Investigating the Relationship between Energy Consumption, CO_2 Emissions,

and the Factors Affecting Them in the United States Building Sector

: A Macro and Micro View

by

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ABSTRACT

The United States building sector was the most significant carbon emission contributor (over 40%). The United States government is trying to decrease carbon emissions by enacting policies, but emissions increased by approximately 7 percent in the U.S. between 1990 and 2013. To reduce emissions, investigating the factors affecting carbon emissions should be a priority. Therefore, in this dissertation, this research examine the relationship between carbon emissions and the factors affecting them from macro and micro perspectives. From a macroscopic perspective, the relationship between carbon dioxide, energy resource consumption, energy prices, GDP (gross domestic product), waste generation, and recycling waste generation in the building and waste sectors has been verified. From a microscopic perspective, the impact of non-permanent electric appliances and stationary and non-stationary occupancy has been investigated. To verify the relationships, various kinds of statistical and data mining techniques were applied, such as the Granger causality test, linear and logarithmic correlation, and regression method. The results show that natural gas and electricity prices are higher than others, as coal impacts their consumption, and electricity and coal consumption were found to cause significant carbon emissions. Also, waste generation and recycling significantly increase and decrease emissions from the waste sector, respectively. Moreover, non-permanent appliances such as desktop computers and monitors consume a lot of electricity, and significant energy saving potential has been shown. Lastly, a linear relationship exists between buildings' electricity use and total occupancy, but no significant relationship exists between occupancy and thermal loads, such as cooling and heating loads. These findings will

potentially provide policymakers with a better understanding of and insights into carbon emission manipulation in the building sector.

DEDICATION

I would like to dedicate this dissertation to my beloved wife, Juri Jeon, and little daughter, Dain Lee, for their endless love, support, and encouragement.

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CHAPTER 1

INTRODUCTION

1.1. Background to Research

Decreasing carbon emissions is the only way to reduce the impacts of global warming. Energy consumption and global warming issues are the most important problems humans face. Global warming is the one of the most critical issues of the last decade, and the threat of global warming is increasing. Several adverse effects of global warming have been observed. The Intergovernmental Panel on Climate Change (IPCC) reported that the global average combined land and ocean surface temperatures climbed about 0.85ºC between1980 and 2012, and global sea level increased by 0.19m between 1901 and 2010 (IPCC 2014). The IPCC also predicted the global surface temperature and sea level will increase by a maximum of 4.8ºC and 0.82m, respectively, by 2100 (IPCC 2014). Therefore, most people or governments feel the need to decrease energy consumption and carbon dioxide emissions. Various factors affect energy consumption and carbon dioxide.

Previous researchers tried to discover the causal relationship between energy consumption and carbon dioxide, which can provide policy makers deep insights into decreasing carbon dioxide. Using the Granger causality test, Soytas et al. (2007) verified that energy consumption causes carbon dioxide emission in the United States. The object data was the whole United States, but data should be narrower to be more practical and helpful because the main energy source for each sector in the United States is different (EIA 2015, Park and Hong 2013). For example, building, transportation, and industrial sectors mainly consume electricity, petroleum, and natural gas, respectively (EIA 2015).

An energy price variable is added because several researchers verified that energy price affects energy consumption (Nesbakken, 1999; Martinsen et al. 2007; Cho et al. 2007; Yuan et al. 2010). If the relationship is verified, it can be utilized practically because energy consumption can be controlled by price.

In addition, according to previous studies, environmental degradation such as municipal waste generation and greenhouse gas emissions correlate with gross domestic production (GDP) per capita, as shown by the Environmental Kuznets Curve (EKC) (Stern et al., 1996). This hypothesis conjectures that environmental degradation initially tends to get worse as per capita income rises until it reaches a certain level. Degradation then subsides at high economic levels. (Shafik, 1994; Stern et al., 1996). Thus, economic growth can become a solution rather than a source of the problem (Rothman and de Bruyn, 1998).

Researchers found various factors that affect energy consumption and carbon dioxide emissions. They were interested in the factors that influence a single building's energy consumption from a microscopic perspective to form more practical suggestions for decreasing a building's energy consumption.

Researchers have also explored ways to reduce individual buildings' energy use. Previous research mainly focused on climate, the building envelope, the building's energy and service systems, indoor design criteria, and building operation and maintenance. Remarkable progress has been made in this research area. However, it is well known that a building's occupants have a significant impact on its energy consumption although, in reality, current building energy systems work independently of occupants. Also, no proper energy model is related to occupancy. Because current systems do not consider the occupants' impact, which can vary greatly, building energy simulations and predictions deviate significantly from actual building energy consumption. Therefore, this dissertation focused on the factors related to building occupancy.

Among the factors related to building occupancy, I first verified the impact of electric appliances on electricity consumption and patterns of use. A wide variety of electrical appliances is used in buildings, and the appliances serve various functions and consume a significant amount of energy. Plug loads are driven by various factors, such as HVAC and lighting. The amount of energy HVAC systems consume depends on the weather, but plug loads do not. Nevertheless, very few studies focused on electric appliances and plug loads even though plug loads constitute a significant portion of a building's energy consumption (Kamilaris et al. 2014; Ouf et al. 2016). 12% to 50% of a commercial building's total electricity is consumed via plug loads, and this figure is expected to continue growing as the types of equipment and appliances continue to increase and occupants continue to supplement their spaces with new equipment and appliances to meet their new needs. Gandhi and Brager (2016) showed that energy consumed by appliances is growing at an annual rate of 0.8%.

Second, there are two types of building occupants. One is non-stationary occupants, such as visitors or students, and the other is stationary occupants, such as faculty members and graduate students. The stationary occupants have a more significant impact on building energy loads. The two groups' energy consumption patterns are very different. For example, non-stationary occupants use small plug loads to, for example, charge smartphones or laptops and sometimes classroom desktops and projectors for class. However, stationary occupants create large plug loads by using such items as computers, monitors, desk lamps, and refrigerators during working hours. Moreover, the appliances also come with appliance heat loads, which increase the cooling load (Yan et al., 2015). Because the two groups' impacts on the energy load are obviously different, they should be analyzed separately (Chen and Ahn, 2014), so I intend to investigate stationary occupants' impact on energy loads and verify the relationships between occupancy and building energy loads.

1.2. Research Objectives

The primary objective of the dissertation is to discover more effective ways to decrease greenhouse gas emissions. To do so, each chapter has specific objectives. Chapter 2 examines and uses the causal relationships between energy resource consumption, energy prices, and carbon dioxide emissions (from 1973 to 2012) to determine the effects of energy sources and prices on carbon emissions. Chapter 3 verifies the Environmental Kuznets Curve's (EKC) relationship with waste generation and GDP across the U.S. This EKC hypothesis conjectures that initially, environmental degradation such as carbon emissions and waste generation tends to worsen as per capita income rises until it reaches a certain level, at which point degradation subsides. Thus, economic growth may become a solution rather than a source of the problem. It also confirmed that total waste generation and recycling of waste influence carbon dioxide emissions from the waste sector. Chapter 4 presents the impact of electric appliances on energy/electricity consumption patterns and ways to reduce electricity consumption. The buildings' electricity usage patterns were analyzed and compared with the number of appliances in the buildings. Chapter 5 presents the relationships between occupancy and building energy loads, such as electricity, cooling, and heating. The relationships were verified using statistical methods. The next objective is to make a proposal to reduce buildings' energy consumption based on the results.

1.3. Dissertation Format

The dissertation is composed of four journal papers. It includes four subsequent chapters, and each chapter represents an independent journal paper that has been accepted or is in review. Therefore, each chapter has its own introduction, methodology, results, and conclusion. Chapters 2 and 3 are already published in Elsevier journals, Chapter 4 has been submitted to a Springer journal, and Chapter 5 is being prepared for publishing in a journal.

Chapter 1 is mainly organized into overall research background and objectives and follows dissertation format. Chapters 2 and 3 focus on verifying the causal relationships for decreasing greenhouse gas from a macroscopic viewpoint. Each chapter analyzes the United States' building and waste sectors. Chapters 4 and 5 concentrate on individual buildings' energy consumption from a microscopic perspective. Chapter 4 present an analysis of the use of buildings' non-permanent electric appliances, and Chapter 5 presents the impact of a building's occupancy.

CHAPTER 2

CAUSAL RELATIONSHIPS OF ENERGY CONSUMPTION, PRICE, AND CO_2 EMISSIONS IN THE U.S. BUILDING SECTOR[1]

2.1 Research Needs

Reducing carbon emissions is the only way to reduce the impacts of global warming. The Intergovernmental Panel on Climate Change (IPCC) reported that the global average combined land and ocean-surface temperature climbed about 0.85ºC from 1980 to 2012, and global sea level increased by 0.19m between 1901 and 2010 (IPCC 2014) due to the increase of carbon present in the atmosphere. IPCC predicted that global surface temperatures will increase by 4.8ºC and sea levels by 0.82m by 2100 (IPCC 2014). Climate change also creates significant impacts on the local and global economies. Stern (2007) estimated that if there is no immediate action to reduce carbon emissions, between 5% and 20% of the annual global GDP will be lost. The Kyoto Protocol is still the most comprehensive policy to reduce carbon emissions. It is a global agreement developed by the United Nations Framework Convention on Climate Change (UNFCCC) in which countries attempted to set binding emissions-reduction targets. The Copenhagen Accord (CA) is another example of the global efforts to reduce greenhouse gas emissions by the UNFCCC. At the 15th session of the conference of parties in Copenhagen, countries pledged to voluntarily cut down the levels of greenhouse gas emissions further (UNFCCC 2015). Most countries have yet fulfilled their carbon cuts.

[1] Lee, S., and Chong, W.O., 2016. Causal relationships of energy consumption, price, and CO_2emissionsin the U.S. building sector. Resour. Conserv. Recycl. 107, 220–226

China, the United States, and the European Union emitted 10.3 billion, 5.3 billion, and 3.7 billion tons of carbon dioxide, and these represent 29 percent, 15 percent, and 11 percent of the total global carbon dioxide emissions, respectively (Olivier et al. 2014). The White House estimated that extreme weathers caused by global warming (due to greenhouse gases) cost the American economy more than $100 billion in 2012 alone. Extreme weather also threatens public health in terms of heat stress, air pollution, and extreme weather events, and it also exposes children, the elderly, and the poor to environmental vulnerability (The White House 2015). Steps have been taken by the United States government to reduce carbon dioxide emissions by enacting policies to better manage energy, water, and resource consumptions, and carbon emissions, such as with an energy efficiency program and the development of renewable energy sources (Greenstone et al. 2013; Grant et al. 2014; DSIRE 2015). Despite these efforts, carbon emission has increased by nearly 7 percent in the United States between 1990 and 2013 (EIA 2015).

According to an EIA report, approximately 78 percent of the global warming potential comes from carbon emissions due to the combustion of fossil fuel since 1990 (US EPA, 2014), and a significant amount of such greenhouse gas is generated by the burning of fossil fuels to generate electricity. Thus, it is important to understanding the causal relationships between energy consumption, energy price, and carbon emission as this would provide insights into the effectiveness of various policies in reducing energy use and carbon emissions. Soytas et al. (2007) confirmed the positive relationship between energy consumption and carbon emissions in the United States using Granger causality test. The context of analysis is an extremely important factor in understanding the causality of energy use and carbon emissions. Energy use differs between and among different sectors based on its purposes and uses (EIA 2015; Park and Hong 2013), for example, buildings in the United States rely mostly on electricity generated by coal, oil, natural gas, and various forms of renewable energy, while vehicular transportation relies mostly on oil. Each sector could have its own unique consumption-carbon-cost relationship, and thus the causality of each sector could be different. Prior studies did not address the causalities of different sectors.

The price of energy is often thought to have impacts (negative and positive) on the demand for energy (Nesbakken 1999; Cho et al. 2007; Martinsen et al. 2007; Yuan et al. 2010). How effective is price as a mechanism to manage energy consumption and thus carbon emissions? The first purpose of this research is to understand and identify the causal relationships between consumption, price, and carbon emission of different energy sources (coal, petroleum, natural gas, electricity) of the building sector (only residential and commercial buildings) in the United States. The building sector is the largest carbon emitting sector in the United States. For example, the building sector emitted 1,912 million metric tons of carbons (38%), compared to 1,743 by the transportation sector (34%), and 1,367 by the industrial sector (27%) in the United States (EIA 2015). The second purpose is to discover which energy source generated the most carbon emissions. This would provide important insights to policymakers on potential ways to reduce carbon emissions.

2.2 Literature Reviews

Prior research showed that relationships exist between energy price and demand, and between energy consumption and carbon emissions. These studies suggested that the total energy consumed and fossil fuel used (coal, natural gas, and oil) had positive causal relationships with carbon emissions (as shown in Table 1). These studies were conducted for Pakistan (Mumtaz et al. 2014), Indonesia (Shahbaz et al. 2013; Hwang and Yoo, 2012), the Middle East, and North African (Omri 2013; Arouri et al. 2012), Sub-Saharan Africa (Al-mulali and Sab, 2012; Menyah and Wolde-Rufael 2010), Bangladesh (Alam et al. 2012; Amin et al. 2012), India and China (Jayanthakumaran et al. 2012), India (Alam et al. 2011), China (Wang et al. 2011; Zhang and Cheng 2009), Brazil (Pao and Tsai 2011), Russia (Pao and Tsai 2010), Europe (Hatzigeorgiou et al. 2011; Acaravci and Ozturk 2010), Commonwealth of Independent States (Apergis and Payne 2010), Turkey (Halicioglu 2009; Soytas and Sari 2009), and the United States (Soytas et al. 2007). Moreover, Shafiei and Salim (2014), Bölük and Mert (2014), Al-mulali (2011), and Chang (2010) indicated that non-renewable and fossil fuels increased carbon dioxide emission in OECD, EU, MENA, and China, respectively.

However, some studies concluded different results. In these studies, the total energy consumption was found to have little to no relationship to carbon emissions. In addition, other studies verified that such relationships were dependent on circumstances. Khan et al. (2014) showed in their study the different causal relationships in different countries. In several groups of countries, the relationships between energy consumption and carbon emissions were not significant. Kivyiro and Arminen (2014) confirmed no causal relationship between energy consumption and carbon dioxide in some Sub-Saharan African countries. Similar results were found in Latin America and the Caribbean (Al-mulali et al. 2013), and in Indonesia and Turkey (Jafari et al. 2012; Ozturk and Acaravci 2010). In addition, Niu et al. (2011), Lotfalipour et al. (2010), and Lean and Smyth (2010) highlighted that electricity and fossil fuels, including coal, natural gas, and oil, did not directly increase carbon emissions in Asia-Pacific countries, in the Association of South

East Asian Nations (ASEAN) countries, and Iran, respectively. Table 2 summarizes these studies.

Table 2.1. Summary of studies on the significant causality among energy consumption and CO_2 emissions

Author	Country/Region	Period	Methodology	Causality
Mumtaz et al. (2014)	Pakistan	1975−2010	Granger causality test (ECM)	Energy → CO_2 (per capita)
Shahbaz et al. (2013)	Indonesia	1975−2011	Granger causality test (VECM)	Energy → CO_2 (per capita)
Hwang and Yoo (2012)	Indonesia	1965−2006	Granger causality test (ECM)	Energy → CO_2
Omri (2013)	MENA	1990−2011	GMM	Energy → CO_2 (per capita)
Al-mulali andSab (2012)	Sub-Saharan Africa	1980−2008	Granger causality test	Energy → CO_2
Alam et al. (2012)	Bangladesh	1972−2006	Granger causality test (VECM)	Energy → CO_2 (per capita)
Jayanthakumaran et al. (2012)	China and India	1971−2007	ECM	Energy → CO_2 (per capita)
Arouri et al. (2012)	MENA	1981−2005	PECM	Energy → CO_2
Amin et al. (2012)	Bangladesh	1976−2007	Granger causality test(VAR)	Energy → CO_2
Hatzigeorgiou et al. (2011)	Greece	1977−2007	Granger causality test (VECM)	Energy → CO_2
Pao and Tsai (2011)	Brazil	1980−2007	ECM	Energy → CO_2
Alam et al. (2011)	India	1971−2006	TY procedure	Commercial energy→ CO_2
Wang et al. (2011)	China	1995−2007	ECM	Energy → CO_2
Pao and Tsai (2010)	BRIC	1971−2005	VECM	Energy → CO_2
Acaravci and Ozturk (2010)	Europe countries	1960−2005	Granger causality test	Energy → CO_2 (per capita)
Apergis and Payne (2010)	Commonwealth of Independent States	1992−2004	Granger causality test	Energy → CO_2 (per capita)
Menyah and Wolde-Rufael (2010)	South Africa	1965−2006	TY procedure	Energy → CO_2
Halicioglu (2009)	Turkey	1960−2005	ECM	Commercial energy→ CO_2 (per capita)
Soytas and Sari (2009)	Turkey	1960−2000	TY procedure	Energy → CO_2
Zhang and Cheng (2009)	China	1960−2007	TY procedure	Energy → CO_2
Soytas et al. (2007)	United States	1960−2004	TY procedure	Energy → CO_2
Shafiei and Salim (2014)	OECD	1980−2011	STIRPAT	Non-renewable energy → CO_2
Bölük and Mert (2014)	EU	1990−2008	Penal data analysis	Fossil Fuel Energy → CO_2 (per capita)
Al-mulali (2011)	MENA	1980−2009	ECM	Oil → CO_2
Chang (2010)	China	1981−2006	VECM	Crude oil, natural gas, coal, electricity→CO_2

Notes:→ represents causality

Table 2.2. Summary of studies on the conditional and no causality among energy consumption and CO_2 emissions

Author	Country/Region	Period	Methodology	Causality
Khan et al. (2014)	Various country groups	1975−2011	VECM	Energy $\dashrightarrow$ CO_2 (depending on country groups)
Kivyiro and Arminen (2014)	Sub-Saharan Africa	1971−2009	VECM	Energy $\dashrightarrow$ CO_2 (per capita) (depending on country)
Al-mulali et al. (2013)	Latin America and the Caribbean	1980−2008	CCR	Energy $\dashrightarrow$ CO_2 (depending on country)
Jafari et al. (2012)	Indonesia	1971−2007	TY procedure	Energy $\nrightarrow$ CO_2
Ozturk and Acaravci (2010)	Turkey	1968−2005	ECM	Energy $\nrightarrow$ CO_2
Niu et al. (2011)	Asia-Pacific countries	1971−2005	VECM	Total energy, coal, oil$\rightarrow$ CO_2 Natural gas$\dashrightarrow$ CO_2 (depending on developed or developing country) Electricity $\nrightarrow$ CO_2(per capita)
Lean and Smyth (2010)	ASEAN	1980−2006	ECM	Electricity $\nrightarrow$ CO_2
Lotfalipour et al. (2010)	Iran	1967−2007	TY procedure	Fossil fuel energy$\nrightarrow$ CO_2 Natural gas, petroleum$\rightarrow$ CO_2

Notes:$\rightarrow$ represents causality; $\nrightarrow$ represents no causality; $\dashrightarrow$represents causal relationship depend on conditions

Table 2.3. Summary of studies on the causality among energy price and energy consumption

Author	Country/Region	Period	Methodology	Causality
Yuan et al. (2010)	China	1993−2007	VECM	Price $\rightarrow$ Industrial, household energy
Martinsen et al. (2007)	Germany		Reference scenario	Oil, natural gas, imported coal price $\rightarrow$ Total energy
Mahadevan and Asafu-Adjaye (2007)	20 countries	1971−2002	VECM	Price $\rightarrow$ energy (net energy importers)
Zhang and Xu (2012)	China	1995−2008	VECM	Price $\dashrightarrow$ energy (depending on sectors and regions)
Cho et al. (2007)	South Korea	1991−2003	Logistic diffusion model	Industrial electricity price $\dashrightarrow$ electricity
Hang and Tu (2007)	China	1985−2004	Own model	Total energy, coal, oil price $\rightarrow$ energy Electricity price $\nrightarrow$ electricity
Asafu-Adjaye (2000)	Asian developing countries	1973−1995	ECM	Price $\dashrightarrow$ commercial energy (per capita) (depending on country)
Nesbakken (1999)	Norway	1993−1995	Discrete-continuous choice models	Price $\dashrightarrow$ household energy (depending on income)
Masih and Masih (1998)	Thailand and Sri Lanka	1955−1991	VECM	Price $\nrightarrow$ energy
Abdel-Khalek (1988)	Egypt	1960−1981	Ordinary least squares	Price $\nrightarrow$ energy

Notes:$\rightarrow$ represents causality; $\nrightarrow$ represents no causality; $\dashrightarrow$ represents causal relationship depend on conditions

Research on the causal relationship between energy price and energy consumption found both negative and insignificant relationships. Yuan et al. (2010) study on both the industrial and household sectors in China, Martinsen et al. (2007) study on the oil, natural gas, and imported coal prices in Germany, and Mahadevan and Asafu-Adjaye (2007) study on net energy import countries like the United States, found negative relationships between prices and demand. Alternatively, Zhang and Xu (2012) and Hang and Tu (2007) concluded that the effects of energy prices on energy consumption varies by sector, region, and energy source in China. Cho et al. (2007) indicated that industrial energy prices had limited effects on energy consumption in the South Korean industrial sector. Asafu-Adjaye (2000) showed that energy prices did not cause energy consumption in Asian developing counties, except in Thailand. Nesbakken (1999) concluded that low-income households are less sensitive to energy prices in Norway. Masih and Masih (1998) found that energy prices did not cause increased energy consumption in Thailand and Sri Lanka. Abdel-Khalek (1988) found evidence that energy consumption is significantly less elastic with respect to energy price than generally believed in Egypt. Table 3 summarizes these studies.

Prior studies found mixed causal relationships between energy consumption, prices, and carbon emission, and these relationships were influenced by their sectors, countries, and geographical regions. Even studies in the same countries generated different results, for example, Halicioglu (2009) and Soytas and Sari (2009) verified that energy consumption causes carbon emissions in Turkey, but Ozturk and Acaravci (2010) showed there was no causality or relationship. Shahbaz et al. (2013) and Hwang and Yoo (2012) concluded that energy consumption affects carbon emissions in Indonesia, but Jafari et al. (2012) showed different results. In addition to the relationships, not many studies could be found to determine the particular relationships between different energy sources (e.g. coal, petroleum, and natural gas) and carbon emissions.

Little to no research were conducted to study the building sector's relationships between energy sources and prices, and carbon emissions, even though the sector generated the largest amount of carbon compared to the other sectors. There is apparently a gap in such literature on understanding the causal relationships between energy consumption, price, and carbon emissions of the building sector. Applying similar techniques and methodologies used by prior research, this paper focuses on identifying such relationships and causalities. The paper also focuses on incorporating different factors and understanding the reliability of the Toda and Yamamoto (TY) method. TY method is considered a more reliable method for the detection of causality between factors. While the Granger causality test, which is the basis of the TY method, has been widely used to determine the causal relationship between the variables, the TY method would avoid the loss of information during the analysis process. TY involves a vector auto-regression (VAR) at different levels to eliminate such loss (Soytas et al. 2007). In addition to the advantage, the TY procedure does not require testing for co-integration. TY employs the vector error correction model, and is robust to the unit root and co-integration properties of the series (Pao and Tsai 2010; Soytas and Sari 2009; Soytas et al. 2007). Loss of information during the analysis could have contributed to the differences in the above results, and thus the TY method is used.

2.3 Methodology and empirical results

2.3.1 Data collection

The building sector analyses (and their data) were divided into residential and commercial sectors. The analyses focus on the causal relationships between different and relevant variables, and these include a) total energy consumed and generated from coal, natural gas, petroleum, and retail electricity consumption (in trillion Btu, and dollars per million Btu); b) the total amount of carbon emissions (million metric tons), which is estimated by multiplying the total energy consumed by the carbon emission factor(s) and ratio(s) (from the U.S. Energy Information Administration database). The data are time series data between 1973 and 2012.

The effect of inflation on energy prices was removed from the data since inflation affects purchasing power and energy demand. Inflation affects the real price of energy and how residents respond to their purchasing decisions. The effect of inflation was eliminated using consumer price index (CPI). In addition to the inflation, no variables used in this research were based on per capita data as it only scales down the effects of variables (Soytas and Sari 2009), and that the goals of the Kyoto Protocol relate to decreasing the percentage of greenhouse gas emissions from the base level of total emissions rather than per capita emissions (Friedl and Getzner 2003). The data used in this research are documented in Appendix A and B.

2.3.2 Unit root test results

In order to apply the TY procedure, the unit root test is used to obtain the maximal integration order (dmax) of the variables. This research conducted two different unit root tests, the augmented Dickey and Fuller (ADF), and Phillips and Perron (PP). The unit root test results are shown in Tables 4−6. Table 5 and Table 6 show that the integration order of energy price and carbon dioxide emission is 2. Thus, the unit root test results identified that the maximal integration order of variables used in this research is 2, which is required for TY procedures for Granger causality testing.

Table 2.4. Unit root test results of energy consumption factors

		Residential Sector		Commercial Sector	
		ADF	PP	ADF	PP
Levels					
Intercept	Coal	-4.482031[a] (0)	-4.122059[a] (2)	-0.805702 (0)	0.01584 (33)
	Natural gas	-3.039682[b] (0)	-3.081159[b] (1)	-1.548438 (0)	-1.507751 (1)
	Petroleum	-2.112495 (0)	-2.092467 (3)	-1.699005 (0)	-2.06400 (10)
	Electricity	-0.748933 (1)	-0.710208 (3)	-0.712182 (0)	-0.658053 (3)
	Total energy	-1.159436 (0)	-1.125040 (2)	-1.112124 (0)	-1.038310 (3)
Intercept and Trend	Coal	-5.038679[a] (0)	-5.038679[a] (0)	-4.098702[b] (0)	-3.58485[b] (10)
	Natural gas	-2.952540 (0)	-2.995373 (1)	-2.356259 (0)	-2.246990 (2)
	Petroleum	-2.196587 (0)	-2.341181 (2)	-2.749468 (0)	-2.807070 (2)
	Electricity	-2.760439 (1)	-2.916113 (4)	-0.874861 (0)	-1.498955 (3)
	Total energy	-2.169160 (0)	-2.173547 (3)	-0.081260 (0)	-0.659810 (3)
First difference					
Intercept	Coal	-4.682785[a] (0)	-4.682785[a] (0)	-7.186396[a] (0)	-13.7574[a] (32)
	Natural gas	-6.439811[a] (1)	-7.144926[a] (8)	-6.497129[a] (0)	-6.589488[a] (3)
	Petroleum	-4.114766[a] (1)	-4.381381[a] (3)	-6.039132[a] (0)	-6.633138[a] (6)
	Electricity	-5.443359[a] (1)	-8.166056[a] (3)	-4.734704[a] (0)	-4.799628[a] (3)
	Total energy	-4.970907[a] (1)	-6.989921[a] (1)	-4.479221[a] (0)	-4.629119[a] (3)
Intercept and Trend	Coal	-4.936664[a] (0)	-4.936664[a] (0)	-7.099508[a] (0)	-14.0101[a] (29)
	Natural gas	-6.352604[a] (1)	-7.158097[a] (7)	-5.891475[a] (1)	-6.480058[a] (3)
	Petroleum	-4.073637[a] (1)	-4.240004[a] (4)	-5.949477[a] (0)	-6.774067[a] (7)
	Electricity	-5.227649[a] (1)	-8.053182[a] (3)	-4.788744[a] (0)	-4.790691[a] (2)
	Total energy	-4.915285[a] (1)	-6.963287[a] (1)	-4.642770[a] (0)	-4.732753[a] (3)

[a] 1% significance; [b] 5% significance; [c] 10% significance
Note: Lag lengths are listed in parentheses and were determined via SIC for ADF and via Bandwidth-NeweyWest for PP.

Table 2.5. Unit root test results of energy prices

		Residential Sector		Commercial Sector	
		ADF	PP	ADF	PP
Levels					
Intercept	Coal price	-0.371867 (0)	-0.345024 (2)	-2.457017 (3)	-1.539086 (3)
	Natural gas price	-2.144372 (0)	-2.269409 (3)	-2.294905 (0)	-2.425483 (3)
	Petroleum price	-0.364550 (0)	-0.516621 (2)	-0.942525 (0)	-0.816964 (2)
	Electricity price	-1.101050 (1)	-0.830667 (3)	-0.886191 (1)	-0.664695 (4)
	Total energy price	-2.374867 (0)	-2.404522 (4)	-3.214622[a] (0)	-3.079131[a] (4)
Intercept and Trend	Coal price	-4.786327[a] (0)	-4.862702[a] (3)	-0.577781 (3)	-1.762547 (3)
	Natural gas price	-1.683947 (0)	-1.986116 (3)	-1.734435 (0)	-1.992723 (3)
	Petroleum price	-0.805558 (0)	-0.938673 (2)	-1.304849 (0)	-1.191638 (2)
	Electricity price	-2.701416 (1)	-2.767226 (4)	-1.655564 (1)	-3.097967 (4)
	Total energy price	-2.054171 (0)	-2.271640 (4)	-2.862026 (0)	-2.820341 (4)
First difference					
Intercept	Coal price	-8.095202[a] (0)	-11.00585[a] (8)	-2.761654[c] (2)	-6.737067[a] (3)
	Natural gas price	-5.148310[a] (0)	-5.212167[a] (3)	-5.202963[a] (0)	-5.281446[a] (3)
	Petroleum price	-5.519236[a] (0)	-5.524486[a] (1)	-7.055603[a] (0)	-7.106894[a] (2)
	Electricity price	-4.691586[a] (0)	-4.691047[a] (1)	-5.016853[a] (0)	-5.008021[a] (1)
	Total energy price	-4.774574[a] (0)	-4.849272[a] (3)	-4.718428[a] (0)	-4.709248[a] (2)
Intercept and Trend	Coal price	-7.814943[a] (0)	-10.52375[a] (8)	-8.416040[a] (1)	-8.929033[a] (7)
	Natural gas price	-5.289425[a] (0)	-5.307445[a] (2)	-5.444114[a] (0)	-5.506960[a] (3)
	Petroleum price	-5.642607[a] (0)	-5.642607[a] (0)	-5.135019[a] (1)	-7.223941[a] (1)
	Electricity price	-4.493760[a] (0)	-4.493760[a] (0)	-4.782328[a] (0)	-4.778194[a] (1)
	Total Energy price	-4.713903[a] (0)	-4.806242[a] (3)	-4.749877[a] (0)	-4.755912[a] (2)
	CO_2emissions	-1.633819 (2)	-6.120377[a] (4)	-1.110919 (2)	-5.100625[a] (4)
Second difference					
Intercept	Coal price	-9.366394 [a] (0)	-	-11.24939 [a] (1)	-
Intercept and Trend	Coal price	-9.239583 [a] (0)	-	-11.10031 [a] (1)	-

[a] 1% significance; [c]10% significance
Note: Lag lengths are listed in parentheses and were determined via SIC for ADF and via Bandwidth-NeweyWest for PP.

Table 2.6. Unit root test results of CO_2 emissions

		Residential Sector		Commercial Sector	
		ADF	PP	ADF	PP
Levels					
Intercept	CO_2 emissions	-1.183406 (0)	-1.205723 (4)	-1.727853 (3)	-1.261508 (4)
Intercept and Trend	CO_2 emissions	-0.930875 (0)	-1.203317 (4)	0.512623 (0)	-0.229426 (4)
First difference					
Intercept	CO_2 emissions	-5.980950[a] (0)	-6.073683[a] (4)	-0.703354 (2)	-4.868260[a] (4)
Intercept and Trend	CO_2 emissions	-1.633819 (2)	-6.120377[a] (4)	-1.110919 (2)	-5.100625[a] (4)
Second difference					
Intercept	CO_2 emissions	-9.150812[a] (1)	-	-10.31891[a] (1)	-
Intercept and Trend	CO_2 emissions	-5.072535[a] (3)	-	-10.52008[a] (1)	-

[a] 1% significance
Note: Lag lengths are listed in parentheses and were determined via SIC for ADF and via Bandwidth-NeweyWest for PP.

2.3.3 Granger causality analysis results

Table 2.7. Granger causality test results

Null Hypothesis	χ^2	Probability	Decision
Residential Sector (energy price → energy consumption)			
Coal price does not affect coal consumption	6.3741	0.4968	Accepted
Natural gas price does not affect natural gas consumption	10.3892	0.0155	**Rejected**
Petroleum price does not affect petroleum consumption	4.9451	0.5509	Accepted
Electricity price does not affect electricity consumption	11.8401	0.1585	Accepted
Total energy price does not affect total energy consumption	4.0821	0.8496	Accepted
Residential Sector (energy consumption→ CO_2 emissions)			
Coal consumption does not cause CO_2	5.6625	0.5797	Accepted
Natural gas consumption does not cause CO_2	4.5030	0.2120	Accepted
Petroleum consumption does not cause CO_2	4.3593	0.6282	Accepted
Electricity consumption does not cause CO_2	16.5523	0.0351	**Rejected**
Total energy consumption does not cause CO_2	12.5932	0.1266	Accepted
Commercial Sector (energy price → energy consumption)			
Coal price does not affect coal consumption	4.6615	0.4586	Accepted
Natural gas price does not affect natural gas consumption	8.2334	0.0414	**Rejected**
Petroleum price does not affect petroleum consumption	12.0738	0.0338	**Rejected**
Electricity price does not affect electricity consumption	3.2542	0.8605	Accepted
Total energy price does not affect total energy consumption	5.2618	0.1536	Accepted
Commercial Sector (energy consumption→ CO_2 emissions)			
Coal consumption does not affect CO_2	12.6400	0.0270	**Rejected**
Natural gas consumption does notaffectCO_2	1.1682	0.7606	Accepted
Petroleum consumption does notaffectCO_2	4.3335	0.5025	Accepted
Electricity consumption does notaffectCO_2	4.6619	0.7011	Accepted
Total energy consumption does notaffectCO_2	3.8919	0.2734	Accepted

To apply the TY procedure, the optimal lag length (k) should also be decided, as the lag length plays a critical role in the Granger causality test to avoid bias causality (Clarke and Mirza 2006). In this research, the optimal lag length was determined by the method proposed in Lutkepohl (1997). The five criteria were checked, including the sequential modified likelihood ratio test statistic (LR), final prediction error (FPE), Akaike information criteria (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criteria (HQ). As consistency is the yardstick for evaluating the criteria, majority voting that selects the optimal lag length by getting more than half of the criteria was adopted to determine the optimal lag length (Lutkepohl 1997). So, among the five criteria, if three or more criteria select the same value, the value is selected as the optimal lag length. Using the maximal integration order (dmax) and the optimal lag length (k), the augmented VAR(k+dmax) level was estimated for the Granger causality test. The results of the Granger causality test are shown in Table 7. At the 5% significance level, five null hypotheses were rejected that had probabilities lower than 0.05. These results are summarized in Figures 1 and 2.

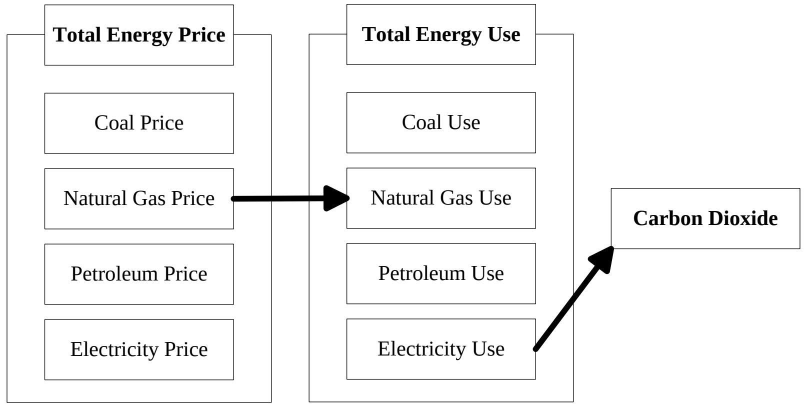

Figure 2.1. Summary of causal relationship in the residential sector

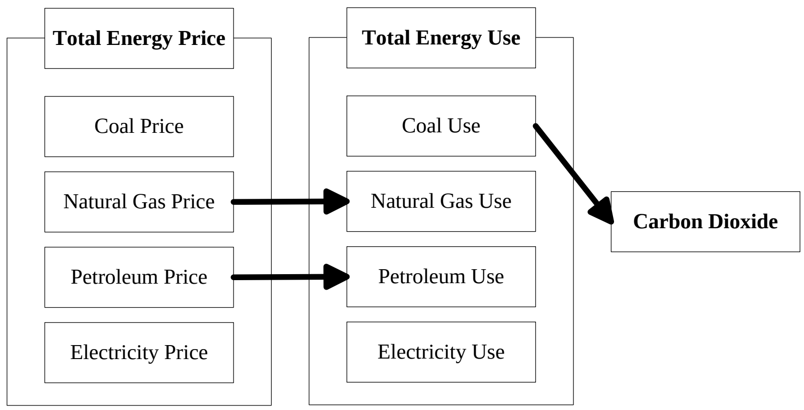

Figure 2.2. Summary of causal relationship in the commercial sector

2.3.4 Generalized impulse response function results

The TY procedure is a method for examining the long-term Granger causality relationships among the variables. However, the Granger causality test does not consider how each variable in general responds to innovations in other variables and how long such variable's shock last, which can provide useful insights about the short run causality (Soytas and Sari 2009). This problem can be solved by the generalized impulse response analysis (Koop et al. 1996; Pesaran and Shin 1998). The analysis can show how one variable initially responds to a shock in another variable and whether the shock is permanent or not (Soytas et al. 2007). Moreover, the generalized impulse response analysis is insensitive to the ordering of variables in the VAR system, and overcomes the orthogonality problem in traditional out-of-sample Granger causality testing (Soytas and Sari 2009). Figures 3 to 6 show the responses of energy consumption and carbon dioxide emissions to shocks of one standard deviation in energy price and energy consumption in the VAR, in the residential and commercial sectors.

Figure 2.3. Generalized impulse responses of energy consumption to energy price in residential sector

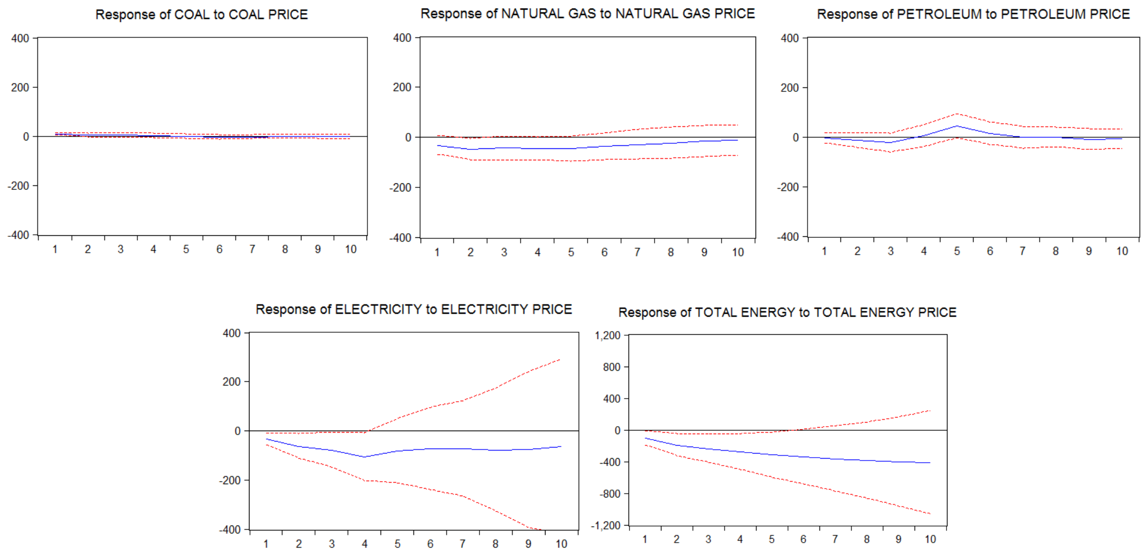

Figure 2.4. Generalized impulse responses of energy consumption to energy price in commercial sector

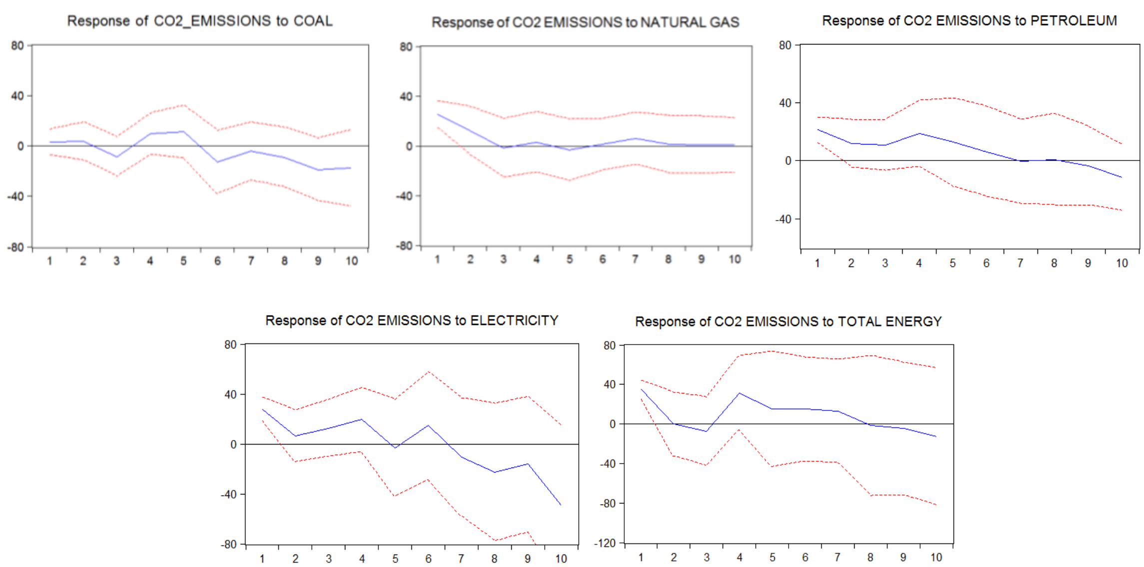

Figure 2.5. Generalized impulse responses of CO_2 to energy consumption in the residential sector

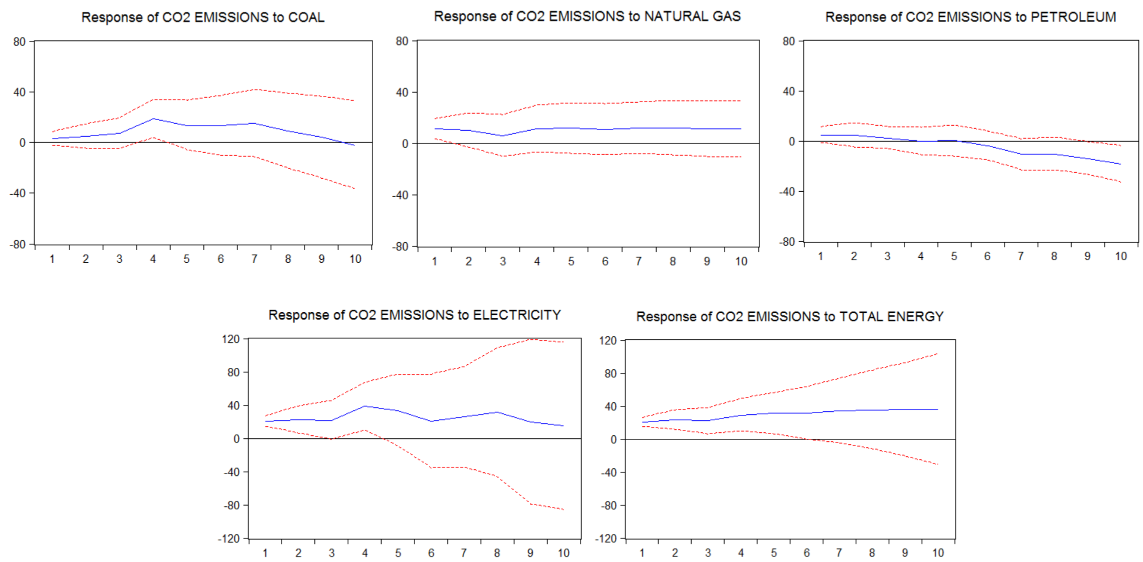

Figure 2.6. Generalized impulse responses of CO_2 to energy consumption in the commercial sector

2.4 Discussion

2.4.1 Energy price and energy consumption

The above Granger causality tests show that changing coal prices do not impact total energy consumption in the building sector. The proportion of energy generated by coal coupled with the low coal price are the reason why coal price has little effect on the total energy consumed by the building sector (*note that this coal refers to direct use coal instead of coal used to generate electricity by power plants). Most of the coal is used to heat air and water, though natural gas and electricity can be substituted for coal, they are more expensive. The analyses find that the price of natural gas influences the consumption in both sectors. The residential buildings used 93.7% and commercial buildings used 77.2%, of the total natural gas for space heating, water heating, and cooking in 2013 (US EIA 2015). These functions can be substituted by electricity, but natural gas is cheaper than electricity in most counties/states.

The analyses show that a significant causality exist between petroleum prices and consumption only for commercial buildings. As petroleum is used mainly for heating of air and water (US EIA 2015). Finally, the causality between electricity consumption and prices is insignificant, and this result corresponds with Azevedo et al. (2011). This indicates that electricity consumption is inelastic in the United States. Electricity is indispensable to every aspect of personal and business lives and thus it is inelastic.

The generalized impulse responses analyze the short-run the causality between energy price and energy consumption for both residential and commercial buildings. As shown in Appendix F, the consumptions of coal, petroleum, and electricity for the residential buildings do not respond to price shocks, whereas price shocks affect the consumption of natural gas. The effects of natural gas price shock also last longer. These results are consistent with the results of the Granger causality tests. In Appendix G (commercial buildings), only the prices of natural gas, electricity, and total energy prices affect energy consumption and the effects are significant in the long run. This result indicates that the consumption of electricity and natural gas are more vulnerable to changes in price. This may be because the commercial sector mostly consumed the electricity and natural gas. According to the EIA database, commercial sector used 3,563 Trillion BTU of natural gas and 4,632 Trillion BTU of electricity in 2014. Total energy use was 18,394 Trillion BTU which includes 9,441 Trillion BTU of energy losses. Thus, the portion of natural gas and electricity use is about 91.5% of total energy use except energy losses. In addition, the results also show that the energy consumption of the commercial buildings is more vulnerable to changes in energy prices than the residential buildings in the short run.

2.4.2 Energy consumption and carbon emissions

The Granger causality tests also affirm the causal relationships between energy consumption and carbon emissions. The results showed that an increase in electricity consumption also increases in the carbon emissions of residential buildings, while only increasing coal consumption increases carbon emissions among the commercial buildings. These results imply that reduction in electricity consumption among the residential buildings would result in the reduction in carbon emissions, similar to coal consumption and carbon emissions for the commercial buildings. Interestingly, the study also finds that carbon emissions are not caused by increasing energy consumption of other energy sources (especially electricity). These results highlight the increasing use (and thus proportion) of lower carbon or carbon neutral energy sources (e.g. renewable and natural gas) to generate electricity over the past decades and possibly the increasing efficiency to generate powers. In the same vein, the results showed that natural gas consumption does not increase the overall carbon emissions in either buildings while coal consumption increases carbon emissions in the commercial sector (the use of coal has been stopped for residential use since 2008). On petroleum, though its carbon intensity is high, its use is limited in both sectors (8.6 percent for residential and 7 percent for commercial over total energy). As a result, the causality tests do not find significant relationships.

The most unexpected result is the causality of the commercial buildings' electricity consumption and carbon emissions. Figures 5 and 6 show the generalized impulse responses of carbon emissions to energy consumption of the residential and commercial buildings. The increase in carbon emissions of each energy resources are mostly caused by to the increase in the consumption of the energy resources in the short run of the residential buildings (except for coal as it is not used in the residential buildings after 2008), but the causality tests show that the effect faded quickly. The effects of energy resource consumption of the commercial buildings last longer than the residential buildings (except for petroleum) and made almost no contribution to increase carbon emissions. This result shows that, in both buildings, there are causalities between carbon emissions and electricity consumption, but there is insignificant causality for natural gas. It is expected that this result is highly related to carbon intensity as shown in the result of the long-run causality. In addition, carbon dioxide emissions levels in the commercial sector are more vulnerable and lasted longer in regards to energy consumption than those of the residential sector in the short run.

2.5 Conclusion

This research investigated the causalities between energy consumption, energy prices, and carbon emissions in the U.S. residential and commercial building sectors using Granger causality testing and generalized impulse response analysis. The results showed that only natural gas prices influence the consumption of natural gas, and carbon dioxide emissions are caused only by electricity consumption in the residential sector in the long run. In the commercial sector, natural gas and petroleum prices affect the consumption of natural gas and petroleum but carbon dioxide emissions are caused only by coal consumption in the long run. Even though only a few long-term causal relationships were determined among energy prices, consumption, and carbon dioxide emissions, there are many more short-term causal relationships. These results verified that, basically, energy prices negatively cause energy consumption and that consumption causes carbon dioxide emissions, but the detailed results varied depending on the sector. By verifying the causal relationships, policymakers can make more effective policies. Using Granger causality (TY method) and generalized impulse response analysis, the analyses concluded the followings:

1. Energy consumption and prices generate different impacts on carbon emissions based on the types of buildings, and energy sources: This concludes that energy policies to reduce energy consumption and carbon emissions have to be separately developed for building and energy types. The control of energy use of residential and commercial buildings are not the same too.

2. The study also concludes the importance of increasing the proportion of energy from low-carbon and carbon-neutral sources: The analyses have shown this has reduced the overall carbon emissions even though energy consumption has been increasing. The more expensive the energy sources are, the more likely they will affect its consumption in the long and short run.

3. Energy prices are only effective tools in managing energy use and carbon emissions if the prices are high enough: The analyses show that low energy prices (like coal) have little effects in reducing carbon emissions and overall energy consumption.

Furthermore, the research find that: 1) Coal consumption should be limited in the commercial sector: The consumption of coal causes carbon dioxide emissions in both the short and long run; 2) Increasing the use of natural gas could reduce carbon emissions: Natural gas consumption does not cause carbon dioxide emissions in the long run, and its impact is lower than electricity in the short run; 3) The carbon intensity of natural gas is much lower than that of electricity: Since natural gas and electricity are consumed by both types of buildings, increasing the use of natural gas and decreasing electricity will be an effective approach in reducing carbon emissions; 4) The use of natural gas can be promoted by reducing its price: In both sectors, natural gas consumption is caused by the price of natural gas, in long run as well as the short run. Thus, by decreasing the price of natural gas, carbon emissions would be expected to decrease; and 5) Finally, decreasing electricity consumption is essential to reduce carbon dioxide emissions: Although no long-run causality was found between electricity consumption and carbon emissions for the commercial buildings, there is a significant causality in the short run while and both short- and long-term causality were exhibited for the residential buildings. The carbon intensity of electricity is the highest of all the energy resources.

The study also shows that there is no causality between electricity prices and consumption in the residential buildings, and thus controlling electricity consumption through price can be futile. Policies should focus on promoting the consumption and use of low-carbon and carbon neutral energy resources (like renewable and natural gas). In the case of the commercial buildings, electricity consumption responds to price, so the consumption can be controlled by making changes to price.

While real data from the U.S. building sector were used in the analyses, the results cannot be validated (due to the lack of alternative sources of data) and applied to other countries. The characteristics of other countries' building sectors can be different. A large number of previous research studies have also reported different results for different countries in terms of these causal relationships. Thus, further research about other countries is necessary to generalize the relationships. In addition, the industrial and transportation sectors also have their own characteristics, so further research should be conducted regarding these sectors. Finally, energy consumption and carbon dioxide emissions can respond to other factors such as weather or economic conditions. Thus, these variables could be considered in future research.

CHAPTER 3

THE CAUSES OF THE MUNICIPAL SOLID WASTE AND THE GREENHOUSE GAS EMISSIONS FROM THE WASTE SECTOR IN THE UNITED STATES[2]

3.1 Introduction

Global Municipal Solid Waste (MSW) amounts to approximately 1.3 billion tons per year and is expected to increase to approximately 2.2 billion tons per year by 2025 (Hoornweg and Bhada-Tata, 2012). Developed countries produce more waste per capita due to the higher levels of waste consumption (e.g., plastics, metals, and paper) (UNEP, 2005). Waste generation in Organization for Economic Cooperation and Development (OECD) countries has increased approximately 14% from 1990 up to now (OECD, 2006). In the case of the United States, the U.S. generates the most waste per capita compared to other OECD countries—approximately 730 kilograms per capita in 2013 (OECD, 2013). Since 1960, the United States' total municipal solid waste generation has increased 288% (EPA, 2015). Moreover, the U.S. produced the most greenhouse gas emissions compared to other OECD countries (OECD, 2013). Based on an U.S. Environmental Protection Agency (EPA) study in 2014, 117.2 Tg CO_2 Eq. of methane (CH4) was emitted from waste in the United States. Approximately 18.1% of total U.S. methane emissions were generated from the waste landfills sector in 2013, which is the third largest contribution of methane emission in the United States (Agency, 2014).

Solid waste, which has reactivity, toxicity, explosiveness, erosive, or other characteristics, can result in adverse effects to human health and the environment (Alam

[2] Lee, S., Kim, J., and Chong, W.O., 2016. The causes of the municipal solid waste and the greenhouse gas emissions from the waste sector in the United States. Waste Manage. 56, 593–599.

and Ahmade, 2013). In particular, waste produces a large amount of greenhouse gas emissions, which is the most critical issue affecting changes to global climate (Bogner et al., 2008). As the amount of GHGs increase in the atmosphere, increased solar heat will be trapped in the gas and, therefore, atmospheric temperatures will continue to increase (Calabrò, 2009; Miah et al., 2011). The best way to reduce the impacts of global warming is by reducing greenhouse gas emissions. According to the Intergovernmental Panel on Climate Change (IPCC), global surface temperature will increase by 4.8º C and sea levels by 0.82 m by 2100 (IPCC, 2014). In addition, the climate change originating from greenhouse gas will drop between 5% and 20% of the annual global GDP if the greenhouse gas does not decrease immediately. Therefore, reduction of greenhouse gas is a critical issue to be resolved.

Several efforts to reduce waste have been made in the past by the U.S. government. In 1976, the Resource Conservation and Recovery Act (RCRA) gave the EPA the authority to manage hazardous waste, which includes its generation, transportation, treatment, storage and disposal. In 1984, the Federal Hazardous and Solid Waste (FHSW) amendments to RCRA focused on waste minimization and phasing out land disposal of hazardous waste (Barke, 1985; U.S. Congress Office of Technology Assessment, 1983). Moreover, according to the Weitz et al. (2002), the U.S. communities' appropriate actions, such as technological advancements, environmental regulations, and emphasis on resource conservation and recovery, have significantly reduced the environmental impacts of municipal solid waste, including greenhouse gas emissions. However, solid waste generation is not decreasing and the recycling rate is not increasing. The U.S. recycling rate is only 26%, and it is lower than other OECD countries (http://www.oecd.org/).

Americans on average recycled and composted 0.68 kilograms out of an individual waste generation rate of 2 kilograms per person per day (EPA, 2015). The highest recycling rate among OECD countries is found in South Korea, which is almost 60% (http://www.oecd.org/). South Korea started implementing recycle performance measures in 1995 and expects to increase to an 87% recycling rate by 2020.

The current situation of the U.S. waste sector is severe. Not only the waste generation per capita, but also the greenhouse gas emissions from the waste sector are significantly high. Thus, the main objective of this research is to mitigate the solid waste and greenhouse gases from waste sector. In order to achieve the main objective, first, we investigated the causal relationship with solid waste across the U.S. If the main cause of the solid waste is verified, the waste can be decreased effectively. Second, it is confirmed that the solid waste and recycling waste influence greenhouse gas emissions from the waste sector. By verifying the relationship between the waste and greenhouse gas from the waste sector, appropriate strategies can be developed for decreasing the greenhouse gas from the waste sector. Lastly, based on the research results, we provide important insights and suggestions to policymakers on potential ways to reduce the solid waste and greenhouse gas emissions from the waste sector. The rest of this paper is organized as follows: Section 2 reviews the related previous literature, Section 3 presents the methodology used in this research and research results, Section 4 discusses the research results, and Section 5 is the conclusion.

3.2 Literature review

The solid waste generation per capita can be correlated to Gross Domestic Production (GDP) per capita. According to the previous research, environmental degradations that include municipal waste per capita, greenhouse gas emissions per capita, dissolved oxygen in rivers, and change in forest area relate to GDP per capita, and this relationship is called the Environmental Kuznets Curve (EKC) (Stern et al., 1996). The EKC hypothesis is that there is an inverted-U relationship between per capita income and environmental degradation (Stern et al., 1996). This hypothesis conjectures that initially environmental degradation tends to get worse as per capita income rises until it reaches a certain level and the degradation subsides and drops at the highest economic level (Shafik, 1994; Stern et al., 1996). Thus, economic growth may become a solution rather than a source of the problem (Rothman and Bruyn, 1998). There have been a lot of studies of the ECK relationship. Most of the studies focused on the relationship between economic growth per capita and carbon dioxide emissions for various countries, and the research showed different results depend on the country. (Apergis and Payne, 2014; Bölük and Mert, 2014; Kivyiro and Arminen, 2014; Omri and Nguyen, 2014; Shafiei and Salim, 2014; Omri, 2013; Arouri et al., 2012; Jayanthakumaran et al., 2012; Saboori et al., 2012; Acaravci and Ozturk, 2010; Dinda and Coondoo, 2006).

Among the previous studies, several studies tried to verify whether or not the EKC relationship exists in the United States. Some studies confirmed that the United States has the EKC relationship for environmental degradation factors. Roach (2013) concluded that the United States has the EKC relationship at the state level for carbon dioxide emissions. Gawande et al. (2000) verified the EKC relationship for hazardous waste in the United States. List and Gallet (1999) provided initial evidence that states' NOX and SO2 emissions have followed an inverted-U shape relationship. However, other research has showed different results. Soytas et al. (2007) concluded that there is no EKC relationship in the case of the U.S. for carbon dioxide emission. Cole et al. (1997) suggested that municipal waste of OECD countries does not have significant EKC relationship. Some prior research analyzed the relationship between the waste and GDP in some countries. Mazzanti (2008) and Mazzanti et al. (2008) concluded that there is de-linking of waste generation from economic growth in Italy. However, in Bangladesh, it was shown that the EKC relationship is supported for waste and greenhouse gas emissions from waste.

There have been various prior studies, however, the studies have some limitations, so additional research is essential. First of all, most previous studies usually focused on carbon dioxide emissions when analyzing the EKC relationship. However, there are various other environmental degradation factors, and municipal solid waste is one of the degradation factors that is most deadly to environment. Second, there is insufficient EKC and municipal solid waste research in the United States. As shown in the previous research, depending on the environmental degradation factors or countries, the relationships either exist or they do not. Moreover, there is insufficient research about the causal relationship between municipal solid waste, recycling waste generation, and greenhouse gas emission. Thus, this research focused on municipal solid waste in the United States and verified the causality between the factors.

3.3 Methodology and empirical results

3.3.1 Data collection

Two causality models are proposed for achieving the research objectives. The first model is for the EKC relationship, which verifies whether or not there is inverse proportion between GDP per capita and MSW generation per capita. The U.S. annual data from 1990 to 2012 used in this study were collected from various data sources. The GDP per capita (current U.S. dollar) and municipal solid waste generated per capita (kilograms per capita), which is comprised of various items such as packaging, furniture, electrical appliances, and food waste, but does not include industrial, hazardous, or construction waste, were collected from the World Bank website database (http://www.worldbank.org/) and OECD website database (http://stats.oecd.org/) for the first model. The second model confirms how the total MSW and recovery waste, which is selectively extracted materials from disposed waste for next use and includes recycling and composting waste generation, causes greenhouse gas emissions from the waste sector. The total MSW and recovery waste generation (tons) and greenhouse gas emissions from the waste sector (Tg CO_2 Eq.) data were obtained from the U.S. Environmental Protection Agency website database (http://www.epa.gov/) for the second model. Figure 1 summarizes the proposed two causality models, and the data used in this research are documented in appendixes A and B.

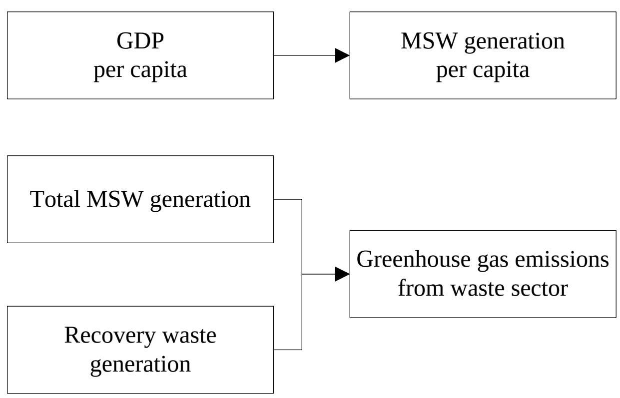

Figure 3.1. Proposed causality models

3.3.2 Theoretical background of methodology – Causality test

Conventional Granger causality is applied by estimating vector autoregressive (VAR) models, and it requires pretests for unit root test and co-integration test. Based upon the two pretests, if co-integration exists, the causality test is applied. However, the unit root and co-integration test might cause size distortions, and it can lead to an inaccurate model for the non-causality test (Clarke and Mirza, 2006). Moreover, the Johansen-type co-integration test is susceptible to the values of the nuisance parameters, so the causality results based upon ECM might be extremely biased (Toda, 1995). Thus, a modified Wald (MWALD) test in an augmented VAR model was proposed by Dolado and Lütkepohl (1996) and Toda and Yamamoto (1995). The MWALD is simpler and relatively straightforward compared to other causality tests and does not need pretesting for co-integration test (Altinay and Karagol, 2005). The basic idea of the Toda–Yamamoto (TY) test is to artificially augment the actual lag length (k) of the VAR model by the maximal order of integration (dmax). Once this is done, the VAR model with a (k+dmax) order is estimated and the coefficients of the last dmax lagged vectors are ignored. The augmented VAR guarantees the asymptotic distribution of the Wald statistic, whether the process is stationary or nonstationary, because the TY test requires the estimation of an augmented VAR (Wolde-Rufael and Menyah, 2010). In addition, the procedure can avoid the potential biases of pretesting that undermine the conventional causality test since the pretesting for the co-integration test is not required (Wolde-Rufael and Menyah, 2010; Zapata and Rambaldi, 1997). Lastly, since TY procedure estimates a VAR in level, there is no information loss due to data differencing (Doğrul and Soytas, 2010).

3.3.3 Unit root test results

The TY procedure requires determining the maximal integration order (dmax) of the variables. Thus, this research investigates the time series properties of the variables by conducting two different unit root tests for Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests. The results of the unit root test that show the integration order of the variables are demonstrated in Table 1 and 2. According to the results, waste per capita, total waste, and recovery waste were I(1), but GDP per capita and CO_2 from waste were I(2). This result indicates that the series of the variables have been integrated by the different orders, and it verifies once again that the TY procedure is the most appropriate to this research (Soytas and Sari, 2006). Then, based on the results, the maximum order of integration is identified as 2 (dmax=2), and using the value the TY test was conducted.

Table 3.1. Unit root test results of the first model

		ADF	PP
Level			
Intercept	GDP per capita	0.057799 (0)	-0.018109 (1)
	Waste per capita	-1.494404 (0)	-1.494404 (0)
Intercept and Trend	GDP per capita	-3.202435 (1)	-2.220288 (1)
	Waste per capita	-1.053742 (0)	-1.083733 (1)
First difference			
Intercept	GDP per capita	-2.971919[c] (3)	-3.010054[c] (1)
	Waste per capita	-4.318115[a] (0)	-4.322330[a] (1)
Intercept and Trend	GDP per capita	-2.769857 (3)	-2.935903 (1)
	Waste per capita	-4.660895[a] (0)	-4.660895[a] (0)
Second difference			
Intercept	GDP per capita	-4.652898[a] (0)	-4.775660[a] (3)
Intercept and Trend	GDP per capita	-4.332957[a] (4)	-4.600143[a] (3)

[a] 1% significance; [b] 5% significance; [c] 10% significance
Note: Lag lengths and Bandwidth are listed in parentheses and were determined via SIC for ADF and via Bandwidth-NeweyWest for PP.

Table 3.2. Unit root test results of the second model

		ADF	PP
Level			
Intercept	Total waste	-1.494404 (0)	-1.494404 (0)
	Recovery waste	-3.996031[a] (2)	-11.51943[a] (21)
	GHG from waste	-0.894238 (0)	-0.971476 (2)
Intercept and Trend	Total waste	-1.053742 (0)	-1.083733 (1)
	Recovery waste	-0.824079 (2)	-0.350148 (21)
	GHG from waste	-1.038904 (0)	-1.367161 (2)
First difference			
Intercept	Total waste	-4.318115[a] (0)	-4.322330[a] (1)
	Recovery waste	-1.321733 (2)	-2.755865[c] (6)
	GHG from waste	-3.038081[b] (0)	-2.976843[c] (1)
Intercept and Trend	Total waste	-4.660895[a] (0)	-4.660895[a] (0)
	Recovery waste	-5.295455[a] (1)	-7.085626[a] (20)
	GHG from waste	-3.035106 (0)	-2.964701 (1)
Second difference			
Intercept	GHG from waste	-7.062914[a] (0)	-7.421130[a] (2)
Intercept and Trend	GHG from waste	-6.870439[a] (0)	-7.205458[a] (2)

[a] 1% significance; [b] 5% significance; [c] 10% significance
Note: Lag lengths and Bandwidth are listed in parentheses and were determined via SIC for ADF and via Bandwidth-NeweyWest for PP.

3.3.4 Optimal lag length selection

The next step to applying the TY procedure is to determine the appropriate lag length (k), which plays an important role in the procedure for avoiding biased causal relationship (Clarke and Mirza 2006). Moreover, the results of the causality test is very sensitive to the lag length. If the selected lag length is less than the actual lag length, bias can be caused by the omission of relevant lags. If the selected lag length is more, the irrelevant lags in the equation cause the estimates to be inefficient (Clarke and Mirza 2006). In this research, the optimal lag length was estimated by five lag order selection criteria. The five criteria are the sequential modified likelihood ratio test statistic (LR), final prediction error (FPE), Akaike information criteria (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criteria (HQ). In the case of the first model, all five criterion selected optimal lag length as 1, so the optimal lag length was determined as 1. In the second model, four criterion chose optimal lag length as 1, and only the AIC criterion selected 3. Thus, the optimal lag length of the second model was also selected as 1. Table 3 and Table 4 show the results in detail.

Table 3.3. Optimal lag length selection results of the first model

Lag	LR	FPE	AIC	SC	HQ
0	NA	2.72E+09	27.39895	27.49852	27.41839
1	101.3302*	10502878*	21.83835*	22.13707*	21.89667*
2	4.309223	11958679	21.95107	22.44894	22.04826
3	2.593084	15212434	22.1516	22.84862	22.28767

* indicates lag order selected by the criterion

Table 3.4. Optimal lag length selection results of the second model

Lag	LR	FPE	AIC	SC	HQ
0	NA	200398.1	20.72144	20.8708	20.7506
1	122.1208*	242.6584*	13.98889	14.58633*	14.10552*
2	7.446642	363.2544	14.31607	15.36159	14.52017
3	13.71036	277.8945	13.84504*	15.33863	14.1366

* indicates lag order selected by the criterion

3.3.5 Causality test results

Using the estimated maximal integration order (dmax = 2) and the optimal lag length (k = 1), the augmented VAR (3) level was estimated for the TY causality procedure. By using the VAR model, the following system equations are estimated as

$$\begin{bmatrix} \mathrm{MSW}_{pc_t} \\ \mathrm{GDP}_{pc_t} \end{bmatrix} = \mathrm{A}_0 + \mathrm{A}_1 \begin{bmatrix} \mathrm{MSW}_{pc_{t-1}} \\ \mathrm{GDP}_{pc_{t-1}} \end{bmatrix} + \mathrm{A}_2 \begin{bmatrix} \mathrm{MSW}_{pc_{t-2}} \\ \mathrm{GDP}_{pc_{t-2}} \end{bmatrix} + \mathrm{A}_3 \begin{bmatrix} \mathrm{MSW}_{pc_{t-3}} \\ \mathrm{GDP}_{pc_{t-3}} \end{bmatrix} + \begin{bmatrix} \varepsilon\mathrm{MSW}_{pc_t} \\ \varepsilon\mathrm{GDP}_{pc_t} \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} \mathrm{GHG}_{waste_t} \\ \mathrm{MSW}_{total_t} \\ \mathrm{MSW}_{rcy_t} \end{bmatrix} = \mathrm{A}_0 + \mathrm{A}_1 \begin{bmatrix} \mathrm{GHG}_{waste_{t-1}} \\ \mathrm{MSW}_{total_{t-1}} \\ \mathrm{MSW}_{rcy_{t-1}} \end{bmatrix} + \mathrm{A}_2 \begin{bmatrix} \mathrm{GHG}_{waste_{t-2}} \\ \mathrm{MSW}_{total_{t-2}} \\ \mathrm{MSW}_{rcy_{t-2}} \end{bmatrix} + \mathrm{A}_3 \begin{bmatrix} \mathrm{GHG}_{waste_{t-3}} \\ \mathrm{MSW}_{total_{t-3}} \\ \mathrm{MSW}_{rcy_{t-3}} \end{bmatrix} + \begin{bmatrix} \varepsilon\mathrm{GHG}_{waste_t} \\ \varepsilon\mathrm{MSW}_{total_t} \\ \varepsilon\mathrm{MSW}_{rcy_t} \end{bmatrix} \quad (2)$$

where GDP_{pc} is GDP per capita, MSW_{pc} is MSW generation per capita, MSW_{total} is total MSW generation, MSW_{rcy} is recovery waste generation, and GHG_{waste} is greenhouse gas emissions from the waste sector. In Eq. (1) $\mathrm{A}_1 \ldots \mathrm{A}_3$ are 2×2 matrices of coefficients with

A_0 being the 2 by 1 identity matrix and ε as the disturbance terms. In Eq. (2) $A_1 . . . A_3$ are 3×3 matrices of coefficients with A_0 being the 3 by 1 identity matrix and ε as the disturbance terms. Eq. (1) can test the hypothesis that GDP per capita does not cause MSW generation per capita with the following hypothesis: H0 = a112 = a212 = a312 = 0, where ai12 are the coefficients of the GDP per capita in the first equation of the system presented in Eq. (1). In the same way, the all causal relationships between variables were verified.

Table 5 shows the results of the causal relationship in detail, and it confirms that only two null hypotheses were rejected at the 5% of significance level. In the first model, which tried to verify the EKC relationship, there is no causal relationship between GDP per capita and waste generation per capita. This means that even if the GDP per capita increases or decreases, it does not affect waste generation per capita. In addition, there is no reverse causality as well. In the second model, it was confirmed that total waste generation significantly causes greenhouse gas emissions from the waste sector, and the sum of lagged total waste generation coefficient was 0.971866, which is positive in the VAR model. In addition, it was also proved that recovery waste generation causes greenhouse gas emissions, and the sum of lagged recovery waste generation coefficient was -0.963539, which is negative in the VAR model. These imply that if the total waste generation increases, then greenhouse gas from the waste sector also increases, but if recovery waste increases, then greenhouse gas decreases.

Table 3.5. Results of the Granger causality test

Null Hypothesis	Values	Lag	Probability	Decision
First model				
GDP per capita ↛ Waste generation per capita	0.438204	3	0.9322	Accepted
Waste generation per capita ↛ GDP per capita	0.595914	3	0.8974	Accepted
Second model				
Total waste generation ↛ GHG from waste	16.76564	3	0.0008	**Rejected**
GHG from waste ↛ Total waste generation	4.143431	3	0.2464	Accepted
Recycling generation ↛ GHG from waste	22.84908	3	0.0000	**Rejected**
GHG from waste ↛ Recycling generation	0.470454	3	0.9253	Accepted

3.4 Discussion

3.4.1 GDP per capita and municipal solid waste generation per capita

The results showed that GDP per capita growth does not, by itself, result in environmental improvement like a decrease in waste generation, and it means that there is no ECK relationship in the waste sector in the United States. This result is in accordance with a previous research (Cole et al., 1997; Soytas et al., 2007). If there was a significant causal relationship between GDP per capita and waste generation per capita in the United States, then it would be expected that the GDP per capita growth itself will cause a decrease in waste generation, and that governments will not have to be concerned about the waste generation problem when GDP per capita is increasing. However, unfortunately there was no causal relationship. Thus, the U.S. governments should find alternative ways to solve the waste generation problem. For example, public support and institutional reform are needed for accomplishing environmental improvement, and promoting waste recycling also can decrease waste generation, but needs incentives or compulsion.

Several previous papers suggested ways to reduce waste. Timlett and Williams (2008) studied increasing the recycling rate in households and concluded that personalized incentives and feedback were significantly effective. Wagner and Arnold (2008) introduced a case study of Nova Scotia in Canada. Nova Scotia implemented a solid waste management strategy that included restricting disposal, increasing recycling, and increasing the use of diverted materials, and about 50% of solid waste decreased in five years. In addition, Mühle et al. (2010) compared the municipal solid waste management of Germany and the U.K. The results showed that the U.K., which accounts for higher levels of land fill and lower use of energy from waste, emits greenhouse gas associated with MSW management at a rate about five times higher than Germany, which highlights recycling and recovery. Thus, the U.S. federal or state governments should enact a law encouraging people to reduce solid waste and increase recycling materials.

3.4.2 Municipal solid waste, recycling waste generation, and CO_2 emission from waste

According to the results, municipal waste generation significantly leads to increased greenhouse gas emissions in the waste sector in the United States. Moreover, the results also verified that the more waste is recycled, the less greenhouse gases are emitted. These results are reasonable, and the results are consistent with previous research. On average, American generates approximately 5.9 lbs./year of PET beverage containers (Barlaz et al., 2003). If it is possible that all of the PET can be recycled, based on data developed by the EPA and used in Solano et al. (2002), about 10.4 lbs./year of greenhouse gas can be avoided (Barlaz et al., 2003). Thus, MSW should be reduced and recycling of waste should be increased for mitigating greenhouse gas emissions.

Decreasing waste materials is the most direct way to reduce greenhouse gas emission from the waste sector, but there can be another way. If the causal relationship between waste and greenhouse gas is broken, greenhouse gas will not increase even if solid waste increases. For example, the greenhouse gas emitted from the solid waste sector can be used as an energy source, because the greenhouse gas is mostly CH_4 and the gas is able to be used for energy. By applying this method, which is simple technology that can be installed at any site, greenhouse gas emissions can be mitigated (Barlaz et al., 2004; Bogner et al., 2008). Another alternative example is increasing the recycling rate, and this method is more efficient. According to the Morris (1996), recycling conserves more energy than incineration for generating energy from waste for most materials. Thus, if most CH_4 generated from waste is utilized as an energy source or if the recycling rate increases, greenhouse gas emissions from the waste sector will not increase even if the amount of waste increases, and the causal relationship will be disconnected.

3.5 Conclusion

Municipal solid waste not only contaminates soil, but also emits greenhouse gas. In order to decrease these adverse effects, solid waste should be reduced. This research tried to verify the causal relationship between solid waste generation and greenhouse gas emission from the solid waste sector in the United States. Several previous studies showed that solid waste per capita decreased when GDP per capita increased, but that is not the case in the United States. The total amount of solid waste causes greenhouse gas emission from the waste sector, and recycling of waste mitigates greenhouse gas. Thus, it is concluded that since there is no causality between GDP per capita and MSW per capita, the government should find alternative strategies to decrease the solid waste per capita. In addition, by reducing MSW and increasing recycling of waste, greenhouse gas emissions from the waste sector are significantly mitigated.

Based on the research results and conclusion, several suggestions were made. First, increasing the recycling of waste is the most critical. The recycling of waste not only decreases solid waste, but also greenhouse gas emissions from the waste sector. In order to increase the recycling of waste, U.S. governments should enact a law that can encourage people to recycle waste. According to the previous research, personalized incentives and feedback can effectively make people to do recycling, so policymakers should consider it. Second, breaking the causal relationship between MSW and greenhouse gas emission from the waste sector is recommended. One of the methods for accomplishing this is applying waste-to-energy technology. So, the government can encourage applying the technology and increasing the efficiency of the technology. Lastly, the U.S. federal or local governments can benchmark a successful case of waste management like Germany or Nova Scotia in Canada. The U.S. generates the most waste among OECD countries, and its recycling rate is lower than other OECD countries. Thus, the U.S. government should pay more attention to solving the problems, and the benchmarking can be a proper solution.

Since this research focused on the United States, further research is needed. The further research can extend to other countries or focus on the states. Because each country or state has its own characteristics, the results can vary. Then, based on the different results, the country or the state should make an appropriate plan to fit the situation. Moreover, other factors can affects municipal solid waste generation and greenhouse gas emission from the waste sector. Thus, if the new factors are considered that cause waste or greenhouse gas, these can be handled more effectively.

CHAPTER 4

THE IMPACT OF MAJOR NON-PERMANENT EQUIPMENT ON ELECTRICITY CONSUMPTION AND PATTERN OF USE IN EDUCATIONAL BUILDINGS CASE STUDY

4.1 Introduction

Increasing energy consumption resulted in increasing carbon emission which in turn affect global climate (International Energy Outlook 2016). The Intergovernmental Panel on Climate Change (IPCC) estimated that the global average-combined land- and ocean-surface temperatures rose by 0.85ºC between 1980 and 2012, while the global sea level raised by 0.19m between 1901 and 2010 (IPCC 2014). IPCC also predicted that global surface temperatures and sea levels would continue increase by 4.8ºC and 0.82m by 2100 respectively (IPCC 2014).

The building sector accounted for over a third of all energy consumed and approximately 30% of all carbon emissions produced globally (Costa et al. 2013; Shaikh et al. 2014). The proportion of energy consumed by buildings would surpass 60% in the near future (Schneider Electric; Shaikh et al. 2014). In the United States, 41% of primary energy was consumed by the building sector, and this is 44% higher than the transportation sector and 36% higher than the industrial/manufacturing sector (U.S. Department of Energy 2012). Prior research affirmed that the building sector has one of the highest energy-saving potentials among other sectors (Gul and Patidar 2015; Shaikh et al. 2014; Ye and Long 2014; Poirazis et al. 2008) and would potentially capable to reduce an amount equal to the entire transportation sector's (WBCSD, 2009; Shaikh et al. 2014). The International Energy Agency (IEA) estimated that the electricity usage of the global building sector would be reduced by 20 exajoules (EJ) annually from 2009 to 2030. This reduction is equivalent to the current annual electricity consumption in the United States and Japan combined (IEA 2011; Ye and Long 2014). Investment and research are thus needed to develop the energy consumption reduction paths.

Prior research showed different concepts of building energy conservation and energy efficiency improvement. Vakiloroaya et al. (2013) reduced energy consumption of cooling systems by improving HAVC energy efficiency and integrated central cooling plant by an approximate 18%. Bhaskoro et al. (2013) proposed an adaptive cooling technique that increased the energy-saving potential of an academic building, and saved up to 305,150 kWh or an equivalent of 45% of cooling load compared to the current system. Bichiou and Krarti's (2011) optimized envelop and HVAC systems using a set of optimization algorithms to reduce the system's life-cycle costs by 10–25%. Du et al. (2014) diagnosed and detected the HVAC system's fault by using combined neural network and a robust diagnostics tool to improve the energy efficiency of building HVAC systems. Khooban's (2012) optimized intelligent control of air supply and pressure of a HVAC system showed better performance than conventional controllers.

Very few studies were found to focus on electric appliances and plug loads even though plug loads constituted a significant portion of a building's energy consumption (Kamilaris et al. 2014; Ouf et al. 2016). 12% to 50% of the total electricity of a commercial building is consumed by plug loads and this is expected continue to grow as the types of equipment and appliances would continue to increase. And, plug loads are driven by different factors than HVAC and lighting. Energy consumed by HAVC systems is influenced by the outdoor temperature but plug loads are not. Occupants would continue to supplement their spaces with new equipment and appliances as the demand for new appliances and computers grows. Study showed that energy consumed by appliances is growing at a rate of 0.8% annually (Gandhi and Brager 2016). Study also showed that the proportion of plug loads would increase as building energy efficiency improve, as increasing efficiency of HVAC and lighting reduce the proportion of energy consumed for heating, cooling, ventilation and lighting. Focusing on efficiency of plug loads would lead to equivalent energy reduction. The National Renewable Energy Laboratory (NREL)'s low-energy office building in Golden, Colorado, attempted to reduce the plug load by using highly efficient fridges and removing mechanically cooled drinking fountains, and these decreased the plug loads by nearly 50% (Lobato et al. 2011).

Spaces in university buildings are classified among the buildings that consume the highest energy consumption per square foot (Deb et al. 2015; Gul and Patidar 2015; Yang et al. 2015). For example, an ASU laboratory building consumed eight to ten times more energy per square foot than any other building types on the ASU campus. Moreover, many university buildings also have high energy conservation potential. According to previous research, the energy-saving potential for a university building ranges from 6% to 29% (Chung and Rhee 2014). Several studies have been conducted regarding plug loads, but university buildings have not been researched (Lobato et al. 2011; Kamilaris et al. 2014; Gandhi and Brager 2016; Ouf et al. 2016).

4.1.1 Space Use and Energy Consumption

Building use influences energy consumption patterns, and the type of appliances and occupants, usage hours, and appliances in the building influence how energy is consumed. There are many electric appliances located in all parts of a university building and they consume a significant amount of energy. The types and number of regular occupants also influence the types of appliances and unique equipment used in the spaces. For example, the use of space drives the controllability of energy consumption of the space. Public spaces, such as share classroom, meeting room and corridor, would not contain appliances that are individually controlled. Individuals have more control over private spaces, such as laboratory and office, where individualized appliances or special equipment could be installed.

4.1.2 Research Objective

The objective of this research is to understand and verify the impact of electric appliances on energy/electricity consumption patterns, and the approaches to reduce electricity consumption in these university buildings. The buildings' electricity usage patterns were first analyzed and compared with the number of appliances in the buildings. The energy saving is then separated by time, particularly during lunch time and in the evening (base on the absence of occupants during the period). Third, the research establishes the relationships between electrical appliances and occupancy where occupants were separated into permanent and temporary occupants. Finally, the results are analyzed to establish the foundations for potential energy savings from electrical appliances. The research is structured into four following sections: Section 2 presents the method of data collection, Section 3 shows the results of this study, Section 4 discusses the results, and Section 5 presents the conclusion.

4.2 Data Collection

4.2.1 Appliances Data

The electric-appliance data was first collected from the selected buildings. The data included the number of monitors, servers (CPUs), laser printers, inkjet printers, fax machines, fridges, vending machines, workstations, and lighting fixtures. These data were initially collected by physical site visits and surveys on 55 buildings on the Arizona State University's (ASU) Tempe campus. 27 buildings were excluded from the study as information from the buildings was incomplete especially when over 30% of the room from these buildings were unavailable for visual inspection or occupants were unable to provide information on the spaces. Only 10 buildings' data were found to be reliable for the research. Table 1 shows the buildings' detailed information.

Table 4.1. Description of the buildings

#	Building name	Purpose of use	# floor	Gross Area (m^2)	Built (year)
1	Business Administration	Academic	4	12,244	1968
2	College Avenue Common	Academic	5	13,827	2014
3	University Center Building A	Administrative	1	4,201	1985
4	Schwada Classroom Office Building	Academic	3	11,797	1979
5	McCord Hall	Academic	4	13,015	2013
6	Ross-Blakley Law Library	Library	3	6,294	1993
7	Memorial Union	Student Services	3	25,295	1955
8	Physical Education Building West	Athletics	3	5,570	1953
9	Dixie Gammage Hall	Academic	2	2,188	1941
10	Center for Family Studies	Academic	2	901	1940

4.2.2 Electricity consumption data

The buildings' electricity consumption data were collected from the ASU's metabolism website. The website provides the ASU buildings' energy consumption data, such as electricity consumption, and cooling/heating load. The electrical energy (kw) data include power lights, electronics, and fans to circulate air throughout the buildings. The electricity data were collected during the summer and fall semesters in 2015. Data from the weekends and holidays were excluded from the analysis.

4.2.3 Occupancy Data

Many of these buildings are occupied by students who are mostly transient occupants. As such, study on the impact of transient occupants on the energy consumption was analyzed. The average and total number of transient occupants were surveyed and assumed as the exact numbers were not tracked or documented. The numbers were gathered from the ASU classroom data, and estimated number of students in each building from prior database. The average and total number of students at different period were worked out from the classroom data and estimated transient occupancy data. For example, it is assumed that the total number of students who remain in the building is equal to the number of students who took classes in the building, and an estimated 90% attendance rate was used in some cases. Through the ASU affairs information system, the number of students who take the class was estimated in 15-minute intervals.

4.3 Findings and discussions

The analyses and results are divided into three sections. The first section includes a study of the electricity consumption patterns of the ten selected buildings. The second section includes an analysis of the equipment loads of these buildings. The analyses focused on the understanding of their impact on the electricity consumption, and to determine the potential savings due to occupant behavioral changes. The final section includes a case study of the impact of transient occupants on the buildings.

4.3.1 Consumption pattern analysis

Electricity consumption data is collected from the Energy Information System (EIS) of ASU. The EIS maintains a platform (campus metabolism website) that tracks energy consumption, such as cooling, and heating and renewable production data from all campuses at ASU. The goals of this analysis are to, first, understand the consumption pattern, which includes peaks and troughs, at different period during the summer semester, and, second, analyze and understand the effects the electrical appliances consumption. The consumption pattern shows peaks and troughs at different hours of the day (refer to Figure 1). More details are needed to develop better understanding of the actual patterns and their relationships with different factors. The consumption patterns of 10 buildings, which are utilized for different purposes, are analyzed to determine the peak loads and minimum loads of the respective days.

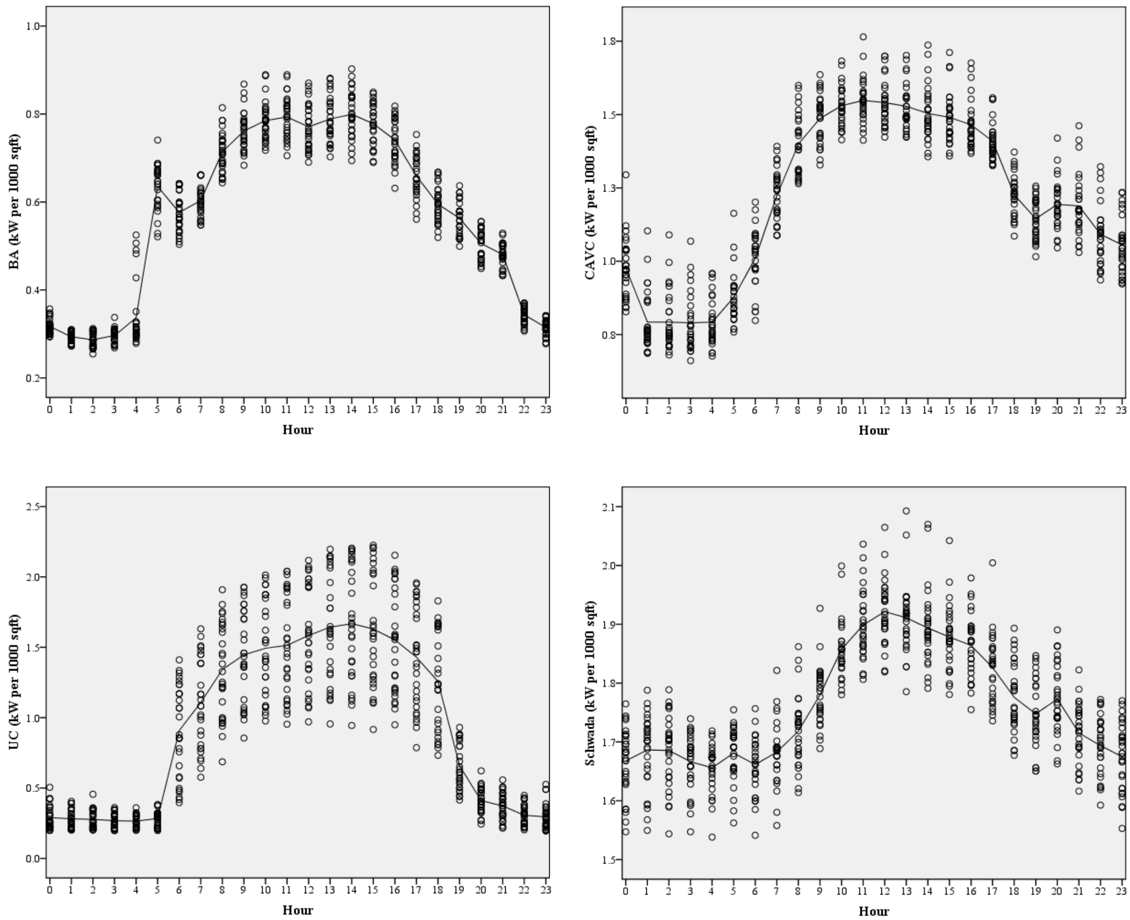

Figure 4.1. Business Administration, CAVC, University Center A, Schwada Building

Figure 1 shows the consumption patterns of similar types of buildings compared to their utilization. Buildings 1, 2, 3, and 4 have the same spatial usages and thus similar space utilization patterns: such as office space, classrooms, and research areas (computer labs and graduate offices). Buildings 1 and 4 have similar square footage, whereas building 3 is about 3,700 ground square meters, and building 2 is about 11,900 square meters. The consumption patterns of these buildings are similar and this suggests that the building space and orientation have very little effect on the pattern of energy consumption. The peak occupancy time of these buildings is between 8 am and 5 pm, while trough energy consumption period took place between 10 pm and 4 am (where least amount of activities took place during this period).

The peak loads vary widely between the buildings. Their peaks occurred at about the same period between 8 am to 4 pm, and is considered the peak time for these types of buildings. Building 5, shown in Figure 2, has similar energy utilization and utilization period, but its pattern of energy consumption is different than the other buildings. Its peak load time occurred between 2 am and 8 am, and the trough loads occurred between 11 pm and 1 am. Building 5 is a new building that has an energy efficient precooling technology and chilled beams to run its cooling system. Air is pre-cooled during the off-peak and cooler hours, and delivered to the occupants when they are in the buildings (from 8 am to 5 pm).

The study also found that the energy consumption during lunchtime was not significantly reduced and this suggested that occupants left their appliances and computers on during lunch.

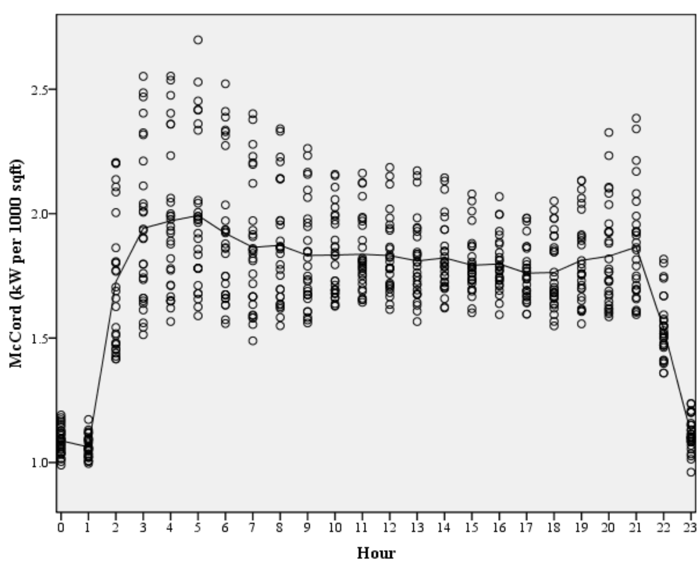

Figure 4.2. McCord Hall

The study found that Building 6, a library with significant office space, had a different energy consumption pattern than the other buildings. While its energy consumption followed a unique pattern during the day and is consistent/does not change at all during the day. The appliances are almost always turned on all the time, and occupants have little to no control over them. The peak load occurred between 8 am and 4 pm, and the trough load occurred between 5 pm and 5 am.

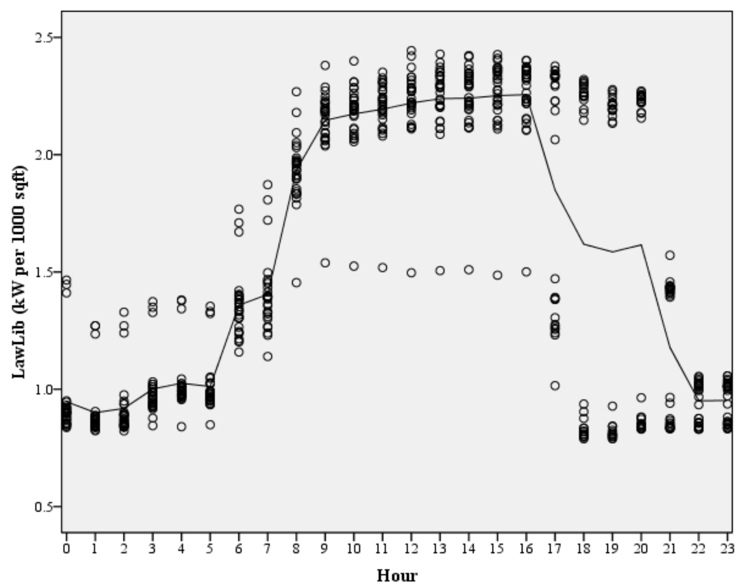

Figure 4.3. Ross-Blakley Law Library

Building 7 spatial usages are extremely diverse. The building is located at the middle of campus and contains different facilities like multiple student centers, conference halls, offices, restaurants, and sports centers. Even though its energy consumption pattern shown in Figure 4 is similar to an office building's most of the time, its energy consumption uniquely peaked during lunch hours. Thorough investigation showed that students and staff utilized the building for lunch, and there are many restaurants in the building (that operate during lunch time). The cooking, serving and large number of transient occupants drive the building energy load dramatically upward during lunch time. The peak load occurred between 10am and 5 pm and the trough load occurred from 8 pm to 2 am.

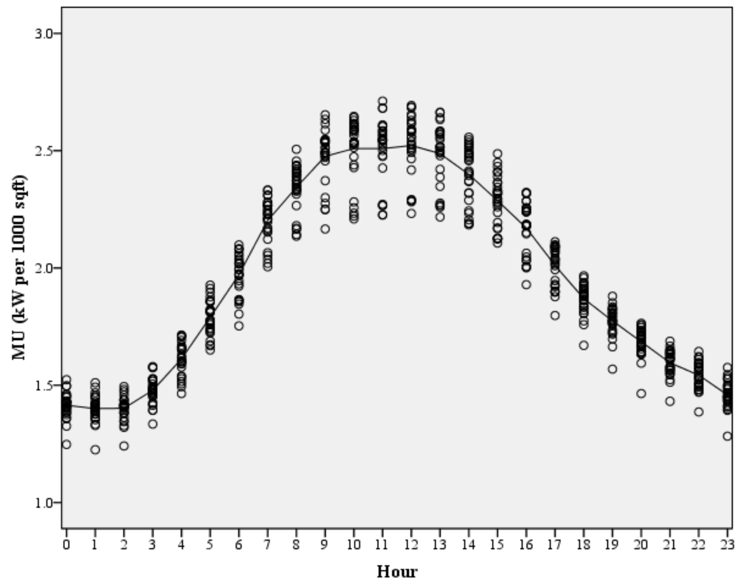

Figure 4.4. Memorial Union

Building 8 is a sport facility that has a sports center and a gymnasium. Its energy consumption is extremely irregular and do not exhibit any regular pattern. Figure 5 shows a pattern of irregularity and it is difficult to identify a pattern of peaks and lows. The points do not converge with one another, and are spread out wide. A visual line could not be identified in this type of pattern. Building 8's electricity consumption deviation throughout the day is extremely large compared to the other buildings, and the pattern is vague and disorderly. The pattern continues through the night. Even though the other buildings exhibited large pattern deviations during the day, their deviations were dramatically reduced during the night. As a result, consistent patterns were determined for all buildings except Building 8.

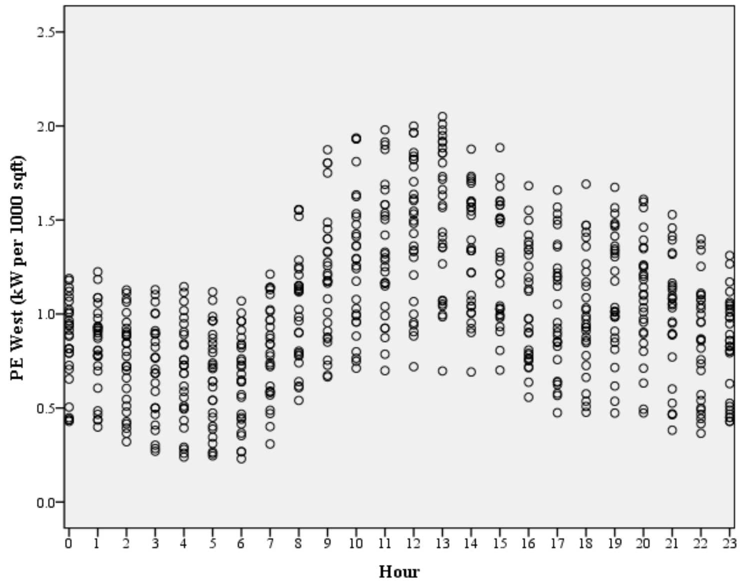

Figure 4.5. Physical Education West

Figure 6 shows the consumption patterns of two office buildings, 9 and 10. They are smaller buildings among the 10. Building 9 is an office building with an auditorium, and building 10 is a general office building. Both buildings exhibited large variations in their consumption patterns, and the patterns are irregular. While most buildings patterns peak between noon and 1pm followed by decreasing consumption after, building 10's energy consumption continued to increase until 4pm. This suggests that use of appliances continued to increase until 4pm. Building 9 and 10 peak times were from 9am to 5pm and 6am to 5pm, and their trough load occurred from 8 pm to 5 am and 10pm to 5am, respectively.

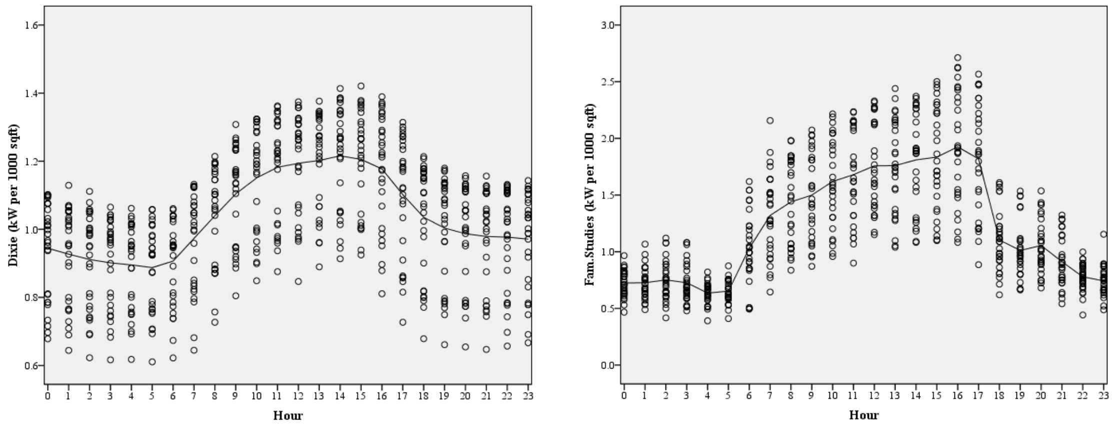

Figure 4.6. Consumption patterns of Building 9 and Building 10

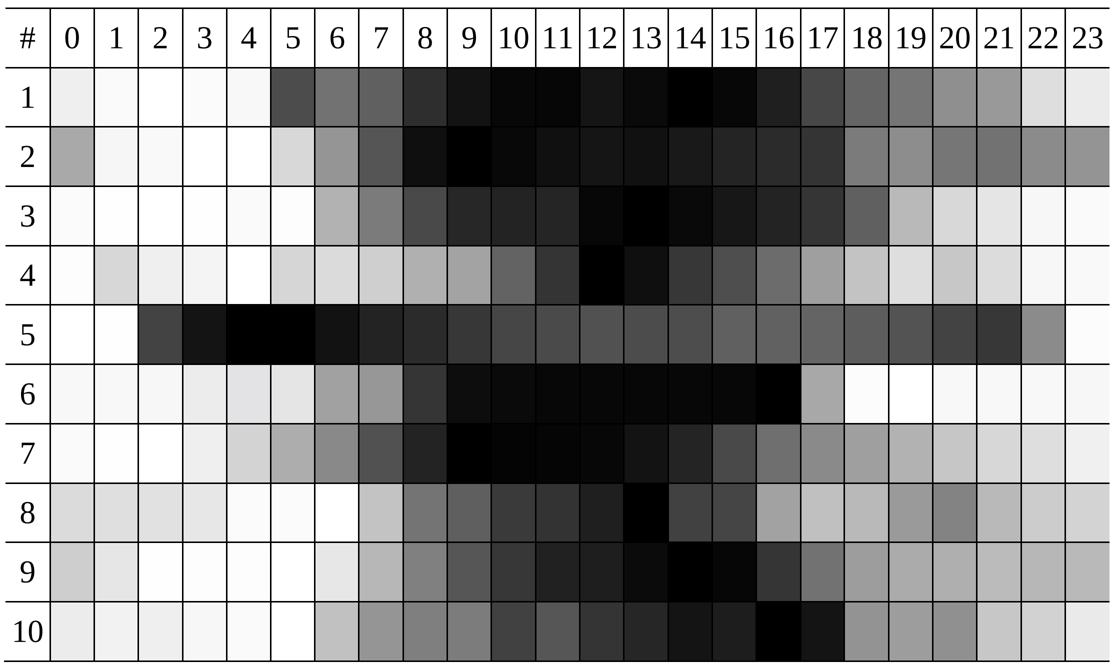

Figure 4.7. Electricity consumption intensity of the buildings

The buildings had similar electricity consumption patterns, even as Buildings 8, 9 and 10 exhibited irregular patterns and were not conclusive. Figure 7 explains the electricity consumption's intensity during a 24-hour period. The figure shows that most of the buildings peak from 8 am to 4 pm except Building 5 (which has a unique consumption pattern because of its precooling technology). However, the buildings had different peak time. For instance, the peak time of buildings 3, 4, and 8 were at 12 noon, while Buildings

1, 2, 7, and 9 were right before or right after 1 pm. Building 6's peak time was from 9am to 4pm, and Building 10's peak time was 4pm. The differences in the buildings' energy consumption characteristics were caused by the building size, utilization types and strategies, and orientation.

4.3.2 Class hours and the pattern of electricity use

Further study was conducted to investigate the effects of occupancy on appliances' energy consumption. The data was collected from the classroom scheduling department for different classes specific to the College Avenue Common building. Figure 8 below shows the number of students taking class and the consumption at different hours of the day. From Figure 8, the number of students increased between 7am and 9am, 2pm and 3pm, and 5pm and 6pm, but the electricity consumption only increased from 7am to 9am. Even though there was a huge drop in the number of students between 9am and 12pm, electricity consumption remained consistent. The figure shows that enrolled students use classrooms just for classes and rarely consume electricity (through plug). This analysis suggests that the number of students inside the building do not impact the electricity consumption throughout the day. Thus, we can safely infer that the permanent occupants (who spend most of the time in the building - the faculty, officers, and researchers) affected the energy consumption more than the transient occupants.

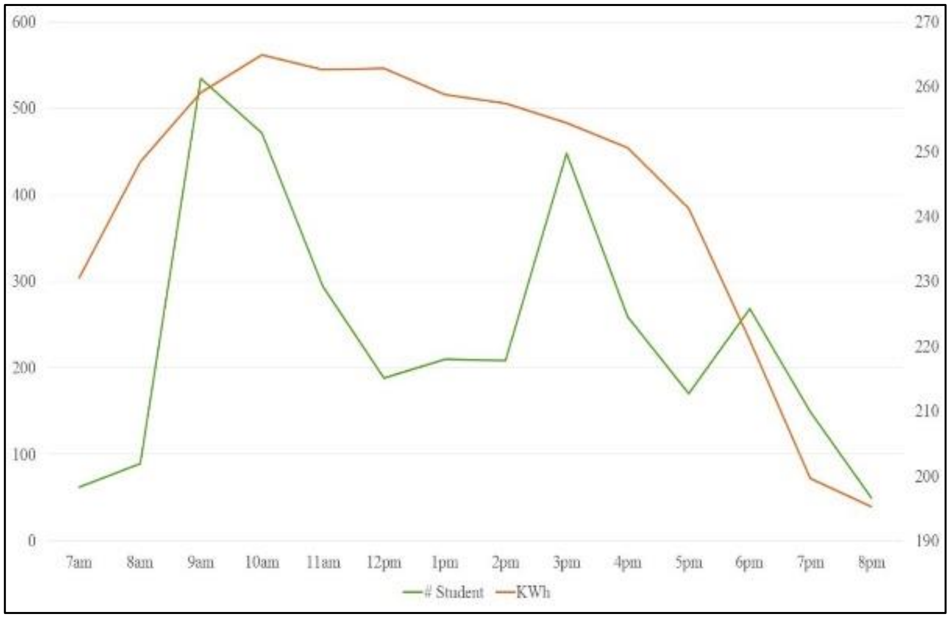

Figure 4.8. The number of students taking classes and the hourly electricity consumption of building 2

4.3.4 Refrigerators and Vending Machines

This section details the analysis of different appliances used in the 10 buildings. This section also includes their energy consumption patterns. The analysis found that refrigerators and vending machines consumed the most amount of energy among all the appliances and their energy consumption is independent of the time periods. Table 2 shows the number of refrigerators and vending machines per area in each building, their peak and minimum load, and the analyses between the number of refrigerators/vending machines and the peak energy load of a building. However, the analysis showed that refrigerators generate very impact on the minimum and peak energy loads on the buildings. There is no relationships between the number of refrigerators per square meter and the minimum and peak energy loads per square meter (see Table 2). On the other hand, data in Table 2 and graphical plot in Figure 9 (for the only four buildings where vending machines located at) suggest that there could be some relationships between the total number of vending machines per square meter and the minimum and peak energy loads.

As discussed before, increasing number of vending machines has a relationship with increasing minimum and peak energy loads (refer to Figure 9). Refrigerators, on the other hand, did not affect the peak and minimum loads as suggested by the case study. The case study highlighted the key reasons for the energy impact difference between refrigerators and vending machines – Their locations and operational process. Building 7 has over four refrigerators per 1,000 m2, and its peak load is significantly higher than Building 4's, while Building 4's minimum load is much higher. Case study also showed that the types and locations of vending machines influence the peak and minimum load. Soda stations in Building 7 were exposed to the sun require more energy. Measurements from the National Renewable Energy Laboratory (NREL) showed that a typical machine dispensing 500 12-oz cans with an illuminated front consumes between 7 and 11 kWh/day in an office environment (Deru et al., 2003). In addition, new Energy Star® certified refrigerators use 1-2 kWh/day. Under the sun, the soda vending machines consumed more energy to cool the drinks. Refrigerators inside the building are not exposed to the outside heat. As a result, outdoor soda vending machines have to be cooled day and night. As a result, the energy load remains more consistent for Building 4, while lower energy use of refrigerators at night helped reduce some energy consumption.

Table 4.2. Fridges and vending machines and electricity load

#	# Fridges (per 1,000 m^2)	# Vending Machines (per 1,000 m^2)	Peak Load (W/m^2)	Min. Load (W/m^2)	Difference between Peak and Min. Loads (W/m^2)
4	0.158	1.104	37.060	33.724	33.724
7	4.689	0.603	43.368	26.092	26.092
2	3.944	0.408	29.902	17.696	17.696
8	0	0.266	18.719	12.185	12.185
10	8.475	0	24.187	10.882	10.882
9	3.108	0	17.987	13.821	13.821
6	2.084	0	31.571	13.670	13.670
5	1.788	0	38.998	32.712	32.712
1	0.734	0	14.413	5.909	5.909
3	0.671	0	19.375	3.466	3.466

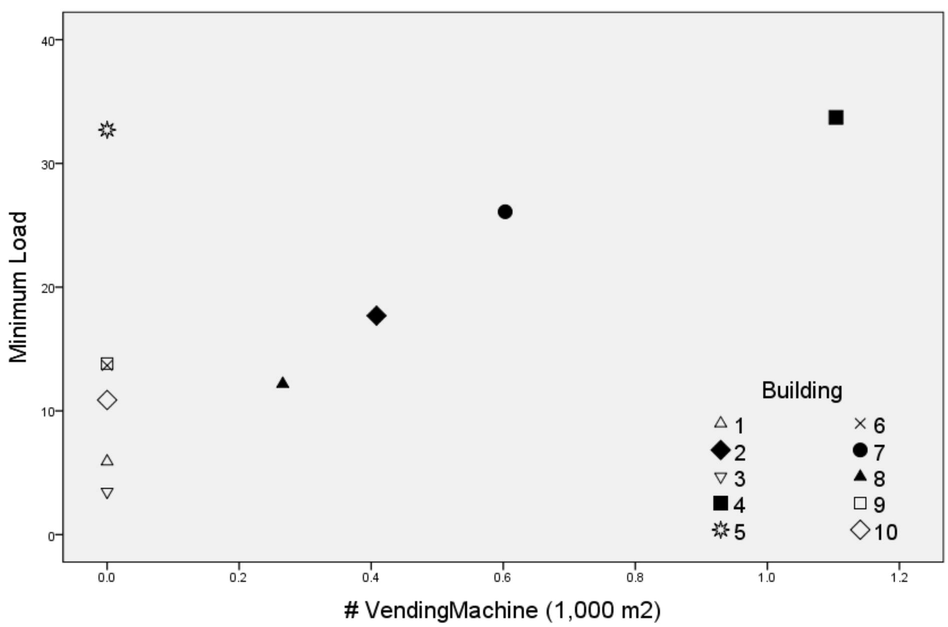

Figure 4.9. Number of vending machine and minimum load

4.3.5 Monitors and Computers

A prior research found that the energy consumption dropped significantly at lunchtime for three office buildings where the study was conducted (Wang and Ding, 2015). The research suggested that the occupants left their office for lunch and likely turned off their computers. Gandhi and Brager (2016) also found a significant drop in energy consumption from computers and monitors at lunchtime and it indicated that the occupants either turn off or put their computers into sleep mode when they left.

These studies were conducted in Asia and their occupants could behave differently than the occupants in the United States. The research found dissimilar energy consumption patterns among the 10 buildings during lunchtime. Figures 1 to 6 show that there was no significant difference in nine buildings while Building 1 electricity consumption fell at lunchtime. Does this explain that occupants do not turn off their computers during lunch?

Normally, the average consumption of LCD monitors is 44.5 watts and 7.5 watts in the sleeping mode, and the average computer electricity consumption is 155 watts and 3.5 watts in the sleeping mode (source: http://michaelbluejay.com/electricity/computers.html). This represents a significant energy-saving potential in occupants turning off or using sleep mode during their absence. Data was collected through both physical and occupants' survey, and then the total number of monitors, computers and laptops were then divided into the total square areas of the buildings then multiply by 100, so that the monitors, computers and laptops can be presented as number per 100 square meters. Buildings 9 and 10 are excluded from the student as their gross floor areas are small and do not have enough monitors and computers in the buildings.

Table 4.3. Saving potential during lunch time I

Building	# Monitors (per 100 m^2)	Computer (W per m^2)	Monitor (W per m^2)	Computer + Monitor (W per m^2)
1	4.583	7.104	2.088	9.193
2	4.583	7.104	2.088	9.193
3	1.508	2.336	0.689	3.025
4	1.183	1.830	0.538	2.368
5	0.908	1.410	0.409	1.819
6	1.366	2.121	0.624	2.745
7	0.590	0.915	0.269	1.184
8	0.372	0.581	0.172	0.753

The research also assumes that all monitors, computers and laptops were turned on during office hours, and a certain proportion (20%) of the computers were left on after office hours. Table 4a shows the total number of monitors and their energy consumed. Table 4b shows the total electricity saving potential if 50 percent of computers and monitors were turned off. The comparison in Tables 4a and 4b highlight the potential savings from these buildings. Buildings 1, 2, and 7 generate the most potential savings of 56.277 kW, 63.553 kW, and 14.975 kW, respectively. These are significant savings if all ASU buildings (over 500) would commit to turning off the computers and monitors during lunch, and after work.

Table 4.4. Saving potential during lunch time II

Building	Saving Potential (W per m^2)	Total Saving Amount (kW)
1	4.596	56.277
2	4.596	63.553
3	1.507	6.331
4	1.184	13.968
5	0.915	11.908
6	1.367	8.604
7	0.592	14.975
8	0.377	2.098

A prior study showed that a large number of computers and monitors were not turned off after work. Bray (2006) conducted an extensive study on the nighttime power status of monitors and computers and found a high potential energy savings could be achieved if monitors and computers are turned off after work. Bray (2006) found that between 25% and 60% of the computers, and 15% to 30% of the monitors were active at night. The author calculated a potential saving percentage of 42.5% on computers and 22.5% on monitors. Similar percentage in this study.

Table 5a shows the hourly consumption of active computers and monitors at night. Table 5b shows each building's average night time consumption and saving potential (7pm - 6am). The results show that there is a potential savings of 17.149 kW to 468.270 kW if all the monitors and desktops are switched off after work. Buildings 1 and 2 could save approximately 45 kW per hour. Approximately 500 kW could be saved every day for all ten buildings. The energy saving potential overnight is far greater than during lunchtime. More energy could be saved over the weekend and holidays if they are turned off.

Table 4.5. Saving potential at nighttime I

Building	# Monitors (per 100 m^2)	Active desktop (W per m^2)	Active monitor (W per m^2)	Desktop and monitor (W per m^2)
1	4.583	3.014	0.463	3.477
2	4.583	3.014	0.463	3.477
3	1.508	0.990	0.151	1.141
4	1.183	0.775	0.118	0.893
5	0.908	0.603	0.086	0.689
6	1.366	0.904	0.140	1.044
7	0.590	0.388	0.054	0.441
8	0.372	0.248	0.032	0.280

Table 4.6. Saving potential at nighttime II

Building	Hourly saving potential (W per m^2)	Hourly saving amount (kW)	Total saving amount (kW)
1	3.477	42.570	468.270
2	3.477	48.073	528.803
3	1.141	4.793	52.723
4	0.893	10.540	115.940
5	0.689	8.966	98.626
6	1.033	6.504	71.544
7	0.452	11.436	125.796
8	0.280	1.559	17.149

Current computer and monitor settings allow them to be set to sleep mode after a fixed time. Sleep mode would reduce power consumption and save energy. Computer and monitor would be configured accordingly and go into sleep mode after idling for a certain period. The sleep mode can be centrally managed by the Information Technology department.

4.3.6 Intelligent Technology

With the rapid advancement in artificial intelligent technology, automated energy control and computational optimization techniques are becoming increasingly popular. Such techniques are often added to energy monitoring system and frameworks through computational algorithms to enhance the efficiency of the building energy control schemes (Shaikh et al., 2014). In addition, phantom loads consumed by different equipment on standby or sleep mode would affect the energy system operation and thus AI algorithms address it effectively. Phantom loads also contributed to a significant of energy consumed by the buildings and they are considered inefficient load. For example, the new school's classroom at ASU consumed 28.7% of its plug load electricity during non-working hours, but only 0.5% of energy for lighting was consumed during those hours. The lighting is controlled by sensors and other intelligent technology to switch idling lighting off when not in used. Unlike lighting, plugs are not controlled by such sensors or technology, and equipment connected to the plugs would continue to consume electrical power. This highlights that artificial intelligent technology offers a great opportunity to reduce building energy loads (Ouf et al., 2016).

4.4 Conclusion

Although the building sector is the highest sector of energy consumption, but the building sector also has a high energy saving potential. This research reconfirmed it and estimated the amount how much the buildings electricity can be saved. Through the simple ways such as turning off the desktops and monitors during lunch time or nighttime, a significant amount of energy can be conserved. And, the research affirms three critical concepts:

Concept 1: While total energy consumption is driven by the total anticipated number of occupants in a building, however, variation and actual energy consumption is driven by the occupants' behaviors and operational procedures: A building energy load is designed at the design phase with a total anticipated permanent and transient occupants, and their occupation period of the building in mind. The total occupancy is used to size the equipment and spaces, so as to provide sufficient good quality air to the occupants. Energy efficiency and consumption are solely dependent on the equipment efficiency and operation procedures.

In order drive up energy conservation effort, this study studied the energy consumption patterns of the occupants, equipment and appliances. These include monitors, desktops, vending machines, and refrigerators in university buildings. Other appliances, such as washer and dryers, are excluded from the study as they do not represent a significant portion of the buildings. The study shows that there is a significant relationships between the energy consumption, occupants' behaviors, and the operational procedures, and the effects are most significant during lunchtime and after office hours.

Concept 2: Controllability and locations of appliances influence the maximum and minimum, and variability of energy use of a building. The analysis shows that vending machines, and to some extent, refrigerators, influence the minimum and maximum energy loads of a building, while computers and monitors influence the variability of energy consumption throughout the day. The locations of the vending machines increase the energy consumption, increase use of refrigerators during the day increases energy consumption but they do not impact the overall energy consumed in the building like the vending machines. Unlike lighting, plug loads are not controlled by sensors or intelligent technology and thus equipment plugged into the plugs have to be turned off manually by their users. Vending machines are beyond the control of the building occupants and operators, even though they are demand a lot of energy. Operators need to develop some solutions to better control the equipment that are connected to the plugs so that they can better manage the energy consumed by the equipment.

Concept 3: Plug loads from buildings consumed significant amount of energy and they behave different from one another. Unlike permanently installed equipment, such as the heating, ventilation and air-conditioning and lighting systems, non-permanent equipment is more diverse and used differently. As a result, the management and control of different equipment and appliances connecting to the plug loads require differing approaches to reduce their energy consumptions. This could be done by dividing the operation of the equipment into different periods and make use of the equipment control. For example, plugs to auto-shut monitors, computers and vending machines should be installed at the connections and automatically turn off during non-working hours and weekends. Such automated system that match with the period of operation and control would reduce energy waste as a result.

This research focused on educational buildings, and thus the results would not be valid or applicable to other commercial or industrial buildings. Building energy consumption is driven by the equipment installed in the buildings and how the occupants behave. Different types of occupants behave differently, and thus energy consumption characteristics differ among building types. For example, a restaurant may have more refrigerators and cooking equipment, and the thermostats are set at lower temperature compared to institutional buildings.

Energy consumption is also influenced by climate zones and human needs. While the building types and climate are different, the factors driving the behavior are quite similar. Many occupants leave for lunch and do not turn off their computers, and they leave their computers on after office hours, and vending machines continue to refrigerate soda even though soda purchases are done sparsely throughout the day. Occupants' behaviors may change by region but their gaps are extremely narrow – for example, they would require different ambient temperatures in different climate zones, they do not turn off their computers during lunch. Thus, more research is needed to better understand the gaps and similarities.

CHAPTER 5

EXAMINING THE RELATIONSHIPS BETWEEN STATIONARY OCCUPANCY AND BUILDING ENERGY LOADS

5.1 Introduction

Energy issue is the one of the most important problem faced by human beings. Global population keeps growing year after year (The World Bank, 2017); this causes increasing amounts of energy consumption, particularly of fossil fuels, which results in increasing greenhouse gas emissions. This leads to and accelerates global warming (Li et al., 2012). Within the total energy consumption that has a direct impact on carbon dioxide emissions, the building sector accounts for approximately 20% of worldwide energy consumption, and building sector's consumption will increase by an average of 1.5% per year from 2012 to 2040 (IEA 2016#). In the case of the United States, the building sector is responsible for 40% of energy use, 75% of electricity consumption, and 38% of carbon dioxide emissions (IEA 2016*). For those reasons, the building sector not only has great potential for energy savings but is affordable and potentially profitable (Diraco et al., 2015; Yan et al., 2015). Therefore, optimization and reduction of building energy consumption is a significantly important topic (Li et al., 2012).

There have been various research studies on building energy conservation. Previous approaches mostly focused on the climate, the building envelope, the building energy and service systems, indoor design criteria, and building operation and maintenance. There has been remarkable progress in these factors (Yan et al., 2015). Conventional approaches appear to be closely aligned with the aforementioned factors (Martani et al., 2012; Chen and Ahn, 2014). However, although it is commonly well known that building occupants have a substantial impact on a building's energy consumption, in reality, current building energy systems are disconnected from human occupancy, and there is no robust energy model related to building occupancy (Kwok and Lee, 2011; Martani et al., 2012; Yan et al., 2015). Because there was no consideration of the occupants' impact, which has a high uncertainty, building energy simulation or prediction deviates significantly from actual building energy consumption (Yan et al., 2015).

Building occupancy plays a critical role in building energy consumption (Liao and Barooah, 2010; Kwok and Lee, 2011; Yan et al., 2015). Firstly, the current building energy approach assumes that all rooms are occupied during office hours, but several rooms, such as conference rooms, are normally left vacant during part of the day (Erickson et al., 2009). Moreover, the actual number of occupants is usually much fewer than the designed occupant capacity. In the case of office buildings, only a third of the design occupancy was present even at peak hours (Brandemuehl and Braun, 1999), since some people may work outside of the office, and others are absent from work due to vacations or illness (Kwok and Lee, 2011). On the other hand, sometimes a person may work overtime at night (Kwok and Lee, 2011). Secondly, occupants interact with a building to increase their personal comfort and meet their needs (Kwok and Lee, 2011). For instance, occupants can control the heating, ventilation, and air conditioning (HVAC) systems, lighting systems, blinds, windows, and individual appliances (Humphreys and Nicol, 1998; Kwok and Lee, 2011; Yan et al., 2015). If occupancy impact is reflected in the building energy system, a large amount of energy can be saved, as has been proved in previous studies. Erickson et al. (2009) suggested that 14% of HVAC energy can be reduced by applying an optimal control strategy based on occupancy estimates. Lo and Novoselac (2010) showed that cooling load can be reduced by 30% through occupancy control. Yang and Becerik-Gerber (2017) confirmed that a minimum of 10.4% and a maximum of 28.3% of the building energy load decrease was accomplished based on occupancy transitions.

There has been diverse and in-depth research, but they still have had limitations. Most previous research counted or estimated only total occupants at one time. However, in reality, there is not just one kind of occupancy. Some occupants may stay for long periods, and others may stay for short periods. For instance, in the case of office buildings, workers normally stay during the total business hours, but visitors remain for a short time period. In the case of university buildings, faculty members and graduate students stay during working hours, but students who take classes usually stay only at class period. The two groups' energy consumption pattern is different. For example, short-term residents use small plug loads, such as charging smartphones or laptops, and sometimes use classroom desktops and projectors. However, long-term occupants consume large plug loads, such as computers, monitors, desk lamps, and refrigerators, during all the working hours. Moreover, the appliances also come with a heat load, and the heat load increases the cooling load (Yan et al., 2015). Since the two groups' impact on the energy load is obviously different, they should be analyzed separately (Chen and Ahn, 2014). However, previous studies did not separate the stationary and non-stationary occupants. Li et al. (2012) counted the two types of occupancy separately, but did not verify occupancy impact on energy consumption. Therefore, the first research objective was to suggest how to estimate stationary occupancy. This study proposed a new and simple approach to infer stationary occupancy. The second objective was to examine the relationships between occupancy and building energy loads, such as electricity, cooling, and heating. The relationships were verified using statistical methods. The last objective was to propose how to conserve building energy consumption, based on the results.

5.2 Research methods

To examine the relationship between the occupancy and energy consumption pattern, it is necessary to estimate building occupancy. There are varied methods to estimate building occupancy, such as sensor networks (Dodier et al., 2006), wireless camera sensor networks (Erickson et al., 2009), radio-frequency identification (RFID) (Li et al., 2012), passive infrared sensors (Duarte et al., 2013), and 3D depth sensors (Diraco et al., 2015); each method has strengths and weaknesses. This study's authors applied existing information technology, also called implicit occupancy sensing (Melfi et al., 2011). Most importantly, if a building has the infrastructure, such as Wi-Fi router, this method is immediately applicable to the building. Moreover, the existing technology does not require additional costs or labor-intensive sensor and hardware installation and maintenance, because it is not originally intended for occupancy sensing. (Melfi et al., 2011; Labeodan et al., 2015). Some previous studies pointed out that the drawback of the existing infrastructure is inaccurate (Yang et al., 2016). Certain applications require precision, but energy management applications do not; an approximate calculation of the number of occupants is enough to manage building energy loads (Melfi et al., 2011). In other words, the application just needs to know that there are roughly 10 occupants in the room, not 8, 9, 11, or 12. Erickson et al. (2009) verified that there was negligible impact (0.28%) on HVAC energy savings estimation of 14%, with a 20% occupancy estimation error.

Among the existing infrastructure in buildings, the Wi-Fi network is usefully applied as a proxy for human occupancy. Previous studies estimated occupancy using Wi-

Fi networks (Melfi et al., 2011; Martani et al., 2012; Chen and Ahn, 2014; Christensen et al., 2014; Depatla et al., 2015; Lu et al., 2016), and these studies concluded that Wi-Fi connection frequency can estimate occupants' residency without difficulty (Chen and Ahn, 2014). Balaji et al. (2013) determined the number of occupants successfully with 86% accuracy using Wi-Fi connections. Moreover, Chen and Ahn (2014) verified that there is a positive relationship between Wi-Fi connections and building energy use. However, Wi-Fi networks have limitations, one of which is that the network cannot differentiate stationary and non-stationary occupants (Chen and Ahn, 2014).

This research proposes to infer the stationary occupancy in buildings using wired Ethernet connections. Estimating each long-term and short-term occupancy separately is necessary for developing energy consumption forecasting and for supporting building energy feedback systems (Chen and Ahn, 2014). One of the greatest differences between long-term and short-term occupants is whether they use wired Ethernet or not. In general, wired Ethernet is faster, more stable, and delivers more consistent speeds than wireless (Reference). However, short-term occupancy use only wireless internet connections, because they do not have access to the wired Ethernet, and most of them do not carry an Ethernet patch cable for using wired Ethernet, though wireless is more inconvenient to use. However, long-term occupants have their own place to work, and for them, wired Ethernet is ready and available. The most stationary occupants use wired Ethernet when they use their desktops or laptops. Thus, it can be assumed that there is a positive relationship between stationary occupants and wired Ethernet traffic. So, in this research, wired Ethernet data traffic is used as a proxy for stationary occupancy.

The object building of this research is Interdisciplinary Science and Technology Building 4 (ISTB4) at Arizona State University (ASU), which has various types of space, such as laboratories, administrative and academic offices, and classrooms. This university building was selected because it contains both long- and short-term occupants who use wired Ethernet and Wi-Fi frequently. Data were collected January 1–30 in 2017, since both cooling and heating were required during this period. The outside temperature data were collected from the U.S. climate data website (http://www.usclimatedata.com); electricity, cooling, and heating load data were collected from the ASU Metabolism system, which provides ASU buildings' energy consumption data, and ISTB4's hourly–based Ethernet traffic and the daily–based number of Wi-Fi connection data were collected from the ASU University Technology Office. This study performed Pearson correlation analysis and regression analysis to determine the relationships between the data, using a statistical software package (Statistical Package for Social Science; SPSS version 17.0).

5.3 Results

Figure 1 shows the Ethernet data traffic pattern for the day. The data traffic begins to increase at 7 am and continues to increase until 2 pm, which is the peak time. The traffic then decreases until 6 pm and remains constant through the night. If there is a huge traffic gap from 9 am to 4 pm, then the gap is because of weekends and holidays, when there is low stationary occupancy. This trend is reasonable and understandable, because during working hours, long-term occupants use the Ethernet, which causes the data traffic increase. In addition, during the nighttime, weekends, and holidays, the data traffic consistently remains low, since there is almost no one using the Ethernet. Thus, it can be surmised that there is a significant positive relationship between permanent occupants and wired Ethernet traffic.

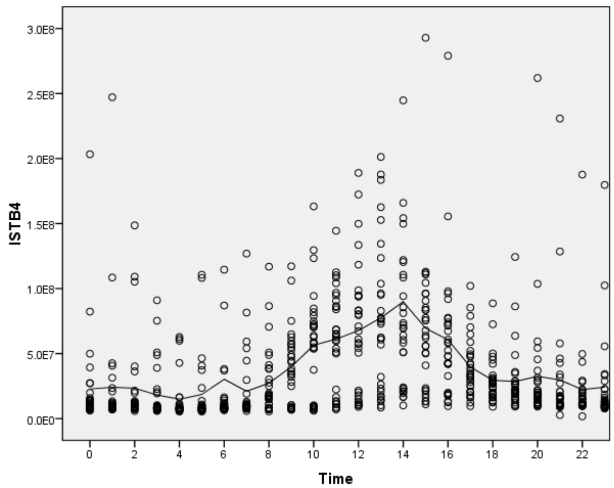

Figure 5.1. Ethernet data traffic pattern for the day

5.3.1 Temperature vs. cooling and heating loads

The relationship between daily average outside temperature and building cooling and heating loads was examined. Table 1 shows the results of the Pearson correlation analysis, and Figure 2 is a scatter plot of the temperature and the loads. There are significant relationships between temperature and cooling and heating loads. In detail, there is a strong positive relationship between outside temperature and cooling load and a moderate negative relationship between the temperature and heating load. In other words, if that day was hot, the cooling load rose almost as much as the outside temperature did. And, if that day was cold, heating load rose to some degree. As shown in Table 2, hourly-based data analysis showed similar results. These results are straightforward and intuitive. In addition, if the outside temperature is lower than approximately 47℉, cooling load remains the lowest, but in case of heating load, there seems no definable borderline. Moreover, it is worth mentioning that it was difficult to determine the cooling and heating load gap between weekdays and weekends in Figure 3, which are scatter plots of the temperature and the loads. In most cases, there are far fewer occupants during weekends and holidays than during weekdays, so cooling and heating loads should also have been far lower, like the data traffic in Figure 1, but it was not.

Table 5.1 Daily-based Pearson correlation analysis – Temperature vs. Energy loads

Energy loads	Temperature
Electricity Load	0.026 (0.891)
Cooling Load	0.879*(0.000)
Heating Load	-0.538*(0.002)

*Correlation is significant at the 0.01 level (2-tailed).

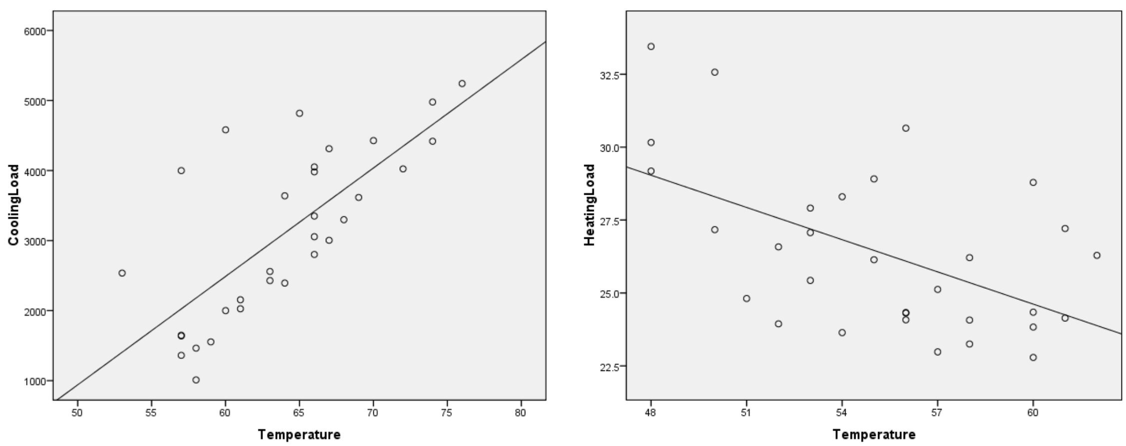

Figure 5.2 Scatter plot of the temperature and the loads

Table 5.2 Hourly-based Pearson correlation analysis – Temperature vs. Energy loads

Energy loads	Temperature
Electricity Load	0.454* (0.000)
Cooling Load	0.848*(0.000)
Heating Load	-0.548*(0.000)

*Correlation is significant at the 0.01 level (2-tailed).

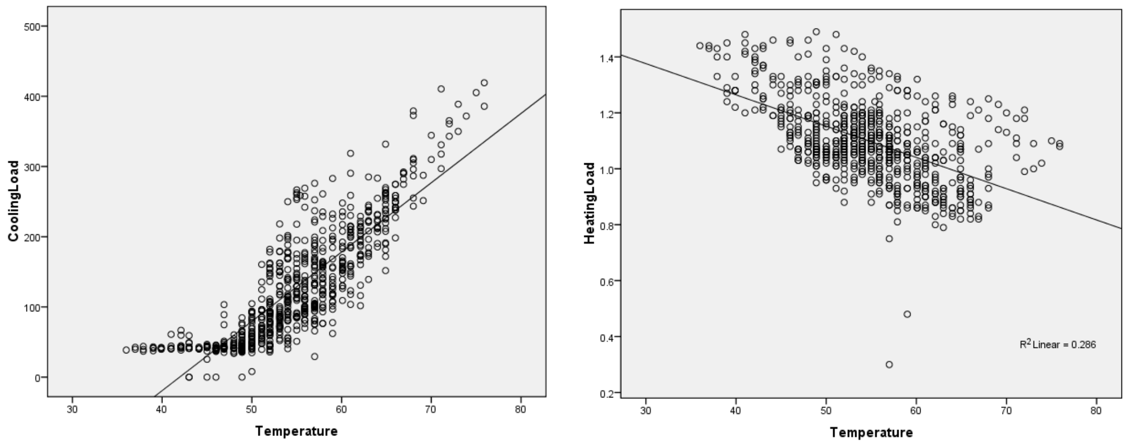

Figure 5.3 Hourly-based Scatter plot of the temperature and the loads

5.3.2 The number of Wi-Fi connections vs. energy loads

The study investigated the relationship between the number of Wi-Fi connections and building energy loads. Table 3 shows the results of the Pearson correlation analysis; the results indicate that there is a strong positive relationship between the number of Wi-Fi connections and electricity load but not between the number of Wi-Fi connections and cooling and heating loads. This means that if the Wi-Fi connections, which implies the number of occupants, grows, electricity load, which is related to electric appliances such as desktop, monitors, or refrigerators, also increases. However, even if the number of occupants increase or decrease, cooling and heating loads are immune to occupancy. Figure 4 displays the relationship between the number of Wi-Fi connections and electricity load. There are two groups based on the number of Wi-Fi connections; the upper group, which has more than 600 Wi-Fi connections, represents weekdays after the beginning class. If one looks only at the upper group, there seems to be a low relationship between the number of Wi-Fi connections and electricity loads, Contrary to this, the lower group, which has lower than 400 Wi-Fi connections, represents weekends, holidays, and weekdays before the beginning class. During these periods, the correlation is stronger than in the upper group.

Table 5.3 Results of the Pearson correlation analysis – Wi-Fi user vs. Energy loads

Energy loads	Wi-Fi User
Electricity Load	0.848* (0.000)
Cooling Load	-0.146 (0.432)
Heating Load	-0.233 (0.208)

*Correlation is significant at the 0.01 level (2-tailed).

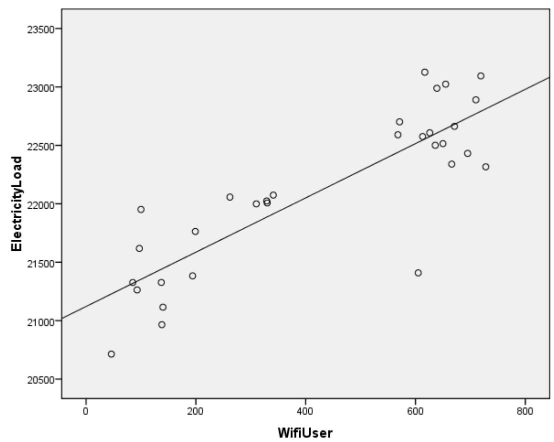

Figure 5.4 Relationship between the number of Wi-Fi connections and electricity load

5.3.3 Data traffic vs. energy loads

The research examined the relationship between wired Ethernet data traffic and building energy loads. Table 4 displays the results of the Pearson correlation analysis. It shows that only the electricity load has a significant moderate relationship with the data traffic. The cooling and heating loads have very week relationships with data traffic. These results are almost same as the Wi-Fi connection results, but there is a difference. The Pearson correlation analysis measures the linear association strength between two variables; the Pearson correlation coefficient was 0.571 between the data traffic and the electricity load. However, if the relationship is not linear, the coefficient can be distorted. Figure 5 shows a scatter plot of the data traffic and the electricity load, and it indicates that the relationship is logarithmic rather than linear. When the logarithmic relationship was applied to the relationship, the correlation coefficient increased to 0.743. If data traffic increased, the electricity consumption also increased. However, the more the data traffic increased, the less the margin of the electricity load increased.

Table 5.4 Results of the Pearson correlation analysis – Wired data traffic vs. Energy loads

Energy loads	Wired Data Traffic
Electricity Load	0.571* (0.000)
Cooling Load	0.148* (0.000)
Heating Load	-0.278* (0.000)

*Correlation is significant at the 0.01 level (2-tailed).

Model Summary and Parameter Estimates

Dependent Variable:ElectricityLoad

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.326	345.699	1	716	.000	898.943	5.958E-7
Logarithmic	.553	886.761	1	716	.000	279.799	37.884

The independent variable is DataTraffic.

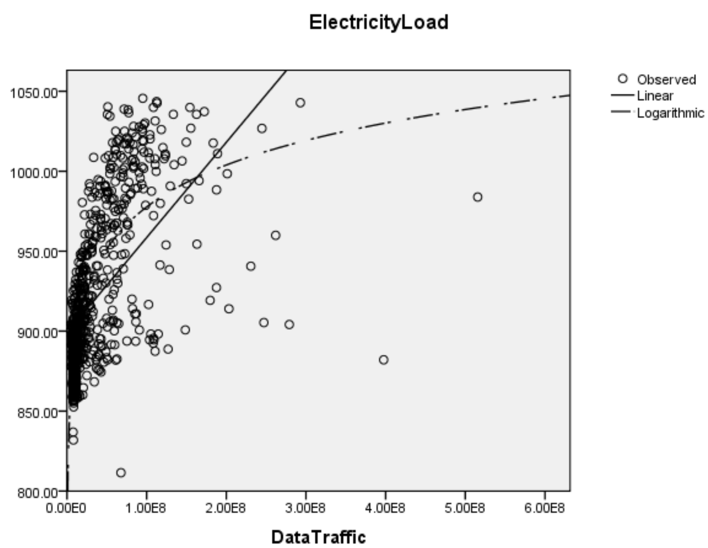

Figure 5.5 Scatter plot of the data traffic and the electricity load

According to the above results, there were significant correlations between the two loads and data traffic, though the correlations were weak. The research authors applied multiple linear regression, in order to verify the relative influences of the data traffic and the temperature to cooling and heating loads. Table 5 shows the results in detail. The magnitude of the standardized coefficient of the regression model measures the relative effect of the independent variables on the dependent variables, so it makes comparison readily in the same units. The dependent variable of the first regression model was cooling load; independent variables were the data traffic and the outside temperature. The result shows that the model was significant and that the R value of the model was 0.849, which was high enough. The standardized coefficient of temperature was 0.864, and the data traffic was -0.074. This indicates that the temperature's influence was overwhelming to cooling load. Though the sign of the data traffic is negative, it can be negligible, because the impact was very limited. In the second regression model, the dependent variable was heating load. The second model was also significant, and the R value was 0.554, which was less than the first model. The standardized coefficient of temperature was -0.496, and the data traffic was -0.152. In case of the heating load, the outside temperature had a much stronger impact to heating load than did the data traffic, but not as much as it did on cooling load. The data traffic also had a certain influence on heating load.

Table 5.5 Results of the multiple linear regression

Variables Entered/Removed

Model	Variables Entered	Variables Removed	Method
1	Temperature, DataTraffic[a]	.	Enter

a. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.849[a]	.720	.719	42.69336

a. Predictors: (Constant), Temperature, DataTraffic

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3358833.235	2	1679416.617	921.378	.000[a]
	Residual	1305069.484	716	1822.723		
	Total	4663902.718	718			

a. Predictors: (Constant), Temperature, DataTraffic

b. Dependent Variable: CoolingLoad

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-421.125	12.912		-32.616	.000
	DataTraffic	-1.251E-7	.000	-.074	-3.635	.000
	Temperature	10.089	.239	.864	42.296	.000

a. Dependent Variable: CoolingLoad

Variables Entered/Removed

Model	Variables Entered	Variables Removed	Method
1	Temperature, DataTraffic[a]	.	Enter

a. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.554[a]	.307	.305	.12038

a. Predictors: (Constant), Temperature, DataTraffic

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.605	2	2.302	158.877	.000[a]
	Residual	10.376	716	.014		
	Total	14.981	718			

a. Predictors: (Constant), Temperature, DataTraffic

b. Dependent Variable: HeatingLoad

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.685	.036		46.283	.000
	DataTraffic	-4.583E-10	.000	-.152	-4.723	.000
	Temperature	-.010	.001	-.496	-15.428	.000

a. Dependent Variable: HeatingLoad

5.4 Discussion

5.4.1 Wi-Fi vs. electricity consumption

The results demonstrate that there is a strong positive relationship between the number of Wi-Fi connections, which imply the total number of occupancy in the building, and electricity load. This is because almost all occupants consumed plug-loads during their stay in the building. For example, students who were short-term occupancy charged their laptops and smartphones, and computers, monitors, and projectors were used during class. Long-term occupants used their own desktop computer, laptop, monitors, and other electric appliances, and also charged a smartphone or other device. The same result was verified by a previous study (Martani et al., 2012).

However, among the two types of occupancy, long-term occupancy might have a larger impact on the electricity load than short-term occupancy. As mentioned at the end of section 3.2, the lower group in Figure 4, which represents weekends, holidays, and weekdays before the beginning class, had a stronger correlation between the number of Wi-Fi connections and electricity load. This implies that the electricity load is more affected by stationary occupancy than by non-stationary. This is because in most cases, the non-stationary occupants did not come to the building on weekends or similar time periods, but some permanent occupants, such as faculties or graduate students, did. When they did, they increased the electricity load by using their electric appliances. However, the upper group in Figure 4, which is weekdays after the beginning class, had a low relationship between the Wi-Fi connections and electricity load. This might be because non-stationary occupancy has a lower impact on electricity load. During this period, the electricity load did not rise, even if the number of Wi-Fi connections increased. Normally, the greatest number of faculty members and graduate students were in the building at that period, so the variation of the Wi-Fi connection might be from the students who attended class. Thus, it is surmised that the students' influence on electricity load was not significant.

5.4.2 Data traffic vs. electricity consumption

It is also proved that there is a significant relationship between the wired Ethernet data traffic as a proxy for stationary occupancy and the electricity load. The relationship is logarithmic rather than linear, which means even if the data traffic increases, after the inflection point the electricity load does not increase that much. There are two probable reasons for the logarithmic relationship. The first reason is that, before the inflection point, the more stationary occupants that came in the building, the more the data traffic increased, since the stationary occupants use the wired Ethernet. At the inflection point, it seems that the most long-term occupancy had entered the building. After the inflection point, a large amount of the data traffic increase might be from preexisting stationary occupants and not from a new stationary occupant. Since the number of stationary occupants did not increase as much as the data traffic did, the slope of electricity load increase decreases. Then, if all or almost all stationary occupants stayed in the building, data traffic and the electricity load might only have increased very slightly, since there was almost no change in the number of stationary occupants. The second reason is because of the heavy data user. In the Figure 5, there are several points that seem like outliers that have a large data traffic with a relatively low electricity load. This can happen when a few occupants use the data overwhelmingly at a specific point of time. Thus, the inflection point and heavy data user should be carefully considered when estimating the stationary occupancy using the data traffic.

5.4.3 Heating & cooling load vs. occupancy

According to the results, there was no correlation between the thermal loads and occupancy. In addition, when comparing the impacts of the outside temperature and occupancy on thermal loads by multiple regression analysis, occupancy's influence was severely limited when compared to the temperature. However, it is reasonable that the more occupants in a building, the higher the HVAC loads. At the least, there must be a significant relationship between cooling load and occupancy, because the presence of occupants causes metabolic heat and increases the indoor temperature (Kwok and Lee, 2011). Furthermore, the various electrical appliances the occupants use also produce internal heat, which also increase the cooling load (Kwok and Lee, 2011).

Surprisingly, previous studies also revealed that there was a lack of correlation between HVAC system and occupancy (Martani et al., 2012), which seems to be due to the current HVAC systems. HVAC systems normally operate based on fixed schedules and maximum occupancy assumptions (Li et al., 2012). In addition, HVAC systems do not consider whether the building is partially occupied; there are only "occupied" or "unoccupied" periods of the day (Li et al., 2012). The object building of this research is operated in a similar way. According to the ASU Facilities Services, the building HVAC system is controlled by periods that are set by manager, and there are only "occupied," "unoccupied," "preoccupancy," and "setback" periods. This system is too rough and simple, so it is not helpful for energy saving. Thus, there seems to be high energy saving potential if HVAC loads can be adjusted automatically based on real-time occupancy information (Liao and Barooah, 2010; Li et al., 2012). For example, during occupied periods, if there are no Wi-Fi connections or wired data traffic in certain rooms, the room does not need cooling or heating. And if there are a few Wi-Fi connections or a little data traffic in a room, the HVAC system only needs to reduce the loads, and vice versa. By doing this simple modification, a large amount of energy can be saved.

5.5 Conclusion

This study investigated the relationship between building occupancy and building energy loads such as electricity, cooling, and heating loads, using correlation and multiple regression analyses. The results revealed that stationary occupants, such as faculty members and graduate students, can be successfully estimated by the existing infrastructure, the wired Ethernet data traffic. There was a significant linear relationship between electricity consumption and total occupancy, and the impact of stationary occupancy on electricity load was higher than was non-stationary occupancy on electricity load. There was a significant logarithmic relationship between electricity load and the Ethernet data traffic, which is a proxy of the stationary occupancy. However, there was no relationship between the occupancy and thermal loads; this might be because the current HVAC systems almost do not consider the state of the occupancy, though the occupancy option is roughly divided, such as “occupied” or “unoccupied.”

It is expected that the research results can be utilized practically and usefully. Since this study applied the existing infrastructure of Wi-Fi connections and Ethernet data traffic, additional cost and labor intensive process, such as sensor installation, is unnecessary. Thus, if the building use a Wi-Fi and the wired Ethernet, the occupants in the building can be estimated immediately in real-time. Furthermore, at present, a large amount of thermal and heating loads are being wasted on vacant or partially occupied room. Thus, if the HVAC systems could consider occupancy information in real time, a huge amount of energy can be conserved. Moreover, the accuracy of building energy simulations or predictions can be improved by applying the occupancy data. This is because the current simulation or prediction do not apply the occupancy information, and it can cause a big difference in accuracy between the simulated and actual consumption.

Unfortunately, this study analyzed only one month of data because of data unavailability, so more long-term period analyses should be made for further research. The object building can be extended to other types of buildings or to a building in another region. This research did not estimate the number of stationary occupants in the building. However, the approximate number, if not an exact estimation, of stationary occupancy can be estimated by using Ethernet data traffic in future research. The final suggestion is to utilize data from existing infrastructure efficiently and successfully. A huge and varied amount of data is produced from existing infrastructure; these data are of great value and can be connected to big data at no additional cost or need for labor. So, by making use of the data, it can be used in various ways, such as optimizing the use of building energy and water, to improve occupant comfort.

CHAPTER 6

CONCLUSION

6.1 Dissertation Summary

In this dissertation, I tried to provide ways to decrease greenhouse gas emissions by verifying the critical factors that significantly impact emissions. Some results were straightforward and predictable, but others were not. All these results are valuable, though, and the unexpected results are more useful. For example, if a government decreases natural gas consumption to reduce its carbon emissions, the results can be the opposite of what was expected. And if a government decides to raise the price of coal to decrease its consumption, the effort can be fruitless.

Chapter 2 presented the causalities between energy consumption, energy prices, and carbon emissions in the U.S. residential and commercial building sectors, using the Granger causality testing and generalized impulse response analysis. The results show that, first, energy consumption and prices have various impacts on greenhouse gas emissions based on building and energy sources. Policy makers can concentrate on promoting the use of low-carbon and carbon-neutral energy resources (like renewable and natural gas). Second, increasing the proportion of low-carbon and carbon-neutral sources, such as natural gas, can reduce carbon emissions. Decreasing energy consumption is not the only way to reduce emissions, however. Lastly, inexpensive energy sources, such as coal, may be unaffected by price.

Chapter 3 presented the causal relationship between solid waste generation, which not only contaminates soil but also emits greenhouse gasses, and greenhouse gas emission from the U.S. solid waste sector. Previous research confirmed that when GDP per capita increased, solid waste per capita decreased, but that is not the case in the U.S. waste sector. Therefore, it was concluded that the government should find alternative strategies to reduce solid waste per capita because no causal relationship exists between GDP per capita and MSW per capita. Moreover, decreasing solid waste and increasing waste recycling mitigate the waste sector’s carbon emissions significantly.

Chapter 4 presented an investigation of electrical appliance usage patterns, which included the use of monitors, desktops, vending machines, and refrigerators in university buildings, to contribute to the reduction of building electricity use. This research also involved the relationship between electricity consumption and occupant influence at lunchtime and nighttime. The results showed that electric appliances affect building energy use significantly. Vending machines use the most plug loads, which significantly contributes to the minimum plug load. Therefore, a possible recommendation is to decrease the number of underutilized vending machines or use energy-efficient vending machines. In addition, a large amount of electricity is wasted at lunchtime and nighttime; therefore, energy-saving potential is very high. If an automated system is applied in buildings, the waste can be prevented.

Chapter 5 presented the relationship between building occupancy and building energy loads, such as electricity, cooling, and heating loads. The results showed that stationary occupants, such as faculty members and graduate students, could be estimated by a building’s existing infrastructure and the wired Ethernet data traffic. A significant linear relationship exists between electricity use and a building’s total occupancy, and the impact of stationary occupants on electricity load was higher than that of non-stationary occupants, such as undergraduate students and visitors, on electricity load. Also, a significant logarithmic relationship exists between electricity consumption and Ethernet data traffic, which is a proxy for stationary occupancy. However, no relationship exists between occupancy and thermal loads because most current HVAC systems do not consider the building's occupancy, but the occupancy status is roughly divided into "occupied" or "unoccupied."

6.2 Future Directions and Recommendations

Chapters 2 and 3 focused on the United States, so it is difficult to extend and apply the results to other countries because each country has unique characteristics. Previous studies showed various results for various countries in terms of causal relationships. Therefore, further research about other countries is necessary to generalize the relationships. And based on the results, each country should make an appropriate plan to fit its situation. Also, more factors can be considered. For instance, energy consumption and carbon emissions can respond to weather or economic conditions, and government policies can affect the generation of solid waste and carbon emission from the waste sector. Therefore, these variables could be analyzed in future research, and more critical factors could be discovered.

Chapter 4 focused on university buildings, so the results might be invalid for or inapplicable to other types of buildings because each building has unique characteristics. For example, a restaurant uses more refrigerators and cooking equipment. In addition, the results can change based on climate zones. The climate in a subtropical desert, for example, is hot and dry in summer, and occupants usually stay indoors during the day. Therefore, occupants' habits will1 differ from those in a mild marine climate zone. Further research accounting for climate in building sectors is necessary. Last, it is essential to discover the most effective ways to save plug loads at lunchtime and nighttime. These periods have extremely high energy saving potential. If the appropriate methods are applied in the buildings, the plug loads can be reduced substantially.

Chapter 5includes some recommendations for future research. First, unfortunately, the research analyzed only a month of data because of data unavailability, so a long-term analysis period such as 1 year or more should be used for further research. Research can also be extended to other building types, such as offices, residential buildings, or buildings in other regions. I did not estimate the number of stationary occupants in buildings. However, the approximate number of stationary occupants can be estimated by using Ethernet data traffic in future research. The final recommendation is to utilize data from existing infrastructures efficiently and successfully. Various kinds of data are produced from existing infrastructures; these data are of great value and can be connected to big data without additional cost or need for labor, which is a great advantage. It can be used in various ways, such as optimizing the use of building energy and water, to improve occupant comfort by making use of the data.

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CHAPTER 2

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APPENDIX I

CHAPTER 2

APPENDIX A. RESIDENTIAL SECTOR DATA

Year	Coal[a]	Natural gas[a]	Petroleum[a]	Electricity[a]	Total energy[a]	Coal price[b]	Natural gas price[b]	Petroleum price[b]	Electricity price[b]	Total Energy Price[b]	CO_2 emissions[c]
1973	94	5,001	2,800	1,976	14,919	6.21	6.52	10.81	38.47	14.01	906.93
1974	82	4,898	2,554	1,973	14,651	10.25	6.61	13.27	42.33	15.74	873.11
1975	62	5,024	2,479	2,007	14,814	10.46	7.13	12.89	43.91	16.22	867.23
1976	59	5,149	2,703	2,069	15,417	9.72	7.83	13.07	44.10	16.66	912.63
1977	57	4,914	2,681	2,202	15,662	9.59	8.71	13.79	44.97	18.03	934.51
1978	49	4,987	2,607	2,301	16,143	9.12	8.87	13.28	44.48	18.06	938.39
1979	38	5,052	2,099	2,330	15,813	8.51	9.23	16.82	43.01	18.94	918.00
1980	31	4,855	1,734	2,448	15,731	8.08	10.03	20.17	43.77	20.79	911.36
1981	30	4,652	1,531	2,464	15,247	8.99	10.58	21.85	45.89	22.28	878.41
1982	32	4,751	1,434	2,489	15,497	8.68	12.02	20.60	47.85	23.24	872.63
1983	31	4,515	1,353	2,562	15,399	7.28	13.55	19.34	48.50	24.57	866.89
1984	40	4,685	1,531	2,662	15,920	7.51	13.15	18.65	46.32	23.56	902.12
1985	39	4,566	1,565	2,709	16,041	6.96	12.67	17.37	46.22	23.28	908.65
1986	41	4,432	1,541	2,795	15,951	6.54	11.88	14.18	45.56	22.52	904.92
1987	38	4,436	1,617	2,902	16,228	5.54	10.89	13.32	44.10	21.65	934.22
1988	37	4,757	1,675	3,046	17,132	5.07	10.32	12.75	42.54	20.69	982.37
1989	31	4,926	1,660	3,090	17,776	4.89	10.13	13.96	41.49	20.40	1,004.88
1990	31	4,519	1,394	3,153	16,937	5.29	9.89	15.27	40.33	20.85	963.38
1991	25	4,684	1,381	3,260	17,406	5.23	9.54	14.29	39.73	20.36	980.10
1992	26	4,820	1,414	3,193	17,337	4.73	9.38	12.76	39.37	19.59	981.42
1993	26	5,098	1,439	3,394	18,211	4.80	9.52	12.14	38.77	19.50	1,039.56
1994	21	4,981	1,408	3,441	18,098	4.14	9.65	11.73	38.06	19.52	1,032.22
1995	17	4,984	1,374	3,557	18,515	3.89	8.87	11.28	37.11	18.98	1,039.04
1996	16	5,391	1,484	3,694	19,506	3.70	9.01	12.63	35.85	18.57	1,099.09
1997	16	5,125	1,422	3,671	18,962	3.55	9.66	12.32	35.35	18.95	1,089.79
1998	12	4,671	1,304	3,856	18,950	3.47	9.31	10.63	34.10	18.93	1,097.44
1999	14	4,857	1,465	3,906	19,541	3.27	8.96	10.72	32.98	18.12	1,121.60
2000	11	5,104	1,554	4,069	20,393	2.99	10.17	14.83	32.19	18.95	1,185.04
2001	11	4,902	1,529	4,100	20,029	3.80	12.21	14.56	32.62	20.25	1,171.45
2002	12	5,006	1,457	4,317	20,767	3.31	9.81	12.75	31.59	18.70	1,202.57
2003	12	5,224	1,547	4,353	21,090	3.07	11.53	14.76	31.89	19.70	1,232.03
2004	11	4,993	1,520	4,408	21,056	3.68	12.73	16.20	31.87	20.67	1,227.26
2005	8	4,958	1,451	4,638	21,586	4.07	14.51	19.70	32.54	22.52	1,260.92
2006	6	4,483	1,224	4,611	20,643	4.00	15.20	21.89	34.72	24.47	1,191.40
2007	8	4,849	1,254	4,750	21,514	3.88	14.07	23.38	34.58	23.88	1,240.55
2008	0	5,018	1,330	4,708	21,664	0	14.42	27.41	35.20	24.60	1,234.27
2009	0	4,899	1,161	4,656	21,087	0	12.64	22.26	36.09	23.58	1,156.78
2010	0	4,887	1,125	4,933	21,819	0	11.72	24.73	35.60	23.60	1,209.66
2011	0	4,817	1,052	4,855	21,376	0	11.00	27.56	35.05	23.31	1,149.69
2012	0	4,252	896	4,690	19,925	0	10.44	28.42	34.82	23.50	1,043.09

[a] Trillion Btu; [b] Dollars per Million Btu ;[c] Million Metric Tons *Data source: http://www.eia.gov/*

APPENDIX B. COMMERCIAL SECTOR DATA

Year	Coal[a]	Natural gas[a]	Petroleum[a]	Electricity[a]	Total energy[a]	Coal price[b]	Natural gas price[b]	Petroleum price[b]	Electricity price[b]	Total Energy Price[b]	CO_2 emissions[c]
1973	160	2660	1607	1517	9553	2.69	4.71	6.21	36.51	13.19	609.25
1974	174	2614	1461	1501	9391	4.66	4.89	10.48	41.49	15.83	586.73
1975	146	2556	1346	1598	9489	5.59	5.63	10.2	43.14	17.33	582.86
1976	144	2717	1500	1678	10065	4.96	6.5	10.05	43.66	17.67	627.48
1977	148	2547	1552	1754	10206	4.93	7.58	10.76	45.43	19.4	645.02
1978	165	2642	1490	1813	10515	4.89	7.75	10.28	45	19.33	647.59
1979	151	2834	1367	1854	10650	4.62	8.51	13.09	43.39	19.83	661.27
1980	117	2666	1318	1906	10576	4.26	9.25	15.66	44.75	21.82	661.85
1981	137	2578	1122	2033	10614	4.52	9.88	17.55	46.58	23.92	662.66
1982	155	2671	1037	2077	10840	4.45	11.18	15.75	47.85	24.6	664.53
1983	162	2505	1170	2116	10923	4.01	12.52	14.96	47.42	25.15	671.31
1984	169	2594	1227	2264	11417	3.98	11.93	14.32	46.16	24.57	704.4
1985	138	2503	1083	2351	11455	3.78	11.39	13.78	45.45	24.82	704.5
1986	136	2383	1162	2439	11591	3.52	10.35	9.3	44.2	23.46	710.71
1987	127	2499	1131	2539	11921	3.11	9.38	9.6	41.31	22.15	735.59
1988	131	2744	1099	2675	12581	2.99	8.75	8.73	39.48	20.98	772.48
1989	115	2800	1041	2767	13186	2.85	8.54	9.42	38.46	20.83	794.08
1990	124	2698	991	2860	13319	2.88	8.26	10.61	37.24	20.85	792.65
1991	115	2807	935	2918	13503	2.66	7.91	9.42	36.63	20.31	794.28
1992	117	2883	893	2900	13445	2.62	7.77	8.79	36.25	19.88	795.86
1993	117	2944	819	3019	13824	2.56	8.07	8.17	35.59	19.94	819.41
1994	117	2978	825	3116	14086	2.43	8.29	7.82	34.63	19.71	833.43
1995	116	3117	769	3252	14689	2.34	7.44	7.74	33.58	19.01	851.32
1996	120	3251	790	3344	15176	2.21	7.7	9.03	32.44	18.67	882.6
1997	129	3306	743	3503	15692	2.16	8.11	8.73	31.51	18.64	926.03
1998	101	3098	702	3678	15984	2.13	7.58	7.17	30.26	18.38	946.82
1999	102	3132	707	3766	16396	2.08	7.19	7.66	28.95	17.69	960.34
2000	86	3261	807	3956	17170	1.93	8.72	11.03	28.69	18.53	1021.97
2001	88	3109	790	4063	17137	2.04	10.79	10.22	29.8	20.15	1027.23
2002	88	3223	726	4110	17342	2.08	8.28	9.11	29.11	18.71	1026.26
2003	83	3271	843	4090	17337	1.98	10.07	10.73	29.37	19.48	1037.06
2004	103	3211	810	4198	17653	2.24	11.17	12.35	29.11	20.12	1053.06
2005	96	3083	762	4351	17825	2.65	12.91	15.93	29.86	21.85	1068.54
2006	64	2908	664	4435	17676	2.7	13.21	18.12	31.57	23.49	1042.87
2007	70	3095	651	4560	18215	2.74	12.17	19.4	31.31	22.96	1077.52
2008	80	3235	666	4558	18355	4	12.68	24.55	32.4	23.93	1075.18
2009	73	3199	666	4460	17854	4.55	10.38	16.59	31.9	22.12	1007.32
2010	70	3173	655	4539	18013	3.93	9.69	19.84	31.45	22.02	1025.01
2011	62	3226	644	4531	17931	4.07	8.97	24.54	30.62	21.59	990.19
2012	44	2969	574	4529	17343	4.38	8.03	24.02	29.57	21.03	932.01

[a] Trillion Btu; [b] Dollars per Million Btu ;[c] Million Metric Tons *Data source: http://www.eia.gov/*

APPENDIX C. UNIT ROOT TEST RESULTS OF ENERGY CONSUMPTION FACTORS

		Residential Sector		Commercial Sector	
		ADF	PP	ADF	PP
Levels					
Intercept	Coal	-4.482031[a] (0)	-4.122059[a] (2)	-0.805702 (0)	0.01584 (33)
	Natural gas	-3.039682[b] (0)	-3.081159[b] (1)	-1.548438 (0)	-1.507751 (1)
	Petroleum	-2.112495 (0)	-2.092467 (3)	-1.699005 (0)	-2.06400 (10)
	Electricity	-0.748933 (1)	-0.710208 (3)	-0.712182 (0)	-0.658053 (3)
	Total energy	-1.159436 (0)	-1.125040 (2)	-1.112124 (0)	-1.038310 (3)
Intercept and Trend	Coal	-5.038679[a] (0)	-5.038679[a] (0)	-4.098702[b] (0)	-3.58485[b] (10)
	Natural gas	-2.952540 (0)	-2.995373 (1)	-2.356259 (0)	-2.246990 (2)
	Petroleum	-2.196587 (0)	-2.341181 (2)	-2.749468 (0)	-2.807070 (2)
	Electricity	-2.760439 (1)	-2.916113 (4)	-0.874861 (0)	-1.498955 (3)
	Total energy	-2.169160 (0)	-2.173547 (3)	-0.081260 (0)	-0.659810 (3)
First difference					
Intercept	Coal	-4.682785[a] (0)	-4.682785[a] (0)	-7.186396[a] (0)	-13.7574[a] (32)
	Natural gas	-6.439811[a] (1)	-7.144926[a] (8)	-6.497129[a] (0)	-6.589488[a] (3)
	Petroleum	-4.114766[a] (1)	-4.381381[a] (3)	-6.039132[a] (0)	-6.633138[a] (6)
	Electricity	-5.443359[a] (1)	-8.166056[a] (3)	-4.734704[a] (0)	-4.799628[a] (3)
	Total energy	-4.970907[a] (1)	-6.989921[a] (1)	-4.479221[a] (0)	-4.629119[a] (3)
Intercept and Trend	Coal	-4.936664[a] (0)	-4.936664[a] (0)	-7.099508[a] (0)	-14.0101[a] (29)
	Natural gas	-6.352604[a] (1)	-7.158097[a] (7)	-5.891475[a] (1)	-6.480058[a] (3)
	Petroleum	-4.073637[a] (1)	-4.240004[a] (4)	-5.949477[a] (0)	-6.774067[a] (7)
	Electricity	-5.227649[a] (1)	-8.053182[a] (3)	-4.788744[a] (0)	-4.790691[a] (2)
	Total energy	-4.915285[a] (1)	-6.963287[a] (1)	-4.642770[a] (0)	-4.732753[a] (3)

[a] 1% significance; [b] 5% significance; [c]10% significance
Note: Lag lengths are listed in parentheses and were determined via SIC for ADF and via Bandwidth-NeweyWest for PP.

APPENDIX D. UNIT ROOT TEST RESULTS OF ENERGY PRICE

		Residential Sector		Commercial Sector	
		ADF	PP	ADF	PP
Levels					
Intercept	Coal price	-0.371867 (0)	-0.345024 (2)	-2.457017 (3)	-1.539086 (3)
	Natural gas price	-2.144372 (0)	-2.269409 (3)	-2.294905 (0)	-2.425483 (3)
	Petroleum price	-0.364550 (0)	-0.516621 (2)	-0.942525 (0)	-0.816964 (2)
	Electricity price	-1.101050 (1)	-0.830667 (3)	-0.886191 (1)	-0.664695 (4)
	Total energy price	-2.374867 (0)	-2.404522 (4)	-3.214622[a] (0)	-3.079131[a] (4)
Intercept and Trend	Coal price	-4.786327[a] (0)	-4.862702[a] (3)	-0.577781 (3)	-1.762547 (3)
	Natural gas price	-1.683947 (0)	-1.986116 (3)	-1.734435 (0)	-1.992723 (3)
	Petroleum price	-0.805558 (0)	-0.938673 (2)	-1.304849 (0)	-1.191638 (2)
	Electricity price	-2.701416 (1)	-2.767226 (4)	-1.655564 (1)	-3.097967 (4)
	Total energy price	-2.054171 (0)	-2.271640 (4)	-2.862026 (0)	-2.820341 (4)
First difference					
Intercept	Coal price	-8.095202[a] (0)	-11.00585[a] (8)	-2.761654[c] (2)	-6.737067[a] (3)
	Natural gas price	-5.148310[a] (0)	-5.212167[a] (3)	-5.202963[a] (0)	-5.281446[a] (3)
	Petroleum price	-5.519236[a] (0)	-5.524486[a] (1)	-7.055603[a] (0)	-7.106894[a] (2)
	Electricity price	-4.691586[a] (0)	-4.691047[a] (1)	-5.016853[a] (0)	-5.008021[a] (1)
	Total energy price	-4.774574[a] (0)	-4.849272[a] (3)	-4.718428[a] (0)	-4.709248[a] (2)
Intercept and Trend	Coal price	-7.814943[a] (0)	-10.52375[a] (8)	-8.416040[a] (1)	-8.929033[a] (7)
	Natural gas price	-5.289425[a] (0)	-5.307445[a] (2)	-5.444114[a] (0)	-5.506960[a] (3)
	Petroleum price	-5.642607[a] (0)	-5.642607[a] (0)	-5.135019[a] (1)	-7.223941[a] (1)
	Electricity price	-4.493760[a] (0)	-4.493760[a] (0)	-4.782328[a] (0)	-4.778194[a] (1)
	Total Energy price	-4.713903[a] (0)	-4.806242[a] (3)	-4.749877[a] (0)	-4.755912[a] (2)
	CO_2emissions	-1.633819 (2)	-6.120377[a] (4)	-1.110919 (2)	-5.100625[a] (4)
Second difference					
Intercept	Coal price	-9.366394 [a] (0)	-	-11.24939 [a] (1)	-
Intercept and Trend	Coal price	-9.239583 [a] (0)	-	-11.10031 [a] (1)	-

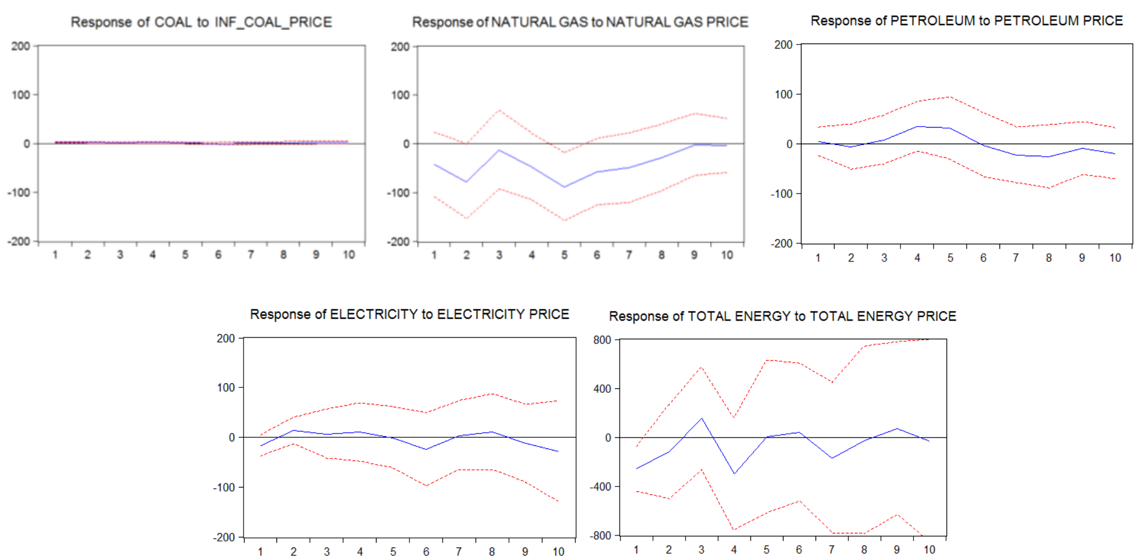
[a] 1% significance; [c]10% significance
Note: Lag lengths are listed in parentheses and were determined via SIC for ADF and via Bandwidth-NeweyWest for PP.

APPENDIX E. UNIT ROOT TEST RESULTS OF CO_2 EMISSIONS

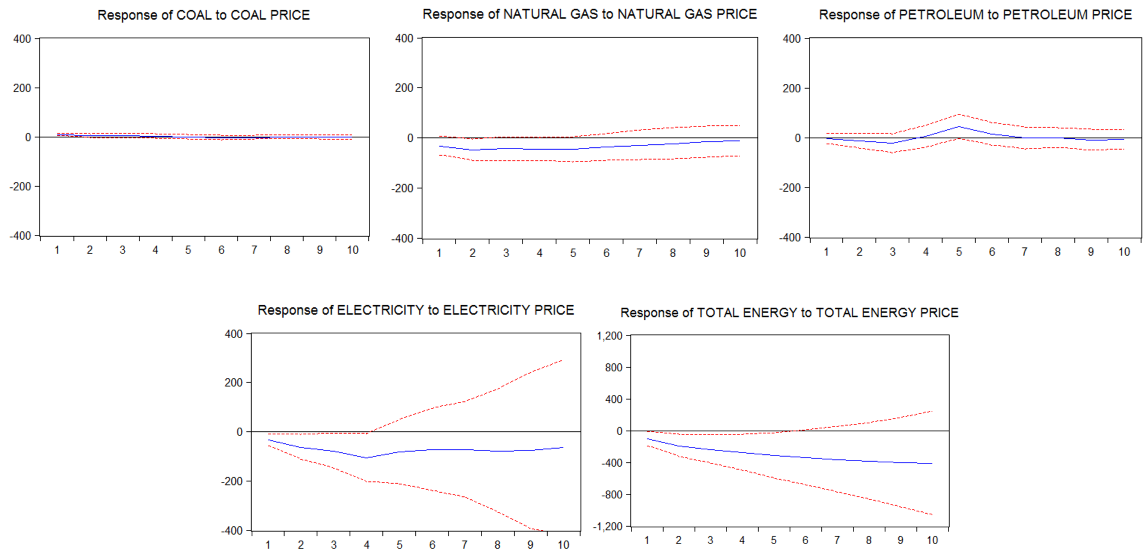
		Residential Sector		Commercial Sector	
		ADF	PP	ADF	PP
Levels					
Intercept	CO_2emissions	-1.183406 (0)	-1.205723 (4)	-1.727853 (3)	-1.261508 (4)
Intercept and Trend	CO_2 emissions	-0.930875 (0)	-1.203317 (4)	0.512623 (0)	-0.229426 (4)
First difference					
Intercept	CO_2 emissions	-5.980950[a] (0)	-6.073683[a] (4)	-0.703354 (2)	-4.868260[a] (4)
Intercept and Trend	CO_2emissions	-1.633819 (2)	-6.120377[a] (4)	-1.110919 (2)	-5.100625[a] (4)
Second difference					
Intercept	CO_2 emissions	-9.150812 [a] (1)	-	-10.31891 [a] (1)	-
Intercept and Trend	CO_2 emissions	-5.072535 [a] (3)	-	-10.52008 [a] (1)	-

[a] 1% significance
Note: Lag lengths are listed in parentheses and were determined via SIC for ADF and via Bandwidth-NeweyWest for PP.

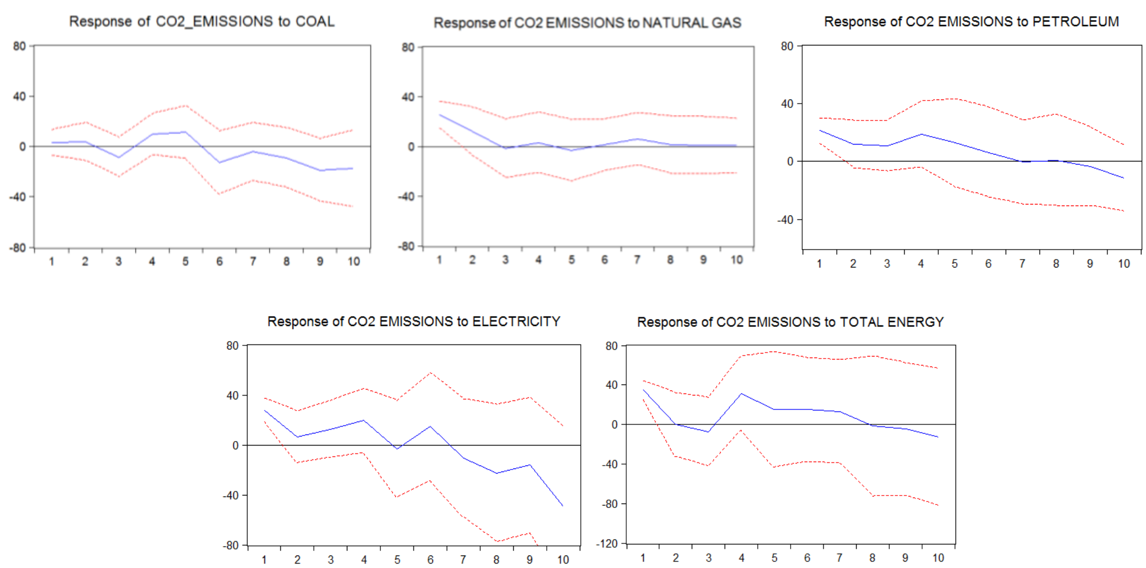
APPENDIX F. GENERALIZED IMPULSE RESPONSE OF ENERGY CONSUMPTION TO ENERGY PRICE IN RESIDENTIAL SECTOR



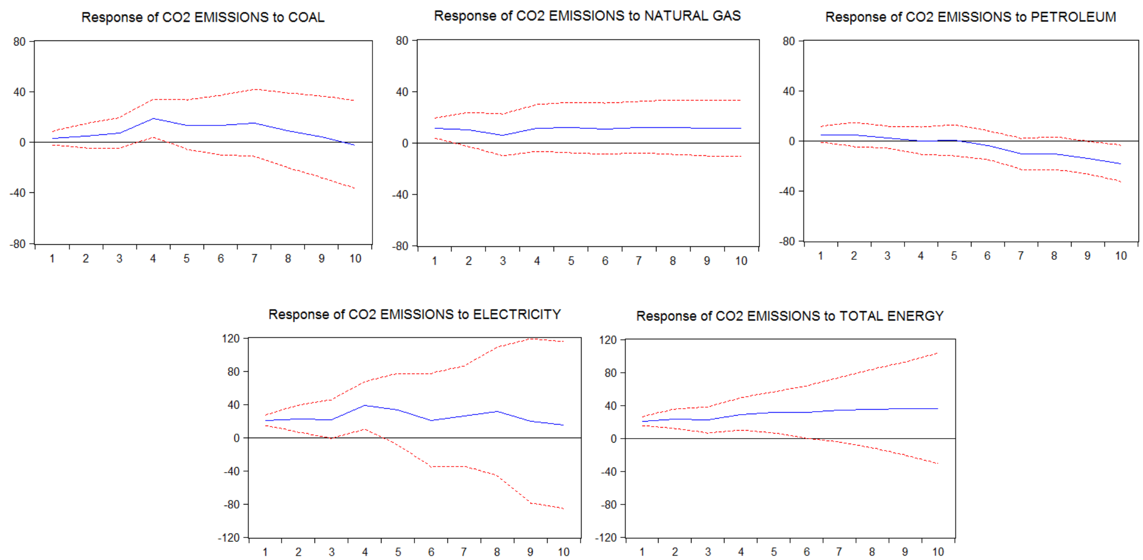
APPENDIX G. GENERALIZED IMPULSE RESPONSE OF ENERGY CONSUMPTION TO ENERGY PRICE IN COMMERCIAL SECTOR



APPENDIX H. GENERALIZED IMPULSE RESPONSES OF CO_2 TO ENERGY CONSUMPTION IN THE RESIDENTIAL SECTOR



APPENDIX I. GENERALIZED IMPULSE RESPONSES OF CO_2 TO ENERGY CONSUMPTION IN THE COMMERCIAL SECTOR



APPENDIX II

CHAPTER 3

APPENDIX A. FIRST MODEL DATA FOR EKC RELATIONSHIP

Year	GDP per capita [a]	Total MSW generation per capita [b]
1990	23,954.5	208.3
1991	24,405.0	207.7
1992	25,493.0	214.9
1993	26,464.8	218.0
1994	27,776.4	221.3
1995	28,782.0	217.3
1996	30,068.2	216.0
1997	31,572.6	223.1
1998	32,949.0	227.1
1999	34,639.1	234.9
2000	36,467.3	243.5
2001	37,285.8	240.8
2002	38,175.4	245.3
2003	39,682.5	246.4
2004	41,928.9	254.1
2005	44,313.6	253.7
2006	46,443.8	257.1
2007	48,070.4	256.5
2008	48,407.1	252.5
2009	46,998.8	244.3
2010	48,357.7	250.5
2011	49,854.5	250.4
2012	51,755.2	250.9

[a] current US dollar; [b] kilograms per capita

Appendix B. SECOND MODEL DATA FOR WASTE GENERATION AND GREENHOUSE GAS FROM WASTE SECTOR

Year	Total MSW generation [a]	Recovery waste generation [a]	Greenhouse gas from waste sector [b]
1990	208.3	33.2	165.0
1991	207.7	37.3	166.4
1992	214.9	41.4	167.5
1993	218.0	44.7	166.7
1994	221.3	51.8	165.6
1995	217.3	55.8	158.6
1996	216.0	58.0	155.4
1997	223.1	60.0	146.8
1998	227.1	61.8	139.7
1999	234.9	65.5	135.5
2000	243.5	69.5	132.8
2001	240.8	69.7	128.3
2002	245.3	71.0	129.3
2003	246.4	75.1	134.9
2004	254.1	78.6	131.0
2005	253.7	79.8	133.2
2006	257.1	82.6	132.5
2007	256.5	84.8	133.1
2008	252.5	84.1	136.0
2009	244.3	82.4	136.5
2010	250.5	85.1	131.1
2011	250.4	86.9	128.5
2012	250.9	86.6	124.0

[a] million tons; [b] Tg CO_2 Eq.