THE INFLUENCES OF URBAN FORMS ON RESIDENTIAL ENERGY CONSUMPTION: A DEMAND-SIDE FORECASTING METHOD FOR ENERGY SCENARIOS

by

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ABSTRACT

AMR MOHAMED MOHAMED ALI. The influences of urban forms on residential energy consumption: a demand-side forecasting method for energy scenarios. (Under direction of DR. JEAN-CLAUDE THILL)

Current trends in energy demand impose increasing stress on the socio-ecological state of developed countries like the U.S. A major challenge lies in how to efficiently manage energy resources in a sustainable way to protect the environment. Various forecasting approaches have been developed to predict energy demand trends. These approaches have not investigated the influence of urban form on household energy consumption. This research combines one of the forecasting methods with sustainable development practices to predict possible energy demand based on different spatial housing forms (compact and dense, mixed uses, and low density).

The research has five objectives; the first is to develop a spatial Planning Support System (PSS) to forecast residential energy consumption. The PSS is integrated with an existing urban simulation model called the Charlotte Land Use and Economic Simulator (CLUES). The second objective is to develop a statistical operational model of household energy consumption that accounts for socio-economic, geometric, spatial, and macroeconomic condition determinants. Inserted in the PSS, this model serves to forecast consumption under a series of scenarios that account for various policies in urban development, environmental protection, and green technology applications at fine (household) through coarse (traffic analysis zone) resolutions, over short- and long-terms.

The third and fourth objectives assess the contribution of the geometries factors and the condition and socio-economic variables, respectively, to various alternatives of residential energy consumption. The fifth objective is to assess the consequences of

different scenarios on social equity and energy share per household across population groups.

The research is conducted in Mecklenburg County over the 2008-2037 horizon. It determines the suitable system architecture of the developed PSS, and finds the drivers that have significant impacts on residential energy consumption. In addition, the study examines the magnitude of different sustainable policies on household energy consumption and population groups. The expected outcome is an enhanced understanding of the energy implications of various policy and planning strategies at the local, regional, and national scales, in the context of various possible future contexts.

DEDICATION

To all who give the strength to continue, and achieve the success in my life

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CHAPTER 1: INTRODUCTION

1.1. Statement of Purpose

Over the past few years, developed countries, such as the United States, have sought to manage energy demand and supply in a way to conserve resources and reduce their short and long-term impacts on the environment. Environmental problems at global, national, regional and city scales have led to the concept of sustainable development.

Historically, the growth of city regions has resulted in increasing consumption of energy. If this trend continues, it will cause climate change, which is one of the major contemporary environmental problems. The management of the consumption of energy will improve energy efficiency and reduce carbon monoxide emissions. The challenge is to sustain the economic and local progress without causing environmental problems (Schrecker et al. 1993). Many practices of sustainable development have been applied in energy management and policy. The main goal of these practices is to protect the environment and conserve energy resources to meet the urgent needs of an increasingly urbanized population. A research question arises: how can we efficiently manage future energy consumption in a sustainable way that protects the environment and decreases carbon monoxide emissions without compromising standard of living?

The major contribution of this dissertation is combining sustainable development concept with one of energy-demand forecasting methods to introduce a new integrated planning support system with assessment capabilities through various policy scenarios.

1.2. Energy Consumption and Urban Development

Urban development and economic growth are vital factors of energy consumption. According to the International Energy Agency, by 2030, metropolitan areas are projected to consume around 73 percent of the world's total energy production (IEA 2008). Therefore, these areas exert an overwhelming impact on the natural environment at local, national and international levels, such as, carbon gas emissions, climate change, and global warming (Malyshev 2009).

Figure 1 shows that China and the U.S. had the highest levels of carbon dioxide emissions in 2008. Energy-related carbon emissions and other greenhouse gases are expected to escalate the average global temperature by almost 6 C° in the long run (Malyshev 2009). In addition, carbon emissions have negative effects on human health. Therefore, action is required to curb the current trends of energy-related carbon emissions at international, national, and local levels.

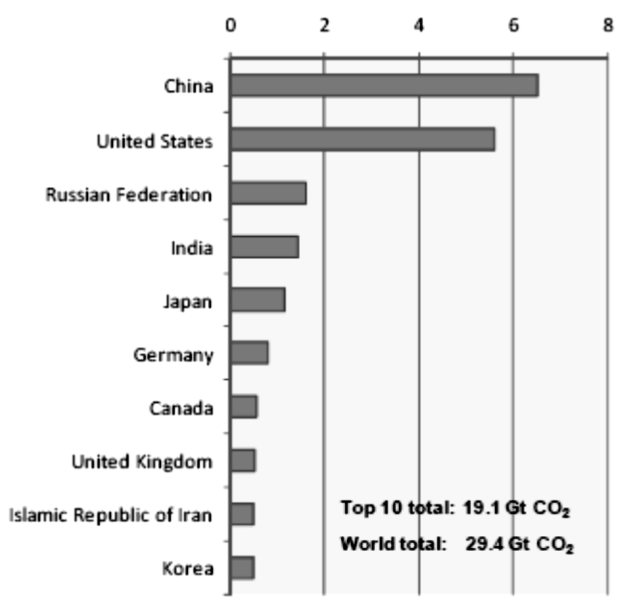

Figure 1: Top 10 CO_2 emitting countries in 2008.
Source: CO_2 Emissions from Fuel Combustion Highlights (IEA 2010).

In the United States, major metropolitan areas have high rates of population growth. According to the U.S. Census Bureau (2011), the total population of the Charlotte metropolitan area is slightly over 1.7 million, which ranks it thirty third among all U.S. metropolitan areas. In addition, the population of the Charlotte metropolitan area has increased by 31.2% since 2000 (U.S. Census Bureau 2011).

The U.S. is a developed and post-industrial nation; the country is one of the top energy consumers on the globe. The energy consumption market can be decomposed into four main sectors; Figure 2 shows the shares of the residential, commercial, industrial, and transportation consumptions in the U.S. The overall trend of the energy consumption shows that it has nearly tripled over the past five decades from almost 32 Quadrillion British thermal unit (Btu) in 1949 to nearly 94.6 Quadrillion Btu in 2009 (EIA 2010b).

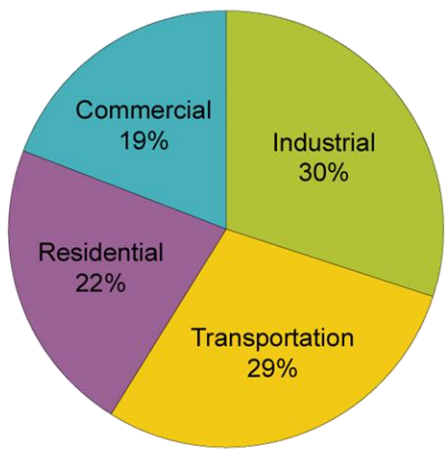

Figure 2: Share of energy consumed by major sectors in the U.S. Economy in 2009.
Source: Annual Energy Review 2009 (EIA 2010b).

It is important to develop strategies for both the short and long term that meet the increasing demand for each sector by maximizing energy efficiency and minimizing carbon gas emissions to sustain environmental resources. However, complexity and uncertainty are major obstacles in forecasting future energy demand. It is essential to have at our disposal a toolbox of flexible policy assessment techniques that combines both sustainable urban development methods and forecasting models of energy demand. Therefore, this research will aim to forecast household energy demand based on What-if scenarios. In addition, it refines the relationship between residential development patterns and energy demand distribution. Moreover, it defines impacts of the spatial characteristics of urban geometry on energy consumption for residential use. The following section will present the research objectives and questions.

1.3. Research Objectives, Questions and Tasks

The foremost goal of this research is to explore the relationships between forms of urban development, technology, and socio-economic household profiles, on the one hand, and residential energy consumption, on the other hand, in the short- and long-term, as well as at multiple spatial resolutions. Various bodies of literature ranging from urban planning, energy studies, and geography will inform this study to achieve its objectives. The research will perform multiple tasks to accomplish its goals as followed:

1. Develop an integrated Planning Support System (PSS) capable of forecasting household energy consumption that is associated with different patterns of urban form emerging in relation to operational user-specified scenarios depicting public policy options and possible socio-economic futures. In addition, the PSS will be integrated with other existing process-based simulation models of land use and transportation.

2. Develop an operational disaggregated model of residential energy consumption integrated to the PSS, which accounts for socio-economic factors, geometry and spatial characteristics of urban development, as well as condition variables recognized as short-

and long-term drivers of energy demand as well as drivers operating at fine (household) through coarse (national or global) spatial resolutions.

3. Assess the relative contribution of various factors of residential energy consumption at multiple spatial and temporal scales, particularly as far as urban geometry parameters are concerned.

4. Assess the sensitivity of patterns of residential energy consumption to condition variables and possible socio-economic futures through scenario analysis.

5. Assess the equity of consequences of changes in condition variables and determining the consequences of possible socio-economic futures on residential energy consumption across spatially and/or socially defined population groups.

The following research questions are formed in the following sequence of work tasks; each question is linked to the previous objectives in order:

Q1.1. What is the system architecture of a spatial PSS that effectively articulates tools for residential energy consumption forecasting and various existing process-based urban simulation models?

Q1.2. What are effective data structures, data flows, and data processing models to forecast the multi-scalar effects of condition variables on residential energy consumption and assess public policy options at multiple scales?

Q2.1. What are the spatial, urban geometry, and socio-economic drivers that have significant impact on residential energy consumption?

Q2.2. Within the framework of the proposed PSS, what are the data models suitable to accommodate diverse spatial and temporal granularities required by the simulation and forecasting modules, and imposed by the stated capability of the PSS?

Q3.1. What is the magnitude of anticipated changes in household energy consumption imputable to changes in energy markets?

Q3.2. What is the magnitude of the impacts of various green technology applications on household energy consumption?

Q3.3. What is the magnitude of various environmental regulations on household energy consumption?

Q3.4. What is the magnitude of impacts of land use and zoning regulations (including housing density) on household energy consumption?

Q4.1. What is the magnitude of sensitivity to each selected socio-economic and condition parameter selected within feasible ranges of variation?

Q4.2. Among the set of scenarios evaluated, what are the scenarios that appear to be more effective at affecting household energy consumption?

Q5.1. Are the impacts of changes in various condition variables and policy scenarios anticipated to be uneven across socio-economic and spatially defined population groups, and if so, what are the magnitudes and dimensions of this differentiation?

The study involves multiple tasks to achieve its objectives. To address the first and second objectives, the study will explore various bodies of literature ranging from urban planning, energy studies, and geography to identify the model's potential predictors. The output of this step will be an integrated PSS model of energy demand. The developed model consists of three sets of parameters; the socio-economic, the urban geometry and spatial predictors, and finally the condition variables, which are specific events that will change the forecast results if they occur.

The third objective simulates residential energy consumption under various conditions. The study will attempt to isolate the common spatial characteristics of urban geometry to determine their impacts on household energy consumption. Afterwards, the fourth objective is to perform assessment analysis for each scenario to determine the influence of each parameter. The last objective addresses how the social equity and the energy share of certain socio-economic groups will be affected under various conditions.

1.4. Structure of the Dissertation

The dissertation is organized into five sections respectively, conceptualizing the research problem, literature review and theoretical background, research analysis, empirical studies and findings, and finally the conclusions and the limitations of the study. The second chapter gives the main scope this study fits, the research problem to be under investigation, and the significance of the study.

The third chapter will investigate certain topics that are related to residential energy forecasting issues. It will contextualize the relationship between energy, economic growth, and sustainable development. Afterwards, it will present the practices of sustainable energy, and the methods of energy forecasting used in the literature. Lastly, it will introduce the influential predictors that have been found to affect energy consumption at the household level.

The fourth chapter will introduce the research design, the proposed methods, the model components, and the data flow. The chapter will go through the details of research methodology to develop an energy demand model for housing development. In addition, it will present the research tasks to be completed.

The fifth chapter will perform the econometric estimation of residential energy consumption and forecast energy consumption through the simulation of urban development and various energy demand scenarios in the study area of Mecklenburg County. In particular, the chapter will test the effects of urban texture on residential energy consumption. In addition, the research will discuss how different housing development will change the energy consumption pattern in the county. Finally, the last chapter, based on the findings, will conclude the study and its limitations. Moreover, it will propose recommendations and outline future research.

CHAPTER 2: CONCEPTUALIZING HOUSING ENERGY-DEMAND

2.1. Factors of Residential Energy Demand

Energy-demand forecasting is an essential stage to comprehend possible futures of any geographical region. The output of demand forecasting is a presentation of different scenarios, whose projection will play a central role in the choice of decision makers in planning (Hicks 2003).

Various factors affect the forecasts of energy supply and demand in the residential sector. The study will mainly focus on the demand side. Two influential factors shape the residential energy-demand; the first is the weather conditions and the second is the price of fossil fuels.

Each location on the earth has different energy climate considerations. Givoni (1998) distinguished four climatic regions to achieve the most appropriate urban design with respect to energy consumption. The first consists of the hot-dry region, which is located in the subtropical latitudes between 15 and 30 degrees north and south of the equator. The second is the hot-humid region, which has uncomfortable summer and fall between the equator and tropical areas.

The third is the cold-climate region, which is defined as regions with average temperatures during the winter months below freezing and with cool summer conditions. The last contains all the regions with cold winters and hot-humid summers, which are located between 30°N and 45°N latitudes (Givoni 1998).

The last class is a bit more challenging to model than the previous zones because it has more complicated climatic conditions through the year. The State of North Carolina falls between 33° 50’N and 36° 35’N and belongs to this class; hence, the state has cold winters and hot-humid summers. Any area that falls in this climate zone requires different urban planning schemes to achieve energy conservation in both warm and cold seasons.

2.1.1. Classification of the Influencing Factors

Energy forecasting methods can be applied in different time-periods and scale resolutions. In addition, many factors affect the prediction of Housing Energy-Demand (HED); hence, understanding the behavior of the energy system is a complicated process. Consequently, the determination of the influential factors is a crucial task to increase the accuracy of forecasting methods and models (Daly 1976).

Previous studies have classified and sub-classified the factors of energy demand based on type (social – economic – environmental – technological), season-times, and geographical scale (macro – meso – micro). Researchers have developed these various categories to analyze the impact of each factor more accurately and efficiently.

Based on this typology, previous studies have recognized three types of factors that affect energy consumption: (1) socio-economic variables that relate to the demographic features of the population (e.g. age, income, and household size), (2) economic environment variables (e.g. economic growth rate, urbanization ratio, and energy price), (3) environmental variables (e.g. temperature, and human comfort zones). Recently, another factor has been brought into consideration, namely the type of technology used by the end users (e.g. the number of electrical appliances) (Barakat and Al Rashed 1993).

Another important sub-classification is based on seasonal patterns. Some factors influence the demand for energy differently according to season. For example, outdoor temperature affects the type of energy source used and the behavior of end users in cooling and heating their home space.

The previous two classifications have further been sub-divided on the basis of the scale of influences that shape the demand market; energy demand studies split the factors that shape the demand market based on geographical scale. Therefore, it is crucial to determine the possible macro and micro factors in the forecasting process, otherwise any missing factor could lead to major catastrophic energy shortage in the future at various geographical resolutions. For instance, the prices of fossil fuels are attached to the world market. Therefore, the marginal effect of demand on price is zero. On the other hand, the prices of fossil fuels affect energy demand at the international, national, and local levels. Many economists draw vague scenarios for the future of oil production. Some economists expect that oil production can be increased to meet all future demands for at least 40 years (Lynch 2001).

On the other hand, other economists predict that oil production will not meet demand in the near future, forcing global energy conservation (Campbell 2002). This unclear vision creates many fluctuations in the oil price; hence, security is another goal in sustainable energy policies beside the environment protection. In addition, some factors have both macro and micro effects on the energy demand; and among others, the climate has micro and macro impacts on the trends of energy market.

Planners, engineers, and decision makers can set certain policies to control the influence of the micro factors on energy demand. On the other hand, macro factors are beyond their control, but their influences can dramatically reshape the energy demand trends at the micro level. For instance, if there is a global shortage in any type of fossil fuel, the demand for the other fossil fuel alternatives would increase at international, national, and local levels. Hence, the price of energy production will increase as well.

These studies have not addressed nor quantified the spatial attributes of the development patterns that affect energy consumption. It can be argued that, within any city region, different forms of housing developments will produce different patterns of energy consumption. Hence, we cannot ignore the spatial impacts of different housing patterns on energy consumption (Yu et al. 2000).

If we extend the existing forecasting methods to explore the impacts of spatial patterns of the future residential developments, our understanding of energy consumption and our knowledge of the energy system will be enhanced in new dimensions. The following section will state the importance of energy demand forecasting in the residential sector.

2.1.2. Residential Development, and Energy Demand Forecasting

Economists, planners, and geographers determine that the form of urban residential development has a direct effect on the consumption rate of any utility. Urban geometry affects the total consumption of energy of any metropolitan area. Urban geometry refers to the spatial characteristics that shape urban fabric, such as building heights, width, size, mass orientation, road widths etc. These characteristics play a major role in creating urban microclimate; moreover, they provide the settings for human contact with the urban environment, such as the behavior of individuals in household energy consumption. Some spatial characteristics cause the urban fabric to gain more solar energy, while others increase the heating loss of the urban fabric so that energy consumption decreases or increases, respectively. Moreover, others affect the city ventilation and wind directions. (Ali-Toudert 2009).

A new concept in sustainable development is to apply appropriate urban geometry characteristics of metropolitan areas according to their geographical location to reduce energy consumption and gas emissions, which will enhance the living environment. Each land use has different spatial characteristics, which are recorded in land use planning regulations in any city. Therefore, each land use has a different energy load. For instance, residential development has different spatial characteristics in building width and height, unit types, lot size, grid size, the distances between the dwellings etc. (Burchell and Listokin 1995; Downing and Gustely 1977; Frank 1989; Speir and Stephenson 2002).

Urban density is one the most important planning measurements used to characterize urban geometry. It can be used as a tool by city planners to control the characteristics of urban geometry, such as the relationship of buildings height and width, measuring floor area ratio, the number of people of any given area, and the number of dwellings of any parcel. Urban density can serve to define the spatial characteristics, such as building width and height, to utilize passive solar energy and building shading to create healthy ventilation for indoors; hence, the reliance on mechanical air conditioning will be decreased. Therefore, the efficiency of energy usage will be enhanced, and carbon emissions will be decreased.

Passive solar energy was an emerging concept during the mid-1970s that emphasizes low energy building designs. The concept of passive space is to store solar energy in the winter and reject solar heat in the summer; moreover, healthy ventilation is created. The concept showed a significant reduction in energy consumption, and it can be extended to cover the outdoors within the urban context as to account for shading.

A spatial planning support system can handle the complexity of urban form. With the capabilities of Geographic Information Systems, it will produce appropriate HED scenarios. By modeling the impacts of spatial characteristics of urban geometry, such a model will support the decision-making process by forecasting the impacts of different housing forms on energy consumption.

Figure 3 presents three different forms of housing use in a given geographical area. The first scenario presents four apartment units in one building, the second is two duplex units, and the last scenario is four units of single-family housing. A variation in energy consumption can be anticipated due to the differences in the spatial characteristics of each scenario. Assuming that the total cubic volume is the same in all three scenarios, we can summarize some impacts of spatial characteristics on energy consumption as follows:

First, there are differences in the perimeter of the built-up area. Therefore, the percentage of solar passive vs. non-passive spaces will be different between the three scenarios. Consequently, the consumption will vary because of the differences of the total area to be cooled or heated in each scenario.

The second observation, in each scenario, the roof area is different. The more scattered footprint, the more roof space that gains the larger amount of the direct sun heat during daytime. This will vary the total amount of energy consumption in each scenario. The impact can be insignificant at the unit level; however, it will be notable at larger scale, for instance, at city level.

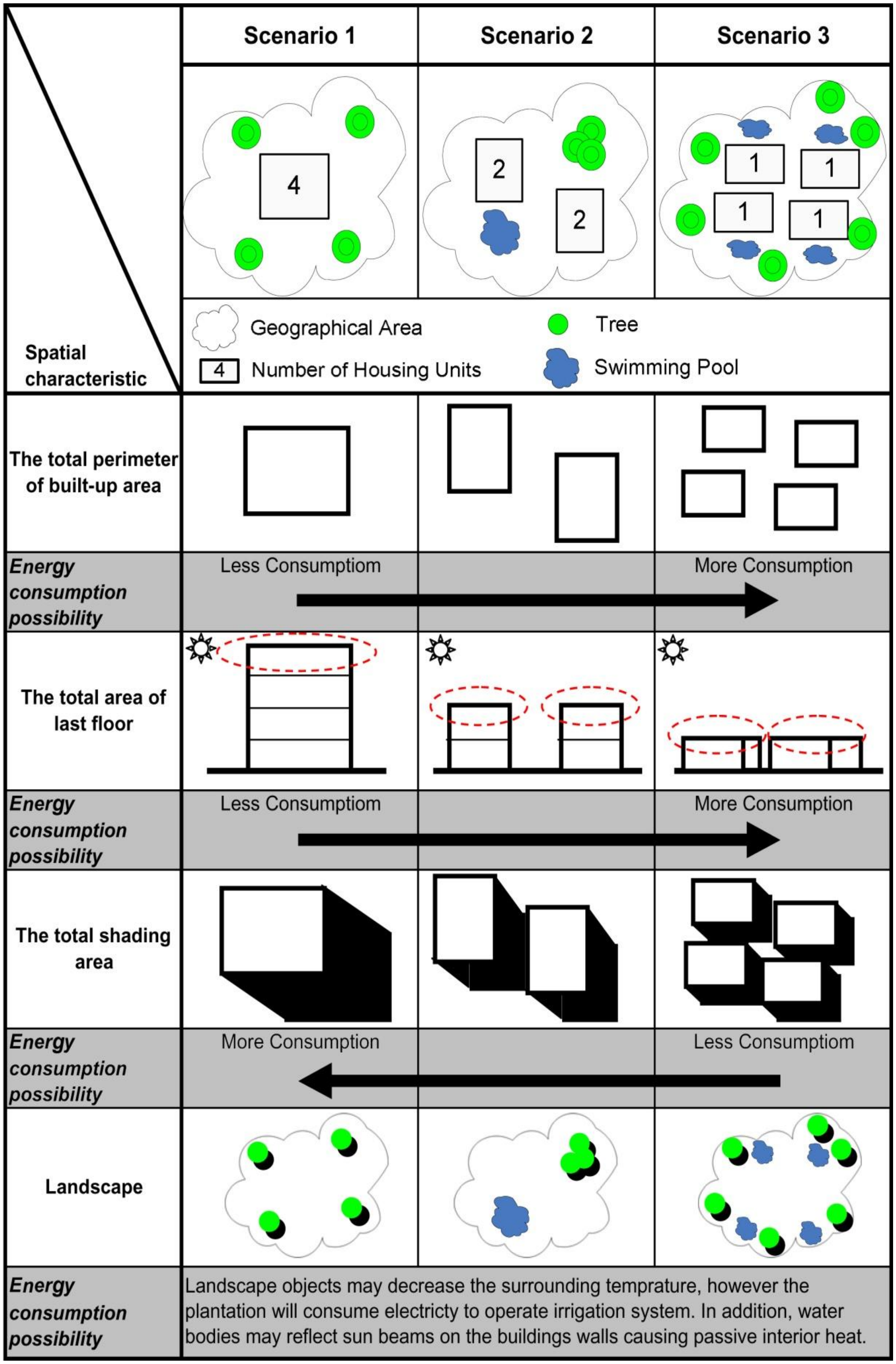

Figure 3: Different housing forms scenarios.

The third observation, there is variation in building height in each scenario, which will cause different impacts on the consumption of the energy because the total area of shade will be different; in addition, shadows will be different on each façade. Therefore, the percentage of solar passive vs. non-passive spaces will be different. Consequently, each scenario will have different energy loads.

The fourth observation is that each building façade has various glazing ratio (the total area of glasses windows). Therefore, the amount of passive solar energy will differ; hence, each scenario will have different consumption patterns.

Last but not least, landscape elements (natural – man made) create different influences on the energy consumption pattern. The total number of trees creates various shaded areas, which affects the percentage of solar passive spaces. In addition, water bodies create ventilation drafts in the surrounding areas; they also reflect sunbeams on the façades.

2.2. Significance of the Study

The study is a part of the Charlotte Land Use and Economic Simulator (CLUES) project. The study achieves several major contributions in modeling residential energy demand. First, the study attempts to define the impacts of different residential built-up forms (compact and dense, mixed uses, and low density) on energy consumption. Second, it proposes and develops an integrated Spatial Planning Support System to forecast different residential energy consumption scenarios at the household, and city levels. It also provides a methodological framework for future energy forecasting studies.

The study increases the decision makers' capabilities to explore different energy alternatives under various situations, such as natural disaster or global shortage in energy fuels. Finally, the study encourages the application of sustainable energy policies, which will positively play a major role in environmental protection and energy conservation at the U.S. national and local levels.

The completion of this study extends the knowledge of how different housing forms affect energy consumption. In addition, it identifies how urban geometry can contribute to energy conservation and environmental protection. The study covers multiple disciplines, such as urban planning, urban economics, urban design, landscape architecture, and GI Science. The study offers alternative views to explain how the energy consumption varies based on housing patterns. The research fills missing pieces in the study of housing development/energy demand forecasting. It integrates a common sustainable development tool, namely a Demand Side Management (DSM) system with energy-demand forecasting methods to enhance future projections.

2.3. The Study Area

2.3.1. The Scope of the Study

Figure 4 presents the major components of an urban system, two of which are at the center of the research concern here, namely housing and energy systems. The first component covers the impacts of various characteristics (spatial – socio-economic) of housing development, mainly the spatial characteristics of urban geometry. The second component addresses only energy demand.

The study considers residential land use only; there is no intention to cover other uses, such as commercial and industrial uses. The research adopts the concept of sustainable development by applying a Demand Side Management approach.

The study will focus on Mecklenburg County, North Carolina, the core of the

Charlotte metropolitan area. The analysis will mainly focus on housing development in the suburbs, where most new residential developments occur. In addition, the output results will be featured at different spatial granularity, but aggregation first to census tracts and then to the county level. The study covers the forecast period from 2008 until 2037 to explore how, and according to what modalities, housing development affects energy consumption changes over time.

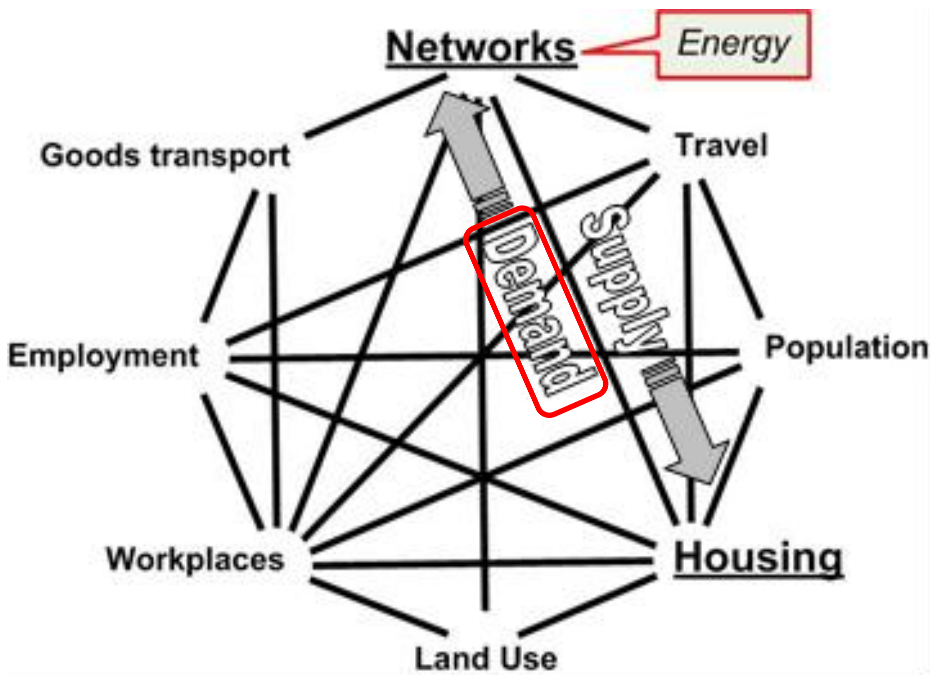

Figure 4: Major components of an urban system and components.
Source: A method to assess the variation of urban canyon geometry from sky view factor transects (Bradley et al. 2001).

The study area is composed of eight municipalities; in addition, each municipality has a sphere of influence as shown in Figure 5. Charlotte is the core city of the county. Cornelius, Davidson, and Huntersville are located in north. Mint Hill, Matthews, Pineville, and small town of Stallings are located in the south. The built-up forms in the central areas are compact and dense; the dominant urban form in the suburbs is low density and sprawled, and the mixed uses built-up forms are mainly located in the spheres of the influences of the towns.

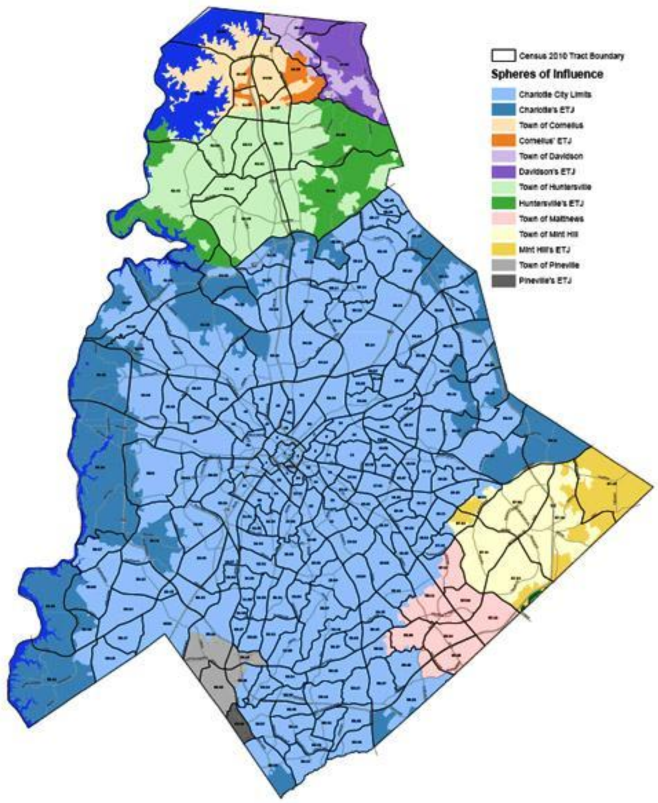

Figure 5: Municipalities in Mecklenburg and their sphere of influence.
Source: Charlotte-Mecklenburg Planning Department (charmeck 2011).

2.3.2. The Energy Profile of the Study Area

Mecklenburg County is located in the State of North Carolina (NC), which is among the states with the highest electricity consumption in the U.S. In 2008, all sectors in NC State consumed almost 125,239,063 Megawatt hours of the produced electricity, ranked 11th among the states. Moreover, the total energy consumption of the residential sector in North Carolina was around 715.3 Trillion Btu, which is ranked 10th among the states (EIA 2010f). In 2010, the average annual electricity consumption per residential customer in NC State is 14,856 kWh, which is ranked 9th among the states (EIA 2010c). In 2009, the average annual natural gas consumption per residential customer in NC State is 250.6 Trillion Btu, which is ranked 29th among the states (EIA 2009d).

Table 1 shows energy sources for residential heating in 2000 in North Carolina. Approximately 49% of household units used electricity as the dominant energy type in space heating, which is higher than the U.S. average. Natural gas is the second highest with a share of 24%, which is lower than the U.S. average (EIA 2010e).

Table 1: The percentage of each energy type in home heating.

Energy Source	North Carolina	U.S. Avg.	Period
Natural Gas	24%	51.2%	2000
Fuel Oil	12%	9.0%	2000
Electricity	49%	30.3%	2000
Liquefied Petroleum Gases	13%	6.5%	2000
Other/None	2%	1.8%	2000

Source: North Carolina State Energy Profile (EIA 2010e)

Table 2: Energy price for residential sector.

Energy Price for Residential Use	North Carolina	U.S. Avg.	Period
Natural Gas	$11.99/ thousand cu ft	$10.24/ thousand cu ft	2010
Electricity	10.22 cents/kWh	11.70 cents/kWh	2010

Source: North Carolina State Energy Profile (EIA 2010e).

Table 2 shows that during 2010, the average retail price of electricity in North Carolina was 10.22 cents/kWh, which is lower than the U.S. average price (11.70 cents/kWh). On the other hand, the average retail price of natural gas was $11.99/thousand cubic feet, which is higher than the U.S. average price ($10.74/thousand cu ft). The retail price could be one factor that explains why electricity is the dominant energy type for home heating in North Carolina. Piedmont Natural Gas is the energy distributor for natural gas in both North and South Carolina. However, electricity is more widely used than natural gas in homes for heating purposes in Mecklenburg County. Duke Energy Company is the electricity provider for Mecklenburg County, North Carolina.

2.4. Data Sets and Limitations

The research will develop a statistical model that can handle various socio-economic, spatial, geometry, and condition parameters. In addition, the variables will be classified based on their spatial (parcel, census groups, city, regional, etc.) and temporal (short, mid, and long terms) resolution impacts.

The first data set contains the property records of Mecklenburg County during the period from 2000 until 2008. It presents the spatial and physical characteristics of each parcel, including perimeter, area, building height, heated area, and type of AC. However, inconsistency has been found in the topology of some polygons. For instance, some polygons overlap with others because of digitizing errors. Moreover, some parcels were merged, and some others were split. Another limitation, some address locations were reported wrong. Therefore, the real property database has been cleaned up to remove the majority of potential error sources.

The second data set retrieves information from another process-based model that will be integrated with the developed PSS. The model is the Charlotte Land Use and Economic Simulator (CLUES), which forecasts land uses, economic activities, household socio-economic characteristics, and transportation development.

The Residential Energy Consumption Survey (RECS) is the third data set used in the research. The RECS consists in a micro-data sample survey that stores energy data for household units. The U.S. Energy Information Administration (EIA) conducted the RECS micro-data survey starting in 1978; the latest data is the 2005 version. In 2005, the survey collected data from 4,382 households sampled to represent the total U.S. household population (EIA 2005). The 2005 RECS micro-data contain demographic, socio-economic, household characteristics, fuel bills, and appliances information. Sample data in Mecklenburg County cannot be isolated from the overall dataset. Instead, a sample of household units from the South zone in the RECS dataset will be used, since the study area is located in this zone. The assumption is that the study area has similar climate, demographic, and energy trends.

Another raster dataset contains the land cover, which it is extracted from a satellite image of Mecklenburg County in 2006, the spatial resolution of this dataset is 30 by 30 meter for each cell. This dataset will be used to track the influences of the tree coverage in each property land on residential energy consumption.

The study is part of a comprehensive project, which is called the Charlotte Land Use and Economic Simulator. The project uses the data from the Charlotte Department of Transportation (CDOT) for the travel demand model, and retrieves employment data from the North Carolina Employment Security Commission and the infoUSA online data (ncesc 2012; infoUSA 2012). In addition, the study takes into account various models of future expected prices of crude oil and natural gas from the Annual Energy Outlook 2010. The aim of this information is to consider the effects of oil and natural gas prices on energy demand; therefore, the output results will achieve forecasts that are more accurate.

CHAPTER 3: LITERATURE REVIEW

Sustaining energy production is a vital matter for every society; urban development and economic growth are related to the efficiency of energy consumption. We are facing many future challenges in the field of energy demand forecasting. In the United States, the increasing demand of energy in all sectors (residential, industrial, commercial, transportation) has led to crucial needs for accurate projection of energy demand and for adopting sustainable development approaches. Sustainable development has major aims, such as reducing the consumption of energy, decreasing carbon monoxide emissions and, protecting the environment in general.

First, the review critically presents the energy profile of the United States. Afterwards, the second section explores the relationship between economic growth, energy consumption, and sustainable development. The third section introduces the practices of sustainable energy. The fourth section introduces the empirical studies that assess the most influential determinants on energy-demand forecasting. It presents how the empirical methods quantify the impacts of various factors (spatial and urban geometry, socio-economic, and condition) on energy consumption.

The last section introduces the empirical studies of energy-demand forecasting. In addition, it presents various conceptual visions that reconcile conflicts between sustainable energy methods to construct the main framework of this study. It is important to mention that this literature review mainly focuses on the residential sector.

3.1. Residential Energy Profile in the United States

The United States is one the largest energy consumers in the world. The U.S. DOE tracks energy consumption in four sectors. Figure 6 presents how the consumption of the industrial sector started to decline from the mid-90s; on the other hand, the consumption share of the other three sectors has been growing. The residential sector accounts for almost 22% of energy consumption in 2010 (EIA 2010b).

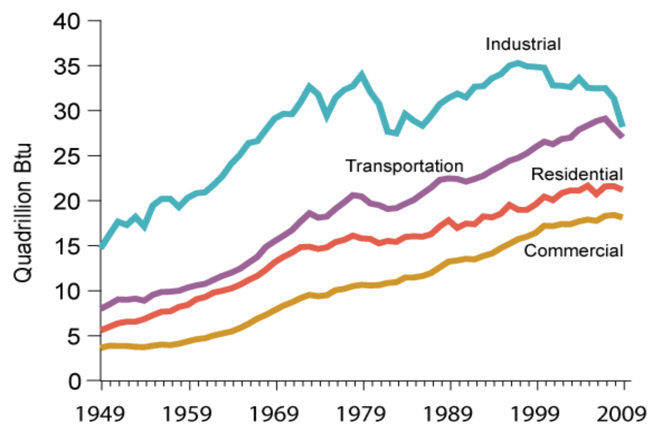

Figure 6: The U.S. Energy consumption by sector, 1949-2009.
Source: Annual Energy Review 2009 (EIA 2010b).

Figure 7 depicts energy consumption in the U.S. residential sector according to its final use: space heating, lighting, and other appliances account for two thirds of total residential energy consumption. Global climate changes cause the warmer seasons to become longer, and the cold seasons to have more extreme lower temperature. Therefore, it is expected that future spending on energy for cooling and heating may significantly depart from past patterns. Presently, cooling accounts for almost 8% of the total residential energy consumption. The southern regions, where the Charlotte metropolitan area is located, have the highest air-conditioning saturation. On the other hand, space heating represents almost 41% of the total energy usage in U.S. homes (EIA 2005).

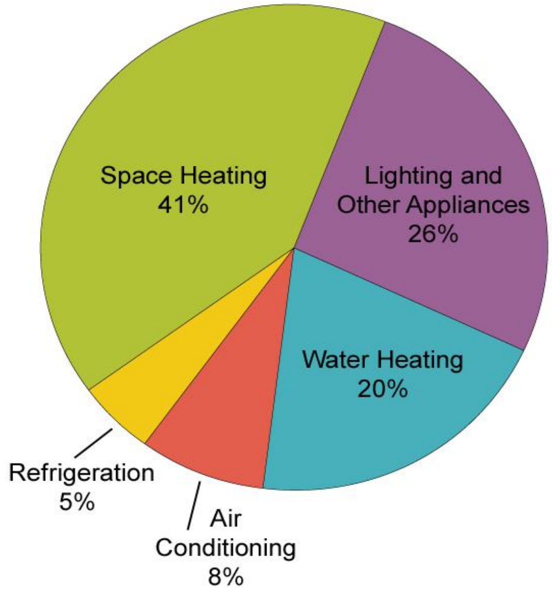

Figure 7: Energy Usage in the U.S. homes.
Source: Residential Energy Consumption Survey (EIA 2005).

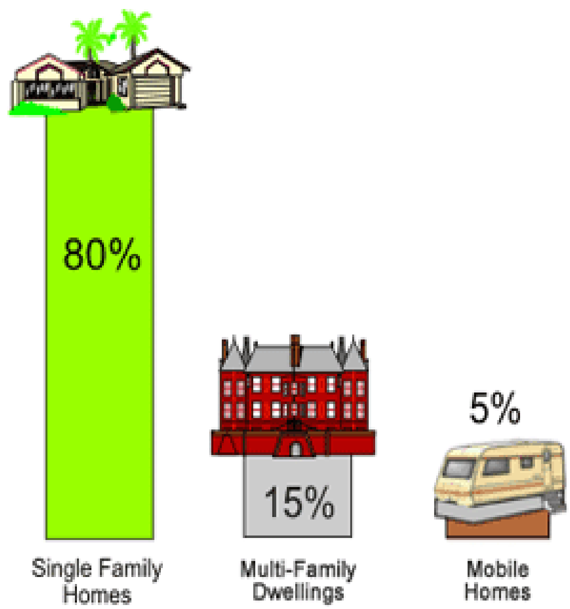

Figure 8: The U.S. Energy usage in different types of homes.
Source: Residential Energy Consumption Survey (EIA 2005).

There are diverse types of energy consumed by U.S. households. Figure 8 presents the distribution of energy usage by housing type. In 2005, single-family housing units consumed about 80%, while multi-family dwellings consumed almost 15%, and mobile homes accounted for 5% of the total energy usage. Figure 9 shows that natural gas and electricity are the most widely consumed sources. Natural gas is mainly used for heating purposes, while electricity may be used in heating, cooling, lighting, and other appliances (EIA 2005).

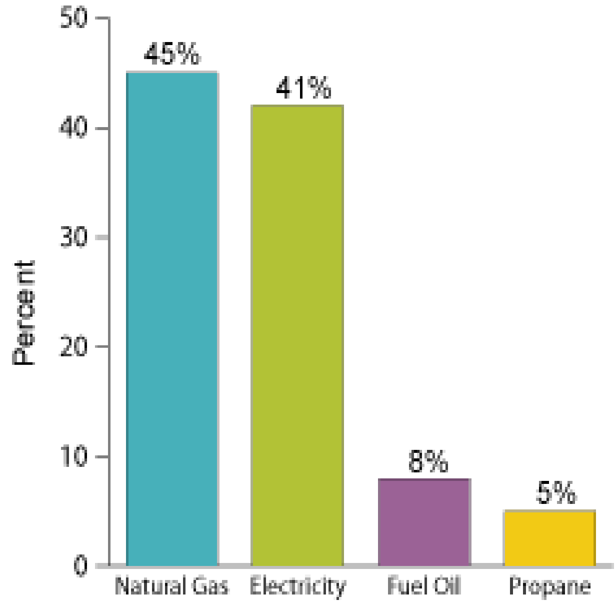

Figure 9: Types of energy consumed in the U.S. Homes.
Source: Residential Energy Consumption Survey (EIA 2005).

3.1.1. Natural Gas Consumption

Natural gas represented almost 25% of the U.S. total energy usage in 2009. The U.S. households consumed about 22.84 trillion cubic feet (Tcf) of natural gas in 2009. Figure 9 indicates that natural gas consumption is 45% of the total used energy in the U.S. household units. Figure 10 shows the major consumers of natural gas in the U.S. in 2009. The residential sector is the third major consumer with 4.8 Tcf, which is almost 21% of the total consumption. Slightly over half of the households use natural gas as their main source of heating fuel (EIA 2010d).

There are several factors affecting the demand for natural gas in the market, for example, the economic growth, the weather conditions, and crude oil prices. The best known household usage of natural gas is for heating purposes. Therefore, the residential sector is mainly affected by the winter weather and oil prices; thus, natural gas consumption at the housing market is seasonal, and it reaches the highest level during the coldest days in the year. The following section will present electricity, the second energy source that is consumed in U.S. homes.

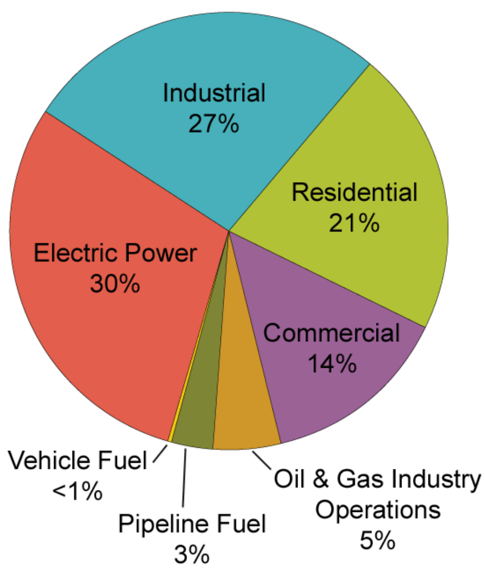

Figure 10: The percentage of natural gas usage per consumer in the U.S. in 2009.
Source: Natural Gas Annual 2009 (EIA 2010d).

3.1.2. Electricity Consumption

The Energy Information Administration indicates that in 2009, the building sector (commercial and residential) consumes almost 75 percent of all generated electricity in the U.S, and it is expected to continue to grow at the same level until 2030 (EIA 2009a). The U.S. Energy Information Administration (EIA 2009a) predicts that by 2010, the total electricity consumption in all sectors (residential, industrial, commercial, transportation) would reach 12.9 Quadrillion Btus, and by 2030, the consumption would be almost 15.7 Quadrillion Btus.

The residential sector is a major consumer of the produced electricity in the U.S. market. Figure 11 demonstrates that according to EIA forecasts, the residential sector would consume almost 36 percent of domestic electricity production in 2030.

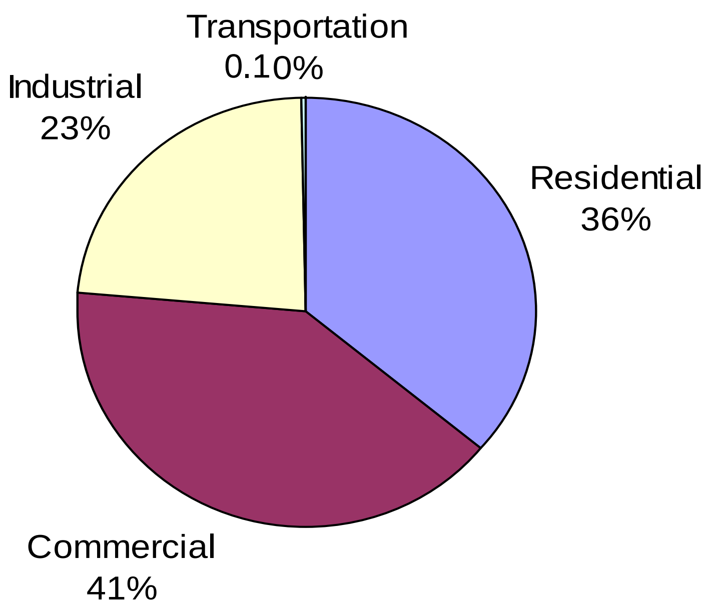

Figure 11: The expected electricity consumption by sector in the U.S. by 2030.
Source: Annual Energy Outlook (EIA 2009a).

Figure 12 presents forecasted electricity consumption of each sector in both years 2010 and 2030. In the residential sector, the expected electricity consumption in 2010 will be 4.8 Quadrillion Btu, and it will reach almost 5.69 Quadrillion Btu in 2030 (EIA 2009a).

The U.S. government promotes sustainable energy policies at the national, regional, and local levels to achieve energy efficiency and decrease air pollution of the environment (Menz 2005).

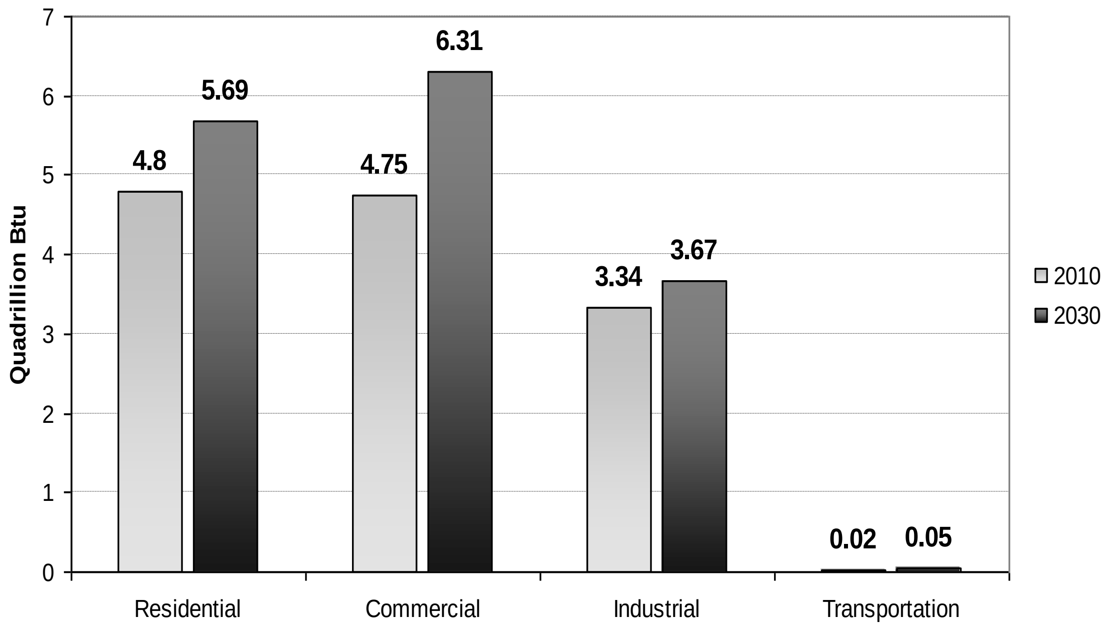

Figure 12: The electricity consumption per sector for years 2010 and 2030 in the U.S. Source: Annual Energy Outlook (EIA 2009a).

3.2. Energy, Economic Growth, and Sustainable Development

3.2.1. Economic Growth and Energy Consumption

Developed countries, such as the U.S., have long considered economic growth and energy consumption as indicators of economic success. Many metropolitan areas have high economic and population growth rates. Moreover, these growth rates are likely to continue; hence, increasing energy consumption (ESDD 2009; EIA 2009a).

Kraft and Kraft (1978) analyzed the causal relationship between energy consumption and economic growth in the U.S. for the period 1947 – 1974. They found a strong unidirectional relationship running from GNP (as an indicator of economic growth) to energy consumption in the United States. The authors concluded that the increase in economic growth would raise energy consumption.

Yet, other researchers reexamined the findings of the Kraft and Kraft study. Akarca and Long (1980), Yu and Choi (1985), and Erol and Yu (1987) found no significant relationship between energy consumption and economic growth. These conflicting findings can be ascribed to the differences in the data definition and measurement techniques, time frame, and the methodological approaches employed in these various empirical studies.

The earlier studies suffered from a number of statistical and methodological shortcomings (Soytas and Sari 2009). More recently, taking advantage of the advances in statistical modeling, Glasure and Lee (1997), Cheng and Lai (1997), Asafu-Adjaye (2000), Hondroyiannis et al. (2002), and Stern and Cutler (2004) have once again revisited the issue and confirmed the strong relationship between energy consumption and economic growth.

The mechanisms of economic growth may affect the environment through many portals, such as pollution (contamination of natural resources), and climate change. Excessive levels of energy consumption result in the degradation of the environmental resources. A considerable number of studies have addressed the relationship among environment, economic growth, and energy consumption. Kolstad and Krautkraemer (1993) concluded that economic growth yields negative impacts on the environment. Later, Shafik (1994), Holtz-Eakin and Selden (1995), Roberts and Grimes (1997), Friedl and Getzner (2003), Canas et al. (2003), Stern (2004), Dinda and Coondoo (2006), Soytas et al. (2007) and Soytas and Sari (2009) confirmed that energy consumption is the main source of carbon emissions.

The combination of economic and urban development is the major player in energy consumption; therefore, the increase in carbon emissions, mainly in metropolitan cities. The current pattern of economic growth has caused serious environmental damage in these city regions. On the other hand, developed countries intend to increase energy production to meet their growing needs in economic and population growth.

To deal with these two conflicting matters, economic development and environmental protection, the concept of sustainable development appears to be an appropriate solution. It maintains the relationship between the growing demand of energy and protecting the environment for both present and future needs.

3.2.2. Sustainable Development and Energy Efficiency

Sustainable development is commonly conceived to be "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland 1987). The concept has become popular after the recommendations of the Brundtland Commission (also known as the United Nations World Commission on Environment and Development) in 1987. The concept implies economic growth together with the protection of environmental quality, each reinforcing the other. The central role of sustainable development tends to balance the conflicts between economy, environment, and social equity as shown in Figure 13. In the U.S., two major movements, New Urbanism and Smart Growth are planning principles that advocate the practices of sustainable development in land use, energy, and ecological planning. However, the practices of sustainable development received major criticism. Owens and Cowell (2002) noted that trying to implement the principles into policies, decisions, and practices reveal more tensions between the goals rather than resolve the conflicts. For instance, the conflict between social equity and environmental protection appears when there is competition to improve the living of poor people through economic growth while conserving the environment through growth management.

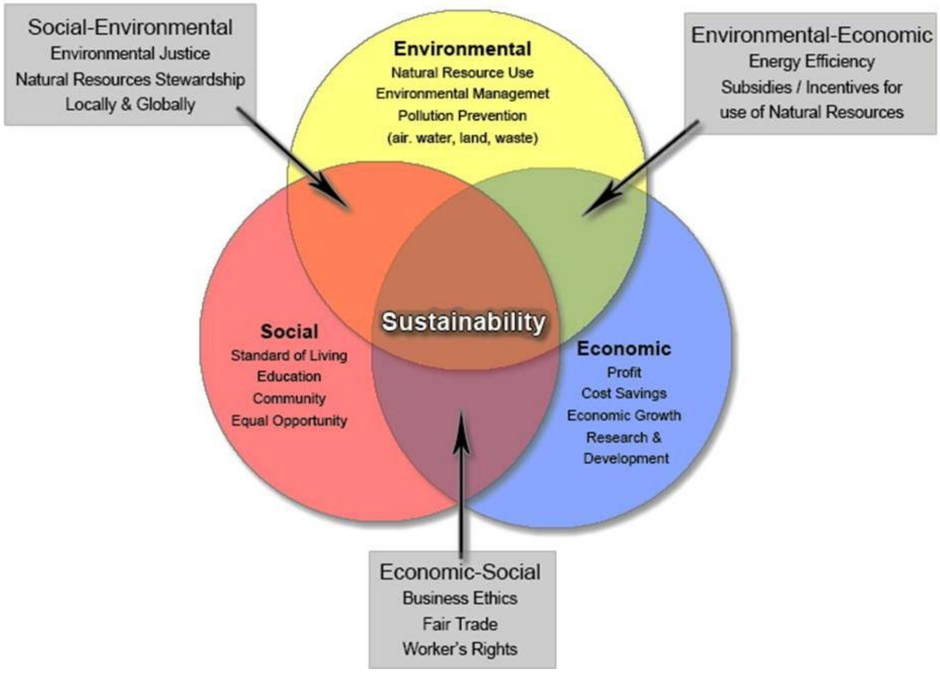

Figure 13: The spheres of sustainability
Source: Sustainability Assessment and Reporting for the University of Michigan's Ann Arbor Campus (Rodriguez et al. 2002).

Godschalk (2004) introduced the sustainable livability prism to provide a comprehensive conceptual method to overcome the shortcomings in sustainable development applications. The livability prism demonstrates the state of the art of sustainable development. Figure 14 shows the structure of the prism, which consists of four primary dimensions, namely equity, economy, ecology, and livability. It deals with the dynamics of development over various spatial and temporal resolutions. In addition, the prism provides a conceptual structure to assess the conflicts between different ecological, economic, social equity, and livability visions. The sustainability/livability prism allows researchers to incorporate the strength of sustainable energy practices with the assessment in empirical studies, and forecasting models. The following sections will present the practices of sustainable energy, the assessment of the most influential determinants on energy consumption, and the forecasting approaches, respectively.

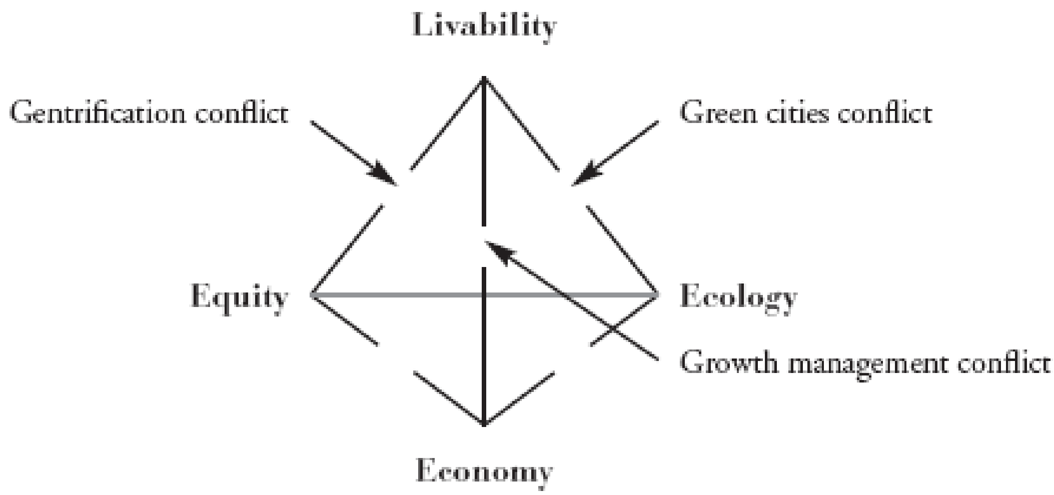

Figure 14: The sustainability/livability prism.
Source: Land Use Planning Challenges: Coping with Conflicts in Visions of Sustainable Development and Livable Communities (Godschalk 2004).

3.3. Sustainable Energy and Demand-Side Management

In first world countries, due to high rates of economic growth and urbanization, the major metropolitan areas, such as the Charlotte metropolitan area, play a major role in energy matters, such as climate change. The application of sustainable development concepts will support using energy more efficiently and decreasing energy consumption; hence, benefiting the environment by reducing carbon emissions. Demand-Side Management (DSM) is one of the most applied concepts of sustainable development in energy conservation; it has been used to enhance energy systems and reduce the consumption of end users. Hence, global warming, climate change and carbon monoxide emissions can be curbed (IIEC 2006; Cheng 2005).

DSM refers to the end-user planning and strategies implementation to enhance energy efficiency, decrease energy costs, optimize the time of usage, or endorse the use of different energy sources. DSM targets the actions that influence the patterns of use of energy consumed by end users (IIEC 2006).

Demand-Side Management (DSM) was first applied in the U.S. in response to the energy crisis of the 1970s (IIEC 2006; EIA 1995). The crisis created high inflation in the U.S. energy market that brought up devastating impacts on all development sectors. Therefore, U.S. energy organizations had to promote energy conservation, and changing the level of energy consumption by increasing the accuracy of demand projections. DSM was first applied in conserving electricity consumption. Nowadays, DSM has become part of the efforts to achieve energy sustainability; it is extended to cover both electricity and natural gas consumption.

The benefits of DSM initiatives are diverse. It is commonly known as a major planning/policy method in decreasing global warming and climate change since energy consumption is reduced. Table 3 shows the common benefits of DSM, which significantly contribute in increasing the efficiency of the whole electricity system at the end user, utility and production system, and society as a whole (IIEC 2006).

Table 3: Demand-Side Management benefits in energy usage.

End-user benefits	Societal benefits	Utility and production system benefits
Satisfy energy demands	Reduce environmental degradation	Lower power-plant capacity
Reduce / stabilize costs	Reduce carbon gases emissions	Lower the cost of service
Improve value of service	Conserve resources	Improve operating efficiency and flexibility
Maintain/improve lifestyle	Protect global environment	Reduce capital needs
productivity	Maximize customer welfare	Improve customer service

Source: International institute for Energy Conservation (IIEC 2006).

Gellings and Chamberlin (1993) discussed six traditional DSM strategies. The authors described each strategy by an energy-load curve (shape) that plots the future demand over the time of occurrence. The load shape is a generic presentation of an aimed energy strategy that achieves certain goals from demand or/and supply side. The six strategies can be described as follows (Figure 15):

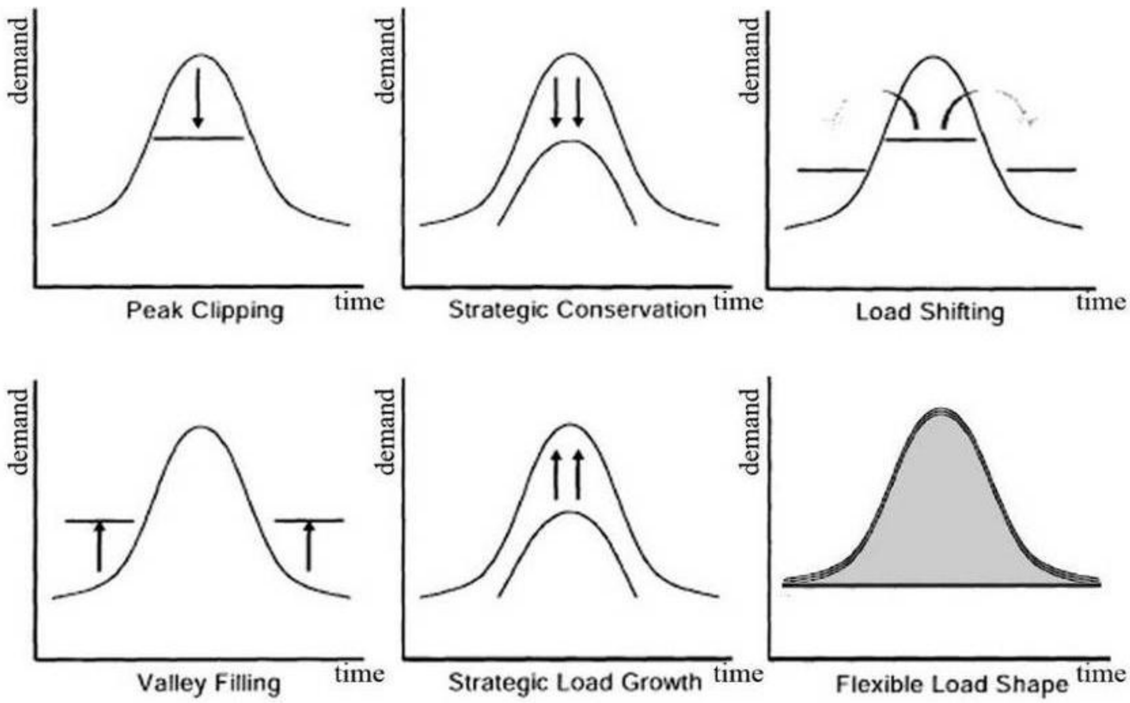

Figure 15: Demand-Side Management load shape objectives.
Source: Demand-Side Management: concepts and methods (Gellings and Chamberlin 1993).

(1) Peak-clipping is the strategy that aims to reduce the system-peak by means of direct load control; peak-clipping reduces the need to operate energy when the maximum system-peaks are not sufficient to meet the demand.

(2) Valley-filling is the form that increases the off-peak loads.

(3) Load-shifting is a method that shifts the loads from peak to off-peak periods.

(4) Strategic-conservation is a concept that reduces utility loads, for instance, improving the efficiency of the appliances and building energy conservation.

(5) Strategic-load growth aims to increase energy production beyond the impulsive effects of the economic growth.

(6) Flexible-load shape refers to the programs that offer many options to the end users in exchange for other benefits on a needs basis. The program can involve variations of integrated energy management systems, or load control devices that offer real time-of-use constraints for the customer. For example, some tools can help the end user control the residential water heater and AC systems (Gellings and Chamberlin 1993).

The first three strategies are considered traditional load management approaches promoted by the utilities to alter the total energy consumption. The major goal of these strategies is to alter the peak and off-peak structures. On the other hand, the last three strategies provide more systematic and larger-scale controlling methods than the first three; they cover the previous goal and extend it to change the patterns of energy consumption.

DSM provides planners, engineers, and decision makers the advantage of increasing energy efficiency and decreasing energy consumption. However, DSM has received some criticisms: Katz (1992) argued that DSM increased the utility (electricity, and natural gas) costs for consumers, while decreasing the profit for the utility companies. Another criticism is that DSM mainly deals with the customer behavior at the household level. To avoid these major shortcomings, many researchers have combined DSM methods with other energy conservation practices to achieve a sustainable framework for residential energy demand.

DSM Energy conservation is a sustainable development concept that refers to the methods used to reduce energy consumption. Mitigation strategies apply energy conservation to eliminate unnecessary usage. Therefore, practices of energy conservation increase environmental quality, financial capital, national security, and human comfort by promoting green energy policies at the macro and micro levels.

Figure 16 shows the two major fields in energy conservation. The first is the green technology applications, and the second is the passive energy methods. Green technologies combine environmental protection practices with new technologies and techniques to take into account the positive and negative impacts on the environment, mainly in the field of energy conservation (Kuehr 2007). It integrates the green applications within the urban context to enhance energy efficiency, and consequently, reduce greenhouse and carbon dioxide gas emissions.

Passive energy policies address the planning and building design considerations to reduce the energy consumption passively. Both of the fields apply solutions at the micro and macro levels. The following sections will explore DSM fields, the green technology applications, and the passive energy policies, respectively.

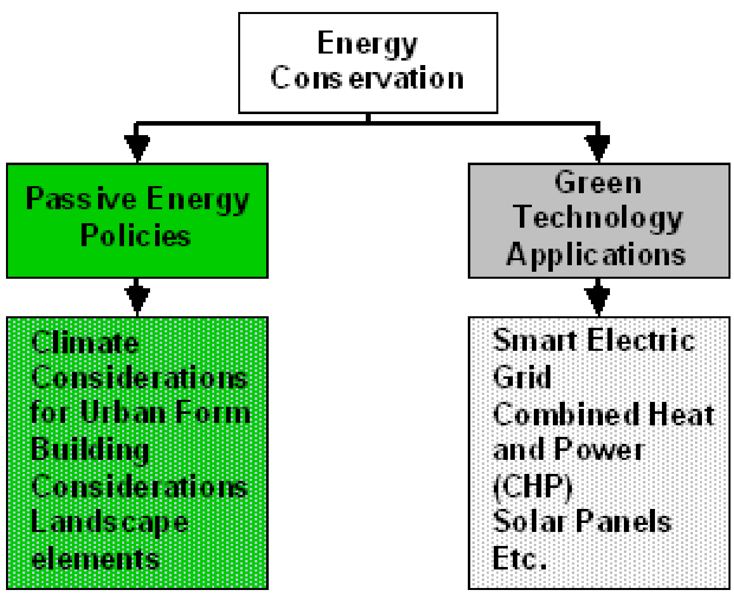

Figure 16: The various policies of DSM energy conservation.
Source: Author's consideration based on the literature.

3.3.1. Green Energy Technology Applications in Urban Context

3.3.1.1. Energy Conservation and Cogeneration Green Applications (CHP)

Cogeneration is one of the most famous green applications in energy conservation and recycling. Cogeneration is also known as Combined Heat and Power technology (CHP). In any power plant, the turbines and engines always release residual thermal heat, which is a wasted form of energy; the CHP units exploit the residual heat from any thermal power source to generate electricity and heating energy (Griffiths 1995).

The mechanism of the CHP system extracts hot exhaust gases from any power facility; these exhaust gases are transported to a boiler that feeds water to the CHP unit to produce both electricity and heating energy. The steam and exhaust gases are transported from the turbines to the CHP unit in the case of power plants, or from Stirling heat engine into the micro-CHP units (Wegener 1995). The CHP units produce clean energy that could be effectively applied to achieve energy efficiency and reduce carbon monoxide emissions. They can be used in industrial, commercial, and residential uses; they differ by size, technology, and capacity. The CHP technology could be applied to serve the whole city region in the location of the power plants or at the district or the neighborhood levels or on-site of each residential parcel.

The CHP units that are used in residential applications share common installation guidelines; the spatial, the technological, and the economical installing considerations. The spatial considerations to install the CHP units concern the characteristics of the parcel or the neighborhood or the district. The first is that the thermal residual heat cannot be transported over long distances; therefore, to operate efficiently, the CHP unit must be installed close to the main thermal source in any dwelling or the thermal facility in any parcel or neighborhood or district. The second spatial consideration is that the site location should have the minimum adequate space to install the CHP unit. The third consideration, it is recommended to deploy the CHP units in mixed uses and high-density areas (OECD 1993; GBP 2007). The CHP units with larger capacity are more sensitive to the spatial scale than the micro-CHP units.

The technological considerations: first, to avoid any possible contamination, the boiler that feeds water to the CHP unit at the scale of cogeneration power plants must be completely oxygen free and de-mineralized (Bernstein and Griffin 2006).

The CHP units have two major economic considerations; the first is the amount of residual thermal energy demand in the household units or residential districts. From the economic point of view, areas with large annual thermal consumption are appropriate candidates for installing the CHP units compared with areas that have low annual consumption. The second consideration is that CHP units are very expensive both to install and to maintain (Manning et al. 2008; Hawkes and Leach 2007). At present, the price of the unit is one of the major economic obstacles in spreading CHP application in residential areas; there are many efforts to overcome this obstacle and make the CHP units available at lower cost in the future (Dijkstra 2009). The micro-CHP units with smaller capacity at the parcel level are more subjected to the economical requirements than the CHP units at larger scale, such as neighborhood and district levels.

In 2004, an EU Directive asked member states to determine their national potentials and standards for high-efficiency CHP, to achieve the integration in the electric grid across all members and to overcome any barrier to the expansion of the CHP technology (Froning and Constantinescu 2007). The EU Commission established promotional schemes to encourage its members to integrate CHP applications in the urban development at neighborhood and district levels in all European Union countries. Recently, cogeneration produces almost 11% of the total generated electricity in the European Union (COGEN Europe 2008).

The U.S. Department of Energy started a national program to integrate CHP technology in the U.S. electric grid in 2009, and the work is still in progress. At present, CHP technology produces almost 8 percent in the U.S. total electricity market. The U.S. DOE aimed to generate almost 20 percent of the electricity by applying CHP technology over the whole country by 2030 (Shipley et al. 2008).

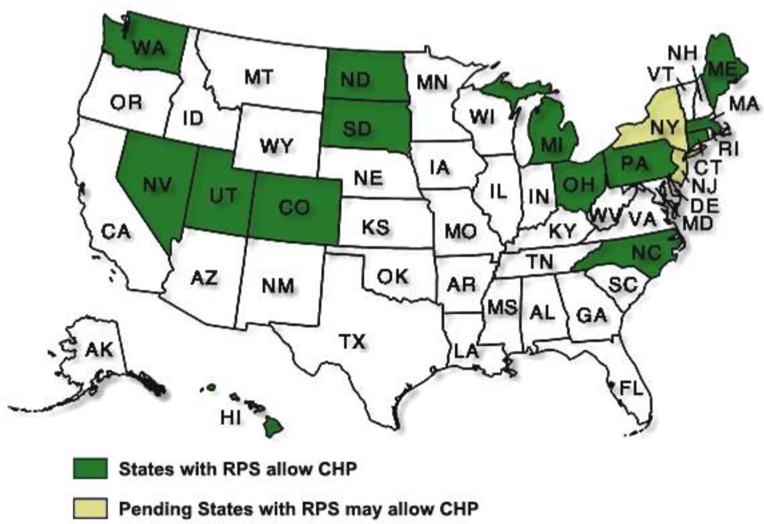

Figure 17: States with renewable portfolio standards that include CHP as of April 2008. Source: Combined Heat and Power: Effective Energy Solutions for a Sustainable Future (Shipley et al. 2008).

Figure 17 shows that North Carolina is one of fourteen U.S. states that have portfolio standards that include CHP green technology in their energy programs. The application of CHP in the U.S. energy market could play a potential role in energy conservation, environmental protection, and electricity regeneration. The efficiency of the energy system could be enhanced by connecting the CHP units with the electric grid; however, the traditional grids are not efficient enough to reach the optimum performance of the CHP units. Smart grid is a widespread network that will replace the traditional grid in the U.S. The smart grid allows the integration of all green technology applications such as CHP; the following section will present the concept of smart grid.

3.3.1.2. Smart Grid

Smart gird is an advanced electric network that utilizes digital technology that can sense any shortage or malfunction in any segment in the network infrastructure. The concept of smart grid is based on a comprehensive solution to achieve energy sustainability. Most of the U.S. electric networks use a traditional grid. There is a big difference between the traditional and smart grids in delivering the service to the end-users and businesses.

The traditional grid is a centralized one-way flow; the large power plants generate and distribute the electricity through the network to the end users. One the other hand, a smart grid is a decentralized two-way power flow of communications from suppliers to consumers and vice-versa through meter devices in the network production, transmission, distribution, and consumption (Kannberg et al. 2003). Electricity transformation in the smart grid depends on the availability of information and communication technologies (ICT); the network will communicate through smart meters and sensors to exchange real-time information of the network performance.

Figure 18 illustrates a comparison sketch between both the traditional and smart grid. Smart grid has embedded digital sensors and meters to gather real-time information on suppliers and consumers to improve the efficiency of the electricity service (NETL

2007). Figure 19 presents a sketch for the characteristics of the smart grid. In case of any failure, the self-healing feature enables the smart grid to isolate any affected area and redirect the power around damaged facilities. The distributed sensors exchange real-time information on the type, place, and area of the outage in the network, and then the smart grid analyzes the network behavior to assess the performance. The smart grid determines the required reinforcements through the network by responding back to the sensors. Therefore, the smart grid is capable to mitigate network failures. The smart grid improves the quality of the service by reducing network losses and shortages time. The grid accommodates various generations' alternatives, such as wind and solar powers, and fuel cells, which allows all customers to self-generate the power (NETL 2007).

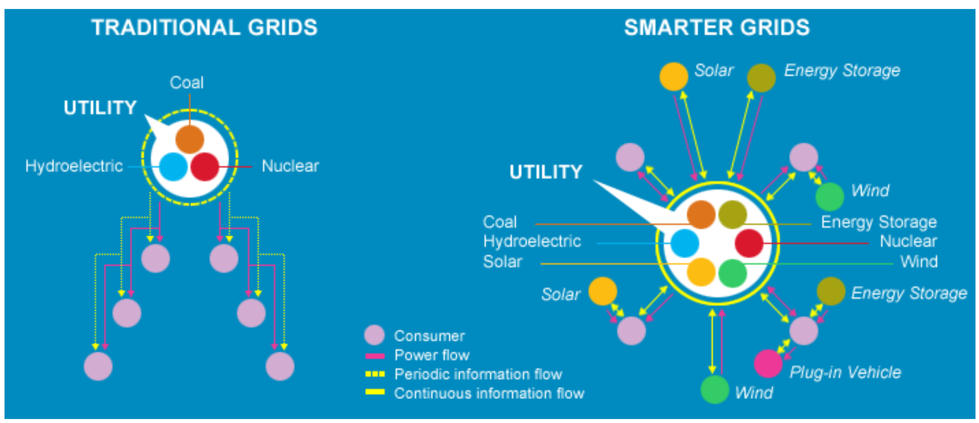

Figure 18: Comparison between the concepts of traditional and smart grids.
Source: What Will an Electric Vehicle-Ready Smart Grid Infrastructure Look Like? (Schwartz 2010).

A smart grid incorporates smart indoor appliances to enhance energy management. In addition, a smart grid enables consumers to compensate their energy saving, for instance, if consumers store the energy through solar panels, they can sell power to their neighbors or back to the grid. The smart grid increases the capacity of the electricity network; hence, this will create an open marketplace to invest in alternative energy resources. Through intelligent sensors, the smart grid can optimize the performance and network assets to minimize the operations and maintenance costs. Therefore, the energy efficiency will increase. The smart grid is flexible to integrate different renewable green energy resources with the network, such as micro-CHP; hence, decreasing the amount of carbon dioxide and greenhouse gases (NETL 2007).

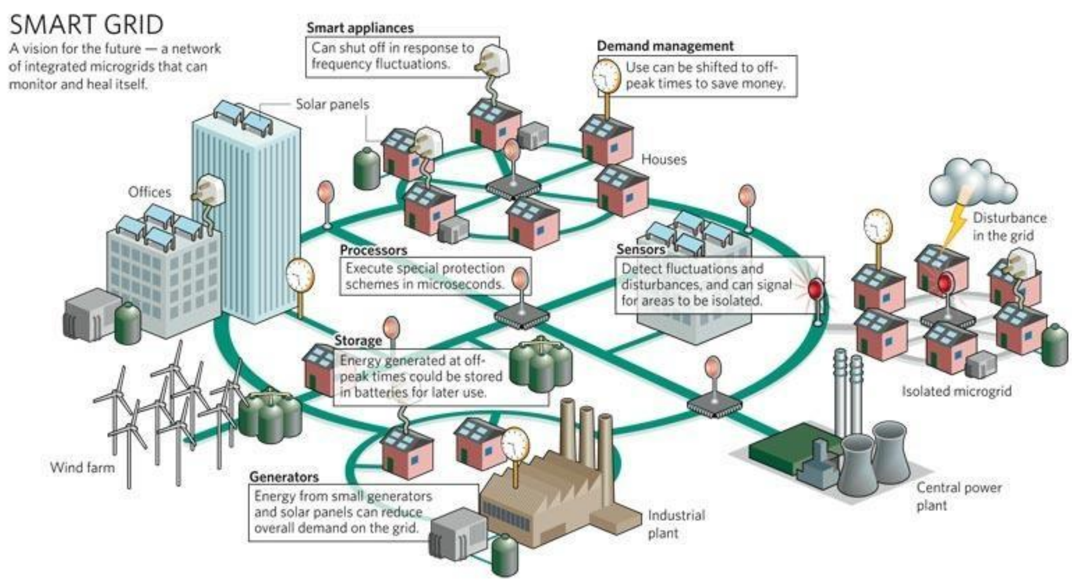

Figure 19: The characteristics of the smart grid.
Source: A Vision for the Modern Grid (NETL 2007).

In the U.S., the city of Austin, Texas, has started to build its smart grid since 2003. Almost 1/3 of its manual meters were replaced with smart meters that communicate via a wireless network (wikipedia 2010). Duke Energy, in the city of Charlotte, started to replace the old network with full-scale smart grid in the middle of 2008 (McNamara and Smith 2007). The main challenges in building the smart grid is the amount of required investment, a long time to replace the traditional network with the smart grid, and a commitment by all stakeholders.

As mentioned before, green technology applications address energy efficiency to reduce the consumption and the greenhouse gases. In this approach, the function of the technology is to utilize the new inventions for both indoor and outdoor activities. On the other hand, passive energy policies address the problem in the other direction by optimizing the urban form to reduce energy consumption. The urban entities, such as buildings, streets, open spaces, and landscape are involved passively in the energy conservation for any metropolitan area.

3.3.2. Urban Geometry and Energy Conservation

The characteristics of urban geometry, such as buildings height, size, density, landscape coverage, and orientation affect indoor energy consumption. These spatial characteristics can be involved in the reduction or increase of total energy consumption of any MSA.

Researchers have recognized four classes of factors of residential energy demand, namely, urban geometry, building design, systems efficiency, and occupant behavior. These factors have been analyzed by different groups of researchers, including urban planners and designers, architects, and system engineers (Ratti et al. 2005).

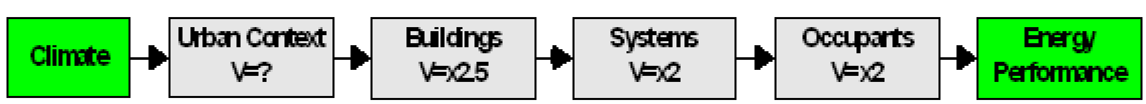

Figure 20: Factors that affect energy consumption in buildings.
Source: Energy and Environment in Architecture (Baker and Steemers 2000).

Baker and Steemers (2000) quantified the contribution of each of the four classes of factors to the total energy consumption of households. In their model (Figure 20), “building design” may affect energy consumption by a factor 2.5; “system efficiency” accounts for a ~2x variation, and "occupant behavior" accounts for ~2x variation. These factors can lead to a total 10 – 20-fold variation in energy consumption of residential buildings.

It should be noted that Baker and Steemers (2000) did not quantify the contribution of the urban geometry (context) due to the complexity of its components. Regardless of the clear relationship between urban geometry and energy consumption, researchers generally neglect this link due to the complexity of the environmental processes involved. In addition, urban geometry dynamically changes through time by horizontal and vertical development, which makes it more difficult to estimate the effects of urban texture.

3.3.2.1. Buildings, Passive Solar Space, and Energy Conservation

According to the Baker and Steemers model (Figure 20), there are two factors related to spatial characteristics that affect energy consumption, namely building design and urban geometry (context). This section focuses on DSM practices to generate energy savings at the building level. It will highlight the variables that relate to urban geometry. Discussion on the materials used in building structures is out of the scope in this research.

Energy storage is an important DSM method to control either the quantity or the delivery characteristics of energy input (Gellings and Chamberlin 1993). The total building volume is a thermal energy-storage that consists of both passive and conventional non-passive spaces. Passive Solar space is a common sustainable application in energy conservation. It aims to use solar energy saving without use of mechanical systems.

Passive solar applications have many advantages, such as, increasing solar gain for heating/cooling storage, enhancing natural ventilation, and conserving the usage of artificial lighting. Figure 21 shows that passive areas are closer to the exterior walls of a building, where the exposure to solar radiation is high, while non-passive zones are far from outer solar gain (Baker and Steemers 1996).

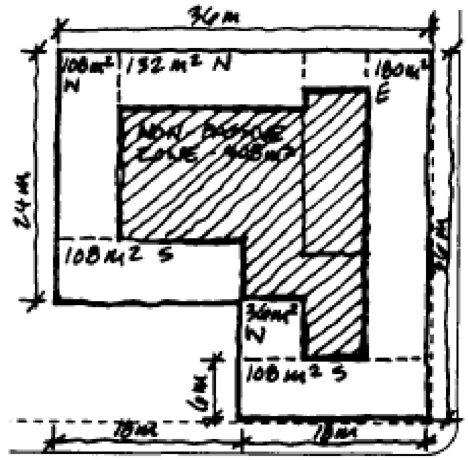

Figure 21: Passive zones (white) and non-passive zones (hatched) on a sketch plan.
Source: Energy and Environment in Architecture (Baker and Steemers 2000).

From a sustainable development perspective, we can enhance space heating, cooling storage, and lighting loads by increasing the percentage of passive solar space to conventional space. Cool storage or air conditioning relies on the percentage of passive solar space to conventional non-passive spaces. The more natural ventilation, the less energy loads from artificial air conditioning. Figure 22 presents both heating and cooling flows through passive space in a room unit. Moreover, the figure demonstrates how the ratio of passive zone affects the usage of artificial lighting. However, in some cases, passives spaces require more energy than conventional non-passive spaces. Mainly, if there are many windows in the building, facades become vulnerable to overheating during the summer and heat losses during the winter (Ratti et al. 2005).

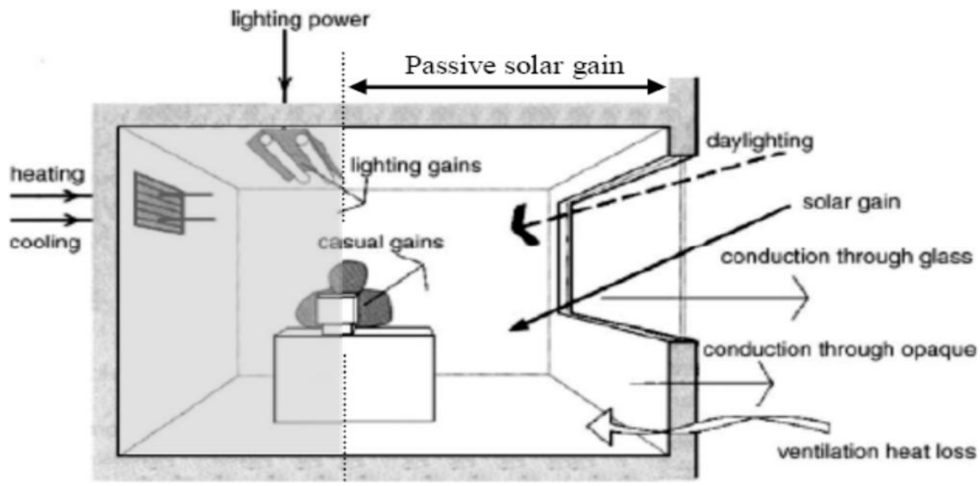

Figure 22: Energy heating and cooling flows within a unit.
Source: Energy and Environment in Architecture (Baker and Steemers 2000).

3.4. The Assessment of Influential Determinants of Energy Consumption

Many empirical studies have assessed the most significant factors of household energy consumption. To cover all sustainable energy spheres, this section will comprehensively present various spatial and urban geometry parameters, socio-economic factors, and finally the condition drivers.

3.4.1. Spatial and Urban Geometry Predictors

Many studies have developed quantitative methods and programs to estimate the effects of building design on energy consumption. In their guidance study, Howard et al. (1994) reviewed various computer-based applications that estimate energy consumption. Few applications consider obstructions and overshadowing in urban areas. Ratti et al. (2005) concluded that the developed applications tended to neglect the effects of urban geometry on energy consumption.

March (1972) developed a mathematical method to determine the optimum shape of a building to reduce heat losses. The author promoted the advantages of compact shapes on energy saving. March's study inspired many researchers to develop variant energy prediction models in many fields.

Ratti et al. (2005) proposed using a Digital Elevation Model (DEM) to predict the effects of urban geometry on energy consumption. In addition, the authors attempted to understand how the spatial characteristics of the urban areas affect energy consumption. Ratti et al. (2005) developed an integrated standalone computer model, which is called the Lighting and Thermal (LT) model. The integrated software estimates in heating, lighting, ventilation, and cooling energy, it sums all these forms to calculate total energy consumption per each office building.

Ratti et al. (2005) standardized the parameters in raster DEM format, to simulate total energy consumption. The authors used the LT model to calculate the impacts of each parameter on energy consumption individually; afterwards, the outputs of each parameter were overlaid onto an integrated raster DEM to present the total annual energy consumption for the study area.

Ratti et al. (2005) quantified the impacts of shading, sunlight, obstruction angles, and buildings orientation, separately. With the LT model, the authors calculated the total energy consumption of CBD office buildings in the three cities of London, Toulouse, and Berlin. The results showed the effects of both passive and non-passive zones. Ratti et al. (2005) determined a significant reduction in energy consumption in passive zones (almost 50%) compared to the non-passive ones. Their model incorporates four urban geometry parameters:

- Distance from the façade (passive zone);
- Orientation of the façade;

- Urban horizon angle (UHA);
- Sky View Factor (SVF).

Distance from the façade is the interior buffer space along the perimeter of a building's footprint; this space encompasses the passive zone that is mostly affected by outdoors climate conditions, such as solar radiation and shade. The researchers assume the value of distance from the façade falls between 3-6 meters from a building's perimeter, this value is fixed in LT model for all buildings. The orientation of the façade equals the angle between the North and the axis of the façade. Urban horizon angle presents the exposure of the buildings to the shades.

Steemers (1992) introduced the UHA parameter, which is used to calculate the effects of the shades on building energy consumption. The sky view factor presents the exposure of the buildings to solar radiation from the sky. Oke (1981) introduced the SVF concept to estimate the solar radiation received by any building's surface. Some researchers use another term for SVF, namely the obstruction sky view. The roofs and walls of the buildings discharge most of the radiation. For instance, larger values for SVF enable more solar radiation to penetrate through building roofs and façades; thus, causing higher indoors temperature (Givoni 1998).

Small but influential empirical studies have addressed the impacts of the sky view factor (SVF) and urban horizon angle (UHA) on household energy consumption. Both concepts have been addressed in the literature starting with Oke (1981; 1982; 1987), Givoni (1998), Baker et al. (1999), Grimmond et al. (2001), Ratti and Baker (2003), Souza et al. (2003), Ratti and Richens (2004), Ratti et al. (2005; 2006), Holmer et al. (2007), and Unger (2009). These empirical studies have indicated strong negative relationship between SVF and solar radiation gain in the urban areas, which means the more SVF, the faster escape of solar radiation energy from household units. Urban areas with low density have high values of SVF, and the household units have more exposure to solar radiation, which could contribute in heating energy savings during cold seasons. However, low density will increase the cooling energy during hot seasons.

On the other hand, the situation is reversed in the case of urban horizon angle, UHA estimates the contribution of buildings shades and shadows in energy saving. Determine the magnitudes of both SVF and UHA will be challenging with a small number of empirical studies that addressed the contribution of the two spatial predictors on household energy consumption.

Two of the proposed spatial parameters in the LT model by Ratti et al. (2005) can be applied to estimate the housing energy-demand (HED) at urban geometry level. The UHA and SVF parameters can represent the passive energy at urban context as well as at buildings design level to achieve energy conservation. The basic concepts encapsulated by the UHA and SVF indicators demonstrate the effects of building heights and urban density on the amount of shades and solar radiation based on the sun’s obstruction angle, respectively. The amount of solar energy gain and shades differ for each building in any given city. Figure 23 shows the geometrical arrangement to calculate the UHA and SVF indices. The basic equation to calculate UHA for a building is as followed:

$$\mathrm{UHA} = \tan^{-1}(\mathrm{H/W}) \tag{1}$$

$$\beta = (\mathrm{H/W}) \tag{2}$$

Therefore:

$$\mathrm{UHA} = \tan^{-1}(\beta) \tag{3}$$

Where H is the height of any building, W is the width between the façade and the shading elements, β is the sun's elevation angle, and θ is the sun's obstruction angle with the perpendicular axis. Oke (1987) proposed a simplified model to calculate the SVF parameter for the buildings footprints in any urban area as followed:

$$\mathrm{SVF} = \cos^2(\beta) = \sin^2(\theta) \tag{4}$$

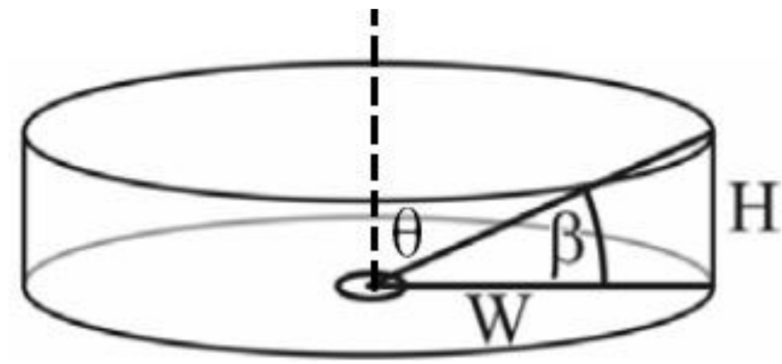

Figure 23: Geometrical definitions for the sky view factor.
Source: Boundary layer climates (Oke 1987).

However, one major criticism is that Ratti et al. (2005) did not explain if they validate their results. In addition, the LT model has fixed parameters and the user cannot customize the mathematical methods in the software; therefore, is hard to validate the LT model with other energy models. The spatial variables SVF and UHA from LT model can be combined with any given forecasting methods to develop a new integrated statistical forecasting method.

Many ecological studies assessed the effects of landscape, mainly tree shading, on energy conservation. This research will focus on the conducted empirical studies in hot climate zones in the U.S. A group of researchers has attempted to quantify urban tree shading effects in the U.S. cities, mainly in the State of California. The collective findings of these studies observed that the tree coverage percentage of a parcel area in a typical American city ranges between 68%-71% in the case of single-family homes, and 6%-8% for multi-family housing. Therefore, single-family use will have the maximum cooling energy savings during summertime (Akbari et al. 1990; Akbari et al. 1997; McPherson and Simpson 2003; Simpson and McPherson 1998; Simpson 2002; Akbari 2002; Parker and Barkaszi Jr 1997; Akbari and Konopacki 2005).

Pandit and Laband (2010) conducted an empirical study in Auburn, Alabama, to determine the annual energy saving from tree shades. The relationship between tree shade and household energy consumption is sensitive to climate season and tree coverage percentage on the residential parcel. The authors identified three classes of tree shades; the first class is light shade with 10% or less of tree coverage, the second class is moderate shade with 10%-25% of tree coverage, and the third class is heavy shade with 25% of tree coverage of the parcel land area. The more tree coverage in winter the greater the increase in heating energy, and vise-versa the more tree coverage in summer the more saving in air-conditioning energy (Pandit and Laband 2010).

Trees adjacent to the building footprints are most likely to have a greater impact on the energy consumption pattern. Huang et al. (1987), Akbari et al. (1990; 1997), Simpson and McPherson (1998), Simpson (2002), Akbari (2002), McPherson and Simpson (2003), Akbari and Konopacki (2005), King (2007), Hardin (2007), Donovan and Butry (2009; 2011), and McPherson et al. (2011) observed that within U.S. hot regions, tree planting reduces annual cooling energy in warm seasons by 3% for the units with low tree coverage and up to 8% for homes with high tree coverage. On the other hand, during cold seasons, adjacent tree planting increases energy demand for space heating, the previous studies stated that the annual heating ratio increases by 113-344

Mj/tree. However, the increasing in heating energy demand due to adjacent tree coverage is negligible compared with cooling energy savings in hot climate regions.

3.4.2. Socio-economic Predictors

The relationship between energy consumption and socio-economic characteristics of the population is one of the important topics at various scales (national – local – household). The research will focus on the empirical studies at the household level. One of the most important studies at high-resolution scale is the empirical study by EIA (1999; 2001; 2005; 2009). The study used the high-resolution data of the Residential Energy Consumption Survey (RECS), which is a sample survey that is conducted by Energy Information Administration of U.S. Department of Energy. The RECS micro-data provide various cross-sectional tables at the household level, such as the household characteristics (income, housing type, size, age, the home's square footage, etc.), energy consumption, the usage type at housing units (space heating, air-conditioning, etc.), and energy sources available in the household (electricity, natural gas, etc.).

EIA (1981) developed a nonlinear regression model based on the RECS micro-data to estimate the annual consumption for each household unit and each energy source used. The high quality of RECS micro-data encouraged many researchers to apply the data and EIA's model to forecast the predominant socio-economic predictors on household energy consumption. The majority of researchers mainly focused on income, household population size, and housing type (single family, multi-family apartments).

O'Neill and Chen (2002) also used the RECS micro-data in their study. The authors applied the EIA's model to identify the demographic factors of household energy consumption in the U.S. during 1993-94. They concluded there is a high positive relationship between household income and energy consumption. However, multicollinearity commonly appears in the results when dealing with variables that are likely correlated, such as income and household size. Using the RECS micro-data of 2005, Min et al. (2010) found that the relationship between energy consumption and household income is significant and positive. The model can be formulated as:

$$\ln E_j = \beta_{j0} + \sum_i \beta_{ij} * X_i \qquad (5)$$

Where E is the estimated annual energy consumption for j used energy source, and β is the coefficient of variable X_{i}.

Various studies focused on household size as another important socio-economic predictor of energy consumption. Various studies have concluded that energy consumption rises when household size increases (Ironmonger et al. 1995; O'Neill and Chen 2002; Min et al. 2010). Table 4 presents the percentage increases in energy consumption in relation with number of people in a household unit in the U.S. during 1993-1994. Min et al. (2010) confirmed that the relationship between energy consumption and household size is significant and positive. It is important to mention that the square footage of the housing unit is important predictor; it reflects the human occupancy and activities in any household.

Table 4: Energy consumption per capita in household in the U.S. 1993-94.

Capita per Household	Energy Usage per capita M. Btu	Increment Percentage
1	120	100%
2	82	137%
3	69	173%
4	57	190%
5	47	196%
6	43	215%
7	41	239%

Source: Extracted by the researcher from Demographic Determinants of Household Energy Use in the United States (O'Neill and Chen 2002).

Energy studies analyzed housing type as one of the major predictors of household energy consumption. Household type, income, and household size create a socio-economic composite index to establish appropriate forecasting methods at high-resolution scale at the end-user level (O'Neill and Chen 2002). After controlling for other socio-economic factors, EIA (2001; 2005), Brown and Wolfe (2007), EPC (2008;2009), Min et al. (2010), and Hernandez et al. (2011) concluded that single-family units consume more energy than multi-family apartments. Min et al. (2010) concluded that the relationship between energy consumption and housing type is significant and positive.

3.4.3. Condition Predictors

The condition parameters will account for the events that may happen and would influence total energy consumption forecasted at various scales (household – national – global). These predictors will have significant impacts under certain conditions. One of the most important predictors in the energy market is the price of crude oil, which affects both the price of natural gas and the coal in the energy market. Crude oil acts as a proxy for energy demand (Wood 2010). The price of crude oil is very sensitive to the market conditions, in case of global energy crisis; the price of crude oil will rise and affect all energy markets at the macro and micro levels.

The second condition driver is the price of natural gas; natural gas sales for the residential sector in the study area is almost 24% (EIA 2010e). There is a positive relation between the prices of crude oil and natural gas. If the price of crude oil increases, it is most likely that the natural gas price will also rise, and vice-versa. Weather conditions play a role in the ratio between the price of both crude oil and natural gas. When the demand increases for natural gas during the cold seasons, the ratio between crude oil and natural gas prices is most likely to be 6:1, while in the warm seasons the demand for natural gas decreases and the ratio is most likely to be 10:1 as shown in Figure 24 (Brown and Yücel 2007).

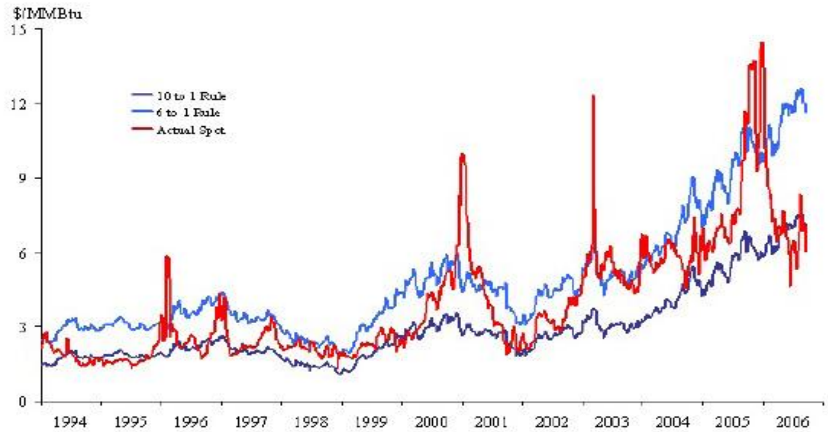

Figure 24: Actual and implied natural gas prices.
Source: What drives natural gas prices? (Brown and Yücel 2007).

Recently, various empirical studies have addressed the implications of green technologies on household energy savings, such as the micro-CHP units and solar panel roofs. According to Shipley et al. (2008), the U.S. Department of Energy started to encourage energy companies to replace the existing electric grid with a new smart one in the whole country to achieve energy reduction between 8% to 20% according to U.S. DOE goal by 2030 (Shipley et al. 2008). The planned smart gird will apply CHP and other green technologies at household and neighborhoods levels. Therefore, it is important to take into account the impacts of green technology applications in the study area.

3.5. Energy Demand Forecast Modeling

3.5.1. The Definition of Energy Demand Forecasting

Energy demand forecasting has become a vital input to micro economic growth and sustainable development of any society. The term of Energy Demand Forecasting consists of two terms; the first is energy demand, and the second is the demand forecast. The Energy Information Administration (EIA) defines energy demand as "the requirement for energy as an input to provide products and/or services" (EIA 2009b). Another definition is common among economists: energy demand is a relationship between the price of a commodity and the quantity purchased at that price over some time period (Daly 1976).

According to Business Dictionary (2009), demand forecasting is defined as the activity of estimating the expected demand of a certain product or service over a specified future period. Energy demand forecasting is used in different decision-making processes. The major concern of these methods and models is how to predict energy demand scenarios. There are various modeling approaches in energy demand forecasting. These approaches have been applied in different time (e.g. hourly – daily – monthly) and scale (e.g. household unit – neighborhood – city) resolutions.

3.5.2. Energy Demand Forecasting

3.5.2.1. Cross-Sectional Econometric Approach

The basic concept of this approach combines economic theory with statistical analyses to produce a system of equations for forecasting energy demand. It establishes a relationship between energy demand and other economic variables. The dependent variable, demand for energy, is expressed as a function of various economic factors. We can apply different predictors, such as population, income per capita (in residential, industrial, or commercial sectors), price of providing the service, and the total consumption of appliances in the study area (Bohr 2009). To account for the dynamic characteristics of energy demand, a lagged dependent variable is often used as a regression variable in the model. It aims to distinguish between short-run and long-run demand elasticity in econometric models (Bohr 2009; Pillai N 2008).

With the recent development in computer and GI-Science, researchers have developed econometric methods that deal with spatial problems (e.g. spatial dependence and spatial heterogeneity); this collection is defined as spatial econometric modeling. The use of spatial econometric approaches is growing fast among different disciplines such as geography and economics (Qingmin 2008; Lin et al. 2005). In the econometric approach, the most common type of formulation used in energy studies is based on the following demand function:

$$E = aY^{\propto} * P^{-\beta} \tag{6}$$

Where E is energy demand per capita, Y is income, P is energy price, a is a coefficient, α is income elasticity of energy demand, and β is price elasticity of energy demand. In addition, a generalization and extension of this model is formulated as:

$$E = f\left(Y, P_i, P_j, POP, T\right) \tag{7}$$

Where P_i is energy price, P_j is price of related fuels, POP is population, and T is technology. Income and price elasticity parameters indicate the changes in energy demand in relation with price and income. Thereby, income elasticity α and price elasticity β of energy demand are calculated as followed, respectively:

$$\alpha = (\Delta E/E)/(\Delta Y/Y) \tag{8}$$

$$\beta = (\Delta E/E)/(\Delta P/P) \tag{9}$$

The practice of the cross-sectional econometric approach has made substantial progress over the last four decades. It has proven substantial success in energy demand forecasting because of its ability to distinct the factors that influence energy consumption (Fisher 1999, p 411).

Many achievements have been made by researchers to give general understanding in the modeling tools. During the 1960s, the major goal was to have better understanding of the relationship between energy demand and various economic variables. Later, Griffin (1993) recognized three major achievements during the period of 1970-90 in cross-sectional econometric modeling. The first is the application of the trans-log function. Wirl and Szirucsek (1990) observed that the researchers preferred to apply the trans-log function in energy demand forecasting due to its flexible properties. Many cross-sectional econometric models, since the 1970s, have applied the trans-log model at the aggregated and disaggregated levels, for instance, Brendt and Wood (1979), Pindyck (1979), Uri (1979a and 1979b), Saicheua (1987), Siddayao et al. (1987), Carlevaro et al. (1992), Christopoulos (2000), Dahl and Erdogan (2000), and Buranakunaporn and Oczkowsky (2007).

The second achievement is the usage of panel data, which allowed researchers to capture the interregional impacts (short and long terms) of the economy on the energy demand. Panel data are two-dimensional data, while time series and cross-sectional data are both one-dimensional. Panel data combine cross-sectional and time-series data. Thus, panel data follow the same cross sectional units (households, firms, cities) over time.

The third achievement is the discrete choice method, which it is used to analyze energy demand between different types of energy along with consumed quantity, such as electricity and natural gas. The method is used in predicting the choices made by people among a set of alternatives, such as the choice of fuel type for space heating.

Fisher and Kaysen (1962) conducted a pioneering study to analyze and estimate the electricity demand in the U.S. market at the national level. The authors were the first who recognized the importance of econometric analysis in energy demand forecasting. Fisher and Kaysen (1962) developed an integrated model of electrical residential consumption using cross-sectional state data during the period of 1951-1967. First, the model estimates the short-run demand for residential electricity by expressing the complementary link between energy needs and the stocks of appliances. Fisher-Kaysen's model predicts the long-run demand by accounting for the changes of the stock of equipment under different assumptions, such as the partial adjustment to an equilibrium stock, or through the appliances penetration of a market (Fisher and Kaysen 1962).

Due to data limitations, Fisher and Kaysen (1962) were unable to reach reliable results of the residential electricity consumption model. The researchers subsequently neglected electricity estimation based on direct estimates of equipment stocks. Another major critique to Fisher-Kaysen demand model is that the authors considered the demand as static. Fisher–Kaysen's model failed to consider properly the income effect and assumed that all incomes are equal. Another source of bias is that the utilization rates of different appliances were assumed to have the same price and income effects. Therefore, the model used the average energy price to estimate market price elasticities, which causes an aggregation bias (Kamerschen and Porter 2004). Also, Bohi (1984) noted that the formulation of Fisher-Kaysen's model results in an aggregation bias. Finally, Bohi (1984) claimed that the demand elasticity for each appliance will not be the same for each individual household unit.

Balestra and Nerlove (1966) applied Fisher-Kaysen's model to calculate the demand for natural gas in the U.S. for both residential and commercial markets. The authors developed a dynamic model to avoid the shortcomings in Fisher-Kaysen's model. Balestra and Nerlove (1966) addressed the changes in the behavior of the consumers. In addition, the authors presented new specifications in the long-run demand model to explain the accumulation of the appliance retrofits.

Halvorsen (1975) applied two-stage least squares (2SLS) to estimate the dynamic energy demand to avoid the shortcomings in Fisher-Kaysen model. Halvorsen's model covered both electricity and natural gas sales for the residential sector. The model converts the average prices into marginal prices by modeling the price as a function of quantity as shown in the following equation:

$$Q = b_0 + b_1 P_m + b_2 Y + b_3 G + b_4 A + b_5 D + b_6 J + b_7 R + b_8 M + b_9 H + b_{10} T + u \quad (10)$$

Where Q is the average annual residential electricity sales per customer, P_m is marginal real price of residential electricity, Y is average real income per capita, G is average real price per therm for residential natural gas, A is the index of real wholesale prices of electrical equipment, D is heating degree days, J is the average July temperature, R is the percentage of population living in rural areas, M is the percentage of housing units in multi-unit structures, H is the average size of households, T is time, and u is a disturbance term.

Until the 1970s, the practices of cross-sectional econometric approach received some critiques. Pindyck (1979) stated that the literature during this period had poor understanding of the long-term impacts of prices and income on the energy demand. This situation created difficulty to forecast energy demand and choose the proper energy and economic policies. Pindyck (1979) proposed to develop cross-sectional econometric models by using international data. The author argued that this step could increase the understanding of the long-term impacts on energy demand to their relationship to the economic growth. In addition, Hartman (1979) observed that most of the early cross-sectional econometric models in all sectors (residential, commercial, and industrial) focused on a single type of fuel, which is crude oil. Therefore, these models limited the decision variable to the fuel price only. Hartman (1979) noticed that the literature during the 1970s paid little attention to other economic variables, such as the type of fuel-burning equipment, gross domestic income, and long-run and short-run demand of energy.

Taylor et al. (1984) attempted to solve the major drawbacks in the previous cross-sectional econometric models. The authors covered the impacts of socio-economic factors on the energy demand more efficiently. They developed a comprehensive model to forecast the residential demand for electricity in the U.S. market. The authors applied the model at the national level during the period of 1950-1980. In their approach, a stock-utilization sub-model is used to determine the short-run electricity demand by the appliance stock. The authors claimed it is difficult to isolate the impacts of variables that affect the behavior of residential customers at the household unit level, such as the prices of natural gas and fuel oil, and appliance ownership.

Nowadays, the fluctuations in oil price, urbanization, and energy efficiency motivate researchers to extend the academic interest in energy demand studies. Kamerschen and Porter (2004) developed a model based on Halvorsen’s equation to estimate the demand for residential, industrial and total electricity in the U.S. market at the national level during the period 1973-1998. Kamerschen and Porter (2004) attempted to determine the sensitivity of sectoral energy price to weather fluctuations. The authors included some major findings; such as, the weather has the greatest impact on residential energy consumption.

Holtedahl and Joutz (2004) examined the residential demand for electricity in Taiwan, over the period 1955-1995. The authors studied Taiwan as an example of developing countries. They mainly aimed to measure how urbanization and economic development impact on electricity demand. The authors measured urbanization by the proportion of the population in cities over 100,000 people. Using a cross-sectional econometric model, they found that urbanization had positive long-run and short-run effects on consumption. Urbanization is an indirect measure of electricity consumption using appliances stock. Holtedahl and Joutz (2004) adopted the Fisher–Kaysen’s model to derive economic development characteristics and electricity by using capital stocks not explained by income. Their model explains both short-run and long-run electricity demand. The authors concluded that electricity consumption and urbanization are strong predictors of economic development.

The cross-sectional econometric approach is still facing bias in forecasting the short-run energy demand or dealing with micro-data. Harvey (1997) mentioned that the majority of cross-sectional econometric models consider the economic variables are static over time. The author argued that would eliminate vital forecasting procedures, which may affect the quality of the output results because some economic variables do change over time. Harvey (1997) suggested another forecasting concept, which is called the structural time series models.

3.5.2.2. Structural Time-Series Approach

Another forecasting approach is structural time-series (time trend) analysis. The basic concept of this approach consists of plotting a variable over time and discerning the pattern of this variable. The approach is used to predict the future path and seasonal (hourly – daily – monthly – yearly) behavior of the system based on past observations.

A structural time-series is defined as an ordered set of values of a certain variable. It is used to predict the future behavior of variables based on their past values. The difference between the cross-sectional econometric and time-series approaches lies in the explanatory variables used. In other words, the explanatory variables are used as causal factors in the cross-sectional econometric approach, while in time-series only previous values of the same variable are used in the forecast process (Bohr 2009; Pillai N 2008).

The main advantage of the structural time-series models is that they are relatively easy to interpret because of the simplicity of their structure. On the other hand, the major disadvantage is that they do not describe the causality of the relationship. Thus, a structural time-series model does not describe why changes occurred in the variable under investigation (Bohr 2009).

The basic principle of the structural time series approach in energy systems modeling can be described as a single freedom degree of the system. Autoregressive moving average (ARMAX) models are the most widely used in energy demand forecasts. ARMAX models are capable of incorporating the external inputs, such as weather or energy price. In addition, they are sufficient for short-term energy demand forecasting (Yang et al. 1995). The ARMAX model is formulated as followed:

$$A(q)E(t) = B(q) * u(t) + C(q) * e(t) \tag{11}$$

Where E(t) is energy demand load at time t, u(t) is weather temperature input at time t, e(t) is white noise at time t, A(q) is autoregressive parameter, and C(q) is moving average parameter. White noise refers to the absence of autocorrelation between the variables at different times and the mean equals zero. ARMAX models have time lag predictors that transform any observations at any given time to the previous one. Some modifications have been applied to these models to enhance the prediction, for instance, applying log function to some variables, such as log[E(t)] for energy demand.

Harvey (1997) introduced the first concept of structural time-series approach. The author introduced the theoretical framework of the structural time-series approach based on the vector error-correction method (VECM). Johansen (1988) introduced the VMCM method to support a better understanding of the nature of any non-stationarity among the different time-series components. In addition, the method can improve long-term demand forecasting. Harvey’s work has been very influential to various researchers, and his new proposed approach has been extensively used in energy demand as an alternative forecasting approach. For instance, Hunt et al. (2003), Hunt and Ninomiya (2005), Adeyemi and Hunt (2006).

Hunt et al. (2003) demonstrated a structural time-series study to determine the trends and seasonal energy demand for the whole economy and each sector in the UK. The authors used quarterly data during the 1971-1997 periods. They analyzed the impacts of price, income, and temperature on energy demand. The authors claimed that their model presented significant results to estimate the trends of the whole economy, the transportation, and industrial sectors; however, their model did not show clear results in the case of the residential sector.

Later, Hunt and Ninomiya (2005) examined the long-run relationship between energy demand, GNP and the energy price in Japan. The authors used annual data for primary energy consumption per capita in Japan from 1887 to 2001. The authors attempted to determine the relationship between the rapid economic growth and the increase of CO_2 emissions. They developed a model to utilize four scenarios for future primary energy demand and the amount of CO_2 emissions. The first case is a low GNP growth (where the economy grows by an average of only 0.1% p.a. over the next 10 years). The second case is a medium GNP growth (where the economy grows on average by just under 1% p.a.). The third case is a high GNP growth (where the economy grows on average by just under 2.2 % p.a.). The last case is the Japanese Government plan (where the economy grows on average by just under 2% p.a.).

Hunt and Ninomiya (2005) concluded that there is a significant amount of uncertainty whether Japan will or will not be able to reduce CO_2 emissions in 2008–2012. The authors pointed that the uncertainty depends primarily on how slowly or fast the Japanese economy grows over the next ten years. In addition, there are other contributors, such as the fluctuations in energy prices over the next ten years.

The structural time-series approach lacks the ability of calibration to identify the turning points in a series. The approach cannot be used to compare the original data under investigation from the same period in each year (Bidwell 2005). Moreover, time-series models are not intuitive and no simple physical interpretation could be attached to their components. Hence, they do not permit engineers and planners to achieve better understanding for the energy system behavior (Rafal and Adam 2005).

3.5.2.3. Engineering End-use Approach

The end-use approach or engineering-economy approach is another commonly used energy demand forecasting technique. It identifies patterns of energy usage based on design energy inputs of various devices and systems. In other words, this approach addresses the final needs of the energy demand at a disaggregated micro level. Chateau and Lapillonne (1978) are the first researchers who applied this approach (Bhattacharyya and Timilsina 2009).

The principle of the approach is to disaggregate the total energy demand into relevant homogenous end-use categories in all sectors (residential, commercial, agriculture and industrial). For instance, in the residential sector, the energy can be used in the form of electricity for appliances for heating, cooling, refrigeration, cooking, etc. (Bohr 2009; Bhattacharyya and Timilsina 2009).

When any conducted study lacks sufficient cross-sectional econometric and time series data, the end-use approach is an alternative. The end-use approach is effectively used to capture structural changes, different development projections, the influences of alternative policies, and new technological developments (Bhattacharyya and Timilsina 2009).

A major criticism to this approach is the ineffectiveness of calculating certain energy policies. It disregards the variation in consumption patterns/behaviors due to the difference in socio-economic factors; thus, reducing the accuracy of forecasting results. Moreover, the approach requires a high level of details of data on each target end-use.

Engineering end-use models assume that energy demand for each activity consists of two factors; the first is the quantity of energy service. Energy service is the magnitude of the physical amenity provided by energy-using appliance or equipment, for instance cooking, lighting, thermal heating, air conditioning or refrigeration (Swisher et al. 1997). The second factor is the energy intensity (energy consumption per unit of energy service). Energy intensity is a measure of energy efficiency of a nation's economy (EIA 2009b). The basic model is formulated as followed (Swisher et al. 1997):

$$E = \sum_{i=1}^{i=n} Q_i * I_i \qquad (12)$$

Where E is the energy demand per household, Q_i is the quantity of energy service i, and I_i is the intensity of energy use for energy service i. The parameter Q_i is calculated as followed:

$$Q_i = N_i * P_i * M_i \qquad (13)$$

Where N_i is the number of customers eligible for end-use i, P_i is the penetration (total units/total customers) of end-use service i (can be > 100%), and M_i is the magnitude or extent of use of end-use service i. Population parameter N_i can be the number of households, commercial, or industrial customers. This parameter can be defined differently for each sector. For instance, it could be calculated as the total number of household units in the residential sector. The definition of N_i must be consistent with the units in the denominator of the penetration variable P_i.

Parameter P_i is the share of customers who use a given electric end-use service. In the residential sector, the penetration is the number of appliances per household. This parameter captures the count of appliances, such as electric stoves, washing machines, lamps, or television sets. In certain cases, the penetration value for some appliances, such as TVs and refrigerators, can be calculated as a saturation level where electricity consumption is expected to be constant. However, it should not be assumed that this value is 100%. Some households can install more than one TV or refrigerator, therefore, penetration value will score greater than 100% (Swisher et al. 1997).

Magnitude M_i depends on the amount of delivered end-use service. In the residential sector, the magnitude indicates the frequency of appliance usage (e.g. kg of clothes washed) or the fraction of maximum usage (e.g. usage hours of television) for a given end-use. For heating and cooling appliances, M_i value is the difference between the indoor and outdoor temperatures ΔT that is needed for the air-conditioning. Magnitude M_i is measured separately for the heating and cooling seasons (Swisher et al. 1997). The following case of residential end-user presents how to calculate the energy demand using engineering end-use model:

In a community of 100 homes N_i, 80% P_i own a TV. The average TV consumes 200 W I_i of electricity and is turned on for an average of 2 hours per day M_i. Therefore, on an annual basis, $Q_i = N_i * P_i * M_i$ = 100 homes * 80% * 2 hr/day * 365 days/yr = 58,400 home-hr/yr. As a result, the community's annual TV energy demand = $Q_i * I_i$ = 58,400 home-hr/yr * 200 W/home = 11,680 kWh/yr.

Chateau and Lapillonne (1978) presented the first attempt to apply the engineering end-use approach in energy demand forecasting. The authors were motivated to apply a new approach (at a disaggregated level) to analyze the set of interrelationships that exist between a country's economic growth pattern and its energy demand.

Chateau and Lapillonne (1978) developed their model for developed countries as a reaction to the 1973-74 oil crisis. The authors named their model MEDEE (Model Demand Energy Europe). The MEDEE model identifies the main macro and micro socio-economic, political, and technological factors (as determinants of energy demand). The model was applied to the National French economy to project the energy demand in each 5-year interval during the period of 1975-2000.

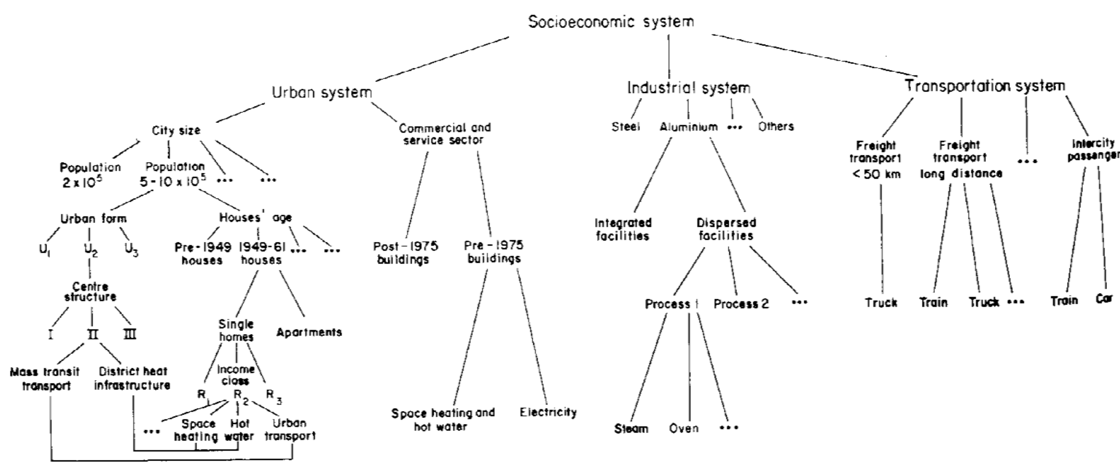

Figure 25: Structural schema of the socio-economic system.
Source: Long term energy demand forecasting: A new approach (Chateau and Lapillonne 1978).

Figure 25 presents the Chateau and Lapillonne model. The MEDEE model analyzes the socio-economic system into three hierarchical steps; the first analytical step partitions the socio-economic system into a set of sub-systems based on the types of energy needs. The second step investigates the direct and indirect factors that affect the energy demand projection. The analysis identifies whether these factors form either deterministic or causal relationships, and then organizes the output into a logical structure to present their interactions into a simplified structure that is used to set up a simulation model. The third step constructs simulation sub-models of the growth rate of the energy demand, and then organizes each sub-model into an overall simulation model. The simulation model runs different scenarios of energy demand based on political, economic, and technological factors, for instance the change in oil price and how it affects the energy demand and price (Chateau and Lapillonne 1978).

Chateau and Lapillonne (1978) conclude that their method may appear complex and it requires many variables and large data collection. However, they claim their new approach organizes the variables into hierarchical subsets, which allows the researchers to analysis the energy demand at any disaggregated level.

Later, the authors applied the MEDEE model to other industrialized countries in North America, Western Europe, and Japan at the national economy scale as well. Their approach gained reputation through the works at the International Institute of Applied Systems Analysis (IIASA) (Lapillonne 1980, 1978) at the International Atomic Energy Agency (IAEA) (Lapillonne and Chateau 1981), and the Lawrence Berkeley Laboratory (LBL) (Finon and Lapillonne 1983).

Wilson and Swisher (1993) applied the MEDEE model to determine the U.S. national primary energy demand using 5-year intervals during the period of 1950-1990. They suggested that the motivation for the “bottom-up” approach arose from the high energy demand forecasts in the 1970s that raised the attention of researchers to achieve energy efficiency and sustainability. Wilson and Swisher (1993) aimed to investigation the direct cost of energy consumption on the climate change; they attempt to analyze the factors that maintain economic growth and high quality of life with lesser energy supplies.

To achieve their goal, Wilson and Swisher (1993) explored the gap between top-down (cross-sectional econometric) and bottom-up (engineering end-use) methods to decrease any conflicts between the two approaches. The end-use modeling system is particularly important in modeling the changes in the market shares of various energy services that will not necessarily be reflected in the econometric energy price.

For example, any increase in the consumption of gas hot water heaters in the residential sector will probably raise both the domestic natural gas and/or electricity consumption. This change in the market might not be precisely determined in the econometric models. Therefore, it is important to merge the results of both the cross-sectional econometric and end-use forecasting systems. This merging process allows both modeling systems to be updated to display the changes in technological and economic parameters through time.

Each of the two modeling approaches has advantages and disadvantages, and by combining the two approaches, the credibility of model outputs. However, Wilson and Swisher (1993) concluded that each approach represents different methods and models and it is hard to produce compatible results for both modeling systems.

Swisher et al. (1997) conducted a wide study that collected powerful and practical tools for designing energy demand model for electricity in Brazil. Bahn et al. (2004) showed in detail the advantages of the MEDEE model over mathematical modeling when dealing with actual problems.

Liao and Cheng (2002) analyzed both space and water heating demands by the aged people in the U.S. The study was conducted at the national level. They used data from the 1996 Residential Energy Consumption Survey from the Department of Energy (DOE), which is rich in demographic, building characteristics, and appliances information in each household. The authors implemented a continuous method to reveal the energy consumption behavior of the aged. They claimed that the aged people compared to the younger groups consume more electricity in the residential sector. Liao and Cheng (2002) found that the aged use more natural gas and fuel oil but less electricity for space heating except for those household heads older than 80. In addition, they claimed that the aged people use less water heating than younger groups.

However, end-use energy demand models have been only used in energy policy studies and have not extensively been utilized for forecasting energy demand. To achieve accurate results in engineering end-use models, we need to have detailed information on stocks of appliances, equipment, and end-use consumption data in any country.

3.5.2.4. Hybrid-Integrated Approach

Various empirical studies have attempted to develop approaches to combine the forecasting methods discussed above; the new approach is known as a hybrid approach. The main objective of this approach is to increase the efficiency of future prediction by combining the advantage of each approach. It attempts to overcome the limitations of individual approaches (Bhattacharyya and Timilsina 2009). These models have become very widespread now; it is difficult to classify any particular model into a specific category.

The hybrid-integrated approach of end-use and econometric methods allows integration of physical and behavioral factors in a common framework. For instance, the econometric method will estimate the influence of price, income, and policy effects. While the engineering end-use approach will account for the new end-uses, alternative fuel mixes, market penetration of appliances and technologies, growth pattern of physical or value of output, population and its distribution amongst income class. The combination of time series and cross-sectional econometric approaches improves the accuracy of determining both the causality and dependency relationships. This combination joins several functional methods to capture the existing trends in the data.

In principle, the hybrid-integrated approaches have capabilities to develop comprehensive urban energy models. Many developed hybrid energy models are embedded within integrated land use transportation models to evolve the simulation of any urban region and forecast its future energy demand in a way that ensure micro/macro-economic consistency (Chingcuanco and Miller 2012).

Almeida et al. (2009) developed the iTEAM (Integrated Transportation and Energy Activity-Based Model), which is a hybrid energy model to evaluate green policies. The authors aimed to enhance the sustainability of the urban systems by assessing the effects of energy green policies on urban systems. The authors applied their model in the Lisbon metropolitan area, Portugal. Almeida et al. (2009) integrated a household location choice sub-model namely UrbanSim, which is an open source simulation land use package that applies agent-base simulation method (Waddell et al. 2003). Hence, the iTEAM model simulates household agents at micro level and aggregates the results to forecast the impacts of various energy policies on urban land use dynamics (Almeida et al. 2009).

Chingcuanco and Miller (2012) developed a hybrid-integrated energy model that combine socio-economic and technological factors. The authors estimated space-heating demand for Toronto-Hamilton region. The authors combined two open sources packages, the HOT2000 software and the Integrated Land Use, Transportation, Environment (ILUTE) modeling system. The HOT2000 calculates the individual space heating per household unit and fuel choices for North America housing market (CanmetENERGY 2011). The ILUTE is an agent-based platform system, which is designed to forecast and project the growth of demographics, land use and travel behavior for any given urban region over time (Chingcuanco and Miller 2012).

From previous examples, the hybrid-integrated models represent households and other non-residential uses (the agents), simulate their decisions, convert these decisions to their respective energy demands, and draw the projections of energy consumption of an urban region.

Hybrid-integrated models have strengths and weaknesses; the major advantages that these models combine top-down and bottom-up methods, capture the socio-economic macro and technological end-user variables. On the other hand, the practical implementation of hybrid models depends on the objectives. The implementation of hybrid approach is mostly data-driven, which requires a lot of computational skills, large data-samples, and resources (Lith et al. 2002; Bhattacharyya and Timilsina 2009). The study will apply the hybrid-integrated approach, which is more appropriate and comprehensive to achieve the research objectives.

CHAPTER 4: INTEGRATED PLANNING SUPPORT SYSTEM DESIGN

4.1. Methodology

This section introduces the research methodology. In addition, the section demonstrates the design of the proposed Housing Energy-Demand model, and it will be integrated with a comprehensive urban model called the Charlotte Land Use and Economic Simulator (CLUES). The construction and the specifications of the proposed model will be introduced.

Figure 26 shows the research methodology modules, processes, and the structure of the developed integrated PSS that entails four components: (1) the scenario builder, (2) the CLUES simulator, (3) the developed eCLUES extension, and (4) the geo-database storage.

The scenario builder is an interface toolbox that allows the user to choose different “What-if” scenarios based on various perspectives. Each perspective presents a certain policy situation and its possible implications on household energy consumption. The scenario builder consists of four major perspectives, the Urban Geometry, the Green Technologies, the Environmental Implications, and the Macroscopic Energy trends. The variety exhibited by the perspectives provides decision makers with great flexibility to design different “What-if” scenarios. Each perspective is a collection of “What-if” scenarios that have similar policy trends. Each scenario has different impacts on the CLUES simulator or the developed energy module (eCLUES). Once the policy perspective is provided through the scenario builder, the data input flows to two modules namely the CLUES simulator and the eCLUES extension. These three modules form the structure of the operational disaggregated model.

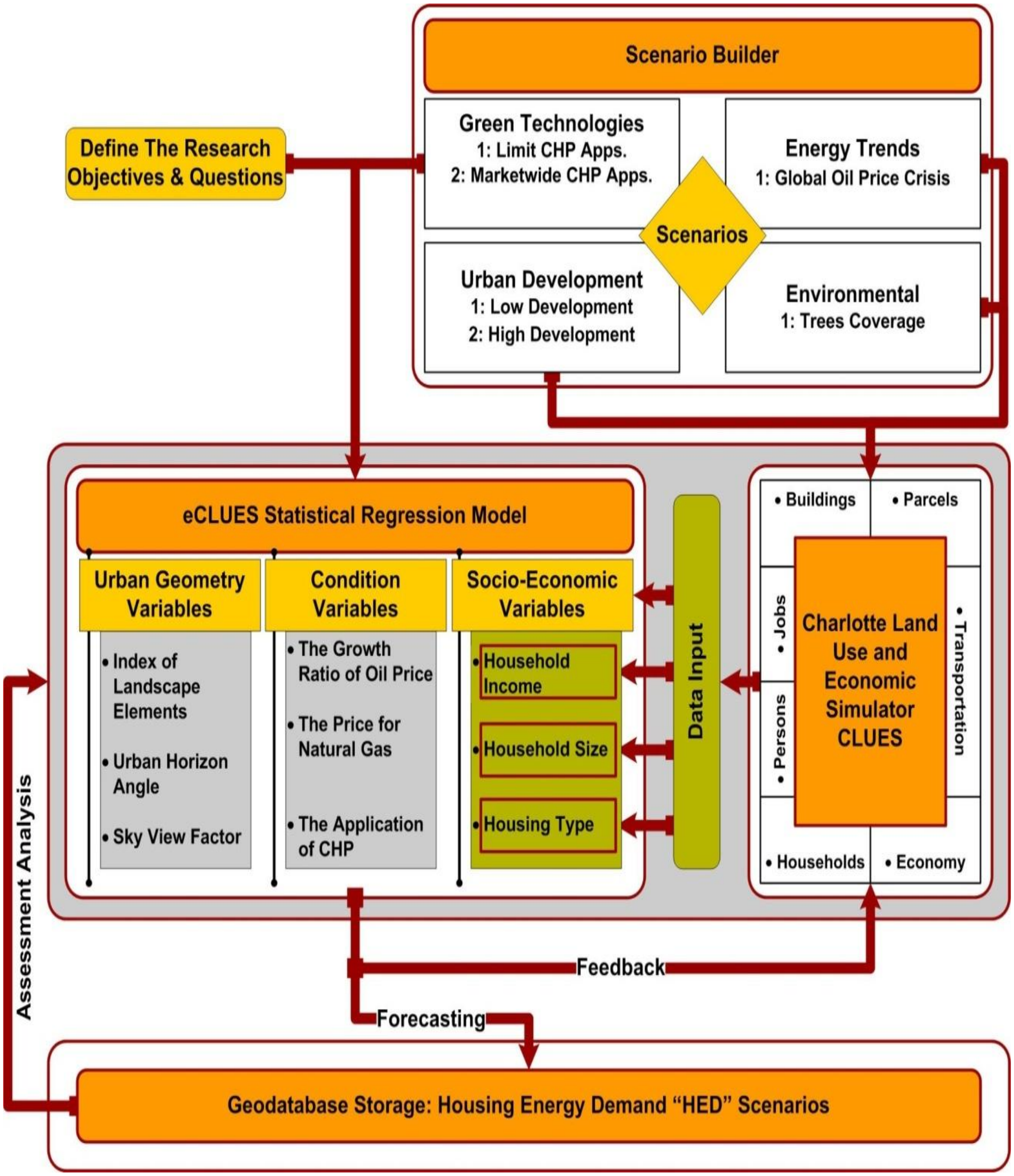

Figure 26: The research methodology and the integrated PSS.

The CLUES module is a simulation system that incorporates the interactions between land use, transportation, and the economy. The module predicts urban development and the characteristics of residential and non-residential land uses. Results generated by the CLUES simulator are fed into the eCLUES module with the socio-economic variables, the income, household size, and housing type.

The eCLUES module is the tool in the integrated PSS that forecasts residential energy consumption at the household level. The module has two components, the empirical model to predict annual residential energy consumption, and an interface that allows the user to assign the independent variables. If the user has a valid statistical HED model, it can used to apply a new desired policy. The units of energy forecasts are in British thermal units (Btu).

The geo-database storage is the last component that contains all the forecasting and analyses outputs in tabular and spatial formats. The outputs of the forecasting process are the annual residential energy consumption at the household level starting from the year 2008 to 2037. For each energy scenario, the user can perform a sensitivity analysis to assess the significance of the geometry and socio-economic characteristics of housing patterns on energy consumption by varying the values of each parameter in the eCLUES module. In addition, the user assesses the effects of energy costs under various scenarios on the social equity for predefined population groups, which is known as energy poverty.

4.2. Model Design

The design scheme of the operational model is composed of the scenario builder, the Charlotte Land Use and Economic Simulator (CLUES) and the developed housing energy demand model (eCLUES) as shown in Figure 27. The scenario builder is an interface that allows the user to customize various "What-if" energy scenarios. The user modifies only the condition parameters to introduce certain events that are anticipated to have an impact on residential energy demand. For instance, the user can establish CHP applications for a specific social group or the whole community.

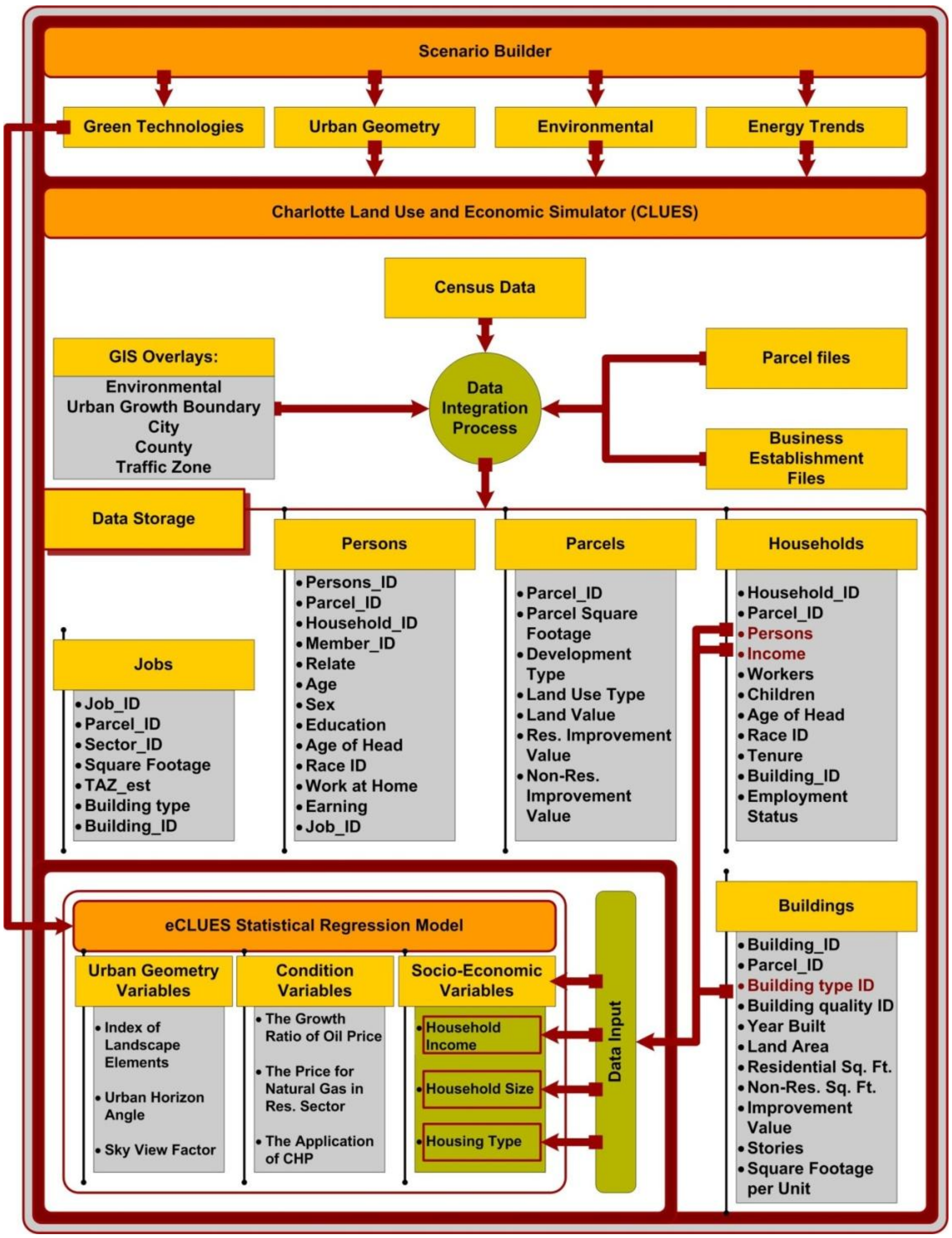

Figure 27: The operational disaggregated model.

The eCLUES extension forecasts residential energy demand under certain scenarios at multiple geographic scales. The study predicts the energy consumption at the household units, and then the outputs are aggregated to suitable levels of geographic granularity, namely traffic analysis zones (TAZ). The eCLUES extension retrieves the socio-economic and housing variables from the CLUES simulator, such as income and household size.

The CLUES model is a customized suite of UrbanSim application, supplemented by the Charlotte Mecklenburg Long-term Economic Impact Scenarios Analysis model (CM-LEISA), and a transportation demand model. The CLUES model is an open source urban simulator model. It applies python scripting language because of its simplicity; in addition, python is an open source scripting language.

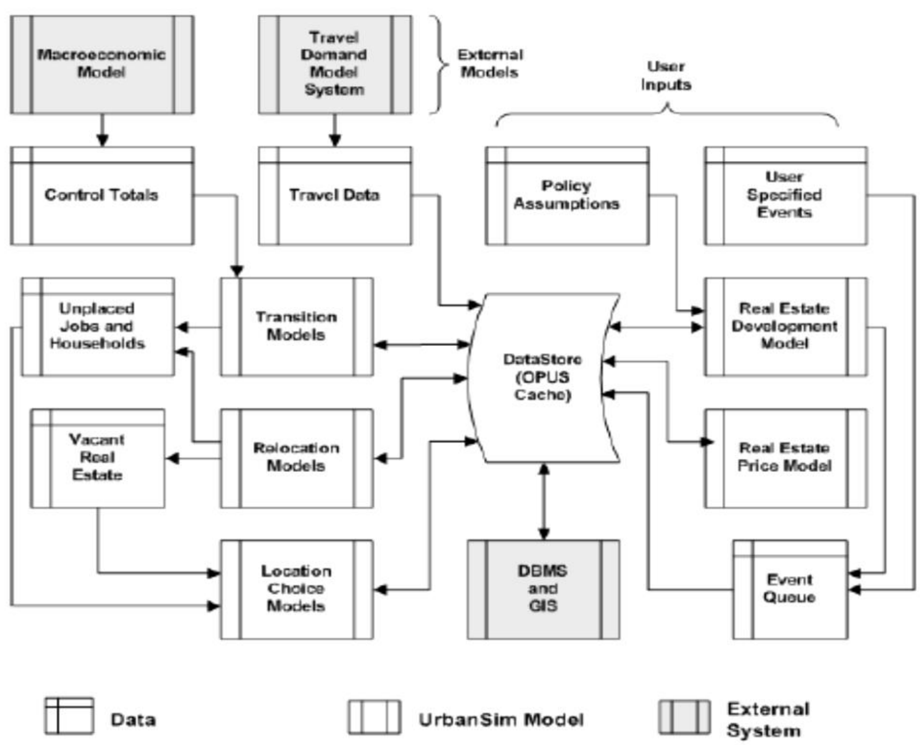

Figure 28: The Components and Data Flow in UrbanSim Model.
Source: Introduction to urban simulation: design and development of operational models (Waddell and Ulfarsson 2004).

UrbanSim aims to simulate land use and development types over periods ranging from less than 5 years to 30 years. Figure 28 presents the components and data flow of UrbanSim. The model consists of sub-models that perform different tasks to simulate household location choice, the demographic transition, the economic transition, employment location choice, land price, and travel demand choices. UrbanSim performs the simulation at the parcel level. The outcomes are stored in tabular data format (Waddell and Ulfarsson 2004).

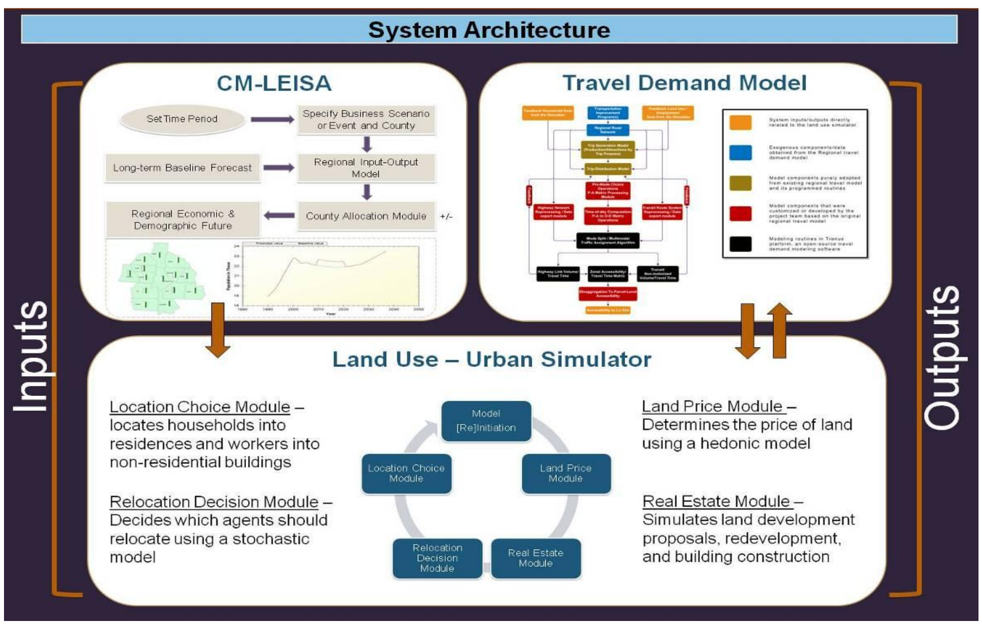

Figure 29: The components of CLUES simulator (CM-LEISA, and travel demand model).
Source: CLUES poster (Thill et al. 2011b).

Figure 29 shows the integration between CM-LEISA and the travel demand model. The Charlotte Mecklenburg Long-term Economic Impact Scenarios Analysis (CM-LEISA) predicts the future employment for the entire study area. In addition, the CM-LEISA model allocates jobs and economic activities (Thill et al. 2011a). The travel demand model produces an accessibility matrix to predict the travel behavior between the locations of residential and non-residential activities, jobs, and employments.

The CLUES simulator predicts the total population and other potential information, such as household size, and income. Afterwards, the model analyzes all population growth to redistribute the population over the housing market. Finally, it predicts development types, determines its characteristics, and forecasts residential and nonresidential square footage that would take place. Moreover, the CLUES simulator retrieves the demographic characteristics from the U.S. census data, such as income and housing type. It assumes that income and household type remain static unless the user defines the local demographic trends in the data inputs to CLUES before performing the simulation. The simulator classifies household units into three types (single – multi-family apartments – condominiums) and distributes the income groups into each residential (Waddell and Ulfarsson 2004). The Python language is used in the CLUES simulator, and will be used to model the eCLUES extension as well.

4.3. Model Specifications

4.3.1. Overall Structure

The statistical model is composed of three sets of independent variables; the first is the socio-economic set, which includes income, household size, housing type, and the residential square footage. The second is the spatial and urban geometry set, which includes the sky view factor, urban horizon angle, and the landscape coverage index. Finally, the condition variables are the application of green energy technology, the growth ratio of crude oil price, and the growth ratio of natural gas price. Residential energy consumption is calculated for each parcel based on the following statistical model:

$$\ln(E) = f[(\text{socio-economic variables set}), (\text{urban geometry variables set}), (\text{condition variables set})] \quad (14)$$

Where E is household energy consumption. Because the property dataset does not contain any energy consumption information and the RECS dataset has limited locational information, a multistep procedure is used to integrate these datasets. This is presented later in this section. Spatial/urban geometry variables and condition variables are discussed in the next two sections, in turn.

Since the property records dataset has no information on energy consumption, which is the dependent variable in the developed statistical model. It was attempted to obtain household energy consumption from the utility providers in the study area; however, this attempt was not successful because one of the utility providers (Duke Energy) did not release the information because of the confidentiality restrictions. The research attempted to collect a sample of residential customers in Mecklenburg County by conducting a survey to acquire information on household energy consumption. However, this idea was constrained by the sample size to present equitably all social groups and housing types in the study area, which required long time. Moreover, the confidentiality was required for the collected data.

After an intensive search, it was found that the U.S. Energy Information Administration (EIA) collected the RECS dataset in 2005 to report the information on household energy consumption, climatic zone, socio-economic, and housing characteristics. Therefore, the 2005 RECS dataset is used to retrieve household energy consumption for the study area. However, the RECS dataset does not report the location of respondents at the county or sub-county level. The survey manager of the RECS dataset was contacted to request the release of each respondent address, but the request was denied due to confidentiality restrictions. Hence, any RECS sample record that would be in the study area of Mecklenburg County cannot be identified and extracted from the complete RECS dataset.

Residential energy consumption profile for the study area is crucial to build the statistical HED forecasting model. The previous data limitations drive the research to choose between two methods to identify the information of household energy consumption. The first is to build a synthetic dataset from the scratch. However, there is no available information to build a consistent synthetic dataset and to achieve reliable results; therefore, this proposed solution is discarded.

The second method is to match the property records and the RECS datasets through some steps and assumptions. The aim of the matching process is to create a combined sample of the two datasets; the combined sample contains energy consumption for each residential parcel, which is the dependent variable. To match both datasets, a random sample is selected from the Mecklenburg County property records to be joined with the RECS dataset. The steps are presented as follows (Figure 30):

(1) First, it should be noted that Mecklenburg County is urbanized and located in the South climatic region of the United States. The climate conditions are one of the most factors influencing residential energy consumption. The observations are located in the same climatic zone share similar consumption pattern. Therefore, only RECS sample units that are located in urban areas and in the Southern region are retained for further use. The state of Florida is excluded because of its different climatic characteristics. The chosen sample has 719 out of the total of 4,383 RECS records.

(2) Identify the independent variables of housing characteristics (the square footage of the unit, and number of floors), and socio-economic (income, and household size) variables that are present in both the RECS dataset and the property records dataset. A set of over 170 thousands property records in Mecklenburg County shares the same characteristics of the independent variables mentioned above as the selected 719 records of the RECS sample.

(3) A sub-sample of 719 cases is selected from the 170 thousands property records and combined with the selected RECS sample on the basis of one to one relationship on the basis of the variables singled under point (2) above. This will enable us to account for the spatial and urban geometry factors that are not recorded in the RECS dataset.

(4) Once the combined sample is created, building height is retrieved from the property records to calculate SVF and UHA, which is explained in section 4.3.3. The SVF and UHA values are assigned to the combined sample of 719 records.

(5) Finally, an HED regression model is estimated based on the combined sample; the natural log value of energy consumption is the dependent variable, and it will be correlated with the socio-economic and housing characteristics, as well as, the assigned spatial variables as shown in Equation 15. The HED model is used in the operational disaggregated model to forecast residential energy demand.

$$\ln \mathrm{E} \quad = \mathrm{f}\,[\propto_1 \mathrm{v}_1 + \propto_2 \mathrm{v}_2 + \propto_3 \mathrm{v}_3 \ldots + \propto_\mathrm{m} \mathrm{v}_\mathrm{m}] \qquad (15)$$

Where E is household energy consumption from RECS data, v_1, v_2, v_3, and v_m are the independent variables present in the RECS dataset and the property records dataset that are mentioned in the second step. The RECS regression model is used to estimate energy consumption for the property records that match with the RECS sample.

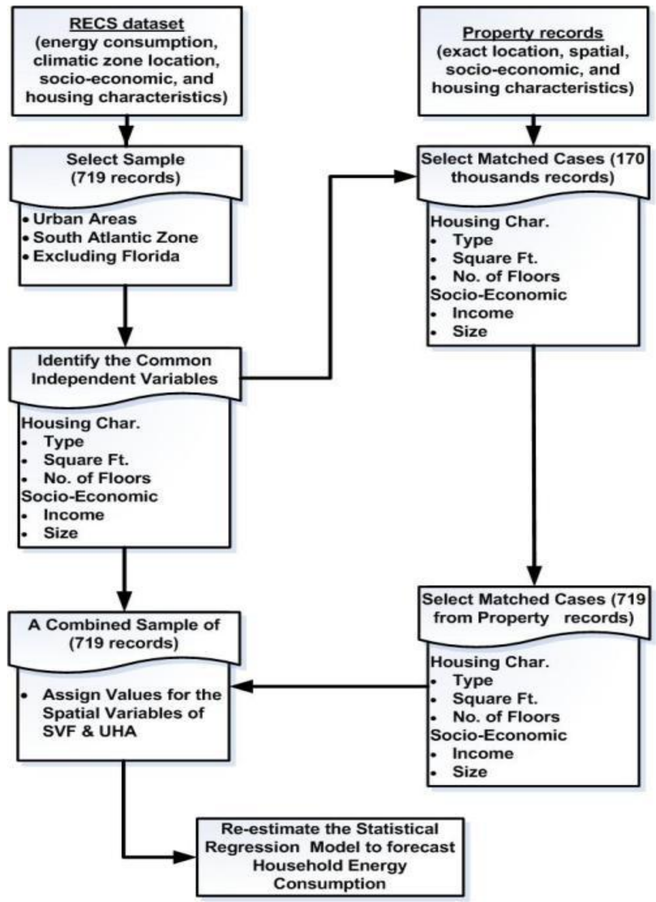

Figure 30: The matching process of the RECS dataset and the property records.

4.3.2. The Socio-Economic Variables Set

The forecasting HED model has four socio-economic variables, income, household size, housing type, and residential square footage. The four variables are retrieved from the data storage of the CLUES simulator, which contains the outputs of the simulation process as presented in the research methodology. The CLUES simulator retrieves income and population size of each household unit from the U.S. census, while it reclaims the housing type from the property records dataset of Mecklenburg County for the existing property records in 2008. The simulator assumes that these values are constants for each simulation year. Afterwards, the CLUES simulator forecasts the values of these socio-economic variables to be provided as data inputs for the followings years.

The CLUES simulator recognizes there housing types (single – multi-family apartments – condominiums). Forecasting energy consumption for single-family unit is straightforward because there is a one-to-one relationship between each household and housing unit and a property record. The eCLUES model sums the energy consumption of any condominiums or multi-family units that are located on the same parcel. The eCLUES extension categorizes household incomes based on the median income. Table 5 shows the annual median income of North Carolina in 2008 and the income group classifications. The U.S. Department of Housing and Urban Development defines low income as up to 80 percent of the median; middle income is between 80 and 120 percent of the median, and high income is more than 120 percent of the median (EPC 2008). It is important to mention that income in the RECS dataset and the property records is reported as a continuous variable.

Table 5: NC State median income and household income groups in 2008.

NC median income $	Low-income $ 80%	Middle-income $ 80-120%	High-income $ 120%
42930	34344 or less	34344 – 57516	57516 or more

Source: The 2009 Statistical Abstract of the United States: Income, Expenditures, Poverty, and Wealth (U.S. Census Bureau 2009).

The eCLUES extension creates various “What-if” statements that can be translated in the pseudo-code in python language as the followed example:

While socio-economic is true:

If Y = “high-income” and;

R = “3” and;

I = “owned single family 2000 sq ft”,

then ln(E) = “calculated value based on the model in Btu”

else if …

4.3.3. The Spatial and Urban Geometry Variables Set

Each variable in the spatial and urban geometry set is calculated through different methods. The first parameter is a reduction ratio for energy saving based on tree coverage percentage on the parcel. The reduction ratio varies between 8% energy saving for homes with 25% of tree coverage of the parcel land area, 5% for the units with 10%-25% of tree coverage, and 3% for the units with 10% or less of tree coverage. The existing percentage of tree coverage per each land parcel is retrieved from a raster data for land cover, which it is extracted from a satellite image of Mecklenburg County in 2006 with a spatial resolution of 30 by 30 meter for each cell. For new parcels, the tree coverage is calculated in two steps; the building footprint area is subtracted from the total new land area. Afterwards, an average value of the tree coverage is assigned for the subtraction result, which equals the total tree coverage for all surrounding parcels divided by their count number. The CLUES simulator predicts the future square footage of residential and non-residential land use. The methods discussed in section 3.4.1 are applied to forecast the other two urban geometry parameters for each parcel under each scenario (Urban Horizon Angle, and Sky View Factor) as followed:

$$\mathrm{UHA} = \tan^{-1}(\mathrm{H}/\mathrm{W}) \tag{16}$$

$$\beta = (\mathrm{H}/\mathrm{W}) \tag{17}$$

Therefore:

$$\mathrm{UHA} = \tan^{-1}(\beta) \tag{18}$$

$$\mathrm{SVF} = \cos^{2}(\beta) = \sin^{2}(\theta) \tag{19}$$

Where H is building height, W is the width between the façade and the shading elements, β is the sun's elevation angle, and θ is the sun's obstruction angle with the perpendicular axis.

The property record in the shapefile reports the exact height of each building as of 2008 up to 2.5 stories, while other heights are classified as three or more stories as one class. To identify the exact height for 3-stories or more buildings, 3D-Google maps were used to identify the exact height for most of the existing high-rise buildings. For new residential buildings, building height is estimated based on the story of the existing surroundings buildings, and the ratio of building square footage.

The solar obstruction angle changes on a daily basis for each building; for simplicity, the HED model applies the average solar obstruction angle of the study area of Mecklenburg County computed by the US Navy, which provides the altitude, and azimuth of the Sun angle for each location in the United States (The U.S. Navy 2012). Afterwards, the Urban Horizon Angle and Sky View Factor are computed through the eCLUES extension. The pseudo code for these variables is translated as followed:

While development is true:

If SVA = "high-rise apartments" and;

UHA = "±43.5º" and;

Landscape = "moderate tree shade 25%";

then ln(E) = "calculated value based on the model in Btu"

else if …

4.3.4. The Condition Variables Set

Three condition variables are anticipated to have significant impact on energy consumption. Each variable presents a certain event to be true or false. The first variable is the growth ratio of the price of crude oil on the basis of annual projections of the U.S. Energy Information Administration between 2009 till 2035. EIA (2011) predicted three projection scenarios for oil prices (high – reference – low) as shown in Figure 31. The HED model applies the high oil price projection in energy-crisis "What-if" scenario, as EIA (2011) forecasts that oil prices increase from 146$ in 2015 to 210$ in 2035 per barrel with an average increasing rate of 5.7 percent per year from 2008 to 2020 and 1.4 percent from 2020 to 2035. On the other hand, the reference oil price is applied in other "What-if" scenarios: the reference oil price case projects an annual increasing rate of approximately 0.7 percent from 2008 to 2020 and 1.4 percent from 2020 to 2035.

The second variable is the annual growth ratio of the residential price per therm for natural gas is also provided from EIA annual energy outlook report in 2011. The annual growth of natural gas price is linked with the annual growth of crude oil price; therefore, it has equivalent growth ratio with the target oil price projection case.

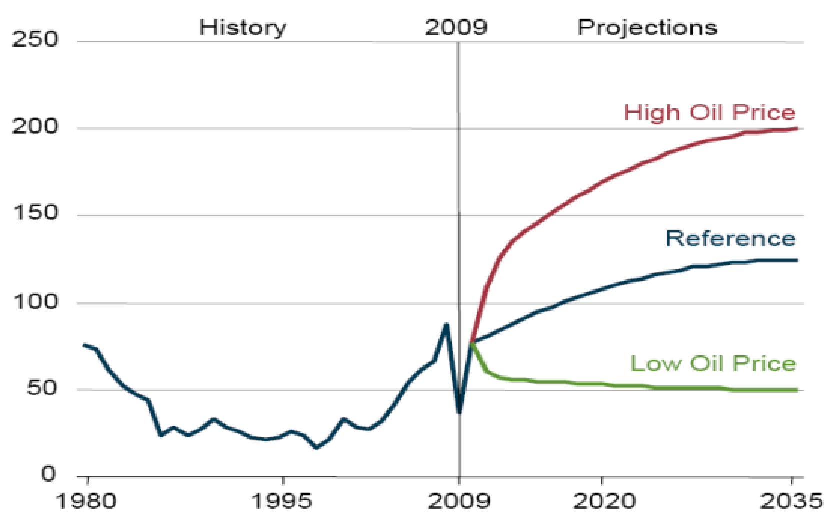

Figure 31: Average annual world oil prices in three cases during 1980-2035.
Source: Annual Energy Outlook 2010: With Projections to 2035 (EIA 2010a).

The third condition variable presents the implementation of Combined Heat Power. The contribution of the application of green technologies in energy conservation will be tested in the future HED scenarios. Based on the installation considerations in section 3.3.1.1, some assumptions will be developed to distribute the CHP units during the forecasting process. The first scenario assumes an implementation of the CHP units in certain housing types and income groups only; it will allocate the CHP units in the high-income groups that live in multi-family and condominiums units.

In the second scenario, the CHP technologies will be implemented marketwide at low cost in the mid-term and the whole study area will be served by the CHP technology. Therefore, contrary to the first scenario, the CHP units will be distributed in mid and low income groups that live in single-family, multi-family, and condominiums units after 10 years from the present. In other words, the usage of the CHP units will be available in single-family, multi-family, and condominiums units first to the high-income group, and after 10 years to mid and low income groups as well.

The eCLUES forecasting model is formulated as followed:

$$\ln(\mathrm{E}) = f[(\mathrm{Y}, \mathrm{R}, \mathrm{I}, \mathrm{A}), (\mathrm{L}, \mathrm{UHA}, \mathrm{SVF}), (\mathrm{CHP}, \mathrm{P} \propto, \mathrm{G} \propto)] \tag{20}$$

Where Y is the income per household, R is the household size, I is the housing type, and A is the residential square footage in the socio-economic set; L is the reduction energy ratio based on the tree coverage percentage in each parcel, UHA is the urban horizon angle of residential buildings, and SVF is the sky view factor in the spatial and urban geometry set; CHP is the utilization factor for green energy technology (Combined Heat and Power), P is the annual growth ratio of crude oil price, and G is the annual growth ratio of the residential price per therm for natural gas in the condition set. Where α is price elasticity for the correspondent energy source (crude oil or nature gas). Price elasticity is given from the report of Bernstein and Griffin (2006).

4.4. eCLUES Execution and The Forecasts Outcomes

The eCLUES extension runs in vector data format. The expected outputs are in tabular format. Afterwards, the tabular outputs are joined with the property records of Mecklenburg County to visualize the results in the form of thematic maps. The outputs of the forecasts are in tabular format to determine the effects of urban geometry parameters on residential energy demand.

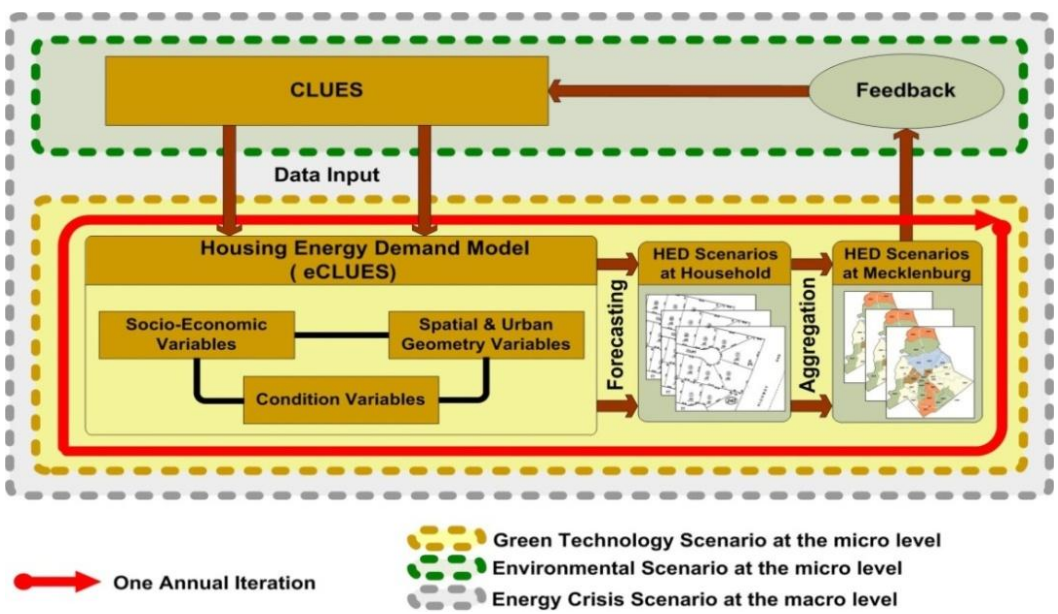

Figure 32: An operational framework for one iteration for the developed eCLUES model.

Figure 32 shows an operational framework for one annual iteration in the eCLUES model. The aim of the first forecasting iteration is to estimate the existing residential energy consumption for the base year for each housing unit. The eCLUES model forecasts future residential energy demand under each specific scenario in the study area during the 2008-2037 period. It is important to mention that the aim of the spatial planning model is to forecast a series of future HED scenarios; it is not meant to decide which scenario is the best solution.

The model allows the adoption of various perspectives of residential energy demand. The emphasis of the first group of perspectives is on urban geometry as a strategy to enhance energy savings, such as applying low or high urban densities. The second group of perspectives adopts the CHP applications of green technologies according to the two scenarios discussed in section 4.3.4. The third group of perspectives monitors the energy demand implications of residential landscapes; the applied scenario assesses the contribution of tree coverage in each property records to energy savings. Finally, the fourth group of perspectives simulates various perspectives under possible macroeconomic conditions consistent with an energy crisis leading to a spike in energy prices. Assuming great global volatility rate in oil price, this will affect the price of other fossil energy fuels, such as natural gas. It is expected that this solution will have macro impacts. Therefore, the eCLUES model will simulate the impacts of the worst situation in case we face an energy shortage at the national and the global levels.

The forecasts outputs of the first year will feedback in the CLUES simulator to predict the transportation, employment, and the housing development for the following year. Afterwards new development values will be derived from CLUES to forecast the following year.

The toolbox of the eCLUES model is developed using Arcpython programming language, which is under the application suite of ArcGIS v10 as shown in Figure 33. Each scenario in the toolbox is customizable. Any text editor can be used to write or modify the code for any provided scenario with programming experience at a beginner level. In addition, the toolbox provides an optional customized What-if scenario according to the user interest.

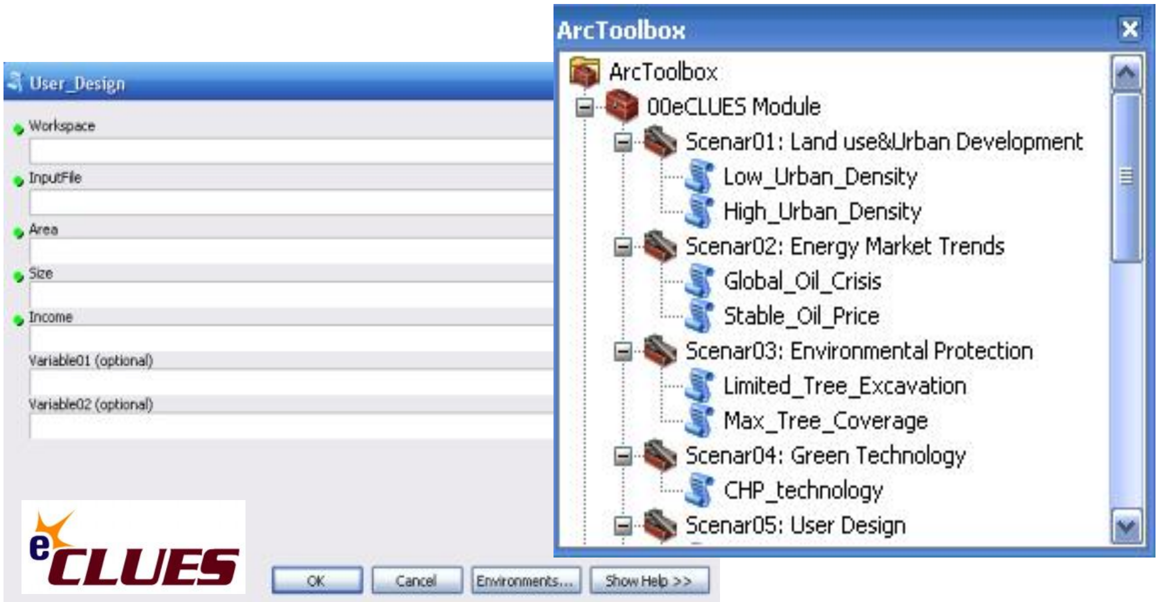

Figure 33: The toolbox of eCLUES module.

The research also has three other objectives to assess the contribution of various factors for the forecasts of household energy consumption. The following chapter will demonstrate the results of the last three objectives.

CHAPTER 5: FORECASTING RESULTS

5.1. Sample Preparation

Data sample preparation is an important step for building the HED regression model; the quality of the sample affects the reliability of the developed energy demand model and its forecasts. After the matching process of the two data sets and developing the regression model as mentioned in section 4.3, it is important to test if the combined sample of 719 records is randomly selected and there is no clustering that could bias regression results.

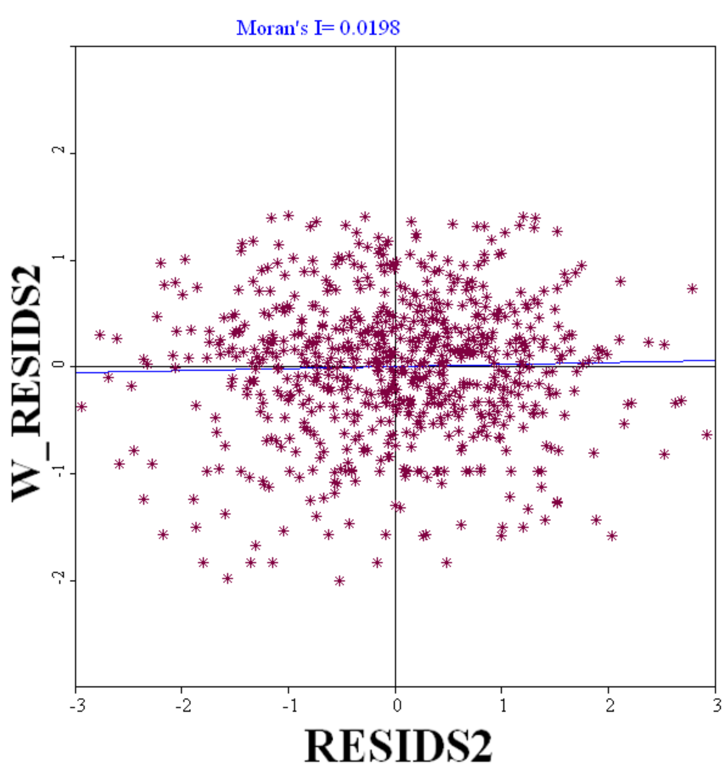

Figure 34: Spatial autocorrelation Moran's I of the residuals.

Figure 34 shows that the Moran's I statistic for the residuals generated by the developed regression model equals 0.0198; it is significant at 5%, this indicates a random spatial pattern of the residuals. In addition, the spatial distribution of the sample indicates no clustering between the residuals in the sample that could affect the prediction process as demonstrated in Figure 35.

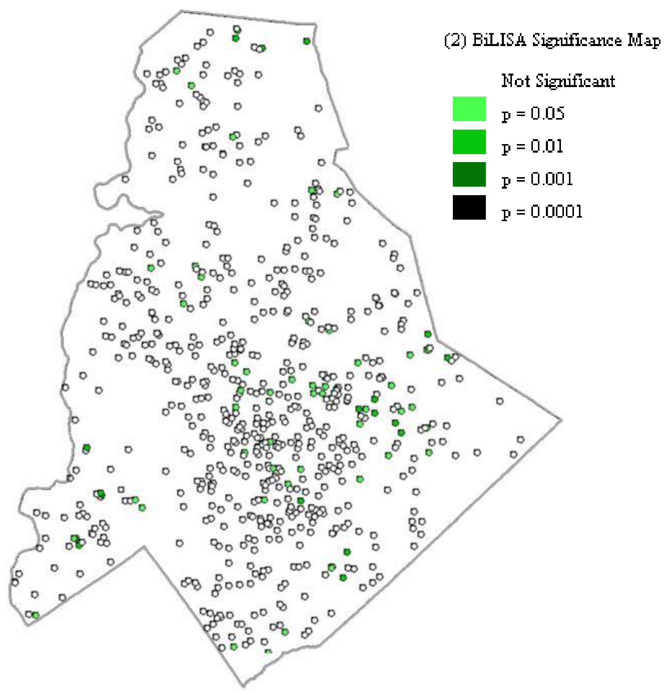

Figure 35: A significance map of the residuals of the transformed log values of household energy consumption.

The first HED model uses the untransformed values of energy consumption in KBtu. The coefficient of determination (R-square) equals 0.378, which indicates that about 38 percent of the variance is explained by the independent variables as shown in Table 6. Inspection of residuals reveals the presence of heteroskedasticity. A natural log transform of the values of energy consumption is used instead to restore homoskedasticity. The new coefficient of determination of the transformed log equals

0.4437, which enhances the prediction by almost 7 percent about the regression on the untransformed values as shown in Table 7.

Table 6: The HED regression model of energy consumption (KBtu).

Model	R	R Square	Adjusted R Square	F Stat.	F Signif.	Durbin-Watson Test
1	0.615	0.378	0.372	61.778	0.0001	0.288

Table 7: The transformed HED regression model of natural log of energy consumption (KBtu).

Model	R	R Square	Adjusted R Square	F Stat.	F Signif.	Durbin-Watson Test
2	0.666	0.4437	0.438	80.551	0.0001	0.002

The variance inflation factor (VIF) test is performed to determine if the predictors in the regression are highly correlated or not. All predictors score a VIF value less than 5, which indicates no multicollinearity problem as shown in Table 8. The scatter plot of standardized residuals, in the transformed regression, falls within ±3 of the standard deviation, which demonstrates no skewness in the distribution of the residuals as shown in Figure 36.

Table 8: Parameter estimates and multicollinearity test for the predictors.

Dependent Variable: logKBTU	Unstandardized Coefficients		Standardized Coefficients	Collinearity Statistics	
	B	Std. Error	Beta	Tolerance	VIF
(Constant)	11.202	0.152			
Annual_inc	0.002	0.001	0.109	0.693	1.444
SqFtperHH	0.077	0.012	0.217	0.675	1.482
SnglFam_du	0.562	0.056	0.388	0.520	1.923
Condo_dummy	-0.277	0.105	-0.084	0.761	1.315
HH_01	-0.426	0.057	-0.334	0.387	2.585
HH_02_04	-0.125	0.050	-0.110	0.411	2.435
SVF	-0.505	0.185	-0.105	0.532	1.881

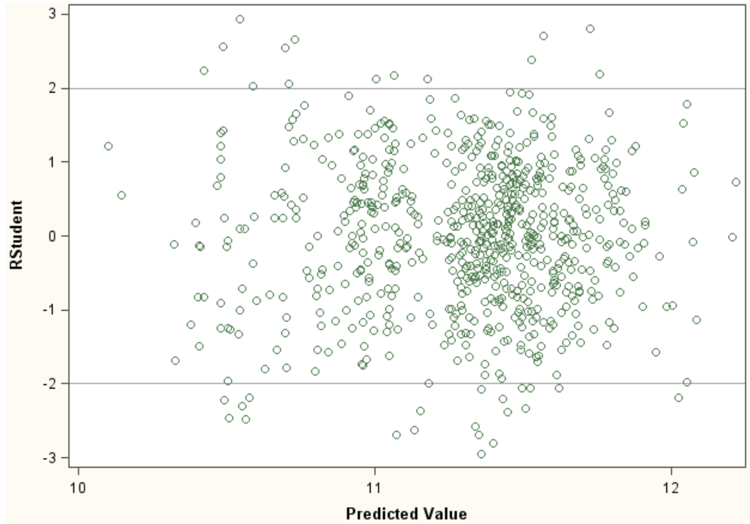

Figure 36: The scatter plot of standardized residuals versus predicted values.

Table 9 reports on the significance of all independent variables; the spatial variable Sky View Factor (SVF) is negatively significant at 0.6% with a t-value equal to -2.731. The negative significance is consistent with the literature findings in the negative significance of SVF. Urban Horizon Angle is omitted in the final specification of the model because it is highly correlated with SVF; hence, it can be concluded that UHA is positively associated with household energy consumption. Housing characteristics are significant predictors. For household type, the dummy variable of single-family unit is highly positive, significant at 0.01% with a t-value equal to 10.002. The dummy variable of condo-unit is significant; however, it is less than single-family with a t-value equal to -2.362 and significant at 0.9%. Residential square footage is positively significant at 0.01% with t-value equals 6.355. The socio-economic variables are significant. The income variable is positively significant at 0.1% with a t-value equal to 3.236. For household size, the dummy variable of unit with one person is negatively significant at 0.01% with a t-value equal to -7.431. The unit with two to four persons is negatively significant as well at 1.2% with a t-value equal to -2.522.

Table 9: t-value significance test for the independent variables.

	t-value	Sig.	95.0% Confidence Interval for B	
			Lower Bound	Upper Bound
Annual_inc	3.236	0.001	0.0001	0.0001
SqFtperHH	6.355	0.0001	0.0001	0.0001
SnglFam_du	10.002	0.0001	0.452	0.672
Condo_dummy	-2.632	0.009	-0.484	-0.070
HH_01	-7.431	0.0001	-0.538	-0.313
HH_02_04	-2.522	0.012	-0.223	-0.028
SVF	-2.731	0.006	-0.867	-0.142

To accomplish the third and fourth objectives, the following sections present a comprehensive assessment for energy demand forecasts at multiple scales through various “What-if” policy scenarios. The first measurement is total energy demand per TAZ to provide the assessment at the macro level. The second measurement is at the micro level, which is the average household energy demand in TAZs; it is used to track the influences of housing characteristics on energy consumption over time. The third measurement is also at the micro level, which is the average energy demand per capita in TAZs. It is very similar to the second measurement, but it is used to identify which socio-economic groups benefit from energy savings or involve in increasing energy consumption over time.

There are three main types of built-up urban forms in Mecklenburg County. The first is dense compact, which is located around the center of Charlotte and the area around it. The second is the low density built-up form, which is located in the suburbs. The third is the mixed land use built-up form, which is mainly located in the spheres of influences of each town in Mecklenburg County (section 2.3.1).

5.2. The Neutral Scenario

The aim of this scenario is to forecast energy consumption without applying any policy, or application. It uses the inputs from the CLUES simulator, where the annual population growth rate of 2.7 percent according to the U.S. 2011 census, and simply extrapolated current trends through the 2037 horizon. The neutral scenario is used as a comparative reference for the assessment process for the designed scenarios. The HED model for the neutral scenario is shown as followed:

$$\ln(\mathrm{E}) = 11.202 + (\mathrm{income}_{\mathrm{HH}} * 0.002) + (\mathrm{Square\ Ft.}_{\mathrm{HH}} * 0.077) + \left(\mathrm{SingleFam}_{\mathrm{dummy}} * 0.562\right) + \left(\mathrm{Condo}_{\mathrm{dummy}} * -0.277\right) + \left(\mathrm{HH}_{01\mathrm{dummy}} * -0.426\right) + \left(\mathrm{HH}_{0204\mathrm{dummy}} * -0.125\right) + (\mathrm{SVF} * -0.505) \quad (21)$$

$$(\mathrm{HED}_{\mathrm{neutral}})_{\mathrm{n}} = \ln(\mathrm{E}) * (1 - \mathrm{P}\alpha) * (1 - \mathrm{G}\alpha) * (1 - \mathrm{L}) \quad (22)$$

Where:

n = the annual population growth as rate of 2.7 percent,

P = the annual growth ratio of crude oil price as a rate of 0.7 percent from 2008 to 2020 and 1.4 percent from 2020 to 2035,

G = the annual growth ratio of natural gas price in the residential sector as a rate of 0.7 percent from 2008 to 2020 and 1.4 percent from 2020 to 2035,

L = the reduction energy ratio based on the tree coverage percentage as a rate of 3 percent if the tree coverage is 10 percent of less and as a rate of 5 percent if the tree coverage is 10 to 25 percent of the land parcel area,

α = price elasticity for the study area at North Carolina State level as rate of –0.31 percent, which is given from the report of Bernstein and Griffin (2006).

In the neutral scenario, total energy consumption per TAZ increases during the period 2008-2037 with an average annual rate of 1.52 percent. Most of the demand growth is concentrated the northern side of Mecklenburg County, specifically, Cornelius and Huntersville; there is also a concentration in Matthews and southern suburbs of

Charlotte as shown in Figure 37. The average household energy consumption equals 52,543 KBtu in 2010, and it declines to reach 50,183 KBtu in 2035. As time goes on, forecasted household energy consumption notably decreases by an average annual rate of 3.3 percent. Figure 38 demonstrates that northern areas have the highest reduction rate in household energy consumption in TAZs. The average forecasted energy consumption per capita is almost around 22,418 KBtu in 2010, and it declines to reach 20,183 KBtu in 2035. It decreases by an annual rate of 3.1 percent. The reduction is mainly at the borders of the county in Davidson in the northeast, and can also be noticed in the far southwest of Charlotte and a few areas in Matthews as shown in Figure 39.

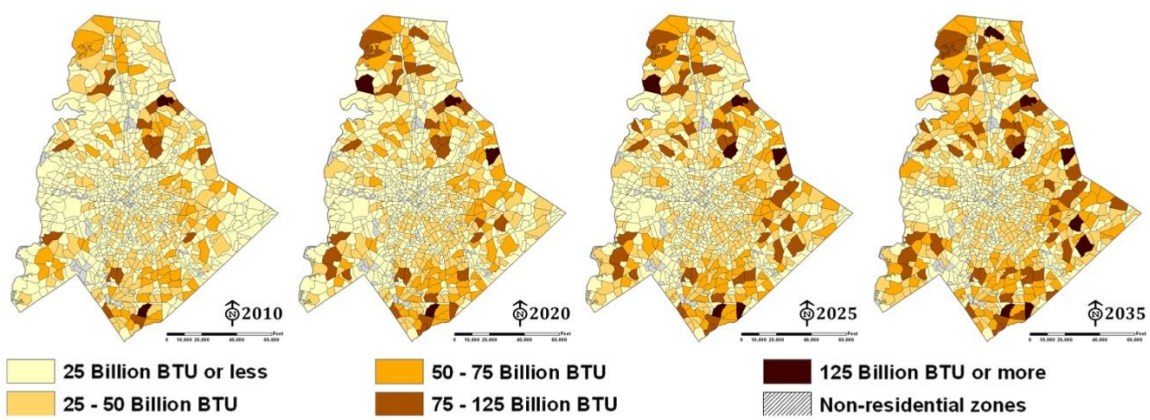

Figure 37: Total forecasted energy demand in TAZs (the neutral scenario).

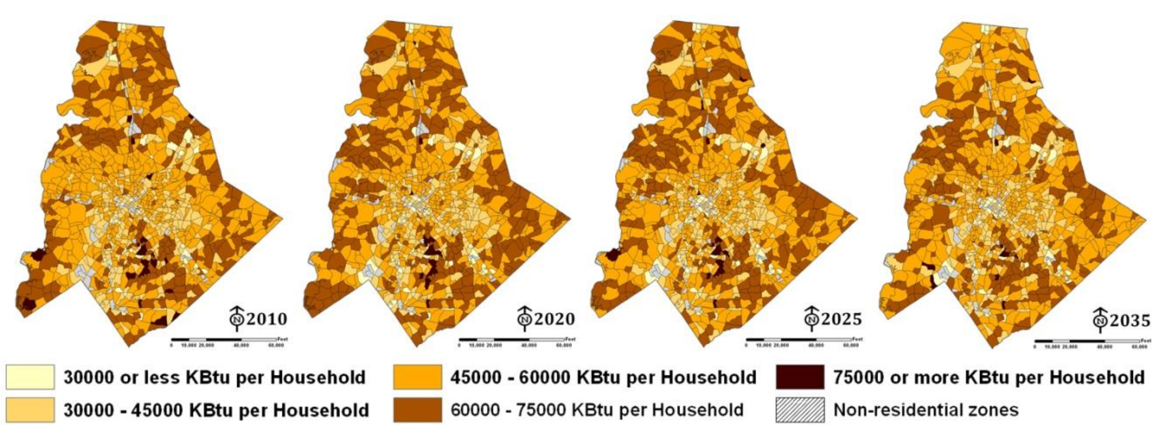

Figure 38: Forecasted household energy consumption in TAZs (the neutral scenario).

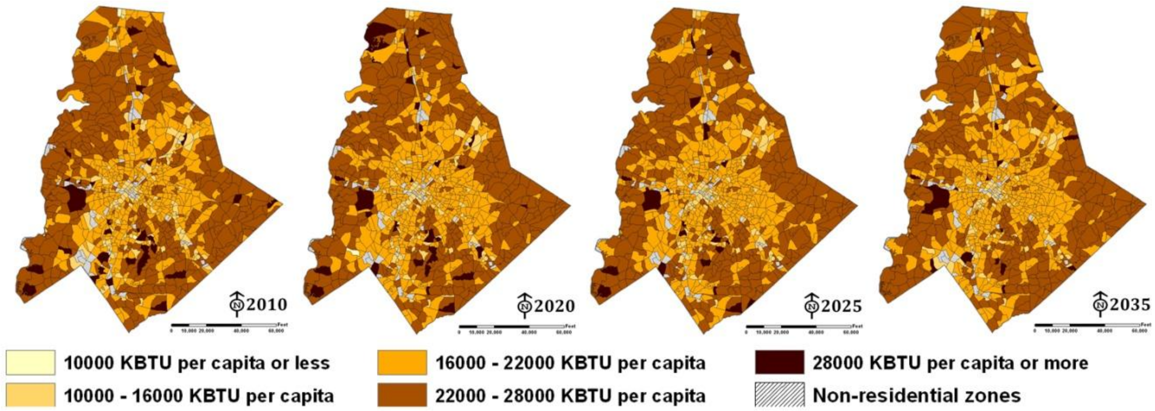

Figure 39: Forecasted energy consumption per capita in TAZs (the neutral scenario).

Even though total energy demand per TAZ increases over time, the two micro measurements indicate drops in energy demand per household and per capita levels. The declines are mainly concentrated in the northern and southern low-density suburbs. By looking at the changes in the population growth in Mecklenburg County from 2000 to 2010, the highest population growth rate occurs in these suburbs, and it is higher than the average growth rate of Mecklenburg County as shown in Figure 40.

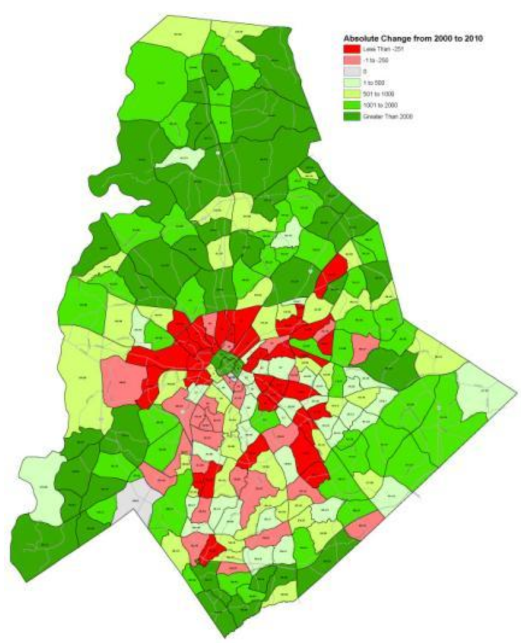

Figure 40: Absolute population change in Mecklenburg County from 2000 to 2010.
Source: Charlotte-Mecklenburg Planning Department (charmeck 2011).

In addition, high-income groups mainly live in these areas, where household square footage is higher than other areas in Mecklenburg County. Therefore, average energy demand per household and per capita over time reflects mainly the relative declines in the low-density suburbs. On the other hand, the population growth decreases in the central dense areas, and the growth rates in these areas are lower than the county average.

Table 10: The parameterization of "What-if" policy scenarios.

Scenario Parameterization	Annual Population Growth Rate	Energy Prices Projections	Tree Plantation Regulations	Target Social Groups
Neutral Scenario	2.70% in CLUES	D.O.E. Reference Oil Prices Scenario	Tree Coverage is 10% or less Tree Coverage is 10-25%	All Social Groups
Low Urban Development	1.80% in CLUES	D.O.E. Reference Oil Prices Scenario	Tree Coverage is 10% or less Tree Coverage is 10-25%	All Social Groups
High Urban Development	3.60% in CLUES	D.O.E. Reference Oil Prices Scenario	Tree Coverage is 10% or less Tree Coverage is 10-25%	All Social Groups
Energy Crisis	2.70% in CLUES	D.O.E. High Oil Prices Scenario	Tree Coverage is 10% or less Tree Coverage is 10-25%	All Social Groups
Tree Coverage	2.70% in CLUES	D.O.E. Reference Oil Prices Scenario	Maximizing Tree Coverage to 25% or more of the Property Area	All Social Groups
Limited CHP	2.70% in CLUES	D.O.E. Reference Oil Prices Scenario	Tree Coverage is 10% or less Tree Coverage is 10-25%	High-income Groups
Market-wide CHP	2.70% in CLUES	D.O.E. Reference Oil Prices Scenario	Tree Coverage is 10% or less Tree Coverage is 10-25%	All Social Groups

The assessment procedures are performed for the following "What-if" scenarios; each policy has a unique parameterization as shown in Table 10. The assessment of the forecasts demonstrates energy savings or increasing in energy demand at multiple scales (TAZ, household, and capita) in relative percentage values to the neutral scenario.

5.3. Urban Development Scenarios

Urban development scenarios assess various population growth rates and their implications on the development in Mecklenburg County. The low urban development scenario assumes a decrease in the population growth by an annual rate of 1.8 percent. Total energy consumption per TAZ slowly increases during the period 2008-2037 with average annual ratio equals to 1.72 percent. Most of energy savings are concentrated in the suburbs of Cornelius and Davidson in the northern part of the county, and the suburbs of Mint Hill and other southern suburbs of Charlotte as shown in Figure 41. The parameterization changes in the two HED models for urban scenarios are shown as followed:

$$(\mathrm{HED}_{\mathrm{LowDev}})_{\mathrm{n_{low}}} = \ln(\mathrm{E}) * (1 - \mathrm{P}\alpha) * (1 - \mathrm{G}\alpha) * (1 - \mathrm{L}) \qquad (23)$$

$$(\mathrm{HED}_{\mathrm{HighDev}})_{\mathrm{n_{high}}} = \ln(\mathrm{E}) * (1 - \mathrm{P}\alpha) * (1 - \mathrm{G}\alpha) * (1 - \mathrm{L}) \qquad (24)$$

Where:

n_{low} = the annual population growth as rate of 1.8 percent,

n_{high} = the annual population growth as rate of 3.6 percent.

The high urban development scenario examines what if the population growth increases more rapidly than projected, and it tracks the implications on the housing development and the economic growth in Mecklenburg County. Total forecasted energy demand in TAZs increases during the period 2008-2037 by an annual rate equal to 3.82 percent countywide. The major observation is the distribution of energy savings is reversed, maximum energy savings are located in mixed uses built-up forms in the spheres of influence. On the other hand, the main increase in energy demand is traced in the suburbs that achieve highest savings in the previous low development scenario as shown in Figure 42.

By observing the distribution of household type from 2000 to 2010 in Mecklenburg County, the highest growth of single-family units is located in northern and southern suburbs as shown in Figure 43. This explains the forecasting results of the two scenarios at TAZ level in relation with the HED regression model, where single family is the most significant independent variable. In addition, high-income groups are mostly located in these suburbs; these social groups usually tend to live in single-family units. The low and high development scenarios tend to decline or increase the growth of high-income groups in these suburbs, respectively. Moreover, the percentage of the tree coverage declines more in the high development, which leads to increase in the carbon footprint larger than in the low development scenario.

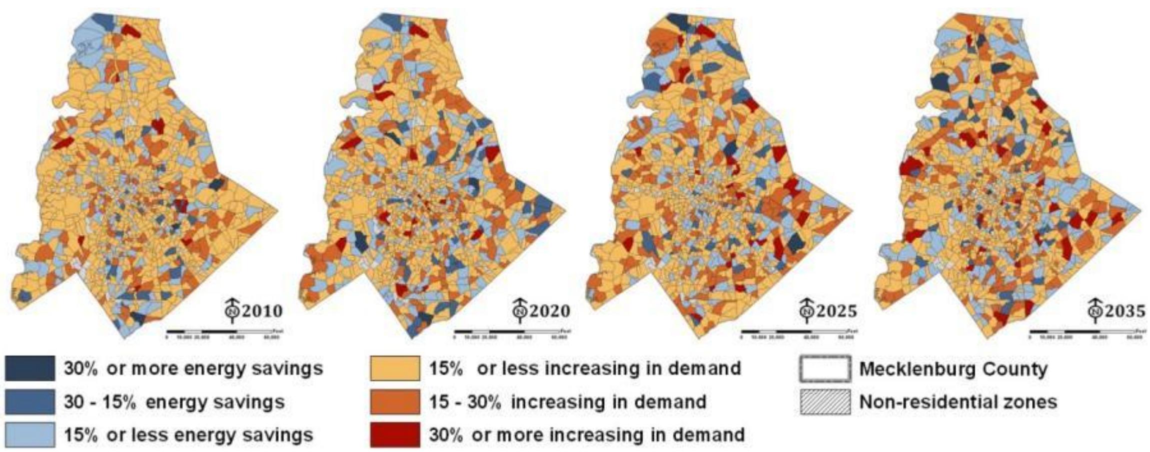

Figure 41: Total forecasted energy demand in TAZs (low urban development).

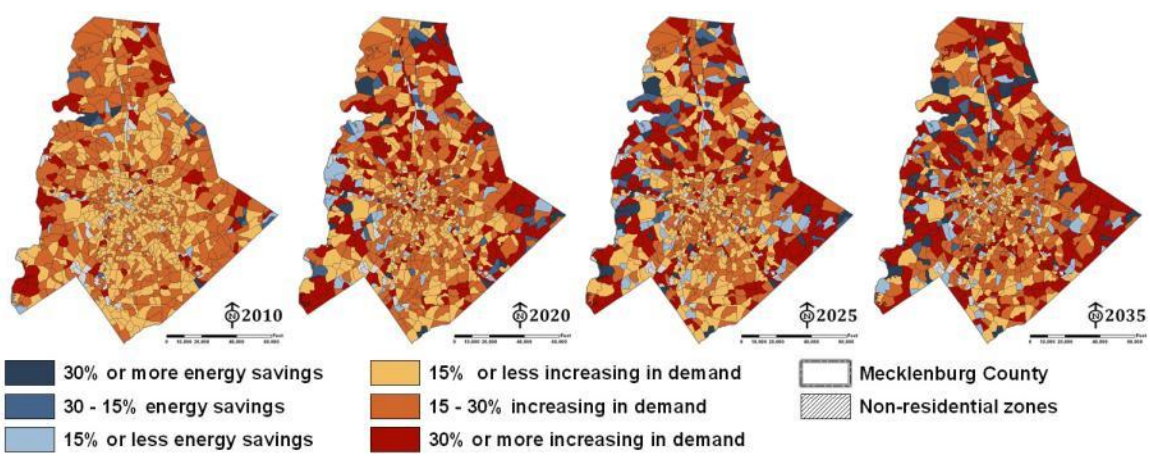

Figure 42: Total forecasted energy demand in TAZs (high urban development).

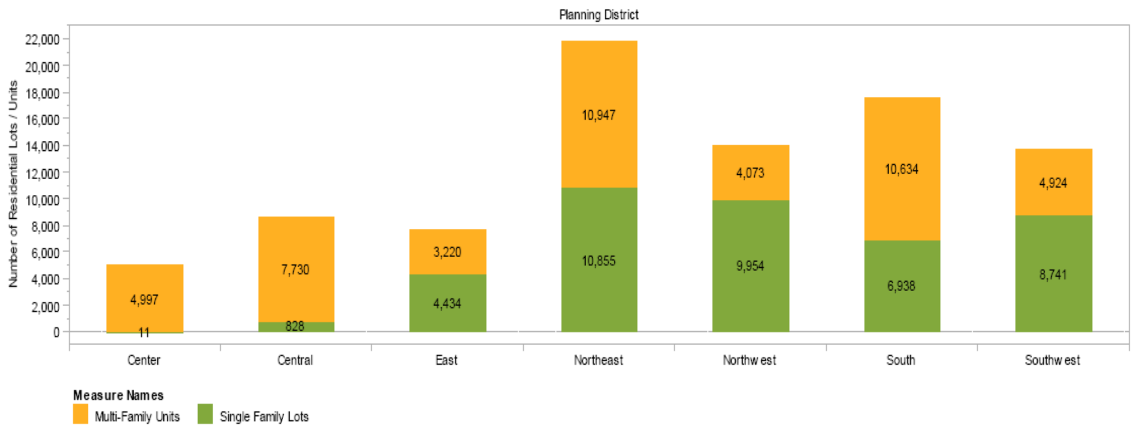

Figure 43: Approved residential units by Planning Department from 2000 to 2010. Source: Charlotte-Mecklenburg Planning Department (charmeck 2011).

The previous measurement examines the policy implications at the TAZ macro level. To provide a comprehensive assessment for the decision makers, two micro measurements are used to assess the consequences at the household and capita levels, respectively.

The most interesting observation in Figure 44 and Figure 45 is that the spatial patterns in low development demonstrate larger average household energy demand than the high development scenario over time. In both scenarios, most of the increase in household energy demand is found in the northern suburbs of Cornelius and Davidson, and the suburbs of Mint Hill and other southern suburbs of Charlotte. Another major observation is that mixed-use built-up forms achieve maximum household energy savings, specifically at the spheres of the influences along road I-485. Households in the central compact form achieve the second highest energy savings over time in both urban scenarios.

By monitoring the changes in the population growth from 2000 to 2010, the highest growth rate occurs in the northern and the southern suburbs, and it decreases in the mixed uses and the central compact areas. Therefore, average household size relatively decreases in the low development, while it increases in the high development scenario. In the HED regression model, the two independent variables of household size are negatively significant with energy consumption.

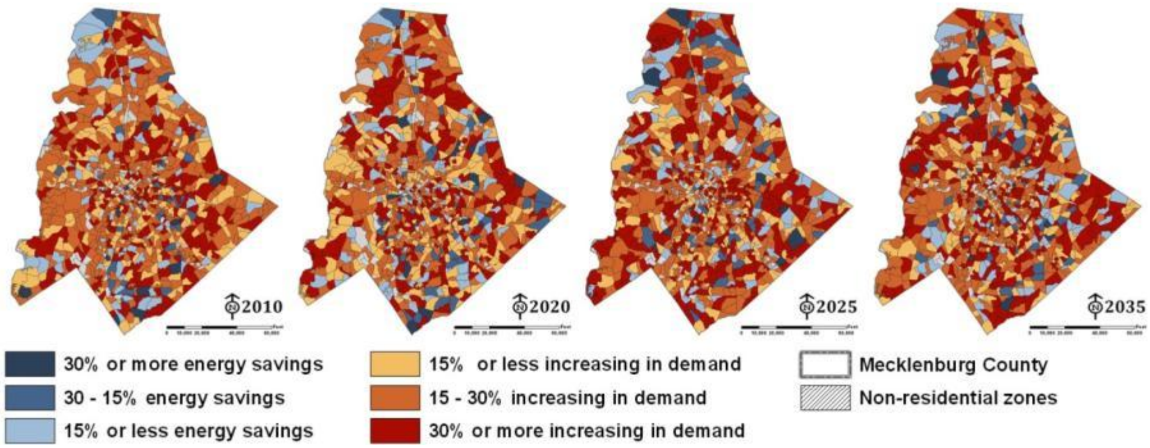

Figure 44: Forecasted household energy consumption in TAZs (low urban development).

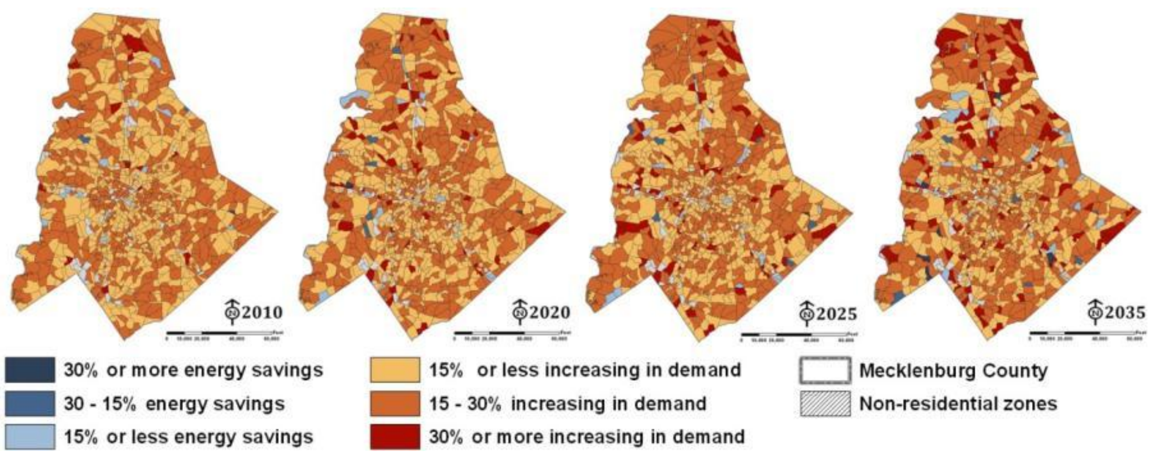

Figure 45: Forecasted household energy consumption in TAZs (high urban development).

The spatial patterns of average energy demand per capita are almost similar to energy consumption patterns at the household level for both urban scenarios as shown in Figure 46 and Figure 47. As time goes on, the largest energy savings occur in the population groups who live in mixed-use areas in the spheres of the influences along road

I-485. The new development in Mecklenburg is planned to be located in the spheres of influences, mainly, the west side of road I-485; therefore, the new households consume less energy than old buildings. In addition, social groups that live in the central compact areas gain the second savings in energy demand at capita level in both urban scenarios.

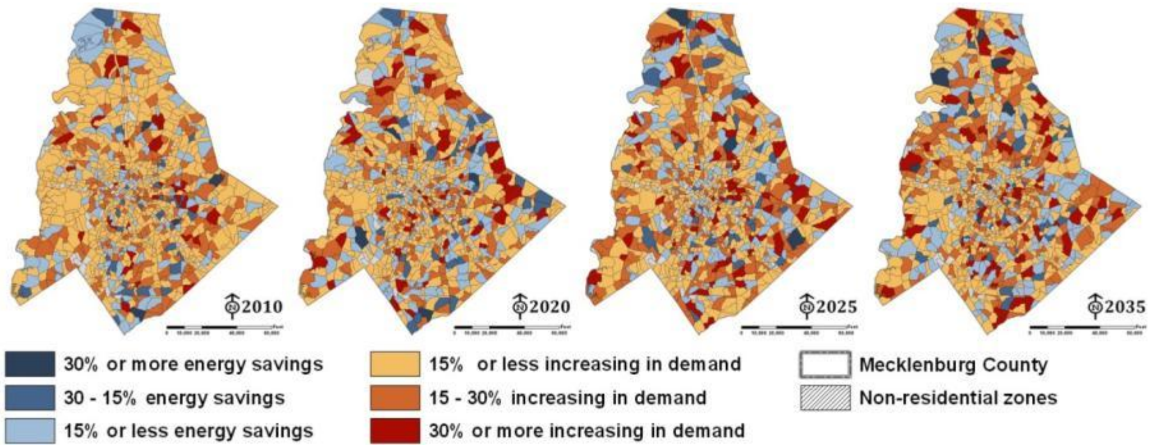

Figure 46: Forecasted energy consumption per capita in TAZs (low urban development).

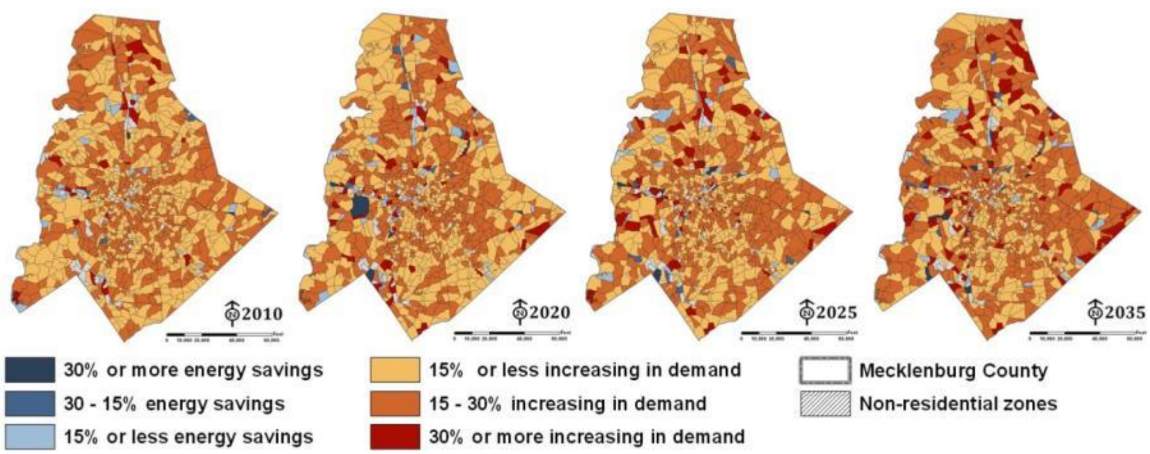

Figure 47: Forecasted energy consumption per capita in TAZs (high urban development).

The overall assessment for both urban scenarios indicates that the spatial patterns of the three measurements of energy consumption demonstrate distinct savings along the southern corridor of highway 77, the southern areas adjacent to corridor I-485 road, and in the east section of highway 85. As time continues, there is a high concentration of energy savings in the mixed uses built-up forms adjacent to the western side of corridor I-485. The suburbs in Cornelius and Davidson and the southern areas of Charlotte are subjected to the high increasing in energy demand over time; mainly because of these areas have the highest concentration of high-income groups and single-family units countywide. The high-density areas around the center of Charlotte experience a slightly consistent energy savings at the micro level.

5.4. Energy Trend Scenario

The purpose of this scenario is to observe the impacts of a global crisis in world oil prices, which increase residential energy prices in Mecklenburg County by 30 percent. Total energy consumption in TAZs increases by 2.53 percent annually.

The primary observation is that maximum energy savings at TAZ level are concentrated in the mixed-use urban forms and the high-density central areas as shown in Figure 48. On the other hand, the northern suburbs of Cornelius and Davidson, and the southern suburbs of Mint Hill and Matthews experience an increase in energy demand over time. The parameterization changes in the HED model for energy scenario are formulated as followed:

$$(\mathrm{HED}_{\mathrm{Energy}})_{\mathrm{n}} = \ln(\mathrm{E}) * \left(1 - \mathrm{P}_{\mathrm{high}}\alpha\right) * (1 - \mathrm{G}_{\mathrm{high}}\alpha) * (1 - \mathrm{L}) \qquad (25)$$

Where:

n = the annual population growth as rate of 2.7 percent,

P_{high} = the annual growth ratio of crude oil price as a rate of 5.7 percent from 2008 to 2020 and 1.4 percent from 2020 to 2035,

G_{high} = the annual growth ratio of natural gas price in the residential sector as a rate of 5.7 percent from 2008 to 2020 and 1.4 percent from 2020 to 2035,

α = price elasticity for the study area at North Carolina State level as rate of –0.31 percent, which is given from the report of Bernstein and Griffin (2006).

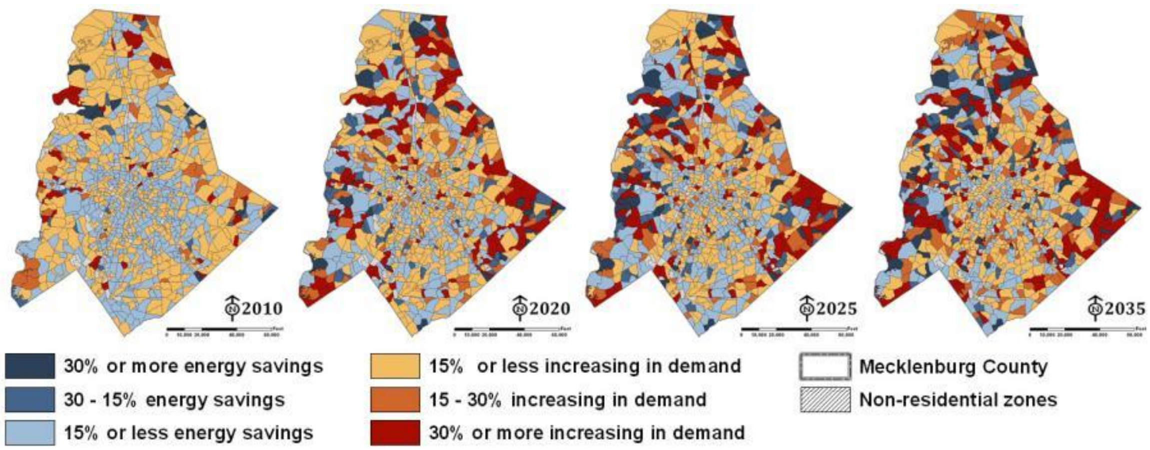

Figure 48: Total forecasted energy demand in TAZs (energy crisis trend).

The spatial distribution of forecasted energy consumption at household and capita levels demonstrates similar energy savings in the mixed-use and the central areas as shown in Figure 49 and Figure 50. The suburbs in the north and the south reveal a slight increasing in household energy demand compared with the forecasts at the TAZ level.

The overall assessment for the spatial distribution of energy trend scenario through the three measurements demonstrates distinct a high concentration of energy savings along the mixed uses built-up areas adjacent to corridor I-485 road, and the central areas. As time progresses, the northern and the southern suburbs experience a consistent energy increasing at the macro and the micro levels. On the other hands, the areas in the spheres of influences and the areas around the center of Charlotte experience a consistent energy savings at all scales. By overlaying the forecasts with the income profile for Mecklenburg County, it reveals that low and middle-income groups are more sensitive to energy prices than high-income groups as shown in Figure 51.

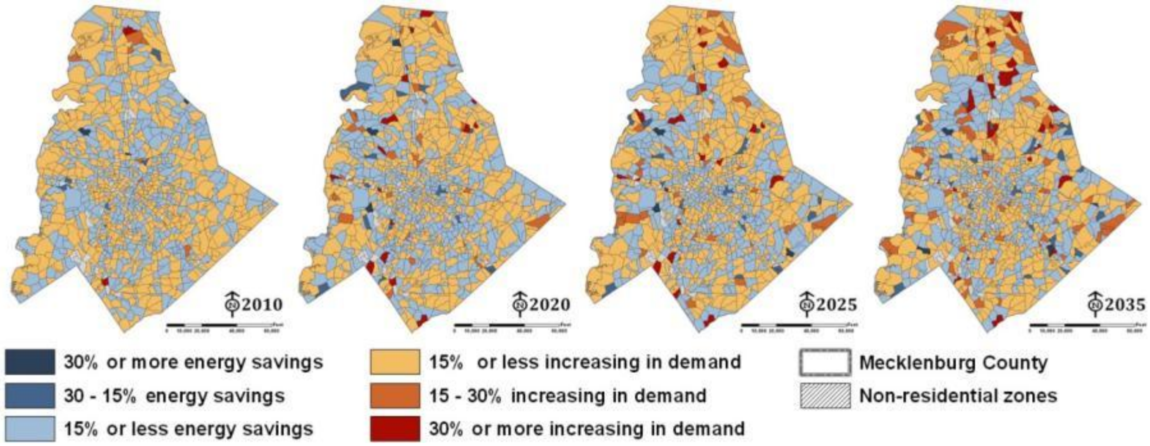

Figure 49: Forecasted household energy consumption in TAZs (energy crisis trend).

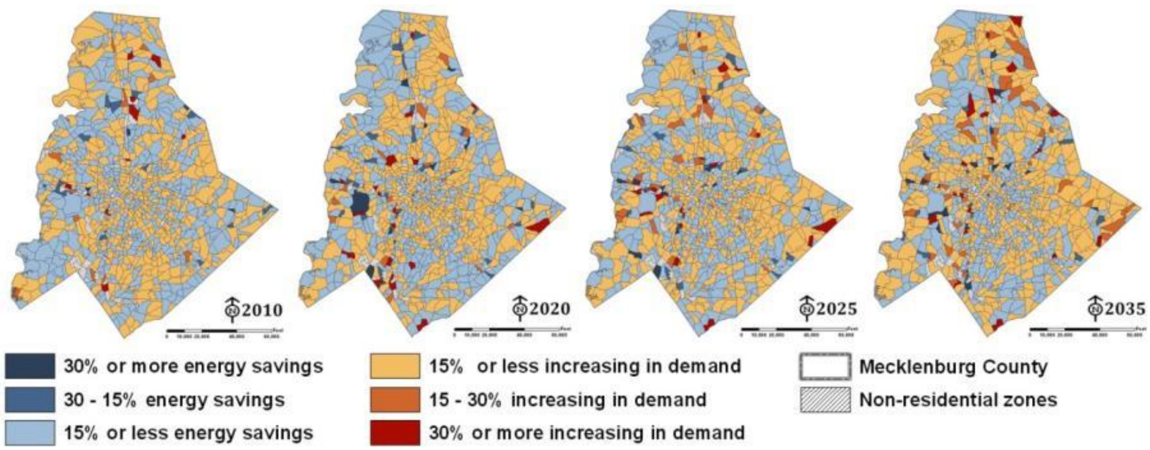

Figure 50: Forecasted energy consumption per capita in TAZs (energy crisis trend).

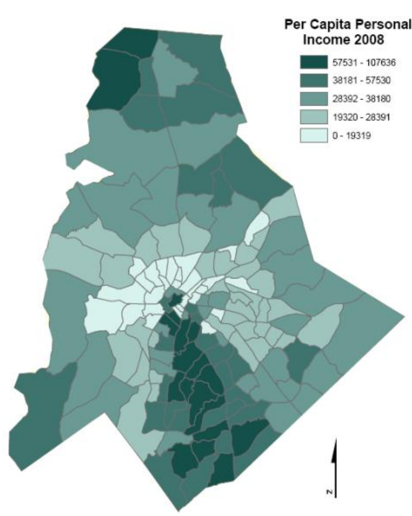

Figure 51: Mecklenburg income per capita by census tracts in 2008.
Source: Charlotte-Mecklenburg Planning Department (charmeck 2011).

5.5. Environmental Scenario

The environmental scenario applies one of passive energy policies to assess the influences of maximizing the tree coverage in the property lands on energy consumption and conservation, specifically the newly developed parcels.

Total forecasted energy consumption in TAZs moderately increases by average annual rate equals 2.43 percent. The spatial patterns present significant energy savings in the mixed uses around road I-485 road and its intersection with highway 77 as shown in Figure 52. On the other hand, there is a remarkable increasing in energy demand at the suburbs, while the central high-density areas demonstrate a marginal increasing. The parameterization changes in the HED model for environmental scenario are formulated as followed:

$$(\mathrm{HED_{envi}})_n = \ln(E) * (1 - P\alpha) * (1 - G\alpha) * (1 - L_{\mathrm{maxTree}}) \qquad (26)$$

Where:

n = the annual population growth as rate of 2.7 percent,

$L_{maxTree}$ = the reduction energy ratio based on the tree coverage percentage as a rate of 8 percent if the tree coverage is 25 percent or more of the land parcel area.

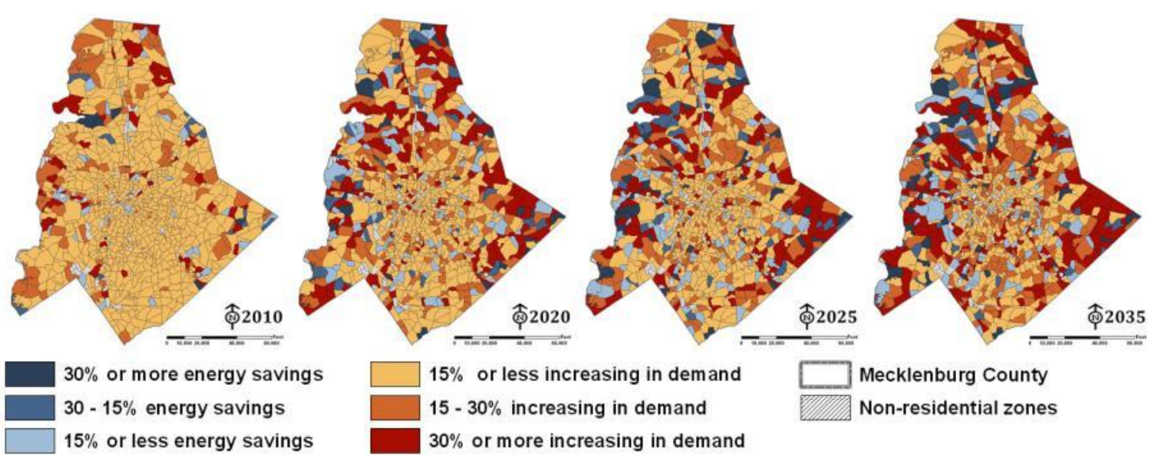

Figure 52: Total forecasted energy demand in TAZs (maximize tree coverage).

The spatial distribution of forecasted energy demand at the household and capita levels demonstrates similar energy savings in the mixed uses areas as shown in Figure 53 and Figure 54. Energy savings are observed in the mixed-use areas along the western section of road I-485. On the other hand, the suburbs experience a slight increasing in energy demand. The results reflect the new development that occurs in the spheres of influences. The new developed areas have high percentage of the tree coverage and high vacancy rates, while expanding new households in the existing suburbs involve in decreasing the tree coverage, which raises carbon footprint causing more energy demand.

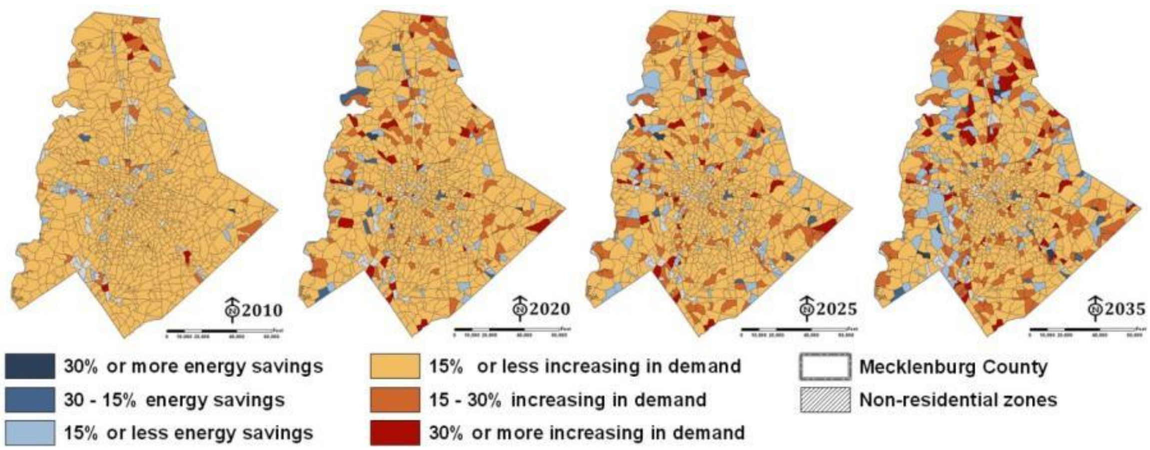

Figure 53: Forecasted household energy consumption in TAZs (maximize tree coverage).

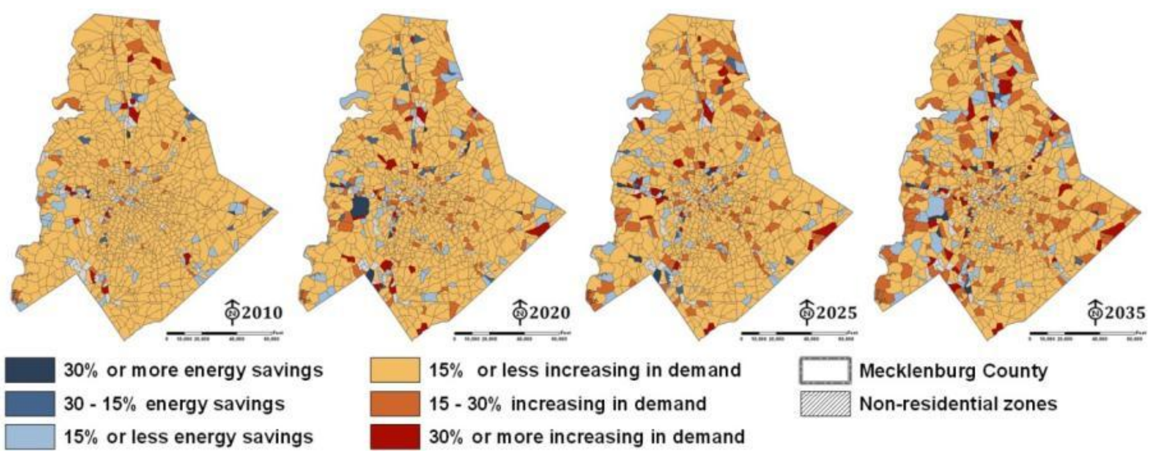

Figure 54: Forecasted energy consumption per capita in TAZs (maximize tree coverage).

The overall assessment of maximizing tree coverage scenario reveals linear spatial pattern of energy savings around the western section of road I-485 road and its intersection with highway 77. As the time progresses, the central compact areas experience a marginal increasing in energy demand, and the northern and the southern suburbs experience a consistent energy increasing at the macro and the micro levels. The assessment reflects the differences between housing expansions in the new versus the existing areas. Middle-income groups who live in mixed uses areas social receive the highest savings in energy demand at micro levels.

5.6. Green Technologies Scenarios

Green technologies scenarios assess the contribution of the two CHP applications as mentioned in section 4.3.4. Limited CHP scenario only targets high-income groups, and market-wide CHP scenario covers the whole county. Both scenarios will be presented simultaneously. Total forecasted energy consumption increases by annual rate of 2.7 percent for limited case, and increases by rate of 2.1 percent for the market-wide case. Most of energy savings at TAZ level is concentrated in the mixed used areas around the western section of road I-485, and in the dense compact central areas as shown in Figure 55 and Figure 56. Both scenarios expose an increasing in energy consumption in low-density areas. They reveal similar spatial patterns in the suburbs at TAZ level. Other two measurements could reveal more findings.

$$(\mathrm{HED}_{\mathrm{limitedCHP}})_{\mathrm{n}} = \ln(\mathrm{E}) * (1 - \mathrm{P}\alpha) * (1 - \mathrm{G}\alpha) * (1 - \mathrm{L}) * (1 - \mathrm{CHP}_{\mathrm{income}<57516}) \quad (27)$$

$$(\mathrm{HED}_{\mathrm{marketCHP}})_{\mathrm{n}} = \ln(\mathrm{E}) * (1 - \mathrm{P}\alpha) * (1 - \mathrm{G}\alpha) * (1 - \mathrm{L}) * (1 - \mathrm{CHP}_{\mathrm{all}_{\mathrm{income}}}) \quad (28)$$

Where:

n = the annual population growth as rate of 2.7 percent,

$CHP_{income<57516}$ = the utilization saving factor for green energy technology as a rate of 10 percent for high-income groups with annual income 57516$ or more,

$CHP_{allincome}$ = the utilization saving factor for green energy technology as a rate of 10 percent for all income groups starting from 2018 to 2037.

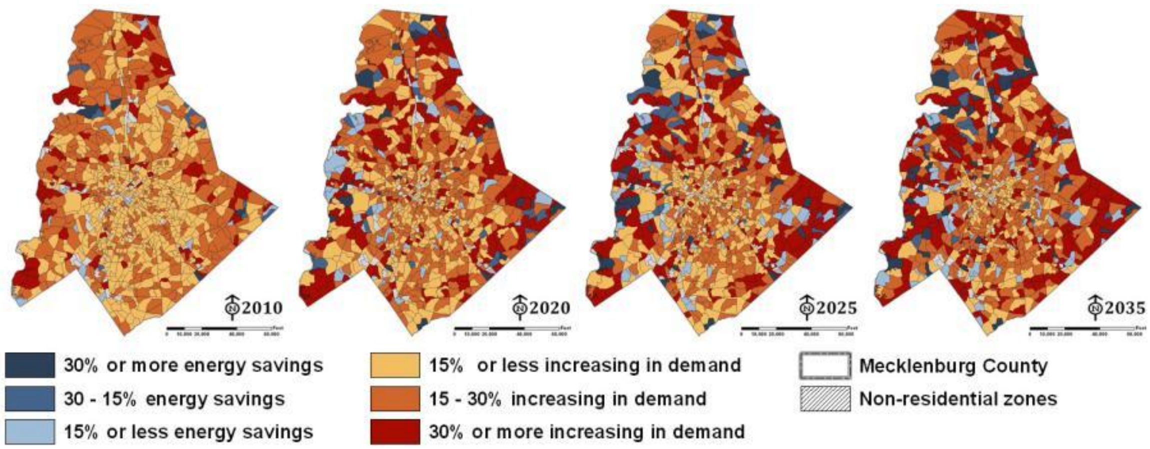

Figure 55: Total forecasted energy demand in TAZs (limited CHP).

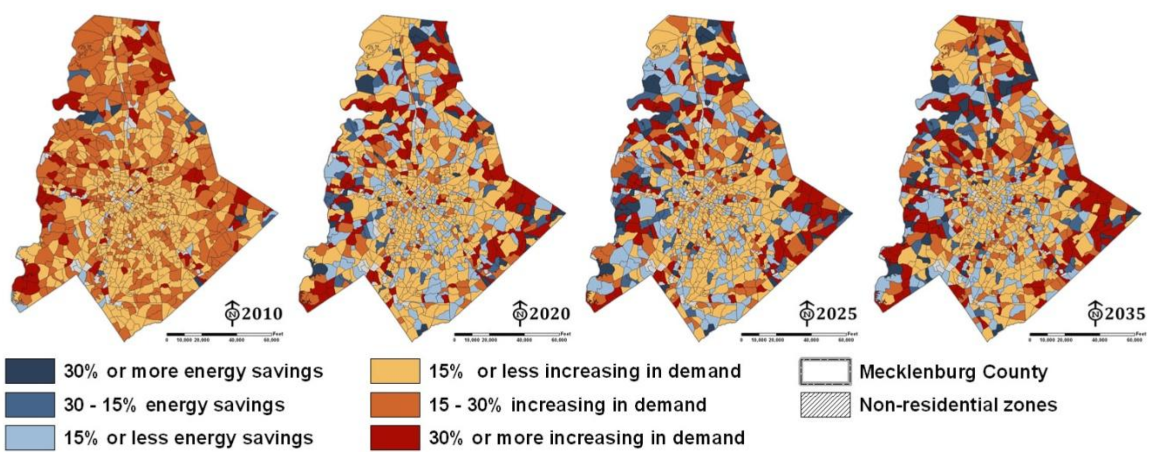

Figure 56: Total forecasted energy demand in TAZs (market-wide CHP).

The spatial distribution of household energy consumption in the limited CHP scenario only reveals minor energy savings in the suburbs of Cornelius and Davidson in the northern part of the county, and the suburbs of Mint Hill and other southern suburbs of Charlotte as shown in Figure 57. The forecasts of the limited CHP scenario at household are driven by the income profile of Mecklenburg County, high-income areas experience maximum energy savings in this scenario. On the other hand, the market-wide CHP scenario presents better energy savings at household level and most of the savings are distributed in the mixed used and the central compact areas as shown in Figure 58.

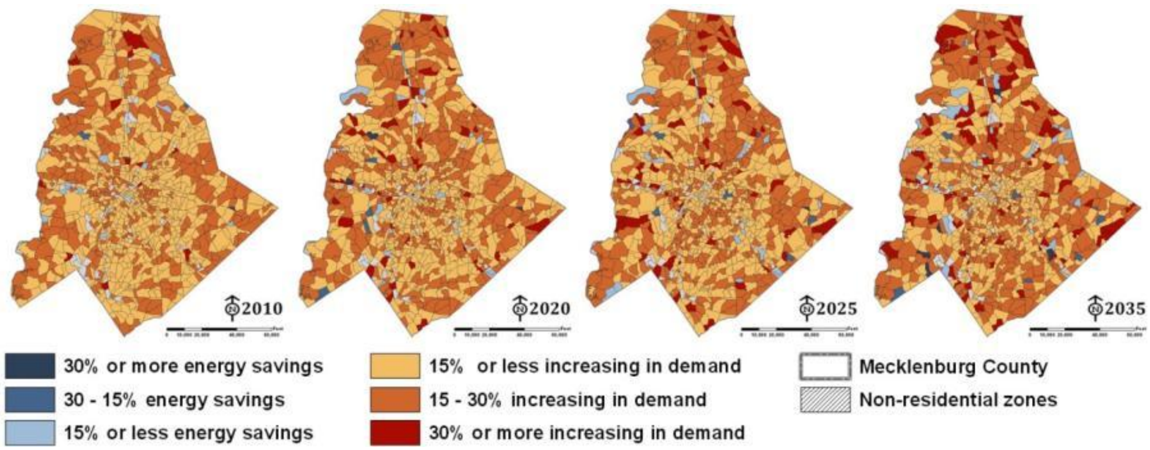

Figure 57: Forecasted household energy consumption in TAZs (limited CHP).

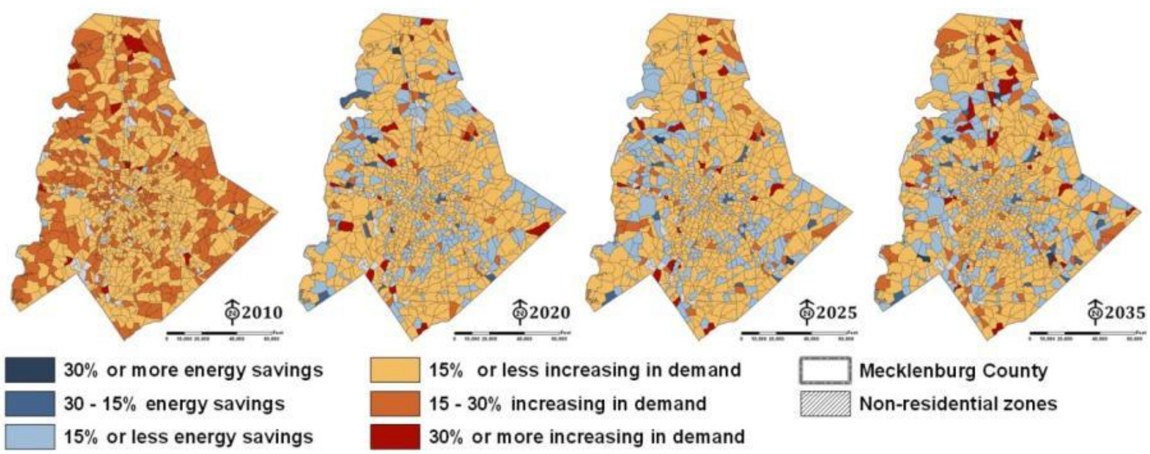

Figure 58: Forecasted household energy consumption in TAZs (market-wide CHP).

In the limited CHP scenario, forecasted energy consumption per capita reveals marginal energy savings that are concentrated in the northern and the southern suburbs as shown in Figure 59. The market-wide scenario demonstrates distinguishing energy savings that occur countywide, mainly in the mixed used along the western section of road I-485 and the central compact areas as shown in Figure 60.

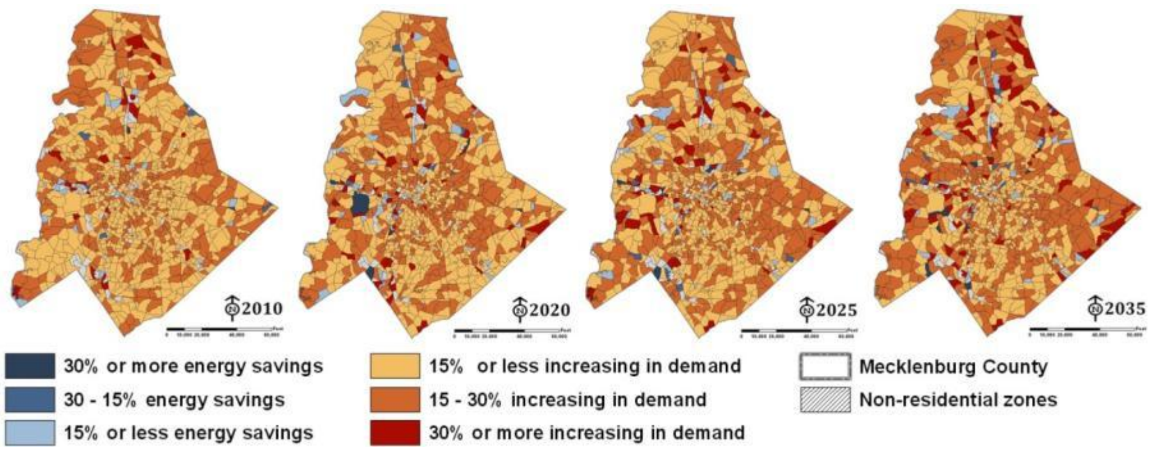

Figure 59: Forecasted energy consumption per capita in TAZs (limited CHP).

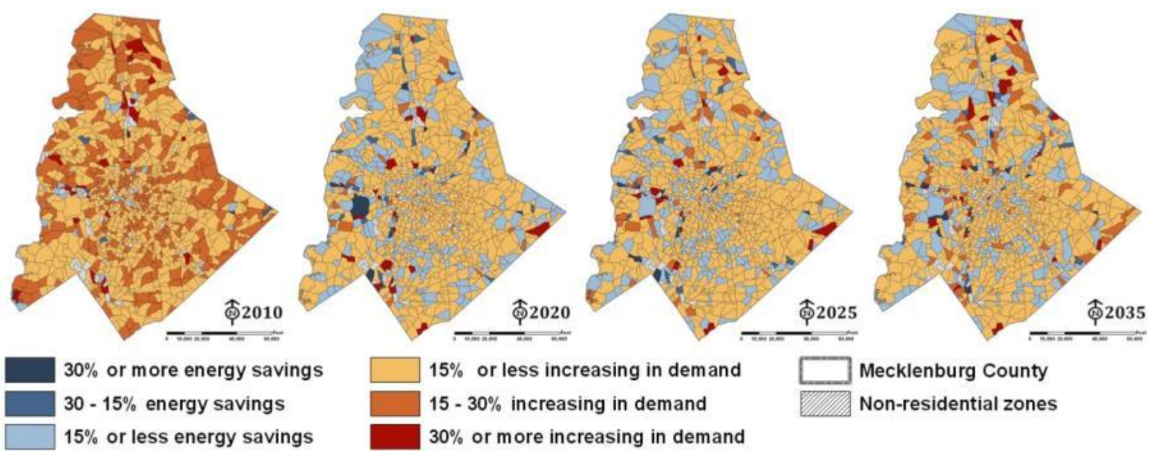

Figure 60: Forecasted energy consumption per capita in TAZs (market-wide CHP).

The overall assessment of the limited CHP scenario displays no distinctive spatial pattern that is affected by the application of the green technology. As time progresses, minor energy savings occur in high-income areas that are concentrated in the northern and the southern suburbs. On the other hand, there is a significant energy savings in the market-wide CHP scenario; the overall spatial distribution shows that most of TAZs benefit from the application of CHP countywide. As time progresses, a consistent saving in energy consumption happens at all levels the mixed uses areas in the spheres of influences, specifically around the western section of road I-485 road and its intersection with highway 77. In addition, energy savings are observed around the central areas. The forecast results for the market-wide CHP scenario support the planning guidelines, as it is recommended to install the CHP units in the mixed uses and the dense compact built-up forms to achieve maximum energy efficiency (see section 3.3.1.1). In general, High-income groups gain the highest savings in energy demand at micro levels because they can afford the prices of the new green technologies.

The assessment process for all designed policy scenarios covers the economic and the environmental of sustainable energy concept at multiple scales over time. However, it is important to examine the social dimension to provide a comprehensive multi-dimensional assessment for the decision makers.

5.7. Energy Poverty

The research's fifth objective assesses the implications of the proposed scenarios on social equity in energy expenditures for predefined social groups. Energy poverty is a known indicator, which refers to the percentage of people in low-income groups that pay 10 percent or more of their income for energy expenditures. The assessment tracks the poverty in three steps; first, it presents energy poverty in the neutral scenario. The Second step tracks the impacts of the first three designed scenarios on social equity. The third step presents energy poverty for the last three designed scenarios, which apply sustainable energy policies. Energy poverty is classified into two groups, poor (10-15%), and very poor (15% or more) of the income is paid for energy expenditures. In addition, the assessment addresses the enhancement of the service quality, it determines whether each policy scenario involves in decreasing or increasing energy poverty over time.

The spatial distribution of energy poverty in the neutral scenario demonstrates a concentration pattern in the central areas around the center of Charlotte. Few TAZs are distributed in the northern suburbs of Davidson and Huntersville, and the southern suburbs of Charlotte as shown in Figure 61.

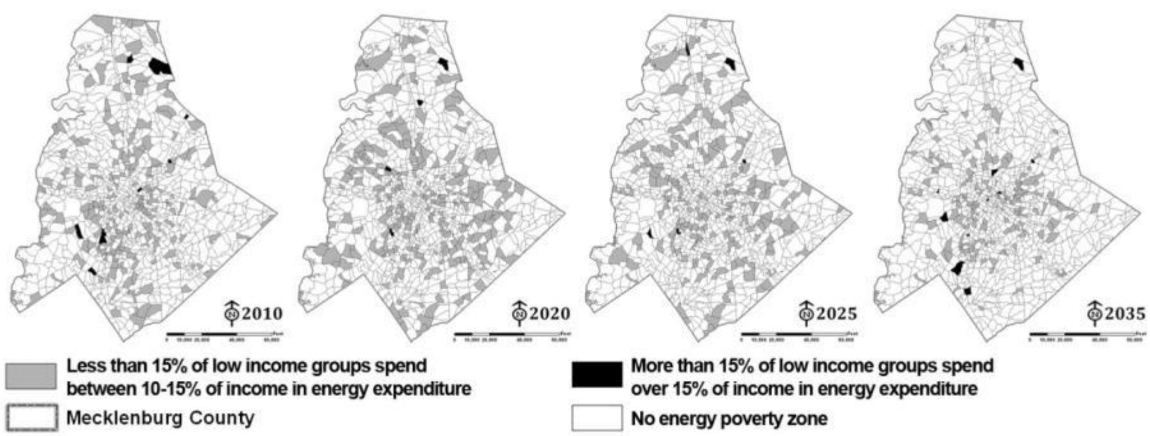

Figure 61: Energy poverty in low-income groups in TAZs (the neutral scenario).

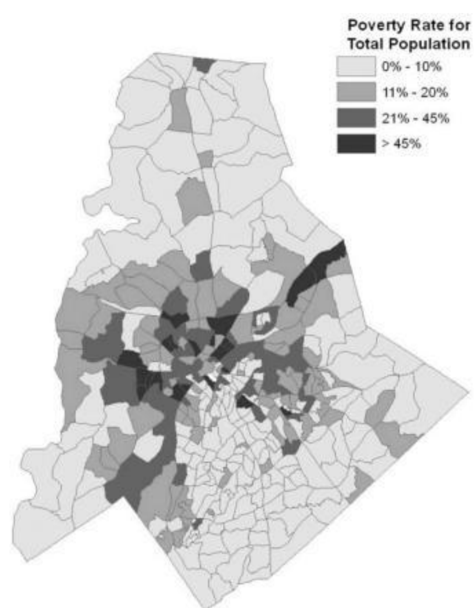

Figure 62: Poverty rates for Mecklenburg County from 2005 to 2009.
Source: Charlotte-Mecklenburg Planning Department (charmeck 2011).

By observing the poverty profile for Mecklenburg County from 2005 to 2009, the spatial distribution of energy poverty is very similar to the poverty rates in the county. However, it is surprising that some of high-income TAZs experience energy poverty problem as shown in Figure 62. The few errors that are found in address locations in the property records affect the quality of energy poverty forecasts in the neutral scenario, and it is expected that the same error will occur in the other scenarios.

Figure 63, Figure 64, and Figure 65 present a comparison between the spatial distributions of energy poverty in the first three designed scenarios. The low urban development policy causes more poverty among low-income groups, mainly in the central areas.

By contrast, energy poverty marginally declines when high development policy is applied. This difference between the two urban scenarios reflects the capita share of energy expenses per household, which it decreases in low urban development and low-income groups spend more in utilities expenditure. On the contrary, the capita share per household increases in high urban development, which splits energy expenses between more customers.

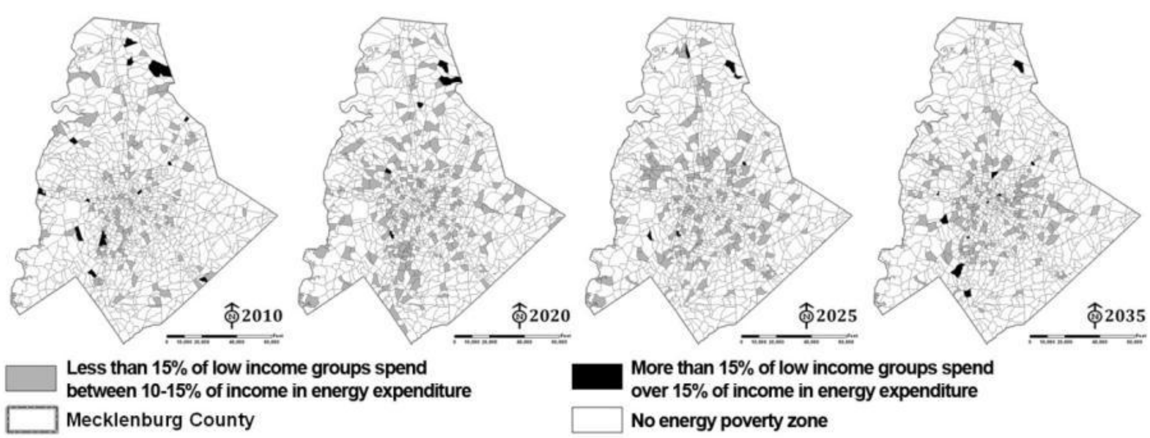

Figure 63: Energy poverty in low-income groups in TAZs (low urban development).

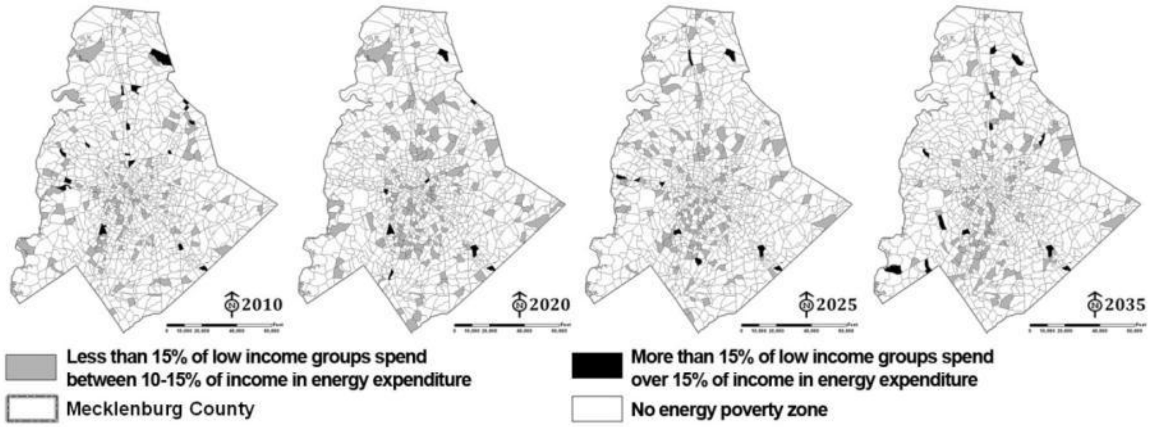

Figure 64: Energy poverty in low-income groups in TAZs (high urban development).

In the case of global energy crisis, the spatial patterns demonstrate a distinct increasing in energy poverty over time. The results of energy scenario reveal that low-income groups are more sensitive to price elasticity than middle and high-income classes. It is remarkable that the same error appears in the high-income suburbs in the urban and energy scenarios as shown in Figure 65.

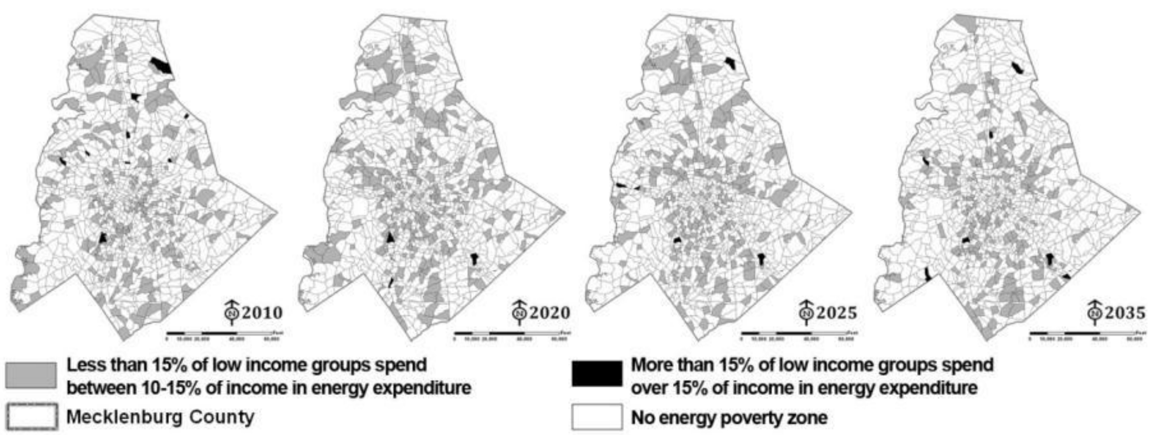

Figure 65: Energy poverty in low-income groups in TAZs (energy crisis trend).

Sustainable energy polices contribute to in subsidizing some of the expenditures through energy savings and enhancing the quality of the service as well. Table 11 presents the contribution of the three green policy scenarios. Both tree coverage and market-wide

CHP scenarios reduce average energy poverty by almost 25 percent. On the other hand, the limited CHP scenario has no distinctive improvement in energy poverty, even though it is involved in energy savings countywide, this result is expected since the limited CHP scenario only focuses on high-income groups.

Table 11: The changes over time in the average of energy poverty (2010 – 2035).

	Maximize tree coverage	Limited CHP	Market-wide CHP
2010	9.59%	9.97%	9.97%
2035	8.34%	9.97%	8.69%
Improvement percentage	25%	0	28%

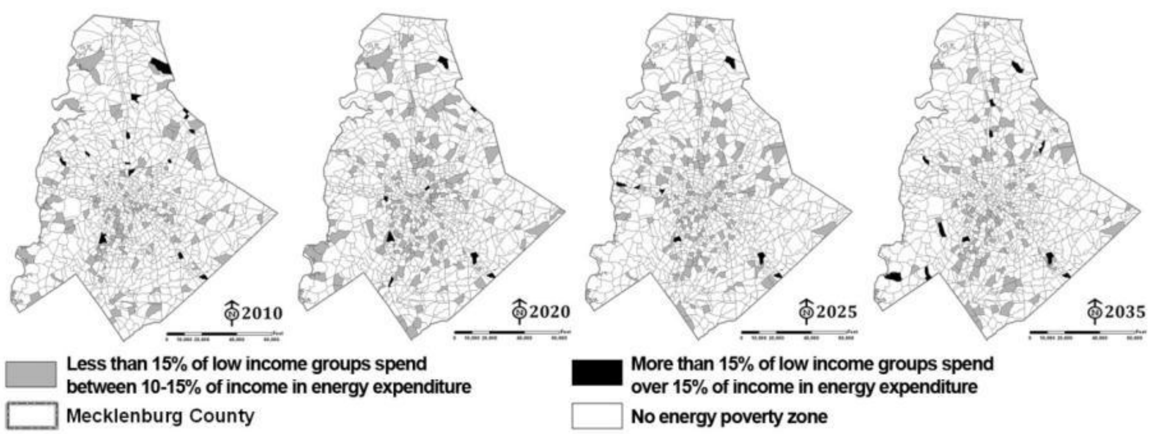

Figure 66: Energy poverty in low-income groups in TAZs (maximize tree coverage).

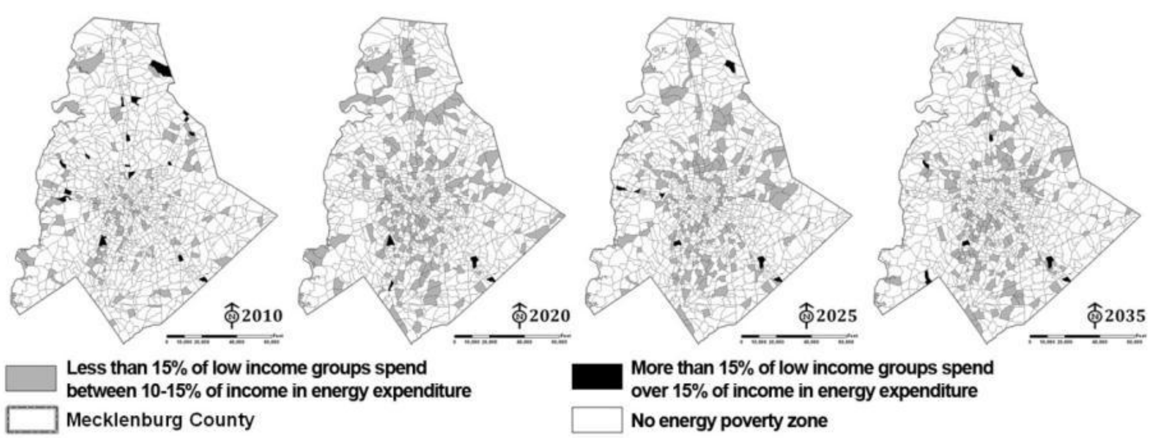

Figure 67: Energy poverty in low-income groups in TAZs (market-wide CHP).

The spatial patterns of energy poverty in the tree coverage scenario reveal distinctive declines over time as shown in Figure 66. The highest drop in energy poverty values is located in the spheres of influences along road I-485. The high percentage of plantation coverage per parcel in these areas not only involves in energy savings but also in decreasing the poverty.

The distribution of energy poverty in the market-wide CHP scenario demonstrates significant reduction over time as shown in Figure 67. The compact central and mixed uses areas experience the maximum drops in energy poverty, respectively. The major concentration of low-income groups is around the compact central areas.

Both green policies scenarios decrease energy poverty and enhance the quality of the service. Maximizing tree coverage policy is more effective in mixed uses built-up forms. On the other hand, the CHP application decreases energy poverty more efficiently in the dense central areas, where the tree coverage is the lowest value in Mecklenburg County. The limited CHP scenario only targets high-income groups; hence, it reveals same distribution as the neutral scenario, it has no effects on energy poverty.

5.8. Summary of the Findings

- From 2008-2015, the growth of total energy demand is slow and the slope is almost horizontal in all scenarios. After 2015, the growth trend is increased faster as presented in Figure 68.
- The energy scenario yields the most significant reduction in the future demand from the economic point of view. However, it increases energy poverty over time and it demonstrates the highest negative impacts from a social perspective.

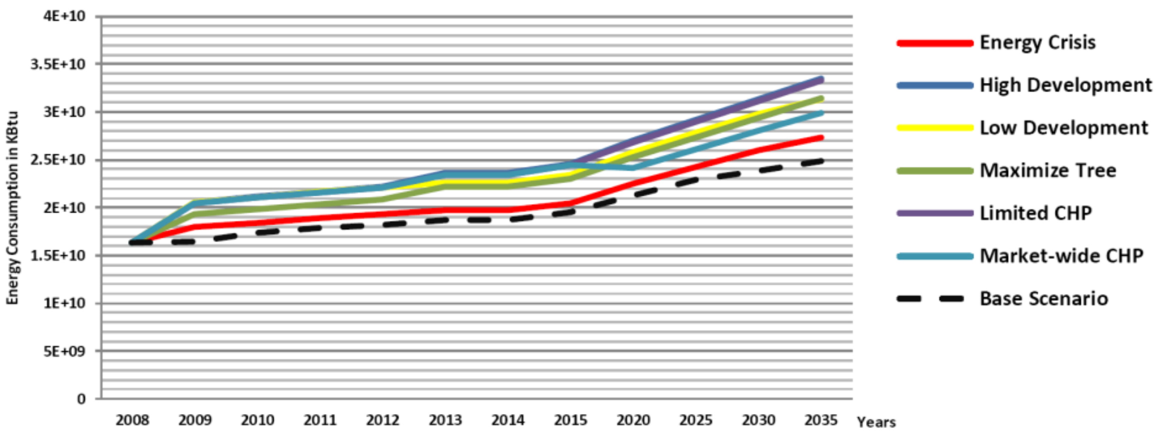

Figure 68: The forecasts of energy demand trends in all scenarios (2008-2037).

- The low development scenario yields lower total energy consumption than the high development scenario. On the other hand, the high development scenario yields better energy savings at micro (household, and capita) levels.
- The scenario of tree coverage maximization yields favorable energy savings at the county, household, and capita levels. However, the effectiveness of applying any passive energy policy, such as tree coverage, is more relevant to new developed lands than to existing developments.
- From 2008-2015, the scenario of limited CHP application, which targets high-income groups, yields minor overall energy savings. From 2020-2035, it is clear that energy consumption slightly drops.
- The market-wide CHP application scenario yields the most significant energy efficiency in the multi-dimensional assessment among all scenarios. From 2008-2015, energy consumption slowly drops. From 2020-2035, a clear decline in energy consumption is anticipated.
- The highest concentration of energy savings in all scenarios is located in mixed-use built-up forms, which is located in the spheres of the influences in

Mecklenburg County. Mixed-use built-up forms achieve the best energy efficiency compared to the dense compact and suburban built forms.

- Both passive energy (tree coverage) and CHP application scenarios reduce energy poverty and improve the service quality for low-income groups. However, passive energy policies are more efficient in areas with high percentage of vegetation cover. On the other hand, the CHP technologies achieve the highest efficiency in mixed-use and compact urban forms. Combining both methods will introduce new comprehensive policy, which might lead to more improvements in energy savings and social equity.
- The sky view factor is negatively significant with energy consumption. The residential areas with higher values of sky view factor are concentrated in suburbs, where there is low density and the common housing type is single-family unit. The sky view factor yields marginal influences in energy savings, specifically in mixed uses areas where the new development occurs. New developed areas are more adaptable than the existing areas to green energy installations (passive solutions and technologies applications).
- As the forecasting time goes on until 2035, housing characteristics (the housing unit square footage and household type) and the spatial variable (the sky view factor) are more significant with urban policies driven scenarios. On the other hand, socio-economic variables (household income and household size) are more significant with market economy driven scenarios (energy crisis in oil price, and the price of green technologies applications).
- High-income groups can afford the new green applications, and they will not

be affected by the increase in energy prices as low and middle-income groups. On the other hand, low-income classes are the most sensitive social group to any increasing in the prices in energy market.

CHAPTER 6: CONCLUSIONS

This research opened with a general question: what are the influences of urban form on residential energy demand? The dissertation addressed a topic, which contains many potential conflicts between economic, environmental, and social aspects. It adopted a comprehensive methodology to examine the contributions of spatial characteristics and socio-economic factors on residential energy consumption.

The research formulated five objectives; each objective was assorted with a group of questions. The first group of questions investigated the system architecture that could efficiently articulate factors, forecasting methods, and assessment tools to develop a comprehensive spatial planning support system (PSS). The second group of questions inquired which suitable data models could accommodate various spatial and temporal resolutions for the developed PSS. The third group dealt with how to quantify the magnitude of various spatial, socio-economic, and condition factors, which affect residential energy consumption. The fourth group of questions asked a series of what-if scenarios to explore how various policies could affect forecasted energy consumption at various micro and macro levels. The final group raised the question on whether the anticipated policy scenarios caused uneven equity across the socio-economic population groups as far as energy consumption is concerned.

To address these questions, the main methodology was to develop a spatial support system, which is integrated with a process-based simulation model of land use and transportation. The first predominant objective of this dissertation was to develop an integrated spatial planning support system to forecast household energy consumption. While prior studies have looked at the influence of urban form, this has seldom been done in an integrated fashion as in this dissertation. A challenge was identify the suitable analytical approaches to build the integrated framework model, which combines the capabilities of forecasting methods, sustainable development concept, and the strengths of empirical energy demand models.

The dissertation fulfilled the first objective and its questions by combining one of sustainable development framework concepts with an energy forecasting approach (hybrid approach). The aim of adopting a sustainable energy concept was to balance the conflicts between economic, environmental, and social equity to ensure the livability of urban communities in the forecasted scenarios. In addition, it provides assessment capabilities over time for the integrated PSS.

The integrated developed PSS covered various conflicting dimensions in energy demand forecasting, the economic, the environmental, and the social equity. This dissertation adopted the framework concept of the livability/sustainability prism. The concept extended the capabilities of the developed PSS to assess the conflicts between the applied policies in energy forecasts, mainly to assess the social equity of energy poverty. Empirical studies of urban forms and energy consumption typically rely less on the influences of the spatial characteristics within an urban context. This dissertation applied two spatial drivers on household energy consumption, the sky view factor, and urban horizon angle.

The second main objective was to develop an empirical operational model for use in the energy module. To accomplish this objective and its questions, the dissertation integrated a scenario builder interface, Charlotte Land Use and Economic Simulator (CLUES), and the developed empirical energy demand module (eCLUES). The CLUES simulator provided the developed energy module with the socio-economic and housing characteristics parameters. The energy module applied a regression model that consists of three broad sets of predictors, namely the socio-economic, urban geometry, and condition predictors. The CLUES simulator and the energy module were built using python language, which is an open source scripting language. However, the full integration between the eCLUES module and the CLUES simulator could not be established, which affected the quality of some of the energy forecasts.

Data on Mecklenburg County household energy consumption could not be secured to build the housing-energy demand (HED) model. A combined sample was created using the property records dataset of Mecklenburg County and the Residential Energy Consumption Survey (RECS) dataset.

The coefficient of determination, the variance inflation factor, and t-value significance tests were performed to check that the conditions of the model were met and statistically accepted. The regression t-value test for the combined sample demonstrated negative significant relationship between the spatial SVF variable with energy consumption, which was consistent with the literature findings. Both spatial variables SVS and UHA were highly and negatively correlated, therefore, the UHA spatial variable was omitted from the regression model. Other socio-economic variables revealed strong significance with household energy consumption.

The HED model did not show any sign of multicollinearity, however a heteroskedasticity problem was presented in the HED model, which could bias the forecasting outputs. To restore homoscedasticity, a natural log was applied to transform the values of energy consumption.

The standardized beta coefficients test was carried out to identify which of the independent variables have a greater effect on the dependent variable. The dummy variable of single-family unit has the greatest relative effect on household energy consumption. Both of the dummy variable of household with one occupant and the square footage of the residential unit have the second highest effect on the consumption, respectively. This result indicates that housing characteristics have the greatest effect on the trends of household energy consumption. On the other hand, the sky view factor has the lowest relative effect on the consumption. Unpredictably, household income has the second lowest effect. In the literature, some studies reported that the relationship between energy consumption and household income is an inverted-U shape relationship not a linear in some cases, which may explain the low beta coefficient value for household income (Foster et al. 2000; Eraso 2010).

The other three objectives assessed the impacts of urban geometry and socio-economic factors on the spatial, non-spatial, and social-equity patterns of household energy consumption, respectively. The third and fourth objectives and their related questions were fulfilled by applying a comprehensive multi-dimensional assessment for various policy scenarios, respectively.

The dissertation predicted various scenarios of household energy consumption in Mecklenburg County during the period of 2008-2037. A comprehensive assessment was applied for four main scenarios, urban development policies, energy market trends, environmental policies, and green technology applications. It was found that the spatial variables were more significant with urban policies driven scenarios. On the other hand, socio-economic variables were more sensitive to market economy driven scenarios.

The fifth objective and its related question were answered by adopting a social equity indicator, which is energy poverty. The fifth objective revealed that even though the energy policy scenario achieved the highest energy savings from the economic viewpoint, it increased energy poverty over time. On the other hand, green policy scenarios were the most efficient scenarios in decreasing energy poverty over time in the study area. However, the spatial distribution of some areas reveals unexpected results. The property records dataset had some errors in the reported address locations for some observations. The dissertation could not solve this problem, which affected the quality forecasting outputs and the assessment process.

One major finding in this dissertation is that any decline in total energy consumption at macro (national, regional, etc.) scale can create positive or negative effects at micro level. These impacts must be assessed at multiple dimensions comprehensively to determine if the quality of energy service is improved or decreased.

6.1. Limitations of the Study and Future Work

One of the main objectives of this dissertation was to develop an integrated planning support system to forecast household energy consumption scenarios; it was not intended to decide which scenario is the most efficient among other scenarios. A second limitation is that the study is constrained to a single case study of Mecklenburg County. Moreover, there is a need for the model calibration process to extend the usage of the developed energy demand model on different case studies. It is important to mention that this dissertation addressed residential energy from the demand side only; it did not cover the whole concept of demand/supply equilibrium.

One major aim in this dissertation was to build an open source extension model. The eCLUES energy extension is developed under Arcpython language. The basic python script is open source, on the other hand; the sophisticated GIS functions in Arcpython, such as reading the geodatabase and creating automated thematic maps, are based on ArcGIS, which is a commercial GIS software package.

For instance, the developed eCLUES toolbox under ArcGIS provides an easy visual interface for any user; otherwise, the user must type the command lines using the basic python, which requires more programing skills. In addition, the built-in functions in Arcpython save a lot of computing time instead if they are only developed using the available functions in the basic python. Another example, there is no equivalent python package yet to be developed that creates automated thematic maps other than Arcpython under ArcGIS.

One major limitation was the lack of available data on household energy consumption to build a real sample for the case study. A combined sample was created based on matching the property records of the study area with the RECS dataset from the U.S. department of energy. A real local sample would improve the regression outputs and other measurements.

Another limitation is that the feedback loop between the CLUES simulator and the eCLUES energy extension could not be fully integrated because the output formats of the CLUES model have unique file extension. The conversion of the CLUES output formats to database file extension could not be automated; it was done interactively before running the eCLUES extension. Moreover, this shortcoming caused no account for the effect of energy price on transportation in the CLUES simulator to feedback the eCLUES energy module. In addition, the developed system was not integrated in the last step of creating the thematic maps. It did not provide predefined legends for the produced maps, and the desired map legend was done interactively.

The proposed future development for this study is to transform the integrated PSS into an integrated decision support system (DSS), which will provide an on-screen and an interactive comparison between the scenarios through various options, such as the thematic maps, and spatial and non-spatial statistics. Moreover, the DSS will be emerged into a web-based application; hence, any user may provide the data and the inputs of the variables to generate the forecasts of residential energy consumption.

The eCLUES module will be extended to cover other land uses (commercial, and industrial). Last but not least, future work will move towards complete open source to avoid the association of the eCLUES usage with the commercial GIS software.

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APPENDIX A: GLOSSARY OF TERMS

Combined Heat and Power (CHP): A generator unit is designed to produce both electricity and heating energy by using the residual heat from one heat source.

Energy Poverty: A factor is used to estimate the percentage of low-income customers that pay 10 percent or more of their income for energy expenditures to the total population of the area under consideration.

HED: An abbreviation refers to Housing-Energy Demand.

Residential Energy Expenditure: The amount of money spent for energy usage in a housing unit during a given period (e.g., month).

The Sky View Factor (SVF): A ratio is used to calculate the received solar radiation (or emitted) for a proportion of the elevation of an urban surface (e.g., residential building) under consideration. The ratio is ranged between zero (no exposure to solar radiation) to one (fully exposed to solar radiation) (Watson and Johnson 1987).

Urban Horizon Angle (UHA): The observed average elevation of an urban surface (e.g., residential building) that falls in the shades. The area is calculated from the center of the considered surface’s façade (Baker and Steemers 2000).

Urban Geometry: A term refers to the spatial characteristics that shape urban fabric, such as building heights, width, size, mass orientation, road widths etc.