4 million US$ as compared with the BAU and HEC scenarios.

Table 5.5: Total Investment and O&M costs

Name of Scenario	O&M Variable Cost (Million US$)	O&M Fixed Cost (Million US$)	Investment Cost (Million US$)	Total Investment and O&M Cost (Million US$)
BAU	999.7	1127.7	4487.6	6615.1
LEC	805.4	1013.4	3900.0	5718.8
HEC	1,334.8	1,222.2	5,595.3	8,152.4

5.6 Sensitivity Analysis

Sensitivity analyses carried out in this study, intended to explore the influence of techno-economic parameters, policy options and extreme dry weather conditions in the expansion of the final electricity generation mix.

5.6.1 Renewable energy penetration

Least-cost optimization results as distinguished in previous sections reveals in-significant penetration into electricity generation of renewable energy technologies due to the high investment costs. Among the reasons behind the insignificant penetration of renewable energy technologies in electricity generation is the absence of non-environmental friendly energy supply constraints. As a result, the market forces decides to choose the least-cost energy supply options for electricity generations which in most cases occurs as non-environmentally friendly sources (Bull, 2001; Lewis, 2007). Based on this fact, the study formulates a renewable energy penetration policy option (REPP) as an alternative scenario to study electricity system behavior under energy supply constraints to promote renewable energy technologies in the generation of electricity. The policy option in REPP requires a compulsory penetration of renewable energy technologies (combined together) to contribute at least 10% of the total electricity generation in 2020 and increasingly to 30% in 2040. REPP scenario assumes energy demands projections and all techno-economic parameters of BAU scenario with the additions of the compulsory policy measures. All modelling inputs of REPP scenario remains the same as in BAU scenario except for the imposed compulsory penetration of renewable energy technologies.

The results of REPP scenario implementations as compared to BAU scenario in terms of the total installed capacity, electricity generation and CO_2 emissions are as illustrated in Table 5.6. The MESSAGE results depicts a huge reduction of CO_2 emission at approximately 48% in REPP scenario as compared to BAU scenario in 2040. The displacement of thermal power plants with renewable energy technologies has resulted into reduction of CO_2 emission and primary energy supply. The total installed capacity shares of renewable energy technologies increases to 17.1% and 34.7% in 2020 and 2040 respectively. BAU scenario composition was 0.8% in 2020 and 10.6% in 2040. The shares of renewable energy technologies in the total generation mix for REPP scenario has increased to 30% in 2040 as compared to 9.9% it had in BAU scenario. Satisfactory inclusion of renewable energy technologies into electricity generation mix as shown in REPP scenario has demonstrated the importance of compulsory measures in policy formulation in favor of renewable energy sources.

Table 5.6: Renewable energy penetration

	Scenario	2010	2015	2020	2025	2030	2035	2040
Renewables shares in electricity generation (%)	BAU	2.5	1.2	0.6	4.0	15.4	11.3	9.9
	REPP	2.5	1.2	10.1	15.1	20.7	25.0	30.0
CO_2 emission level (kilo tonnes of CO_2)	BAU	1182.3	2134.0	4982.8	4889.3	3266.5	11189.3	23652.3
	REPP	1182.3	2134.0	3874.6	2927.7	1906.2	4380.7	12198.3
Primary energy supply (GWh)	BAU	6202.7	10906.2	21862.9	19430.5	12604.3	34901.5	73083.1
	REPP	6202.7	10906.2	18778.3	14069.0	8924.9	18971.2	41212.6
Renewables installed capacity shares (%)	BAU	0.0	1.2	0.8	3.1	12.7	9.5	10.6
	REPP	0.0	1.2	17.1	20.7	18.1	24.1	34.7

Even though the compulsory policy measures resulted in the expansion of renewable energy technologies shares, REPP scenario depicts additional investments costs as compared to BAU scenario. The comparison in the investments costs between BAU and REPP scenarios is as depicted in Figure 5.11. Meeting REPP scenario requirements will necessitate considerable investment cost of 7,665.8 million US$ as compared to 4,487.6 million US$ for BAU scenario. Contrariwise, as shown in Figure 5.12, REPP scenario accommodation exhibit a decrease in the operation and maintenance variable costs (O&M). There is a decrease to 680.6 million US$ in the operation and maintenance variable costs for REPP scenario when compared to 999.7 million US$ for BAU scenario in the entire study period. MESSAGE modelling results, show that REPP scenario demands a more aggressive approach to investment in renewable energy technologies. For that reason, if the country chooses to implement the policy, additional policies such as renewable energy feed-in tariff and institutional frameworks that are essential for the growth of renewable energy technologies must be in place. The compulsory policy measures as revealed in MESSAGE modelling helps in tapping of the enormous potential of renewable energy resources into electricity generations for the benefit of the environment and security of supply.

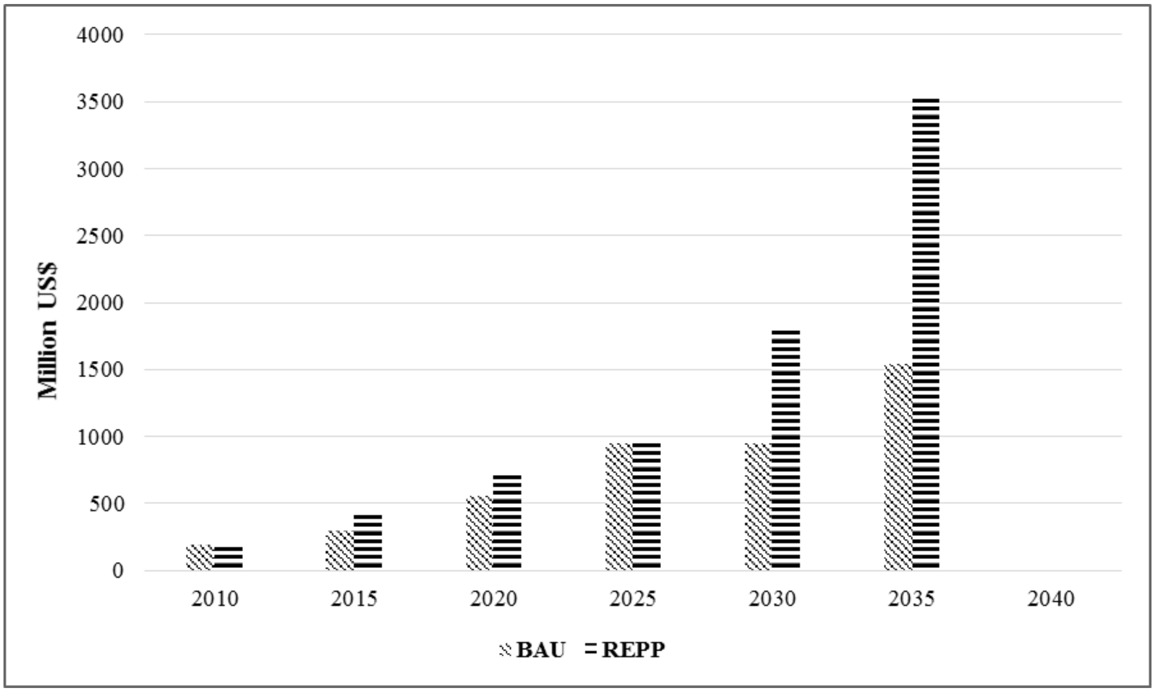


Figure 5.11: Investments costs comparison between BAU and REPP scenarios

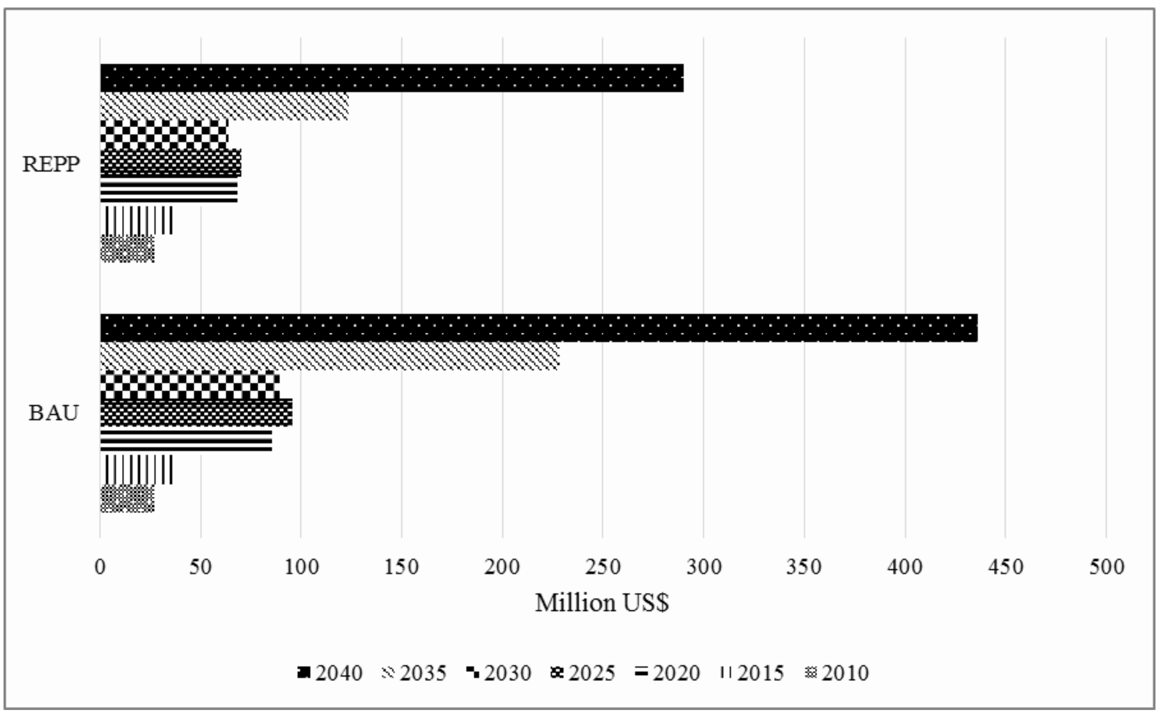


Figure 5.12: Variable O&M costs comparison between BAU and REPP scenarios

5.6.2 Discount rate adjustment

Adjustments was carried out on BAU scenario to approximate the influence of discount rate on the upcoming pattern of electricity generation capacity, electricity production or economic effectiveness of a number of electricity generation plants. The discount rate adjustments carried out were 6%, 8%, 12% and 14% in comparison to a study-adopted value of 10%. Adjustments of discount rate value to 6% preferred early capacity addition of 500 MW wind power plant into electricity generation in 2035 while 8%, 10% and 12% favors addition in 2040 with no addition for the 14% values. Solar PV and thermal failed to be competitive in all discount rates adjustments. These technologies require special policy option for their inclusion into electricity generation to be realistic. Adjustments of discount rate values to 12% and 14% were in favour of capacity addition of CCGT and GT power plants as opposed to lower values (6% and 8%) which preferred coal power plants.

Higher efficiency coupled by a lower operating and maintenance costs, shorter construction time and fuel cost characterizes CCGT and GT power plants thus turn out to be more attractive for capacity addition in comparison to other technologies options. The discounts rates of 6%, 8%, 12% and 14% resulted into coal fired power plants total installed capacity of 6652 MW, 6108 MW, 5385 MW and 4773 MW respectively. In other words, a higher value of discount rate leads to the postponement of large-scale investments. According to the minimum cost criterion, a discount rate of 10% gives greater preference for the fossil fuel scenarios. A decrease or increase of discount rate has insignificant influence on capital investments of hydro, biomass and geothermal which seems to be due mainly to the limited resources potential.

5.6.3 Dry Weather scenario

Experience has shown weather conditions affects electricity generation capacity causing outages and rationing (Loisulie, 2010; MEM, 2013c). The alternative dry weather scenario was formulated to analyse electricity system behavior under uncertain weather conditions. All modelling inputs of dry weather scenario remains the same as in BAU scenario except for the imposed generation's constraints of hydropower to 20% of the total generations in the period 2020-2040. The MESSAGE least-cost results in Table 5.7 depicts the generations will incline to coal and NG power plants at approximately 42.8% and 30.2% respectively in 2040. The capacity additions for coal power plants will expand to 9772 MW as compared to 6040 MW in BAU scenario. Because of imposed hydropower constraints, the CO_2 emission will increase to 86938.67-kilo tonnes of CO_2 as compared to 51296.6-kilo tonnes of CO_2 in BAU scenario.

Table 5.7: Electricity generation shares by technology (%) - dry weather scenario

	2010	2015	2020	2025	2030	2035	2040
Coal_PP	-	-	25.11	34.92	41.15	52.93	42.85
HFO_PP	2.03	0.23	-	-	0.004	0.03	0.01
NG_PP	28.86	54.56	54.41	41.00	22.06	15.60	30.20
CCGT_PP	0.00	76.62	89.11	87.23	92.20	90.55	97.88
GT_PP	100.00	23.38	10.89	12.77	7.80	9.45	2.12
Hydro_PP	66.65	43.98	19.90	20.04	20.23	20.03	16.98
Wind_PP	-	-	-	-	-	-	2.20
Biomass_PP	2.46	1.23	0.59	0.41	0.13	0.07	-
GeoTh_PP	-	-	-	3.63	16.29	11.22	7.71
Solar_PV	-	-	-	-	-	-	-
Solar_Th	-	-	-	-	-	-	-
Electricity Import	-	-	-	-	0.13	0.12	0.05
Total %	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Based on MESSAGE modelling results, if the country chooses to implement measures because of dry weather conditions, more usage of coal and NG as primary energy supplies will be the least cost option. The additional capacity in terms of coal and NG power plants to replace hydropower plants would decrease both the risks of a dry weather condition and energy security uncertainties. However, the weaknesses of coal and NG development into dry weather scenario are the higher CO_2 emissions as compared to BAU scenario as depicted in Figure 5.13. The capital investment cost of dry weather scenario will require less than 535.52 million US$ as compared to capital investment in BAU scenario. Less capital investment cost in dry weather scenario is due to lower capital investment cost and shorter construction time of coal coal-fired and NG power plants. Despite hydro power plant lower operation and maintenance costs, coupled with zero fuel consumption for final electricity generation, they have higher capital investment costs and longer construction life (Sharma, 2010).

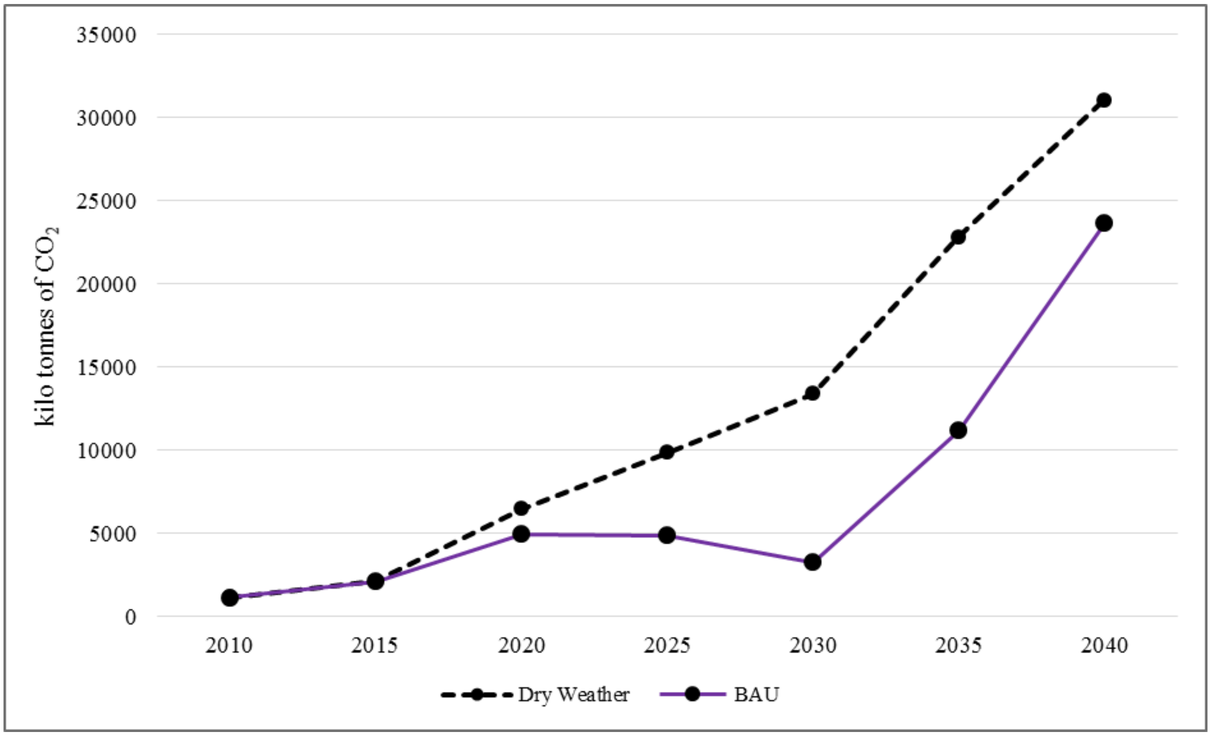


Figure 5.13: Comparison in CO_2 emissions between Dry weather and BAU scenarios

5.7 Conclusion

The study presented a modelling approach on the energy supply options for electricity generation in Tanzania. The modelling approach emphasized optimal results based on the least-cost as assumed in MESSAGE. Based on the results presented, MESSAGE turned out to be a useful tool to address energy supply options for electricity generation in Tanzania. The projected total installed capacity increases gradually from 804.2 MW in the base year to 10811 MW, 9190.9 MW and 13325.6 MW in 2040 for BAU, LEC and HEC scenarios respectively. The increase in the total installed capacity would call for capital investment cost of 4488 million US$, 3903 million US$ and 5573 million US$ respectively for BAU, LEC and HEC scenarios. Hydropower plants dominate the capacity additions followed by coal, CCGT, geothermal and GT power plants to meet the electricity generation expansion in both scenarios. Total primary energy supply dominated by coal and NG rises to 73083 GWh, 57529 GWh and 110,700 GWh in 2040 for BAU, LEC and HEC scenarios respectively, as compared to base year amount of 6203 GWh.

In meeting final electricity demands, CO_2 emissions will expand from 1182-kilo tonnes of CO_2 to 10.5%, 9.5% and 11.7% respectively for BAU, LEC and HEC scenarios with decreases of CO_2 in the REPP scenario. Renewable energy sources as concluded in REPP scenario were identified as promising candidates for meeting the future electricity demand in Tanzania. Potential contribution of renewable energy sources to the savings of coal and NG reserves would be a great contribution to the economy and the environment. However, the dry weather scenario has shown a shift to coal and NG power plants generations at approximately 42.8% and 30.2% respectively resulting into higher CO_2. The sensitivity analysis tests results has shown lower discount rates to favor investments on wind and coal power plants while higher discount rates favor NG power plants. The least-cost results has shown implications concerning capital investment costs versus environmental impacts concerns. Least cost modelling results have concluded that meeting final electricity demands without considerations of environmental impacts concerns is cheaper. Policy makers should balance the capital investment costs and environmental concerns in the energy planning of the country.

CHAPTER SIX

PREDICTION OF THE CONTRIBUTION OF RENEWABLE ENERGY SOURCES IN ELECTRICITY GENERATION IN TANZANIA [5]

6.1 Abstract

This paper analyses through modelling the contribution of renewable energy in electricity generation in Tanzania. Two scenarios with regards to the Tanzanian power sector were developed representing a renewable energy promotion scenario and the base case scenario. The base case scenario was developed as an overall scenario to predict the supply of energy resources for power generation, whereas the renewable energy promotion scenario was imposed with constraints requiring the gradual introduction of renewable energy technology into electricity generation. The analysis of the power sector for the two scenarios was based on installed capacity, power generation, CO_2 emissions and investment costs using Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE). The results from two scenarios show power generation will be optimally expanded from 11,291 GWh in 2015 to 54,981 GWh in 2035. The total installed capacity will be 2,383 MW in 2015 as compared to 13,177 MW in 2040. Total investment cost for the renewable energy promotion scenario is higher compared to the base case scenario. Renewable energy promotion scenario showed reduction in CO_2 emission contrary to the base case scenario. It is evident from results that without intervention in promoting renewable energy, its contribution in power generation will remain insignificant. The study concludes that it is possible to have renewable energy shares in the power generation mix with an associated rise in investment costs and reduction in CO_2 emission.

6.2 Introduction

Renewable energy is an important energy resource due to its availability and is generally clean, hence environmentally friendly (Dincer, 2000). The use of renewable energy sources in electricity generation is essential for socioeconomic development as it enables production of various products

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and services, which are essential for human wellbeing ranging from domestic to industrial use with ensured security in supply. Tanzania's total primary energy supply in 2011 is estimated at 20.75 MTOE while energy net imports stood at 1.64 MTOE (IEA, 2013a). The total electricity generated in 2011 was estimated at 4,076 GWh with total system loss of 23% for interconnected grids. Tanzania's annual per capita electricity consumption stood at 81 kWh in 2011/2012, with the target being 200 kWh in 2015/2016 (MEM, 2012). In Tanzania 18.5% of total population have access to electricity (Msyani, 2013).

Total installed capacity for power generation as of 2012 was hydro 565 MW, natural gas 501 MW and oil products 375 MW with a negligible contribution from renewable energy sources (MEM, 2013c). Main sources of energy for electricity generation in Tanzania are coal, oil products, natural gas and hydro. Figure 6.1 illustrates electricity generation using different sources energy from 1990-2011(IEA, 2013a). Power available for isolated grids through imports from Uganda and Zambia is 8 MW and 5 MW respectively (MEM, 2012; Vernstrom, 2010). Isolated grids comprise of installed capacity of 21.6 MW both being from thermal sources (Mgonja, 2011). The sector has seen a rapid growth in power demand. It is projected the power demand will rise to 75% from the current status of 18.5% (MEM, 2012, 2013c). country's distribution networks as of 2011 comprised of 400/240 V lines having a length of approximately 26,565km with a system loss of 23.5% (MEM, 2012).

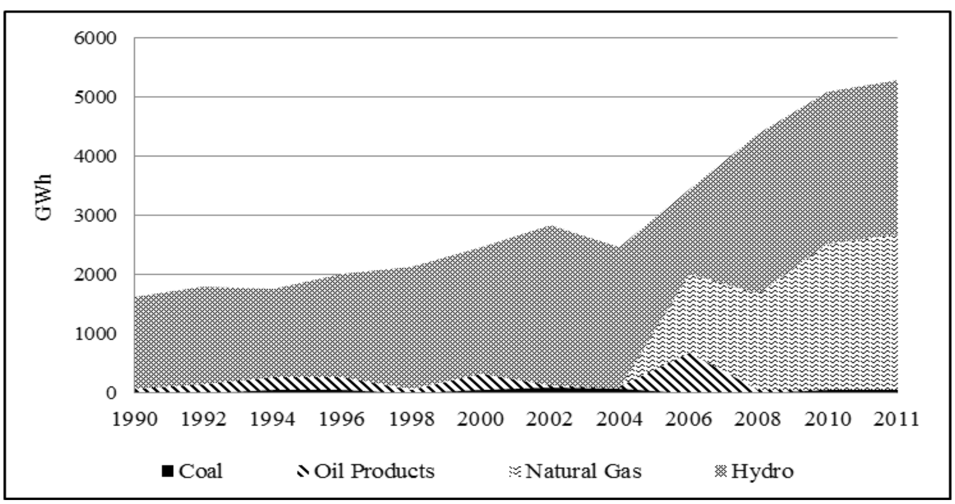

Figure 6.1: Power generation by fuel type

The power sector has been faced with recurrent challenges in power generation that have seriously affected national socio-economic development and the environment. Major challenges facing the power sector are generation challenges, aging infrastructure, power demand growth outstripping supply, high transmission and distribution losses, among many others (Kihwele et al., 2012). Generation challenges have also been due to country's over reliance on hydro for electricity generation (Kihwele et al., 2012; MEM, 2013c). The country's spatiotemporal distribution of rainfall suggests a decrease in the overall annual rainfall accompanied by intensified and prolonged dry and wet spell weather events making the predictability of seasonal weather patterns more challenging (Casmiri, 2009; Loisulie, 2010; Valimba, 2004). These effects can be traced back to 2006 where power demand was then 540 MW while the six hydro power plants production reached a minimum record of 50 MW at some points (IEA, 2012; Loisulie, 2010).

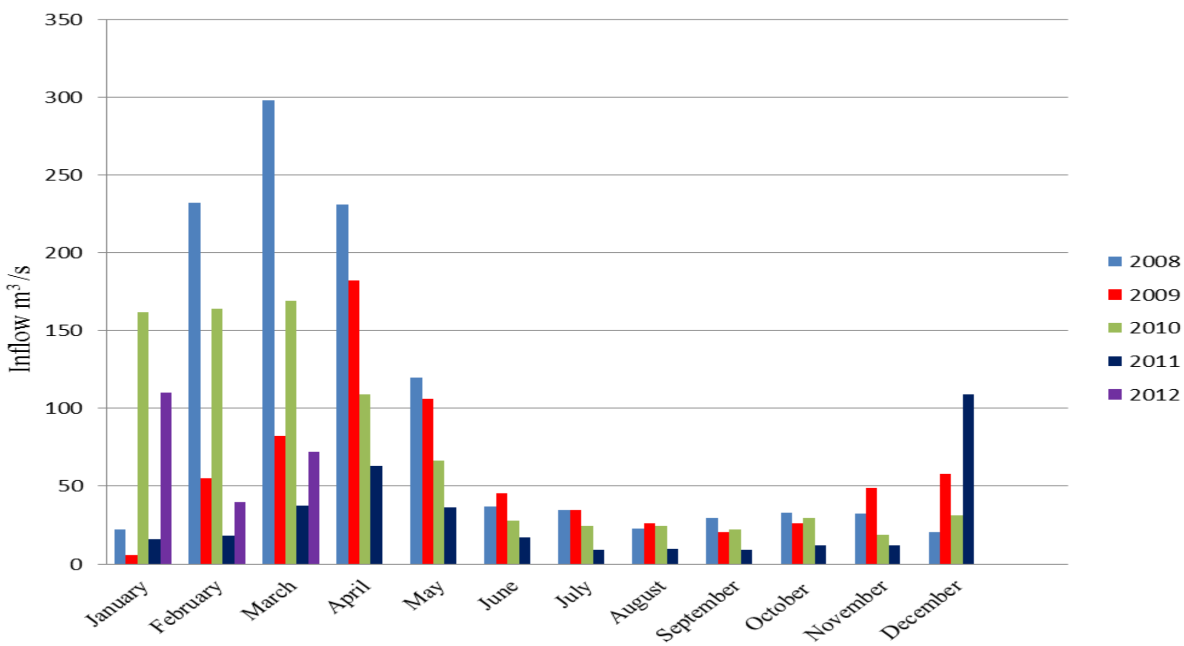

Figure 6.2: Mtera hydro reservoir inflows

An example of weather patterns predictability challenges were as those witnessed at Mtera dam, which is the largest hydroelectric dam in Tanzania. The dam built to ensure that there is sufficient water dammed throughout the year to supply the Kidatu hydropower plant. The dam has a catchment area of 68,000 square kilometers with a storage volume of 3,200 million cubic meters (Casmiri, 2009). Mtera dam has experienced high unpredictability in annual rainfall since 2008 as illustrated in Figure 6.2 (MEM, 2013c). The data in Figure 6.2 indicate an overall decrease in rainfall with the frequency of below-average rainfall increasing (MEM, 2013c).

As a solution to hydropower generation challenges, the alternate option focused on thermal generation using locally available natural gas and imported oil products. Status shows the decline in hydropower dependence with the recent share being at 35% in 2012 as compared to more than 50% prior to 2000 (MEM, 2013c). Tanzania is now shifting from hydro generation to thermal generation as a measure to fill in the gap due to the frequent drought occurrences. This shifting has caused a high cost of electricity due to the use of thermal emergency power producers (EPP's). Electricity has turned out to be an expensive commodity primarily due to the dominance of thermal generation and secondly the obsolescence of hydropower plants as depicted in Table 6.1. More than half of hydropower plants in operations are of over twenty years of age. The average life span of hydropower plant is estimated at 50 years after which they will require major overhaul (Yüksel, 2010). Thermal power generation has the consequence of high electricity tariffs as compared to hydro-power generation. The average cost of electricity from hydro is 0.063 US$/kWh as compared to 0.33 US$/kWh for oil products thermal generations (Evans et al., 2009; MEM, 2012; Sims et al., 2003) even though the cost is even down to 0.22 US$/kWh.

Table 6.1: Hydro Power Plants in Tanzania

Plant Name	Installation Year	Plant Capacity (MW)	Firm Energy (MW)
Mtera	1988	80	195
Kidatu	1975	204	601
Hale	1967	21	55
Kihansi	2000	180	492
Pangani Falls	1995	68	201
Nyumba ya Mungu	1968	8	20

Power generation is an important area with strong potential to contribute towards sustainable economic growth. The use of renewable energy sources is one of solutions in addressing the challenges related to the recurrent drought affecting hydropower generation and the environment (Hossain, 2012). Renewable energy resource potential in Tanzania has not been fully exploited, predominantly due to the limited policy interest and investment levels as is the case for the rest of Africa (Karekezi and Kithyoma, 2003) although the trend is rapidly changing in recent years. This study focused on modeling the contribution of renewable energy sources into electricity generation using the Model for Energy Supply Strategy Alternatives and their General Environmental Impacts abbreviated as MESSAGE. Modelling results from the study will be used as a tool for the policy and decision makers to arrive at a relevant solution interactively in the use of renewable energy resources to meet the power demands of Tanzania. Through the output of this study, it is expected Tanzania will realize sustainable economic development, a stable power supply based on a balanced energy resource mix and ensured energy security due to the use of local energy resources.

6.3 Methodology

In this study, a bottom-up integer programming based optimization model known as Model for Energy Supply Strategy Alternatives and their General Environmental Impacts (MESSAGE) was used. The model works on the principle of reference energy system which allows representation of the entire energy network including existing and future technologies (Pinthong and Wongsapai, 2009; Rečka, 2011; Selvakkumaran and Limmeechokchai, 2011; Van Beeck, 1999). MESSAGE has an objective of planning to meet demand while minimizing total energy system cost. Mathematical techniques used in MESSAGE are composed of linear and mixed-integer programming (Van Beeck, 1999).

MESSAGE has been chosen in optimizing the scenarios in this study due to its features that provide a flexible framework for the wide-ranging modeling of diverse energy supply systems. MESSAGE is the sophisticated model that has the capability to optimize energy supply under user defined constraints such as energy policy constraints, rates of technology penetration in the market, fuel availability and environmental emission control (AlFarra and Abu-Hijleh, 2012; IAEA, 2008). Furthermore, MESSAGE considers current installations and expedient life span, the indigenous availability of energy resources, options for technology expansion and replacement of retired units (Hainoun et al., 2006).

6.4.1 Modelling Scenarios

The modeling process applied two scenarios to analyze the contribution of renewable energy in power generation, which are the base case scenario (BCS), and renewable energy scenario (RES).

The renewable energy in this study is limited to wind, solar PV, solar thermal, geothermal and biomass, excludes hydropower. One important features of renewable energy when it comes to contribution in electricity generation is their failure to compete under least-cost basis. Hydropower is quite different from the other renewable energy such as solar PV and solar thermal as under least cost basis, hydropower is so competitive. Furthermore, hydropower is a mature technology in Tanzania, and has been extensively in use for over forty years. For modelling purposes of this study, hydropower treatment is like other technologies, which are cost competitive such as coal, natural gas among many others.

The BCS is an overall electricity generation scenario. The scenario intends to illustrate how the electricity generation mix would take into account renewable energy technologies (RETs) into power generation. In the BCS, renewable and non-renewable technologies compete equally for the share in electricity generation. The main feature of BCS is to consider the growth of energy systems, and to minimize total discounted energy costs based on the technology and resource cost as inputs to the model. This scenario focuses on optimizing investments to get a least cost composition of energy sources and technologies to supply electricity in Tanzania.

The RES development requires a mandatory minimum share of renewable energy penetration into electricity generation. The scenario target is to introduce steadily the generation of electricity with renewable energy technologies into the total country generations. In the RES scenario, it is required to have a 15% share of wind, solar PV, geothermal, biomass and solar thermal (added together) of the total electricity generation by 2040 starting from 5% in 2020 and progressively increase the share to 10% in 2025 and 15% in 2030 through 2040. The basis for these growth rates is the country has never crossed a share of 1% renewable energy (excluding hydro) prior to 2010 of the total generation. These growth rates are realistic to start with and corresponds to targets set by a number of Sub-Saharan countries with similar economic characteristics as Tanzania.

6.4.2 Data

Data for the study consisted of electricity demand, technologies, technological constraints and efficiencies, technology's lifetime, investments, fixed costs and capacity boundary. These data are needed to optimize the energy investment through the least cost supply solution in the long-term.

Additionally the annual load curve distributed hourly and monthly to capture the variations of demand for fuels within a year was generated.

The study applied seven different technologies using natural gas (subdivided into two technologies), biomass, geothermal, solar, wind, coal and imported oil products as fuels for the optimization of power generations under the two scenarios. Natural gas technologies that were used in the optimization were gas turbine (GT) and combined cycle gas turbine (CCGT) power plants. Technologies for solar were solar PV and solar thermal. Other technologies were coal, biomass, geothermal, hydro and wind power plants. Data for this study has been collected from the Tanzania Electric Supply Company Limited (TANESCO), Ministry of Energy and Minerals (MEM) - Tanzania and International Energy Agency (IEA).

6.4 Results and Discussions

The optimal energy mix considering resources investment costs, installed capacity and technologies for the diversification of electricity supply in Tanzania is analyzed in the next sections.

6.4.1 Load Curves

The annual load curve distributed hourly and monthly was generated to capture energy consumption behavior. The hourly generation data collected from TANESCO for the years 2009 to 2012 were explored to reveal load demands characteristics in Tanzania. Hourly load curves were generated by taking average and maximum of values in load demands for a particular hour throughout a year. The hourly load curve is illustrated in Figure 6.3. It is evident that there is a sharp decrease in demand from 21:00 to 4:00 where the lowest demand point is depicted. This is explained by the fact that most of load demands in households are switched off for the night. The load demands start to peak slowly again at 5:00 and continues with the trend up to 10:00. At this time horizon most of load consumers at household level are awake for the day's activities and industry consumers often starts the days' work at 8:00.

The load starts to level off from 10:00 to 18:00 though there are some drops in demand from 13:00 to 18:00. This is because most industrial activities schedules for a lunch break at 13:00 and after that, they wind up the day's activities. The hourly load curve shows there is a very sharp rise in the load demand from 18:00 and reach peak level at 21:00. This attributes mainly by a growing demand by a household consumer for lighting and other activities. Load peak hours of the day are observed between 18:00, 21:00, and the lowest load demand being between 4:00 and 5:00.

The daily, hourly load pattern displays a constant load during the day followed by an evening peak with the exception of Sunday. The Sunday hourly load pattern displays a morning and an evening peak and is typically at a lower demand level than the rest of the week. An average hourly load curve divides into five parts to capture the variations in load demands in the MESSAGE model.

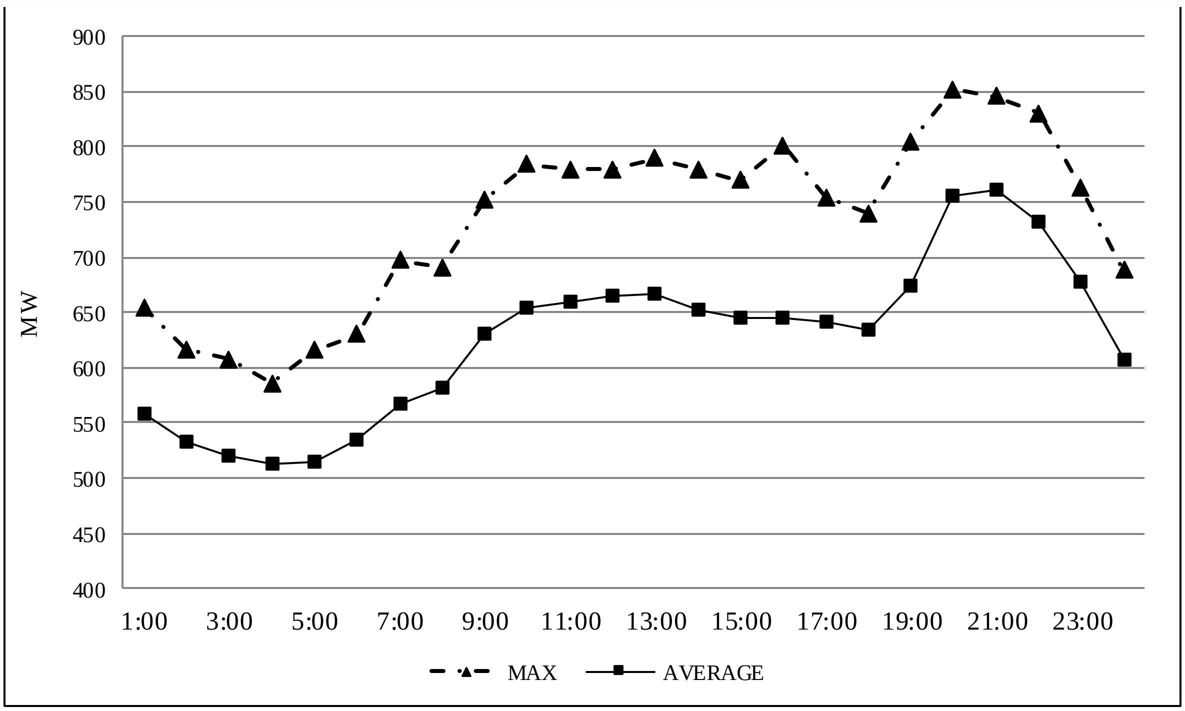

Figure 6.3: Hourly load curves

6.4.2 Scenario Analysis

Optimization results for electricity generation mix in BCS are as illustrated in Figure 6.4. Electricity generation mix in the BCS is dominated by natural gas, hydro and coal. In BCS a total of 11,291 GWh will be generated in 2015 as compared to 54,981 GWh in 2035. Matching these results with official projections a total of 11,246 GWh and 47,724 GWh were projected as demands in the year 2015 and 2035 respectively (MEM, 2012, MEM, 2013). The marginal difference between the least-cost and official projections attributes to the reserve margin considered in optimizations.

In relation to the modeling results for BCS, natural gas will have the largest share at 44%, followed by coal and hydro at 31.8% and 24% respectively in 2015. The dominance of natural gas will continue through 2040 when natural gas will command a share of 54.3%. The share of hydro will increase from around 24% in 2015 to 40% by 2030 and then decrease to 25% in 2040. The share of hydro and geothermal are limited due to potential constraint of 4700 MW and 650 MW respectively despite their low operating cost advantages (Dincer, 2000; Kihwele et al., 2012; Kusekwa, 2013). Power generation is expected to almost triple by 2025. Combined cycle gas turbine (CCGT) leads natural gas technologies for power production commanding a share of 79%, 90% and 100% in the years 2015, 2020 and 2025 respectively. That is to say, among natural gas technologies the CCGT are more preferred as compared to GT. This is attributes to good availability, better efficiency and short construction times as compared to gas turbine (GT) technology, which is suitable for peak times. CCGTs are the highly favored option where gas is available at reasonable prices due to the peak efficiency of 60% as compared to 40% for GT (Sharman, 2005; Sims et al., 2003).

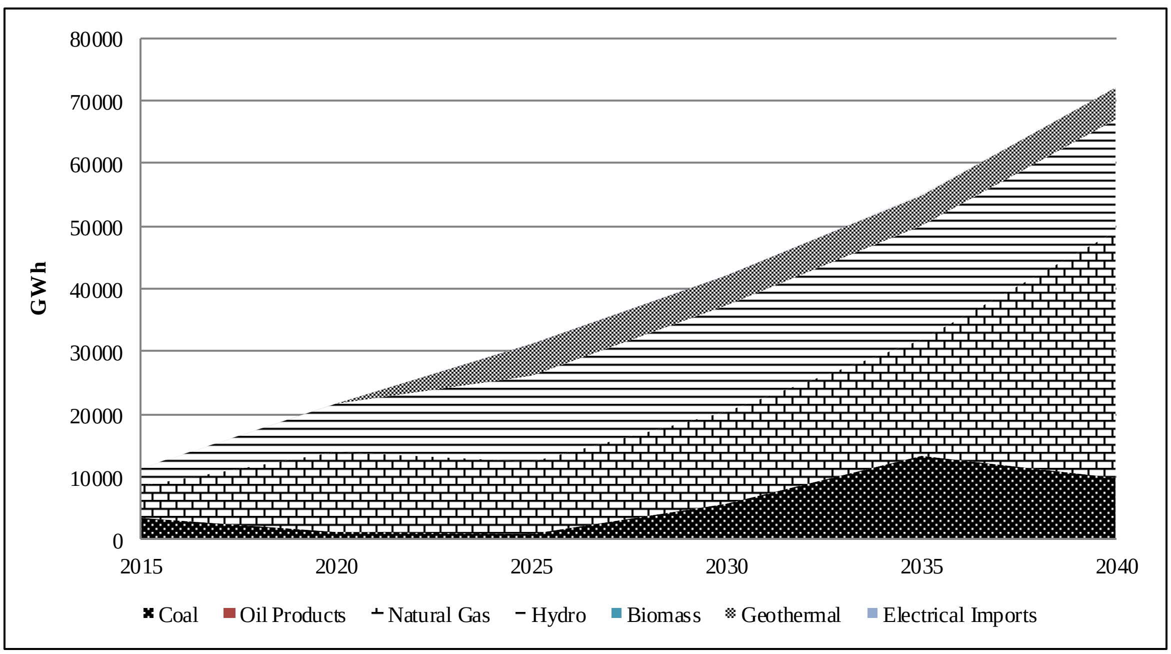

Figure 6.4: Electricity generation mix – BCS

Renewable energy technologies were not able to be competitive in the BCS as the optimization was based on meeting demand at a least cost composition of energy sources and technologies. This is due to cost profiles for renewable energy such as solar technologies being of high capital investment and low running costs, due to no fuel requirements (Evans et al., 2009). The only renewable energy technology that was able to penetrate into the energy mix in 2020 was geothermal. Geothermal is characterized by high availability capable to provide base load power for 24 hours a day and lower operating costs as compared to other renewable energy technologies (Evans et al., 2009; Karekezi and Kithyoma, 2003; Sims et al., 2003).

The optimization results for installed capacities of various technologies to produce electricity through 2040 in the BCS are illustrated in Figure 6.5. Total installed capacity for the years 2015, 2035 and 2040 are 2,383 MW, 9,083 MW and 13,177 MW respectively. Relating these optimization results with official projections, a total of installed capacity for 2015 and 2035 was projected at 2,088 MW and 7,645 MW respectively (MEM, 2012, 2013c). The contribution of fossil fuel sources in BCS for 2035 will be 1808 MW equivalent to 76% of the total installed capacity whereas hydro will contribute 24%. In the year 2040, natural gas will contribute 55%, which is the largest share among fossil fuels in the total installed capacity followed by 11% and 29% from coal and hydro respectively with the rest from geothermal. There is little contribution of renewable energy in the base case scenario and the contribution of fossil fuel technologies constitutes more than half of the total installed capacity.

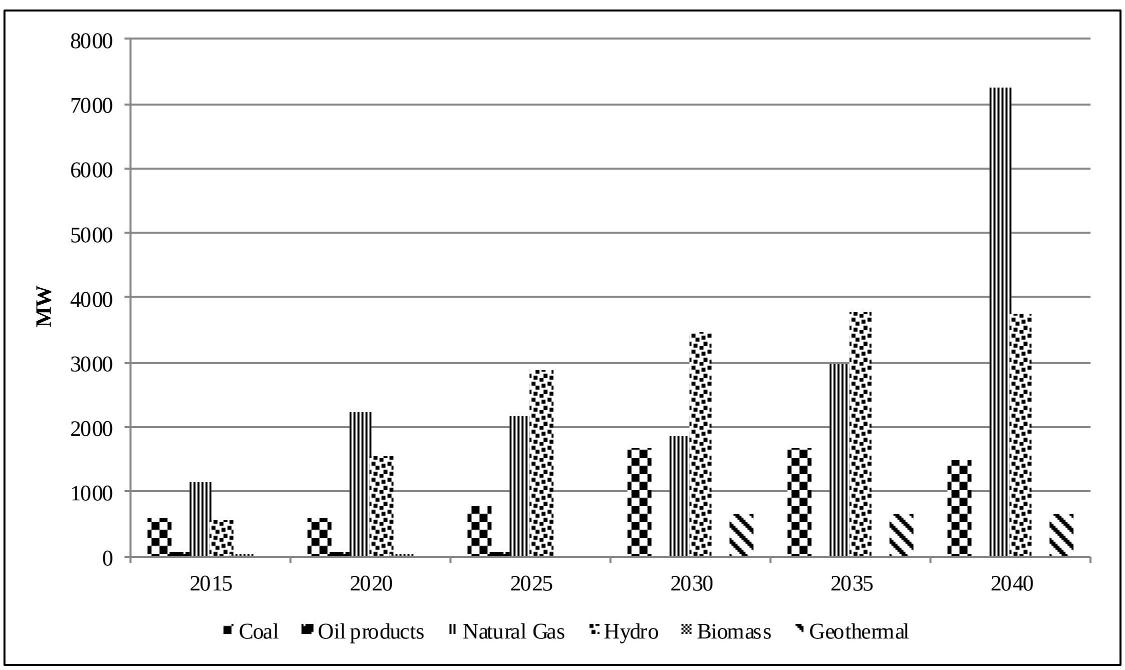

Figure 6.5: Total Installed capacity – BCS

The optimization results for electricity generation mix in the RES are as illustrated in Figure 6.6. Electricity generation mix for the RES show an increase in the share of renewable energy from 5% in the year 2020 to 10% in 2025 and 15% in 2030 through 2040. Overall electricity generation in the renewable energy promotion scenario show natural gas power plants to contribute 45.6% of the total electricity generated in the year 2040 followed by 25% from hydro power plants and 14% from coal. The amount of electricity from fossil fuel sources will decrease from 49,023 GWh in BCS to 42,987 GWh in RES, the difference being taken by renewable energy sources. In the year 2040, the total contribution from renewable energy sources will amount to 10,876 GWh as compared to 4840 GWh in the BCS.

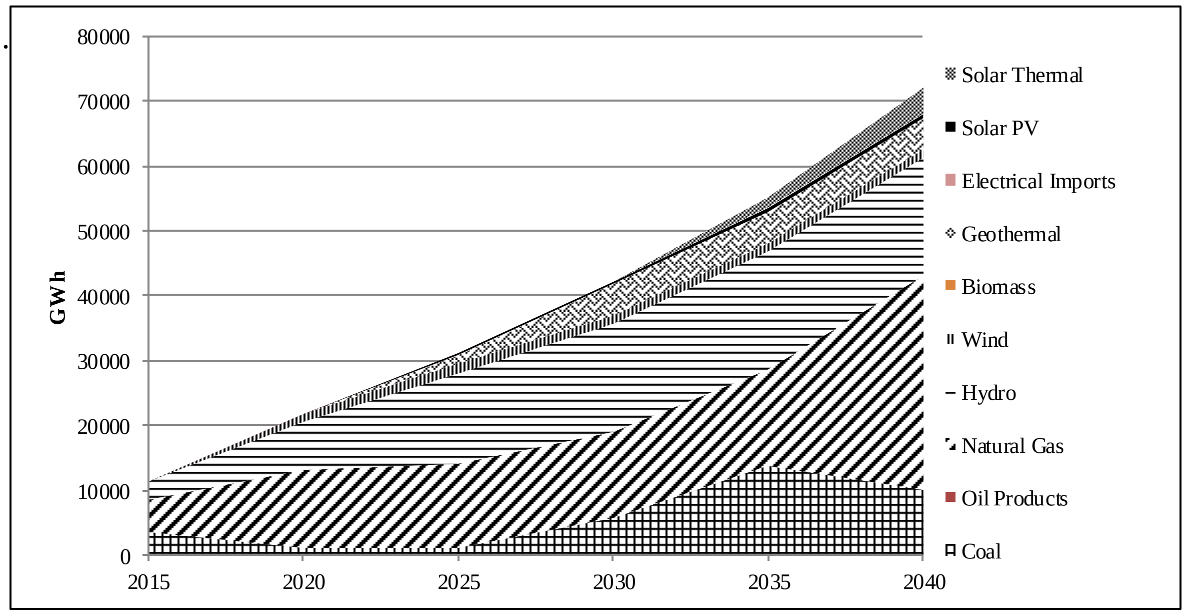

Figure 6.6: Electricity generation mix – RES

Total installed capacity in RES is as illustrated in Table 6.2 for the period from 2015 to 2040. A total of 1216 MW in renewable energy sources will be installed in 2035 of which wind, solar thermal and solar PV geothermal will contribute 500 MW, 516 MW and 200 MW respectively. The contribution of coal and natural gas for the year 2035 will be 1800 MW and 3618 MW respectively in the total installed capacity. Hydro power plants contribute 3775 MW and 3759 MW to the total installed capacity in the years 2035 and 2040 respectively. Installed capacity for solar PV will increase gradually from 44 MW in 2030 up to 200 MW in 2035 and then retreat to 156

MW in 2040. This is due to availability of geothermal which is cheaper than solar PV. Solar thermal will increase gradually from 516 MW in 2035 to 1400 MW in 2040.

Table 6.2: Total Installed Capacity (MW) -RES

	2015	2020	2025	2030	2035	2040
Coal	412	412	712	1800	1800	1500
Oil Products (HFO)	63	63	63	0	0	0
Natural Gas	541	1394	2228	2313	3618	6278
Hydro	565	1564	2875	3475	3775	3759
Wind	0	0	0	500	500	0
Biomass	10	10	0	0	0	0
Geothermal	0	0	200	650	650	650
Electrical Imports	0	200	200	200	0	0
Solar PV	0	0	0	44	200	156
Solar Thermal	0	0	0	0	516	1400
Total	**1590**	**3642**	**6277**	**8983**	**11059**	**13743**

6.4.3 Comparison of BCS and RES

Comparison of investment costs between BCS and RES is as illustrated in Figure 6.7. Compared with RES, higher investment costs for renewable energy technologies drive the use of hydro, coal, oil products, geothermal and natural gas technologies in electricity generation under the BCS. The general trend of RES shows the replacement of coal- and oil-based generation with renewable energy technologies. This is achieved after imposing constraints that require the introduction of renewable energy shares. The consequence of the replacement is associated with the rise in investment costs. There is an increase of approximately 10% in investment cost under RES as compared to BCS. It is more expensive to implement renewable energy electricity generation as compared to conventional fossil fuel. Furthermore, simulation results reveal that without imposing constraints, it is difficult to have a reasonable share in renewable energy technologies for electricity generation.

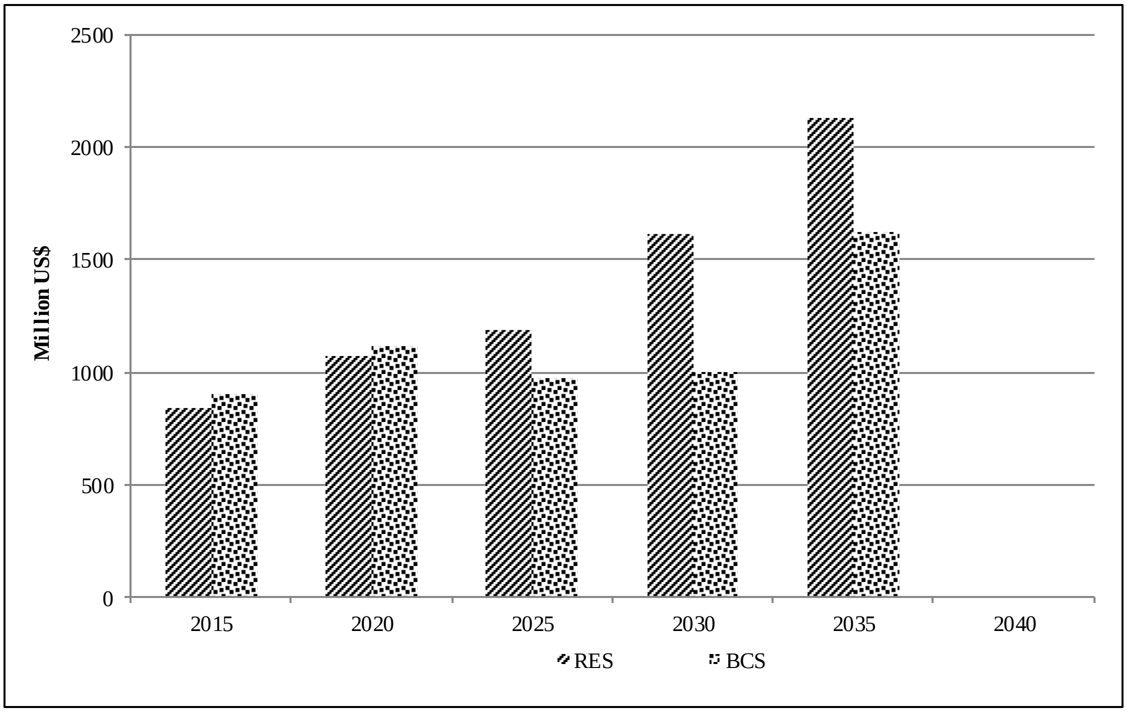

Figure 6.7: Investments cost comparison

Comparison of scenarios in terms of environmental impacts has shown BCS to produce more CO_2 as compared to RES. The level of emissions under BCS and RES are illustrated in Figure 6.8. The level of CO_2 in 2015 is the same for both scenarios, but decreases in RES as imposed constraints are effected. As the share of renewable energy increases, the amount of CO_2 decreases too. The CO_2 emissions saving in RES amounts to 2,565 kilo tonnes of CO_2 in 2040 as compared to BCS. The saving in CO_2 will help curbs greenhouse emissions which are on increase globally causing climate change (Ziuku and Meyer, 2012).

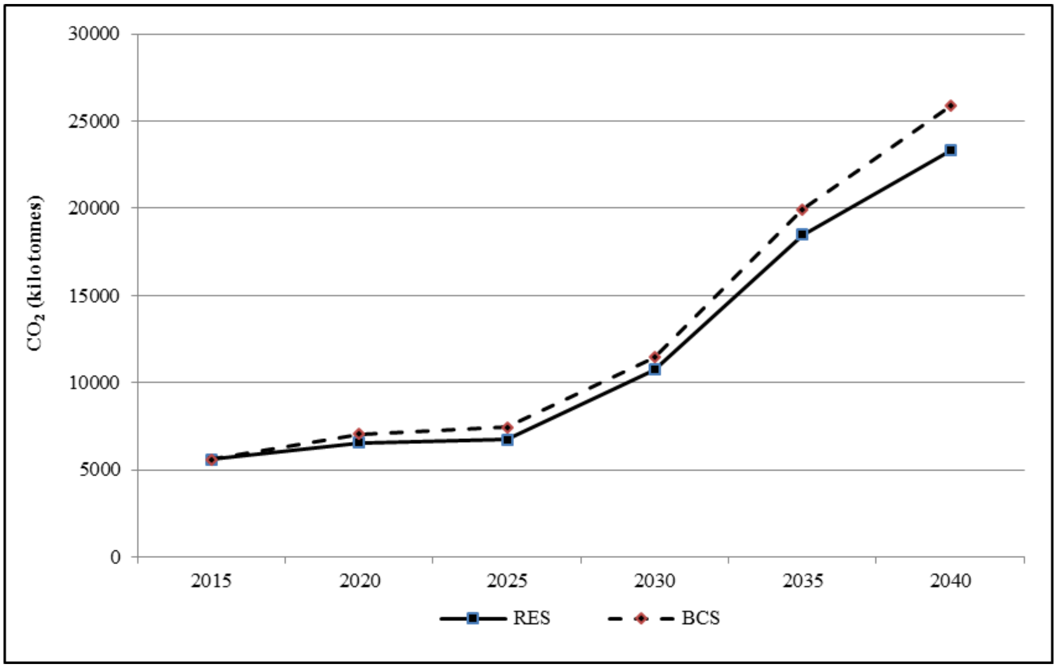

Figure 6.8: CO_2 Emissions levels comparison

6.5 Conclusion

Optimization of the renewable energy scenario showed that it is possible to have a share of renewable energy mix in electricity generation with an associated rise in investment costs. Inclusion of renewable energy sources in the power mix will increase the investment cost by 10% as compared to BCS in the period 2015 - 2040. Renewable energy for generations of electricity is more expensive to implement than fossil fuels. Apart from cost implications, renewable energy sources in the energy mix will replace a considerable amount of coal, natural gas and oil products and hence result in a less polluted environment. Renewable energy sources can play a leading role in moving Tanzania on a more secure, reliable and sustainable energy track. The potential of renewable energy sources in Tanzania is enormous, but their contribution in Tanzania power generation relies on government support to make them cost-competitive. This has been demonstrated by the analysis of the two scenarios, which indicate that without policy interventions renewable energy will not be able to penetrate the power generation mix. The government should implement REFiTs, which is in draft stage to encourage investment in renewable energy generation. REFiTs have the potential to successfully, increase overall electricity generation while reducing the greenhouse gas emission and other economic development problems related to energy use.

CHAPTER SEVEN

MAIN FINDINGS AND DISCUSSIONS

7.1 Introduction

This paper-based dissertation titled, "Modelling of Energy Demand and Supply Patterns in Tanzania" primary objective was to develop long-term energy demand and supply patterns for Tanzania that would enable the country to meet her growing energy demand sustainably using the current and future available energy resources. This chapter, presents summaries of the main findings and general discussions resulting from papers presented in chapters two, three, four, five and six. The dissertation first part as given in chapter two and three, applied machine-learning approach to analyse the influence of selected indicators in the prediction of energy demand. The second part of the dissertation as given in chapter four, five and six, applied bottom-up modelling approach to simulate future energy demand through formulated scenarios and then optimize electricity supply options.

7.2 Machine Learning Approach

In addressing the general objective, the analysis of the influence of selected indicators in the prediction of energy demand preceded the study through the use of machine learning approach involving ANN-MLP, MLR and SVR. The analysis was based on selected socio-economic and environment indicators that were determined to have influence in the energy demand of Tanzania. These indicators included population, GDP, per capita energy use, total primary energy supply, gross national income per capita, electricity, GHG emissions and year. The selected indicators were grouped to form economic, energy and environment indicator models. The economic indicators model considered in the analysis took GDP, gross national income per capita, population and year as explanatory variables and energy demand as dependent variable. In the energy indicators model, the choice of explanatory variables was based on per capita energy use, total primary energy supply, electricity, population and year as explanatory variables while energy demand was a dependent variable. Similarly, for the environment indicators model energy demand was the dependent variable with GHG, population and year were taken as explanatory variables.

7.2.1 Cross-validation (CV) process

The experimental set-up for machine learning is as given in Section 2.4.2 and Section 3.4.2 of this dissertation. The analysis was carried out using Weka, which is a suite of machine learning software written in Java applicable for data mining tasks. The training and testing of data for all the experiments were done and cross-validated using k folds cross-validation. In the k fold cross validation, the original full sample data is divided into $k-$ subsamples data lacking overlays. For a 10 folds cross validation as applied in this dissertation, the division was k1, k2, k3 …… to k10. In the first case run, k1 up to k9 is selected as a training set to develop a model. The developed model uses the remaining k10 to test its performance. For the second case run, k10 and k1 to k8 forms a training set that develop a model, which then uses k9 to test its performance. The cross-validation process is repeated in a similar manner to ensure each fold is used only once as the validation data. The k performances from all folds are then averaged by Weka and then presented on the output-pane. With the 10 fold cross validation, 10 different models are build using 10 different folds, which gives the average performance. A 10 folds cross-validation process in a simplified form is as depicted in Figure 7.1.

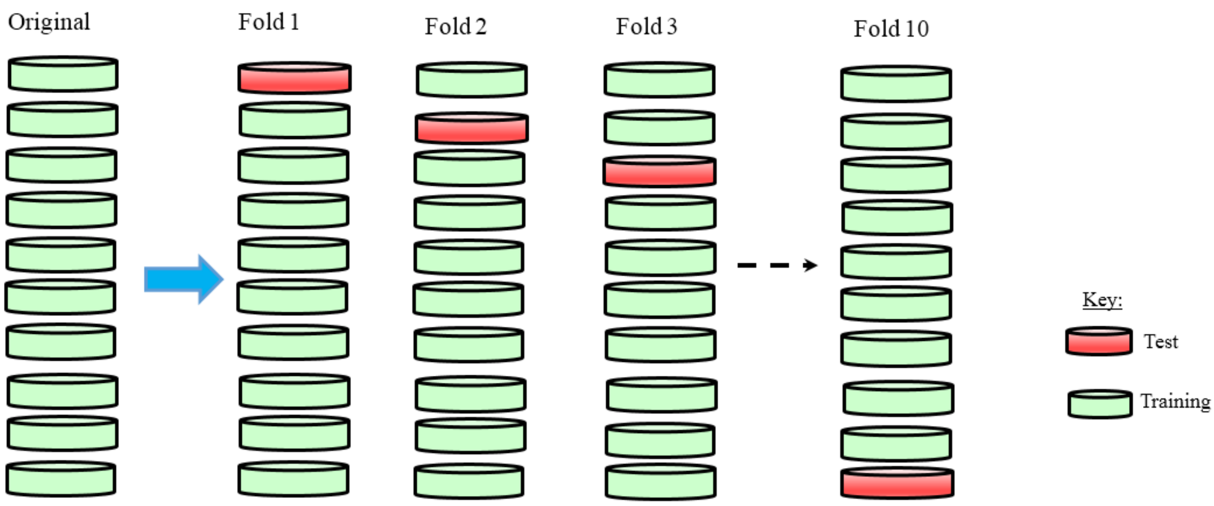

Figure 7.1: Simplified cross-validation process

The choice of 10 folds cross validation bases on an extensive test previously done on a number of datasets using different learning techniques, which concluded it as the best number of folds for error estimation. The following literatures provides details on the benefits and deficiency of 10 cross validation; Bengio and Grandvalet (2004), Witten and Frank (2005), Markatou *et al.* (2005), Abu-Nimeh *et al.* (2007), Schaffer (1993), Arlot and Celisse (2010). Using 10 folds means that of the total sample data set, 90% is for training and the remaining 10% for validation process. In practice, 90% is very near to 100% that makes the cross validation to produces a reasonable estimation of test performance as opposed to using 100% sample data set for training and test its performance against another hidden test set.

7.2.2 Machine learning major results

The results of ANN-MLP and MLR (Kichonge *et al.*, 2014d) as presented in Chapter Two of this dissertation unanimously suggests a higher generalization accuracy in the prediction of energy demand with the use of the energy indicators models than economic and environment indicators models. A similar case is also observed in the application of SVR (Kichonge *et al.*, 2015b) as mentioned in Chapter Three of which the generalization performance of the polynomial-SVR kernel and energy indicators model outperformed economic and environment indicators models in the prediction of energy demand. The graphical representation as shown in Figure 7.2 of the generalization accuracies indicated that it is difficult to differentiate the accuracies of ANN-MLP, MLR and SVR, though the values of ANN-MLP seem to lie closer together than that of MLR and SVM. This is indicative of superior correlation and therefore predictive ability of ANN-MLP than its counterparts MLR and SVM. Table 7.1 supports the situation in which ANN-MLP outperforms others with CC value of 0.9995 as compared to corresponding values of 0.9993 and 0.9990 produced by MLR and SVR respectively. In addition to that, ANN-MLP is lower among others in terms of MAE, RMSE, RAE and RRSE values. On the whole, the results depicted in Figure 7.3 shows the deviations of ANN-MLP are in the range of +0.214 and -0.188 for all years much less as compared to MLR and SVR. The maximum deviation is obtained by SVR at +0.303 in 2004 followed by -0.286 in 2001 for MLR. As also shown the minimum deviation is obtained by ANN-MLP at -0.002 in 2004.

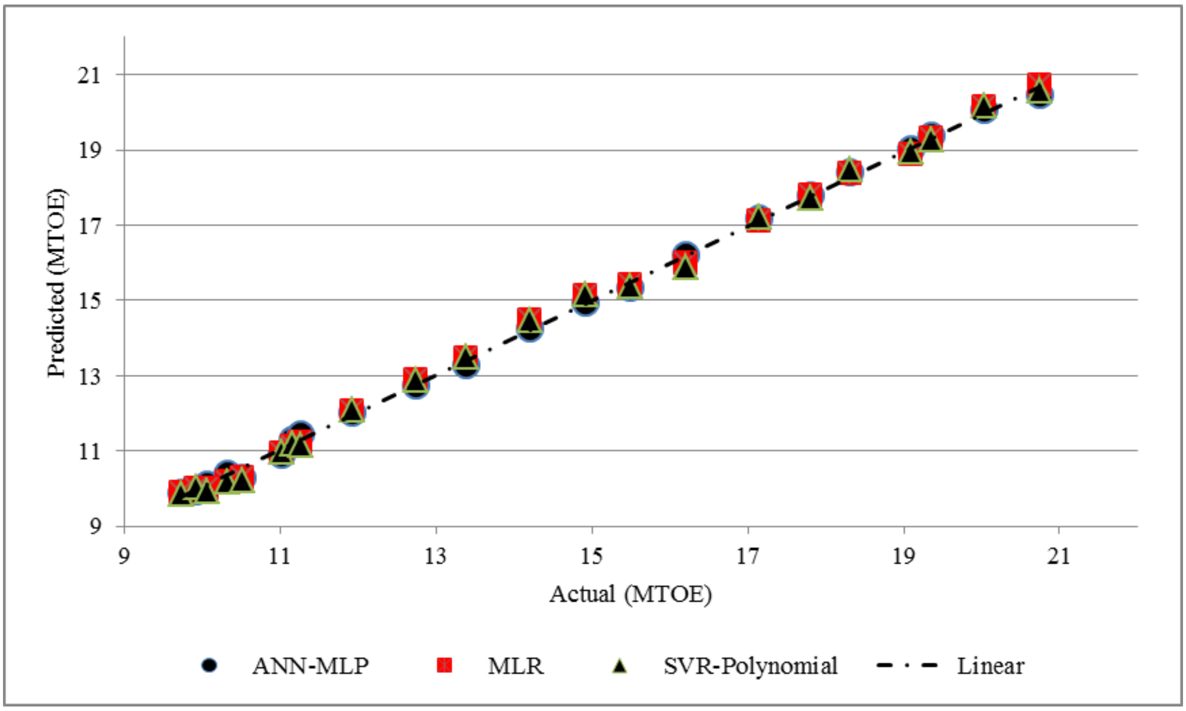

Figure 7.2: Generalization accuracies of ANN-MLP, MLR and SVR

Table 7.1: ANN-MLP, MLR and SVR results - energy indicators model

	ANN-MLP	MLR	SVR (polynomial)
CC	0.9995	0.9993	0.999
MAE	0.0873	0.1102	0.1448
RMSE	0.1155	0.1329	0.1629
RAE	2.57%	3.25%	4.27%
RRSE	3.04%	3.51%	4.30%

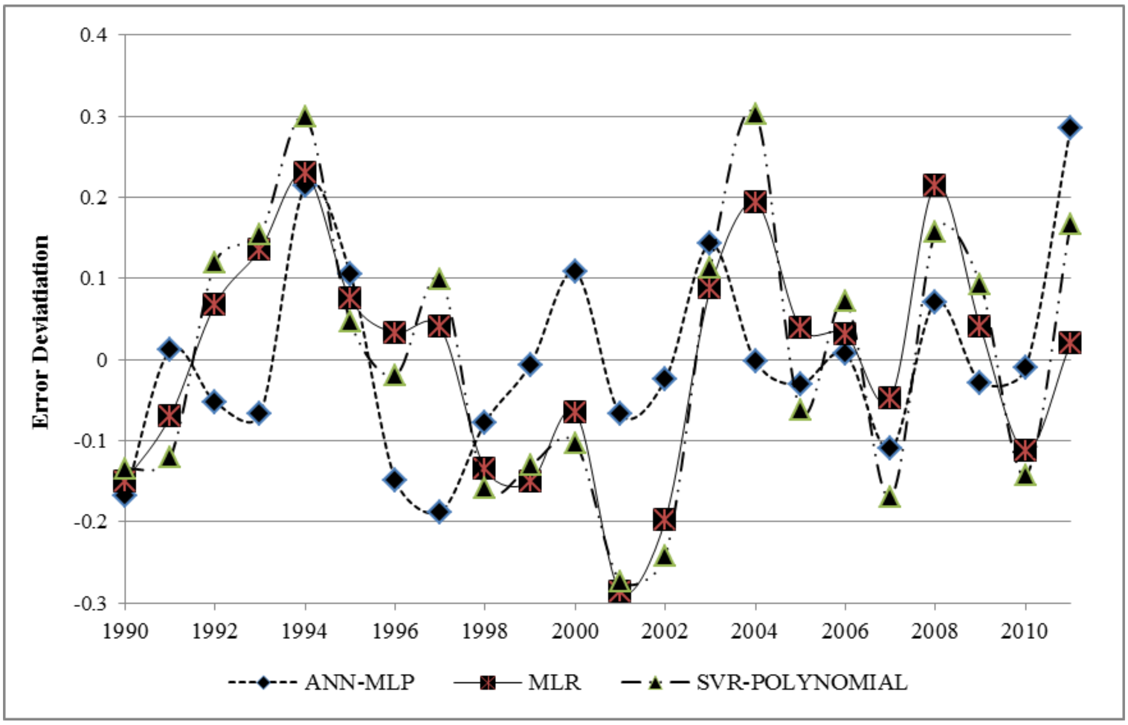

Figure 7.3: Comparison of deviations of ANN-MLP, MLR and SVR

In this work the likely influences of social, economic and environment indicators to energy demand for Tanzania as sought in the research question is established. It is shown that the presence of a strong relationship between energy indicators and the determination of energy demand in Tanzania is obvious and that the energy indicators model formulated from time series data involving per capita energy use, electricity, population and year showed greater accuracy in the prediction on test data. Economic and environment indicators models reached satisfactory prediction results on the test data though they produced less accurate predictions as compared to energy indicators model using performance indices as discussed in Chapter Two and Chapter Three. Literature comparison show a different scenario for Turkey in which usage of economic indicators was found to be more suitable than the usage of energy indicators in the estimation of energy demand using ANNs. This is due to the fact that more precise and dependable results with GDP were obtained (Sözen and Arcaklioglu, 2007). In terms of techniques, artificial neural network showed superior accuracy in energy prediction for Greek by outperforming linear regression and support vector machine methods (Ekonomou, 2010). From the comparison and analysis of the techniques presented in Section 7.2, Machine Learning approaches (ANN-MLP, MLR and SVR) reached a satisfactory analysis and prediction results on the test data. However, ANN-MLP performance was superior among the three techniques due to minimum deviations and errors. Findings from this work show ANN-

MLP is the best technique for the analysis of influential energy demand indicators for Tanzania although MLR and SVR are viable alternatives due to their good performances. It is therefore established from the results the likely influences of social, economic and environment indicators to energy demand for Tanzania.

7.3 Bottom-up Modelling Approach

To accomplish the primary objective of this dissertation, bottom-up models (end-use) namely MAED and MESSAGE were selected for the purpose. The MAED scenario approach was applied to simulate possible development paths of a country and the associated energy demands. Simulation of future energy demand considered business as usual (BAU), high economic consumption (HEC) and low economic consumption (LEC) scenarios. The simulation of energy demand considered four main economic sectors namely industry (subdivided into manufacturing and a combined agriculture, construction and mining subsectors), service, household and transport (subdivided into freight and passenger) for a study period from 2010-2040. A summary of the main assumptions and other data based on socio-economic and technological development which were considered in the simulation are given in Appendix II – XVI. MESSAGE optimization approach was applied to establish separately the least cost supply options for electricity generation in Tanzania.

The choice of bottom-up models was based on the fact that they are more appropriate for Tanzania and other developing countries due to their flexibility (Grubb et al., 1993; Hourcade et al., 1996). Bottom-up models as opposed to top-down models, capture rural-urban socio-economic differences and are capable of accounting for non-monetary transactions (Bhattacharyya, 2012; Bhattacharyya and Timilsina, 2010). One of the major advantages of bottom-up approach is in allowing modelling technological details resulting in a disaggregated description of energy technology processes. Moreover, bottom-up models are able to take into considerations important characteristics of the energy systems of developing countries. The important characteristics of the developing countries energy system among many others includes, the high dominance of biomass which is a non-commercial energy, low access to electricity and the poor performance of the electricity sector and the economy in general (Bhattacharyya and Timilsina, 2010; Urban, 2009). Suitability of these models for this dissertation is further enhanced by their ability to take account of non-cost/price policies prevailing in developing countries. However, the main drawback of bottom-up models is in their incompetence to analyse cost/price-induced effects though this is not a major concern for energy modelling (Bhattacharyya and Timilsina, 2009).

7.3.1 Energy demand simulation major results

Simulation outcomes as discussed and presented in Chapter Four depict an exponential increase in the total energy demand. It has been shown that there is a growth of energy demand to three times as was in the base year just before the end of study period in 2040. The differences in total final energy demand are a result of presumed economic growth rates. BAU, LEC and HEC scenarios simulation results propose an increased demand in biomass for service and household sectors thus making it a dominant energy form in the entire study period. The average biomass shares in the three scenarios is greater than 75 % of total final energy demand. Results project higher demand of biomass in the service and household sectors whereas there is an observed decrease in the industry sector due to assumed technological improvement to substitute biomass. Wilson (2010) approximates sustainable biomass energy potential at 12 MTOE. Simulation results as discussed in Chapter Four project biomass demand exceeding sustainable biomass energy potential throughout the entire study period. As reported in Lema (2009), Songela (2009), Felix and Gheewala (2011) and WB (2009) biomass use in Tanzania has induced a severe strain on the resources causing deforestation estimated at 130,000 and 500,000 hectares per year. Simulation results concur with these studies since projected demand exceeds sustainable biomass energy potential posing a risk to forests status in the future. Even though this is true, there is an urgent need of ensuring sustainable usage of biomass resources in the country to capture its availability for future generation use. Avoiding use of energy from biomass is impossible at present thus a balance to ensure less damage to the environment is of great concerns. Higher biomass needs in the service and household sectors attributes primarily to thermal applications.

Biomass usage for thermal applications in service and household sectors can be relieved by substituting to coal, natural gas and renewable energies. The country has been blessed with huge amount of natural gas, coal and bio-fuel sources with additions of renewable energies (MEM, 2013a, c; Wilson, 2010). The use of natural gas, coal, bio-fuels and renewable energies for thermal applications in service and household sectors will significantly decrease population relying on biomass in the form of wood fuel and charcoal (Mwihava, 2010; NBS, 2008).

Simulation results show the important role played by imported energy composed mainly of fossil fuel and particularly motor fuels, in the final energy demand of the country. Results depicted imported fuel commanding a 6% share of the total final energy demand in the base year and observe an increase to approximately 17% at the end of study period. The higher share of fossil fuels in the total final energy demand attributes to the high demand in the industry sector dominated by the energy intensive industries. Besides, thermal applications demands in the household and service sectors will contribute to an increased share of fossil fuels because of life style changes indicating a shift from biomass dependency. Moreover, motor fuel demand will contribute nearly as much as other fossil fuel in the total final energy demand. The increase of motor fuels depicts significant growth in the number of vehicles and total mobility. However, the share of imported energy specifically fossil fuel for thermal applications could be reduced by substituting to coal and natural gas which are locally available resources, thus increasing energy security by decreasing energy imports into a country. In addition to that, substitution to coal and natural gas will significantly decrease the share of imported energy. Despite difficulties in finding substitutes for motor fuel, efforts are underway to promote bio-fuels and natural gas as alternative transport fuel (GNV, 2015; Moreno and Fallen-Bailey, 1989).

The significant outcome deduced in the development of electricity demand projection is the shift from household dominance of the total shares towards industry and service sectors. The decrease in household shares of electricity describes the changes in life styles leaning towards dependence on the service sector. However, the growth rate of electricity demand is constantly greater than that of energy demand over the entire study period depicting more mechanization in the industry and service sectors. The per capita electricity consumption, which measures the significant improvements in the basic quality of life and other socio-economic development, indicates its value in 2025 will be higher the current values of lower middle-income Sub-Saharan Africa countries such as Ghana & Zambia for BAU and HEC scenario only. Likewise, the per capita electricity consumption in 2040 for BAU, LEC and HEC scenarios will be higher than the present values possessed by lower-middle income countries.

7.3.2 Electricity supply options optimization results

Medium and long-term energisation plans for Tanzania were achieved using MESSAGE, which is a bottom-up optimization model. Special consideration was given to electricity owing to its distinct nature as an energy form and its importance to the socio-economic development of Tanzania. The energisation plan (Kichonge *et al.*, 2015a) and as presented in Chapter Five was based on evolution of electricity demand using MAED (Kichonge et al., 2014a) and as presented in Chapter Four. Chapter Six presents an energisation plan based on evolution of electricity demand using Power System Master Plan (PSMP) projections (MEM, 2012). Optimization results based on formulated scenarios show electricity generation and the total installed capacity increases towards the end of study period in 2040. Least-cost results indicate the dominance of hydro, coal, geothermal and natural gas with an insignificant contribution from renewable energy as possible supply options for future electricity generation. Although coal and natural gas energy resources are locally available and give least-cost advantages, their combination is heavily founded in non-environmental friendly sources. Drawback on the applications of hydro and geothermal are on the potential limitations at 4700 MW and 650 MW respectively leaving the least-cost options to coal and natural gas only.

The optimized results reveal that under a least-cost basis without policy interventions, it is difficult to have a significant share of non-hydro renewable energy sources in the generation mix as indicated in Kichonge et al. (2014c). However, as shown in the optimization results, wind technology is the most promising among renewable energy technologies available in the country. The technology reaches competitiveness in the electricity generation in 2040 explained by its lower investment costs and availability in delivering electricity. With the introduction of compulsory policy measures in REPP, wind technology reaches a significant share earlier as compared with solar PV and solar thermal technologies. In contrast, solar PV and solar thermal technologies had no contribution under least-cost basis explained by lower capacity factor and higher investment costs. Even with compulsory measures introduced in REPP scenario, the contribution of solar PV and solar thermal remain statically small as compared to geothermal and wind technologies. The optimization results as presented also suggests the potential of geothermal technology in the electricity generation for which it has shown competitiveness in BAU, LEC and HEC scenarios. Geothermal technology is most preferred for base load generation but the lack of information about the real potential availability and its quality for electricity generation hinders its penetration into electricity generation. Biomass resources employed in the electricity generation in this dissertation was limited to the use of solid residues from sugar plantations at 19.7 MW due to un-availability of information about its potential for electricity generation. The potential of biomass from sugar plantation in the electricity generation is promising and calls for increased effort into its utilization.

Renewable energies have advantages of less GHG emission, lower operating and variable costs and most importantly require no primary energy supply. Demonstration over the immense potential of renewable energy sources in reduction of GHG emissions levels over the entire modeling period is as shown in Figures 5.9, 5.13 and 6.8. The major drawbacks of the renewable energy sources integration into electricity generation lies in higher investments costs as depicted in Figures 5.11 and 6.7. However, apart from policy intervention, the huge discoveries of natural gas and coal could provide an alternative solution to investment cost barriers of renewable energy technologies. Petrochemicals which is an essential part of the chemical industry, could be derived from natural gas and coal and thus develop into a major player in the country's economy and society wellbeing. With the policy intervention that favours renewable energy, part of the profit from petrochemical industry could fund the integration of renewable energy sources into electricity generation and thus displacing the huge dependency on coal and natural gas in the electricity generation as depicted in the optimization results. These measures will have positive impact on the levels of emissions reduction as depicted in the dissertation optimization results. The success of introducing renewable energy into the generation mix has a positive impact to society as it supplements on-going efforts for the provision of an environmentally friendly source of energy for industry and household use as stipulated in the country energy policy (Kichonge et al., 2014c; URT, 2003).

The enormousness at which hydropower has in the generation of electricity from the optimized results of this dissertation is huge and needed special attention. The hydropower potential in the country has previously affected by the decrease in an overall annual rainfall accompanied with intensified and prolonged dry and wet spells weather events making the predictability of seasonal weather patterns more challenging (Loisulie, 2010). Dry-weather scenario introduced for the purpose, reveals that with less availability of hydropower at 20%, the electricity generations swings heavily to fossil fuel power plants technologies. In dry-weather scenario, higher shares of electricity generation comes from coal and natural gas power plants. The shift to fossil fuels power plant technologies goes in line with the increase in the expenditure for primary energy supply. Moreover, less availability of hydropower reveals huge impact in the environment including the increase of GHG.

The optimization results with MESSAGE suggests the importance of natural gas, hydro, coal and most important renewable energy in backing up electricity generation in the country's power system. The balanced combination of these resources as represented in REPP scenario, has established the reduction in terms of costs and GHG emissions as compared to the system without diversification of resources. The balanced portfolio of technologies incorporating fossil fuel and renewable technologies ensures less effect to the power system due to prolonged dry and wet spells weather events and thus less GHG emission levels. The findings have established that it feasible to have a sustainable and economical supply of energy to Tanzania that will meet her energy demand and ensure for short, medium and long term energisation plans using currently available energy resources. It is through the optimized use of available energy resources where the quest in energizing the country will be realized as shown in the research findings.

7.4 Key Challenges and Uncertainties

i) Key challenges in accomplishing this study was on data access and availability. The data concerning energy modelling were to the large extent, disconnected and thus delayed the whole modelling process. In some cases, some of the data were as assumed/adopted from countries with similar developments path as Tanzania. It was even difficult to predict future energy demand using machine-learning approaches due to abstract data involving 22 years annual data set. Most important indicators intended for use in machine learning, were left out of process due to either broken time series data or un-availability of data.

ii) Modelling the future of energy systems in Tanzania as is the case in other developing countries encompasses risks, due to uncertainties on energy cost, macro-economic growth, technology development and policies implementation. Cost of energy has an effect in the scenario formulation, as they tend to be volatile and hard to predict their future growth due to many factors such as geo-political issues among many others. It is challenging to be certain on macro-economic growth of Tanzania as a rapidly developing country due to its fast changes as observed recently after discovery of natural gas.

   Technological development in general result in advances from one point to another without the need to progress through all phases in in the middle (leap-frogging), which paves way to missing over periods observed in historic data. With leap-frogging, the effect in scenario formulation is challenging in modelling development of a technology at a specific time due to un-expected rapid positive changes. Policies preparations and implementation worldwide have are determined by a number of issues including administration in office at a particular period, legislation periods, and developments plans, unexpected political decisions spurred by public debates or outcry. It is therefore, concluded that the scenarios presented in this dissertation are an indicator of possible future development paths.

iii) Machine learning comparison with bottom-up models as applied in this dissertation was not realistic due to a number of factors inherited from the models themselves. Machine learning approach are simple and quick in information processing as compared to bottom-up models. They require a minimum of a single indicator for prediction purposes and as a result cannot explain energy demand drivers as opposed to bottom-up models, which works on scenario basis and are able to disaggregate energy demand. Under data issues and dissimilarity upon which machines learning approach and bottom-up models, it was a challenge to make fruitful comparisons of these approaches out-puts.

CHAPTER EIGHT

CONCLUSIONS AND RECOMMENDATIONS

8.1 Conclusions

The primary objective of this dissertation was to develop a long-term energy demand and supply pattern for Tanzania that would enable her to meet her growing energy demand sustainably using the current and future available energy resources. Specific objectives and research questions were formulated and the work carried out in addressing the general objectives. From the aforementioned analysis and discussions as presented, the followings are the main conclusions drawn in line with the objectives and research questions of the study.

i) In this dissertation, machine-learning approaches have been used to build socio-economic and energy indicator models to analyse and predict energy demand. The first model built is an economic indicators model with two economic indicators, a year and one demographic indicator as input units. The second model is an energy indicators model with two energy indicators, a year and one demographic indicator as input units. The last model built up with environment indicators model including one environment and one demographic indicators. all models out-puts units were energy demand. The models were built and then processed into three stages namely; the training, the testing and the evaluation stages. The cross-validation with 10-folds was also adopted for training. The training set was split into 10 folds with 9 folds used for the training and the remaining fold for the validation process aimed. The training algorithm used in this dissertation for artificial neural network was the back propagation algorithm, which permits the input signal to be broadcasted to the output layers, then the error is processed at the output layer and propagated back to the input layer to adjust the weights as the network is trained.

   The models were trained, tested and evaluated using indicators time series data for the period extending from 1990 to 2011. The most appropriate ANN-MLP architecture, the best performing MLR model and the best SVR kernels among polynomial-SVR, normalized polynomial-SVR, RBF-SVR and the PUKF-SVR kernels was selected by considering performance indices to represent the best generalizing ability. Based on the results found with machine learning, it is concluded that the proposed models have generated reasonably good generalizing performance results concerning the analysis of the influence of social, economic and environment indicators in the energy demand of Tanzania. The findings have established a stronger correlation of the energy indicators to energy demand than other indicators. The prediction using a model made up of energy indicators showed greater accuracy as compared to economic and environment indicator models. Even though the energy indicators had more accurate results, the use of economic and environment indicators is established as possible alternatives in the analysis and prediction of energy demand of Tanzania owing to acceptable performances showed.

ii) Comparison of machine learning approaches in the prediction of energy demand using social, economic and environment indicators showed that ANN-MLP technique together with energy indicators model produced more accurate and reliable results. The statistical performance indices applied to evaluate the estimating ability of ANN-MLP, MLR and SVR approaches showed greater accuracy is as reached with ANN-MLP. Good performance of ANN-MLP technique attributes to higher correlation coefficient, minimum deviations and errors as compared to MLR and SVR. Although ANN-MLP outperformed MLR and SVR techniques, the results produced with these approaches showed a satisfactory performance. Based on the dissertation findings, the conclusion is reached that ANN-MLP is the best machine learning approach for the prediction of energy demand of Tanzania with the use of energy indicators. Furthermore, MLR and SVR techniques are viable alternatives to ANN-MLP in the prediction of energy demand of Tanzania due to their good performances.

iii) Simulations of future energy demands under various scenarios using a bottom-up approach have shown that the country's energy demand will grow up exponentially towards the end of study period reaching 91.3 MTOE, 74.3 MTOE and 62.1 MTOE for HEC, BAU and LEC scenarios respectively. The energy balances for HEC, BAU and LEC scenarios are dominated by biomass followed by fossil and motor fuels added together and electricity. Biomass dominates both scenarios with annual growth rates of 3.44%, 2.79% and 4.15% for BAU, LEC and HEC scenario respectively. Simulation results reveals the projected biomass consumption exceeds the sustainable biomass usage throughout the entire study period and thus calling for alternative source of energy. Electricity demand annual growth rate is projected to increase at a rate of 8.51%, 8.01% and 9.48% for BAU, LEC and HEC scenario respectively while the growth rate for fossil fuels is at 9.97% for BAU scenario, 8.01% for LEC scenario and 10.39% for HEC scenario. The projected growth in electricity demand and therefore the per capita electricity consumption supersede lower middle-income economic status values in 2025 indicating quality of life improvement. Furthermore, simulation results depicts higher growth rate in electricity demand as related to the total final energy demand. However, the more significant result observed in the development of electricity demand projection in the period 2035-2040 is the change from household and service dominance toward industry sector command at 39.7% as compared to 24.7% and 35.6% for household and service sectors respectively. Sectorial energy demand shows service sector as a dominant sector in the entire period at an average of 41% while household, industry and transport sectors accounts for 31%, 21% and 7% of the total share respectively. The final energy intensity is established to decrease continuously from base year value of 10 kWh/US$ to 10 kWh/US$, 7.9 kWh/US$, and 7.3 kWh/US$ for LEC, BAU and HEC scenarios, respectively in the year 2040 which is a suggestion of improved mechanization and automation.

iv) Modelling of the energy resource mix to meet short to long-term energisation plan for Tanzania has shown the self-sufficiency of the country in generating its future electricity using its own energy resources. The optimization of energy mix has indicated the important role of natural gas, coal, hydro and geothermal energy resources in future energisation plan. The optimized results reveal that under a least-cost basis and without policy interventions, it is difficult to have a significant share of non-hydro renewable energy sources in the generation mix. However, as shown in the optimization results, wind technology and geothermal are the most promising among renewable energy technologies available in the country. The wind technology reaches competitiveness under least-cost basis in 2040 explained by its lower investment costs and availability in delivering electricity.

With the introduction of compulsory policy measures in REPP, wind technology reaches a significant share earlier than other renewable technologies. In contrast, solar PV and solar thermal technologies had no contribution under least-cost basis explained by lower capacity factor and higher investment costs. Results suggests the potential of geothermal technology in the electricity generation for which it has shown competitiveness under least-cost basis and enter generation mix earlier than other renewable energy technologies. The results have established that it is feasible to have a sustainable and economical supply of energy to

Tanzania that will meet her energy demand and be sufficient for short, medium and long-term energisation plans using currently available energy resources.

8.2 Dissertation Contribution to Science and Technology

The followings are the summaries of the main contribution of this dissertation to science and technology as far as energy demand and supply patterns for Tanzania are involved:

i) The dissertation through findings as presented in Chapter Two and Chapter Three, add body of knowledge to researcher and scholars that exists in the analysis of the influence of socio-economic and environment indicators in the energy demand of Tanzania;

ii) The findings provides a platform for more comparative studies using machine learning and other advanced techniques in determining the level of influences and relationship between socio-economic indicators and energy usage in Tanzania;

iii) The dissertation through findings as presented in Chapter Four, provides vital information to policy analysts, scholars, environmentalists and decision makers on possible future energy demand trend under various scenarios representing economic development paths of the country and the influence of each;

iv) The findings as provided in Chapter Five and Chapter Six, provides vital information to policy analysts, scholars, environmentalists and decision makers into energy resources possible utilization options that ensure access to adequate and affordable energy services that ensures environmental quality, economic development and energy security.

8.3 Recommendations

The following are the recommendations deduced from this dissertation:

i) Renewable energy potential can play a leading role in moving the country on a more secure, reliable and sustainable energy track. Realising this important role for renewable energy depends on whether existing and future policies successfully encourages the behaviour of project developers and investors. The dissertation results has opened-up through modelling the importance of renewables and recommends for policy interventions that ensures a significant contribution of renewables is realized in the energisation of Tanzania.

ii) Dissertation findings have revealed a huge dependence of biomass for thermal applications in the household and service sectors that will continue to strain the country's forests to a level of severe deforestation as much of these biomass originate from forests. A recommendation is made to the government and other regulatory bodies to ensure the sustainable use of biomass through policy intervention that ensures affordable utilization of coal and natural gas as substitute fuels. These policy interventions should be complimented by introduction of efficient cook stoves that will ensure minimization of CO_2 into atmosphere.

iii) Usage of geothermal and biomass technologies for electricity generation lack important information about their energy potential availability and the quality possessed. The geothermal and biomass technologies have shown an important role in contributing to the electricity generation. The dissertation results recommends fast tracking for detailed assessment of these potential for future use.

iv) To control GHG, investments in new technologies such as combined cycle gas turbines (CCGT), for energy conversion purposes is highly recommended. In doing so it is possible to mitigate the environmental limitations while achieving optimized energisation plan.

v) To finalize, the results of this dissertation should be complemented with additional studies using top-down and bottom-up energy models to determine energy demand and supply options for comparative and improvement purposes. Likewise, complemented studies should be conducted in the analysis of the influence of socio-economic and environment indicators towards energy demand using hybrid artificial intelligence techniques, SVR with genetic algorithm among many other artificial intelligence (AI) approaches.

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Appendix I: Selected Socio-economic and Energy Indicators

YEAR	Population (Millions)	TPES (MTOE)	GNI per capita (current US$)	GDP (Billion 2005 US$)	Electricity (TWh)	Energy use per capita (kg of oil equiv. per capita)	CO_2 Emissions (Million tonnes CO_2)
1990	24.57	9.73	200	7.45	1.3	381.9	1.71
1991	25.27	9.93	180	7.61	1.43	377.12	1.68
1992	25.99	10.06	180	7.65	1.44	369.4	1.67
1993	26.73	10.33	170	7.75	1.46	367	1.73
1994	27.49	10.52	160	7.87	1.43	361.9	1.81
1995	28.28	11.02	170	8.15	1.71	368.08	2.52
1996	29.09	11.16	190	8.52	1.9	362.5	2.8
1997	29.98	11.27	210	8.82	1.79	356.69	2.6
1998	30.91	11.93	250	9.15	1.96	368.55	2.4
1999	31.86	12.75	280	9.59	1.87	384.24	2.19
2000	32.49	13.39	310	10.06	1.98	393.58	2.57
2001	33.86	14.2	310	10.66	2.11	407.01	2.76
2002	34.57	14.92	310	11.43	2.25	416.58	3.17
2003	35.26	15.49	330	12.22	2.03	421.4	3.31
2004	36.31	16.2	360	13.17	2.07	428.91	3.79
2005	37.27	17.14	380	14.14	2.65	441.51	5.04
2006	38.67	17.81	390	15.1	2.69	445.86	5.49
2007	39.45	18.31	410	16.17	3.29	445.18	5.31
2008	40.67	19.1	450	17.38	3.53	446.73	5.62
2009	41.92	19.35	500	18.42	3.55	443.29	5.38
2010	43.19	20.04	530	19.72	4.11	445.67	5.84
2011	44.48	20.75	540	20.99	4.27	447.57	6.26

Appendix II: Energy intensities - Motor fuels

Item	Unit	2010	2015	2020	2025	2030	2035	2040
Agriculture	[kWh/US$]	0.080	0.079	0.077	0.075	0.073	0.072	0.070
Construction	[kWh/US$]	0.512	0.510	0.508	0.506	0.504	0.502	0.500
Mining	[kWh/US$]	0.241	0.239	0.237	0.235	0.234	0.232	0.230
Manufacturing	[kWh/US$]	0.157	0.162	0.166	0.171	0.175	0.179	0.184
- Basic material	[kWh/US$]	0.280	0.278	0.277	0.275	0.273	0.272	0.270
- Machine equipment	[kWh/US$]	0.450	0.448	0.447	0.445	0.443	0.442	0.440
- Non-durable goods	[kWh/US$]	0.076	0.076	0.076	0.075	0.075	0.074	0.074

Appendix III: Energy intensities - Electricity specific applications

Item	Unit	2010	2015	2020	2025	2030	2035	2040
Agriculture	[kWh/US$]	0.024	0.024	0.024	0.023	0.023	0.023	0.023
Construction	[kWh/US$]	0.215	0.215	0.215	0.215	0.214	0.214	0.214
Mining	[kWh/US$]	0.481	0.481	0.481	0.481	0.480	0.480	0.480
Manufacturing	[kWh/US$]	0.606	0.653	0.699	0.745	0.791	0.836	0.882
- Basic material	[kWh/US$]	0.776	0.775	0.774	0.773	0.772	0.771	0.770
- Machine equipment	[kWh/US$]	3.420	3.416	3.413	3.410	3.407	3.403	3.400
- Non-durable goods	[kWh/US$]	0.239	0.239	0.238	0.238	0.238	0.238	0.238

Appendix IV: Energy intensities - Thermal applications

Item	Unit	2010	2015	2020	2025	2030	2035	2040
Agriculture	[kWh/US$]	0.348	0.347	0.345	0.344	0.343	0.341	0.340
Construction	[kWh/US$]	0.488	0.487	0.485	0.484	0.483	0.481	0.480
Mining	[kWh/US$]	0.030	0.030	0.030	0.030	0.029	0.029	0.029
Manufacturing	[kWh/US$]	1.829	1.799	1.770	1.741	1.712	1.683	1.655
- Basic material	[kWh/US$]	2.123	2.119	2.115	2.112	2.108	2.104	2.100
- Machine equipment	[kWh/US$]	0.265	0.264	0.263	0.263	0.262	0.261	0.260
- Non-durable goods	[kWh/US$]	1.874	1.869	1.863	1.857	1.851	1.846	1.840

Appendix V: Energy intensity - Intracity transportation

Item	Unit	2010	2015	2020	2025	2030	2035	2040
Car diesel	[l/100km]	10.000	9.833	9.667	9.500	9.333	9.167	9.000
Car petrol	[l/100km]	11.000	10.500	10.000	9.500	9.000	8.500	8.000
Motorbike	[l/100km]	3.000	2.917	2.833	2.750	2.667	2.583	2.500
Bus - big	[l/100km]	17.000	16.833	16.667	16.500	16.333	16.167	16.000
Bus - small	[l/100km]	13.000	12.833	12.667	12.500	12.333	12.167	12.000

Appendix VI: Energy intensity - Intercity transportation

Item	Unit	2010	2015	2020	2025	2030	2035	2040
Air plane	[l/1000seatkm]	150.000	149.167	148.333	147.500	146.667	145.833	145.000
Car diesel	[l/100km]	7.250	7.042	6.833	6.625	6.417	6.208	6.000
Car petrol	[l/100km]	8.000	7.833	7.667	7.500	7.333	7.167	7.000
Motorbike	[l/100km]	2.500	2.483	2.467	2.450	2.433	2.417	2.400
Bus - big	[l/100km]	50.000	49.833	49.667	49.500	49.333	49.167	49.000
Bus - small	[l/100km]	15.000	14.833	14.667	14.500	14.333	14.167	14.000
Train	[l/100km]	250.000	246.667	243.333	240.000	236.667	233.333	230.000
Boat	[l/100km]	100.000	99.167	98.333	97.500	96.667	95.833	95.000
Electric train	[kWh/100km]	1200.000	1166.667	1133.333	1100.000	1066.667	1033.333	1000.00

Appendix VII: Mean biomass efficiencies in thermal applications - ACM

Item		2010	2015	2020	2025	2030	2035	2040
Agriculture	[%]	15.00	15.43	15.76	16.00	16.88	17.00	17.50
Construction	[%]	15.00	15.43	15.76	16.00	16.88	17.00	17.50
Mining	[%]	15.00	15.43	15.76	16.00	16.88	17.00	17.50

Appendix VIII: Mean fossil fuels efficiencies in thermal applications - ACM

Item		2010	2015	2020	2025	2030	2035	2040
Agriculture	[%]	40.00	40.33	40.67	41.00	41.33	41.67	42.00
Construction	[%]	40.00	40.33	40.67	41.00	41.33	41.67	42.00
Mining	[%]	40.00	40.33	40.67	41.00	41.33	41.67	42.00

Appendix IX: Dwelling factors for thermal applications - Rural Household

Item	Unit	2010	2015	2020	2025	2030	2035	2040
Cooking	[kWh/dw/yr]	2359.108	2465.923	2572.739	2679.554	2786.369	2893.185	2981.000
Dw with hot water	[%]	100.000	100.000	100.000	100.000	100.000	100.000	100.000
HW per cap	[kWh/cap/yr]	34.856	45.713	56.570	67.428	78.285	89.143	100.000
Electr. cons. for appliaces	[kWh/dw/yr]	293.959	294.965	295.972	296.979	297.986	298.993	300.000
Electr. penetration	[%]	3.000	5.000	7.000	9.000	11.000	13.000	15.000
FF for lighting	[kWh/dw/yr]	179.845	169.871	159.897	149.923	139.948	129.974	120.000

Appendix X: Dwelling factors for thermal applications - Urban Household

Item	Unit	2010	2015	2020	2025	2030	2035	2040
Cooking	[kWh/dw/yr]	2328.398	2273.665	2218.932	2164.199	2109.466	2054.733	2000.000
Dw with hot water	[%]	100.000	100.000	100.000	100.000	100.000	100.000	100.000
HW per cap	[kWh/cap/yr]	71.991	84.992	97.994	110.995	123.997	136.998	150.000
Electr. cons. for appliances	[kWh/dw/yr]	4065.890	4221.575	4377.260	4532.945	4688.630	4844.315	4989.000
Electr. penetration	[%]	14.650	17.208	19.767	22.325	24.883	27.442	29.98
FF for lighting	[kWh/dw/yr]	72.940	65.784	58.627	51.470	44.313	37.157	30.000

Appendix XI: Service sector basic data

Item	Unit	2010	2015	2020	2025	2030	2035	2040
Labour force in SS	[%]	10.399	10.499	10.599	10.700	10.800	10.900	11.000
Floor area per employee	[m^2/cap]	15.000	15.833	16.667	17.98	19.533	20. 67	22.000
Labour force in SS	[million]	1.495	1.763	2.043	2.348	2.691	3.070	3.476
Floor area of SS	[million m^2]	22.6	28.2	34.8	42.012	48.92	59.62	69.96

Appendix XIIa: Service sector thermal efficiencies

Item	Unit	2010	2015	2020	2025	2030	2035	2040
Efficiency - Biomass	[%]	15.000	23.333	26.667	30.000	33.333	36.667	40.000
Efficiency - Fossil fuels	[%]	62.000	62.667	63.333	64.000	64.667	65.333	66.000
COP heat pumps	[ratio]	2.500	2.917	3.333	3.750	4.167	4.583	5.000

Appendix XIIb: Penetration of energy forms into thermal applications - Service sector

Item	Unit	2010	2015	2020	2025	2030	2035	2040
Biomass	[%]	93.782	90.295	86.623	83.56	79.952	76.473	72.66
Electricity	[%]	0.980	1.650	2.320	2.990	3.660	4.330	5.000
Fossil fuels	[%]	5.18	7.65	10.12	12.59	15.06	17.53	20.00

Appendix XIII: Electricity penetration projections – Rural Households

Item	Unit	2010	2015	2020	2025	2030	2035	2040
BAU	[%]	3	10	15	22	28	34	42
HEC	[%]	3	12	20	25	35	45	50
LEC	[%]	3	8	12	16	20	24	30

Appendix XIV: Electricity penetration projections – Urban Households

Item	Unit	2010	2015	2020	2025	2030	2035	2040
BAU	[%]	15	22	30	37	45	53	60
HEC	[%]	15	25	35	45	55	65	75
LEC	[%]	15	20	25	30	35	45	50

Appendix XV: GDP structure by main economic sectors

Item	Unit	2010	2015	2020	2025	2030	2035	2040
Agriculture	[%]	24.129	23.107	22.086	21.064	20.043	19.021	18.000
Construction	[%]	7.027	7.189	7.351	7.514	7.676	7.838	8.000
Mining	[%]	2.391	2.326	2.261	2.195	2.130	2.065	2.000
Manufacturing	[%]	9.615	10.346	11.077	11.807	12.538	13.269	14.000
Service	[%]	54.695	54.912	55.130	55.347	55.565	55.782	56.000
Energy	[%]	2.144	2.120	2.096	2.072	2.048	2.024	2.000

Appendix XVI: Efficiencies, ratios and other factors - Manufacturing

Factors		**2010**	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**
COP of heat pumps	[ratio]	2.5	2.5	2.56	2.600	2.633	2.667	2.700
Eff. of cogeneration	[%]	40	40	40	40	40	40	40
Heat/electricity ratio	[ratio]	4	4	4	4	4	4	4
Eff. of Fossil Fuel, steam gen.	[%]	40	40.8	41.667	42.5	43.333	44.167	45
Eff. of Fossil Fuel, furn./dir. heat	[%]	33	33.3	33.667	34	34.333	34.667	35
Eff. of Fossil Fuel, sp./w heating	[%]	47	47.7	48.167	48.625	49.083	49.542	50
Eff. of Biomass, steam generation	[%]	15	15.5	16	16.5	17	17.5	18
Eff. of Biomass, furn./dir. heat	[%]	15	15.5	16	16.5	17	17.5	18
Eff. of Biomass, sp./w heating	[%]	15	15.5	16	16.5	17	17.5	18
Eff. of Fossil Fuel, mean	[%]	39.837	40.324	40.819	41.319	41.819	42.317	42.811
Eff. of Biomass, mean	[%]	15	15.5	16	16.5	17	17.5	18

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