EVALUATION AND FORECAST OF ENERGY CONSUMPTION IN DIFFERENT SECTORS OF THE UNITED STATES USING ARTIFICIAL NEURAL NETWORKS

by

Arash Kialashaki

A Dissertation Submitted in
Partial Fulfillment of the
Requirements for the Degree of

Doctor of Philosophy
in
Engineering

at
The University of Wisconsin-Milwaukee
December 2014

ABSTRACT
EVALUATION AND FORECAST OF ENERGY CONSUMPTION IN DIFFERENT SECTORS OF THE UNITED STATES USING ARTIFICIAL NEURAL NETWORKS

by

Arash Kialashaki

The University of Wisconsin-Milwaukee, 2014
Under the Supervision of Professor John R. Reisel

The United States is a country which consumes a vast amount of energy. In order to keep the development of the United States sustainable (diverse and productive over the time) energy planning should be carried out comprehensively and precisely. This dissertation presents a specific mathematical modeling approach towards energy demand modeling of the United States and forecast future energy demand. To generate more detailed and accurate results, this dissertation investigates the energy demand of each sector separately using the analysis of trend for unique set of independent parameters which affect the energy demand in that sector.

In solving a forecast problem with artificial neural networks, the most important part is to choose the independent variables that provide the most precise estimate of the dependent variable. While including too many variables makes the model complicated and increases the calculation time significantly, excluding important independent variables makes integrity of the model questionable and reduces its predictive ability. In this study, correlation coefficient analysis is applied to initially select the independent variables.

In terms of forecasting the energy demand in the residential sector, the MLR and ANN models show two different trends while their performances are at a similar level of accuracy during the test period.

ANN model anticipates a small increase in the energy demand of the transportation sector. Although a small increase has been estimated by the ANN, the United States should keep trying to reduce energy consumption in order to reduce CO_2 gas and meet its national and international commitments.

ANN is also applied to forecast the industrial energy demand and perform future projections for the period 2013-2030. Based on model trained with historical data of period 1980-2012, the price of energy significantly affects the amount of energy used in the industrial sector. Hence, ascending price scenario and descending price scenario will result in 7% and 25% increase in the energy demand of this sector, respectively.

Based on model trained with historical data of period 1987-2012, the U.S. trade significantly affects the amount of energy used in the commercial sector. Hence, ascending trade scenario and descending trade scenario will result in 5% and 2% increase in the energy demand of this sector, respectively.

This dissertation is dedicated to

my beloved wife, Zahrasadat

for her emotional and mental support

and

my parents

for supporting and encouraging me to believe in myself.

Without their patience, understanding, support, and most of all love, the completion of this work would not have been possible.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I would like to express my gratitude towards many individuals whose help and assistance, made this dissertation possible to carry out. I would like to express my deepest gratitude to my advisor, Dr. John Reisel, for his continuous guidance, care, patience, support, and providing me with an excellent atmosphere for doing research. I believe, I was truly fortune to have such an exceptional teacher and scientist as my mentor in my life and advisor in my Ph.D. study. His high standards on research and teaching and his commitment towards students made it a privilege to work with him.

I sincerely appreciate my dissertation committee members: Prof. Adel Nasiri, Prof. Junhong Chen, Dr. Seifoddini, and Dr. Chris Yuan for their support, patient, insights and suggestions. I am also grateful for their time and efforts in evaluating this research work.

Additionally, I want to express my gratitude towards the Department of Mechanical Engineering at University of Wisconsin–Milwaukee for giving me the opportunity to pursue my Doctoral studies and contributing the financial support.

Above all, I would like to thank my wife, Zahrasadat Alavi for her ubiquitous support, encouragement, quiet patience and unwavering love which were undeniably the bedrock upon which the past five years of my life have been built. Her tolerance of our distance is an indication of her unyielding devotion and love. She was always there cheering me up and stood by me through the good times and bad.

This success was not possible without her support and strength during several years of my study. I would also like to thank my parents, my sister, and in-law family,

especially my parents-in-law. They were always supporting me and encouraging me with their best wishes.

CHAPTER 1

INTRODUCTION

Mathematical modeling makes it possible to predict the behavior of a broad range of energy systems in response to fluctuations in affecting parameters. In other words, energy models which explain the properties of a system mathematically are powerful tools for studying energy production and demand problems. As a practical matter, the only means for constructing a comprehensive model is through careful integration of separate mathematical descriptions of the systems' components. Over the years, there have been many attempts to develop accurate mathematical models of energy systems, and these have achieved varying degrees of success. One of the modeling techniques that have shown great promise employs the method of artificial neural networks. The efforts described in this work involve developing and employing artificial neural network modeling techniques for use in predicting energy consumptions in various sectors of the United States economy.

1.1 **Mathematical Modeling**

Mathematical models integrate scientific and technical knowledge with the purpose of predicting system behavior. Such knowledge is incorporated into the computational codes that computers execute in model utilization. From this perspective, the significance of mathematical and computational modeling of energy systems is clear; it is the most efficient and effective method for predicting the behavior of systems [1].

A mathematical model is a description of the behavior of a system. It is made up of three components [2]:

1. Input variables (statisticians call these regressor variables), which act on the system.
2. The system structure and parameters/properties which is the necessary physical description of the system
3. Output variables which describe the reaction of the system to the input variables. Energy use is often a response variable.

In this study, mathematical models based on numerical simulation permit the study of a complex energy system that otherwise would be too complicated, too costly, or even impossible to thoroughly investigate. The artificial neural network (ANN) technique is one that can overcome the limitations of traditional approaches by solving a complex modeling problem which is difficult to analytically describe. There are some other methods to mathematically describe a system such as Multiple Linear Regression (MLR).

1.2 **Energy Modeling**

Energy consumption modeling seeks to quantify energy requirements as a function of input parameters. Because of the power of the mathematical models in the analysis of the past conditions and for forecasting the future, mathematical models are widely used in energy demand modeling. Based on the ability of mathematical energy models, and since the availability and use of energy is one of the most essential elements of development in industrial countries, many studies have been performed to develop mathematical energy models for use in evaluating the future availability of energy and to help policy makers to plan accordingly.

Energy models may be used for various reasons. The most common goal of the energy models is the determination of regional and national energy supply requirements and the response of energy consumption in a particular sector to an upgrade or addition of technology. Energy models are useful as they can guide policy decisions regarding energy supply and transmission. By quantifying the consumption and predicting the impact or savings due to retrofits, decisions are made to support energy supply, and retrofit technology incentives.

Energy models rely on data to simulate energy consumption. Based on the level of detail of the input data, different modeling techniques may be used. Different modeling methods have various positive and negative points, capability and applications.

Energy models in existence are dominated by two different approaches. Top-down modeling is based on macroeconomic modeling principles and techniques and is intended to include all important economic interactions of the society. Bottom-up modeling is based on disaggregation and technical parameters. Each of these methods is based on the different levels of input information, different calculation or simulation, and provides results with different applications.

1.2.1 Overview of the top-down models

The top-down method considers the energy sector as an energy sink and does not distinguish energy consumption due to individual end-uses. Top-down models explain the effects on the energy consumption due to long-term changes of the energy sector. The primary purpose of top-down models is to determine the supply requirements. These types of models mostly use macroeconomic indicators such as gross domestic product (GDP) and energy prices, environmental conditions, and energy intensity of end-users. As indicated in Figure 1-1, there are three groups of top-down models. Econometric models are mainly based on price and income. Technological models mainly focus on broad technological characteristics of entire system [3]. Statistical models, which are the primary focus of this study, rely on historical data. Once the relationship between end-uses and energy consumption has been established, the model can be used to estimate the energy consumption of sector.

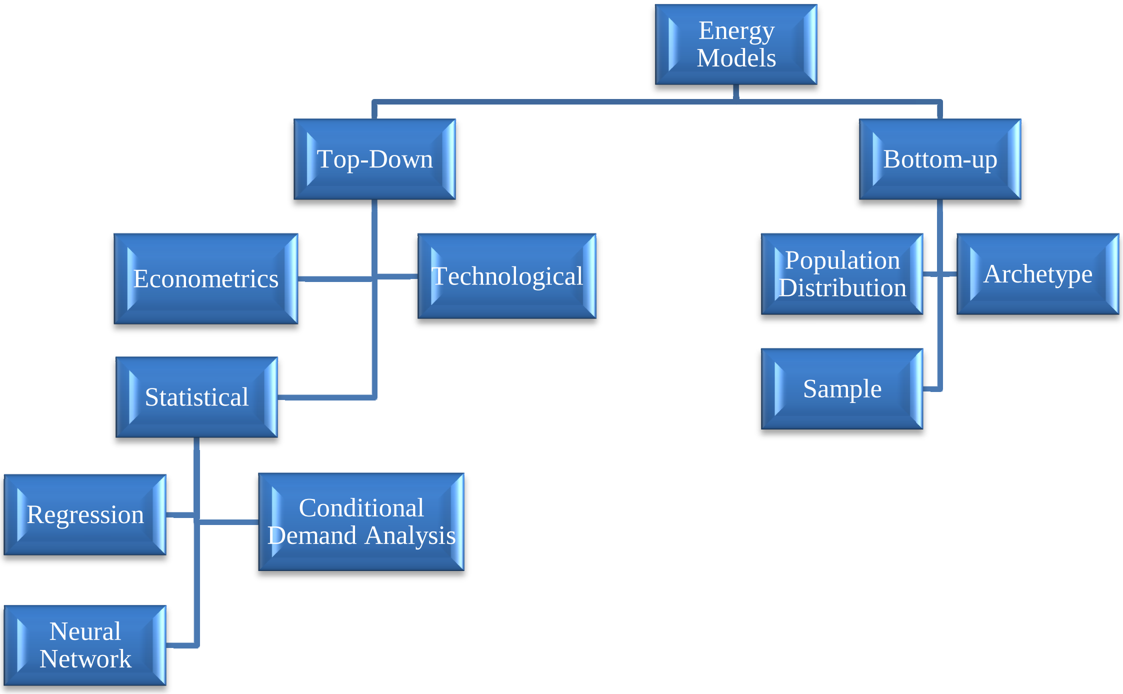


Figure 1-1: Energy modeling approaches

The regression model building consists of selecting an appropriate set of regressors from a set that quite likely includes all of the important variables; however, one is not sure that all of these candidate regressors are necessary for adequate modeling of the historical data of energy consumption. In such a situation, one is interested in screening the candidate variables to obtain the regression model that contains the best subset of regressor variables. A number of criteria may be used for evaluating and comparing the different regression models obtained. A commonly used criterion is based on the coefficient of multiple determinations.

Artificial Neural Networks (ANNs) are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in the nature, the network function is determined largely by connection between elements. A network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. This study discusses ANNs in more detail.

1.2.2 Overview of the bottom-up models

The bottom-up modeling approach encompasses all models which use input data from a hierarchal level less than that of the sector as a whole. These models employ energy consumption of individual end-uses and extrapolate to represent the nation based on the representative weight of the modeled sample.

Bottom-up models are capable of determining the energy consumption of each end-use and identify the areas of improvement. The strength of the bottom-up approach is that it can determine the total energy consumption of the energy sector without relying on historical data. However, the level of detail required by these models is greater than that of top-down models and the calculation or simulation of the bottom-up models can be complex [3].

1.3 Energy Consumption in the United States

1.3.1 Energy Production and Consumption

The United States is a country which consumes a vast amount of energy. In fact, the United States is the largest consumer of primary energy among the OECD nations [4]. In 2009, it ranked 1st globally with respect to the consumption of primary energy sources such as petroleum, natural gas, coal, hydroelectric, nuclear, geothermal, solar and wind, followed by China [4]. The United States relies on petroleum imports to meet its oil demand, and therefore is the leader globally in terms of crude oil imports. Also, the country is the largest consumer of natural gas in the world: about 11% of its natural gas in 2010 supplied by imports, primarily from its North American neighbors [5].

In 2007, the United States imported 707 Mtoe of energy and exported only 188 Mtoe. The country was self-sufficient in energy until the late 1950s when energy consumption began to outpace domestic production. By 2007, net energy imports accounted for 22.4% of all energy consumed. At the same time, most (84%) of the imported energy was in the form of oil. The United States now imports more oil and natural gas than any other country [5].

While the United States consumes vast quantities of energy as mentioned above, it has also pledged to cut its greenhouse gas emissions by 2050. This was done through passage of the American Clean Energy and Security Act in June 2009. This measure aims to promote clean energy investments and to lower US greenhouse-gas emissions by more than 80% by 2050 [6].

The production and distribution energy data for the United States are shown in Figure 1-2. The left-hand side of the figure shows the distribution of energy sources in the United States. This distribution is similar to that of worldwide energy sources: fossil fuels account for 82% of energy use, nuclear energy produces 8.5%, and renewables account for 9.3%.

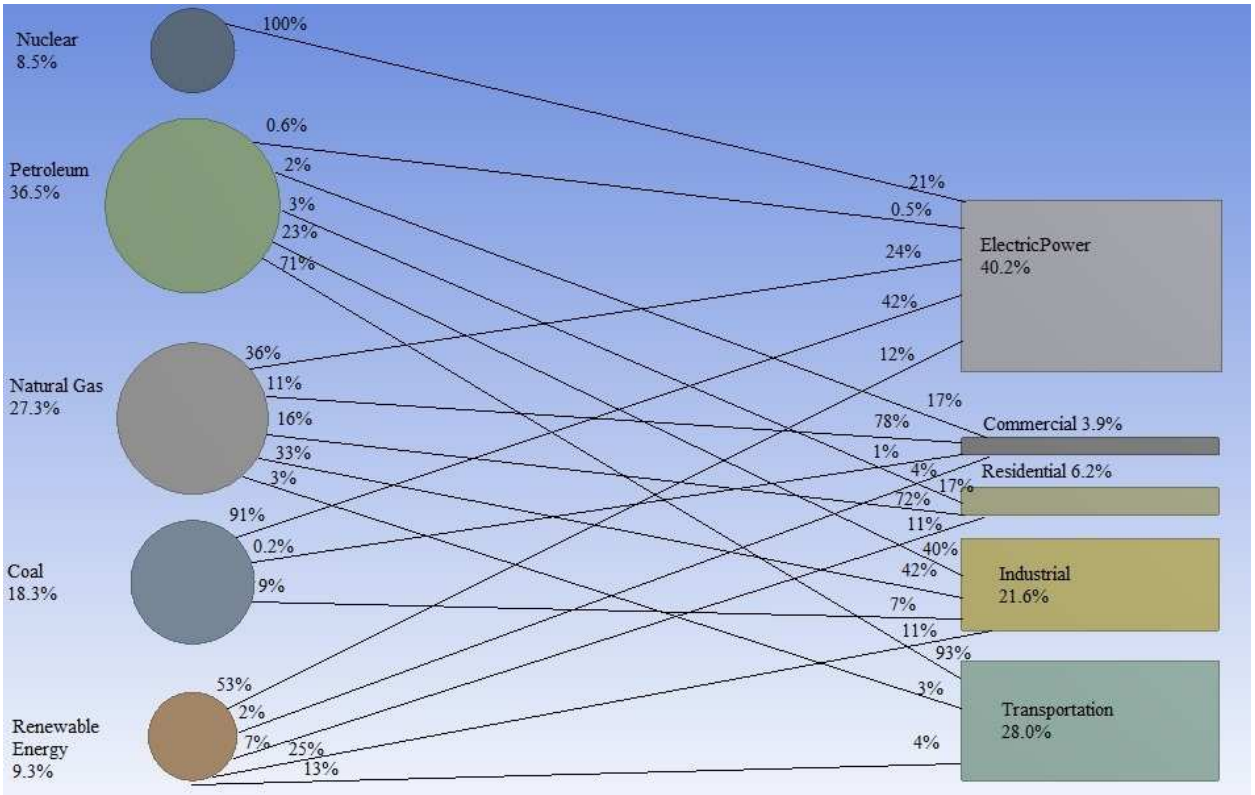


Figure 1-2: Share of energy sources and uses in the United States [7]

The right-hand side of Figure 1-2 presents the patterns of energy use in the United States, where more than 40% of the energy is used to generate electricity. The remaining nonelectrical uses are transportation, non-electricity generating industrial uses, and residential and commercial energy use. Lines with percentages noted at both ends, connect energy sources and energy uses in Figure 1-2. The percentages on the left-hand side of the lines are percentages of the eventual use from that source. The percentages on the right-hand side of the lines show the distribution of energy sources for each use. For example, 36% of natural gas was used to produce electricity, and 24% of electricity was produced from natural gas. The percentages make it clear that not all energy sources can be used in all applications. For example, 100% of nuclear power and 91% of coal are used to generate electricity: these fuels are not widely used for other purposes. As can be seen, the transportation sector relies almost exclusively (93%) on petroleum and relatively little of other fuels are used in this sector.

1.3.2 Renewable energy

Renewable energy production in the United States has grown in recent years, with an average annual growth rate of 4.6% over the last decade. Renewable energy consumption of the United States is also increasing with an average annual growth rate of 4.5% over the past decade. Since the total energy consumption is also increasing, the share of renewable energy remained approximately unchanged during last two decades with an ascending trend through last five years [7].

In 2012, the United States ranked third in total renewable energy supply following the People’s Republic of China and India [8]. The United States has some renewable energy fostering policies which are in common with some other countries, but also differs in its approach in various ways. Renewable electricity production in the United States is discussed in Chapter 7 of this study in more details.

1.4 Energy Modeling and Forecast

1.4.1 The Importance of Energy Consumption Forecasts

Energy planning is impossible without a reasonable knowledge of past and present energy consumption and likely future demands. These consumption patterns are significantly affected by energy prices. Any demand analysis and consumption forecast, therefore most take explicit account of energy prices, because prices not only affect choices among alternative energy sources, but also choices between use of energy versus other alternative inputs such as capital and labor, or choices between energy and non-energy consuming activities.

However, prices of specific energy resources are only one set of parameters that affect use. Others, such as availability, reliability of supply, convenience in use, technical and economic characteristics of energy-using equipment and appliances, population growth, income, rate of urbanization, as well as social habits are as important as or even more important than price in determining energy consumption. Hence any analysis of past and current consumption patterns and forecast of future consumption have to take these other factors explicitly into consideration.

Consumption forecasts could be made either on the basis of statistical evaluations and projections of past consumption trends, or on the basis of specific micro-studies. The former approach is appropriate in industrialized nations in which data coverage is excellent.

There are three interrelated reasons for the importance of accurate energy consumption forecasts. The first is that the timely and reasonably reliable availability of energy supplies is vital for the functioning of a modern economy. The second is that the expansion of energy supply systems usually requires many years. And the third is that investments in such systems generally are high capital intensive. If supply shortage develops as a consequence of forecasts that are too low, more expensive foreign energy supplies may have to be imported, emergency equipment may have to be installed, and forced outages may occur. Overestimates of future demand may be equally costly, if expansion plans are based upon them and would lead to unnecessary idle capacity that means wasted financial resources.

The large time horizon for new energy supply installations increases the need for accurate forecast of energy demand. Thermal power plants may need 4 to 6 years to complete, although high-cost gas turbines or diesel power plants can usually be commissioned on an emergency basis within 1 to 2 years. Nuclear power plants need 8 to 12 years to build and hydroelectric power plants require about 5 to 8 years. Therefore, it would be better to model energy consumption with good accuracy in order to avoid costly mistakes.

1.5 **Current Study**

Energy modeling and analysis is important because energy is at the core of economic and industrial activity in industrialized countries. Energy cost can affect not only industries with large consumption, but also industries as a whole and even the cost-of-living of citizens, notably because of the impact of energy prices on transport cost and heating. While respecting the environmental requirements of sustainable development, the energy policies based on energy models should be designed with the objective of securing economic growth and safeguarding the wellbeing of the citizens; this requires accurate models.

Most of the previous studies in this area were not comprehensive and detailed. While some of them mainly focused on one of the sectors, some others analyzed energy consumption of a country as a whole and do not study the effective parameters of each sector. Proven studies show that the accuracy and reliability of the ANNs models are higher compared to other methods of numerical energy modeling [9-11].

Because of the scarcity of a comprehensive energy consumption study of the United States in the open literature and the importance of the accuracy and reliability, this study builds a solid, precise and reliable model about energy consumption in the United States. This study focuses on each sector separately and takes effective parameters on each sector into account. Moreover, as the prices of energy carriers increases, renewable energy demand grows rapidly and renewable energy production technologies improve significantly. Hence, in this study, a chapter pays attention to renewable energy consumption and important factors and constraints in this sector. Finally, by incorporating energy consumption in all of the possible sectors, this study generates a broad outlook of future energy consumption of the United States in near future.

1.6 **Dissertation Organization**

There currently exists a need for reliable energy consumption analysis and forecast in different sectors of the United States. Therefore, the objectives of this research are to (1) identify the effective parameters on energy consumption in these different sectors, (2) design and use artificial neural networks to analyze the energy consumption in the different sectors using the significant parameters, and (3) forecast the future energy consumption in a specific time frame. To describe this work, the dissertation has been divided into eight chapters, including this introductory chapter.

Chapter 2

Objective: To review past studies about energy modeling and forecast in the open literature and to introduce the methodology and mathematical backgrounds of artificial neural networks analysis and multiple linear regression analysis.

This chapter elaborates the methodology of this dissertation as well as mathematical background of methods.

Chapter 3

Objective: To evaluate the energy consumption in the residential sector of the United States using artificial neural networks

Hypothesis: It is expected that the energy consumption in the residential sector of the United States is a function of household size, GDP, median household income, and the cost of the energy sources.

Methods to test the Hypothesis: Collecting the data on the effective parameters, building the ANNs, training the network and matching the test set with the generated results of the network, evaluating the performance of the model by error analysis, using the future trends of the effective parameters as feed of the network to forecast the energy consumption of the residential sector in the United States.

Chapter 4

Objective: To evaluate the energy consumption in the transportation sector of the United States using artificial neural networks

Hypothesis: It is expected that the energy consumption in the transportation sector of the United States is a function of population, number of vehicles, GDP, passenger transport amount, and the gasoline price.

Methods to test the Hypothesis: collecting the data on the effective parameters, building the ANNs, training the network and matching the test set with the generated results of the network, evaluating the performance of the model by error analysis, using the future trends of the effective parameters as feed of the network to forecast the energy consumption of the transportation sector in the United States.

Chapter 5

Objective: To evaluate the energy consumption in the industrial sector of the United States using artificial neural networks

Hypothesis: It is expected that the energy consumption in the industrial sector of the United States is a function of population, import and export, employment, GDP, and the prices of energy sources.

Methods to test the Hypothesis: collecting the data on the effective parameters, building the ANNs, training the network and matching the test set with the generated results of the network, evaluating the performance of the model by error analysis, using the future trends of the effective parameters as feed of the network to forecast the energy consumption of the industrial sector in the United States.

Chapter 6

Objective: To evaluate the energy consumption in the commercial sector of the United States using artificial neural networks

Hypothesis: It is expected that the energy consumption in the commercial sector of the United States is a function of population, import and export, employment, household income, GDP, and the prices of energy sources.

Methods to test the Hypothesis: collecting the data on the effective parameters, building the ANNs, training the network and matching the test set with the generated results of the network, evaluating the performance of the model by error analysis, using the future trends of the effective parameters as feed of the network to forecast the energy consumption of the commercial sector in the United States.

Chapter 7

Objective: To evaluate the renewable energy production and consumption of the United States

Hypothesis: It is expected that the renewable energy consumption in the United States is a function of geographical parameters, cost of traditional energy sources, federal and state policies.

Methods to test the Hypothesis: quantifying the effective parameters, collecting the data on the effective parameters, evaluation of effective parameters on renewable energy development via comparison of states with common geographical conditions and different renewable energy production status and via analysis of energy production portfolio of leading states.

Chapter 8

Objective: To summarize and generate a broad outlook of future energy consumption of the United States in near future, and suggest areas for future work of the interested researchers.

The period for which data is analyzed and used for the models is slightly different for each chapter. In period of study for each chapter, all of the independent variables which are subjects of this study are available. Data regarding more extended periods or monthly or quarterly data are not available for all variables within the open literature. In addition, smaller intervals of data are not necessarily helpful; for example, the effect of energy price change in monthly periods does not usually affect the energy demand of the industrial sector in the same period.

In summary, the main goal of these eight chapters is to provide a numerical method to evaluate the important parameters which affect energy consumption of different sectors in the United States and to propose a detailed image of the future of energy consumption in the United States.

CHAPTER 2

ARTIFICIAL NEURAL NETWORKS AND MULTIPLE LINEAR REGRESSIONS

2.1 **Introduction**

Energy consumption is one of the hardest sectors of the economy to analyze, model and forecast. The structure of energy demand for the entire sector is unclear. For example, the energy demand in any economic sectors might not be strongly correlated with common factors with the other sectors. While energy markets are complex, energy models are simplified representations of energy production and consumption, regulations, and producer and consumer behavior. Projections are highly dependent on the data, methodologies, model structures, and assumptions used in their development.

2.2 **Energy Demand Modeling**

Energy demand modeling seeks to quantify the energy requirements as a function of input parameters. Models may be used for various reasons. The most common goal of the energy models are the determination of regional and national energy supply requirements and the change in energy demand of a particular sector to an upgrade or addition of technology.

The reasons for modeling energy consumption are as varied as the ways in which energy is used in processes [12]. Energy models are useful as they can guide decisions of policy regarding energy supply and transmission. By quantifying the consumption and predicting the impacts or savings due to retrofits, decisions are made to support energy supply, retrofit, and technology incentives. Researchers and scientists tried to develop integrated energy models for both traditional and renewable energy sources as well as energy-demand side. Comprehensive overviews of the various types of energy modeling are presented in several review papers [13-15].

The practice of modeling energy demand is necessarily a synthesis of data and method [12]. Energy models rely on data to simulate energy consumption. Based on the level of detail of the input data, different modeling techniques may be used. Different modeling methods have various positive and negative points, capabilities, and applications.

2.3 **Previous studies**

The relationship among energy consumption and economy has been studied and reported in the literature such as Min et al. [16], Jin-Ming and Xin-Heng [17], Geem and Roper [18], Cayla et al. [19], and Swan and Ugursal [3]. Total and sectoral energy modeling and prediction studies have been carried out by many researchers. Geem [10] developed ANN models for South Korea’s transport energy forecasting by considering various independent variables such as GDP, population, oil price, number of vehicle registrations, and passenger transport amount. In Geem’s study, the ANN models obtained robust results in terms of *RMSE* as well as R^2, when compared with multiple linear regression models. Also, Murat and Ceylan [20] described the logic of ANN and *k*-fold cross-validation method. They proposed possible application of ANNs to forecast energy demand for next 20 years of Turkey.

Many of previous works using ANNs in energy demand modeling have been done for the electricity sector. For instance, Ekonomou investigated long-term electricity demand in Greece using ANNs. Ekonomou used multilayer perceptron models to test several possible architectures in order to choose one with the best generalizing ability to be selected. After all simulations, the chosen MLP and ANN models had the following characteristics: 2 hidden layers with 20 and 17 neurons in each of them, a Levenberg-Marquardt back-propagation learning algorithm and a logarithmic sigmoid transfer function. Performed predictions with ANN technique were found to be much more accurate than those obtained by a linear regression model [21]. Ermis et al. used a feed-forward back propagation ANN to be trained based on the data for 1965 to 2004 and then forecast the world green energy consumption to the year 2050. They investigated energy consumption equations and related environmental aspects in different sectors. In terms of calculated errors for performance evaluation (absolute mean relative error, standard deviations in the relative errors, and R^2) ANN had lower errors and better performance [22]. By using ANNs, S□zen proposed numerical equations to estimate Turkey’s energy dependence based on basic energy indicators and sectoral energy consumption. Moreover, different strategies to preserve the supply and demand balance of Turkey are evaluated in this paper. According to results of the developed models, this study could be used to predict of energy dependency from the sectoral energy consumption per capita with a high confidence ($R^2 \approx 1$, average deviations= 0.0073%) [23]. Another research work on energy consumption in Turkey, Kankal et al. forecasted future projections based on socio-economic variables like GDP, population and employment. Different scenarios were analyzed and the results of the model based on those scenarios were compared with the official forecast. The proposed ANN model predicted the energy consumption better than the multiple linear and power regression models in terms of relative errors and *RMSE*'s [24].

For Turkey as a country which had the highest average population growth rate among the International Energy Agency (IEA) member countries, Hamzacebi [25] explored net electricity energy consumption on a sectoral basis until 2020 and the results are compared with official forecasts of the Turkey. In 2007, Akay and Atak used Grey Prediction with Rolling Mechanism (GPRM) to forecast electricity demand of Turkey. GPRM was chosen because of the high prediction accuracy and the little computational effort required [26]. Duran used Ant Colony Optimization (ACO) to estimate energy demand of Turkey. The presented model used population, gross domestic product, imports, and exports to plan the energy demand of the Turkey until 2025 based on three proposed scenarios [27]. Ünler proposed a model using particle swarm optimization (PSO) method to forecast energy demand of Turkey. GDP, population, imports, and exports are used as independent indicators to forecast energy demand and the results are compared with the results of the ACO model developed for same problem [28]. As another approach for forecasting short-term gross annual electricity demand for Turkey, Kucukali and Baris applied fuzzy logic. The proposed model used GDP as the sole independent parameter and captured the system behavior of the period 1970-2014 [29]. In 2012, Bilgili et al. applied artificial neural network (ANN), linear regression (LR), and nonlinear regression (NLR) to estimate the electricity consumption of the residential and industrial sectors in Turkey. Installed capacity, gross electricity production, population and total subscribership were selected as independent variables. Prediction of the electricity consumption is based on two different scenarios and the results of the three methods were compared [9]. The comparisons showed good agreement between the actual data and forecasting results. Also, the performance values of the ANN method were better than performance values of the LR and NLR models.

In 2008, Adams and Shachmurove built an econometric model of the Chinese energy economy. This model is based on an energy balance and used to forecast Chinese energy consumption and imports to 2020 [30]. For Iran as a case study, Azadeh et al. presented an integrated algorithm for forecasting monthly electricity consumption based on a supervised multi-level perceptron ANN, computer simulation and design of experiments. Electricity consumption data for Iran from 131 months from 1994 to 2005 were analyzed and applied to the proposed algorithm to show the applicability of ANN and its superiority to conventional time series and simulated-based ANN according to statistical analysis of the results [31]. Regarding the industrial sector of Iran, Azadeh et al. developed an ANN to forecast annual electricity consumption. In addition, the ANN forecast is compared with actual data and conventional regression model to show the superiority of ANN models [32]. In 2010, Azadeh et al. applied a fuzzy regression algorithm to estimate energy consumption of Iran. They showed that the proposed algorithm is capable of managing imprecision, ambiguity, and lack of data due to fuzzy regression mechanism [33].

Use of AI techniques to forecast energy demand modeling is not limited to Turkey, Iran and China. For example, Geem and Roper, estimated energy demand of South Korea with an ANN model. This model has four independent variables including GDP, population, import, and export amounts [18]. In 2013, Kialashaki and Reisel developed energy demand models which are able to forecast energy demand for the residential sector of the United States. In this study multiple linear regression models and ANN models are compared and one of the ANN models is chosen based on the model evaluation parameter [34].

2.4 **Linear regression**

Multiple linear regression analysis is one of the oldest and most common methodologies used to analyze the dependency of a quantity on a set of independent variables [35]. A MLR model explicitly describes a relationship between independent and dependent variables.

In this study, the method of least squares-fit is used to estimate the regression coefficients in MLR model. Producing a fit using a linear model requires minimizing the sum of the squares of the residuals. A plot of residuals visually gives a good insight about

Goodness of Fit. The Goodness of Fit is also measured by Coefficient of Determination (R^2) and Adjusted Coefficient of Determination ($\bar{R}^2$) which indicates how closely obtained values match the dependent variable of the model. The following equation shows the regression equation for the proposed linear regression model:

$$\begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} f_1(x_1) & \cdots & f_p(x_1) \\ \vdots & \ddots & \vdots \\ f_1(x_n) & \cdots & f_p(x_n) \end{pmatrix} \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_p \end{pmatrix} \tag{2.1}$$

where y_i is the scalar response, β_1 to β_p are scalar regression coefficients, $f_i(x)$ is the vector component showing each independent parameter, subscript p indicates the number of independent variables, subscript n shows the number of historical observations, and ε_1 to ε_p are the scalar noise terms (biases) of the model. This model is called linear because it is linear in the coefficients β_j. Regarding bias terms, it is assumed that they are independent of each other, normally distributed with the mean equal to zero.

Multiple linear regression technique is applied to determine unknown coefficients of β_0 to β_p. This process is done by minimizing the sum of the squares of the deviations of simulated data from the historical data.

2.5 **Artificial Neural Networks**

2.5.1 Structure of the Network

An artificial network is an information-processing system that has certain performance characteristics in common with biological neural networks. Artificial neural networks have been developed as generalizations of mathematical model of human cognition based on the assumptions that [36]:

- Information processing occurs at many simple units called neurons.
- Signals are passed between neurons over connection links.
- Each connection link has an associated weight which multiplies the signal transmitted.
- Each neuron implies an activation function to its net input to determine its output.

The discovery and widespread dissemination of an effective general method of training a multilayer neural network in 1980s played a major rule in the application of neural networks as a tool for solving a wide variety of problems. There has been a substantial increase in the interest in the artificial neural network methods in recent years. Several successful applications of ANN can be found in various fields of mathematics, engineering, medicine, economics, metrology, psychology, and neurology.

A multiple-input neuron is shown in Figure 2-1. As shown in Figure 2-1, the input vector P is represented by a rectangle on left. It is indicated that P is a single vector of R elements. These inputs go to the weight matrix W, which has R columns but only one row in this single neuron case. A constant 1 enters the neuron as an input and is multiplied by a scalar bias b. The net input to the transfer function f is n, which is the sum of the bias and the product $W \times P$. The neuron’s output a is a scalar in this case. If there is more than one neuron, the network output is a vector.

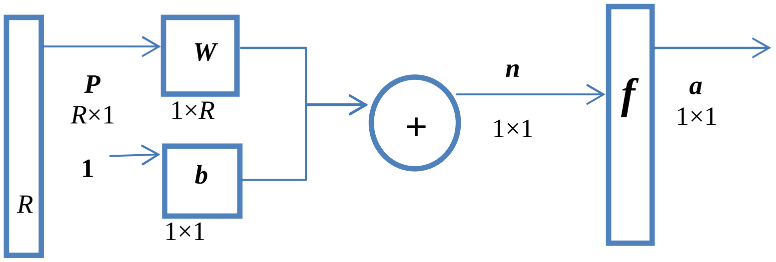


Figure 2-1: Neuron with *R* inputs

The layer includes the weight matrix, the summers, the bias vector b, the transfer function boxes and the output vector. A layer whose output is the network output is called an output layer. The other layers are called hidden layers. Single-layer networks suffer from the disadvantage that they are only able to solve linearly-separable problems. Multilayer networks are more powerful than single-layer networks. Moreover, the bias gives the network an extra variable and networks with bias are more powerful than those without.

2.5.2 Learning Process

Learning is defined in this context of neural networks as [37]:

The learning is a process by which the free parameters of a neural network are adapted through a process of stimulation by the environment in which the network is embedded.

The procedure used to perform the learning process is called a “learning algorithm”, the function of which is to modify the synaptic weights of the network in an orderly fashion to attain a desired design objective [38].

The very general nature of the backpropagation training method means that a backpropagation net (a multilayer, feedforward net trained by backpropagation) can be used to solve problems in many areas. It is simply a gradient descent method to minimize the total squared error of the output computed by the net. The training of a network by backpropagation involves three stages: the feedforward of the input training pattern, the calculation and backpropagation of the associated error, and the adjustment of the weights. After training, application of the net involves only the computations of the feedforward phase. Even if the training is slow, a trained network can produce its output very rapidly.

With processing steps on inputs and targets, neural network training becomes more efficient. In this study, normalization is applied to both the input and the target vectors. This normalization scales the inputs and the targets so that they fall in the range [-1,1]. In this normalization, it is assumed that the input and target vectors have only finite real values, and the elements of each vector are not all equal. Matrix x is normalized into matrix y so that

$$y = \frac{(y_{max} - y_{min}) \times (x - x_{min})}{(x_{max} - x_{min})} + y_{min} \qquad (2.2)$$

where y_{min} and y_{max} are 1 and -1 respectively. The settings of normalization are saved in structure parameters. After network has been trained, those structure parameters are used to transform future inputs applied to the network.

In this study, data are randomly divided into 3 sets: 70% for training, 15% for validation process, and 15% for test process. The training process is the optimization of the performance function by tuning the weights and biases. The mean square error (MSE), which is the performance function of this study, is defined as

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 = \sum_{i=1}^{N} v_i^2(x) \tag{2.3}$$

where N is the number of observations for training, and t_i and a_i are targets and outputs, respectively. Levenberg-Marquardt (LM) optimization is used to optimize the performance function of the network. This technique, which is a variation of Newton's method, was designed for minimizing functions that are sums of other non-linear functions. This method is well-suited to the performance function of this study: the MSE. In this method Hessian matrix is approximated as

$$\boldsymbol{H} = \boldsymbol{J}^T \boldsymbol{J} \tag{2.4}$$

and the gradient is computed as

$$\boldsymbol{g} = \boldsymbol{J}^T \boldsymbol{v} \tag{2.5}$$

where

$$\boldsymbol{J} = \begin{bmatrix} \frac{\partial v_1(\boldsymbol{x})}{\partial x_1} & \cdots & \frac{\partial v_1(\boldsymbol{x})}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial v_N(\boldsymbol{x})}{\partial x_1} & \cdots & \frac{\partial v_N(\boldsymbol{x})}{\partial x_n} \end{bmatrix} \tag{2.6}$$

and v is the vector of network errors. By application of the following modification to Hessian matrix, it becomes invertible and the approximated Hessian matrix has the same eigenvalues as the original Hessian matrix.

$$\boldsymbol{G} = \boldsymbol{H} + \mu \boldsymbol{I} \tag{2.7}$$

This leads to the Levenberg-Marquardt algorithm:

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k - [\boldsymbol{J}^T(\boldsymbol{x}_k)\, \boldsymbol{J}(\boldsymbol{x}_k) + \mu_k \boldsymbol{I}]^{-1}\, \boldsymbol{J}^T(\boldsymbol{x}_k)\, \boldsymbol{v}(\boldsymbol{x}_k) \tag{2.8}$$

where

$$\mathbf{x}^T = [x_1\ x_2\ x_3 \ldots x_n] = [w^1_{1,1}\ w^1_{1,2} \ldots b_1^1 \ldots b_s^1\ w^2_{1,1} \ldots b^M_S\ ] \qquad (2.9)$$

and

$$\mathbf{v}^T = [v_1\ v_2\ v_3 \ldots v_N] = [e_{1,1}\ e_{2,1} \ldots e_{S,1}\ e_{1,2} \ldots e_{S,M}] \qquad (2.10)$$

The algorithm starts with μ set to a small value. If the step does not yield to a smaller value for $F(x)$ the step is repeated with a larger value of μ. Eventually, $F(x)$ should decrease since we would be taking a small step in the direction of steepest decent. LM algorithm provides a good compromise between the speed of the Newton's method and the assured convergence of steepest descent [38]. Table 2-1 contains the important parameters of LM algorithm to train the ANN in this study.

Table 2-1: Important parameters in LM training algorithm and their values

Parameter	**Value**
Maximum number of epochs to train	100
Performance goal	0
Maximum validation failures	10
Minimum performance gradient	1e-10
Initial μ	0.001
μ decrease factor	0.001
μ increase factor	10
Maximum μ	1e10

2.5.3 Training algorithm

The training of a network by backpropagation involves three stages: the feedforward of the input training pattern, the calculation and backpropagation of the associated error, and the adjustment of the weights. After training, application of the net involves only the computations of the feedforward phase. Even if the training is slow, a trained network can produce its output very rapidly.

The nomenclature used in the training algorithm for the backpropagation net is presented in Table 2-2.

Table 2-2: nomenclature used in the training algorithm

x	Input training vector $\mathbf{x}=(x_1, \ldots, x_i, \ldots, x_n)$
t	Output target vector $\mathbf{t}=(t_1, \ldots, t_i, \ldots, t_n)$
v_{ij}	Weight of the link between i^{th} input unit to j^{th} hidden unit
w_{jk}	Weight of the link between j^{th} hidden unit to k^{th} output unit
δ_k	Portion of error correction weight adjustment for w_{jk} that is due to an error at output unit Y_k; also the information about the error at unit Y_k that is propagated back to the hidden units that feed into unit Y_k.
δ_j	Portion of error correction weight adjustment for v_{ij} that is due to the backpropagation of error information from the output layer to the hidden unit Z_j.
α	Learning rate
X_i	Input unit i: For an input unit, the input signal and the output signal are the same
v_{0j}	Bias on the hidden unit j.
Z_j	Hidden unit j The net input to Z_j is denoted z_in_j: $z\_in_j = v_{oj} + \Sigma\, x_i v_{ij}$ The output signal (activation) of Z_j is denoted z_j $z_j = f(z\_in_j)$
w_{0k}	Bias on output unit k.
Y_k	Output unit k The net input to Y_k is denoted y_in_k: $y\_in_k = w_{ok} + \Sigma\, z_j w_{jk}$ The output signal (activation) of Y_k is denoted y_k $y_k = f(y\_in_k)$

The algorithm used for training is as follows [36]:

Step 0. Initialize weights.

Step 1. While stopping condition is false do step 2-9

Step 2. For each training pair, do step 3-8.

Feedforward:

Step 3. Each input unit (X_i) receives input signal x_i and broadcasts this signal to all units in the layer above (the hidden units).

Step 4. Each hidden unit (Z_j) sums its weighted input signals,

$z\_in_j = v_{oj} + \Sigma\, x_i v_{ij}$

applies its activation function to compute its output signal,

$z_j = f(z\_in_j)$

and sends this signal to all units in the layer above (output units)

Step 5. Each output unit (Y_k) sums its weighted input signals

$y\_in_k = w_{ok} + \Sigma\, z_j w_{jk}$

and applies its activation function to compute its output signal

$y_k = f(y\_in_k)$

Backpropagation of error:

Step 6. Each output unit (Y_k) receives a target pattern corresponding to the input training pattern, computes its error information term,

$\Delta_k = (t_k - y_k) f'(y\_in_k),$

calculates its weight correction term to update w_{jk}

$\Delta w_{jk} = \alpha \delta_k z_j$

calculates its bias correction term to update w_{0k}

$\Delta w_{0k} = \alpha \delta_k$

and sends δ_k to units in the layer below.

Step 7. Each hidden unit (Z_j) sums its delta input

$\delta\_in_j = \Sigma \delta_k w_{jk}$

multiplies by the derivatives of its activation function to calculate its error information term

$\delta_j = \delta\_in_j\, f'(z\_in_j),$

calculates its weight correction term to update v_{ij} later

$\Delta v_{ij} = \alpha \delta_j x_i$

and calculates its bias correction term to update $v_{0,j}$ later

$\Delta v_{0,j} = \alpha \delta_j$

Update weight and biases:

Step 8. Each output unit (Y_k) updates its bias and weights

$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk}$

Each hidden unit (Z_j) updates its bias and weights

$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij}$

Step 9. Test stopping condition

2.5.4 Initialization

In the ANN models developed in this study, Nguyen-Widrow technique has been used for initialization of the parameters. This technique is one of the most effective neural network weight initialization methods available. This algorithm chooses values in order to distribute the active region of each neuron in the layer approximately evenly across the layer's input space.

The initialization of the weights from the input units to the hidden units is accomplished by distributing the initial weights and basis so that, for each input pattern, it is likely that the net input to one of the hidden units will be in the range in which that hidden neuron will learn most readily. The procedure consists of following steps [36]:

For each hidden unit ($j=1,2,\ldots,p$):

- Initialize the weight vector: $v_{i,j}(old)$ = random number between -0.5 and 0.5.
- Compute $\|\mathbf{v}_j(\text{old})\|$ which is the norm of the vector v_j.
- Reinitialize weights and bias:

$$v_{i,j} = \frac{\beta v_{i,j}(old)}{\|\mathbf{v}_j(\text{old})\|} \qquad (2.11)$$

$v_{0,j}$ = random number between $-\beta$ and β

where n is the number of input units, p is the number of hidden unites, β is the scale factor:

$$\beta = 0.7\ (p)^{1/n} \qquad (2.12)$$

Weights from the hidden units to the output units are initialized to random values between -0.5 and 0.5.

2.6 **Selection of the independent variables**

In solving a forecast problem with artificial neural networks, the most important part is to choose the independent variables that provide the most precise estimate of the dependent variable. Moreover, since the future trends of dependent variables are unknown, the probability percentage of occurrence of these variables is significantly important. Hence, the process of choosing independent variables must be done with special consideration.

While including too many variables makes the model complicated and increases the calculation time significantly, excluding important independent variables makes integrity of the model questionable and reduces its predictive ability. In this study, correlation coefficient analysis is applied to initially select the independent variables.

The correlation coefficient (ρ_{XY}) between random variables X and Y is defined as

$$\rho_{X,Y} = \mathrm{cov}(X,Y)/[(V(X)V(Y)]^{1/2} \qquad (2.13)$$

where, cov(X,Y) is the covariance between the random variables X and Y and $V(X)$ and $V(Y)$ are variances of random variables X and Y, respectively. The correlation coefficient is a dimensionless quantity that can be used to compare the linear relationships between pairs of variables in different units [39]. Calculating linear correlation before fitting a model is a useful way to identify variables that have a simple relationship, provided it is done along with the P-value calculation and confidence interval test for some chapters.

2.7 **Overfitting**

Overfitting is important in machine learning. It usually appears when the model is highly complicated and has too many parameters compared to the number of observations. Especially when the learning performed is too long or when the training set is too short, the learner may adjust to very specific random features of the training data. The performance of the model in terms of prediction will generally decline. In other words, minor fluctuations of data will be exaggerated.

In the current study, however, the overfitting problem is very unlikely to happen since the training examples are not rare compared to the number of effective parameters. In addition, the model that is employed is not excessively complex.

CHAPTER 3

ENERGY DEMAND IN THE RESIDENTIAL SECTOR OF THE UNITED STATES

3.1 **Introduction**

The United States is a nation which consumes a vast amount of energy. In 2009 in the United States, fossil fuels accounted for 83% of total energy consumption, renewable energy supplied 8.0% and nuclear electric power provided 8.8%. The pattern of energy use varies by sector as explained in CHAPTER 1. After the electric power sector (40.3%), the transportation sector was the second largest consumer of primary energy (28.5%), followed by industrial (20%), residential (7%), and commercial (4.3%), as shown in Figure 3-1. The major primary energy source in the residential sector is natural gas (43%) while electricity (42%) and petroleum (10 %) occupy small portions as shown in Figure 3-2 [5].

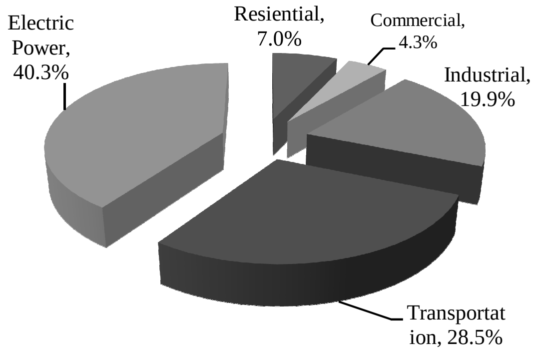


Figure 3-1: Energy consumption by sector in United States [5]

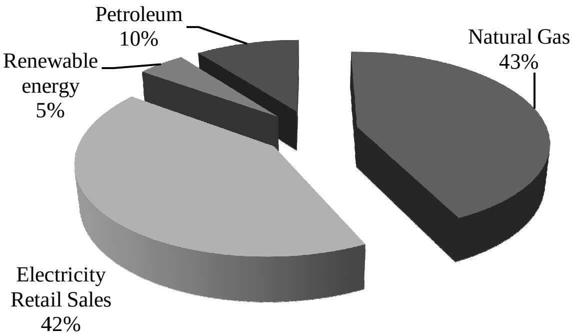


Figure 3-2: Major primary energy sources in residential sector [5]

To assist in planning for future energy needs, the purpose of this chapter is to develop a model for residential energy demand that incorporates past trends. Two sets of models are developed. The primary model described in this chapter employs an Artificial Neural Network (ANN) technique to predict United States residential energy demand. Seven independent variables (resident population, gross domestic product, household size, median household income, cost of residential electricity, cost of residential natural gas, and cost of residential heating oil) have been tested for the modeling. The results of the ANN models are compared to those predicted by the more traditional Multiple Linear Regression (MLR) modeling technique so that any advantages to the ANN modeling technique can be discerned. By studying the possible scenario for growth of parameters, future residential energy demand in United States is then forecast based on the models.

3.2 **Background**

Modeling and predicting energy consumption play a vital role in developed and developing countries for policy makers and related organizations. Underestimation of consumption would lead to potential outages that are devastating to life and economy, whereas overestimation would lead to unnecessary idle capacity that means wasted financial resources. Therefore, it would be better to model energy consumption in order to avoid costly mistakes. Also it is better to accurately use models that can handle nonlinearities among variables as the expected nature of energy consumption data is nonlinear.

Swan and Ugursal [3] provide a review of the various modeling techniques used for modeling residential sector energy consumption. In their research, two distinct approaches are identified: top-down and bottom-up. Each technique relies on different levels of input information, different calculation or simulation techniques, and provides results with different applicability. A critical review of each technique, focusing on the strength, shortcomings and purposes, is provided along with a review of various models.

Both regression models and neural network models used in the current study are categorized as statistical models which are a division of the top-down approach. Models, using a bottom-up approach can account for energy consumption of individual end-uses, individual houses, or groups of houses and then extrapolate to represent the region or nation based on the representative weight of the modeled sample. Researchers have applied a variety of statistical techniques to utilize this and other information to regress the energy consumption as a function of house characteristics.

It is well-known that Artificial Neural Networks (ANN) can model any nonlinear relationship to an arbitrary degree of accuracy by adjusting the network parameters. In addition to many different algorithms reported in the literature, the accuracy and prediction performance of ANN models need to be studied for energy consumption prediction problems in order to give decision makers an opportunity to make sound decisions regarding their activities. Finally, as with any other modeling problem, inputs to a model should cover all possible variables that influence the output variable of interest.

Regarding the residential sector, Gilland [40] projected the world energy demand for the period of 2000 to 2020 on the basis of plausible assumptions regarding population growth, economic growth and a relation between elasticity of energy demand and growth of gross domestic product per capita by world region. Min [16] presented a novel approach to modeling residential energy by both end use and fuel type for the entire United States at a high resolution. Their model provides an in-depth look at how energy is used by residences in different parts of the country and the variances between home energy use characteristics both within and across different regions.

Cayla et al. [19] characterize quantitatively the impact of income on household energy consumption in the residential and transport sector of France. Their analysis show that the economically-poorest households are particularly constrained since the share of their budget represented by these energy services is very large. As an alternate fuel used in residential sector, wood energy consumption has been studied by Song et al. [41]. They found that the composite non-wood energy price positively associated with U.S. residential wood energy consumption in the long-run with elasticity 1.82. Wage rate was negatively associated with wood energy consumption in both long-run and short-run. They also suggest that the estimated trend in residential wood energy consumption is significantly negative, about -3% per year.

3.3 **Energy Modeling**

A neural network is a massively parallel distributed processor made up of simple processing units which has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

1. Knowledge is acquired by the network from its environment through a learning process.
2. Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

The procedure used to perform the learning process is called a “learning algorithm”, the function of which is to modify the synaptic weights of the network in an orderly fashion to attain a desired design objective [38].

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in the nature, the network function is determined largely by connection between elements. A network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements.

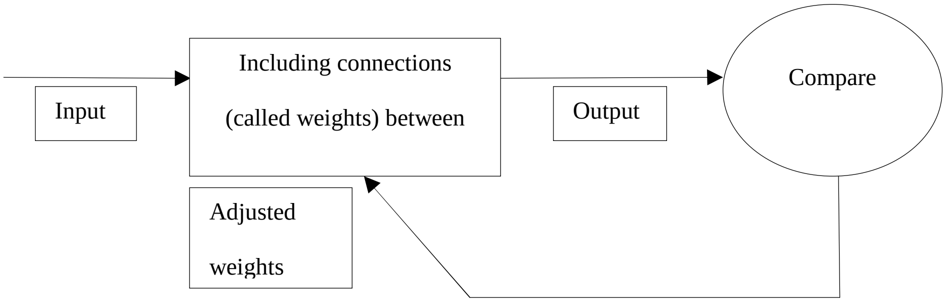


Figure 3-3: Training algorithm of neural networks

Commonly, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown in Figure 3-3. In Figure 3-3, the network is adjusted, based on a compression of the output and the target, until the network output matches the target. Typically many such input/target pairs are used in this supervised learning, to train a network [38].

3.4 **Effective Parameters on Energy Demand of the Residential Sector**

This chapter considers various independent variables such as resident population, gross domestic product, household size, median household income, cost of residential electricity cost of residential natural gas, and cost of residential heating oil to build a residential energy model of the United States. Figure 3-4 and Table 3-1 show the detailed trends of the parameters.

The data in this study come from different sources. The information for GDP, population, median household income, and household size are from the U.S. Census Bureau. The information related to energy consumption in residential sector is taken from U.S. Energy Information Administration. Finally, the data for total energy consumption in residential sector of the United States are from the Annual Energy Review 2011 published by DOE/EIA. [42] [7] [5]

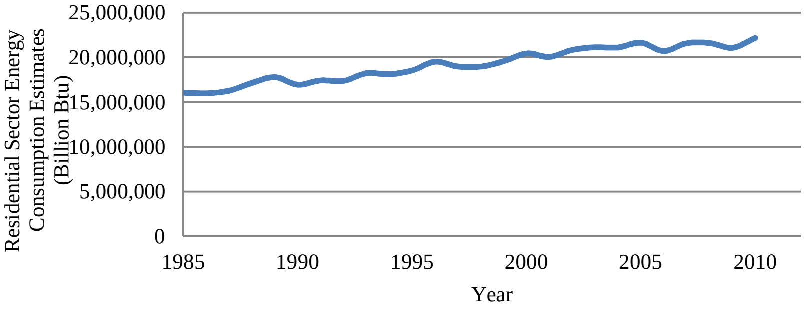


Figure 3-4.a: Residential Sector Energy Consumption Estimates [5]

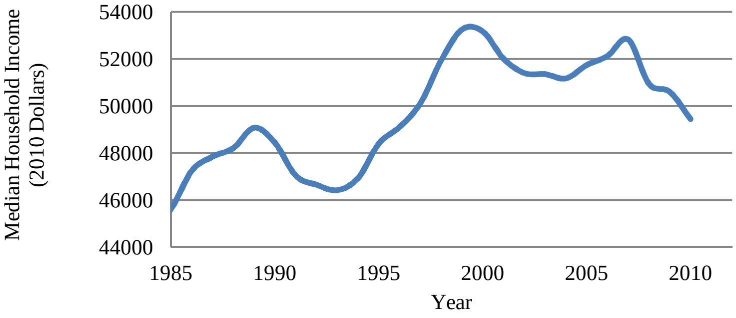


Figure 3.4.b: Median Household Income (U.S. Census Bureau) [42]

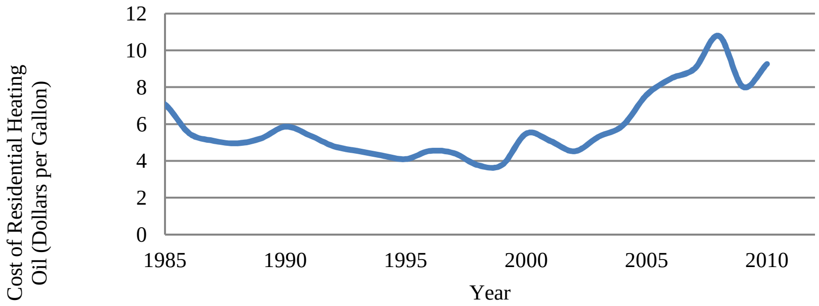


Figure 3.4.c: Cost of Residential Heating Oil (U.S. Energy Information Administration) [7]

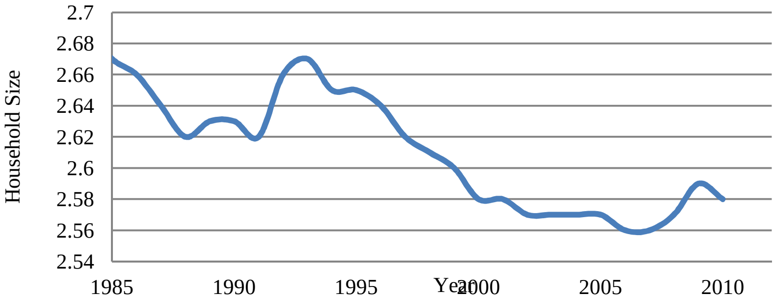


Figure 3.4.d: Household Size (U.S. Census Bureau) [42]

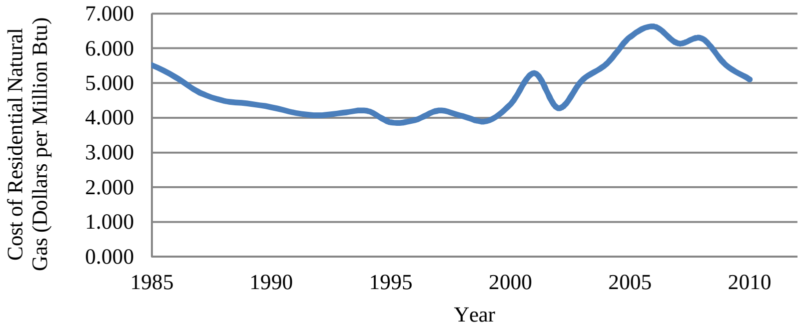


Figure 3.4.e: Cost of Residential Natural Gas (U.S. Energy Information Administration) [7]

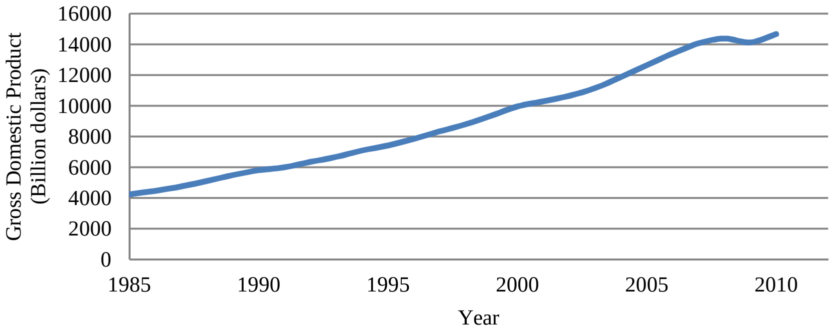


Figure 3.4.f: Gross Domestic Product [42]

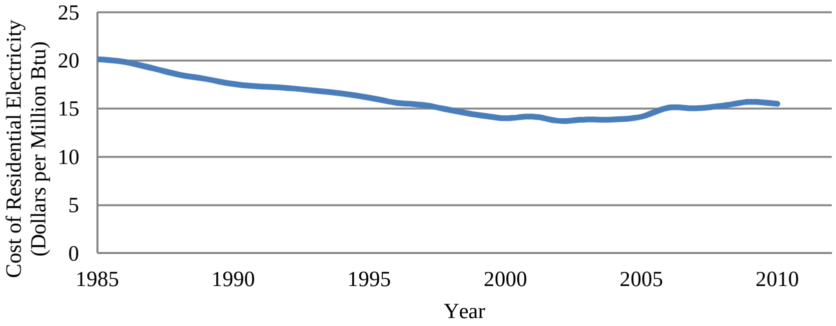


Figure 3.4.g: Cost of Residential Electricity (U.S. Energy Information Administration) [7]

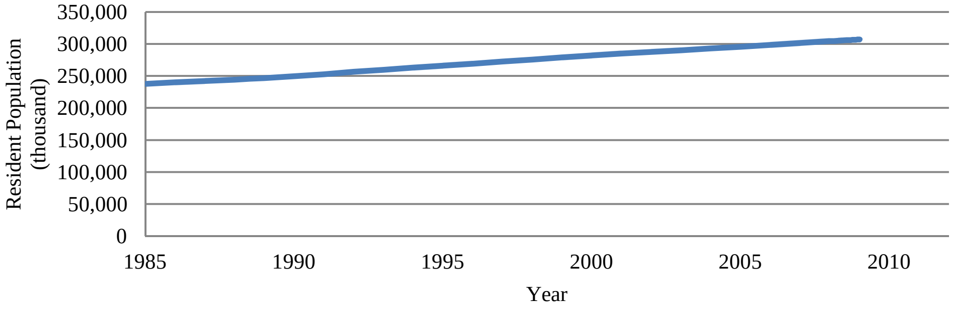


Figure 3.4.f: Resident Population (U.S. Census Bureau) [42]

Table 3-1: Trend of the independent variables and energy consumption estimates [5] [42] [7]

Year	Resident Population (thousand)	Gross Domestic Product (Billion dollars)	Household Size	Median Household Income (2010 Dollars)	Cost of Residential Electricity (Dollars per Million Btu)	Cost of Residential Natural Gas (Dollars per Million Btu)	Cost of Residential Heating Oil (Dollars per Gallon)	Residential Sector Energy Consumption Estimates (Billion Btu)
1984	235,825	3930.9	2.69	44802	20.169	5.719	7.571	15,959,563
1985	237,924	4217.5	2.67	45640	20.129	5.517	7.056	16,041,334
1986	240,133	4460.1	2.66	47256	19.842	5.169	5.5	15,975,109
1987	242,289	4736.4	2.64	47848	19.221	4.730	5.097	16,263,213
1988	244,499	5100.4	2.62	48216	18.531	4.494	4.955	17,132,613
1989	246,819	5482.1	2.63	49076	18.081	4.412	5.233	17,785,725
1990	249,623	5800.5	2.63	48423	17.558	4.308	5.864	16,945,297
1991	252,981	5992.1	2.62	47032	17.301	4.145	5.394	17,420,310
1992	256,514	6342.3	2.66	46646	17.15	4.072	4.8	17,355,685
1993	259,919	6667.4	2.67	46419	16.875	4.147	4.546	18,217,687
1994	263,126	7085.2	2.65	46937	16.572	4.203	4.301	18,112,431
1995	266,278	7414.7	2.65	48408	16.154	3.872	4.102	18,518,963
1996	269,394	7838.5	2.64	49112	15.616	3.937	4.545	19,504,218
1997	272,647	8332.4	2.62	50123	15.394	4.210	4.421	18,964,947
1998	275,854	8793.5	2.61	51944	14.852	4.050	3.769	18,954,918
1999	279,040	9353.5	2.6	53252	14.355	3.906	3.791	19,556,929
2000	282,172	9951.5	2.58	53164	14.024	4.392	5.489	20,424,794
2001	285,082	10286.2	2.58	52005	14.199	5.284	5.089	20,042,076
2002	287,804	10642.3	2.57	51398	13.75	4.279	4.525	20,810,265
2003	290,326	11142.1	2.57	51353	13.89	5.086	5.31	21,109,915
2004	293,046	11867.8	2.57	51174	13.886	5.547	5.909	21,092,623
2005	295,753	12638.4	2.57	51739	14.181	6.326	7.576	21,626,073
2006	298,593	13398.9	2.56	52124	15.119	6.625	8.459	20,698,278
2007	301,580	14061.8	2.56	52823	15.054	6.143	9.014	21,565,031
2008	304,375	14369.1	2.57	50939	15.328	6.282	10.78	21,596,245
2009	307,007	14119	2.59	50599	15.724	5.521	8.019	21,063,265
2010	3.09349	14660.4	2.58	49445	15.511	5.106	9.252	22,153,450

This study considers all the possible combination of variables for the model. Each of these models is based on some of the listed indicators.

The model building problem consists of selecting an appropriate set of regressors from a set that quite likely includes all of the important variables; however, we are not sure that all of these candidate regressors are necessary to adequately model the historical data of energy demand. In such a situation, we are interested in screening the candidate variables to obtain the regression model that contains the best subset of regressor variables. In addition, to make the model easy to use, we would like the model to use as few regressor variables as possible.

First, the models are built using the multiple linear regression method. This approach requires the fitting of all the regression equations involving one candidate variable, all regression equations involving two regression variables, and so on. Then these equations are evaluated according to some suitable criteria to select the best regression model. Since there are 7 candidate regressors, there are 2^7 total equations to be examined.

A number of criteria may be used for evaluating and comparing the different regression models obtained. A commonly used criterion is based on the Coefficient of Multiple Determination shown with $R^2{}_p$:

$$R_p^2 = 1 - \frac{SS_E(p)}{S_{yy}} \tag{3.1}$$

where $SS_E(p)$ and S_{yy} denote the error sum of the squares and total sum of the squares, respectively, for a p-variable model.

A second criterion is to consider the mean square error for a p-variable equation:

$$MS_E(p) = \frac{SS_E(p)}{(n-p)} \tag{3.2}$$

Regressors are usually chosen so that $MS_E(p)$ is a minimum. A third criterion is the C_p statistics, which is a measure of the total mean square error for the regression model.

$$C_p = \frac{SS_E(p)}{\hat{\sigma}^2} - n + 2p \tag{3.3}$$

We choose the ‘best’ regression equation either a model with minimum C_p or a model with a slightly larger C_p that does not contain as much bias. More details can be found in [20] and [21].

Another criterion is based on a modification of R^2_p that accounts for the number of variables in the model. This statistics is called the adjusted R^2_p defined as

$$\overline{R_p^2} = 1 - \frac{n-1}{n-p}(1 - R_p^2) \tag{3.4}$$

The regression model that has the maximum value of $\overline{R_p^2}$ would usually be selected. The results of the regression models are indicated in appendix A. Table 3-2 contains the summary of the best models among all possible models.

Table 3-2: Evaluating criteria of each number of independent variables

Number of independent parameters	**1**	**2**	**3**	**4**	**5**	**6**	**7**
R^2_p	0.95697	0.97068	0.97168	0.97255	0.97297	0.97349	0.9735
MSE	1.78E+11	1.27E+11	1.28E+11	1.29E+11	1.33E+11	1.37E+11	1.45E+11
C_p	7.8449	0.019459	1.3009	2.6789	4.374	6.001	8

The best regression models are based on two, three and four independent variables. Adding more independent variables, such as models using 6 and 7 independent variables, only increases the calculation time and increases the model complexity without a correspondingly significant improvement in R^2_p. Table 3-3 shows the selected independent parameters for the models.

Table 3-3: Selected independent parameters for the models

	Resident Population	**GDP**	**Household Size**	**Median Household Income**	**Cost of Residential Electricity**	**Cost of Residential Natural Gas**	**Cost of Residential Heating Oil**
Model 1		✓			✓		
Model 2		✓		✓	✓		
Model 3		✓		✓	✓		✓

Stepwise regression is probably the most widely used variable selection technique. The procedure iteratively constructs a sequence of regression models by adding variables at each step. Forward selection is a variation of stepwise regression and is based on the principle that regressors should be added to the model one at a time until there are no remaining candidate regressors that produce a significant increase in the regression sum of squares. Backward elimination starts with all candidate regressors (*k*) in the model. Then, the regressor with the smallest partial *F*-statistic is deleted. Next, the model with *k-1* regressors is fit and the next regressor with potential elimination is found. The algorithm terminates when no further regressor can be deleted.

Forward selection and backward elimination are simplifications of stepwise regression that omit the partial *F*-test for deleting variables from the model that have been added at previous steps. This is the potential weakness of forward selection and backward elimination; that is, the procedure does not explore the effect that adding or deleting a regressor at the current step has on regressor variables added or deleted at earlier steps [39].

In this chapter, stepwise regression method has been used. In order to select the appropriate independent variables for the any of the models, all the possible MLR models have been tested. For instance, to select the best three parameters for the second model, all possible MLR models with 3 of 7 independent variables have been tested and the independent variables corresponding to the best model were selected for further analysis. The following equations show the regression equations for the proposed MLR models 1, 2, and 3:

$$Y_1 = \beta_{1,1} X_2 + \beta_{2,1} X_5 \tag{3.1}$$

$$Y_2 = \beta_{1,2} X_2 + \beta_{2,2} X_4 + \beta_{3,2} X_5 \tag{3.2}$$

$$Y_3 = \beta_{1,3} X_2 + \beta_{2,3} X_4 + \beta_{3,3} X_5 + \beta_{4,3} X_7 \tag{3.3}$$

where Y_i is ith model, $\beta_{j,i}$ is the i^{th} regression coefficient of the i^{th} model and X_is are shown in the Table 3-3.

In the next step, based on the historical trend of the parameters, the future trends of the independent variables are forecasted. The selected regression models take the future trends of the independent variables as input to generate the estimated energy demand in next 20 years. Figure 3-5 presents the estimated energy demand in the residential sector of the United States based on the forecast of selected independent variables using best regression models.

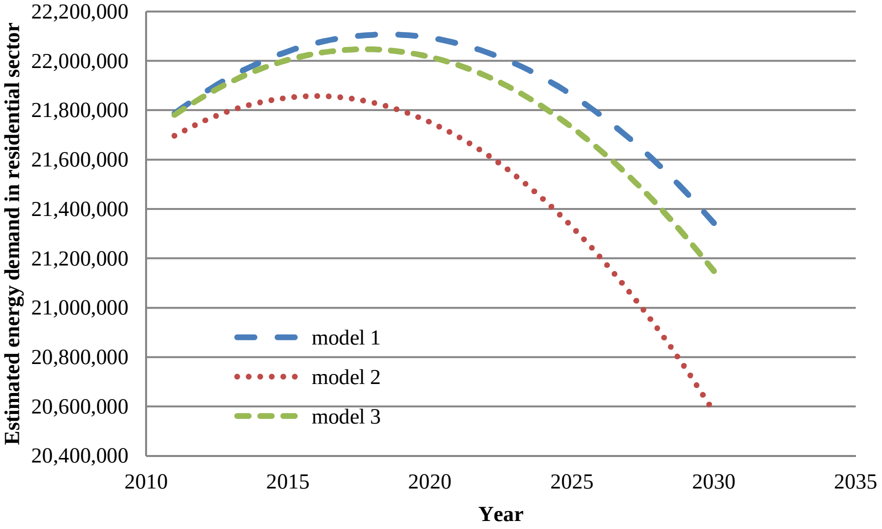


Figure 3-5: Estimated energy demand of the residential sector 2010-2030 using MLR models

3.5 **Artificial Neural Network Modeling**

For modeling the problem using ANN, a feed-forward multilayer perceptron neural network has been used which is coupled with back-propagation technique. This network is a generalization of single layer perceptron. The network consists of a set of sensory units that constitute the input layer, one hidden layer of computation nodes, and an output layer of computation nodes. The input signal propagates through the network in the forward direction, on a layer-by-layer basis.

Essentially, error back-propagation learning consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass, an activity pattern (input vector) is applied to the sensory nodes of the network, and its effects propagate through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. Back-propagation allows quick convergence on a satisfactory local minimum for error in the kind of networks to which it is well-suited. It is simply a gradient descent method to minimize the total squared error of the output computed by the network [36].

During the forward pass, the synaptic weights of the network are all fixed. During the backward pass, on the other hand, the synaptic weights are all adjusted in accordance with an error-correction rule. Specifically, the actual response of the network is subtracted from a target response to produce an error signal. This error signal is then propagated backward through the network, against the direction of synaptic connections.

The synaptic weights are adjusted to make the actual response of the network move closer to the desired response in a statistical sense.

The applied technique has four distinctive characteristics [37]:

- The model of each neuron in the network includes a nonlinear activation function. The nonlinearity is smooth and differentiable everywhere. The used form of nonlinearity that satisfies this requirement is sigmoidal nonlinearity defined by the logistic function

$$y_j = \frac{1}{1 + exp\left(-v_j\right)} \tag{3.4}$$

where v_j is the weighted sum of all synaptic inputs plus the bias of neuron j and y_j is the output of the neuron.

The presence of non-linearity is important because otherwise the input-output relation of the network could be reduced to that of a single-layer perceptron.

- The network contains one layer of hidden neurons. These neurons enable the network to learn complex tasks by extracting progressively more meaningful features from the input vector. The theoretical results show that one hidden layer is sufficient for a back-propagation net to approximate any continuous mapping from the input patterns to the output patterns. The hidden layer neurons influence the network performance prediction.

- The network exhibits a high degree of connectivity as determined by the synapses of the network. A change in the connectivity of the network requires a change in population of synaptic connections or the weights.

- In the forward pass, the function signal appearing at the output of neuron *j* is computed as

$$y_j(n) = \varphi\left(v_j(n)\right) \tag{3.5}$$

where $v_j(n)$ is the induced local field of neuron *j* defined by

$$v_j(n) = \sum_{i=0}^{m} w_{ij}(n)x_i(n) \tag{3.6}$$

In Equation (2.6), m is the total number of inputs excluding the bias applied to neuron j and $w_{ij}(n)$ is the synaptic weight connecting neuron *i* to neuron *j* and $x_i(n)$ is the input signal of neuron *j*. The index *i* refers to the *i*th input terminal of the network. The transfer function accepts inputs varying from 0 to 1 and produces outputs over a finite range from 0 to 1. Figure 3-6 shows a signal-flow graph of output neuron.

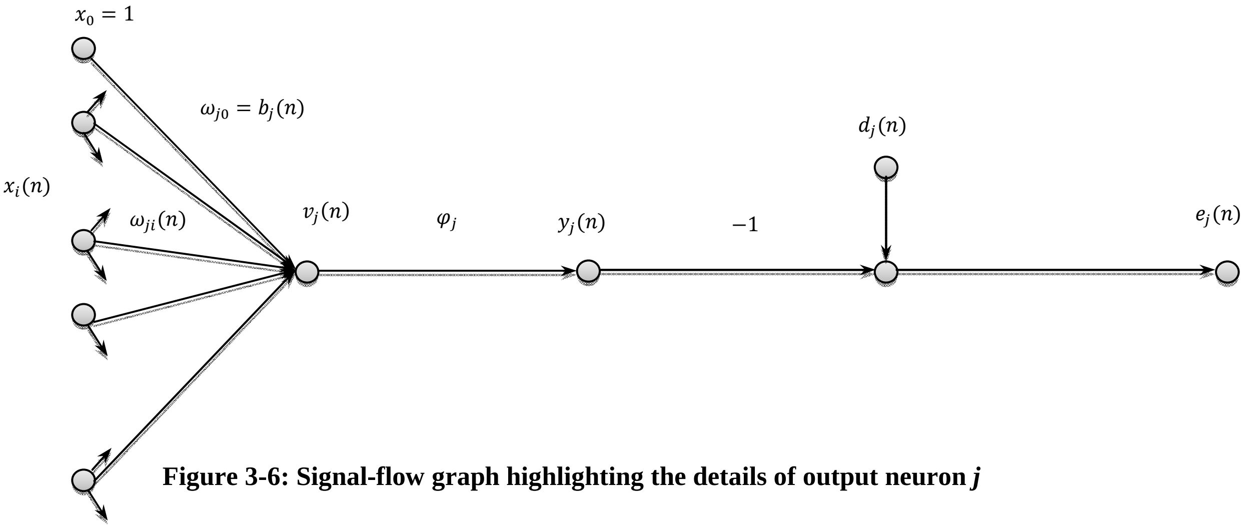


Figure 3-6: Signal-flow graph highlighting the details of output neuron *j*

The steps of the analysis are as follows:

1. Divide the available data into training, validation and predicting set;

2. Select the proper architecture and input parameters;

3. Train the model using the training set;

4. Evaluate the model using validation data;

5. For different architectures and input parameters, repeat steps 2 through 4;

6. Apply the test on the final network architecture.

In the estimation of energy demand of the residential sector, three models are built. Each of these three contains a set of independent variables which are same independent variables as ones used in MLR modeling. Figure 3-7 shows the output of the model for the period of 1984-2010 compared with known energy demand in same period.

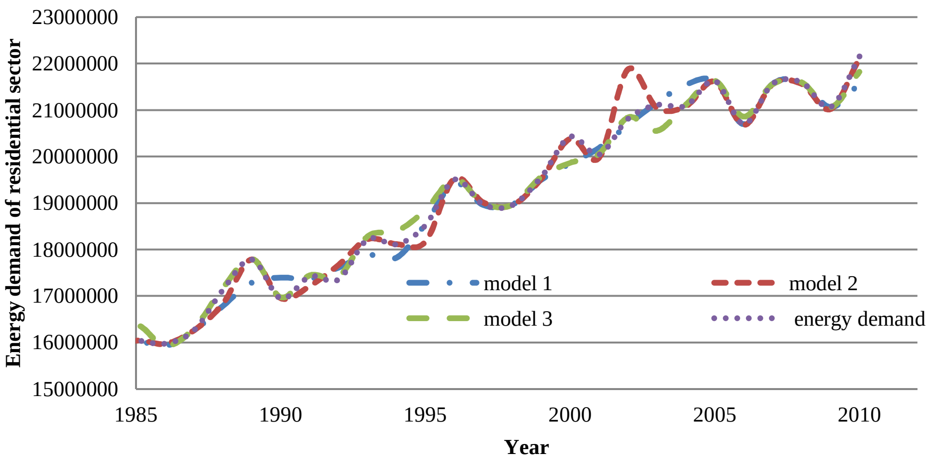


Figure 3-7: Energy demand of the U.S. residential sector, comparing ANN models to the actual data

3.6 **Forecasting Scenario**

To forecast the energy demand in the residential sector, individual variables (resident population, gross domestic product, household size, median household income, cost of residential electricity cost of residential natural gas, and cost of residential heating oil) should be analyzed and their trends for the future should be forecasted first. This forecast has been made based on the historical data from 1980 using a regression method. The extrapolated trend is linear for GDP per capita, resident population, median household income, and household size. However, the trends of the cost of residential heating oil, cost of residential natural gas, and cost of residential electricity follow a quadratic trend during the forecast period. The forecasted results based on historical data are shown in Figure 3-8.

Using the forecast of individual variables, the energy demand has been forecasted for the period of 2010 to 2030. The models, which have been developed and trained by the historical data points and performances during the test period, are now used to generate the future demand of energy. The forecasted values of the individual variables are fed to the trained networks as input vectors. The models give the future energy demand by applying the weights which are set up after the training process. The results are presented in Figure 3-9 and also summarized in Table 3-5.

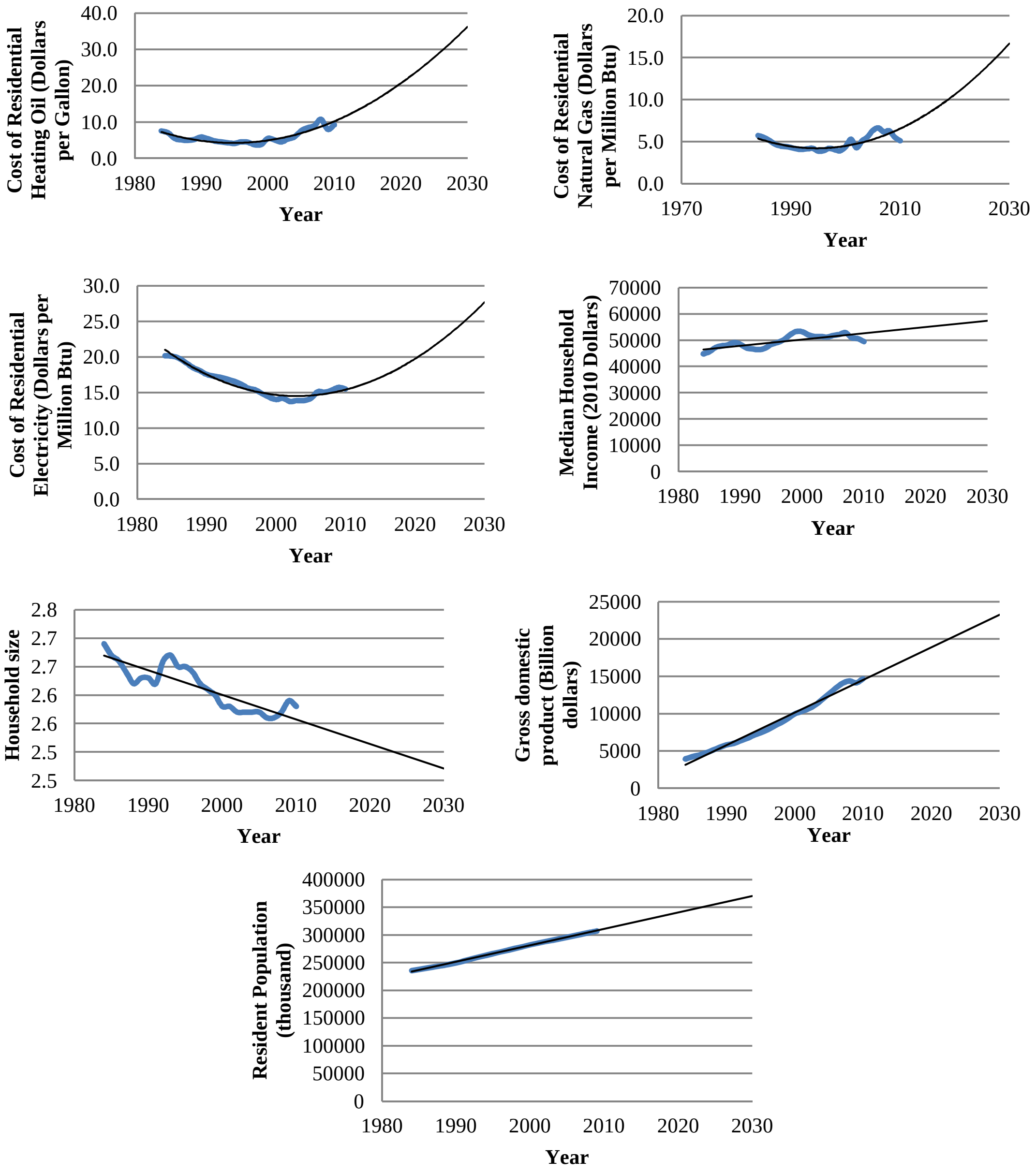


Figure 3-8: Forecasted independent variables based on historical data

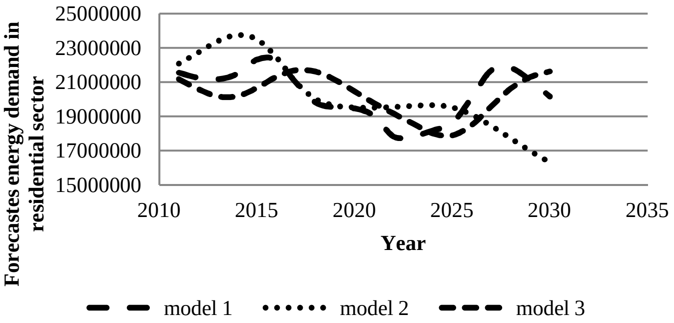


Figure 3-9: Forecasted energy demand in the U.S. residential sector using ANN

Table 3-4: Forecasted energy demand in the U.S. residential sector using ANN

year	model 1	model 2	model 3
2011	21542000	22081000	21173000
2012	21246000	22731000	20581000
2013	21167000	23395000	20160000
2014	21485000	23748000	20181000
2015	22308000	23495000	20662000
2016	22282000	22442000	21313000
2017	20956000	20991000	21697000
2018	19808000	20014000	21610000
2019	19528000	19628000	21133000
2020	19460000	19521000	20453000
2021	19026000	19513000	19766000
2022	17817000	19550000	19158000
2023	17829000	19614000	18566000
2024	18174000	19653000	18006000
2025	18592000	19528000	17881000
2026	20105000	19104000	18490000
2027	21678000	18448000	19580000
2028	21822000	17715000	20624000
2029	21097000	16979000	21292000
2030	20158000	16314000	21620000

As can be seen in Figure 3-8, noticeable decreases took place for the GDP per capita and median household income during 2007 until 2010. This happened due to the great variations in economic growth during the periods of the economic downturn, which occurred in the United States beginning in 2007 and whose impacts are still experienced. Therefore, because of the nature of the ANNs modeling approach, these fluctuations are reflected by the model in its future predictions. In addition, the results of the ANN models are in agreement with the predicted results for the growth of energy demand in the residential sector published in International Energy Outlook, 2011. This corresponding study shows a 0.1% annual growth which means the delivered energy consumption in residential sector of the United State remains almost constant for next 20 years.

3.7 **Discussion**

As previously explained, Table 3-3 shows the independent variables selected for MLR models. The same sets of variables are selected for ANN models. Although the results of 6 different models (3 ANN models and 3MLR models) were presented above, the evaluation of the models was not performed. This section targets the evaluation of the models. Results presented in Table 3-5 indicate that the R^2 of the models are not significantly different and all of the models are generating the energy demand data corresponding to the test period that are close to the real data. However, in terms of prediction, the trends of the models are different.

Table 3-5: Comparison of the performance of MLR models and ANN models

	MLR Models			ANN Models		
	1	**2**	**3**	**1**	**2**	**3**
R^2_p	0.95697	0.97068	0.97168	0.98229	0.98489	0.98957

Although, the results from regression models show a decrease with different slopes corresponding to different models for energy demand in the near future, the results from ANN express no significant change in demand in same time frame (except model 2). Since the regression models only see the overall long-term trend, they are not sensitive to the recent fluctuations. Being more sensitive to the outcomes of economic crises, it seems that the approximately uniform results with slower growth predicted by the artificial neural networks are likely more realistic.

Because the ANN is a black-box method and it contains hidden trends implicitly in addition to explicit independent variables, it is difficult to explain the wavy forecasted results which remain with no significant change in given time period. However, there are some factors which may be being captured in the model that may help explain the results:

1) Home appliance makers may spend more money on research in order to progress to more environmentally-friendly and fuel-efficient products.

2) Due to the growing cost of the energy, people modify their behavior and use energy more efficiently.

3) Development of education and improvement of public awareness about restricted energy sources decreases the energy demand nation-wide.

3.8 **Conclusion**

Both multiple linear regression and artificial neural network models for the residential sector of the United States have been developed applying various independent variables. Models show robust outcomes when their R^2 is considered.

In terms of forecasting, the models show two different trends while their performances are at a similar level of accuracy during the test period. Sensitivity of the ANN models to the recent fluctuations caused by the economic recession may be the reason for the difference as regression models only forecast based on the total trend of the individual parameters.

Although a small increase in the energy demand in residential sector of the United States has been estimated by the ANN, the United States should keep trying to reduce energy consumption in order to reduce CO_2 emissions and meet its national and international commitments. Furthermore, improved economic conditions in the near future may cause ANN models to revise their forecasts upwards in terms of energy consumption.

Due to the uncertainty in any extrapolation techniques, more research should be done to closely observe the accuracy of the ANN and MLR models developed in this study for predicting the energy demand.

CHAPTER 4

ENERGY DEMAND IN THE TRANSPORTATION SECTOR OF THE UNITED STATES

4.1 Introduction

While, as discussed previously, the United States consumes vast quantities of energy, it has also pledged to cut its greenhouse gas emissions by 2050. This was done through passage of the American Clean Energy and Security Act in June 2009. This measure aims to promote clean energy investments and to lower US greenhouse-gas emissions by more than 80% by 2050. Part of this reduction will need to be achieved in the transportation sector. Moreover, a new efficiency standard for automobiles set joint fuel economy and greenhouse-gas emission standards for 2011 model cars and trucks to increase fuel economy to 6.7 liters per 100 kilometer (35 miles per gallon) by 2020 [6]. The major primary energy source in the transport sector of the United States is oil (94.1%) while liquefied gas (2.4%) and biomass (3.5%) occupy small portions as shown in Figure 2 [5].

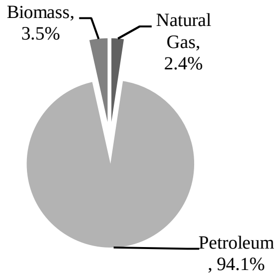


Figure 4-1: Major primary energy sources in transport sector

In order to assist in planning for future energy needs, the purpose of this chapter is to develop a model for transport energy demand that incorporates past trends. Two models are developed. The primary model described in this research employs an artificial neural network (ANN) technique to predict United States transport energy demand. Five independents variables (population, GDP, oil price, amount of passenger transportation, and number of vehicles) have been tested for the modeling. The results of the ANN models are compared to those predicted by the more traditional multiple linear regression modeling technique so that any advantages to the ANN modeling technique can be discerned. By studying the possible scenario for growth of parameters, future transport energy demand in United States is then forecasted based on the models.

4.2 **Background**

As the energy demand in the transportation sector grows rapidly compared to the other energy consuming sectors, modeling energy demand in this sector to estimate the future demand is getting more popular among energy analysts. There have been some successful models which focus on the estimation of energy demand in transportation sector. Geem, after modeling the energy demand in South Korea, developed an ANN network to estimate the nationwide energy demand for transportation sector of South Korea. He built different models by using different combination of independent variables. Also ANNs are compared with the multiple linear regression models. The ANN models obtained robust results in terms of $RMSE$ as well as R^2, when compared with MLR models [10]. To project transport energy consumption in Thailand, Limanond et al. generated log-linear model and feed-forward neural network models based on GDP, population and number of registered vehicles as independent variables. Two log- linear models were created. The first model explains transport energy usage in terms of gross domestic product, while the second explains per-capita transport energy use based on per-capita GDP. The models can account for up to 93–95% of the variability in transport energy demand. The final ANN models include all five socio-economic variables as inputs, and estimated transport energy demand as an output. The three ANN model structures with the highest performance are used to arrive at the final energy demand projection. The results are projected for 2010-2030 and also compared with their previous study done by LEAP [44]. Murat and Ceylan investigated future energy demand in transportation sector of Turkey using ANNs and socio-economic indicators. The structure of their model consists of a feed-forward neural network trained by a back propagation algorithm and the socio-economic indicators used are GNP, population and annual average vehicle-km; the period of study is 1970 to 2001. The logic of the ANN and the application of k-fold cross-validation method are described in detail. The data is partitioned into six groups and whichever provides the total minimum error is selected as the best network architecture. The best of the network architectures is obtained as 3×14×1 and used for all the modeling process [20]. Jin-ming and Xin-heng compared the results of their model for energy demand of China which is based on ANN with the results from trend extrapolation. The ANN model showed higher precision [17].

Several studies were carried out on the United States' energy consumption forecast using different methods and approaches in the recent years. L. Parshall et al. evaluated the ability of Vulcan to measure energy consumption in urban areas, a scale of analysis required to support goals established as part of local energy, climate or sustainability initiatives. The Vulcan Project is a NASA/DOE funded effort under the North American Carbon Program to quantify North American fossil fuel carbon dioxide (CO_2) emissions at space and time scales. They also highlighted the methodological challenges of this type of analytical exercise and review alternative approaches [45].

4.3 **Description of the ANN Model**

This portion of the study primarily focuses on the artificial neural networks and multiple linear regression techniques for forecasting the transportation energy demand of the United States based on several indicators. The study considers various independent variables such as population, GDP per capita, oil price, number of registered vehicles and amount of passenger transportation to build a transport energy model of the United States. Figure 4-2 shows the detailed trends of the parameters.

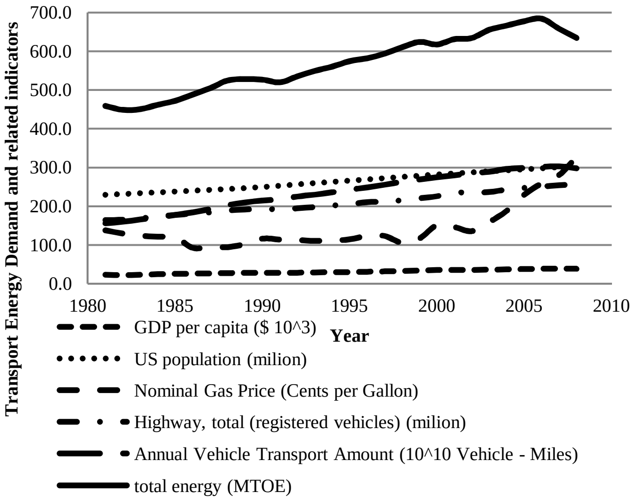


Figure 4-2: Transport Energy Demand and related indicators

The data in this study come from different sources. While GDP is a common factor of most studies, in this study the GDP per capita is tested. GDP per capita is a measure that results from GDP divided by the size of the nation's overall population. So, in essence, it is theoretically the amount of money that each individual receives in that particular country. The GDP per capita provides a much better determination of living standards as compared to GDP alone. The information for GDP per capita comes from the World Bank [46].

The data for the Number of U.S. aircraft, vehicles, vessels, and other conveyances are from the Research and Innovative Technology Administration (RITA), U.S. Department of Transportation, National Transportation Statistics [47]. Finally, the data for total energy consumption in transportation sector of the United States are from the Annual Energy Review 2011 published by DOE/EIA [5].

The population information is from U.S. Census Bureau [42] and oil price information is from U.S. Energy Information Administration for unleaded regular gasoline. The amount of Annual Vehicle - Miles of Travel is provided by United States Department of Transportation - Federal Highway Administration [48].

Table 4-1: Variables applied in each model

Model	GDP per capita	US population	Nominal Gas Price	Highway, total registered vehicles	Annual Vehicle Transport Amount
1	✓	✓			✓
2	✓			✓	✓
3			✓	✓	✓
4		✓	✓		✓
5	✓		✓	✓	✓
6	✓	✓	✓	✓	✓

This study considers six models. Each of these models is based on some of the listed indicators. Table 4-1 lists the variables which are applied in each model. First, the models are built using the multiple linear regression method. The model building problem consists of selecting an appropriate set of regressors from a set that quite likely includes all of the important variables; however we are not sure that all of these candidate regressors are necessary to adequately model the historical data of energy demand. In such a situation, we are interested in screening the candidate variables to obtain the regression model that contains the best subset of regressor variables. In addition, to make the model easy to use, we would like the model to use as few regressor variables as possible. The equations used in this technique are

$$y_1 = \beta_1 x_1 + \beta_2 x_2 + \beta_5 x_5 + \beta_0 \tag{4.1}$$

$$y_2 = \beta_1 x_1 + \beta_4 x_4 + \beta_5 x_5 + \beta_0 \tag{4.2}$$

$$y_3 = \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_0 \tag{4.3}$$

$$y_4 = \beta_2 x_2 + \beta_3 x_3 + \beta_5 x_5 + \beta_0 \tag{4.4}$$

$$y_5 = \beta_1 x_1 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_0 \tag{4.5}$$

$$y_6 = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_0 \tag{4.6}$$

In Equations 4.1 - 4.6, the variables, y_1 to y_6 are energy consumed in the transportation sector, x_1 to x_5 are the regresors which are indicators of energy consumption, while β_0 to β_5 are the coefficients of regression.

For modeling the problem using ANN, a feed-forward multilayer perceptron neural network has been used which is coupled with back-propagation technique. This network is a generalization of single layer perceptron. The network consists of a set of sensory units that constitute the input layer, one hidden layer of computation nodes, and an output layer of computation nodes. The input signal propagates through the network in the forward direction, on a layer-by-layer basis.

Overfitting is important in machine learning. It usually appears when the model is highly complicated and has too many parameters compared to the number of observations. Especially when the learning performed is too long or when the training set is too short, the learner may adjust to very specific random features of the training data. The performance of the model in terms of prediction will generally decline. In other words, minor fluctuations of data will be exaggerated.

In the current study, however, the overfitting problem is very unlikely to happen since the training examples are not rare compared to the number of effective parameters. In addition, the model that is employed is not excessively complex.

4.4 **Results**

The data are divided into three categories: 25 data points (1981-2005) are used for training, 4 data points (2006-2009) are used for validation, and 21 data points are subsequently predicted (2010-2030) to generate results for the future demand. The MATLAB neural network toolbox was used to train the developed neural network models. All models with 3 and 4 parameters show satisfactory results in terms of R^2, Root Mean Squared Error (RMSE):

$$R^2 = 1 - \left(\frac{\sum_{k=1}^{n} \left(d_k - y_k(x)\right)^2}{\sum_{k=1}^{n} (y_k(x)^2) - \frac{(\sum_{k=1}^{n} y_k(x))^2}{n}} \right) \tag{4.7}$$

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n} (d_k - y_k(x))^2}{n}} \tag{4.8}$$

where n is the number of data points (2006-2009) and x is the vector of independent variables. Then, a new model which includes the effect of 5 most important parameters to estimate the demand was developed. Since all of the R^2 values are above 0.950, all of the models are working satisfactorily. The results presented in Table 4-2 show that improvement is gained in estimating the values of energy demand using ANN in comparison to MLR modeling. Figure 4-3 shows the results of the ANN models and MLR models for the test period (2006-2009).

Table 4-2 : Results of the models corresponding to the test period

Method	Error	Model 1	Model 2	Model 3
ANN	***R^2***	0.9962	0.9840	0.9798
MLR	***R^2***	0.9930	0.9930	0.9890
	RMSE	20.3059	145.8258	187.6521
Method	**Error**	**Model 4**	**Model 5**	**Model 6**
ANN	***R^2***	0.9910	0.9955	0.9923
MLR	***R^2***	0.9858	0.9931	0.9935
	RMSE	24.3806	161.2944	42.0043

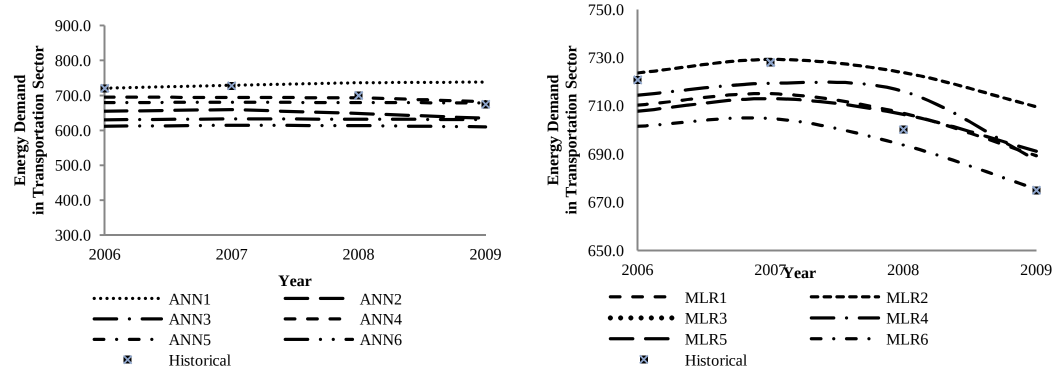


Figure 4-3: Performances of ANN and MLR models in validation period (MTOE)

Most of the ANN models have better performances in predicting the energy demand during the test period when compared to the values forecasted by MLR models. As discussed, similar results were seen by Ekonomou in his comparison between ANN and MLR modeling [21]. While both models are providing acceptable levels of predictions for most cases, the improvement seen in the ANN models suggests that the modeling scheme employed in ANN techniques offers advantages which may become more apparent as one tries to predict over longer time periods. A longer time period of historical data results in a better learning process and consequently higher performance of model in the forecast period.

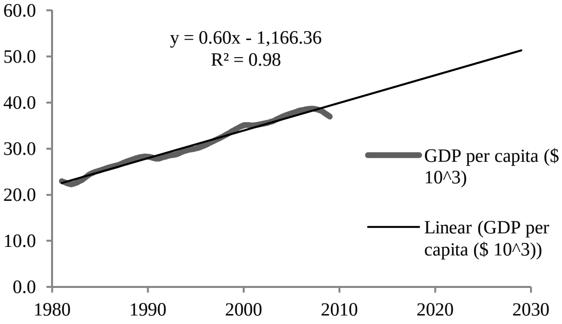
The regression coefficients of the MLR models are presented in Table 4-3. Positive values of this coefficient show the positive correlation of the regressor with the energy demand and negative values express a negative correlation between the regressor and the energy demand. Although most of the regression coefficients have reasonable sign, some of them have non-acceptable signs. For example, the coefficient of gas price should be always negative since an increase in the gas price should result in a decrease in demand. In addition, the coefficient of Annual Vehicle Transport amount should be always positive because more transportation needs more fuel. These rules are not satisfied in all of the models.

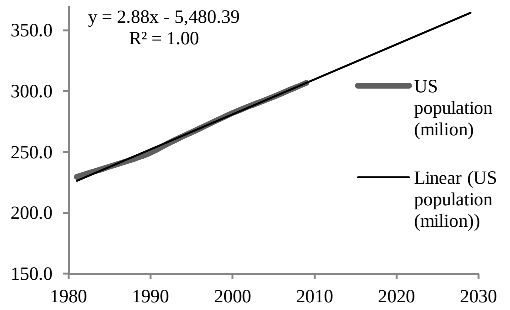
Table 4-3: Coefficient of regression in MLR models

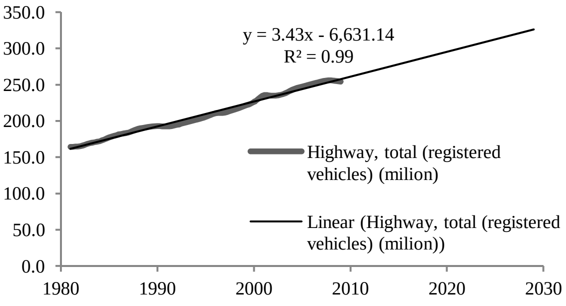
Model	**GDP per capita**	**US population**	**Nominal Gas Price**	**Highway, total (registered vehicles)**	**Annual Vehicle Transport Amount**
1	12.095	-0.2875			0.4663
2	10.812			0.2418	0.3303
3			0.0092	1.6436	0.6478
4		0.2258	-1.1224		1.9783
5	0.0385		0.0358	0.4062	11.028
6	0.0884	0.1063	0.8189	10.655	-0.9336

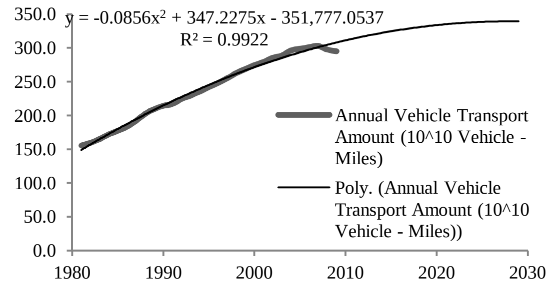
4.5 **Forecasting Scenario**

To forecast the energy demand in the transportation sector, individual variables (US population, GDP per capita, Nominal Gas Price, Highway total registered vehicles, Annual Vehicle Transport Amount) should be analyzed and their trends for the future should be forecasted first. This forecast has been made based on the historical data from 1980 using a regression method. The extrapolated trend is linear for GDP per capita, US population, and total registered vehicles in highways. However, the trends of the annual vehicle transport amount and nominal gas price follow a quadratic format during the forecast period. The forecasted results based on historical data are shown in Figure 4-4. Also, the quality of the regression for each of the individual variables is given by the coefficient of determination (R^2) on the extrapolated graph.









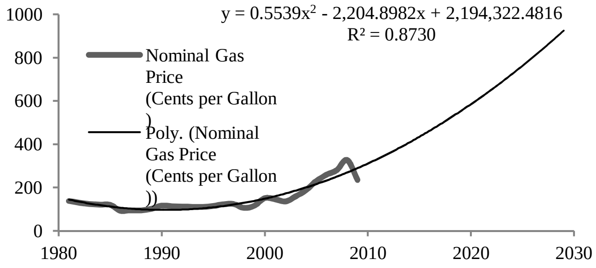


Figure 4-4: Historical and future trend of independent variables

Using the forecast of individual variables, the energy demand has been forecasted for period of 2010 to 2030. The models, which have been developed and trained by the historical data points and performances of which have been evaluated during the test period, are now used to generate the future demand of energy. The forecasted values of the individual variables are fed to the trained networks as input vectors. The models give the future energy demand by applying the weights which are set up after the training process. The results are presented in Figure 4-5 and also summarized in Table 4-4.

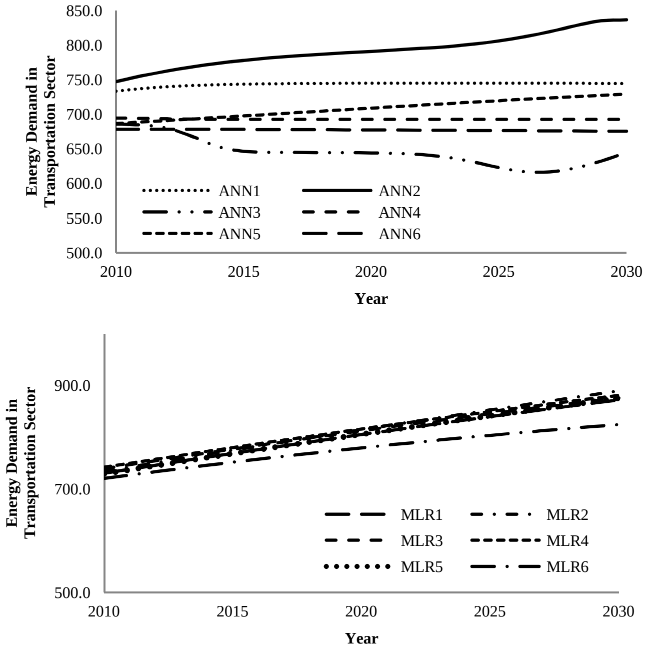


Figure 4-5: 20-years forecast of energy demand in transportation sector using ANN and MLR (MTOE)

As can be seen in Figure 4-4, fluctuations take place for the GDP per capita, Nominal Gas Price, Highway total registered vehicles, and the Annual Vehicle Transport Amount during 2007 until 2010. This happened due to the great variations in GDP for the periods of the economic downturn, which hit the United States beginning in 2007 and whose impacts continue to the present. Therefore, because of the nature of the ANNs modeling approach, the fluctuations are reflected by the model during the future predictions.

Table 4-4: Results of the ANN and MLR compared with forecast by Annual Energy Outlook 2011

Year	**ANN1**	**ANN2**	**ANN3**	**ANN4**	**ANN5**	**ANN6**	**MLR1**	**MLR2**	**MLR3**	**MLR4**	**MLR5**	**MLR6**	**Projection (EIA, 2011)**
2010	733.6	747.7	685.9	694.8	686.7	678.3	730.7	734.0	739.5	742.1	729.0	720.5	
2011	737.4	755.9	684.6	694.3	688.8	678.4	738.5	742.3	747.4	749.8	737.0	727.0	
2012	740.0	763.0	680.1	693.6	691.0	678.4	746.2	750.5	755.0	757.4	744.9	733.3	
2013	741.7	769.0	667.9	693.2	693.2	678.4	754.0	758.7	762.6	765.1	752.7	739.6	
2014	742.9	774.0	653.1	693.0	695.5	678.3	761.6	766.9	770.2	772.8	760.5	745.8	
2015	743.7	778.2	646.6	692.9	697.7	678.2	769.1	775.0	777.6	780.1	768.2	751.7	671.7
2016	744.2	781.7	645.1	692.8	700.0	678.1	776.5	783.0	784.8	787.5	775.8	757.6	
2017	744.6	784.6	644.8	692.8	702.2	678.0	783.9	791.0	792.0	794.8	783.4	763.3	
2018	744.8	787.0	644.8	692.8	704.5	677.8	791.1	798.9	799.2	801.9	790.9	768.8	
2019	744.9	789.3	644.6	692.8	706.7	677.7	798.4	806.8	806.1	809.2	798.3	774.3	
2020	745.0	791.3	644.3	692.8	708.9	677.5	805.5	814.6	813.0	816.2	805.7	779.6	683.5
2021	745.0	793.3	643.5	692.8	711.2	677.4	812.5	822.4	819.9	823.0	812.9	784.7	
2022	745.1	795.6	641.6	692.8	713.3	677.2	819.5	830.0	826.5	829.7	820.1	789.7	
2023	745.1	798.3	637.8	692.8	715.5	677.1	826.4	837.7	833.1	836.6	827.3	794.6	
2024	745.1	801.7	631.2	692.8	717.6	676.9	833.2	845.2	839.5	843.2	834.3	799.3	
2025	745.1	806.3	622.9	692.8	719.7	676.7	839.9	852.8	846.0	849.7	841.3	803.8	697.6
2026	745.1	812.3	617.0	692.8	721.8	676.5	846.6	860.3	852.3	856.2	848.3	808.3	
2027	745.0	819.9	616.7	692.8	723.8	676.4	853.1	867.7	858.4	862.6	855.1	812.6	
2028	744.9	828.4	622.4	692.8	725.7	676.2	859.6	875.0	864.6	869.0	861.9	816.8	
2029	744.8	835.4	632.3	692.8	727.6	676.0	866.0	882.3	870.6	875.3	868.7	820.9	
2030	744.4	836.9	644.8	692.8	729.3	675.8	872.3	889.5	876.4	881.2	875.3	824.7	718.8

In addition, the results of the ANN models are in agreement with the predicted results for energy demand in transportation sector published in International Energy Outlook, 2011. Those projections are shown in Table 4-4.

4.6 **Discussion**

Although the results of 10 different models were presented above, the evaluation of the models was not performed. This section targets the evaluation of the models. Results presented in Table 4-2 indicate that the R^2 and the RMSE of the models are not significantly different and all of the models are generating the energy demand data corresponding to the test period close to the real data. However, in terms of prediction, the trends of the models are different.

Although, the results from regression models show a uniform increase with different slopes corresponding to different models for energy demand in the near future, the results from ANN express no significant change in demand in same time frame. Considering the trend of the demand in recent years, it can be seen that the rate of the growth moved closer to zero and it was even negative during 2007 until 2010. Since the regression models only see the overall long-term trend and they are not sensitive to the recent fluctuations, such models estimate a growth trend similar to the demand growth in the 25 years prior to 2007. Being more sensitive to the outcomes of economic crises, it seems that the approximately uniform results with slower growth predicted by the artificial neural networks are more realistic.

Because the ANN is a black-box method and it contains hidden trends implicitly in addition to explicit independent variables, it is difficult to explain the uniform forecasted results. However, there are some factors which may be being captured in the model that may help explain the results:

1) Automobile makers may spend more money on research in order to progress to more environmentally-friendly and fuel-efficient products. The Energy Independence and Security Act of 2007 further mandates an increase in light-duty vehicle fuel economy to an average of 6.7 liters per 100 km (35 miles per gallon) by model year 2020. As a result of the more stringent standards, the average fuel economy of new light-duty vehicles in the United States (including credits for alternative-fuel vehicles and banked credits) rises from 7.92 liters per 100 km (29.7 miles per gallon) in 2011 to 6.59 liters per 100 km (35.7 miles per gallon) in 2020 and 6.25 liters per 100 km (37.6 miles per gallon) in 2035. For instance, Figure 4-6 shows the trend of fuel economy for new light duty vehicles during last 30 years. The improvement trend of fuel economy has more rapid growth since 1998 and this improvement will affect the fuel economy of the whole fleet in future. This rapid growth trend has been captured by ANN and has been applied to the forecast shown in the Figure 4-5. Hence, in future studies, researchers may consider fuel economy as one of the parameters of MLR analysis.

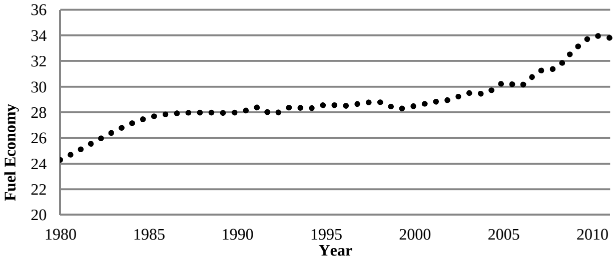


Figure 4-6: Fuel economy of new light duty vehicles [47]

2) Public transportation becomes more popular while people change their modes of transportation. The average energy intensity per passenger-kilometer for light duty vehicles is similar to that for airplanes, and much larger than that for buses and rail.

3) Development of data networks and remote working decreases the transportation demand nation-wide.

4) Delivery of freight become more efficient using optimal logistic methods. For freight, trucks are much more energy-intensive than rail. Although long-haul trucks are much more efficient than other types of trucks, a shift even from long-haul trucks to rail would achieve significant energy efficiencies.

4.7 **Conclusions**

Both multiple linear regression and artificial neural network models for the transportation sector of the United States have been developed applying various independent variables. Models show robust outcomes when their R^2 and *RMSE* are considered.

In terms of forecasting, the models show two totally different trends while their performances are at a similar level of accuracy during the test period. Sensitivity of the ANN models to the recent fluctuations caused by economic recession may be the reason for the difference while regression models only forecast based on the total trend of the individual parameters.

Although a small increase in the energy demand in transportation sector of the United States has been estimated by the ANN, the United States should keep trying to reduce energy consumption in order to reduce CO_2 gas and meet its national and international commitments. Furthermore, improved economic conditions in the near future may cause ANN models to revise their forecasts upwards in terms of energy consumption. Keeping up with recent technology in hybrid and electric vehicles can be effective methods.

Due to the uncertainty in any extrapolation techniques, more research should be done to closely observe the accuracy of the ANN and MLR models developed in this study predict the energy demand.

CHAPTER 5

ENERGY DEMAND IN THE INDUSTRIAL SECTOR OF THE UNITED STATES

5.1 Introduction

The availability and use of energy is one of the most essential elements of development in industrialized countries. People's prosperity, industrial competitiveness and the overall functioning of society are dependent on safe, secure, sustainable and affordable energy. As the industrial activities expand throughout the years, the need for development of energy production becomes more important.

Clarifying the relationship between energy demand and economic growth by means of energy models has been a crucial issue for countries around the world during last two decades ([49-52]). The ability to forecast energy demand due to economic growth is helpful in estimating the potential required future energy production and supply infrastructure. If we could detect conditions under which economic growth leads to an increase in energy demand, we might be able to manage the high dependency of industry on energy and increased energy burdens at lower cost. Climate change caused by industrial activities is currently one of the most important environmental problems, and it must be dealt with adequately [53]. Successful planning for future energy needs can assist in this endeavor.

Among energy demands of the various economic sectors of a country, industrial energy consumption is one of the hardest end-uses to analyze, model and forecast. The structure of the energy demand for an entire industrial sector is unclear. For example, energy demand of the industrial sector might not be strongly correlated with population size because industrial products may be sold in domestic markets or exported to global markets. To describe how the dependent variable (energy demand in industrial sector) and independent variables (such as prices of energy carriers) interact, the relationship between the variables was determined using covariance and correlation methods.

Figure 5-1 shows the trend of the consumption of energy in industries of the OECD and the United States during the period 1970-2011. As shown in Figure 5-1, among the various countries in the OECD, the United States has a significant share of energy consumption. Growing demand for energy made the development of conventional energy resources as well as economic production of non-conventional energy resources necessary.

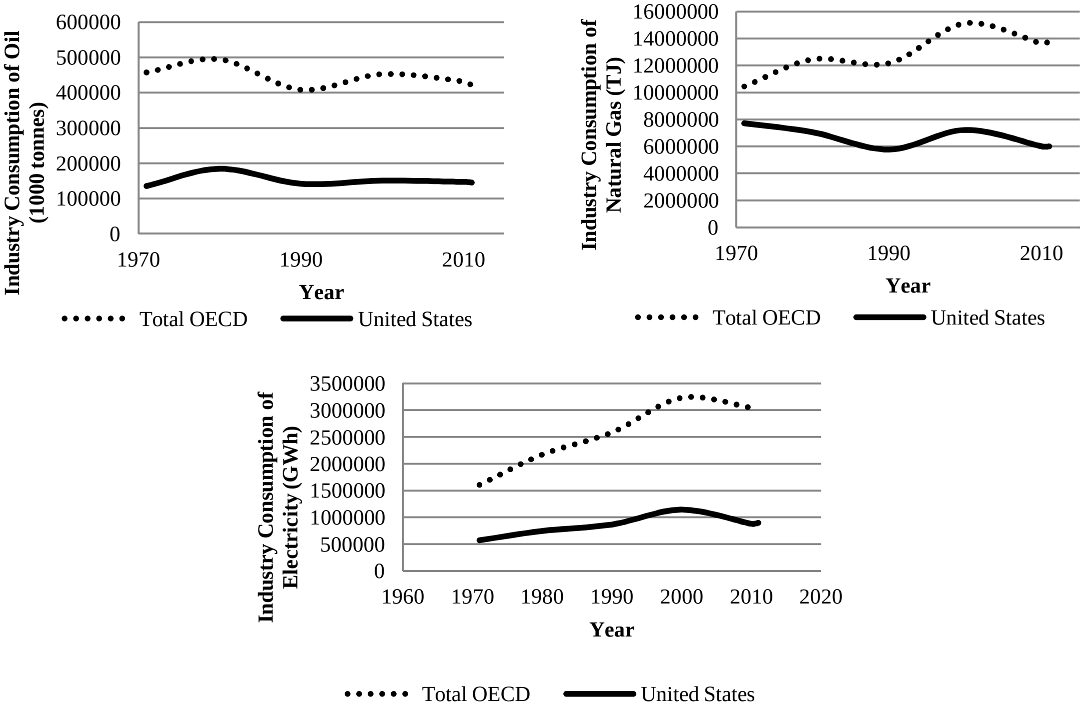


Figure 5-1: Consumption of different energy carriers in OECD and the United States [54]

5.2 **Studies on energy demand modeling in the industrial sector**

Planners, policy-makers, and the private sector rely on energy forecasts to help make policy and investment decisions. Hence, there are many studies related to energy demand forecasting in the literature for countries around the world. Recently, researchers applied artificial intelligence (AI) techniques in their studies as a forecasting method.

This review of the past studies not only included some of the most recent and accredited research of the energy modeling and forecast of countries around the world, but also shows the trend of applying artificial intelligence (AI) techniques in this field.

In the United States, the Energy Information Administration (EIA) has published energy forecasts since 1982. These energy forecasts which are presented in each year’s

Annual Energy Outlook, are the main sources of policy decisions in the United States. To make projections, EIA used the Intermediate Future Forecasting System (IFFS) between 1982 and 1993, and used National Energy Modeling Systems (NEMS) since 1994. IFFS and NEMS apply balanced supply demand approach; however, NEMS uses this approach in more detail [55]. Auffhammer evaluated the rationality of published forecasts of EIA under symmetric and asymmetric loss and found evidence of asymmetric loss in areas including oil, coal and electricity prices and natural gas consumption [56].

In the open literature, there is an insufficient number of studies regarding energy demand forecasts for the United States to give a comprehensive and clear picture of the future; however, some of the researchers have precisely evaluated energy demand for different sectors and tried to describe the perspective of energy demand in the United States. Wilkerson et al. analyzed how the National Energy Modeling system (NEMS) projects energy demand in the residential and commercial sectors with special focus on the role of consumers' preferences and financial constraints. Their baseline models forecasted energy demand in the year 2035 [57]. Dowlatabadi and Oravetz studied historic aggregate energy intensity trends of the US for the period of 1954-1994. Their price-induced energy efficiency formulation generated more price-sensitive energy use trajectory [58]. Other important studies of different sources of energy demand in the United States are also available [59-61].

In the published literature, various techniques have been applied to explore the relation between energy demand of the United States and its economic development. They concluded that to sustain long-term growth it is necessary to either increase energy supplies or increase the efficiency of energy usage. These studies suggest that development of the industrial sector is closely correlated to increase in energy demand. Stern analyzed the relation between energy and economic growth (expressed in terms of GDP) in the United States by using a multivariate approach. In this study, the presence of a causal relationship between energy use and economic growth was investigated using the data related to the period of 1947-1990 and it was concluded that a causal relation between final energy use and GDP existed [49]. Cleveland et al. discussed the role of energy in the economy. They accounted for energy quality and examined the importance of energy quality in evaluating the relation between energy use and GDP from 1947 to 1996 [62]. In 2007, Ewing et al. investigated the effect of energy consumption on industrial output in the United States. Monthly data and a generalized variance decomposition approach have been applied to assess the impact of energy on real output. They suggested that unexpected shocks to fossil fuel energy sources have the highest impact on the variation of output [63]. Focusing on renewable and non-renewable sources, Bowden and Payne examined the causal relationship between energy consumption and real GDP between 1949 and 2006. This study, which provides details of various economic sectors, revealed that energy consumption in the industrial sector and renewable energy consumption are not causally related; however, results indicate unidirectional causality from industrial non-renewable energy consumption and real GDP [64]. Warr and Ayres examined the energy-GDP relationship for the period 1946-2000 by redefining energy in terms of exergy and the amount of useful work provided from energy inputs. They concluded that to sustain long-term growth it is necessary to either increase energy supplies or increase the efficiency of energy usage [65]. A summary of these studies between 2000 and 2010 is given in Table 5-1.

Table 5-1: A summary of studies on relation between energy demand of the United States and economic development of the country

Reference	Year Published	Data Time Period	Method	Outcome
[64]	2000	1947-1996	Aggregation energy flows	Relatively strong relationship between energy use and economic output
[54]	2007	1960-2004	Granger causality relationship	No causal relation between income and carbon emissions Granger causal relation between income and energy use
[65]	2007	2001:1-2005:6	Generalized variance decomposition method	The traditional energy sources explain a greater amount of output variance than does the renewables.
[68]	2008	2001:1-2005:6	Autoregressive distributed lag (ARDL)	Real industrial output is long-run forcing variable for nearly all measures of disaggregate energy consumption
[69]	2009	1949-2006	Toda-Yamamoto causality	No Granger-causality between renewable or non-renewable energy consumption and real GDP
[70]	2009	1980-2004	panel cointegration and error correction model to infer causal relationship Granger Causality	presence of both short-run and long-run causality from energy consumption to economic growth
[71]	2009	-----	Review of methods used to assess the energy consumption and economic growth relationship and some of the results obtained through their use	Research papers using the same methods with the same variables, just by changing the time period examined, have no more potential to make a contribution to the existing literature
[67]	2010	1946-2000	Exergy analysis using vector-error correction model to test Granger causality	No evidence of either short or long-run causality flowing from GDP to exergy
[66]	2010	1949-2006	Toda-Yamamoto long-run causality test to examine Granger-causality	Unidirectional causality from industrial non-renewable energy consumption and real GDP
[70]	2014	1996-2012	Artificial Neural Network, multiple Pearson product-moment correlation coefficients	Exploration of new sources of fossil fuels, development of new renewable sources, and the trends of economic development in high energy consuming countries as effective parameters on energy demand.

5.3 **Materials and Methods**

5.3.1 Energy Demand Modeling

Projections in energy models of the industrial sector focus on the factors that shape the U.S. energy system in the industrial sector over the long term. Under the assumption that current laws and regulations remain unchanged, these models provide a basis for examination and discussion of energy demand and the direction it may take in the future. While energy markets are complex, energy models are simplified representations of energy production and consumption, regulations, and producer and consumer behavior.

Projections are highly dependent on the data, methodologies, model structures, and assumptions used in their development. The practice of modeling energy demand is necessarily a synthesis of data and method [12]. Energy models rely on data to simulate energy consumption. Based on the level of detail of the input data, different modeling techniques may be used. Different modeling methods have various positive and negative points, capability and applications.

5.3.2 Selection of the independent variables

In solving a forecast problem with artificial neural networks, the most important part is to choose the independent variables that provide the most precise estimation of dependent variable. Moreover, since the future trends of dependent variables are unknown, the probability percentage of occurrence of these variables is very important.

Hence, the process of choosing independent variables must be done with special consideration.

Calculating linear correlation before fitting a model is a useful way to identify variables that have a simple relationship. The correlation coefficient, P-value, and the lower and upper bounds for a 95% confidence interval between the energy consumption in the industrial sector of the United States and various independent variables are given in Table 5-2. Results presented in Table 5-2 which are corresponding to data in the period of 1996-2012 confirm a linear correlation of energy prices (electricity, natural gas, diesel fuel and propane) and total energy consumption in the industrial sector. Since the P-values for price of electricity, diesel fuel, and propane are less than 0.01, there is a very strong presumption against the null hypothesis; however, in case of price of natural gas, presumption against null hypothesis is low. Result of the correlation coefficient analysis between GDP and energy consumption in the industrial sector shows unreasonable relationship between them; however, two variables that have a small or no linear correlation might have a strong nonlinear relationship.

Table 5-2: Correlation coefficients, P-value and values of 95% confidence interval between the energy consumption and independent variables (1996-2012)

		Average Retail Price of Electricity, Industrial	Natural Gas Price, Delivered to Consumers, Industrial	Refiner Price of No. 2 Diesel Fuel to End Users	Refiner Price of Propane to End Users
Correlation Coefficient		-0.8967	-0.3923	-0.7401	-0.6945
P-value		1.0944 e-6	0.1194	6.8178 e-4	1.9785 e-3
Confidence Interval	**Lower bound**	-0.9625	-0.7344	-0.9004	-0.8810
	Upper bound	-0.7312	0.1089	-0.4027	-0.3210

Before development of the MLR models, the underlying assumption of homoscedasticity of variances must be tested. This assumption simplifies mathematical and computational treatment of the model. Violations in homoscedasticity may result in overestimating the goodness of fit as measured by the Pearson coefficient. Based on Bartlett’s Test for Equality of Variances, the probability associated with the Chi-squared statistic is equal to 0.8870. Hence, the associated probability for the Chi-squared test is larger than 0.05 and the assumption of homoscedasticity was met [71].

5.4 **Results and discussion**

5.4.1 Data analysis and future trend of independent variables

Data from the period of 1980-2007 are applied to train the network. Data for the years of 2008-2012 are used exclusively in the test procedure to evaluate the performance of the model. The data are from the following sources: the total energy consumed by industrial sector is from the Energy Information Administration (EIA) office of Department of Energy [72]; the prices of energy carriers (electricity, natural gas, diesel fuel and propane) are taken from monthly reports of the EIA [73]; and GDP data are obtained from the World Bank [74]. The trends of the independent parameters for the period of 1980-2012 are shown in Figure 5-2.

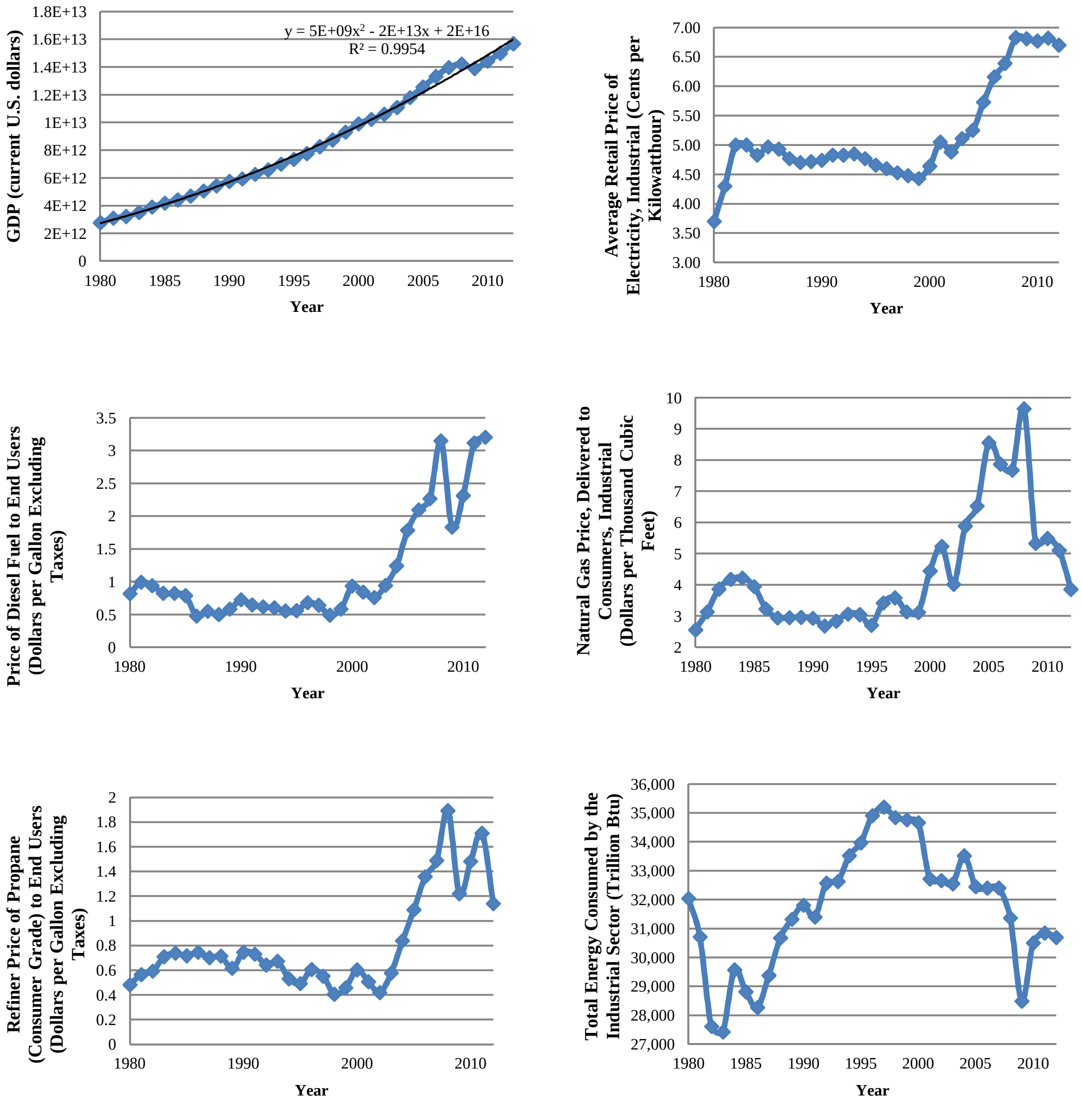


Figure 5-2: Trend of change of independent parameters and total energy consumed in industrial sector of the U.S., 1980-2012

As can be observed in Figure 5-2, all independent parameters except GDP have been fluctuating significantly, particularly since 2005; GDP has been growing smoothly since 1980. In order to estimate the future trend of energy demand in the industrial sector based on independent parameters, we need to anticipate the behavior of independent parameters in the future. For the future trend of GDP, a second order polynomial equation is fitted to the GDP growth curve. The value of R^2 shown in the GDP graph of Figure 5-2 confirms the accuracy of the fitted curve. For the other independent variables, we define three scenarios for potential future changes:

- *Constant Price Scenario (CPS)*: In this scenario price remains at the level of the average price of last five years of data set.
- *Ascending Price Scenario (APS)*: In this scenario, prices grow with annual rate of 4%.
- *Descending Price Scenario (DPS)*: In this scenario, prices slake with annual rate of 4%.

The value of ±4% in the APS and DPS was chosen to represent realistic bounds for these prices. According to the defined scenarios, real data corresponding to 2008-2013 and the future trends of independent variables are shown in Figure 5-3.

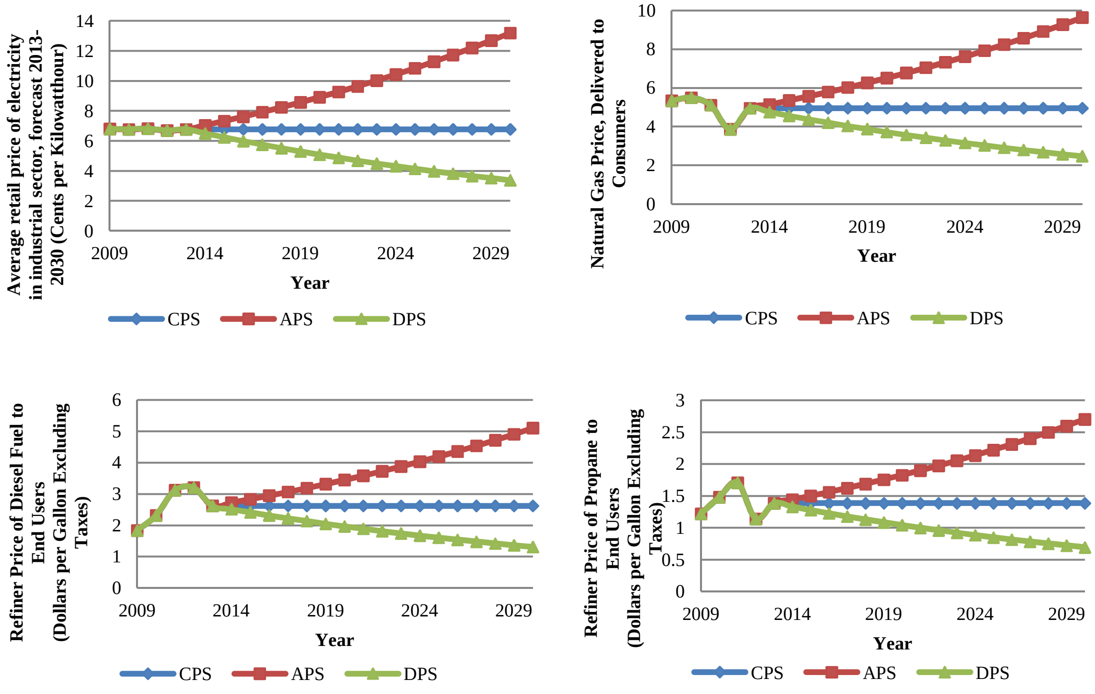


Figure 5-3: Independent variables of 2008-2013 and the future trends of them

5.4.2 Results

Initially, the training process was applied and the ANN model was obtained to get predictive equations based on data from 1980 to 2009. Next, the testing process is done to examine the performance of the model over the period of 2010-2011. Comparison of the industrial sector energy consumption between the actual data and generated results of the model is shown in Figure 5-4.

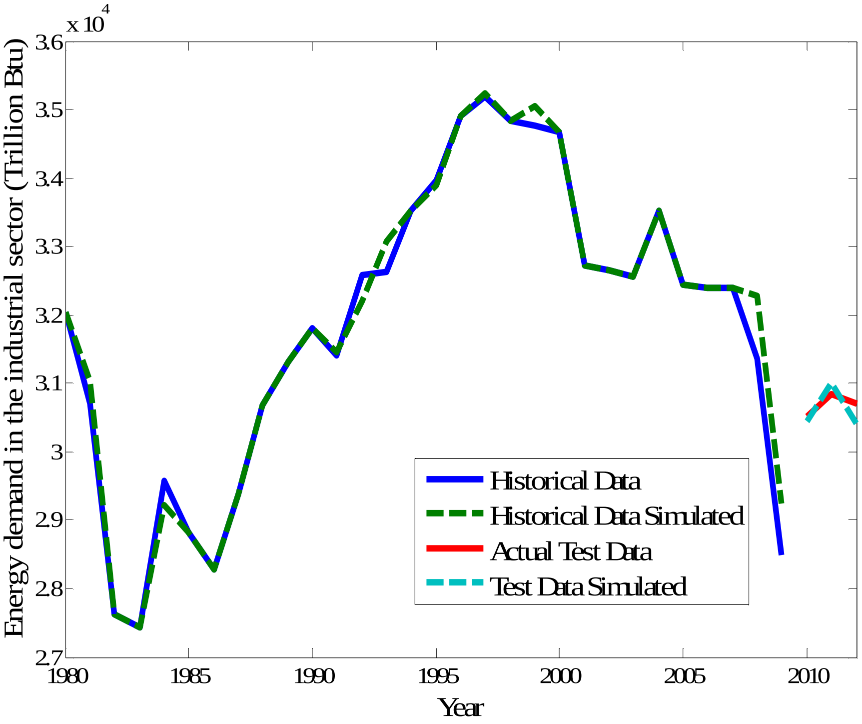


Figure 5-4: Energy demand in the industral sector of the US; actual and simulated data

Figure 5-4 shows good agreement between the actual data and the forecasted results. The results of the tests which evaluate the performance of the model and accuracy of its forecast are shown in a linear regression graph (Figure 5-5), and an error histogram (Figure 5-6). The information contained in Figure 5-5 and Figure 5-6 confirm the accuracy of the ANN model.

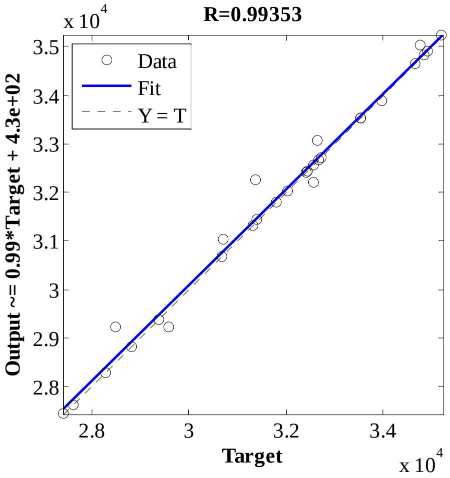


Figure 5-5: Linear regression graph of the ANN results

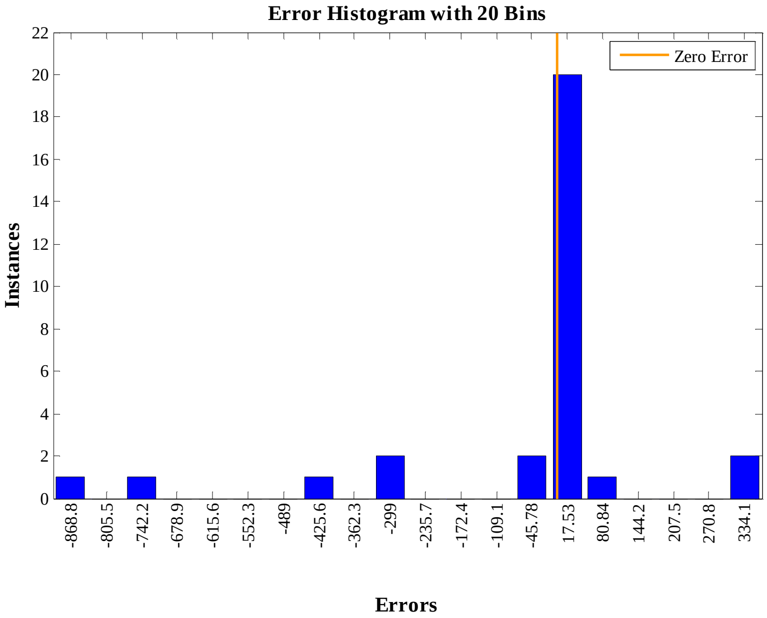


Figure 5-6: Error histogram graph of ANN simulation

Following the network training process and the evaluation of the model performance in the training period, the model is tested over a short period of actual data which is not included in the training process. In this test process, the evaluation of the method performance is measured by R^2 parameter which is defined as

$$R^2 = 1 - \left(\frac{\sum_{k=1}^{n} \left(d_k - y_k(x)\right)^2}{\sum_{k=1}^{n} (y_k(x)^2) - \frac{(\sum_{k=1}^{n} y_k(x))^2}{n}} \right) \tag{5.1}$$

where d_k is the actual energy demand of k^{th} year, and y_k is the corresponding predicted value. If value of R^2 is less than 0.99, the training process is repeated with all weights and biases initialized. Table 5-3 shows the performance of the model over the test period.

Table 5-3: Performance of the ANN model over the test period

Year	Actual	ANN	Relative Error
2010	30,501.533	30434.85	-0.0022
2011	30,843.130	31004.98	0.0052
2012	30,696.042	30395.33	-0.0098

After the training process and examination of the trained network during the test period, the model is used to forecast the industrial energy demand based on the three pre-defined scenarios. The predicted results of the best-fit model are shown in Figure 5-7. Moreover, the predicted values of the model corresponding to the three described scenarios are presented in Table 5-4.

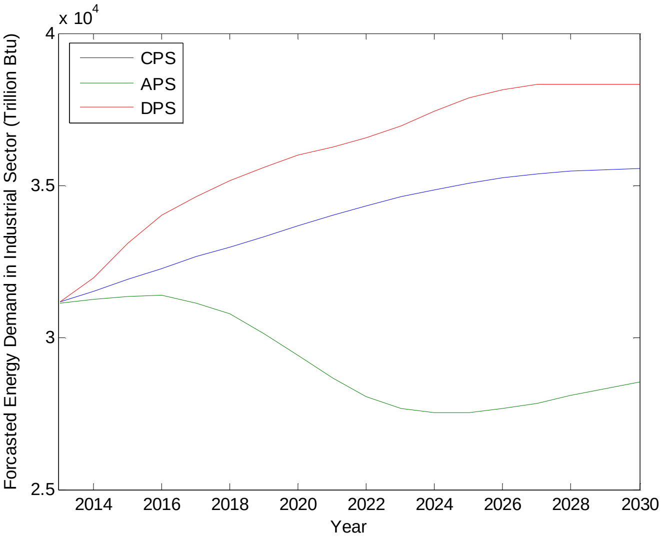


Figure 5-7: Forecasted Energy Demand in the U.S. Industrial Sector, 2013-2030

Table 5-4: Forecasted energy demand of industrial sector of the U.S. based on prescribed scenarios

Forecasted energy demand of industrial sector (Trillion Btu)			
	Scenarios		
Year	APS	CPS	DPS
2013	31115	31175	31175
2014	31247	31533	31935
2015	31345	31890	33072
2016	31367	32241	34022
2017	31129	32641	34644
2018	30767	32972	35140
2019	30113	33293	35600
2020	29406	33653	35988
2021	28673	33995	36271
2022	28065	34315	36555
2023	27675	34606	36940
2024	27507	34862	37419
2025	27513	35076	37853
2026	27640	35247	38129
2027	27827	35390	38290
2028	28075	35471	38309
2029	28315	35521	38316
2030	28542	35533	38302

5.4.3 Discussion

To project the future trend of the industrial sector energy demand using an ANN model, the independent parameters including GDP, and price of energy carriers such as electricity, natural gas, diesel fuel, and propane were varied according to three scenarios. The "business-as-usual" scenario which is defined as the CPS in this study is based on the assumption of uniform price of energy careers, while GDP grows with its usual trend. According to the ANN model prediction using CPS, the total consumption of the industrial sector is expected to be around 35,500 Trillion Btu by 2030 which is around 16% higher than the corresponding value in 2012.

On the other hand, the effects of the ascending price scenario (APS) should not be underestimated. APS can happen in cases of any disturbance in energy supply and demand such as wars, rapid economic growth of developing countries, etc. In addition, energy policy makers may keep the price of fuels and energy carriers high in order to protect the environment and make renewable energy projects economically feasible. The APS scenario considered results in a reduced energy demand in the industrial sector of approximately 28,300 Trillion Btu per year by 2030 and will negatively impact the performance of this sector. However, a higher price for fossil fuels may lead to more investment in renewable energy sources and makes development of sustainable energy sources economically beneficial.

If new sources of fossil fuels are introduced in the near future and if these sources are even less expensive as current sources, or if renewable energy sources are produced in more economical processes compared to current processes, the overall prices of energy sources would likely decline. If fuel prices decline to the benefit of energy consumers, then the industrial sector benefits and the industrial sector will respond to this improvement by increasing production and resulting in more consumption of energy. In this scenario (DPS), the energy demand of industrial sector may reach 38,300 Trillion Btu per year in 2030.

Protection and augmentation of the industrial sector plays an important role in the economic decision making process in the United States. Currently, the industrial sector has the largest share of total energy consumption among all general sectors. As such, others have produced predictions for the future energy needs of the industrial sector. For comparison purposes, the results of the three scenarios are presented along with the predictions from the EIA presented in the Annual Energy Outlook 2013 [75]. As demonstrated in Figure 5-8, the results of ANN method based on DPS are consistent with Annual Energy Outlook report. This consistency is good, and suggests that the EIA expects some price drops in energy. Alternatively, the ANN method results considering CPS and APS may be useful as scenarios for planners to consider if they have reasons to be less optimistic on the possibility of declining energy prices. The ANN technique presented here therefore provides a tool for use by planners and information on a wide range of scenarios.

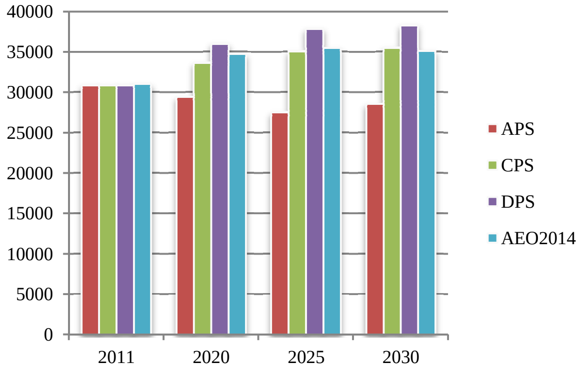


Figure 5-8: Industrial energy demand outlook, current study vs. Annual Energy Outlook 2013

5.5 **Conclusions**

In the United States, the industrial sector is the driving engine of economic development, and the energy consumption in this sector may be considered as the fuel for this engine. In order to keep this sector sustainable (diverse and productive over the time) energy planning should be carried out comprehensively and precisely. The ANN method is a promising tool for use in forecasting the industrial energy demand depending on the selected applied independent variables.

In this chapter, ANN was applied to forecast the industrial energy demand and perform future projections for the period 2013-2030. Among all effective independent parameters on energy demand in industrial sector, energy cost and GDP growth have been considered in this study based on correlation coefficient analysis. Based on model trained with historical data of period 1980-2012, the price of energy significantly affects the amount of energy used in the industrial sector.

In 2012, 30,696 Trillion Btu of energy were used in the industrial sector of the United States. Based on the energy demand forecast with ANN model, if GDP increases with its historical trend since 1980, and if the energy prices decrease with annual rate of 4%, the energy demand in industrial sector grows significantly. According to this scenario, the energy demand increase will be 25% in 2030. This result, which is in close accordance with published predictions of the Energy Information Administration of Department of Energy, may be considered as an indication of the need for development of new and low-cost energy sources. However, national and international commitments of the United States should not become neglected with regards to making progress towards sustainable development.

If a mitigation energy policy is applied by the government by increasing the energy price by 4% annually, the ANN model predicts that energy demand may decreases up to 7% by 2030. Funds provided from this policy may be spent in development of new and clean energy sources which were not beneficial previously. Nevertheless, this increase in energy price may negatively affect development of the industrial sector. To ease the effect of inflation in the price of energy and to protect the industry and consumers, some additional considerations such as energy efficiency improvement may be applied.

As a result of the competitive advantage of low natural gas prices, a boost to the industrial sector is expected, industrial production expands and natural gas use will increase over the next 10 to 15 years. Low natural gas prices and increased availability of natural gas and related resources such as hydrocarbon gas liquids (HGL) benefit the U.S. industrial sector in multiple ways: Natural gas is used as a fuel to produce heat and to generate electricity and, is also used as a feedstock to produce chemicals. In addition, with generally lower energy prices resulting in more rapid economic growth, demand for industrial products increases.

CHAPTER 6

ENERGY DEMAND IN THE COMMERCIAL SECTOR OF THE UNITED STATES

6.1 Introduction

Development in the industrial, transportation, residential and commercial sector caused a rapid growth in energy demand. Growth of GDP, population increase, and life-style improvement are other reasons for the energy demand increase. The increase in GDP which is a result of high commercial activities of the society leads to an increase in the energy demand in the commercial sector. Although the commercial sector has one of the smallest energy demands among the different economic sectors, providing future energy security, mitigation of greenhouse gases and movement towards sustainability requires plans of action regarding energy demand in all sectors including the commercial sector.

Energy demand in the commercial sector of the United States has been studied by many researchers in a variety of methods. Some of these studies evaluated the energy utilization of the commercial sectors using exergy analysis [76-78]. Since buildings play an important role in energy consumption of the commercial sector, some researchers focused on building energy performance and studied the energy demand of the residential and commercial sectors cumulatively [78] [79] [80] [81] [82] [83]. For instance, Utlu and Hepbasli analyzed the energy utilization efficiency of the Turkish residential-commercial sector in 2001 by means of energy and exergy analysis. The energy efficiency value of the Turkish residential-commercial sector which found to be 55.75%, which clearly emphasizes and clarifies the importance if the planned studies towards increasing efficiencies [78]. Xing et al. developed two macro-model for commercial and residential sectors. These models are simulation models that estimate changes in energy consumption according to building type, and application over a 5-year period. In the model corresponding to the commercial sector, total energy consumption was divided into two parts: air conditioning and other electrical appliances. Compared to a business-as-usual scenario, implementation of commercial measures achieved a significant reduction in energy consumption [82]. In 2010, Forouzanfar et al. used a logistic based approach to forecast the natural gas consumption for residential and commercial sectors of Iran. Nonlinear programming and genetic algorithms were applied to estimate the logistic parameters. They studied gas consumption data of the 1995-2005 period and generated promising results of yearly gas consumption for the period of 2006-2008 [83].

Regarding the commercial sector of the United States, Horowitz investigated the effects of two types of publicly-funded energy efficiency programs on energy intensity in 42 states; electric utility demand side management (DSM), and market transformation (MT) programs. This study showed that in 2001, DSM reduced electricity intensity of the commercial sector by 1.9% relative to 1989, while the outcome of MT programs was 5.8% at the same time. Moreover, this study also suggest that in 2001the combined effects of these public programs led to 2.3% reduction in total retail electricity sale of the United States [84]. In 2008, Mansur et al. investigates the national energy model of fuel choice of the United States. This study which is the first study to explicitly consider how climate change may impact fuel choice in the residential and commercial sectors, suggests that the fuel choice component may be an important aspect of adjustment to climate change. In their model, they estimated parameters using a cross section of the residential and commercial sectors of the United States.

The approach used here differs from the existing literature in three aspects. First, the commercial sector is considered as an independent sector and energy demand of this sector is separately modeled in this study. In contrast with many studies which combine residential and commercial sector, the historical data and the future of energy demand in the commercial sector are studied autonomously because of the differences in the functioning and the effective parameters of the residential and commercial sectors. Second, since the energy demand analysis is conducted for the commercial sector based on the effective parameters, the historical trend of the effective parameters is analyzed on for last 30 years. Third, due to the importance and significant share of United States' energy demand, this study concerns the United States as a case study. This chapter evaluates the energy demand in the commercial of the United States using artificial neural networks and regression analysis.

6.2 **Energy consumption in the commercial sector**

Energy-use sectors in the United States are a group of major energy-consuming components of the United States' society developed to measure and analyze energy use. These sectors are mostly referred to as: residential, commercial, industrial, transportation and electric power. The commercial sector, which is the subject of this chapter, consists of service-providing facilities and equipment of businesses; federal, state, and local governments; and other private and public organizations. In this sector, which consumes the least amount of energy of the sectors, energy is mostly used for space heating, water heating air conditioning, lighting, refrigeration, and cooking. Energy consumption in this sector also includes electricity produced by generators and thermal output to support the activities mentioned in the commercial sector definition.

In 2013, carbon dioxide emissions from the energy consumption in the commercial sector of the United States were more than 960 million tones. The commercial sector has an important role to play, accounting for 18% of the United States' CO_2 emissions from the energy consumption. However, there are other gains to be had from the commercial sector investing in energy planning and energy efficiency improvements. Some of those gains are countering and reducing the effect of volatile energy prices, improving business competitiveness, mitigating overall energy demand and increasing the nation's energy security.

Due to the type of energy-consuming activities in the commercial sector and the difference between operating equipment in this sector and other sectors such as transportation and industrial sectors, the energy portfolio of commercial sector is notably different. For instance, the types of the buildings that use most of the energy in this sector are office and retail buildings, educational and health-care buildings and lodging. Hence, heating and lighting processes consumes most of the energy in the commercial sector.

The activities of commercial sector in the United States are mostly dependent on electricity and the consumption of electricity in this sector had been increasing between 1950 and 2006. This continuous growth was interrupted by the economic downturn. On the other hand, demand for natural gas, which is the second source of energy in the commercial sector, has experienced a lower growth rate during the same period. Share of petroleum products in energy sources of the commercial sector has declined since 1970s and the share of other sources, such as coal and renewable energy is too small to be compared with the major sources. Figure 6-1 shows the trends of energy consumption by sources during last three decades. Figure 6-2 shows the share of each source in providing energy for commercial activities of the United States in 2012.

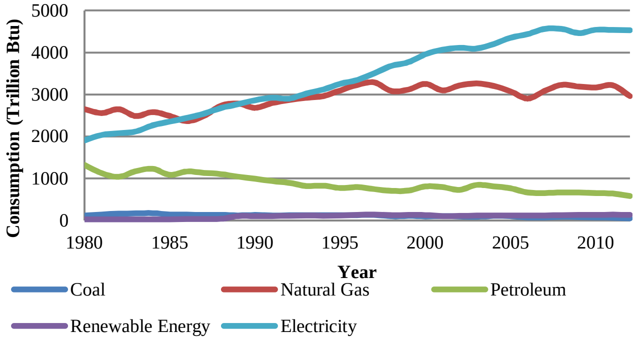


Figure 6-1: Energy consumption from different sources in commercial sector of the United States, 1980-2012 [85]

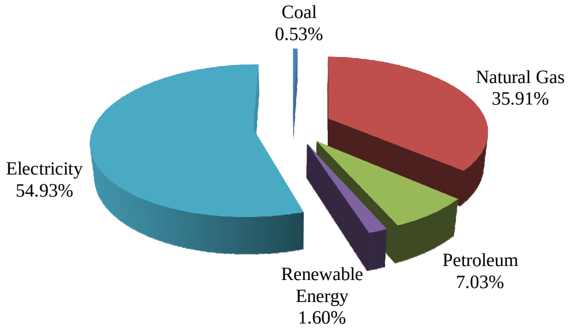


Figure 6-2: Share of energy sources in energy consumption of the commercial sector, 2012 [85]

The U.S. Department of Energy (DOE) evaluates published model codes and standards to help states and local jurisdictions better understand the impacts of updating commercial building energy codes and standards. DOE has established a methodology for evaluating the energy and economic performance of model commercial energy codes and standards, as well as proposed changes. Energy and economic calculations are performed through a comparison of baseline and improved buildings for both energy savings and cost effectiveness. Depending on the complexity of the proposal being analyzed, analysis or modeling of changes between representative building types is performed to find savings. Incremental costs for the improvements is developed using engineering cost estimates of a typical upgrade. National or climate zone energy savings are typically reported. In considering cost-effectiveness, longer term energy savings are balanced against incremental initial costs through a Life-Cycle Cost perspective. Savings By Design (SBD) is an example of these programs. SBD is California□s nonresidential new construction energy efficiency program, administered statewide and funded by Utility customers through the Public Purpose Programs surcharge applied to gas and electric services.

6.3 **Artificial neural network model**

There are multiple explanations about the ANN technique. While some researchers define it as “a regression technique which presents higher nonlinearity between independent and dependent variables” [18] , others explain it as “an information-processing system that has certain performance characteristics in common with biological neural networks” [36] or “inspired by biological systems, an ANN is a large number of neurons which collectively perform tasks that even the largest computers have not been able to match” [24]. However, all of these different explanations agree on the most important characteristics of ANNs: ANNs can be trained to overcome the limitations of the conventional approaches to solve complex problems. This technique learns from given examples by constructing input-output mapping [23] [38]. Empirically, various successful applications of ANNs have established their role for pattern recognition and forecasting in different areas [20].

In previous chapters, the structure of the ANN models is described in details. In the field of energy modeling and forecast, many researchers have paid attention to this approach to overcome the complexity and grasp the nonlinear relation of input and output parameters of this field. In Table 6-1, some of the most important and recent studies of this field with application of ANNs are summarized. Since most of them are focusing on sectors other than the commercial sector, and few of them concern the United States despite its importance and great share of energy consumption, this study seeks to analyze and forecast the energy demand in the commercial sector of the United States.

Table 6-1: Summary of most recent and important applications of ANNs in the energy demand modeling

Sector	Study	Country
Residential	[86], [11]	United States
	[87]	Greece
	[9]	Turkey
	[88-90]	Canada
Electrical	[31]	Iran
	[25], [9], [91]	Turkey
	[21]	Greece
Industrial	[32]	Iran
	[9]	Turkey
Commercial	[92]	India
Transportation	[10]	South Korea
	[44]	Thailand
	[20]	Turkey

6.4 Selection of Independent Parameters

To figure out how the effective parameters change the energy demand in the commercial sector the following steps are taken. First, all potential effective parameters are considered and the historical data about them is gathered from reliable sources including but not limited to Monthly Energy Review of U.S. Energy Information Administration, World Bank data, and Foreign Trade section of U.S. Census Bureau. Table 6.2 presents the historical values of the considered parameters for the commercial sector during 1987-2012.

Table 6-2: Historical values of the considered parameters for the commercial sector

Year	Price of Electricity, Commercial (C/kWh)	N. Gas Price, Commercial ($/1000ft^3)	GDP (USD)	Abs. U.S. trade with World (10^6 USD)	Population Estimate (million)	Total Energy Consumed Commercial Sector (Trillion Btu)
1987	7.08	4.77	4.6989E+12	152119	242.3	11946.009
1988	7.04	4.63	5.0619E+12	118526	244.5	12578.091
1989	7.2	4.74	5.4397E+12	109399	246.8	13193.433
1990	7.34	4.83	5.7508E+12	101718	249.6	13319.766
1991	7.53	4.81	5.9307E+12	66723	253.0	13499.773
1992	7.66	4.88	6.2618E+12	84497	256.5	13440.871
1993	7.74	5.22	6.5829E+12	115566	259.9	13819.679
1994	7.73	5.44	6.9933E+12	150626	263.1	14097.529
1995	7.69	5.05	7.3384E+12	158804	266.3	14690.053
1996	7.64	5.4	7.7511E+12	170213	269.4	15171.991
1997	7.59	5.8	8.2565E+12	180523	272.6	15681.225
1998	7.41	5.48	8.741E+12	229758	275.9	15967.551
1999	7.26	5.33	9.301E+12	328819	279.0	16376.26
2000	7.43	6.59	9.8988E+12	436105	282.2	17175.34
2001	7.92	8.43	1.02339E+13	411897	285.0	17136.642
2002	7.89	6.63	1.05902E+13	468265	287.6	17345.42
2003	8.03	8.4	1.10893E+13	532350	290.1	17345.779
2004	8.17	9.43	1.17978E+13	654830	292.8	17658.934
2005	8.67	11.34	1.25643E+13	772372	295.5	17856.745
2006	9.46	12	1.33145E+13	827970	298.4	17710.372
2007	9.65	11.34	1.39618E+13	808762	301.2	18256.135
2008	10.36	12.23	1.42193E+13	816198	304.1	18405.496
2009	10.17	10.06	1.38983E+13	503582	306.8	17889.797
2010	10.19	9.47	1.44194E+13	635362	309.3	18055.642
2011	10.23	8.91	1.49913E+13	772764	311.6	17968.978
2012	10.09	8.1	1.56848E+13	729611	313.9	17413.286

Energy consumption in each economic sector is dependent on a set of parameters which is different from other sectors. Calculating the linear correlation before fitting a model is a useful way to test the significance of the effects of various parameters on the energy demand, provided it is done along with the P-value calculation and confidence interval test. The correlation coefficient, P-value, and the lower and upper bounds for a 95% confidence interval between the energy consumption in the commercial sector of the United States and various independent parameters are given in Table 6.3. Results presented in Table 6.3, which are corresponding to data in the period of 1987-2012, do not confirm a linear correlation of energy prices (electricity, natural gas, diesel fuel and propane) and total energy consumption in the industrial sector. In other words, historical increases of energy prices in the commercial sector are followed by no reaction, or even a reverse reaction of this sector and the energy consumption increased. This behavior shows that the level of energy prices is so low that it may be neglected in the total expenditure of commercial units. Result of the correlation coefficient analysis between GDP, population and trade balance of the United States and energy consumption in the commercial sector shows reasonable relationship between them. Since the P-values for independent variables are less than 0.01, there is a very strong presumption against the null hypothesis.

Table 6-3: Correlation coefficients, P-value and values of 95% confidence interval between the energy consumption in the commercial sector and independent variables

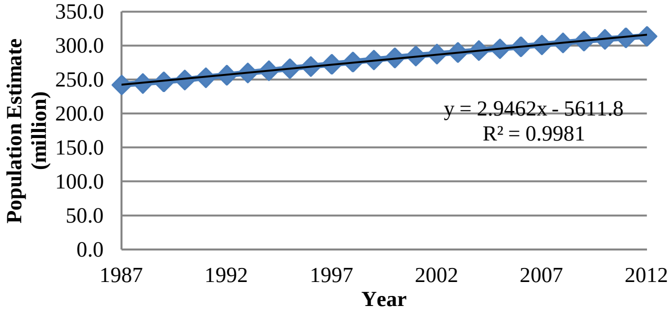
		Average Retail Price of Electricity, Commercial	**Natural Gas Price, Delivered to Consumers, Commercial**	**GDP**	**Absolute value of U.S. trade in goods with World**	**Population**
Correlation Coefficient		0.74047	0.84689	0.93916	0.89551	0.96086
P-value		1.5247e-5	4.9028e-8	1.2405e-12	6.4975e-10	6.9774e-15
Confidence Interval	**Lower bound**	0.4951	0.6839	0.8673	0.7780	0.9135
	Upper bound	0.8764	0.9294	0.9727	0.9525	0.9825

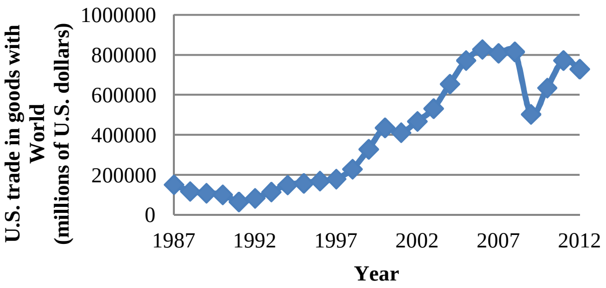
Based on the analysis of the independent parameter and their effect on the energy demand in the commercial sector, for this study, “GDP”, “U.S. Trade with world”, and “population” are chosen as parameters of the model.

6.5 **Results and discussion**

6.5.1 Data analysis and the future trend of independent variables

Data from the period of 1980-2007 are applied to train the network. Data for the years of 2008-2012 are used exclusively in the test procedure to evaluate the performance of the model. Data are gathered from reliable sources. The trends of the independent parameters for the period of 1980-2012 are shown in the Figure 6-3.





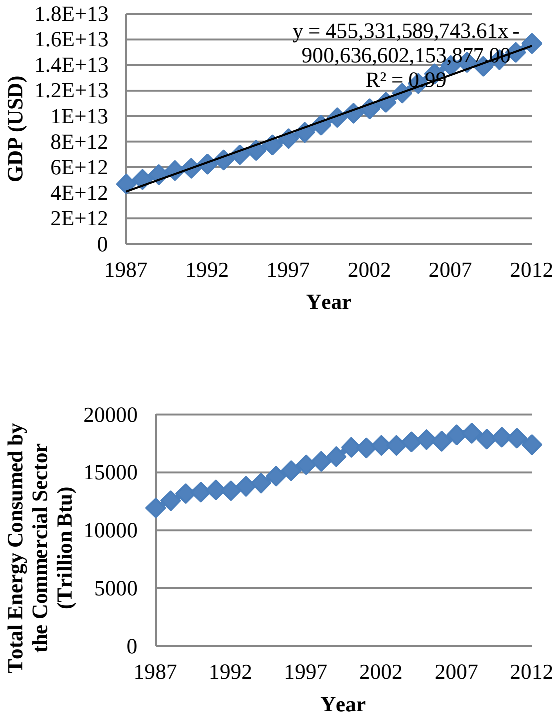


Figure 6-3: Historical trend of the considered parameters and energy demand for the commercial sector

As can be observed in Figure 6-3, except for U.S. trade which has been fluctuating since 2005 (when the initial signs of economic crises appeared), all independent parameters have been growing smoothly. Because of possibility of non-linear correlation between the independent parameters and the energy demand, the neural network modeling has been chosen for this study. A non-linear transfer function is embedded in this ANN to grasp this non-linear relation of the parameters. In order to estimate the future trend of energy demand in the industrial sector based on independent parameters, we need to anticipate the behavior of independent parameters in the future.

For the future trends of population and GDP, two linear functions are set, as shown on the graphs. The accuracy of this modeling is tested and shown with R^2. The definition of R^2 (goodness of fit) is fully described in previous chapters. The value of R^2

shown in the GDP graph of Figure 6-3 confirms the accuracy of the fitted curve. Regarding the future trend of U.S. trade with world, three scenarios are defined as:

- Constant Trade Scenario (CTS): In this scenario U.S. trade remains at the level of the average of last five years of data set.
- Ascending Trade Scenario (ATS): In this scenario, trade grows with annual rate of 2%.
- Descending Trade Scenario (DTS): In this scenario, trade slakes with annual rate of 2%.

The value of ±2% in the ATS and DTS was chosen to represent realistic bounds for these prices.

6.5.2 Results

Initially, the training process was applied and the ANN model was obtained to get predictive equations based on data from 1987 to 2008. Next, the testing process is done to examine the performance of the model over the period of 2009-2012. Comparison of the industrial sector energy consumption between the actual data and generated results of the model is shown in Figure 6-4.

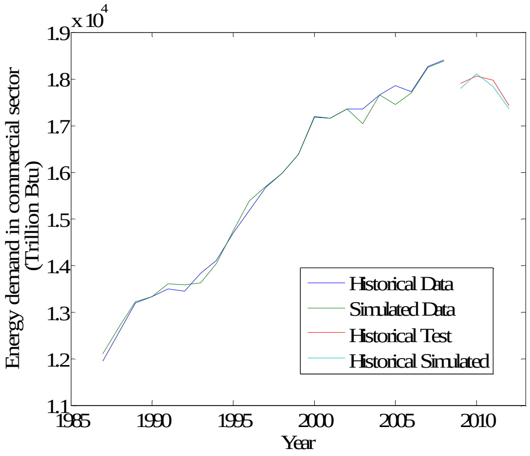


Figure 6-4: Demand in commercial sector of the US; actual and simulated data

Figure 6-4 shows good agreement between the actual data and the forecasted results. The results of the tests which evaluate the performance of the model and accuracy of its forecast are shown in a linear regression graph (Figure 6-5), and an error histogram (Figure 6-6). The information contained in Figure 6-5 and Figure 6-6 confirm the accuracy of the ANN model.

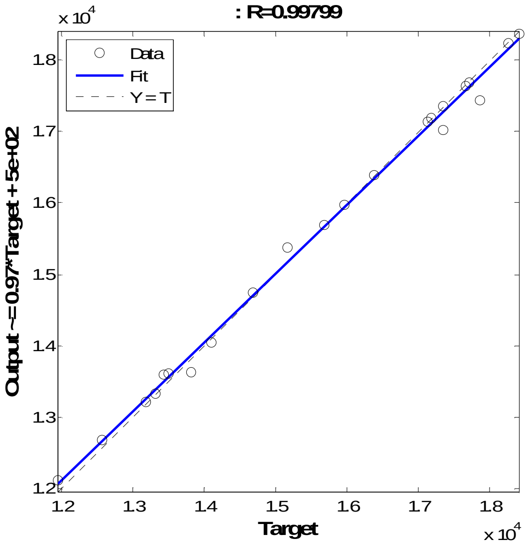


Figure 6-5: Linear regression graph of the ANN results

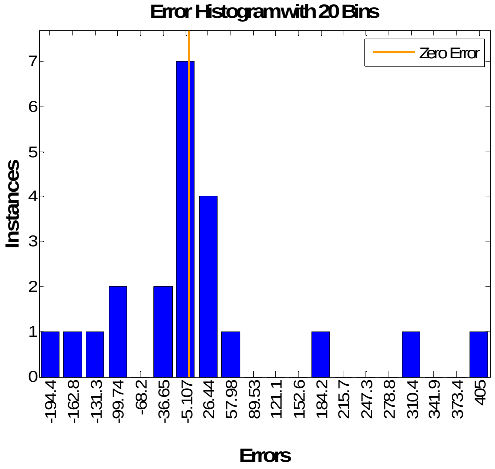


Figure 6-6: Error histogram graph of ANN simulation

Following the network training process and the evaluation of the model performance in the training period, the model is tested over a short period of actual data which is not included in the training process. Table 6-4 shows the performance of the model over the test period.

Table 6-4: Performance of the ANN model over the test period.

Year	Actual	ANN
2009	17,889.797	17,778.602
2010	18,055.642	18,098.680
2011	17,968.978	17,835.239
2012	17,413.286	17,349.970

After the training process and examination of the trained network during the test period, the model is used to forecast the industrial energy demand based on the three pre-defined scenarios. The predicted results of the best-fit model are shown in Figure 6-7.

Moreover, the predicted values of the model corresponding to the three described scenarios are presented in Table 6-5.

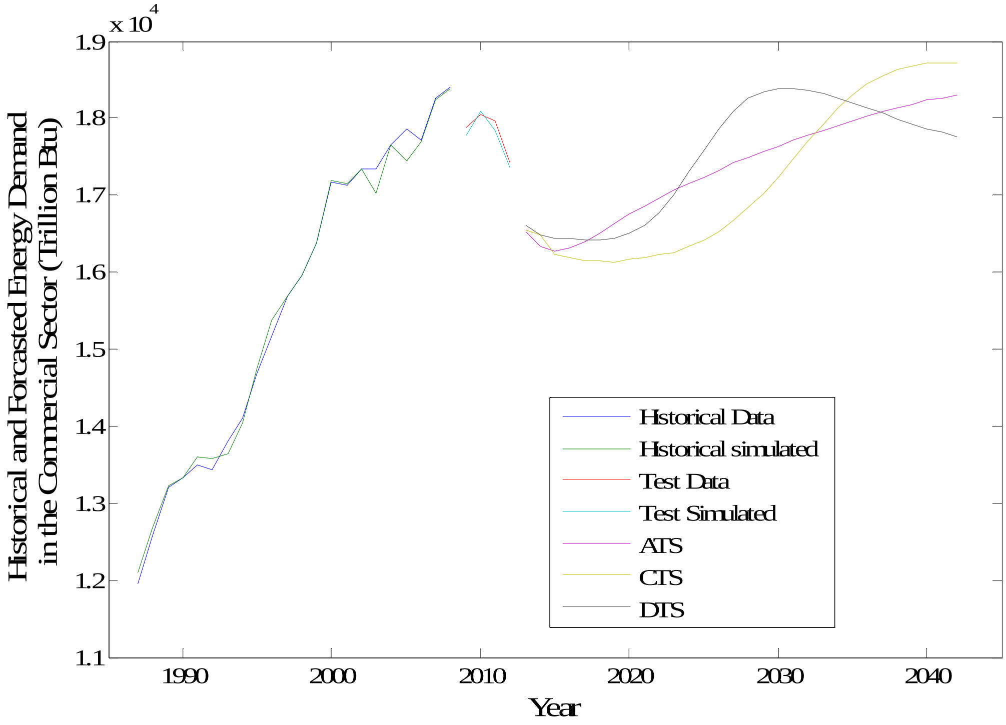


Figure 6-7: Performance of the ANN model in the commercial sector of the U.S.

Table 6-5: Forecasted energy demand of the commercial sector of the U.S. based on prescribed scenarios.

Forecasted energy demand of industrial sector (Trillion Btu)			
	Scenarios		
Year	ATS	CTS	DTS
2013	16525	16548	16604
2014	16338	16475	16492
2015	16270	16226	16442
2016	16311	16194	16433
2017	16391	16153	16417
2018	16513	16143	16427
2019	16626	16136	16442
2020	16753	16173	16506
2021	16858	16190	16606
2022	16971	16223	16782
2023	17059	16261	17006
2024	17160	16337	17296
2025	17237	16414	17584
2026	17328	16530	17868
2027	17416	16675	18097
2028	17485	16830	18249
2029	17568	17030	18348
2030	17634	17236	18387
2031	17712	17475	18391
2032	17773	17697	18363
2033	17848	17930	18320
2034	17905	18123	18261
2035	17972	18306	18199
2036	18024	18440	18131
2037	18084	18556	18063
2038	18129	18626	17996
2039	18181	18684	17932
2040	18227	18719	17871
2041	18260	18722	17814
2042	18297	18724	17762

6.6 **Discussion**

To forecast the future trend of the commercial sector energy demand using an ANN model, the independent parameters including GDP, and population, and U.S. trade were varied according to three pre-defined scenarios. The “business-as-usual” scenario which is defined as the CTS in this study is based on the assumption of uniform U.S. trade, while GDP grows with its usual trend. According to the ANN model prediction using CTS, the total consumption of the industrial sector is expected to be around 18,724 Trillion Btu by 2042 which is around 7.5% higher than the corresponding value in 2012.

On the other hand, the effects of the ascending trade scenario (ATS) should not be underestimated. ATS can happen in cases of significant growth in the economy. In this case, since the demand for energy increases from all sectors, energy prices rise. The consideration of ATS scenario results in growth energy demand in the commercial sector of approximately 5.1% by 2042 and energy demand will climb to 18,297 Trillion Btu. However, a higher level of U.S. trade may lead to improvement in the economy and increase purchasing power.

If, for any reason, another economy downturn happens and the U.S. trade with other countries decline with a moderate rate of 2%, rate of growth in energy demand will be on its lowest value compared to the other scenarios. In this scenario (DTS), the energy demand of industrial sector may reach 17,762 Trillion Btu per year in 2042, which is only 2.0% higher than 2012.

Growth in the commercial sector plays an important role in the economic decision making process in the US. To evaluate the future energy demand of this sector, others have produced predictions for the future energy needs. For comparison purposes, the results of the three scenarios are presented along with the predictions from the EIA presented in the Annual Energy Outlook 2013 [75]. As demonstrated in Figure 6-8, the results of ANN method based on DPS are approximately consistent with Annual Energy Outlook report, especially in near future; however, for the period of 2030-2040, annual energy outlook forecasts more growth in the energy demand. Alternatively, the ANN method results may be useful as scenarios for planners to consider different scenarios. The ANN technique presented here therefore provides a tool for use by planners and information on a wide range of scenarios.

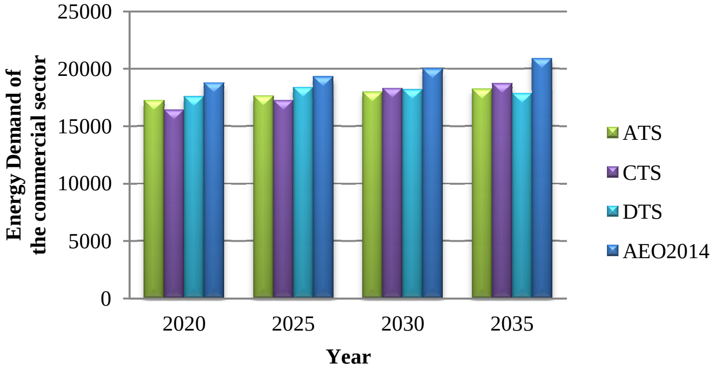


Figure 6-8: Commercial energy demand outlook, current study vs. Annual Energy Outlook 2013.

6.7 **Conclusions**

To assure the reliability and sustainability of energy for the country, the commercial sector is one of the sectors for which energy planning should be carried out comprehensively and precisely. Similar to other sectors, in the commercial sector, the

ANN method is a promising tool for use in forecasting the energy demand depending on the selected applied independent variables.

In this study, ANN was applied to forecast the commercial energy demand and perform future projections for the period 2013-2042. Among all effective independent parameters on energy demand in the commercial sector, U.S. energy trade, population, and GDP growth have been considered in this study based on correlation coefficient analysis. Based on model trained with historical data of period 1987-2012, the level of U.S. international trade significantly affects the amount of energy used in the commercial sector.

In 2012, 17,413 Trillion Btu of energy were used in the commercial sector of the US. Based on the energy demand forecast with ANN model, if GDP increases with its historical trend since 1987, and if the U.S. trade decreases with annual rate of 2%, the energy demand in the commercial sector grows only 2% by 2042. According to ATS scenario, the energy demand increase will be 5% by the end of 2042. Finally, CTS results in 7% increase in energy demand by 2042, while this scenario assumes the U.S. trade will remain in the level of average of 2008-2012. These results, which are in accordance with published predictions of the Energy Information Administration of Department of Energy especially for near future, may be considered as an indication of the need for development of new and low-cost energy sources. However, all of these scenarios suggest that energy demand in the commercial sector will not jump significantly and it will slightly increase.

If a mitigation energy policy is applied by the government by increasing the energy price annually, the ANN model predictions must be reviewed. Currently, based on correlation analysis, the level of energy prices are so low that the effect of these prices may be neglected in commercial growth. However, to protect the environment and guaranty the sustainable development of the country, regulation, incentives, and punishments should be considered by energy policy makers. Funds provided from this policy may be spent in development of new and clean energy sources which were not beneficial previously.

CHAPTER 7

ANALYSIS OF ELECTRICITY PRODUCTION FROM RENEWABLE RESOURCES IN THE UNITED STATES; LESSONS FROM LEADING STATES

7.1 Introduction

Renewable energy production in the United States has grown in recent years, with an average annual growth rate of 4.6% over the last decade. By the end of 2012, total production reached 2600 TW.h (see Figure 7-1) [93].

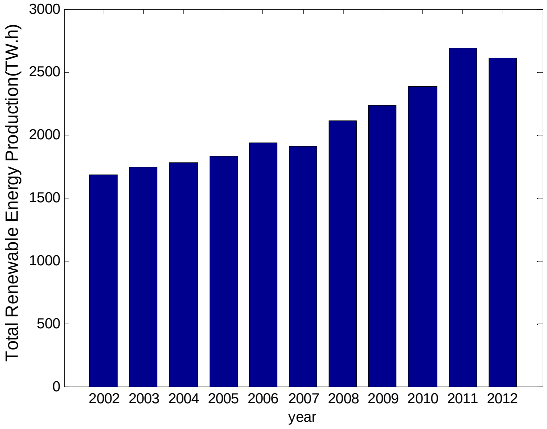


Figure 7-1: Renewable energy production in the United States 2002-2012 [93]

Renewable energy consumption of the United States is also increasing with an average annual growth rate of 4.5% over the past decade. Reflecting this increase, a growing number of states are investing in renewable energy projects, especially wind power generation. Figure 7-2 shows the trend of the share of renewable energy in the total energy consumption in the United States. [93]

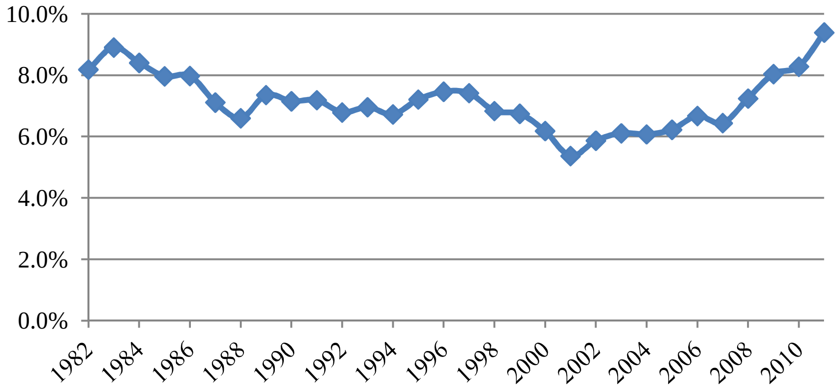


Figure 7-2: Share of renewable energy in the total energy consumption of the United States [93]

In 2012, the United States ranked third in total renewable energy supply behind the People's Republic of China and India [8]. The only significant difference between the U.S. pattern of renewable energy supply and the worldwide pattern is the source of biomass-derived fuels. In the United States, ethanol derived from corn is the dominant biomass-derived fuel, whereas worldwide, animal waste used as fuel and ethanol derived from sugarcane are the dominant biomass-derived fuels. However, the United States has some renewable energy fostering policies which are similar with those in some other countries.

Figure 7-3 and Figure 7-4 compare the share of different energy sources in the net electricity generation in the United States in the years 1997 and 2012. "Total Renewable Sources" is the energy supplied from hydropower, biomass, geothermal, solar, and wind. "Other gases" represents blast furnace gas, and other manufactured and waste gases derived from fossil fuels. The data in 1997 also includes propane gas in the category of "other gases".

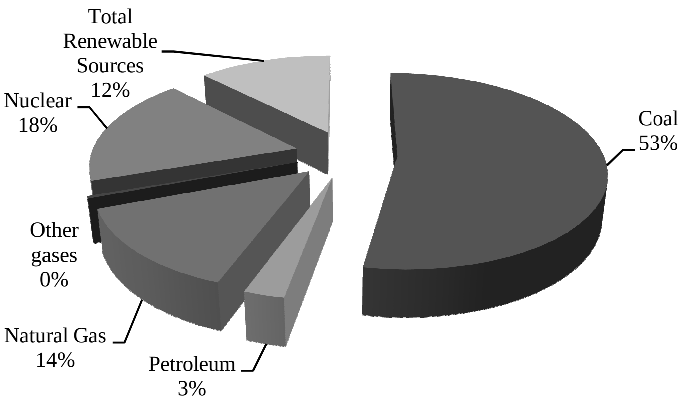


Figure 7-3: Share of energy sources in electricity net generation, 1997 [93]

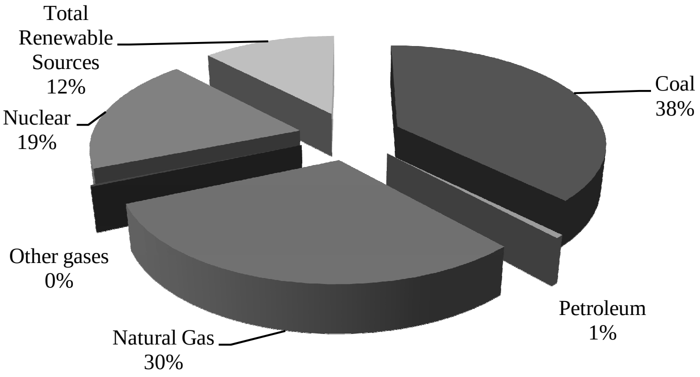


Figure 7-4: Share of energy sources in electricity net generation, 2012 [93]

While the share of renewable energy sources remained constant during this period of 15 years, the share coal decreased significantly. Primarily, natural gas displaced the coal in the electricity generation processes; however, coal is still the largest single energy source for electricity generation. It should also be noted that Figure 7-3 and Figure 7-4 are for the entire United States, and the source portfolio can differ significantly between states. Also, the total capacity for generation increased during the 15 years, so growth existed in individual sources even if the percentage of power from that source did not change much.

To gain a better understanding of the factors that have led to increased use of renewable energy in the United States, this chapter investigates the policies and market factors that have been promoting renewable energy development for electricity generation in the United States. The focus of this chapter is on the states that have experienced a significant amount of renewable energy investment during recent years. Both federal and state level (local) policies are studied in this chapter. Below, first a brief review of different forms of renewable energy is provided, and then an analysis of the conditions that exist in several particular states is provided.

7.2 **Different Forms of Renewable Energy**

Humans have been using renewable energy for millennia. As recently as 150 years ago, renewable energy played a vital role in meeting the needs of humans, when wood supplied up to 90% of human energy demand. However, the energy density and easy transportability of fossil fuels transformed the world and the method used by humans to meet their energy needs; this led to a dramatic decrease in the use of renewable energy. But during the last 20 years, because of the research and development investment by both industry and governments (primarily the U.S. Department of Energy in the United States) significant improvements have appeared in the cost, performance and reliability of renewable energy systems. Coupled with rising costs of fossil fuels and concerns over the environmental impact and security of fossil fuels, these improvements in renewable energy systems have led to increasing use of renewable energy systems.

7.2.1 Hydroelectricity

Hydropower is considered a renewable energy resource because it uses the Earth's water cycle to generate electricity. Water evaporates from the Earth's surface, forms clouds, precipitates back to the ground, and flows toward the ocean. Hydropower is mostly dependent upon precipitation and elevation changes; high precipitation levels and large elevation changes are necessary to generate significant quantities of electricity. Therefore, an area such as the mountainous Pacific Northwest has more productive hydropower plants than an area such as the Gulf Coast, which might have large amounts of precipitation but is comparatively flat.

Table 7-1: Hydroelectricity generation in top 10 states 2009-2010 [94]

	State	**2009 (Thousand MW-h)**	**2010 (Thousand MW-h)**	**Percent Change**
1	**Washington**	66,112	72,933	-9.4
2	**California**	33,876	27,888	21.5
3	**Oregon**	30,288	33,034	-8.3
4	**New York**	25,201	27,615	-8.7
5	**Montana**	9,230	9,506	-2.9
6	**Idaho**	9,161	10,434	-12.2
7	**Alabama**	9,089	12,535	-27.5
8	**Tennessee**	8,306	10,212	-18.7
9	**Arizona**	6,626	6,427	3.1
10	**South Dakota**	5,765	4,432	30.1

By the end of 2009, hydroelectricity provided 10% of the total electricity generation in the United States. However, hydropower production depends on water availability and can vary significantly from year to year. Depending on water availability, between 6-9% of the U.S. electric generation was produced by hydropower between 1998 and 2009. Table 7-1 shows the hydroelectricity generation in top 10 states during 2009 and 2010 [94].

7.2.2 Wind Energy

Wind power systems convert the kinetic energy of the wind into other forms of energy such as electricity. Although wind energy conversion is relatively simple in concept, turbine design is the most challenging technical subject in this area. Modern turbines typically begin generating power at wind speeds of 9 miles per hour and the output increases up to 28 miles per hour. Utility scale wind farms typically require average wind speeds of at least 14 miles per hour to economically convert wind energy into electricity [95]. Wind power has been one of the largest new sources of energy across the country in recent years, averaging 36.5% of all new energy capacity between 2008 and 2012 [96].

Cumulative installed wind power in the United States has increased with an average annual growth rate of 30% between 2003 and 2012. By the end of 2012 total installation reached 60,007 MW. The 13,131 MW of wind power capacity installed in the U.S. in 2012 represented 29.4% of the total global market for new wind capacity, up from a U.S. market share of 21% during 2011. The U.S. remained one of the largest single markets in 2012, installing wind power capacity at a rate equivalent to China, which installed approximately 13,000 MW for a total of 75,564 MW now deployed in that country [96].

Based on an 80-meter height, the potential of land-based wind power alone is enough to power the United States 10 times over [96]. The state which leads the United States for new wind capacity installations in 2012 was Texas with 1,826 MW followed by California and Kansas. Considering wind power additions during 2012, 890 utility-scale wind projects have been installed in 39 states and Puerto Rico. However, in only two states (South Dakota and Iowa) does the percentage of electricity generated by wind energy exceed 20%. Table 7-2 shows wind energy share of electricity generation of the top 10 states and their capacity installations for the year 2012. The importance of wind energy generation becomes significant when one considers that the U.S. is home to a vast wind energy resource and many excellent reviews of the two past decades of progress in renewable energy technologies are available [97-103].

Table 7-2: Wind energy share of electricity generation of top 10 states and their capacity installations [96]

Ranking	**State**	**Wind energy share of state's generation**	**Capacity installation**	
			Total 2012 additions (MW)	Cumulative through 2012 (MW)
1	Iowa	24.5%	814	5,133
2	South Dakota	23.9%	-	783
3	North Dakota	14.7%	235	1,680
4	Minnesota	14.3%	267	2,987
5	Kansas	11.4%	1,441	2,713
6	Colorado	11.3%	496	2,301
7	Idaho	11.3%	355	973
8	Oklahoma	10.5%	1,127	3,134
9	Oregon	10.0%	640	3,153
10	Wyoming	8.8%	-	1410

The Federal Production Tax Credit (initially of 15 USD per MWh generated) is a strong driver of wind power development in the United States and paid for the first ten years of a project's lifetime. While utilities are increasing their ownership of wind projects assets, Independent Power Producers (IPPs) are the number one project owner of the market. Five companies own 42% of the installed wind power capacity in the U.S., although this has decreased when compared to 2010 and 2011 as the market gets more diversified [96].

7.2.3 Solar Energy

The conversion of solar energy into electricity is done in two ways: through direct conversion using photovoltaic cells and indirect conversion using solar thermal power plants. Photovoltaic cells are used across the U.S. in a wide range of applications ranging from single cells to charge a battery to systems that power homes. The U.S. and especially the southwest of the U.S., is endowed with vast solar resources. For instance, there is at least 640,000 km^2 of land suitable for constructing solar power plants in the southwest of the U.S. alone [104]. The solar irradiation is crucial in selecting candidate site for a concentrating solar power plant. For instance, the cost of electricity is 31% lesser for a concentrating solar power plant operating in a site where daily direct normal irradiance amounts to 7.9 kWh/m^2 than that of a concentrating solar power plant operating in a site of 5.5 kWh/m^2 [105].

While not in widespread use, in 2011 solar thermal-power generating units were the main source of electricity at 13 power plants in the U.S.: 11 in California, one in Arizona and one in Nevada. In 2012, the total amount of solar energy converted to electricity was 4,342 TW.h which represented an increase of more than 387% between 2010 and 2012 [93].

With solar energy use growing rapidly in recent years, a variety of studies have paid exclusive attention to solar energy development policies and barriers, for example

[106-109]. In addition, other studies consider solar energy application as a part of the total renewable energy share in the Unites States including [110-113].

In 2008, just as the solar industry was beginning to significantly expand across United States, the supply of capital available for renewable energy investments reduced drastically because of the economic downturn. Application of supporting policies such as 1603 Treasury Program, Depreciation of Solar Energy Property, DOE Loan Guarantee Program, Solar Investment Tax Credit, Solar Tax Exemptions and third-Party Financing helped the economy to recover [114]. Since 2010, the economy has grown rapidly and now the U.S. has over 7,700MW of installed solar electric capacity. This capacity is enough to power more than 1.2 million American households. In 2011 alone, 10 states installed more 30 MW in solar energy capacity. As shown in Table 7-3, California ranks first among the states in cumulative solar electric capacity followed by Arizona and New Jersey. However in terms of installed solar electric per capita, Arizona ranks first [115].

Table 7-3: Ranking of the states by cumulative solar electricity capacity and installed solar per capita place [115]

Rank	State	Cumulative Solar Electric Capacity (MW)	Rank	State	Installed Solar Electric (Watts Per Capita)
1	California	2,902	**1**	Arizona	167
2	Arizona	1,097	**2**	Nevada	146
3	New Jersey	971	**3**	Hawaii	137
4	Nevada	403	**4**	New Jersey	110
5	Colorado	270	**5**	New Mexico	91
6	North Carolina	229	**6**	California	76
7	Massachusetts	198	**7**	Colorado	52
8	Pennsylvania	196	**8**	Delaware	48
9	Hawaii	191	**9**	Vermont	34
10	New Mexico	190	**10**	Massachusetts	30

7.2.4 Biomass

Biomass resources range from agricultural and forest product residues to crops grown specifically for energy production. Direct combustion systems, co-firing systems, and gasification systems are methods used to harvest energy from biomass sources. However, burning biomass is not the only way to release its energy. Biomass can be converted to other useable forms of energy, such as methane gas or transportation fuels, such as ethanol and biodiesel.

Investment in the development of biomass during the last decade has kept the share of biomass energy in renewable energy consumption approximately constant. For example, total biomass energy resources including wood, waste, and biofuels had a share of 49% of the renewable energy consumption in 2011 and 2012 [93]. Table 7-4 shows the trend of various types of biomass sources consumption in United States during last 15 years. In 2012, the 222 electricity-generating biomass plants in the United States have an average capacity of 34 MW and a cumulative capacity of 7475 MW. About 70% of this is in the forest products and sugarcane industries [116]. Research focuses on improving the conversion efficiency of commercial plants, reducing costs further and resolving issues related to biomass residual ash [117-119].

Table 7-4: Biomass energy consumption of various types of biomass sources in the United States from 1998-2012 [70]

Year	**Biomass energy consumption (Trillion Btu)**					**Total renewable energy consumption (Trillion Btu)**
	Wood	Waste	Biofuels	Total	Share	
1998	2,184	542	201	2,927	45%	6,493
1999	2,214	540	209	2,963	45%	6,516
2000	2,262	511	236	3,009	49%	6,106
2001	2,006	364	253	2,623	51%	5,163
2002	1995	402	303	2,700	47%	5,729
2003	2,002	401	404	2,807	47%	5,948
2004	2,121	389	499	3,009	49%	6,081
2005	2,137	403	577	3,117	50%	6,242
2006	2,099	397	771	3,267	49%	6,649
2007	2,070	413	991	3,474	53%	6,523
2008	2,040	436	1,372	3,848	54%	7,186
2009	1,891	453	1,568	3,912	51%	7,600
2010	1,988	469	1,837	4,294	53%	8,090
2011	2,014	469	1,948	4,431	49%	9,072
2012	1,985	471	1,909	4,365	49%	8,851

7.3 **Federal Policies**

The Energy Policy Act of 2005 (EPAct) mandates an increase in the renewable energy share to 10% in total annual electricity generation by the year 2020 in the United States, an increase compared to the 2005 share of 8.5%. In June 2007, a new energy bill was proposed for cutting the projected use of gasoline by 20%. Hence, a new Alternative Fuel Standard was announced to enable the United States to use 35 billion gallons of alternative fuels by 2017 which reduces the forecasted gasoline consumption in 2017 by 15% [120].

The U.S. Department of Energy Management Program (FEMP) works with key individuals to accomplish energy change within organizations by bringing expertise from all levels of project and policy implementation to enable federal agencies to meet energy related goals and to provide energy leadership to the country. Federal agencies increase national security by conserving natural resources by using renewable energy, which also helps meet regulatory requirements and goals. For instance, in fiscal year 2013 and thereafter, the Energy Policy Act of 2005 requires no less than 7.5% of the total electricity consumed by the Federal Government to come from renewable energy [121].

Financial incentives and federal tax breaks are very important for encouraging renewable energy development. Some of the main policies are categorized and described below [122].

7.3.1 Predictable Tax Policies

a. **Federal Renewable Energy Production Tax Credit (PTC):** PTC is an inflation-adjusted tax credit for electricity produced from qualifying renewable energy sources or technologies. At various times, several forms of renewable energy have become eligible for this credit. They include closed and open-loop biomass, geothermal, landfill gas, irrigation-produced power, municipal solid waste, wind energy facilities, and marine and hydrokinetic energy. Since Congressional appropriations affect the funding for the PTC, annual availability of this incentive has a high uncertainty and this has limited the effectiveness of PTC. There has been a clear trend toward the use of the PTC compared to the use of the 1603 Treasury program [96].

b. **Federal Renewable Energy Investment Tax Credit (ITC):** The Energy Investment Tax Credit is the alternative to the production tax credit discussed above. Investors can either take the ITC, which generally provides for a 30% tax credit, or the PTC described above.

7.3.2 National Renewable Electricity Standards

Renewable Portfolio Standards (RPS) and State Mandates or Goals: An RPS is typically a requirement that a percentage of electric power sales come from renewable energy. Some states have specific mandates for power generation from renewable energy while others have voluntary goals. In 2011, 37 states, the District of Columbia, Guam, Puerto Rico, and the U.S. Virgin Island and the Mariana Islands had an RPS, mandate, or goal. Compliance with RPS policies can sometime require or allow for the trading of renewable energy credits (RECs). Weiser et al. [123] provide an introduction to the history, concept and design of the RPS and reviewed previous experience with the policy as applied at the state level.

7.4 **State Policies**

The leading role of the individual states in establishing renewable energy policies started in the late 1990s. This role includes establishing renewable energy portfolio standards, extension of green products application, disclosure policies, and subsidies. Study and evaluation of the state policies can be helpful in developing a better understanding of the policies at the federal level. There have been a considerable number of studies of the renewable energy development policies at the state level such as [112] [124-125], [100], [98].

Of course, investment in renewable energy projects is dependent upon the quality of the renewable sources (wind sources, sun radiation, corn production, etc.) access to transmission (for wind power), the cost of conventional generation, the need for new energy supplies, and the willingness of power companies to integrate new sources in their systems. Table 7-5 presents the renewable energy production in the ten highest producing states in 2009 and shows the shares of these states in the total renewable energy production in the U.S. Moreover, the share of renewable sources in total renewable energy production of each State is shown [126].

Table 7-5: Renewable electricity production, by state, in 2009 [35]

State	Electricity produced from renewable sources (GWh)	Share from total renewable Electricity produced in U.S.	Solar, as percent of renewable energy generated	Wind, as percent of renewable energy generated	Hydroelectric, as percent of renewable energy generated	Geothermal, as percent of renewable energy generated	Biomass waste, as percent of renewable energy generated
Washington	74.905	17.5%	0.0%	6.3%	91.2%	0.0%	2.5%
California	58.881	13.8%	1.3%	10.3%	56.8%	21.4%	10.2%
Oregon	35.299	8.3%	0.0%	11.1%	86.5%	0.0%	2.4%
New York	30.286	7.1%	0.0%	8.6%	84.1%	0.0%	7.3%
Texas	28.967	6.8%	0.0%	90.6%	4.4%	0.0%	5.0%
Alabama	11.081	2.6%	0.0%	0.0%	78.5%	0.0%	21.5%
Montana	10.442	2.4%	0.0%	8.9%	90.2%	0.0%	0.9%
Iowa	10.309	2.4%	0.0%	89.0%	9.2%	0.0%	1.8%
Idaho	10.168	2.4%	0.0%	4.3%	90.0%	0.7%	4.9%
Tennessee	9.125	2.1%	0.0%	0.4%	89.2%	0.0%	10.4%

Renewable energy production in the United States has historically been concentrated in California and to the lesser extent, in a few other states. However, recent development has distributed renewable energy production among larger number states. In 2010, the 10 states listed in Table 7-5 collectively produced 66% of the total renewable electricity of the country. A complete version of Table 7-5 including all of the states' renewable electricity production is included in the Appendix 1. In addition to federal incentives, improved economics and the broader market drivers, the main factors that have been fostering development in these states consists of renewable portfolio standards and other forms of renewable energy mandates, states tax and financial incentives, and voluntary purchases of green power by consumers.

As of 2012, 30 states and the District of Columbia have an enforced renewable portfolio standard or similar law. Under these standards, each state determines its own level of renewable energy generation, eligible technologies and non-compliance penalties. Most states have met or passed their required level of renewable generation. The most important factors which have helped to create a favorable environment for RPS compliance are (1) a surge of new RPS-qualified generation capacity timed to take advantage of federal incentives that either have expired or were scheduled to expire and (2) significant reductions in the cost of renewable energy technologies such as wind and solar. The attractiveness of renewable projects to investors has been supported by declining equipment costs for wind and solar systems and improvement in the performance of renewable technologies [127].

In the following sections we examine the drivers of increased renewable energy development in 5 states that at the end of 2009 hosted the vast majority of the U.S. renewable energy production. In addition, New Mexico as a special case has been studied, and Iowa and Nebraska have been compared to investigate the role of state regulations in renewable electricity development.

7.4.1 Washington

Washington has produced the most amount of renewable energy nationally during 2010. In 2010, 17.5% of the renewable energy of the United States was produced in Washington. The primary renewable energy capacity source and generation source in Washington is hydroelectricity. In renewable electricity profile of the Washington, hydroelectric with 91.2% has the largest share, followed by wind (6.0%). Washington biomass is already producing electricity, steam and fuels. The forest industry is responsible for most of the bioenergy produced in the state, but opportunities exist to expand this market to include other biomass resources [128].

In 2011, Washington was the leading producer of electricity from hydroelectric sources and produced 29% of the Nation's net electricity generation. Moreover, Washington ranked sixth in the nation in net generation of electricity from wind energy in 2011. Due to the large potential of electricity generation in this state, electricity prices for industrial, residential and commercial sectors are lower than the U.S. average by 36%, 27%, and 22%, respectively [128].

The physical geography of Washington is primarily responsible for the large amount of renewable energy being used for electricity production in the state. The primary factor driving hydroelectric energy production investment in Washington has been natural potential of renewable energy production. Large, fast-flowing rivers produce the most hydroelectricity. The Columbia River, which forms part of the border between the states of Washington and Oregon, is a large river that produces massive amounts of hydroelectric energy. The Grand Coulee Dam on Washington's Columbia River is the largest hydroelectric power producer in the United States, with a total generating capacity of 6,809 MW.

According to the renewable portfolio standards, Washington has a target of producing 15% of its needed energy from renewable sources. The Energy Independence Act (referred to as I-937) calls for state electric utilities serving 25,000 or more costumers to acquire 15% of their electricity from new renewable resources by 2020 and undertake all cost-effective energy conservation. Solar, wind, hydro, biomass, geothermal, landfill gas (LFG), and marine are eligible renewable sources. Seventeen out of the state’s 62 utilities are required to meet EIA targets. These seventeen qualifying utilities provide 81% of the electricity in Washington.

Having plenty of renewable energy potential and sufficient policies to support the investment, Washington is the most successful state in the production of electricity from renewable sources.

7.4.2 California

Although California plays an important role in the production of fossil fuels in the United States, its role in renewable energy market is also significant. California has been the historic leader in wind energy development. Initially, California’s wind energy industry boomed as a result of state and federal tax incentives and the 1978 Public Utility Regulatory Policies Act [129]. Since the early 1980’s, the wind energy industry grew substantially in California, resulting in a total installed capacity of more than 5.5 GW by the end of 2012 [96].

California has the most diverse renewable energy resources among the states. Producing 13.8% of the renewable electricity of the nation, California has used all possible renewable sources to generate electricity. In 2011, California ranked third in the Nation in conventional hydroelectric generation, first in net electricity generation from other renewable energy resources, and first as a producer of electricity from geothermal energy [128].

In terms of RPS, California has one of the highest expectations of renewable energy development compared to other states. California mandates 33% of electricity consumption of the state should be supplied from renewable sources by the end of 2020. The allowable renewable sources include solar, wind, biomass, geothermal, LFG and municipal solid waste, small hydro, biodiesel, and marine. This new RPS preempts the California Air Resources Boards' 33% Renewable Electricity Standard and applies to all electricity retailers in the state including publicly owned utilities (POUs), investor-owned utilities, electricity service providers, and community choice aggregators. All of these entities must adopt the new RPS goals of 20% of retail sales from renewables by the end of 2013, 25% by the end of 2016, and the 33% requirement being met by the end of 2020 [130].

In California, RPS supports the diverse energy portfolio sufficiently. For example, in September 2012, a law was signed which requires an incremental 250 MW of renewable Feed-in Tariff (FIT) procurement from small-scale bioenergy projects that commence operation on or after June 1, 2013.

As another example, California Energy Commission promotes development of geothermal energy resources and technologies through research, development and demonstration partnerships and consultant contracts, as well as through financial assistance to eligible applicants via competitive project solicitations. Funding is provided through the Energy Commission's Geothermal Grant and Loan Program [131]. The effectiveness of this supporting law on bioenergy and geothermal production and the diversification of energy portfolio become clearer when attention is paid to the fact that supporting regulations of these sources have not been provided by many states.

Although the share of California in providing fossil fuels for the United States is significant, energy policy makers of this state have promoted the diverse renewable energy production in California by providing sufficient legislative supports and tax incentives.

7.4.3 Oregon

By the end of 2010, Oregon produced 8.3% of the renewable electricity in the United States. Oregon is one of the nation's leading generators of hydroelectric power, ranking second. Hydroelectric has a share of 86.5% in Oregon’s renewable electricity profile followed by wind and biomass 11.1% and 2.4% respectively. In 2010 and 2011, Oregon’s abundant hydroelectric power contributed to below-average residential electricity prices in the state. Major transmission lines connect Oregon’s electricity grid to California and Washington State, allowing for large interstate electricity transfers [128].

The Oregon RPS requires Oregon utilities to deliver a percentage from renewable sources, including biomass, geothermal, hydropower, ocean-thermal, solar, tidal, wave, wind, and hydrogen, by 2025. The target of standards for three largest utilities of the state (Portland General Electric, PacificCorp, and Eugene Water and Electric Board) is 25% in 2025. All other electric utilities depending on size have standards of 5% or 10% in 2025. Also, the Oregon Department of Energy has incentives for the expansion of renewable energy usage in transportation sector [132].

The main factor fostering renewable electricity production in Oregon is the abundant amount of hydropower potential incorporated with the proper RPS.

7.4.4 New York

The state of New York was the 4th largest producer of renewable electricity in the United States with production of 7.6% of total renewable electricity of the country. Similar to other states ranked higher than New York in Table 7-5, hydroelectric has the largest share in renewable energy profile of this state. The 2,353-MW Robert Moses Niagara hydroelectric power plant was the fourth largest hydroelectric power plant in the United States in 2010 and, in 2011, New York produced more hydroelectric power than any other state east of the Rocky Mountains [128].

During 2010, New York had the second lowest energy consumption per capita after Rhode Island which may be a result of maintaining fourth highest average electricity prices in the Unites States and the extensive use of mass transportation system.

Future development will likely be driven by incentives available through system benefit fund and an RPS that is being developed. According to Renewable Portfolio

Standards, New York has the goal of 30% renewable electricity share in overall electricity profile of the state by 2015. Production of 24% of electricity from renewable source in 2011 shows that New York still, has to try hard to achieve its RPS goal by 2015. If RPS is, in fact, implemented, this could be an important driver for renewable energy development including wind and biomass over the long term. Consumer interest in green power may also continue to provide support for new development.

Although New York has a low amount of energy consumption per capita, energy policy makers of this state have provided legislation to encourage the use of the extensive hydropower potential in this state to promote sustainable development via renewable electricity production.

7.4.5 Texas

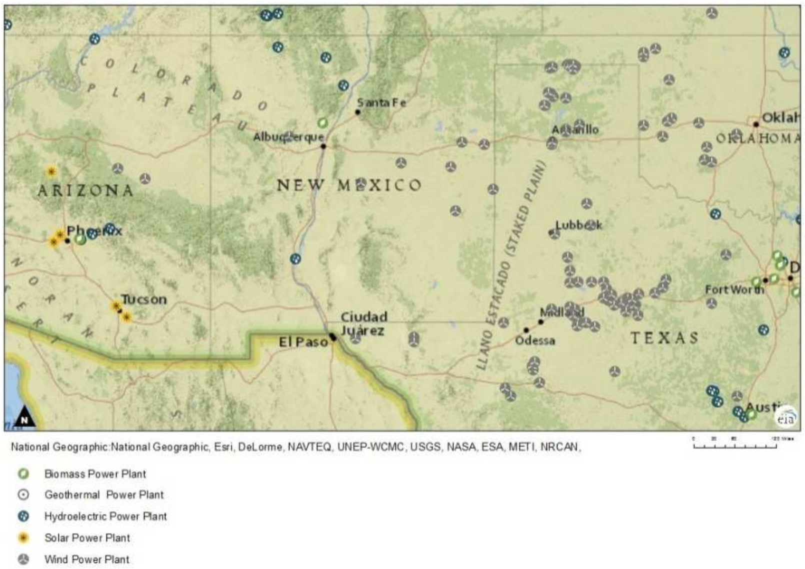
Texas leads the Nation in non-hydroelectric renewable energy potential. This state is rich in renewable energy potential, including wind, solar, and biomass resources. Wind resource areas along the Gulf of Mexico coast south of Galveston, and in the mountain passes and ridgetops of the Trans-Pecos offer Texas some of the greatest wind power potential in the United States. Solar power potential is also among the highest in the United States, with high levels of direct solar radiation suitable to support large-scale solar power plants concentrated in West Texas. Due to its large agricultural and forestry sectors, Texas has an abundance of biomass energy resources. Although Texas is not known as a major hydroelectric power state, substantial untapped potential exists in several river basins, including the Colorado River of Texas and the lower Red River [128].

The main difference between Texas, and the four states ranked higher in renewable electricity production is that more than 90% of renewable electricity produced in this state is from wind power. Texas had summer wind capacity of 10,388 MW by the end of 2011. With 1,826 MW (about 14% of the 2012 installed capacity in the U.S.) installed in 2012, Texas deployed the most new wind capacity for the year, propelling the Texas past the 12,000 MW mark for total installed wind capacity. As recently as 2006, the entire nation had only 10,000 MW installed [96].

The RPS mandates the providers of electricity in Texas generate 5,880 MW by 2015 and the target has increase to 10,000 MW in 2025. In addition, each provider is supposed to supply new renewable energy capacity based on the market share of energy sales multiplied the renewable capacity target. After RPS was implemented, Texas wind corporations and utilities invested 1 billion USD in wind power. Wind power development has accelerated by more than 4 times since RPS was implemented. In order to diversify the Texas' renewable generation profile, a target of 500 MW of non-wind renewable capacity is required by Texas State Senate Bill 20. This goal indirectly fosters the development of solar power and biomass in the state. In order to get clean energy from remote areas to the cities, Senate Bill 20 also has a goal to increase transmission capacity [133-134].

7.4.6 Special Case: New Mexico

New Mexico ranked 40th among the 50 states in generation of renewable electricity in the United States in 2009. Having abundant amounts of fossil fuels made the price of energy products very low, compared to other states. For instance, natural gas price for residential consumption is about 18% lower than the U.S. average in 2012. Limited water resources in this state affected the hydroelectric potential significantly; however solar energy potential is high. New Mexico ranked fourth in the United States in installed solar photovoltaic capacity, which increased from 43 MW in 2010 to 116 MW in 2011.



National Geographic:National Geographic, Esri, DeLorme, NAVTEQ, UNEP-WCMC, USGS, NASA, ESA, METI, NRCAN,

Figure 7-5: Installed power plants in New Mexico [44]

As shown in Figure 7-5, the energy production pattern in New Mexico is obviously different from neighboring states. While Texas produced 26,251 thousand MW-h of renewable electricity during 2010 and most of its wind farms are located close to the border with New Mexico, New Mexico produced only 1,832 thousand MW-h wind electricity last year.

In contrast with most states which implemented their RPS program as early as 1990s, 2006 was the first compliance year for New Mexico investor-owned utilities to demonstrate they have met the RPS requirements in their Renewable Energy Portfolio Reports to the Public Regulation Commission. In 2006, the RPS was 5% of retail sales in kWh’s, reaching 10% by the year 2011, but actually, in 2011, renewable energy supplied 6.5% of electricity generated in the New Mexico. The State’s Renewable Portfolio Standard requires that 20% of all electricity sold by investor-owned electric utilities, and 10% sold by cooperatives, come from renewable energy resources by 2020. By not requiring renewable energy generation until later than many states with larger renewable energy production, and by having somewhat weaker requirements, it is likely that New Mexico has positioned itself to be trailing many other states in terms of renewable energy production for years – despite the comparable conditions that exist for some renewable energy production with regards to more successful states such as Texas.

7.4.7 Special Case: Iowa vs. Nebraska

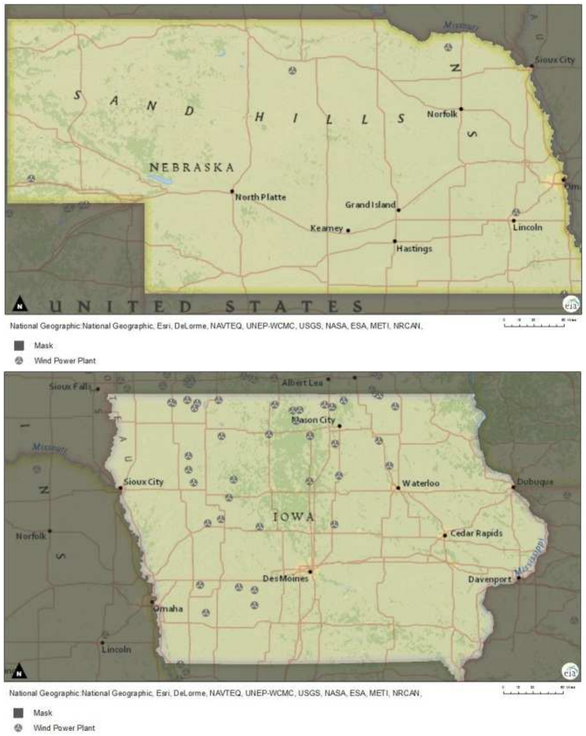
It is valuable to compare the renewable electricity production in two states which are neighbors: Iowa and Nebraska. Table 7-6 presents the renewable electricity production portfolio of these two states.

Table 7-6: Renewable electricity production in Iowa and Nebraska (thousand MW-h), 2010 [134]

	Iowa	**Nebraska**
Geothermal	-	-
Hydroelectricity	948	1314
Solar	-	-
Wind	9170	422
Biomass	190	17

As clearly shown, the wind energy harvesting system is more developed in Iowa compared to Nebraska. While most of the wind farms of the Iowa are located on the west side of this state (close to the border with Nebraska) and the geographical condition is similar on both sides of the border, wind power development in Nebraska is far behind.

Geographical location of wind harvesting farms of the Iowa and Nebraska are shown in Figure 7-6.



National Geographic:National Geographic, Esri, DeLorme, NAVTEQ, UNEP-WCMC, USGS, NASA, ESA, METI, NRCAN,

National Geographic:National Geographic, Esri, DeLorme, NAVTEQ, UNEP-WCMC, USGS, NASA, ESA, METI, NRCAN,

Figure 7-6: Geographical distribution of the wind harvesting facilities in Nebraska and Iowa, 2010 [136-137]

In terms of RPS, Iowa requires its two investor-owned utilities to own or to contract for a combined total of 105 MW of renewable generating capacity and associated energy production. Wind is one of the eligible sources in this requirement. In 2001, a voluntary goal of 1,000 MW of wind generating capacity by 2010 was established [137]. Iowa was ranked first in wind generation, with 24.5% generation from wind energy in 2012. Iowa also had the sixth wind power capacity addition in 2012. This state surpassed the 5,000 MW total installed-capacity mark, adding 814 MW during 2012.

The reason of the significant difference between renewable electricity production in Iowa and Nebraska should be sought in applied energy policies of these two states. While Iowa established its RPS in 1990, Nebraska has not established any RPS or state mandates yet. Nebraska has the potential to meet a significant portion of its electricity needs with renewable energy while generating substantial economic and environmental benefits for the state. RPS, if established, would support the investment and development of renewable electricity facilities in this state.

7.5 Lessons from the Leading States

The discussion of the conditions that exist with regards to renewable energy production in the five most successful states, and the comparison with some less successful states, leads to a number of lessons that can be drawn from these states. From this, we propose the following 5 main points that can be learned and applied when seeking to spur further renewable energy development in the United States.

1- Geographical parameters are key factor affecting renewable energy produced by a state. As shown in Table 7-5, more than 67.5% of the renewable electricity generated by 10 top-ranked states is from hydroelectric power. Simply said, there are some regions of the United States in which hydroelectric power is the lowest-cost energy resource, while this resource is not available for others. As such, care must be taken when developing renewable energy standards for individual states. If a state does not have access to plentiful hydroelectric power, it should not expect to produce as large a percentage of its total power from hydroelectric power as a state with great hydroelectric potential. Similarly, a state in a less favorable location for wind energy should not expect to produce as much energy from wind power and should instead look towards other renewable sources for renewable energy.

2- State tax and financial incentives, as well as state RPS policies, have a crucial effect on renewable energy production and development. This impact is can be clearly seen in the comparison of Iowa and Nebraska. The effect of policies is more pronounced when renewable energy is nearly competitive with more traditional generation resources - for example in states with particularly strong wind sources.

3- There are only few states (e.g. California) that have a diverse renewable energy portfolio. In terms of renewable energy sources, most of the states are dependent exclusively on wind while among 10 top-ranked states only two of them have used all renewable sources to generate electricity. More diverse energy profile is a result of availability of diverse sources and proper and detailed supporting regulations and infrastructures.

4- State drivers also function within the context of current federal policies and incentives, which have played an important role in encouraging recent renewable energy development. The most notable and effective of these of these are Federal Production Tax Credit and Renewable energy production incentive.

5- The PTC should offer opportunities for wind power growth in almost every region of the country, while various regions will get additional boosts from such drivers as RPS (California and Pacific Northwest). Currently, state RPS policies such as those developed by New York and California will play a distinguishable role in wind energy progress and prosperity.

6- Numerous affecting parameters are working as package and support one another's effectiveness. Just creating an RPS without regards to the geographical potential of a state will not be effective. Moreover, relying on geography when fossil fuels are cheap (such as in New Mexico) isn't enough either. For the United States, as a country seeking to encourage fostering renewable energy application while holding diverse energy portfolio, we believe that a first step should be a general assessment of the potential economic, employment and cost reduction benefits associated with different forms of renewable energy technologies, as well as a detailed assessment of current local capabilities. When local strategies and potentials become clear, a set of state and federal policy tools to implement those strategies must be selected.

7.6 **Summary**

Although the share of renewable sources in electricity net generation remained steady during 15 years (between 1997 and 2012), renewable energy production is growing in the United States as a whole and more rapidly in some individual states based on multiple factors which play a role in this growing process. It is impossible to consider only one single parameter for renewable energy development in the United States. For example, geographical parameters are key factor affecting renewable energy produced by a state. In addition state and federal policies such as RPS have a significant effect on renewable electricity development at the state level. As shown, a state can maximize its attractiveness to renewable power companies by establishing a combination of direct and indirect policies to support the development. Financial and tax incentives are among the most effective direct supports for utility companies. States without mandates and incentives have much less renewable electricity facilities and production compared to other states.

Some geographical factors that have allowed some states to be successful in developing large amounts of renewable power may not be present in other states; this limits the renewable energy potential of these other states. But proper application of financial incentive packages and aggressive but reasonable renewable energy targets should sufficiently spur renewable energy growth in the United States as it attempts to reduce its reliance on limited and pollution-producing fossil fuels.

CHAPTER 8

SUMMARY, CONTRIBUTIONS, AND FUTURE WORKS

8.1 **Summary**

Energy production and consumption cycles are complex. To assist in analyzing and understanding the cycles, energy models are created. Energy models are simplified representations of energy production and consumption, regulations, and producer and consumer behavior. Energy demand modeling of the United States, which is the quantification of energy requirements as a function of input parameters in different sectors, is the focus of the present study. In this work, different approaches of the energy demand modeling have been explained and their strength and weaknesses have been discussed. Because of the multiplicity of the effective parameters and discrepancies on their sphere of influence, the energy demand and the effective parameters were studied separately for different sectors. Energy demands in these sectors (transportation, residential, industrial, and commercial) form the total energy demand of the United States. To choose an energy model with adequate-flexibility and high-accuracy, two types of energy models (MLR models and ANN models) were developed for transportation and residential sectors. Based on the proposed results, ANN modeling approach is chosen for the rest of the sectors. The ANN was chosen because of its abilities in capturing the non-linear relationship among the effective parameters, and its ensuing high-level of accuracy.

For each sector, the most effective parameters on energy demand were chosen based on linear correlation test. Then, the ANN model was developed for each sector and the performance of the model was proposed. Based on the past trends of the independent parameters, the future trends of them were anticipated. Where possible, multiple scenarios for the future trend of independent variables were developed and the response of energy demand to these scenarios was demonstrated. Finally, the future energy demand of the sectors was compared with the officially published energy demand forecast from the United States Energy Information Agency.

Projections are highly dependent on the data, methodologies, model structures, and the assumptions used in their development. For this study, the author tried to mainly rely on the officially published data. When required data was not available or the availability period was shorter than required, the analysis method was chosen so that the results experienced the least amount of negative impact from this shortage.

In Chapter 7, the renewable energy electricity production in the United States was investigated. This chapter also contained a review the federal and state policies amplifying the renewable electricity production such as Energy Policy Act of 2005, tax credits and Renewable Portfolio Standards. In addition, this chapter presented some lessons from leading states in renewable electricity production and analyzed how coordination of geography and regulations intensifies the development of renewable electricity production.

Projections in the “Evaluation and Forecast of Energy Consumption in Different Sectors of the United States Using Artificial Neural Networks” focused on the factors that shape the U.S. energy system over the long term. Under the assumption that current laws and regulations remain unchanged, this work provides a basis for examination and discussion of energy demand and the direction it may take in the future. In this work, some chapters include alternative cases that explore important areas of uncertainty for markets, technologies, and policies in the U.S. energy economy.

8.2 **Contributions**

Some of the important scientific contributions resulting from this PhD dissertation, which were published in established technical journals and presented in international conferences, are as follows:

First, there is serious study of the energy demand in the transportation sector of the United States. This study also encompasses the comparison of performance of the MLR models and the ANN models in the energy demand modeling. The results are presented in ASME 2014 8th International Conference on Energy Sustainability [138].

Development of the ANN model for the residential sector of the United States and forecast of future trends in this sector was performed. This study also encompasses the comparison of performance of the MLR models and the ANN models in the energy demand modeling [11].

Development of first ANN energy model for the industrial sector of the United States was made. This study also analyzes and compares different possible scenarios of the energy price in future. The response of energy demand to these scenarios is also presented [34], [70].

Development of first ANN energy model for the commercial sector of the United States was made. This study also analyzes and compares different possible scenarios of the economy development in future. The response of energy demand to these scenarios is also presented.

8.3 **Future Work**

Energy demand modeling is a broad area that needs specific research for each sector. In the current study, some mathematical energy models were developed and appropriate theories behind them were considered. There are still some areas need more research to complete this study. The following topics are suggested for future exploration:

- In this study, ANN and MLR models are considered and compared for energy the demand modeling. However, as explained in Chapter 2, there are several approaches for energy demand modeling. These approaches, such as top-down energy models, are definitely worth exploring for all sectors.
- In solving a forecasting problem with the artificial neural networks, the most important part is to choose the independent variables that provide the most precise estimate of the dependent variable. To reduce the calculation time and cost, this research considers the most important effective parameters in each sector. However, by means of more powerful computation facilities, researchers may include more parameters and evaluate their effect on the energy demand. Including more parameters may also need more detailed approach in analysis and

comparison. The author suggests that future researchers be aware of the mutual effect of effective parameters.

- For further progress, future researchers, if they have access to National Energy Modeling System (NEMS), may develop energy demand models using NEMS while applying same data set for mathematical models. This approach provides the opportunity of comparison between the mathematical models and the NEMS models. Moreover, researchers can evaluate the performance of these models in short and long-term periods.

Another part of future work should be devoted to the investigation of the effect of geographical parameters, federal and state regulations and incentives on the renewable energy development. In this study, the author tried to consider a large part of energy production (electricity). However, to move towards sustainable development and meet national and international commitments, regulations and incentives must embrace all aspects of energy production and demand.

In addition, since the projections of this study are dependent on the historical data, and because of the dynamic property and the learning propensity of neural networks, it is recommended that researchers always train the network based on the most recent data available and compare it to the past studies.

Appendix 1

State renewable electricity production, by state [126]

State	Electricity produced from renewable sources (GWh)	share from total renewable energy produced in	Solar, as percent of renewable energy	Wind, as percent of renewable energy	Hydroelectric, as percent of renewable energy generated	Geothermal, as percent of renewable energy generated	Biomass waste, as percent of renewable energy
Washington	74.905	17.5%	0.0%	6.3%	91.2%	0.0%	2.5%
California	58.881	13.8%	1.3%	10.3%	56.8%	21.4%	10.2%
Oregon	35.299	8.3%	0.0%	11.1%	86.5%	0.0%	2.4%
New York	30.286	7.1%	0.0%	8.6%	84.1%	0.0%	7.3%
Texas	28.967	6.8%	0.0%	90.6%	4.4%	0.0%	5.0%
Alabama	11.081	2.6%	0.0%	0.0%	78.5%	0.0%	21.5%
Montana	10.442	2.4%	0.0%	8.9%	90.2%	0.0%	0.9%
Iowa	10.309	2.4%	0.0%	89.0%	9.2%	0.0%	1.8%
Idaho	10.168	2.4%	0.0%	4.3%	90.0%	0.7%	4.9%
Tennessee	9.125	2.1%	0.0%	0.4%	89.2%	0.0%	10.4%
Maine	7.963	1.9%	0%	6.3%	47.8%	0.0%	45.9%
Minnesota	7.48	1.8%	0%	64.1%	11.2%	0.0%	24.7%
Oklahoma	6.969	1.6%	0%	54.6%	40.3%	0.0%	5.1%
Arizona	6.941	1.6%	0%	1.9%	95.4%	0.0%	2.4%
North Carolina	6.84	1.6%	0%	0.0%	69.5%	0.0%	30.3%
South Dakota	6.611	1.5%	0%	20.8%	79.2%	0.0%	0.0%
Pennsylvania	6.577	1.5%	0%	28.2%	35.5%	0.0%	36.2%
Georgia	6.502	1.5%	0%	0.0%	51.1%	0.0%	48.9%
North Dakota	6.15	1.4%	0%	66.6%	33.2%	0.0%	0.2%
Arkansas	5.283	1.2%	0%	0.0%	69.3%	0.0%	30.7%
Illinois	5.257	1.2%	0%	84.7%	2.3%	0.0%	12.7%
Colorado	5.133	1.2%	1%	67.3%	30.7%	0.0%	1.2%
Florida	4.664	1.1%	2%	0.0%	3.8%	0.0%	94.5%
Wisconsin	4.586	1.1%	0%	23.7%	46.1%	0.0%	30.2%
Nevada	4.444	1.0%	5%	0.0%	48.5%	46.6%	0.0%
Wyoming	4.271	1.0%	0%	76.0%	24.0%	0.0%	0.0%
South Carolina	4.25	1.0%	0%	0.0%	55.9%	0.0%	44.1%
Michigan	4.083	1.0%	0%	8.8%	30.6%	0.0%	60.6%
Virginia	3.72	0.9%	0%	0.0%	40.3%	0.0%	59.7%
Indiana	3.699	0.9%	0%	79.3%	12.3%	0.0%	8.4%
Louisiana	3.577	0.8%	0%	0.0%	31.0%	0.0%	69.0%
Kansas	3.473	0.8%	0%	98.0%	0.4%	0.0%	1.6%

Kentucky	3.02	0.7%	0%	0.0%	85.4%	0.0%	14.6%
New Hampshire	2.71	0.6%	0%	2.8%	54.5%	0.0%	42.7%
Missouri	2.527	0.6%	0%	36.6%	60.9%	0.0%	2.5%
West Virginia	2.307	0.5%	0%	40.7%	59.3%	0.0%	0.0%
Massachusetts	2.27	0.5%	0%	1.0%	43.9%	0.0%	55.1%
Maryland	2.241	0.5%	0%	0.0%	74.4%	0.0%	25.5%
New Mexico	2.072	0.5%	0%	88.4%	10.5%	0.0%	0.7%
Vermont	1.829	0.4%	0%	0.8%	73.6%	0.0%	25.6%
Nebraska	1.807	0.4%	0%	23.4%	72.7%	0.0%	3.9%
Mississippi	1.504	0.4%	0%	0.0%	0.0%	0.0%	100.0%
Utah	1.476	0.3%	0%	30.4%	47.2%	18.8%	3.8%
Alaska	1.452	0.3%	0%	0.9%	98.7%	0.0%	0.4%
Connecticut	1.13	0.3%	0%	0.0%	34.6%	0.0%	65.4%
Ohio	1.129	0.3%	1%	1.2%	38.0%	0.0%	59.8%
New Jersey	0.868	0.2%	2%	1.5%	2.1%	0.0%	94.0%
Hawaii	0.817	0.2%	0%	31.9%	8.6%	24.6%	34.6%
Rhode Island	0.144	0.0%	0%	2.1%	2.8%	0.0%	95.1%
Delaware	0.138	0.0%	0%	2.2%	0.0%	0.0%	98.6%
United States Total	427.376	100.0%	0%	22.1%	60.9%	3.6%	13.1%

References

[1] I. Herrera and G. F. Pinder, Mathematical Modeling in Science and Engineering: An Axiomatic Approach, John Wiley & Sons, Inc., 2012.

[2] J. Beck and K. Arnold, Parametric estimation in engineering and science, New York: John Wiley & Sons, 1977.

[3] V. I. Ugursal and L. G. Swan, "Modeling of end-use energy consumption in the residential sector: A review of modeling techniques," *Renewable and Sustainable Energy Reviews*, pp. 1819-1835, 2009.

[4] U. E. I. Administration, "International Energy Outlook," Washington, DC, 2011.

[5] U. E. I. Administration, "Annual Energy Review," U.S. Energy Information Administration, 27 September 2012. [Online]. Available: http://www.eia.gov/totalenergy/data/annual/#petroleum. [Accessed 5 July 2013].

[6] "THE AMERICAN CLEAN ENERGY AND SECURITY ACT," Center for Climate and Energy Solutions, [Online]. Available: http://www.c2es.org/federal/congress/111/acesa. [Accessed 9 June 2014].

[7] "Monthly Energy Review," 25 4 2013. [Online]. Available: http://www.eia.gov/totalenergy/data/monthly/index.cfm#renewable.

[8] Renewables Information, Paris: International Energy Agency, 2012.

[9] M. Bilgili, B. Sahin, A. Yasar and E. Simsek, "Electric energy demands of Turkey in residential and industrial sectors," *Renewable and Sustainable Energy Reviews,* vol. 16, pp. 404-414, 2012.

[10] Z. W. Geem, "Transport energy demand modeling of South Korea using artificial neural networks," *Energy Policy*, vol. 39, pp. 4644-4650, 2011.

[11] A. Kialashaki and J. R. Reisel, "Modeling of the energy demand of the residential sector in the United States using regression models and artificial neural networks," *Applied Energy,* vol. 108, pp. 271-280, 2013.

[12] L. A. Greening, G. Boyd and J. M. Roop, "Modeling of industrial energy consumption: An introduction and context," *Energy Economics,* vol. 29, pp. 599-608, 2007.

[13] S. Jebaraj and S. Iniyan, "A review of energy models," *Renewable and Sustainable Energy Reviews,* vol. 10, pp. 281-311, 2006.

[14] T. Fleiter, E. Worrell and W. Eichhammer, "Barriers to energy efficiency in industrial bottom-up energy demand models—A review," *Renewable and Sustainable Energy Reviews,* vol. 15, pp. 3099-3111, 2011.

[15] L. Suganthi and A. A. Samuel, "Energy models for demand forecasting—A review," *Renewable and Sustainable Energy Reviews,* vol. 16, pp. 1223-1240, 2012.

[16] J. Min, Z. Hausfather and Q. F. Lin, "A high-resolution statistical model of residential energy end use characteristics for the United States," *Journal of Industrial Ecology,* vol. 14, no. 5, pp. 791-809, 2010.

[17] W. Jin-ming and L. Xin-heng, "The forecast of energy demand on artificial neural network," in *International Conference on Artificial Intelligence and Computational Intelligence*, Shanghai, China, 2009.

[18] Z. W. Geem and W. E. Roper, "Energy demand estimation of South Korea using artificial neural network," *Energy Policy,* vol. 37, pp. 4049-4054, 2009.

[19] J. M. Cayla, N. Maizi and C. Marchand, "The role of income in energy consumption behavior: evidence from French households data," *Energy Policy,* vol. 39, pp. 7874-7883, 2011.

[20] Y. S. Murat and H. Cylan, "Use of artificial neural network for transport energy demand modeling," *Energy Policy,* vol. 34, pp. 3165-3172, 2006.

[21] L. Ekonomou, "Greek long-term energy consumption prediction using artificial neural networks," *Energy,* vol. 35, pp. 512-517, 2010.

[22] K. Ermis, A. Midilli, I. Dincer and M. Rosen, "Artificial neural network analysis of world green energy use," *Energy Policy,* vol. 35, pp. 1731-1743, 2007.

[23] A. Sozen, "Future projection of the energy dependency of Turkey using artificial neural network," *Energy Policy,* vol. 37, pp. 4827-4833, 2009.

[24] M. Kankal, A. Akpinar, M. I. Komurcu and T. S. Ozsahin, "Modeling and forecasting of Turkey's energy consumption using socio-economic and demographic variables," *Applied Energy,* vol. 88, pp. 1927-1939, 2011.

[25] C. Hamzacebi, "Forecasting of Turkey's net electricity energy consumption on sectoral bases," *Energy Policy,* vol. 35, pp. 2009-2016, 2007.

[26] D. Akay and M. Atak, "Grey prediction with rolling mechanism for electricity demand forecasting of Turkey," *Energy*, vol. 32, pp. 1670-1675, 2007.

[27] D. Toksarı, "Ant colony optimization approach to estimate energy demand of Turkey," *Energy Policy*, vol. 35, pp. 3984-3994, 2007.

[28] A. Unler, "Improvement of energy demand forecasts using swarm intelligence: The case of Turkey with projections to 2025," *Energy Policy*, vol. 36, pp. 1937-1944, 2008.

[29] S. Kucukali and K. Baris, "Turkey’s short-term gross annual electricity demand forecast by fuzzy logic approach," *Energy Policy,* vol. 38, pp. 2438-2445, 2010.

[30] G. Adams and Y. Shachmurove, "Modeling and forecasting energy consumption in China: Implications for Chinese energy demand and imports in 2020," *Energy Policy*, vol. 30, pp. 1263-1278, 2008.

[31] A. Azadeh, S. Ghaderi and S. Sohrabkhani, "A simulated-based neural network algorithm for forecasting electrical energy consumption in Iran," *Energy Policy,* vol. 36, pp. 2637-2644, 2008.

[32] A. Azadeh, S. Ghaderi and S. Sohrabkhani, "Annual electricity consumption forecasting by neural network in high energy consuming industrial sectors," *Energy Conservation and Management*, vol. 49, pp. 2272-2278, 2008.

[33] A. Azadeh, M. Saberi and O. Seraj, "An integrated fuzzy regression algorithm for energy consumption estimation with non-stationary data: A case study of Iran," *Energy*, vol. 35, pp. 2351-2366, 2010.

[34] A. Kialashaki and J. R. Reisel, "Forecasting United States' energy demand of industrial sector using artificial neural networks," *International Journal of Energy and Statistics*, 2014.

[35] S. A. Abdul-Wahab, C. S. Bakheit and S. M. Al-Alawi, "Principal component and multiple regression analysis in modelling of ground-level ozone and factors affecting its concentrations," *Environmental Modelling & Software*, vol. 20, no. 10, pp. 1263-1271, 2005.

[36] L. Fausett, Fundamentals of Neural Networks; architectures, algorithm, and application, Englewood Cliffs: Prentice Hall, 1994.

[37] S. Haykin, Neural Networks, A Comprehensive Foundation, Upper Saddle River: Prentice Hall, 1999.

[38] M. T. Hagan, H. B. Demuth and M. Beale, Neural Network Design, Boston: PWS Publishing, 1996.

[39] D. C. Montgomery and G. C. Runger, Applied Statistics and Probability, John Wiley & Sons, Inc., 1994.

[40] B. Gilland, "Population, Economic Growth, and Energy Demand, 1985-2020," *Population and Development Review,* vol. 14, no. 2, pp. 233-244, 1988.

[41] N. Song, F. Aguilar, S. Shifley and M. Goerndt, "Analysis of U.S. residential wood energy consumption," *Energy Economics,* vol. 34, pp. 2116-2126, 2012.

[42] United States Census Bureau, 23 Jnauray 2014. [Online]. Available: http://www.census.gov. [Accessed 10 February 2014].

[43] R. H. Myers, Classical and Modern Regression, PWS Pub. Co, 1997.

[44] T. Limanond, S. Jomnonkwao and A. Srikaew, "Projection of future transport energy demand of Thailand," *Energy Policy,* vol. 39, pp. 2754-2763, 2011.

[45] L. Parshall, K. Gurney, S. A. Hammer , D. Mendoza, Y. Zhou and S. Geethakumar, "Modeling energy consumption and CO2 emissions at the urban scale: Methodological challenges and insights from the United States," *Energy Policy,* vol. 38, pp. 4765-4782, 2010.

[46] "World Development Indicators & Global Development Finance," World Bank, [Online]. Available: http://datatbank.worldbank.org. [Accessed 01 February 2014].

[47] Research and Innovative Technology Administration, "National Transportation Statistics," Bureau of Transportation Statistics, [Online]. Available: http://www.bts.gov/publications/national_transportation_statistics. [Accessed 17 February 2014].

[48] "Highway Statistics 2009," U.S. Department of Transportation, [Online]. Available: http://www.fhwa.dot.gov/policyinformation/statistics/2009/vm202.cfm. [Accessed 05 January 2014].

[49] D. Stern, "Energy and Economic Growth in the USA," *Energy Economics,* vol. 15, no. 2, pp. 137-150, 1993.

[50] D. Stern, "A Multivariate Cointegration Analysis of the Role of Energy in the U.S. Macroeconomy," *Energy Economics,* vol. 22, no. 2, pp. 267-283, 2000.

[51] J. Asafu-Adjaye, "The Relationship Between Energy Consumption, Energy Prices and Economic Growth: Time series evidence from Asian Developing Countries," *Energy Economics,* vol. 22, pp. 615-625, 2000.

[52] U. Soytas, R. Sari and B. T. Ewing, "Energy Consumption, Income, and Carbon Emissions in the United States," *Ecological Economics,* vol. 62, pp. 482-489, 2007.

[53] Organization for Economic Coopertation and Development (OECD), The Economics of Climate Change Mitigation: Policies and Options for Global Action Beyond 2012, Paris: OECD, 2009.

[54] Organization for Economic Cooperation and Development, Energy Statistics of OECD Countries, Paris: OECD, 2013.

[55] J. J. Winebrake and S. Denys, "An evaluation of errors in US energy forecasts: 1982–2003," *Energy Policy,* vol. 34, pp. 3475-3483, 2006.

[56] M. Auffhammer, "The rationality of EIA forecasts under symmetric and asymmetric loss," *Resources and Energy Economics,* vol. 29, pp. 102-121, 2007.

[57] J. T. Wilkerson, D. Cullenward, D. Davidian and J. P. Weyant, "End use technology choice in the National Energy Modeling System (NEMS): An analysis of the residential and commercial building sectors," *Energy Economics,* vol. 40., pp. 773-784, 2013.

[58] H. Dowlatabadi and O. A. Matthew, "US long-term energy intensity: Backcast and projection," *Energy Policy,* vol. 34, pp. 3245-3256, 2006.

[59] F. Ackerman and J. Fisher, "Is there a water–energy nexus in electricity generation? Long-term scenarios for the western United States," *Energy Policy,* vol. 59, pp. 235-241, 2013.

[60] B. Tonn, K. Healy, A. Gibson, A. Ashish, P. Cody, D. Beres, S. Lulla, J. Mazur and A. Ritter, "Power from Perspective: Potential future United States energy portfolios," *Energy Policy,* vol. 37, pp. 1432-1443, 2009.

[61] A. Osmani, V. Gonela and I. Awudu, "Electricity generation from renewables in the United States: Resource potential, current usage, technical status, challenges, strategies, policies, and future directions," *Renewable and Sustainable Energy Reviews,* vol. 24, pp. 454-472, 2013.

[62] C. J. Cleveland, R. K. Kaufmann and D. I. Stern, "Aggregation and the role of energy in the economy," *Ecologocal Economics,* vol. 32, pp. 301-317, 2000.

[63] B. T. Ewing, R. Sari and U. Soytas, "Disaggregate energy consumption and industrial

output in the United States," *Energy Policy,* vol. 35, pp. 1274-1281, 2007.

[64] N. Bowden and J. E. Payne, "Sectoral analysis of the causal relationship between renewable and non-renewable energy consumption and real outpu in the USA," *Energy Sources, Part B,* vol. 5, pp. 400-408, 2010.

[65] B. Warr and R. Ayres, "Evidence of causality between the quantity and quality of energy consumption and economic growth," *Energy,* vol. 35, pp. 1688-1693, 2010.

[66] R. Sari, B. T. Ewing and U. Soytas, "The relationship between disaggregate energy consumption and industrial production in the United States: an ARDL approach," *Energy Economics,* vol. 30, pp. 2302-23013, 2008.

[67] J. E. Payne, "On the dynamics of energy consumption and output in the US," *Applied Energy,* vol. 86, pp. 575-577, 2009.

[68] N. Apergis and J. E. Payne, "Energy consumption and economic growth in Central America: Evidence from a panel cointegration and error correction model," *Energy Economics,* vol. 31, pp. 211-216, 2009.

[69] F. Karanfil, "How many times again will we examine the energy-income nexus using a limited range of traditional econometric tools?," *Energy Policy,* vol. 37, pp. 1191-1194, 2009.

[70] A. Kialashaki and J. R. Reisel, "Development and Validation of Artificial Neural Network Models of the Energy Demand in the Industrial Sector of the United States," *Energy,* 2014.

[71] A. Trujillo-Ortiz and R. Hernandez-Walls, *Homvar: Homogeneity of variances,* 2003.

[72] "Monthly Energy Review-Total Energy," U.S. Energy Information Administration, 29 October 2013. [Online]. Available: http://www.eia.gov/totalenergy/data/monthly/#consumption. [Accessed 1 10 2013].

[73] "Monthy Energy Review-Energy Prices," Energy Information Administration, 29 October 2013. [Online]. Available: http://www.eia.gov/totalenergy/data/monthly/pdf/sec9.pdf. [Accessed 2013 09 2013].

[74] "Data-GDP (current US$)," The World Bank, 2013. [Online]. Available: http://data.worldbank.org/indicator/NY.GDP.MKTP.CD?cid=GPD_29. [Accessed 26 September 2013].

[75] U.S. Energy Information Administration, "Analysis & Projections, AEO2014 EARLY RELEASE OVERVIEW," 16 December 2013. [Online]. Available:

http://www.eia.gov/forecasts/aeo/er/pdf/0383er(2014).pdf. [Accessed 10 January 2014].

[76] Z. Utlu and A. Hepbasli, "Estimating the energy and exergy utilization efficiencies for the residential–commercial sector: an application," *Energy Policy,* vol. 34, no. 10, pp. 1097-1105, 2009.

[77] Z. Utlu and A. Hepbasli, "Analysis of energy and exergy use of the Turkish residential–commercial sector," *Building and Environment,* vol. 40, no. 5, pp. 641-655, 2005.

[78] Z. Utlu and A. Hepbasli, "A study on the evaluation of energy utilization efficiency in the Turkish residential-commercial sector using energy and exergy analyses," *Energy and Buildings,* vol. 35, no. 11, pp. 1145-1153, 2003.

[79] D. J. Sailor, "Relating residential and commercial sector electricity loads to climate-evaluating state level sensitivities and vulnerabilities," *Energy,* vol. 26, no. 7, pp. 645-657, 2001.

[80] J. C. Lam, H. Tang and D. H. Li, "Seasonal variations in residential and commercial sector electricity consumption in Hong Kong," *Energy,* vol. 33, no. 3, pp. 513-523, 2008.

[81] J. C. Lam, "Building envelope loads and commercial sector electricity use in Hong Kong," *Energy,* vol. 20, no. 3, pp. 189-194, 1995.

[82] R. Xing, T. Ikaga and M. Strubegger, "A Forecast of Effective Energy Efficient Policies for the Building Sector in Shanghai through 2050," in *World Renewable Energy Congress 2011*, Sweden, 2011.

[83] M. Forouzanfar, A. Doustmohammadi, M. B. Menhaj and S. Hasanzadeh, "Modeling and estimation of the natural gas consumption for residential and commercial sectors in Iran," *Applied Energy,* vol. 87, pp. 268-274, 2010.

[84] M. J. Horowitz, "Electricity intensity in the commercial sector: Market and public program effects," *Energy,* vol. 25, no. 2, pp. 115-137, 2004.

[85] Energy Information Administration, "Monthly Energy Review," 26 February 2014. [Online]. Available: http://www.eia.gov/totalenergy/data/monthly/#consumption. [Accessed 6 March 2014].

[86] R. Issa, I. Flood and M. Asmus, "Development of a neural network to predict residential energy consumption," in *Proceedings of the sixth international conference on the application of artificial intelligence to civil & structural engineering computing*, 2001.

[87] G. Mihalakakou, M. Santamouris and A. Tsangrassoulis, "On the energy consumption in

residential buildings," *Energy and Buildings,* vol. 34, no. 7, pp. 727-736, 2002.

[88] M. Aydinalp, I. Ugursal and A. S. Fung, "Effects of socioeconomic factors on household appliance, lighting, and space cooling electricity consumption," *International Journal of Global Energy Issues,* vol. 20, no. 3, pp. 302-315, 2003.

[89] M. Aydinalp, I. Ugursal and A. S. Fung, "Modeling of the space and domestic hot-water heating energy-consumption in the residential sector using neural networks," *Applied Energy,* vol. 79, no. 2, pp. 159-178, 2004.

[90] M. Aydinalp-Koksal and I. Ugursal, "Comparison of neural network, conditional demand analysis, and engineering approaches for modeling end-use energy consumption in the residential sector," *Applied Energy,* vol. 85, pp. 271-296, 2008.

[91] K. Kavaklioglu, H. Ceylan, H. K. Ozturk and O. E. Canyurt, "Modeling and prediction of Turkey's electricity consumption using Artificial Neural Networks," *Energy Conversion and Management,* vol. 50, pp. 2719-2727, 2009.

[92] S. Jebaraj, S. Iniyan and H. Kota, "Forecasting of commercial energy consumption in India using Artificial Neural Network," *International Journal of Global Energy Issues,* vol. 27, no. 3, pp. 276-301, 2007.

[93] "Monthly Energy Review," 25 April 2013. [Online]. Available: http://www.eia.gov/totalenergy/data/monthly/pdf/mer.pdf.

[94] "RENEWABLE & ALTERNATIVE FUELS," U.S. Energy Information Administration, [Online]. Available: http://www.eia.gov/cneaf/solar.renewables/page/hydroelec/hydroelec.html. [Accessed 5 August 2013].

[95] "Frequently Asked Questions," 31 July 2013. [Online]. Available: http://www.windenergyamerica.com.

[96] E. Williams, J. Hensley and E. Salerno, "AWEA U.S. Wind Industry Annual Market Report Year Ending 2012," American Wind Energy Association, 2013.

[97] J. I. Lewis and R. H. Wiser, "Fostering a renewable energy technology industry: An international comparison of wind industry policy support mechanisms," *Energy Policy,* pp. 1844-1857, 2007.

[98] L. Bird, M. Bolinger, T. Gagliano, R. Wiser, M. Brown and B. Parsons, "Policies and market factors driving wind power development in the United States," *Energy Policy,* pp. 1397-1407, 2005.

[99] B. Parsons, M. Milligan, B. Zavadil, D. Brooks, B. Kirby, K. Dragoon and J. Caldwell, "Grid Impacts of Wind Power: A Summary of Recent Studies in the United States," *Wind Energy,* pp. 87-108, 2004.

[100] F. C. Menz and S. Vachon, "The effectiveness of different policy regimes for promoting wind power: Experiences from the states," *Energy Policy,* pp. 1786-1796, 2006.

[101] C. Bohn and C. Lant, "Welcoming the Wind? Determinants of Wind Power Development Among U.S. States," *The Professional Geographer,* pp. 87-110, 2009.

[102] E. Wilson and J. Stephens, "Wind Deployment in the United States: States, Resources, Policy, and Discourse," *Environmental Science & Technology,* pp. 9063-9070, 2009.

[103] M. Fischlein, J. Larson, D. M. Hall, R. Chaudhry, T. R. Peterson, J. Stephens and E. J. Wilson, "Policy stakeholders and deployment of wind power in the sub-national context: A comparison of four U.S. states," *Energy Policy,* pp. 4429-4439, 2010.

[104] V. Fthenakis, J. E. Mason and K. Zweibel, "The technical, geographical, and economic feasibility for solar energy to supply the energy needs of the US," *Energy Policy,* vol. 37, pp. 387-399, 2009.

[105] Y. Azoumah, E. W. Ramde, G. Tapsoba and S. Thiam, "Siting guidelines for concentrating solar power plants in the Sahel: Case study of Burkina Faso," *Solar Energy,* vol. 84, pp. 1545-1553, 2010.

[106] J. E. Burns and J.-S. Kang, "Comparative economic analysis of supporting policies for residential solar PV in the United States: Solar Renewable Energy Credit (SREC) potential," *Energy Policy,* pp. 217-225, 2012.

[107] H. Cassard, P. Denholm and S. Ong, "Technical and economic performance of residential solar water heating in the United States," *Renewable and Sustainable Energy Reviews,* pp. 3789-3800, 2011.

[108] C. L. Kwan, "Influence of local environmental, social, economic and political variables on the spatial distribution of residential solar PV arrays across the United States," *Energy Policy,* pp. 332-344, 2012.

[109] R. Wiser, G. Barbose and E. Holt, "Supporting solar power in renewables portfolio standards: Experience from the United States," *Energy Policy,* pp. 3894-3905, 2011.

[110] S. R. Bull, "Renewable Energy Today And Tomorrow," in *IEEE,* 2001.

[111] J. D. Guggenberger, A. C. Elmore and M. L. Crow, "Predicting performance of a renewable energy-powered microgrid throughout the United States using typical meteorological year 3

data," *Renewable Energy,* pp. 189-195, 2013.

[112] M. A. Delmas and M. J. Montes-Sancho, "U.S. state policies for renewable energy: Context and effectiveness," *Energy Policy,* pp. 2273-2288, 2011.

[113] B. K. Sovacool, "Rejecting renewables: The socio-technical impediments to renewable electricity in the United States," *Energy Policy,* pp. 4500-4513, 2009.

[114] "Finance & Tax," Solar Energy Industries Association, [Online]. Available: http://www.seia.org/policy/finance-tax. [Accessed 31 July 2013].

[115] "Research and Resources," Solar Energy Industries Association, 14 March 2013. [Online]. Available: http://www.seia.org/news/us-solar-market-grows-76-2012-now-increasingly-competitive-energy-source-millions-americans. [Accessed 4 August 2013].

[116] "Biomass Plants," 15 5 2013. [Online]. Available: http://biomassmagazine.com.

[117] J. Cook and J. Beyea, "Bioenergy in the United States: progress and possibilities," *Biomass and Bioenergy,* pp. 441-455, 2000.

[118] H. L. Chum and R. P. Overend, "Biomass and renewable fuels," *Fuel Processing Technology,* pp. 187-195, 2001.

[119] E. Hughes, "Biomass cofiring: economics, policy and opportunities," *Biomass and Bioenergy,* pp. 457-465, 2000.

[120] Head of Communication and Information Office, "Energy Policies of IEA Countries: The United States," International Energy Agency (IEA), Paris, 2007.

[121] "Federal Energy Management Program," 20 11 2012. [Online]. Available: https://www1.eere.energy.gov/femp/technologies/renewable_energy.html.

[122] "Renewable Energy Incentives," 24 July 2012. [Online]. Available: http://www.eia.gov/energyexplained/index.cfm?page=renewable_home#tab3.

[123] R. Weiser, C. Namovicz, M. Gielecki and R. Smith, "Renewables Portfolio Standards: A Factual Introduction to Experience form the United States," BERKELEY NATIONAL LABORATORY, 2007.

[124] H. Yin and N. Powers, "Do state renewable portfolio standards promote in-state generations," *Energy Policy,* pp. 1140-1149, 2010.

[125] S. Carley, "State renewable energy electricity policies: An emperical evaluation of

effectiveness," *Energy Policy,* pp. 3071-3081, 2009.

[126] U. E. I. Administration, "State Renewable Electricity Profiles 2010," U.S. Department of Energy, Washington D.C., 2012.

[127] O. o. I. a. I. Energy, "Annual Energy Outlook 2013," U.S. Energy Information Administration, Washington, DC, 2013.

[128] "State Profiles and Energy Estimates," U.S. Energy Information Administration, [Online]. Available: http://www.eia.gov/state/. [Accessed 1 August 2013].

[129] M. Gielecki, F. Mayes and L. Prete, "Incentives, Mandates, and government programs for promoting renewable enrgy in renewbale energy issues and trends 2000," Energy information Administration, 2001.

[130] K. Zocchetti, "Renewables Portfolio Standards (RPS) Proceeding," 30 May 2013. [Online]. Available: http://www.energy.ca.gov/portfolio/index.html.

[131] "Geothermal Energy Research Funding," California Energy Commission, [Online]. Available: http://www.energy.ca.gov/geothermal/index.html. [Accessed 12 August 2013].

[132] "A Renewable Portfolio Standard (RPS) for Oregon," Oregan Department of Energy, [Online]. Available: http://www.oregon.gov/ENERGY/RENEW/Pages/RPS_home.aspx. [Accessed 1 August 2013].

[133] "Texas Renewable Portfolio Standard," June 2013. [Online]. Available: http://seco.cpa.state.tx.us/re/rps-portfolio.php.

[134] "State Profile and Energy Estimates," July 2012. [Online].

[135] "New Mexico State Profile and Energy Estimates," U.S. Energy Information Administration, July 2012. [Online]. Available: http://www.eia.gov/state/?sid=NM. [Accessed 19 August 2013].

[136] "Nebraska State Profile and Energy Estimates," U.S. Energy Information Administration, July 2012. [Online]. Available: http://www.eia.gov/state/?sid=NE. [Accessed 2013 August 2013].

[137] "Iowa State Profile and Energy Estimates," U.S. Energy Information Administration, July 2012. [Online]. Available: http://www.eia.gov/state/?sid=IA. [Accessed 19 August 2013].

[138] Kialashaki, Arash, and John Reisel. "Transport Energy Demand Modeling of the United States Using Artificial Neural Networks and Multiple Linear Regressions." ASME 2014 8th International Conference on Energy Sustainability collocated with the ASME 2014 12th

International Conference on Fuel Cell Science, Engineering and Technology. American Society of Mechanical Engineers, 2014.

Arash Kialashaki

Email: arash@uwm.edu

Website: https://sites.google.com/site/kialashaki

Education:

PhD, Mechanical Engineering (December 2014)

University of Wisconsin-Milwaukee, Milwaukee, WI

Minor: Industrial Engineering

Advisor: Professor John Reisel

Thesis Title: Evaluation and Forecast of Energy consumption in Different Sectors of the United States Using Artificial Neural Networks

GPA: 3.912/4

Master's Degree in Mechanical Engineering (December 2011)

University of Wisconsin-Milwaukee, Milwaukee, WI

Advisor: Professor John Reisel

GPA: 3.90/4

Master's Degree in Energy Systems Engineering (2007)

K.N.Toosi University of Technology

Thesis Title: Energy Demand Modeling on Transportation Sector

Graduated cum laude with 16.8 (out of 20) G.P.A.

B.S. Degree in Mechanical Engineering (2005)

Amirkabir University of Technology

Research Interests

- Technical and Economic Analysis of Energy Systems
- Modeling of Energy Systems
- Energy Efficiency Improvement
- Renewable Energy
- Sustainable Engineering

- Fluid Mechanics
- Fuel Cells and Hydrogen Generation Technology
- CFD and Numerical Heat Transfer

Journal Papers

A. Kialashaki, J. Reisel, “Modeling of the Energy Demand of the Residential Sector in the United States Using Regression Models and Artificial Neural Networks”, Applied Energy, Vol 108, 2012

A. Kialashaki, J. Reisel, “Modeling of the Energy Demand of the industrial Sector in the United States Using Artificial Neural Networks”, International Journal of Energy and Statistics, 2.03 (2014): 207-226.

Kialashaki A, Reisel JR, Development and validation of artificial neural network models of the energy demand in the industrial sector of the United States, Energy (2014), http://dx.doi.org/10.1016/j.energy.2014.08.072

A. Kialashaki, J. Reisel, “Modeling of the Energy Demand of the Commercial Sector in the United States Using Artificial Neural Networks”, In preparation

Conference Papers and Presentations

- **A. Kialashaki**, J. Reisel, “Transport Energy Demand Modeling of the United States Using Artificial Neural Networks and Multiple Linear Regressions”, 2014 ASME Energy Sustainability Conference, June 30 – July 2, 2014

- Reisel, John R., Jablonski, Marissa, **Kialashaki, Arash**, Munson, Ethan, Hosseini, Hossein, “Analysis of the Impact of Participation in a Summer Bridge Program on Mathematics Course Performance by First-Semester Engineering Students.” 121st ASEE Annual Conference and Exhibition, June 15-18, 2014, Indianapolis, IN

- **A. Kialashaki**, J. Reisel, “Effects of Federal and State Policies in Production of Electricity from Renewable Energy Sources”, Sustainability Summit, Milwaukee, WI, March 26th – March 28th, 2014

- **A. Kialashaki**, J. Reisel, “Renewable Energy Development for Electricity Production : Federal and State Policies”, Western Energy Policy Research Conference, Portland, OR, September 2013

- **A. Kialashaki**, J. Reisel, Modeling of the Energy Demand of the Residential Sector in the United States, Western Energy Policy Research Conference, Boise, ID, August 2012

- **A. Kialashaki**, J. Reisel, Transport Energy Demand Modeling of The United States Using Artificial Neural Networks, Green Energy Summit, Milwaukee, WI, March 7th – March 9th, 2012

- **A. Kialashaki**. M. Amidpour, "Effects of Fuel Demand Reduction Regulations in Transportation Sector", International Conference of Fuel, Energy and Environment - May, 2008.

- **A. Kialashaki**. M. Amidpour, "Study of Currant Demand and Demand Control Policies for Gasoil", International Conference of Fuel, Energy and Environment - May, 2008.

A. Kialashaki. M. Amidpour, "Study of Currant Demand and Demand Control Policies for Gasoline in Transportation Sector", 13th IIES International Oil and Gas Conference- 30 Nov – 1 Dec 2008