Energy Behaviour in Dutch Student Houses

An Analysis of Energy Use and Energy Time of Use in a Field Lab Setting

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Abstract

Energy Consumption sheds light on living standards, behavioural factors and consumers' activities. Analysing residential energy consumption is vital to investigate the significant proportion of energy use by households in national energy budgets. Energy use among rented apartments and student houses is of relevance considering the rising urbanization and increase of rented facilities. Hence, a closer examination of energy use in rented apartments could pave way for better energy management and savings. This study aims to elicit the determinants of energy use among student tenants in experimental field labs in two major cities in the Netherlands, employing theories from social psychology and economics. Subsequent to this, a predictive analytics of energy time of use is conducted to examine efficient energy management measures. Multiple linear regression and linear mixed effects regression are employed in the research. The study finds out that certain socio-psychological variables have significant impact on the self-reported energy behaviour of the individuals, albeit less in the case of measured direct electricity consumption. With respect to energy time of use, different energy use patterns were found for student tenants in comparison with household users. The time factor was found significant in determining energy use, albeit there was no significant influence of socio-psychological variables on energy time of use. This underlines the earlier findings on energy use getting confined to certain peak times during the day. The results call for better energy management aimed at evening out electricity peak values and the role of psychological factors to impact energy use through an individual's perceived energy behaviour.

Keywords: Energy Use, Time of Use, Techno-economic models, Social Psychology, Linear Mixed Effects Regressions

Management Summary

Relevancy Research

Global energy sector is witnessing rising energy demand in certain regions while stabilisation of demand is achieved in other regions. The Dutch energy sector is moving towards a path of stabilisation particularly in the case of residential energy consumption. However, increased renewable integration and management of peak demands call for greater flexibility in the energy systems. For realising a flexible and robust energy system, closer examination of energy use patterns as well as their determinants is important. This becomes more relevant and interesting to be investigated in the context of renting tenants who have different payment structures than independent households who pay as per they use.

Aim and Research Methods

The aim of the research is to find the socio-psychological and socio-demographic determinants of electricity use in the context of Dutch student houses via a field lab experiment. Additionally, electricity time-of-use is also analysed with aforementioned variables for investigating how an integrative model combining economics and social psychology explains electricity use patterns.

The research methods include surveys among electricity users, collection of periodic electricity readings from meters and other supplementary data which were used for OLS regression analyses and Linear Mixed –Effects Regressions.

Theoretical Framework

Literature shows several studies which look at energy use or pro-environmental behaviour using different theories from social psychology. There are also techno-economic models and engineering analyses. To get a comprehensive picture, an integrative model combining social psychology with traditional energy analysis is employed in the work. The research draws mainly from the *Theory of Planned Behaviour* and *Value Belief Norm Theory of Pro-*

Environmental Behaviour. The relevant themes from the two theories were combined and the integrative framework was developed. The integrative model looks at the impact of socio-psychological variables and demographic variables on electricity use and time-of-use through the perspectives of attitudes, values, behavioural control and so on. The theoretical model and the analyses contribute towards suggestions for energy management in the field labs and similar urban contexts.

Results

Based on the integrative model developed in the theoretical framework, separate analyses were conducted for aggregate electricity use and electricity time of use. The results show that certain socio-psychological variables and socio-demographic variables impact direct energy use. Nonetheless, the analyses with self-reported energy behaviour have more explanatory power. Energy time of use analyses shows the strong relation between time order and energy use, albeit no relation was found for socio-psychological variables. The results point towards possible interventions aimed at energy behaviour of users which can achieve energy savings targets.

Conclusion

The study brings out a novel way of analysing energy time of use using the integrative framework of social psychology and traditional energy models. It sheds light on the importance of considering consumer behaviour and responses to sustainability in formulating energy policies. Robust energy systems and sound energy management can be realised if individual’s behavioural characteristics are also considered while, pricing energy and deploying smart systems or other modes ensuring flexibility.

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Chapter 1: Introduction

Electricity consumption is a significant indicator of growth and development of an economy (Stern, 2003, 2011). Electricity is a crucial input of socio-economic progress and ensures higher human development (Bergasse et al, 2013). Though industrialisation ensured pervasive electrification in developed economies (Mazur, 2011), energy poverty and threats of black-outs are not completely eliminated. Furthermore, rising carbon emissions and deteriorating environmental quality bring energy to the limelight of sustainability debates. In the European Union (EU), the energy sector alone contributes to approximately 55 percent of total greenhouse gas emissions (Eurostat, 2016). As the EU aims to be the pioneer in realising a sustainable, secure and affordable energy system, examining the energy sector and formulating effective management practices are necessary. This includes managing energy use and energy time of use in residential and commercial sectors, in order to reduce emissions and ensure sustainability.

In addition to transport and industrial sectors, the substantial energy consumption by households calls for efforts to better understand energy use, for accomplishing energy and emissions reduction (Fumo & Biswas, 2015). Moreover, to plan an effective energy management program, sound understanding of energy use patterns, determinants of energy use and associated energy behaviours of the households are needed (Haas, 1997; Kavousian et al., 2013). It is in this regard, researchers began examining residential electricity use patterns and load profiles more closely to realise cleaner, reliable, robust and sustainable energy systems. This study is an attempt to contribute to the aforementioned literature by analysing the socio-psychological determinants of energy use and energy time of use, while integrating social psychology to the traditional economic models. The study is novel in its inclusion of social psychology to investigate energy time of use. Within energy, the study focuses on electricity, which is the second most commonly used source of energy in the Dutch energy space (IEA, 2017).

Built environment is the largest consumer of the energy in the Netherlands accounting for 41% while industry and transport follows, with 25% of consumption (Enipedia, 2017). Residential energy use contributes to about 29 percent of total energy consumption in the EU and about 20 percent of total energy consumption in the Netherlands (Deloitte, 2015). Households consume on an average 162 GJ and the carbon emissions associated with it are 10.2 tons (Meirmans, 2013). The per capita electricity consumption in the country is 6821 kWh per the statistics from 2013 (World Bank, 2017). Consequently, energy sector is one of the major carbon emitters in the Netherlands contributing to approximately 150 MtCO2e[1] per year (UNFCCC, 2015). Effective planning and execution of demand-side energy management programs are required to reduce or stabilize residential electricity consumption, to ensure energy security and to avoid adverse impacts on the environment (Beerepoot, & Beerepoot, 2007; Pina et al., 2012). Understanding the factors affecting energy demand can help households to manage electricity expenditure and facilitate improved planning and operational processes for electricity utilities (Fan et al., 2014). This study attempts to elicit a comprehensive scenario of energy behaviour which could pave way for effective policies and energy management.

Energy time-of-use refers to the energy usage with respect to time. Understanding energy time-of-use is vital to energy producers, distributors, policy makers and consumers as it can lead to better energy practices, flexible energy systems, demand side management as well as better price strategies for consumers. Energy time of use has been studied previously within the scope of practice theory and economic models (Galvin & Sunikka-Blank, 2016; Gram-Hanssen, 2014; Torriti, 2014). This research is the first study to examine energy time

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[1] Metric tons of CO_2 equivalent

of use through the perspective of social psychology. Though residential energy use has been studied profoundly, there has not been much attention paid to the energy use among consumers who live in rented homes, student houses and hotels which elicit different patterns of energy consumption. This cohort of consumers is equally relevant for managing national energy demand. They come under the category where energy bills are included within the total rent as a fixed amount. In such cases, there can be little effect of price signals when consumers are ‘shielded to some extent from the costs of energy consumption’ (Murtishaw & Sathaye, 2006, p. 302). As per the Dutch government statistics, there are about 3 million rental homes and about 40% of Dutch population live in rented homes (Majcen et al., 2013). This number is set to increase with the rising population flow into cities and skyrocketing prices of property as seen in several major global cities (Beswick et al., 2016). As more city dwellers move into rented homes with different energy payment structures, closely studying them are essential to arrive at effective urban energy management practices. This study analyses energy use and energy time of use among student tenants residing in field labs in two Dutch cities. It tries to bridge the gap in literature connecting energy use and a system where prices do not signal electricity consumption.

1.1.Energy Consumption in the Netherlands

Final Energy Demand includes all energy supplied to the final consumer for all energy uses. It can be disaggregated to the final end-use per sector like industry, agriculture, households etc. (IEA World Energy Outlook, 2006). The final energy demand has been staying constant for the 2000-2008 period in the Netherlands and then saw a 10 percent decline till 2015 (PBL Netherlands Environmental Assessment Agency, 2016). The same period also witnessed a reduction in emissions from the energy sector by about 10 percent (UNFCCC, 2015). Though the fall could be attributed to economic slump during the period, projections show further fall in total energy demand in the coming years albeit at lower rates.

Besides, it could also be attributed to 'decoupling of energy sector emissions and economic growth' (Obama, 2017) as was found for several developed countries in this decade, including the United States. The decoupling could be attributed to lower energy intensity, renewable integration and improvement in energy efficiency which can in turn reduce total energy demand.

Regarding the energy matrix, electricity is the second most commonly used source of energy in Dutch households, after gas. In the case of Dutch residential electricity consumption, there was an increase of about 6% in 2004-2014 period (Figure 1).

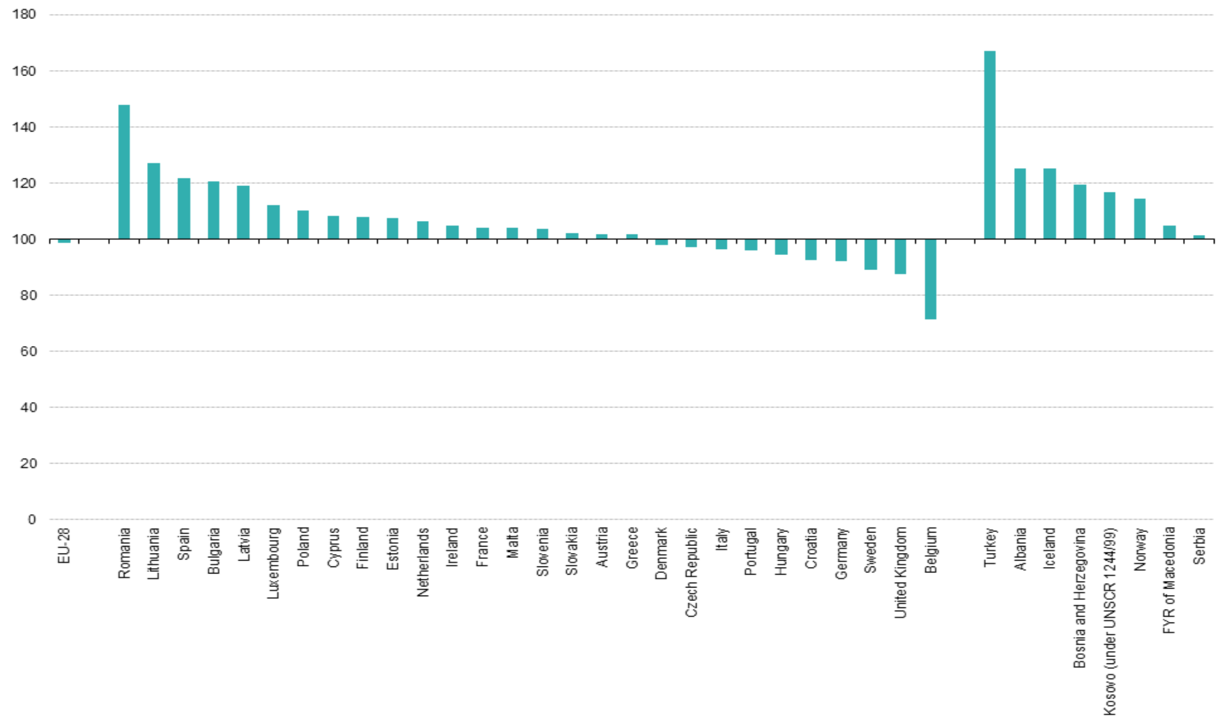


Figure 1: Percentage change in Residential Electricity Consumption in Europe (2004-2014) - Source: Eurostat

Developing policies and plans to achieve the targets of EU-2020 guidelines is still a challenge for the Netherlands (Papachristos, 2015). The EU targets to achieve 20% energy savings by 2020 (against the projected use of energy in 2020) which is roughly equivalent to turning off 400 power stations (Europe 2020 Strategy). The Dutch energy policies aim to realise energy balance, greater renewable penetration and lowered CO_2 emissions in the coming years (Government of the Netherlands, 2016). A closer look at the emissions from energy consumption (Figure 2) for the Netherlands highlights the need for sound energy management practices for achieving the set targets.

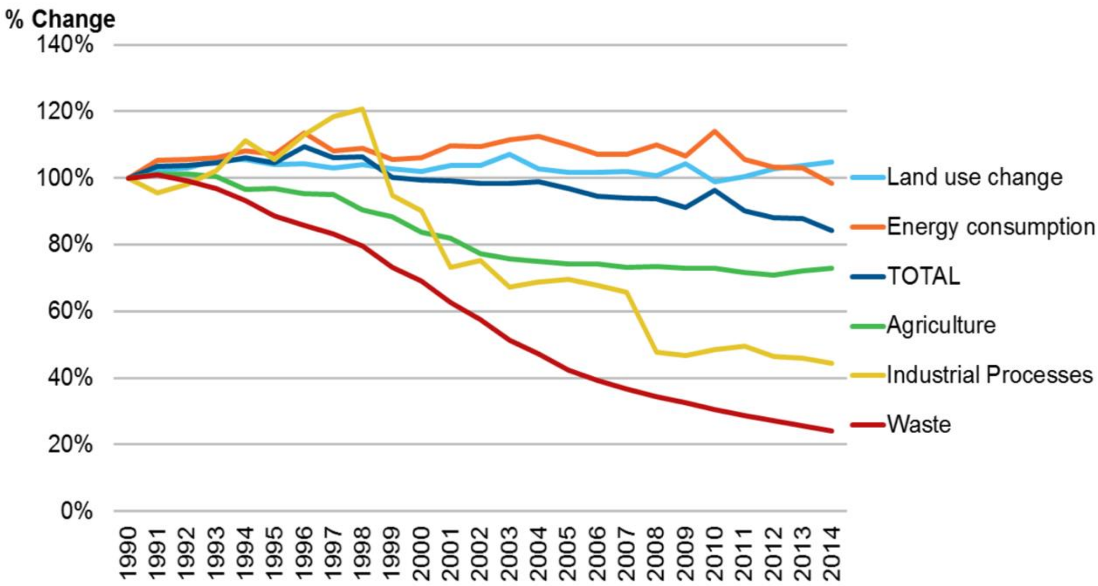


Figure 2: Percentage Change in Emissions from Energy Sector vs Other Sectors- Source-IEEFA and UNFCCC

The energy sector is a major contributor towards emissions, which calls for comprehensive developments in the energy sector combining renewable integration, enhancing demand side management as well as better pricing strategies to cut down emissions.

1.2.Energy Consumption in Rented Homes

Energy consumption in rental housing is an important component towards better energy management in the Netherlands owing to the fact that, about 40% of the Dutch population lives in rented homes (Majcen et al., 2013). There are a few studies which reflect on the differences in energy use and adoption of energy efficiency measures when home-ownership changes. A pioneering study by Stern and Gardner (1981) puts forth that home ownership can influence the type of energy behaviour that is adopted by the residents. Barr et al. (2005) studied about 1265 households in Devon, UK and found that home owners were more energy conscious than the renters/tenants. Vassileva et al. (2012) studied rented apartments in Sweden and proposes that individual behavioural characteristics of consumers must be included in energy use analyses for more insights about differences arising from home ownership. In the case of regulated rental housing in the Netherlands, it was found that there exists a positive rent premium for dwellings with higher energy efficiency labels (Hillrichs, Aydin & Brounen, 2016). This means that landlords can charge higher rents for dwellings with higher energy efficiency, whereas tenants are willing and can pay for better energy efficiency.

Analyses of energy use when consumers are not directly paying for their consumption like in the case of renting tenants, requires further research. This can be extended with the inclusion of technological variables and more behavioural and economic explications pertaining to the said consumer group. This thesis examines the energy use among students living in student houses in the two Dutch cities to derive the determinants of energy use and predict future use cases when users pay a fixed rate upfront for energy use. The research tries to look at the cohort of student tenants who forms a part of the renting community. The thesis chose to focus on student tenants as it is a part of the *Energy Behaviour* project as well as students are often tenants, living in rented apartments in urban areas. The study considers the caveat that students could have different electricity use patterns compared to other residential users, though the aggregate electricity use can be used for generalisations.

1.3.Energy and Social Psychology

Social Psychology investigates the energy behaviour of consumers due to the relevance of social, cognitive and personal forces along with the economic factors in explicating energy consumption. The limitations of rational-economic models call for employing social psychology, since cognitive and social interactions among human beings influence energy consumption and conservation (Yates, 1983). Literature finds evidence for the significance of social attitudes (Karimi & Saffarinia, 2005) and social norms (Nowak, Rychwalska & Szamrej, 2014) in determining energy behaviour. Socio-psychological variables can thus strengthen the traditional economic models and a comprehensive model combining multiple theories could better elicit energy use and energy time of use.

Literature on pro-environmental behaviour and energy conservation draws often from social psychology. Social psychological research connects pro-environmental behaviour to the residential energy use and finds determinants of pro-environmental behaviour in values, norms and attitudes (Wilson & Dowlatabadi, 2007). Black, Stern & Elworth (1985) finds evidence for the relevance of attitudes in reinforcing curtailment behaviours like thermostat settings in households. Kempton, Darly and Stern (1992) shows that energy use behaviour can be distinguished by psychosocial characteristics, including frequency (or repetitiveness), cost, and associated amenity losses. Guerin, Yust & Coopet (2000) reviews about 40 U.S.-based studies of residential energy use and found that variables from social, natural and built environments as well as human behaviour interact to influence the energy consumption.

This thesis is an exploratory research incorporating socio-psychological models into traditional economic models to analyse energy use and energy time of use. Additionally, other constructs and variables are included for improving the explanatory power of the model and to see how energy use is affected.

1.4.Energy Use and Energy Time of Use

Energy Use studies focus generally on the aggregate energy consumption with respect to a given time-period. On the other hand, energy time of use studies delve into the spread of energy use over time. Energy time of use connects energy use to activities and instants of time. It is widely used for energy pricing, as pricing energy based on time of use is an accepted way for managing energy demand. In this thesis, aggregate energy use and energy time of use are studied for the same user group so as to see the similarities and differences among the two with respect to the socio-psychological variables included. Energy Time of Use is gaining more relevance in the literature as understanding the time of use of energy is important to realise effective demand side management which further paves way for flexible energy systems.

With the 14% renewable energy targets set by the Dutch policymakers, ensuring flexibility comes to the forefront for realising the targets (Denholm & Hand, 2011). Evening out peaks in electricity demand, via supply and demand side management is essential for realising flexible electricity systems. The following Figure 3 gives a snapshot of the energy load curves for the Netherlands for 2015. The data is average hourly electricity consumption in the country per day, for four months. The graph shows the higher electricity demand in winter months over summer as well as morning and evening peak demand periods.

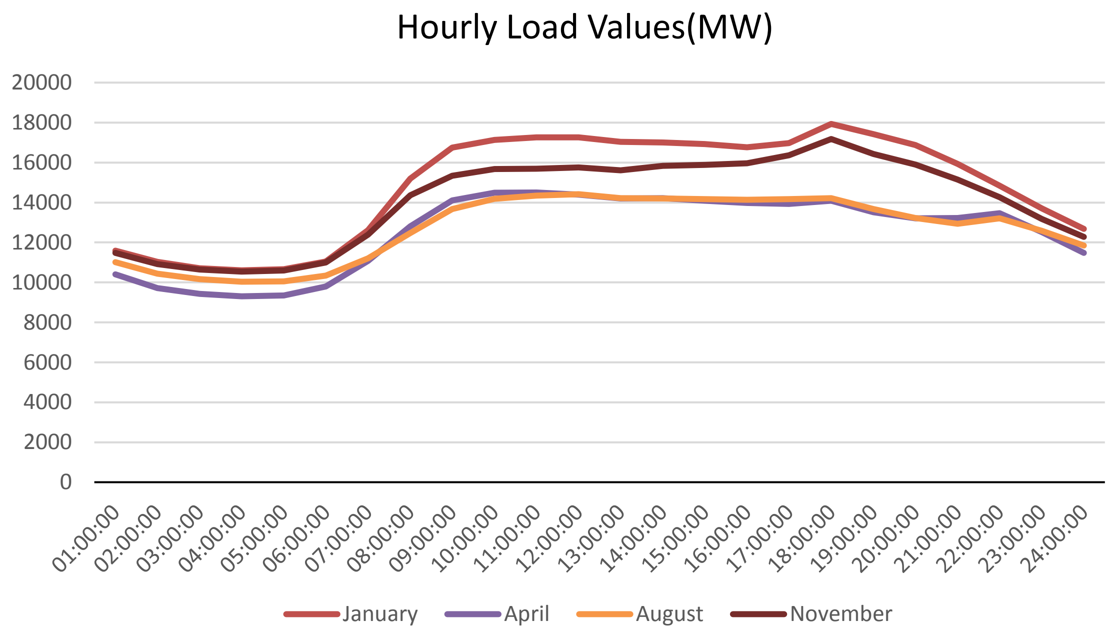


Figure 3: Hourly load values for Netherlands in 2015- Source: ENTSO-E

Electricity grid peak reduction calls for demand and supply side flexibility. Supply side flexibility can be realised through renewable integration, affordable and accessible energy storage as well as innovations in flexible gas or coal power plants (Martinot, 2016). On the demand side, automated demand response, electric vehicles, storage etc. can contribute to flexibility (Clark & Lampe, 2015). These can be supported with management of transmission and distribution networks, flexible and innovative market designs and grid operations (Martinot, 2016). Nevertheless, deploying the right measures requires profound understanding of energy use patterns of the customers and feasible options for flexibility.

1.5.Energy Management

Energy Management entails optimisation and ensuring robust performance of one of the most vital technical systems in the world: the energy system. It refers to the "strategy of adjusting and optimizing energy, using systems and procedures so as to reduce energy requirements per unit of output while holding constant or reducing total costs of producing the output from these systems" (Murali Krishna & Manickam, 2017, pp, 153). It includes optimising energy generation, transmission as well as distribution. In addition, demand side management is gaining more importance and it is becoming a prominent component of energy management. Studying energy use and energy time of use more closely is important for formulating better energy management practices both via demand and supply side measures. Regarding this, the research draws from energy use and energy time of use to arrive at improved energy management solutions for the Dutch student houses.

Energy Management is an important component in this thesis for the project partners. It is of importance to the installation company Becktro to understand the energy use patterns to design and install optimal systems. The Student Hotel which houses the field lab looks forward to energy use insights to implement better energy saving measures, energy efficient infrastructure and smart pricing strategies for the residents. The knowledge partners AMS and Climate-KIC are looking forward to the contribution to energy behaviour research which can realise effective incentives and strategies to motivate prudent energy use among urban residents.

1.6. Objectives of the Thesis

The objectives of the study focus on examining the determinants of energy consumption among consumers who are not paying for the bills directly. The following are the main objectives of the thesis which attempts to study energy use in an experimental setting.

- To elicit the determinants of energy use among the investigated group of students.
- To examine the relationship between aggregate energy use with economic and socio-psychological variables under consideration.
- To analyse the relationship between energy time of use and socio-psychological variables
- To propose effective energy saving measures based on analysis of electricity consumption patterns.

1.7. Research Questions

Main Research Question 1: What are the determinants of energy use among the users who do not pay for their bills?

Sub-Questions:

1. Are there energy use patterns visible which vary based on season, time of use and other variables?
2. How does energy time of use vary with respect to socio-demographic and socio-psychological factors?

Main Research Question 2: What do the energy models predict for the future energy use in the building and what are the possible energy saving options?

Sub-Questions:

1. How is the incorporation of behavioural aspects affecting the energy model? Are there improvements in the explanatory power?
2. What are the differences in energy use and energy time of use pointing towards better energy management practices in the Student Hotel?

1.8.Structure of the thesis

The thesis is structured as chapters which follow from the introduction and background presented in the initial section. The remainder of this thesis is structured as follows.

Chapter 2: This chapter describes the theoretical framework for the study. Various theories used in the study as well as their contributions towards the model are explicated. Chapter 2 also delves into the literature pertaining to energy consumption. It is divided into subsections based on the various approaches adopted. Following this, the integrative model and the research hypotheses are discussed.

Chapter 3: This section describes the field setting of the project.

Chapter 4: The chapter presents the empirical framework which includes the data, model and methodology following from the theories introduced and the theoretical model.

Chapter 5: The results from the analyses are explained in the chapter for both energy use and energy time of use. It is divided into explorative analyses and regression model analyses.

Chapters 6: This chapter presents the discussions from the findings.

Chapter 7: This section concludes the findings, refers to the contribution of this thesis, provides limitations of the study and puts forth ideas for further research.

Chapter 2. Theoretical Framework and Literature Review

An explication of the theoretical framework is conducted in this section followed by a literature review. Different theories from techno-economic modelling of energy use and behavioural approaches are examined and the appropriate ones are chosen to find the determinants of energy use and energy time of use. The section starts with an explication of traditional neo-classical economic models in energy use studies. It is followed by the literature review on behavioural models to explicate the possible deviation of consumer choices from rationality. Further, the illustration of the integrative model and elicitation of the research hypotheses are presented.

2.1. Theoretical Approaches to Energy Consumption

The rational choice models derived from neo-classical economics are among the most widely used theories in literature. Rational choice theory was employed in the energy conservation literature extensively in the 1970s (Martiskainen. 2007). However, the limitation of rational choice theory to account for the influence of social norms, moral behaviours, habits and cognitive limitations have led researchers to integrate or employ other theoretical models (Jackson, 2005; Martiskainen. 2007). Models from behavioural economics and social psychology are used to improve the models in this regard. This study incorporates the theories of Utility Maximisation, the Theory of Planned Behaviour and VBN theory of pro-environmental behaviour to analyse energy use behaviour. The rationale behind choosing these theories and the particular model employed, are elaborated in this section and the following section. As the study aims to integrate behavioural models to techno-economic modelling, a closer look at all the relevant models is required. Inclusion of technological structures could strengthen the behavioural models and inclusion of behavioural aspects can explain the human decisions in energy use which deviate from perfectly rational choices. As the literature delves into multiple aspects within energy use, certain aspects have been chosen for this literature review. Since energy use in rented homes and apartments come closer to residential energy consumption, the literature on residential energy consumption forms the central part in the literature review.

2.1.1. Economic Models

Utility Maximisation or Rational Choice Models

Microeconomic theories of consumer choice are built on the assumptions that individuals make utility maximising choices subject to budget constraints. Consumers opt for choices which offer higher utility compared to the ones offering lower utility. According to the neoclassical economics pioneer Alfred Marshall, “Utility is taken to be correlative to Desire or Want. It has been already argued that desires cannot be measured directly, but only indirectly, by the outward phenomena to which they give rise: and that in those cases with which economics is chiefly concerned the measure is found in the price which a person is willing to pay for the fulfilment or satisfaction of his desire” (Marshall, 1920, p.14). Utility is often considered as a proxy for well-being, personal benefit, or the “betterness” of an outcome (Kahneman, Diener & Schwartz, 1999). Rational choice theory follows a linear model where information has the central role. Information creates knowledge; knowledge shapes attitudes and attitudes lead to certain behaviours (Karatasou Laskari & Santamouris, 2013). Figure 4 gives an overview of factors contributing to energy consumption in an economic model based on rational choices.

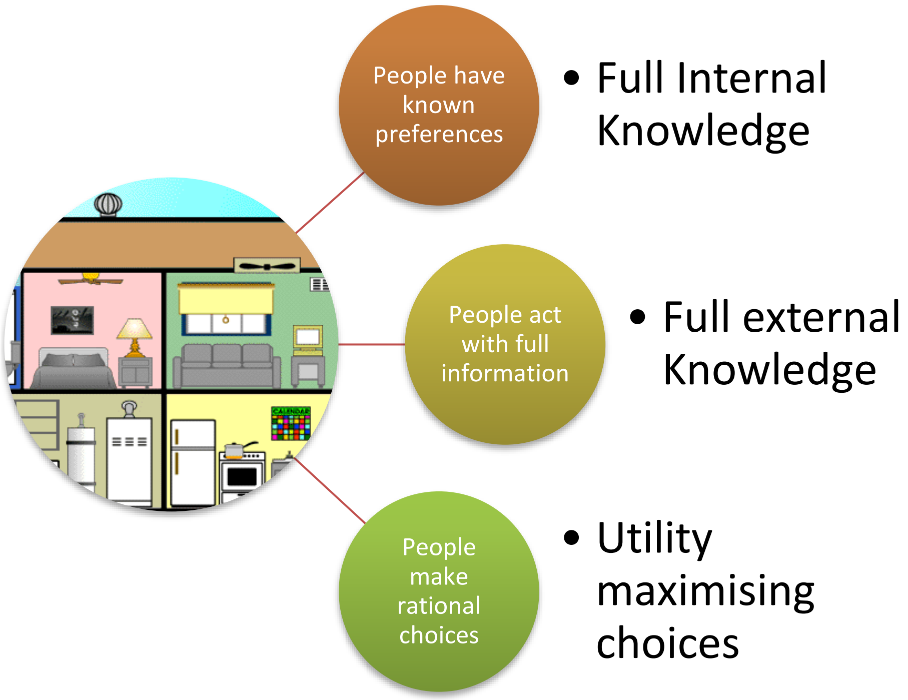


Figure 4: Factors leading to energy behaviour-derived from economic models

Traditional modelling of energy use in economics draws primarily from neoclassical economic system of Utility maximising behaviour of the consumer and rational choice models. The two major strands of research within economic modelling of energy use follows discrete choice models and engineering analyses. In discrete choice models, the choices of individuals among different alternatives are characterized by various attributes (Wilson & Dowlatabadi, 2007). The stated preference models and revealed preference models come under the ambit of this research. Demand for energy is similar to a household's preference for goods or services. These preferences vary across population and empirical studies show how it varies with household size, composition, age and so on (Kriström, 2013). Though economic studies emphasise the role of income and price to determine energy demand, there are mixed results in the literature. There are numerous studies that report contrasting findings, as several price and income elasticities have been reported for energy demand (Jorgensen & Joutz, 2012; Dahl, 1993, 2002; Espey & Espey,2004). This variation in estimates places limitation on arriving at conclusions about the power of income and price as strong determinants of energy use.

In the case of Engineering-economic analyses, aggregate or sectoral level questions are examined within the purview of rational choice. This has also been extended to the residential energy use context mostly studying the response towards technological improvements in energy use. Two pioneering models in this field include the Oak Ridge National Library Hirst Residential Energy Consumption (ORNL) model (Hirst & Carney, 1978) and the Residential End-Use Energy Planning System (REEPS) model (Goett & McFadden, 1982), which were developed using residential energy use data for the United States. Both use simulation samples of representative households to arrive at forecasts on the residential energy use. The ORNL model elicits details on annual energy uses by fuel, end use, and housing type as well as estimates costs associated with each of these factors. Finally, the model develops forecasts for aggregate residential energy use for different fuel usage, end use and equipment. REEPS models also follows similar simulation methods, but incorporates different categories and includes income factors of households more accurately. Major differences between the models include income categories, the period for simulation, consideration of households at the end or beginning of a period and fuel categories. Many models followed these and corrected for the limitations of the earlier models. Long range energy alternatives planning (LEAP) system is widely used in energy studies (Kadian et al, 2007; Thuy & Limmeechokchai, 2015) and Larsen & Nesbakken (2004) developed a model for residential energy use in Norway incorporating household information using the simulation engine ERÅD.

2.1.2. Integrating Behavioural Approaches

Behavioural economics attempts to bring in more psychological understanding into energy use. Neo-classical economic models based on utility theory rests on the rational decision making power of the consumer. This may not always be the case and studies show the cases where customers deviate from rational choices (Camerer & Loewenstein, 2004). Time inconsistency, bounded rationality and reference dependence are cases which challenge the axioms on which utility theory is based (Wilson & Dowlatabadi, 2007). In addition, social and environmental psychology sheds more light on attitudes and energy behaviour. Van Raaij and Verhallen (1983) examined the Dutch household electricity consumption incorporating home characteristics and 'energy-related attitudes'. These attitudes are related to behaviour but do not necessarily cause any particular behaviour. The authors found out that energy-related attitudes have significant impact on residential energy use and feedback, home improvements, such as energy efficient appliances and continuous innovation can induce energy savings.

There are numerous theories that explain behaviour and behaviour change from the perspective of social psychology. These theories have been used in studies looking at energy behaviour as well as factors causing changes in certain behaviours. Among the various theories explaining behaviour, a few have been used commonly in energy literature. From the early theory of Reasoned Action to the Reasonable Person model, there are many models and theories which are used to explain behaviour. The following table gives an overview of these theories.

Table 1

Behavioural Models in Energy Literature

Theory	**Key Authors**	**Main Concept**
Rational Choice Theory	Elstar 1986, Homans 1961	Consumers weigh costs and benefits of actions and choose the one with highest net benefit.
Theory of Reasoned Action	Ajzen and Fishbein, 1980	Attitudes towards the behaviour and social norms lead to

		behavioural intentions
Theory of Planned Behaviour (TPB)	Ajzen, 1991	Attitudes, subjective norms and perceived behavioural control lead to behavioural intentions
Ecological Value Theory	Wiseman and Bogner, 2003	A set of ecological attitudes are incorporated to see the impact on personality and thus environment related choices
Value Belief Norm Theory (VBN Theory)	Stern et al., 1999 Stern, 2000	Values, Beliefs and Norms lead to pro-environmental behaviour
Attitude Behaviour Context Model	Stern and Oskamp, 1987 Stern, 2000	Behaviour is an outcome of personal attitudes and contextual factors
Theory of Interpersonal Behaviour	Triandis, 1979	Intentions and habits influence behaviour which are also affected by facilitating external conditions
Reasonable Person Model	Kaplan, 2000	Concurrence of self-interest as well as altruistic motives and personal control lead to behavioural intentions

As the inclusion of economic variables and socio-demographic variables alone could not provide a holistic understanding of energy behaviour, studies began to include psycho-social factors such as attitudes, beliefs and values. These have been found to better predict pro-environmental behaviours (de Groot & Steg, 2010). The initial analysis was investigating the research questions and the available data. Based on the survey questions as well as the research objectives, several theories on pro-environmental behaviour were considered. The examination started with theory of reasoned action and progressed to theory of planned behaviour (TPB). Following this, other theories like Theory of Interpersonal Behaviour and Ecological value Theory were also considered, though the lack of information on user habits and the necessary ecological attitudes ruled out those theories from the model. The next step was analysis of literature which has combined theories from social psychology to study pro-environmental behaviour. Oom Do Valle et al. (2005) combines the TPB and the model of Altruistic Behaviour to study recycling behaviour in Portugal. The study found that the principles of TPB were fully elicited by the model while there was only a partial demonstration for variables from the model of Altruistic Behaviour. Onwezen et al. (2013) found that attitude, subjective norms and perceived behavioural control along with constructs from the norm activation model can form pro-environmental intentions or behaviours. TPB and VBN Theory have also been combined to study green lodging choices (Han, 2015). The study finds that the unified model has better predictive power than the theories when applied in isolation.

After the initial analysis of various theories, it was decided to employ **Theory of Planned Behaviour** and **Value Belief Norm Theory (VBN) of Pro-environmental behaviour** in this research. Though both theories are based within social-psychology, they adopt different approaches to integrate the motivations behind human behaviour. TPB focuses on deliberations rooted in rational choices (Lopez-Mosquera & Sanchez, 2012) while VBN theory looks at the role of values and moral norms in channelizing behaviour. In the context of energy behaviour, TPB focuses on the respondent's prospects to change energy behaviour based on his or her attitudes and norms in response to certain factors which could provide individual gains. VBN theory looks more closely the values and beliefs held by an individual which lead to energy use behaviours. As investigating energy use based on these theories in isolation may fail to give a comprehensive picture, both have been combined in this study. These theories when combined provide an effective framework to examine the energy use intentions and behaviours. The theories are explained in detail in the next section. To further strengthen the model, socio-demographic aspects are included as well.

Theory of Planned Behaviour

Theory of Planned Behaviour (TPB) lies on the assumption that human behaviours essentially arise from individuals' intentions to perform certain behaviours (Hansson et al., 2012). It attempts to explain human behaviour in terms of a few psychological constructs (Armitage & Connor, 2001). These are *Attitudes, Subjective Norms* and *Perceived Behavioural Control (*Ajzen & Madden, 1986). *Attitude* is the degree of positive or negative acceptance, *Subjective Norm* refers to the human perceptions arising from social pressures whether to perform a behaviour or not, and *Perceived Behavioural Control* is the perceived self-capability to successfully behave in a certain way. The theory looks at behaviours under the volitional control of people and energy use is one of them.

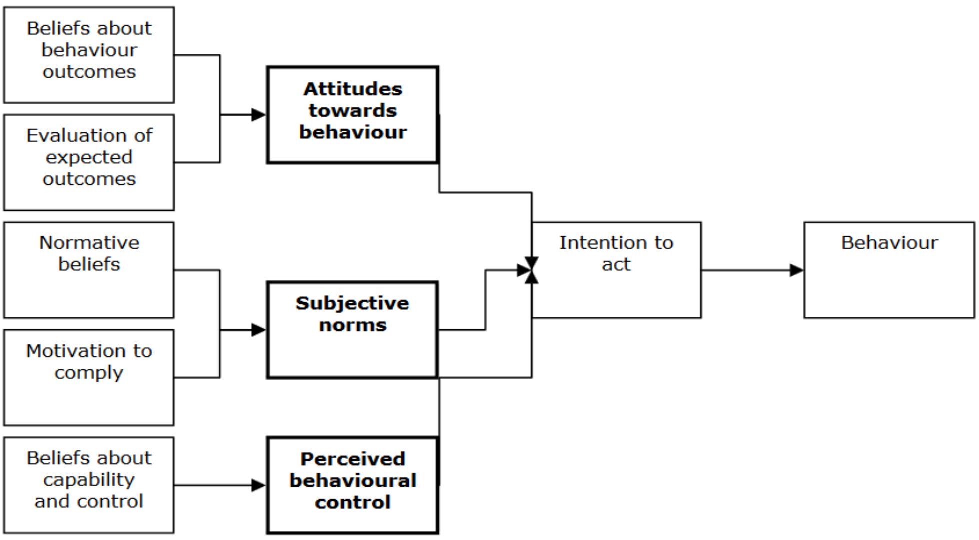


Figure 5: Schematic model of Theory of Planned Behaviour: Adapted from Ajzen & Madden, 1986 and sourced from Morris et al., 2012

Theory of Planned Behaviour has been employed in studies examining pro-environmental behaviour. To explicate how the theory explains a pro-environmental energy use action, a hypothetical case is illustrated. Assume that a consumer is interested in switching to green electricity from fossil fuels based electricity. The decision of purchasing green electricity is distinguished by the components of TPB. Attitudes arise from the positive beliefs the person has towards green electricity. It may be due to contribution to a greener planet, reduction in carbon emissions, helping wind energy cooperatives and so on. The subjective norms can be explained in relation to the social pressures, like to be viewed as someone who promotes sustainability, pressure to switch to green electricity when the entire neighbourhood has adopted green energy sources etc. Perceived behavioural control in the context can be the person's own belief in his agency to make sustainable energy choices, capabilities to switch to green electricity and control over his or her own contribution to global carbon emissions.

Chen (2016) extends the TPB model by including moral obligation, and examines people's intentions to engage in energy savings and carbon reduction behaviours. The study conducted in the context of Taiwan, found out that human attitudes and subjective norm play a significant role in predicting intentions to engage in energy savings and carbon reduction behaviours. Additionally, one's moral obligation to reduce impact of climate change problems was also found to explain the intentions significantly. Paul, Modi and Patel (2016) analyse green product consumption of Indian consumers within the ambit of TPB by extending it with an additional variable of environmental concern. The extended model is found to have greater explanatory power and the findings suggest that TPB mediates the association between environmental concern and the intention to purchase green products.

VBN Theory of Pro-Environmental Behaviour

The Value Belief Norm theory proposed by Stern et al (1999) derives from theoretical works on values and norm-activation processes. The VBN theory of environmentalism postulates a causal chain of five variables: values, the New Ecological Paradigm (NEP), awareness of consequences (AC) beliefs, ascription of responsibility (AR) to self-beliefs, and personal norms (PN) for pro-environmental action. The following figure is an elicitation of the VBN theory.

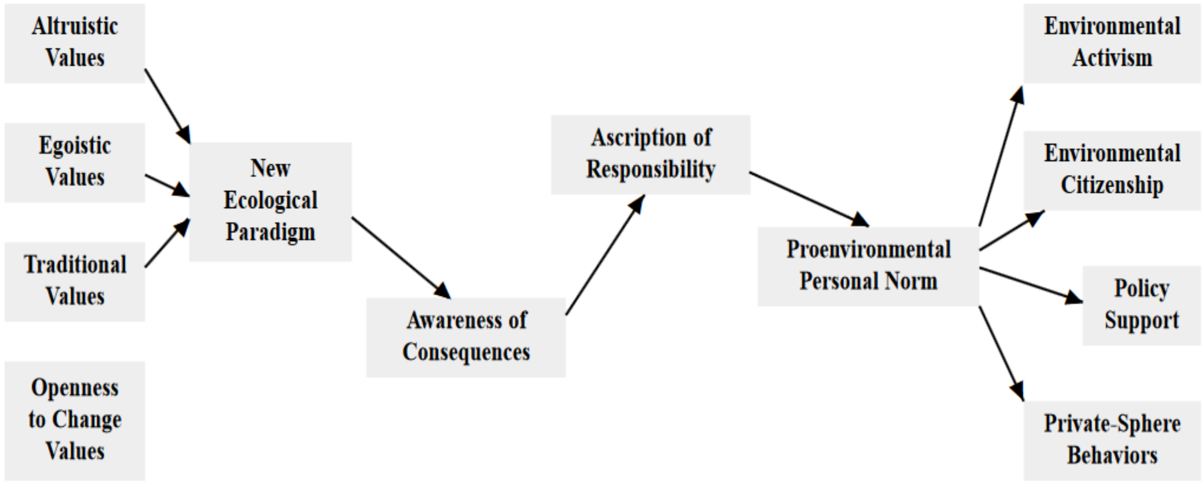


Figure 6: Schematic model of VBN theory for environmentalism showing the causal relationships- Source Stern et al., 1999

Norm-activation theory suggests that that 'pro-environmental actions happen in response to personal moral norms held by individuals about such actions' (Schwartz 1972, 1977). Individual's personal environmental values are the principal drivers of the pro-environmental behaviour and it moves to a set of three core beliefs. The values possessed by an individual impact the New Ecological Paradigm. New ecological paradigm or worldview (NEP) is a view that 'human actions have substantial adverse effects on a fragile biosphere' (Dunlap et al, 1992). The causal chain moves from stable elements of personality and beliefs to more focused beliefs on human-environment interaction. Then it proceeds to threats to valued objects and responsibility for an action. It finally activates a sense of moral obligation and creates a predisposition to act in support of pro-environmental deeds.

An illustration of the theory using an example explains VBN theory in the context of energy use. Imagine the situation of office employees being asked to reduce electricity use in an office building. A pro-environmental behaviour in this case would entail switching off lights when not in use, shutting down and turning off computers after office hours, not leaving appliances unnecessarily on standby mode and so on. The key drivers of behaviour are personal and organizational environmental values. This might include concern for the planet, saving energy bills for the employer, organizational values like resource optimization etc. Beliefs entail Performance Management, response to consequences like global warming, commitment towards the company arising from adverse consequences which may occur to the company if electricity is squandered by employees and so on. The norms in this context will be the sense of including pro-environmental behaviour in personal and professional roles. These will lead to the pro-environmental behaviour of more energy conscious actions in the organisation.

Choi, Jang and Kandampully (2015) apply an extended version of VBN theory to study the decision of consumers about green hotels. The study includes subjective norms and green trust into the traditional VBN theory to analyse the decision-making process of consumers when they decide to visit a green hotel. The study uses structural equation modelling found that all except subjective norms explained consumers' intention to visit a green hotel. Chen (2015) analyses VBN theory to study pro-environmental behaviour in Taiwan and confirms the existence of the causal sequence of the variables. The relations between psycho-social variables and pro-environmental behaviour have been verified repeatedly in the literature (Hines et al, 1986, Bramberg & Möser, 2007). Bramberg and Moser (2007) conducted a meta-analytic structural equation modelling and found that in addition to attitude and behavioural control, there exists a third predictor of pro-environmental behavioural intention which is personal moral norm. The study also indicated that problem awareness could have an indirect impact on an individual's intentions. There are numerous studies which have considered the relation among energy use, energy conservation and socio-demographic and psychological variables (Abrahamse & Steg, 2009, 2011; Barr, Gilg, & Ford, 2005; Ek & Soderholm, 2010; Han, Nieuwenhijsen, Vries, Blokhuis, & Schaefer, 2013; Martinsson, Lundqvist, & Sundstrom, 2011; Nair, Gustavsson, & Mahapatra, 2010; Vassileva, Wallin, & Dahlquist, 2012).

2.2. Studies based on Socio-demographic factors

2.2.1. Energy Consumption based on Home-Ownership

Though residential energy use has been studied many a times, there have not been many studies on the energy use in rented apartments. There are studies which show the existence of significant differences in the way homeowners and tenants use energy (Levinson & Niemann, 2004; Sjogren, 2007). Levinson and Niemann (2004) investigates American households and finds that tenants in utility-included apartments use more energy, and the additional utility costs that they pay, are not significantly large. The paper also finds a second inefficiency where landlords have fewer incentives to adopt energy efficient measures if the utility costs are not included in the rents. Vassileva et al. (2012) studies the relation between energy consumption and behavioural characteristics in the context of rented apartments in Sweden. The study found household income to be a major factor determining energy use among tenants. The paper also highlights the need to include more individualised social understanding of energy use and the households should be treated individually. Homeowners tend to make larger capital investments in energy conservation measures (e.g., household improvements to increase energy efficiency, purchase of new technology and energy-saving devices) than those living in rental housing (Frederiks et al., 2015). There could be differences in energy use behaviour emerging from split-incentives and intentions driven by certain attitudes.

2.3. Studies on Energy Time-of-Use

Studies which examine the timing of energy use have been on a rise in the recent years. There are studies which use Time of Use Data, employing engineering analyses and econometric models. These have been explained in this section.

Time of use is an important determinant of energy consumption in addition to occupant characteristics, weather, lifestyle of occupants and appliance ownership and usage

(Torriti, 2014). There is also reference to the importance of occupancy in determining energy use profiles (Stokes et al., 2004). Presence of members at the residence could shed light on the use of appliances and thus their energy consumption. If occupancy and usage patterns are known, it can lead to energy savings via intelligent control (Erickson et al., 2009). Time use surveys are an integral part of this method where they are correlated with energy readings to find patterns and relations. These studies include deterministic models related to weather, stochastic prediction of appliance use and comparison of timing of human activities with electricity demand (Torriti, 2014). Wood and Newborough (2003) conducted a pioneering study which investigated the time of use of electricity in UK households. The study divides energy use into three categories- predictable, moderately predictable and unpredictable. Predictable consumption occurs when household members are asleep or house is unoccupied and moderately predictable is related to habitual use patterns. Habitual use patterns include watching TV at a regular time for a particular TV show or switching off lights every day when leaving for work. The unpredictable consumption forms a large proportion of the consumption and tends to be irregular depending on the user's discretion. This arises when the consumer wants to cook or wash the clothes whenever he or she feels like doing it. The study highlights the potential of information-feedback to reduce the rates of energy consumption. It emphasizes the need to 'identify and implement means for influencing end users before/during/after they use appliances' (Wood & Newborough, 2003, p. 836) in the residential sector.

Studies belonging to electrical engineering use either actual data or simulated end-of-use data and construct electricity consumption profiles for households. Energy efficiency, availability of appliances and appliance ratings are often included in such studies. McLoughlin et al. (2012) studied 4200 Irish households using a multiple linear regression model and found that Time-of-Use for maximum electricity demand was strongly influenced by household age, occupation and occupant characteristics. The authors found that adults and children were using more electricity later in the evening compared to single occupants. The social class was found to have an impact as Higher Professionals were consuming more electricity than lower or middles class consumers. Time of use and energy consumption was examined in the context of Sweden to see availability of leisure time and reduced carbon emissions (Nässén & Larsson, 2015). The results show that a decrease in working time by 1 percent may reduce energy consumption by 0.7 percent and greenhouse gas emissions by about 0.8 percent. Time dependence of energy-related practices has been dealt with in Torriti (2017a). The study finds time dependence for certain activities like washing with high degree of time-dependence and use of computers with the least. There are also certain activities with higher seasonal dependence than others. The following figure from Torriti (2017a) elicits the time dependence of activities.

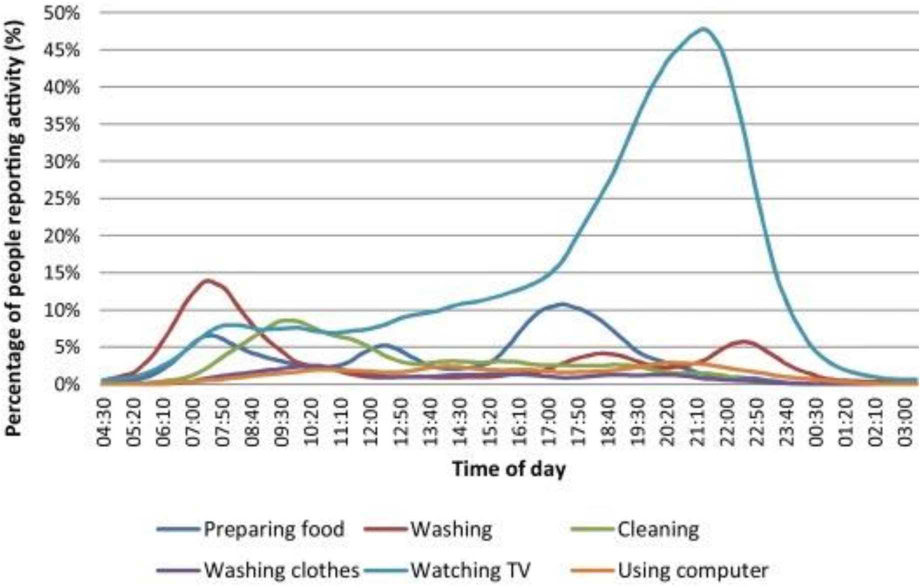


Figure 7: Time dependence of activities (Torriti, 2017a)

Within energy econometrics, aggregate macroeconomic data is used to find correlations between energy demand profiles and socio-economic variables. These studies use household production theory (Filippini & Hunt, 2012), survey data on appliances (O'Doherty et al., 2008) and energy billings and employ time series analyses (Hondroyiannis, 2004; Dilaver & Hunt, 2011). Studies also use physical non-end use data like temperature and day light and have found relationship between energy use and external temperature (Parker, 2003; Hart & De Dear, 2004). Jalas and Juntunen (2015) studied the relation between time of use, activities and energy demand in Finnish households using a household economics approach. The study used expenditure data and time of use data, and found that increases in household energy consumption are due to increasing consumption intensity and housing related consumption.

2.4. The Integrative Theoretical Model and Research Hypotheses

There are multiple factors which affect the electricity use patterns of consumers. The major factors affecting the customer's load profile are (1) customer electricity use behaviour and residence characteristics, (2) time of day, week or year and (3) local climate factors such as temperature, humidity or solar radiation (Räsänen et al, 2008). Huebner et al. (2016) incorporate different types of variables to explain energy consumption in residential buildings in the UK. The authors include building factors, socio-demographic variables, appliance ownership and use, self-reported behaviours and attitudes, and find that appliance use and ownership explains the most of energy consumption. Fragniere et al. (2016) examines energy use coupling behavioural aspects with techno-economic modelling. The study which looks at the deployment of LED bulbs in a hypothetical setting puts forth the significance of behavioural variables and not perfectly rational choices in explaining energy behaviour. The mixed results from literature and plethora of models, has highlighted the importance to incorporate factors from multiple theories and to employ multiple ways to gather data.

Based on the literature review and the analysis of theories, an integrative model has been developed for the thesis. The model derives from the two major theories namely the Theory of Planned Behaviour and VBN Theory of Pro-Environmental Behaviour. Variables are constructed based on the psychological constructs from the theories. In addition, there are socio-demographic variables, other socio-psychological variables and weather related variables specifically for Energy Time of Use Analysis. The theoretical model is presented in the schematic diagram (Figure 8) which follows.

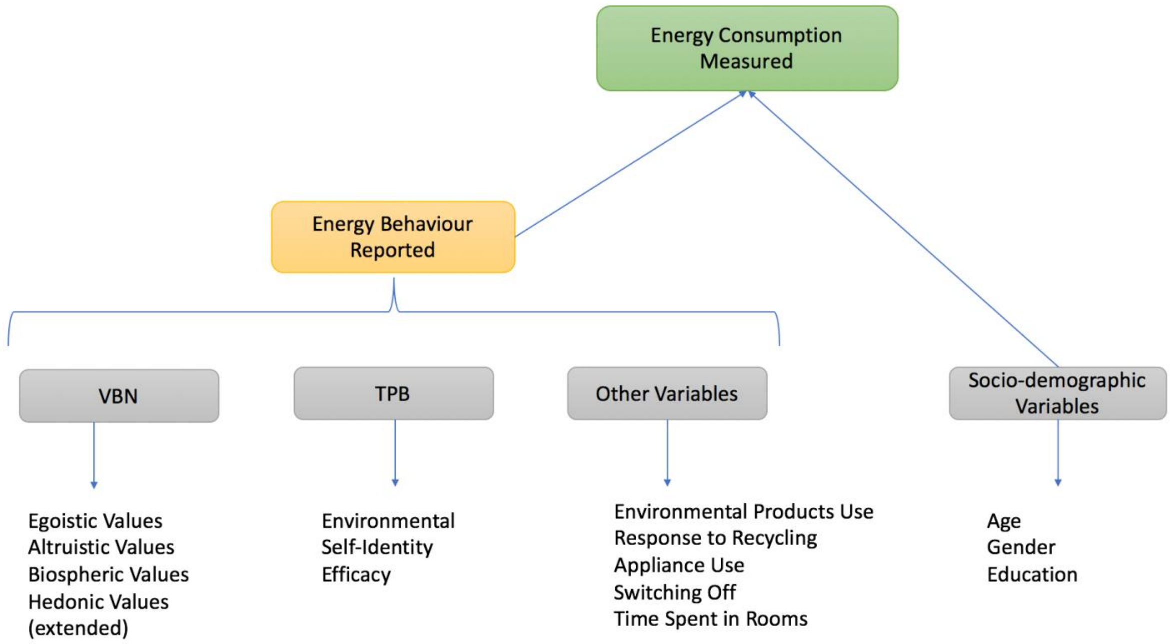


Figure 8: Schematic diagram of the theoretical framework

2.4.1. Variables and Drivers of Energy Use

Literature sheds light on the relevance of building variables in explaining significant proportion of energy consumption (Guerra Santin et al, 2009; Huebner et al., 2015). However, as the thesis looks at the Student Hotel as a field lab, the building characteristics do not vary considerably. The building factors are accounted for indirectly and literature shows that occupant characteristics could explain the variation in energy use among consumers in similar buildings (Gill et al., 2010; Gram-Hanssen, 2010).

Many studies have included socio-demographic variables in their energy models and found different results. Huebner et al. (2016) finds that larger household size and larger household income leads to greater energy consumption. But the effect of income disappeared once building characteristics and appliance data were controlled for. For age as a socio-demographic factor, literature has ambiguous results. There are studies which find non-liner effect of age (Kavousian, Rajagopal, & Fischer, 2013), no effect (Bedir, Hasselaar & Itard, 2013) and higher use with older head of the household (Tiwari, 2000). Literature looking at energy consumption and psychological variables mostly finds evidence for impact of attitudes and perceived behavioural control on energy savings, but no impact on energy consumption (Abrahamse &Steg, 2009). Brandon and Lewis (1999) also finds no evidence for impact of environmental attitudes on historic energy consumption, albeit Huebner et al. (2013) finds that self-reported habit strength is significantly related to self-reported energy consumption behaviour and thus to actual energy consumption.

Data for the analysis of energy behaviour was elicited through surveys. The survey had questions on Likert scale from 1-7 and in the case of socio-psychological variables, the sub-questions were combined to receive the responses for certain constructs. The thesis includes socio-demographic variables namely Age, Gender, Education and Nationality of the energy consumer. There is also question on the city, in which the respondent resides. The socio-psychological variables are based on various constructs. The following figure gives an overview of the variables included in the study.

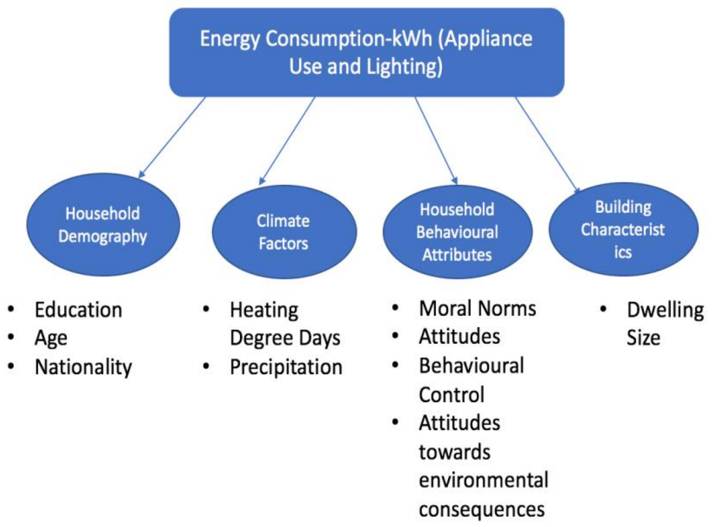


Figure 9: Variables in the model

The weather variables were not included in the final model due to unavailability per station for the times (throughout the day for the five chosen time periods) at which energy use were being studied.

Theory of Planned Behaviour and the VBN theory form the backbones of the adopted theoretical framework. Three values from the VBN theory have been included in the models namely the Altruistic values, Egoistic values and Biospheric values. In addition to these, Hedonic values also have been included in the survey. Hedonic values can be explained as the degree of happiness or sadness felt by an individual regarding a decision or choice (Bagai, 1999). It aligns with the other three values and collectively brings out the personal values possessed by an individual which could affect environment related behaviour. The personal values were formulated from the value scale developed by Schwartz (Schwartz, 1992) as "*guiding principles in their life*" on a 9-point perceived importance scale (-1 = *opposed to my principles*, 0 = *not important*, 7 = *extremely important*). The survey consisted of four items for hedonic values one of which being 'Gratification for oneself: doing pleasant things', four constituents for egoistic values which include 'Ambitious: hard-working, aspiring', four items for altruistic values where one is 'Helpful: working for the welfare of others' and four items for Biospheric values with one item being 'Preventing pollution: protecting natural resources'.

There are also variables eliciting pro-environmental behaviour, environmental self-identity, Self-Efficacy and Perceived Sustainability. There were several questions to elicit the pro-environmental behaviour of students in the Student Hotel. These include questions on the Appliance Use behaviour, Switching off, recycling of waste and purchase of environmentally friendly products. Self-efficacy assessed the perceived efficacy in terms of reducing energy consumption and the survey had three items on it. It indirectly shows the behavioural control over energy use. Environmental self-identity contributes towards the environmental identity as perceived by an individual himself or herself. It was assessed with the scale developed by van der Werff et al. (van der Werff, Steg, & Keizer, 2013). The construct had three items of which one is 'I see myself as an environmentally friendly person'. More details on the variables are explained in the Data, Model and Methodology sections within the Empirical Framework.

2.4.2. Research Hypotheses

On the basis of the integrative model and the chosen variables, the following are the hypotheses arrived at. Energy use in the following context refers to the aggregate electricity values measured by the meters for 10 months. In the cases mentioned below a positive influence denotes a rise in energy use or electricity use pattern with more pronounced peaks. A negative influence denotes lower energy use and evened out electricity peak values. Some of the associations are reversed in the case of self-reported energy behaviour.

H1: City is associated with energy use; could be positive or negative

H2: Age is positively associated with energy use

H3: Gender is associated with energy use; it could be positive or negative

H4: Education is negatively associated with energy use

H5: Being a EU national is associated with lower energy use

H6: Biospheric values are negatively associated with energy use

H7: Altruistic values are negatively associated with energy use

H8: Egoistic values are positively associated with energy use

H9: Environmental Self-identity is negatively associated with energy use

H10: Efficacy is negatively associated with energy use

H11: Recycling behaviour is negatively associated with energy use

H12: Purchase of environmental products is negatively associated with energy use

H13: Switching off appliances is associated negatively with energy use

H14: Prudent Appliance Use behaviour is negatively associated with energy use

The same hypotheses are also tested for self-reported energy behaviour elicited though the survey questions. For Energy time of use, there are two additional hypotheses.

H15: Time order is associated with energy use, which could be positive or negative

H16: Time interaction variables are associated with energy use, which could be positive or negative

Chapter 3. Study Design

The thesis falls within the scope of the *Energy Behaviour* Project which is conducted in five major cities in the Netherlands. For this thesis, two cities have been chosen for the ease of data collection and availability of survey information. The project consists of obtaining electricity and water use data from the inhabitants of student houses and hotel guests living in The Student Hotel, which is a partner in the study. The Student Hotels are buildings which are rented to students during the academic seasons and to hotel guests during vacation periods. There are rooms of sizes from 10 sq. m to 14 sq. m. The students share kitchen with other tenants in the same corridor and the architecture varies among different cities. The following is the layout for student hotel in Rotterdam where the rooms marked in blue box are included in the research.

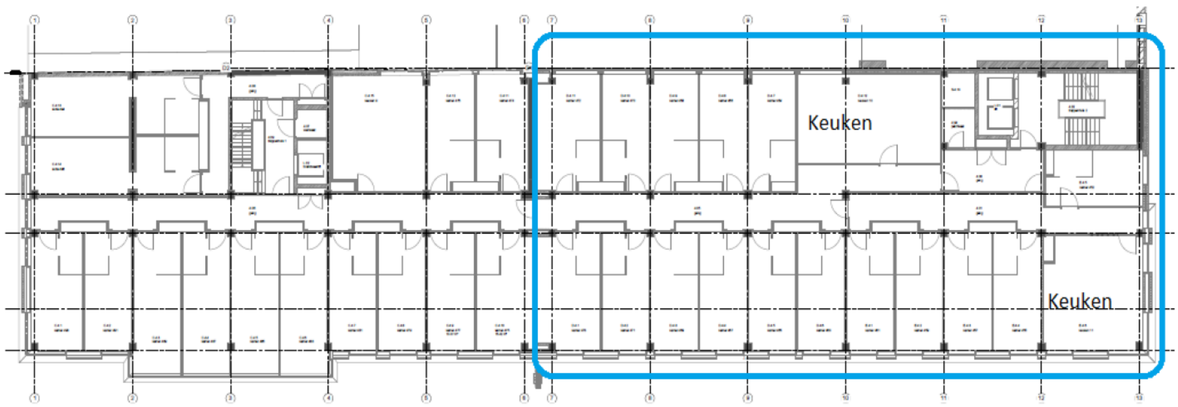


Figure 10: Layout of rooms in student hotel in Rotterdam

For the thesis, a total of 105 rooms from Rotterdam and The Hague are included. These rooms are occupied by students belonging to different universities in and around the cities. These students have completed the survey on behavioural aspects impacting energy use. The electricity data is received from the electricity meters installed at the student hotels. The data is accessed remotely through software called Plugwise, for the required periods. There is data available on the occupancy in rooms from the insertion of cards for the room, on the thermostat setting and the amount of hot water flowing through the water pipes. The following figure shows the electricity meter installation for the project in a student hotel followed by the interface of the Plugwise application for data retrieval and visualisation.

Figure 11: Electricity meter installation at Student hotel

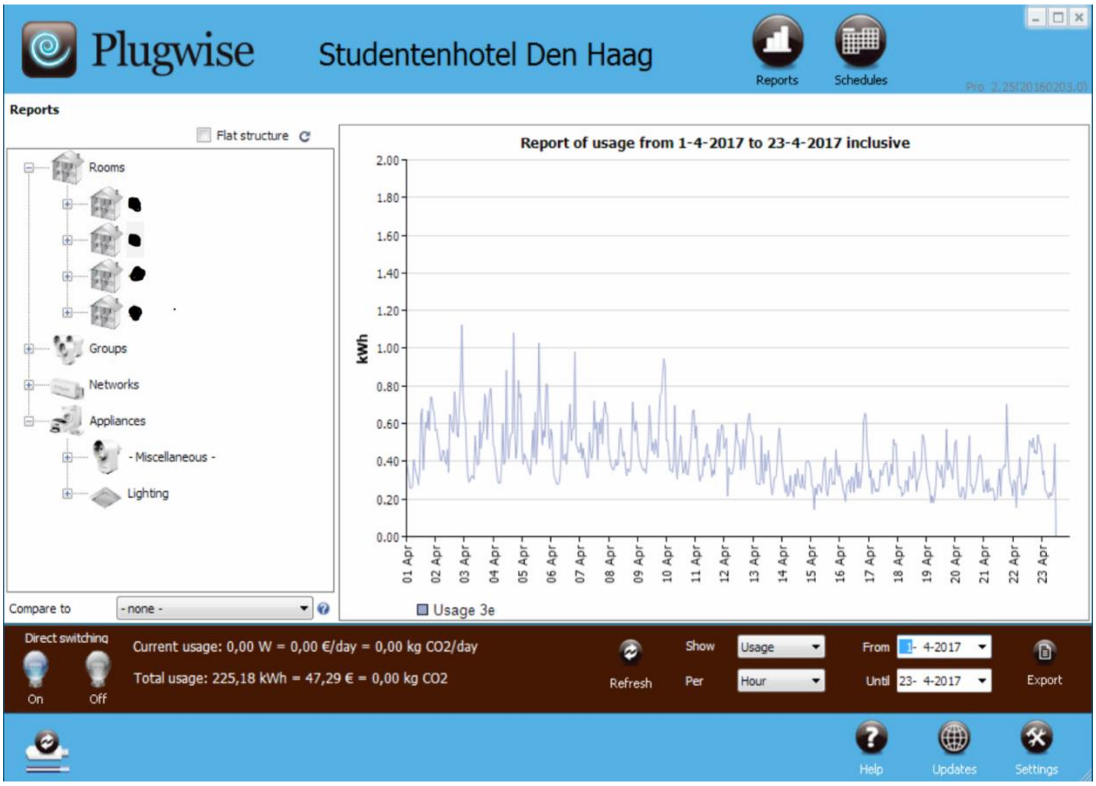


Figure 12: Interface of the Plugwise Application showing electricity use for a room for 12 days per hour

Figure 13: Card reader in the rooms

The measurement of occupancy is available from the card readers for the rooms. In addition to the readings from the meters and readers, the project gathers information from the surveys including demographic and socio-psychological variables to capture possible energy savings which forms the core focus of the Energy Behaviour Project. These surveys include information on personal attributes as well as other variables.

Chapter 4. Empirical Framework

Empirical studies analysing energy use in built environment, can be divided into two categories based on the hierarchical position of data inputs (Swan & Ugursal; Fumo, 2014). These are called the top-down and bottom-up approaches. In a top-down approach, the total energy consumption of the residential sector is considered. On the other hand, bottom-up studies, use data from small samples with similar characteristics and whose results can be extrapolated to arrive at findings about a segment of the residential sector (Fumo, 2014). In this thesis, a bottom-up approach is adopted where the energy consumption of student tenants in rented apartments is examined. Furthermore, statistical methods are employed for analyses and prediction of the determinants of energy consumption. Statistical methods do not require building characteristics, but incorporates measured data. These include Regressions or Conditional Demand Analysis, Artificial Neural Network, Genetic Algorithm, and Support Vector Machine (Foucquier, 2013). The study employs Multiple Linear Regressions and Linear Mixed Effects (LME) Model for Electricity Consumption and Electricity Time of Use respectively, as the dependent variables.

The empirical analysis is divided into two sections. The first section is explorative analyses conducted for investigating new insights from the available data within the integrative framework. There are separate analyses for Energy Use and Energy Time of Use. The subsequent section delves into model testing. In this segment, regression analyses are conducted with the aggregate electricity use (kWh) and the self-reported energy behaviour as the dependent variables. It explains the analysis undertaken for finding the socio-demographic and socio-psychological determinants of energy use. The second part of the model testing focuses on the energy time of use and the role of socio-psychological variables in eliciting energy time of use. Due to lack of time-varying explanatory variables, this analysis is limited to a longitudinal analysis of electricity data with respect to the explanatory variables. A pictorial representation of the empirical analysis is depicted below.

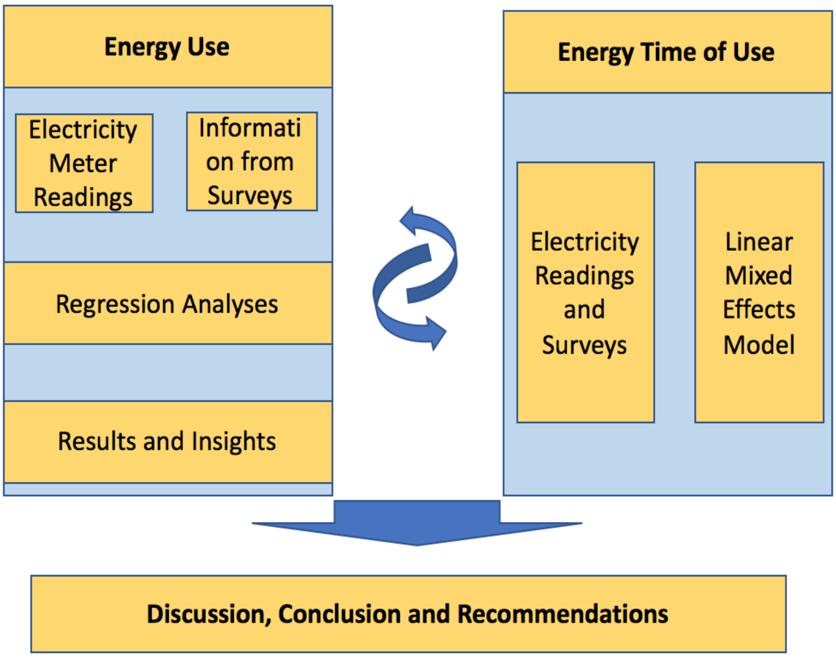


Figure 14: Diagram depicting the empirical framework

4.1. Data

The data is collected from student rooms with 15 minutes' precision using advanced electricity reading meters. This electricity data is supported with information elicited through surveys among the student hotel residents[2]. The questions relevant to the theoretical framework of the thesis have been chosen from the survey in this analysis. For the analysis, 105 residents have been considered based on availability of survey data and after removal of outliers. The period used for measurement of electricity data is from September 2015 to June 2016. Regression analyses are used to find the determinants predicting energy use and 10 month aggregates of energy use are incorporated in these analyses. The variables included in the analysis and their explanations are provided below.

[2] The survey is available upon request

Table 2

Variables included in the model

Variable	**Explanation**
Electricity Use	Aggregate electricity use
Hedonic Values	Values processing pleasure and dis-pleasure
Egoistic Values	Self-Enhancement values
Altruistic Values	Self-transcendent or pro-social values
Biospheric Values	Eco-centric values
Environmental Identity	Importance of environment in self-identity
Efficacy	Perceived efficacy in energy use
Environmental Products	Users' acceptance or reluctance towards use of environmental products
Energy Behaviour	Use of energy as reported by consumers
Appliance Use	Users' modes of using appliances
Switching Off	Users' response to switching of electrical appliances, lights after use.
Time Spent in Rooms	Average number of hours spent in room per week
Age	Age of the respondent
Gender	Gender of the respondent
Education	Education of the respondent divided into two categories
Nationality	Nationality as EU citizen or non-EU citizen
City	City where the respondent resides: Rotterdam or The Hague

There are variables which represent the various constituents of the integrative theoretical model. In the case of socio-psychological constructs, multiple questions in the survey have been combined to arrive at single values per construct.

Table 3

Sample Characteristics

Characteristic	**Number**	**Percentage**
	Gender	
Male	45	42.8
Female	60	57.2
	Education	
Bachelor Student	79	75.2
Master Student	23	21.9
PhD	1	0.95
Other	2	1.9
	Nationality	
EU-citizen	60	57.2
Non-EU Citizen	45	42.8
	Age	
Below 20	55	52.4
20 and above	50	47.6
	Time Spent in Rooms (Weekly Averages)	
Less than 45 hours/week	21	20
45 hrs/week-90 hrs/week	65	61.9
More than 90 hrs/week	19	18.1

4.2. Model & Methodology

In this study, statistical models are adopted to elicit the determinants of energy use. Regression analysis forms the main framework for the analysis. Two sets of regressions are employed for eliciting the impact of socio-psychological variables on measured energy consumption as well as on self-reported energy behaviour. In addition to this, the linear mixed effects model (LME) is used to elicit the impact of demographic and socio-psychological variables in energy time of use. The models are explained in the subsequent sections.

4.2.1. Model

Aggregate Energy Use

In view of the electricity data and information from the surveys, the econometric model for analysis is developed based on the theoretical framework. The measured electricity readings as well as the question in the survey which elicits energy behaviour are included in the model. Statistical models are widely used in energy consumption literature (Kialashaki & Reisel, 2013). Among the statistical models, regressions are common in studies examining energy consumption through bottom-up models. Due to the small sample and the nature of the variables, linear regression models are chosen for finding the determinants of energy use. A multiple linear regression approach is adopted to best suit the data and the objectives of the study. Ordinary Least Square regression is employed as it is the 'best linear unbiased estimator' and suits for the model in the thesis research. The variables for the regressions are chosen based on the drivers of energy consumption by Guerin, Yust and Coopet (2000) as well as Xu and Ang (2014) and the integrative theoretical model developed for this thesis. The regression models are as follows:

Energy Use (measured)=α_0 + α_1 City + α_2 Age + α_3 Gender + α_4 Education + α_5 Nationality + α_6 Hedonic Values +α_7 Altruistic Values + α_8 Egoistic Values + α_9 Biospheric Values + α_{10} Environmental Identity + α_{11} Environmental Product Use + α_{12} Recycling + α_{13} Appliance Use + α_{14} Switching off Behaviour + α_{15} Efficacy……………………...…… (1)

Energy Behaviour (self-reported) =β_0 + β_1 City + β_2 Age + β_3 Gender + β_4 Education + β_5 Nationality + β_6 Hedonic Values +β_7 Altruistic Values + β_8 Egoistic Values + β_9 Biospheric Values + β_{10} Environmental Identity + β_{11} Environmental Product Use + β_{12} Recycling + β_{13} Appliance Use + β_{14} Switching off Behaviour + β_{15} Efficacy……………………………. (2)

Energy Time of Use

This model incorporates demographic and socio-psychological variables. The time factor which is separated into five different 2 hour slots, is incorporated to gauge the impact of time on electricity use. As the emphasis is on finding the difference in electricity use over time for different consumers, a Linear Mixed Effects model has been employed for the analysis. A Linear Mixed Effects (LME) model is an extension of a linear model. It is different from linear regression models, as LME has both fixed effects and random effect components. The covariates can be scale predictors, variables showing repeated effects or interaction among factors. In the thesis, LME has been chosen because of the capability to account for the repeated effects arising from the time factor in the analyses. In the case of the longitudinal data like electricity use, mixed effects regressions facilitate the assessment of individual change across time. Other variables from social psychology are also added in the model to study their impacts on electricity use. A major advantage of LME is that it allows to “effectively partition the overall variation of the dependent variable into components corresponding to different levels of data hierarchy” (Galecki & Burzykowski, 2013, p. 13).

As linear mixed effects model is more flexible and makes generalizations possible for non-normal data, it has been adopted in this study.

The model that is adopted is:

$Y_i = X_i \beta + Z_i \upsilon_i + \epsilon_i$

i=1…….N individuals

Y_i= response factor for individual i

X_i= design matrix for fixed effects

Z_i=design matrix for the random effects

$\epsilon_{i=}$ Error factor

The time factor is included as fixed effect along with the demographic and socio-psychological variables. The time factor in this model is the time order: this is the order of time per day divided into two hours' periods. Thus, it will be included as 1- 00.00 -2 am, 2- 6.00-8.00 am, 3-10.00- 12.00, 4-17.00-19.00 and 5- 20.00-22.00. The participants are taken to have random effects as based on their choice from the population. The equation for the model is:

Energy Use (measured)=γ_0 + γ_1 Time Order+ γ_2 Age + γ_3 Gender + γ_4 Education +γ_5 Nationality + γ_6 Hedonic Values +γ_7 Altruistic Values + γ_8 Egoistic Values + γ_9 Biospheric Values + γ_{10} Environmental Identity + γ_{11} Environmental Product Use + γ_{12} Recycling + γ_{13} Appliance Use + γ_{14} Switching off Behaviour + γ_{15} Efficacy + γ_{16} City…………….…… (3)

Time interaction effects were included in the robustness checks and different combinations of the variables were used.

4.2.2. Methodology

Aggregate Energy Use

In the first stage, basic examination of the data was conducted. This included considering the descriptive statistics of the data, correlation tables and various patterns within the data. Some interesting insights among these were tested and are explained in the explorative analysis part. The data was cleaned and outliers were removed. 105 observations were chosen after this and basic statistical tests were conducted on those. The first stage was running the OLS regressions for energy use. Linear Ordinary Least Squares regressions were performed with measured electricity values as the dependent variable. The second step was regressions with self-reported energy behaviour as the dependent variable. The independent variables include demographic variables and socio-psychological variables. Different variables are included in the robustness checks and five models are presented for each of the regressions. In view of multicollinearity, VIF (Variance Inflation Factor) were measured and were found to be less than 4 and the respective regressions were accepted. The regressions with direct energy use were tested with energy behaviour as an additional variable, though these regressions suffered from multicollinearity. The energy behaviour variable was thus dropped from subsequent analyses for direct energy use as dependent variable. Tests were conducted also for heteroscedasticity and the data was found to be of constant variance.

Energy Time-of-Use

In addition to the energy use, a closer investigation of energy time of use is conducted in the thesis. The following figure shows the electricity use for lighting and appliances as an aggregate for Rotterdam and The Hague. The weeks from December 20 to January 5 has been avoided in the analysis as most students were away from the rooms due to holidays. The trough in the electricity use curve during the said period can be seen in the following figure.

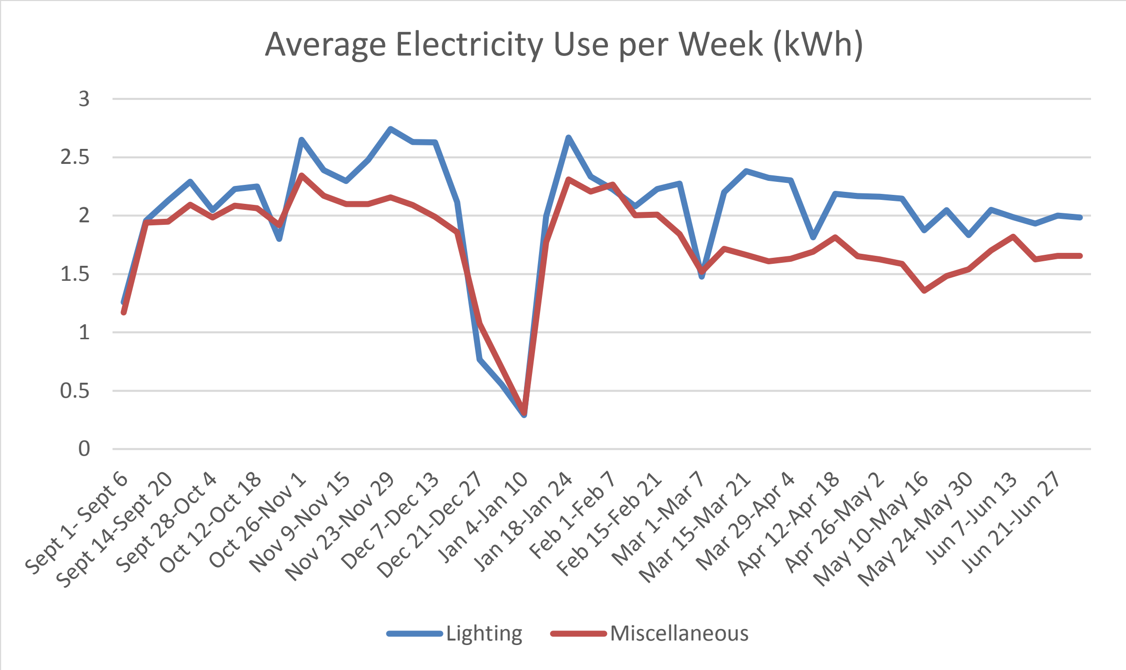


Figure 15: Energy Use over the entire period of study

This research is novel for connecting energy time of use and social-psychological theories. The time of use of electricity is analysed in the context of variables found in social-psychology and socio-demographic factors. The limitation with the available data and surveys, restrict the study to certain analyses of energy time of use. In the analyses, the variation in energy use over time is looked at with social-psychological constructs and how different users behave differently towards electricity consumption.

For analysing energy time of use, a LME has been employed. An LME is appropriate to investigate a pattern of change over repeated measurements over time (Maruyama, 2008). These models have both fixed effects and random effects. The fixed effects can be attributed to the features possessed by the whole population (time order in energy use) and parameters with random effects are associated with individual experimental units drawn (energy consumers). Additionally, mixed effect models are commonly used to study human behaviour over time (Shek & MA, 2011). Considering the type of electricity time of use that is available and the research questions, a linear mixed effects model was adopted. The time order of electricity use was incorporated in the model. The long structure of data has been used where time has been factored in as two hour aggregates. The model with time effects and additional variables (socio-psychological and demographic) were tested and analysed using the Linear Mixed Effects package in the software R. Akaike Information Criterion and Log likelihood were considered while choosing the best models.

Chapter 5. Results

This section presents the results from the analyses. The results are divided into two sections- explorative analyses and the regression model testing.

5.1. Explorative Analysis

5.1.1 Aggregate Energy Use

The analysis closely looks at the electricity use and electricity time of use. The data for 105 rooms on energy consumption with respect to the cities, gender, nationality and so on provide certain interesting insights. The following figure depicts the distribution of aggregate electricity consumption for the sample against the age of the participants in the study. The age is mostly in the range 18 to 25 with a few respondents above 25. This shows the age range for the sample under consideration which is mostly the youth from urban areas attending educational centres/Universities.

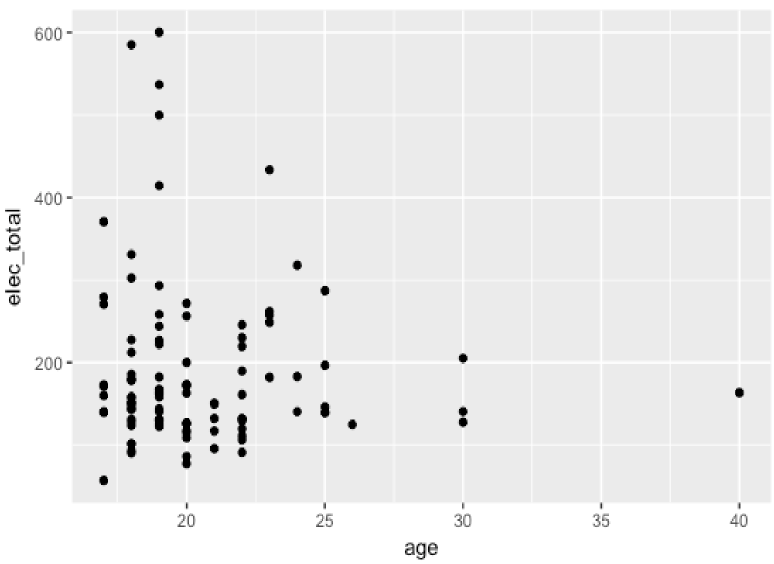


Figure 16: Total Electricity consumption (10 months) versus Age

The study is conducted in two cities in the Netherlands and the Figure.17 shows the spread of weekly electricity consumption versus time spent in rooms. The gradient shows the change in time spent in rooms. The time spent by an occupant in the room varies from 0 to

125 hours per week. The data is presented for the weeks excluding the holiday weeks which show erratic presence patterns.

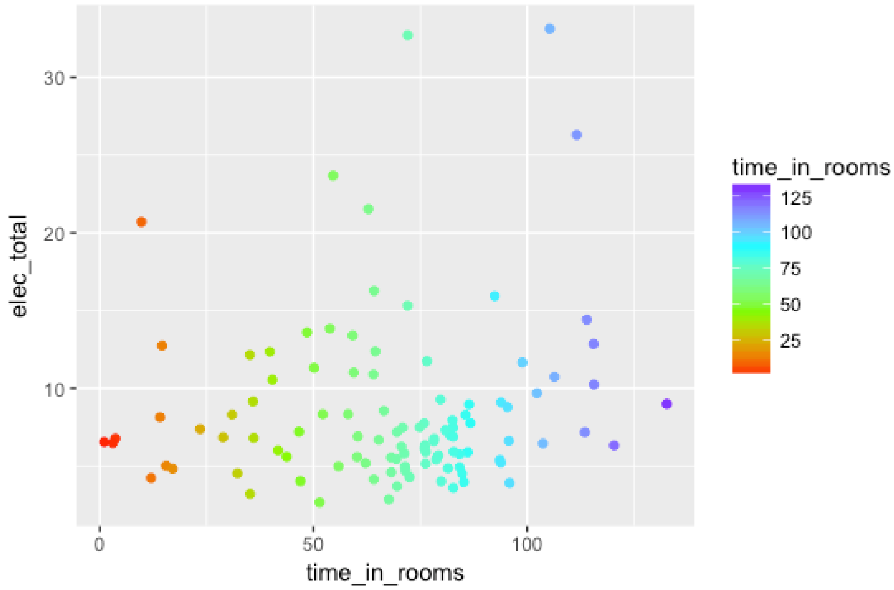


Figure 17: Electricity Consumption per week vs time spent in rooms in a week (Averages)

The Figure.18 shows the variation in electricity consumption versus time spent in rooms based on the two cities considered in this research. The data show a greater spread in energy consumption for Rotterdam, with more respondents who has higher amounts of electricity consumption. The difference in electricity consumption among cities was found to be significant (two sample t test- t=-2.53, df=103).

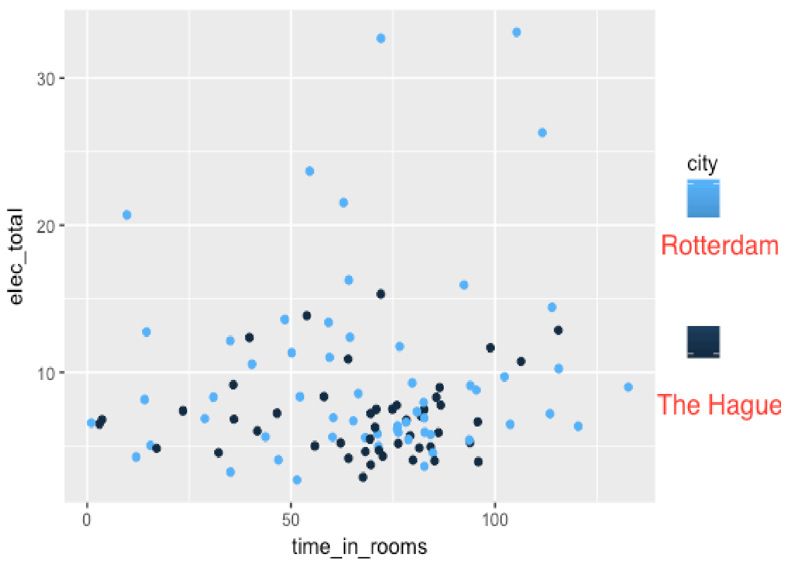


Figure 18: Weekly Electricity Consumption vs Time spent in Rooms based on the city of the consumer

There are also interesting patterns in how EU citizens and non-EU citizens use electricity. Most of the non-EU citizens were found to spend more time in their rooms. They were associated with higher energy use in aggregate terms. However, the EU residents were spending less time in their rooms, but had higher electricity use per time spent in rooms. Though a basic analysis of the graph showed differences among the two groups, it was not found statistically significant in a two-sample t test (t=-0.388, df=103).

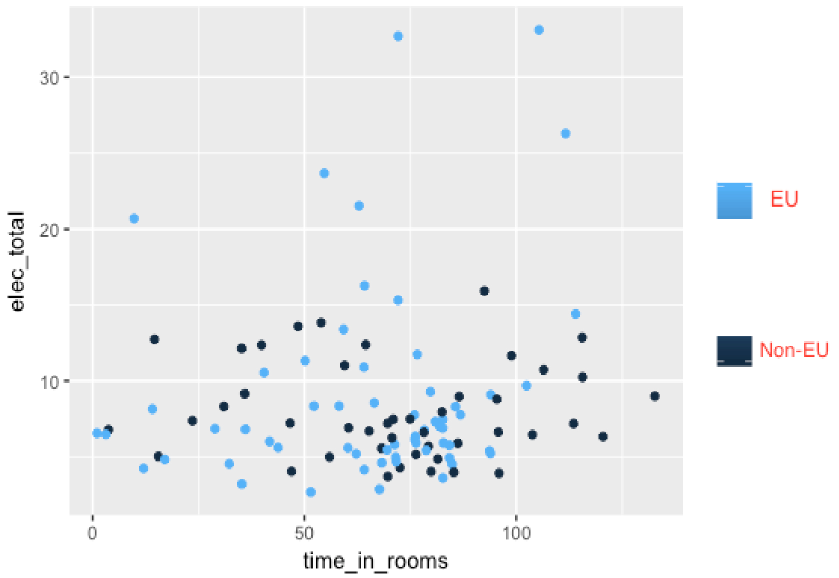
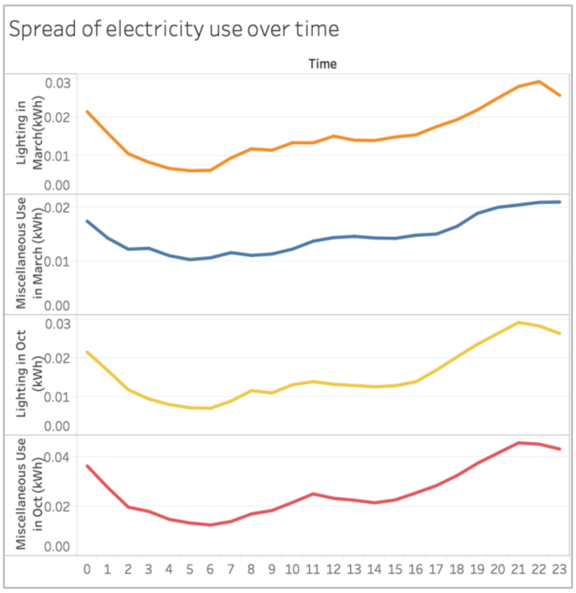


Figure 19: Weekly Electricity Consumption vs Time Spent in rooms based on nationality of the consumer

5.1.2. Energy Time of Use

Energy time of use examines the patterns in energy consumption over time. This is interesting in the case of energy management, owing to the supply-demand fluctuations in the electricity system. To study the energy time of use closely from the context of social psychology as well as to arrive at sound energy management policies, a linear mixed effects regression model of the energy time of use was employed. The total electricity consumption is divided into the use of lighting and use for miscellaneous purposes. The miscellaneous purposes mainly account for the use of electricity via the sockets for charging laptops or phones, use of electric kettles, additional lamps, small microwaves, hairdryers and such small electrical appliances. Other appliances like washing machines, dryers and cooking stoves are not measured as part of the study. The following figure is an illustration of spread of electricity use over time for two selected months separated for lighting and miscellaneous purposes.



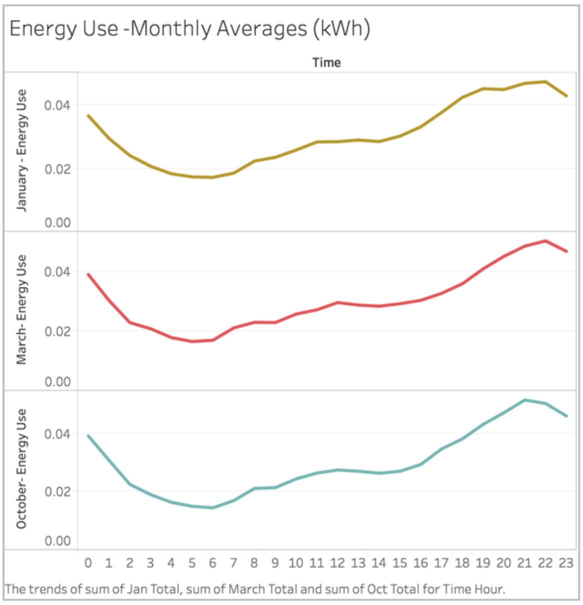


Figure 20: Electricity use vs time, Figure 21: Energy Use- Monthly Averages

It can be seen from the figures that, there are specific patterns in the energy use of the students. The morning peaks tend to start around 9 am which stays high till 11 am and then the use flattens until the evening peaks. The evenings have higher electricity use especially for lighting from 8 pm which lasts up to 12 to 1 am. The time order variable which underscores this peak evening usage, has a significant impact on the electricity use ($t=3.39$, $df=448$).

The data shows higher miscellaneous energy use for October and January, which refers to the seasonal variations in energy use. The difference between miscellaneous use and lighting use was not found to be statistically significant for October (two sample t test-$t=1.47$, $df=190$). However, it was found significant for the month of March (two sample t test-$t=-2.91$, $df=190$). The above-mentioned analyses were conducted for the city of Rotterdam. The

Figure: 21 above, shows the electricity use in the student hotels in terms of the three months which are considered for the study. The higher evening peaks are visible for all the three months considered. The differences based on the two cities in which the hostels are situated – Rotterdam and The Hague is elaborated in the graph below (Figure 22). The daily average use (lighting and miscellaneous combined) is higher for Rotterdam compared to The Hague for most of the times of the day in the month of March and the difference was found to be significant (two sample t test- t=8.04, df=190).

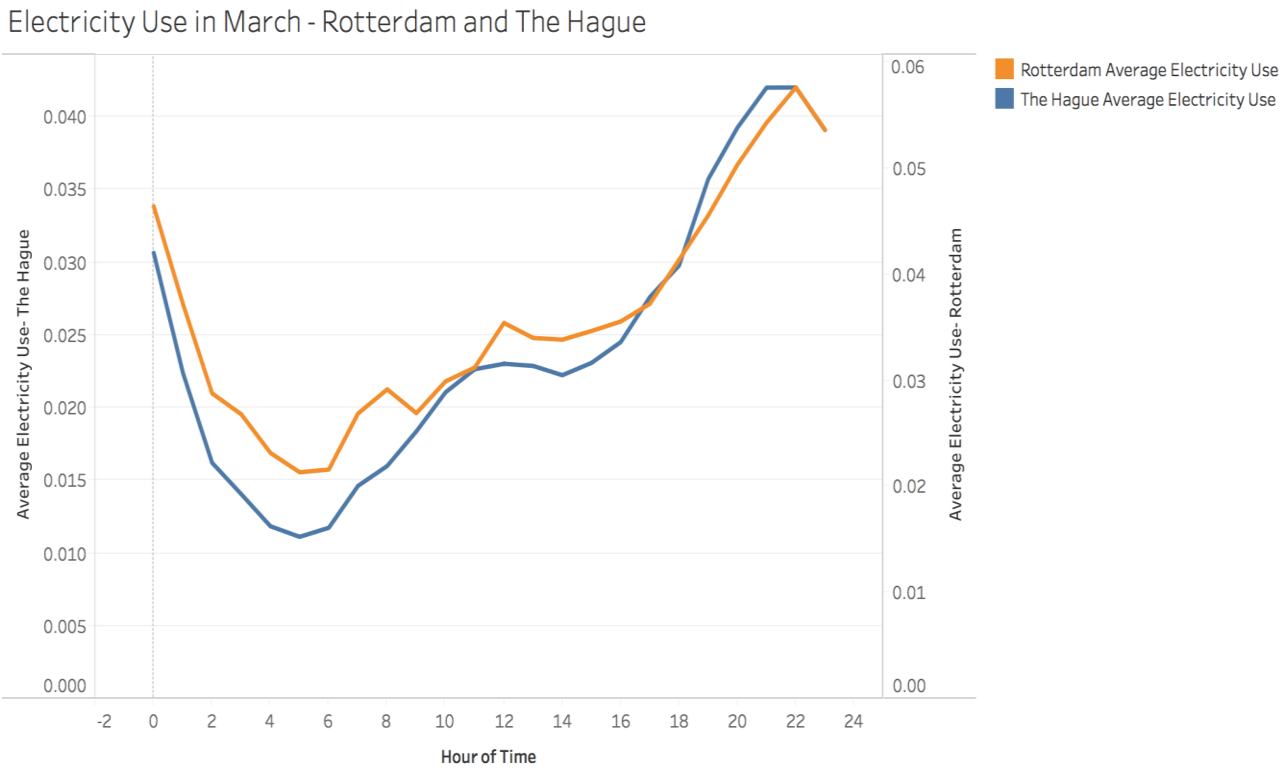


Figure 22: Electricity Use in March- Difference among cities

The electricity time of use highlights certain seasonal differences in the pattern of energy use. The winter month January shows higher use for both lighting and miscellaneous purposes compared to March. In addition, October and March has quite similar values for electricity use with October showing slightly higher use for appliances and lighting. The difference between the electricity use in March and October was found to be significant (two sample t test-t= 1.75, df=190). Figure: 23 has the data for the both the cities combined, but distinguished based on the two months chosen here for example.

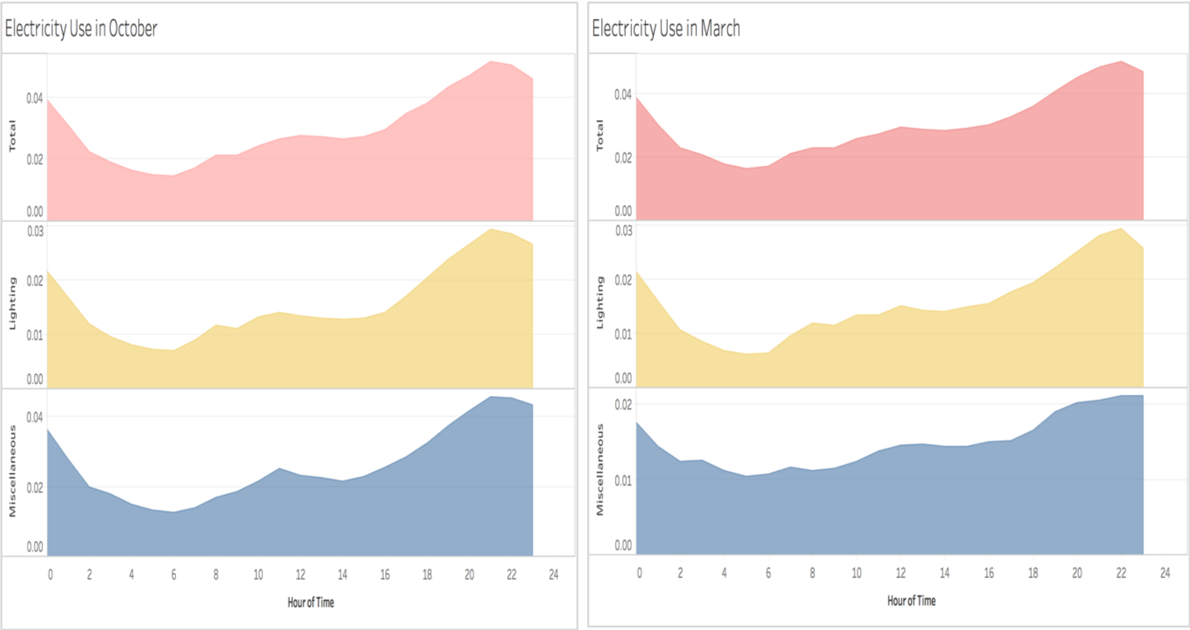


Figure 23: Electricity Use- Monthly differences

Other pictorial representations are available in the appendix. There are graphs on spread of energy use based on gender, more illustrations of energy time of use and so on.

5.2. Regression Model Testing

This section explains the results from the regression analyses. Prior to results, the descriptive statistics and correlation table for the data are presented below.

Table 4

Electricity Consumption and Survey Results

Descriptive Statistics- Means, Medians and Standard Deviations of variables in the model

Variable	*n*	*Mean*	*Median*	*Standard deviation*
Electricity Consumption	105	188.83	158.43	100.81
City	105	0.55	1	0.49
Gender	105	0.42	0	0.49
Age	105	20.38	19	3.38
Education	105	0.75	1	0.43
Nationality	105	0.57	1	0.49
Hedonic Values	105	7.28	7.33	1.44
Egoistic Values	105	5.83	5.8	1.41
Altruistic Values	105	7.57	7.75	1.45
Biospheric Values	105	7.44	7.75	1.46
Energy Behaviour	105	4.53	4.4	1.05
Efficacy	105	5.27	5.33	0.98
Environmental Identity	105	5.21	5.33	0.93
Recycling	105	3.40	3.33	1.06
Environmental Product	105	2.94	3	0.89

Appliance Use	105	5.50	5.5	0.90
Switching Off	105	4.52	4.5	1.61

The following table provides a glance at the correlation matrix with the variables included in the model.

Table 5

Electricity Consumption and Survey Results

Correlation Matrix

Variables	1	2	3	4	5	6	7	8
1. Elec Use	1	0.19^{**}	0.13	-0.04	0.02	-0.21^{*}	-0.05	0.08
2.City	0.19^{**}	1	0.28^{**}	-0.15	0.02	0.19^{*}	0.08	0.08
3.Gender	0.13	0.28^{**}	1	0.08	-0.22^{**}	-0.11	-0.06	-0.02
4.Age	-0.04	-0.15	0.08	1	-0.70^{***}	-0.21^{**}	-0.05	-0.08
5.Education	0.02	0.02	-0.22^{**}	-0.70^{***}	1	0.31^{***}	0.07	0.19^{*}
6.Nation	-0.01	0.19^{*}	-0.11	-0.21^{**}	0.31^{***}	1	0.15	-0.08
7.Hedonic	-0.05	0.08	-0.06	-0.05	0.07	0.15	1	0.33^{***}
8.Egoistic	0.08	0.08	-0.02	-0.08	0.19^{*}	-0.08	0.33^{***}	1
9.Altruistic	-0.05	-0.05	-0.30^{***}	-0.04	0.10	0.21^{**}	0.24^{**}	0.06
10.Biospheric	-0.13	-0.10	-0.34^{***}	0.10	0.03	0.14	0.34^{***}	0.03
11.Energy_bh	-0.03	-0.19^{*}	-0.14	0.14	-0.11	0.05	0.10	0.06
12.Efficacy	0.03	0.02	-0.07	-0.01	-0.01	0.13	0.12	0.15
13.Envtl_idt	-0.06	0.21^{**}	-0.20	0.23^{**}	-0.14	-0.05	0.05	0.05
14.Recycling	-0.05	-0.21^{**}	0.02	0.10	0.12	0.23^{**}	0.03	0.01

15.Env_prod	-0.08	-0.17*	-0.22**	-0.04	0.18*	0.09	0.14	0.30***
16.Appl_use	-0.08	-0.17*	-0.07	0.10	-0.06	0.15	0.14	-0.01
17.Switch_off	0.01	-0.21	-0.09	0.19	-0.14	-0.09	0.01	0.06

	9	10	11	12	13	14	15	16	17
1.Elec	-0.05	-0.13	-0.03	0.03	-0.06	-0.15*	-0.28**	-0.08	0.01
2.City	-0.05	-0.10	-0.19*	0.02	-0.21**	-0.21**	-0.07*	-0.17*	-0.21**
3.Gndr	-0.30***	-0.34***	-0.14	-0.07	-0.20**	0.02	-0.22**	-0.07	-0.09
4.Age	-0.04	0.10	0.14	-0.01	0.23**	0.10	-0.04	0.10	0.19*
5.Educ	0.10	0.03	-0.11	-0.01	-0.14	0.12	0.18*	-0.06	-0.14
6.Nation	0.21**	0.14	0.05	0.13	-0.05	0.23**	0.09	0.15	-0.09
7.Hedon	0.24**	0.34***	0.10	0.12	0.05	0.03	0.14	0.14	0.01
8.Egois	0.06	0.03	0.06	0.15	0.05	0.01	0.30***	-0.01	0.06
9.Altruis	1	0.75***	0.32***	0.53***	0.17*	0.28***	0.37***	0.20**	0.25***
10.Bios	0.75***	1	0.35***	0.41***	0.26***	0.25***	0.42***	0.25**	0.29***
11.En_bh	0.32***	0.35***	1	0.40***	0.36***	0.33***	0.46***	0.69***	0.85***
12.Effic	0.53***	0.41***	0.40***	1	0.27***	0.21**	0.27***	0.30***	0.35***
13.En_idt	0.17*	0.26***	0.36***	0.27***	1	0.35***	0.43***	0.32***	0.33***
14.Recyl	0.28***	0.25***	0.33***	0.21**	0.35***	1	0.34***	0.28***	0.24**
15.En_prd	0.37***	0.42***	0.46***	0.27***	0.43***	0.34***	1	0.40***	0.33***
16.Apl_use	0.20**	0.25**	0.69***	0.30***	0.32***	0.28***	0.40***	1	0.45***
17.Swi_off	0.25***	0.29***	0.85***	0.35***	0.33***	0.24**	0.33***	0.45***	1

*** p<0.01, ** p<0.05, * p<0.1

5.2.1. Aggregate Energy Use

Based on the models which have been explained in the model section, the regression results are presented below. The table 6 contains the results for the dependent variable as Aggregate Energy Consumption based on equation (1). The aggregates of Electricity Consumption for ten months have been used for the regression analyses. The independent variables differ in the different models and the R^2 is also provided in the tables.

Table 6

Regression with Aggregate Electricity Consumption as dependent variable

VARIABLES	(1) Model1	(2) Model2	(3) Model3	(4) Model4	(5) Model5
city	52.22**	48.43**	52.960**	53.555**	53.268**
	(19.975)	(20.29)	(20.721)	(20.818)	(20.856)
nationality			-2.721		0.196*
			(21.223)		(0.112)
age	-1.976				
	(3.939)				
edu	7.028			16.405	
	(31.367)			(23.792)	
recycling	18.075*	18.678*	19.642*	18.375*	19.421*
	(9.933)	(9.969)	(10.306)	(10.132)	(10.101)
hedonic		6.788			
		(8.649)			
egoistic		1.594			3.620
		(8.007)			(7.294)
altruistic		7.550			
		(11.128)			
biospheric	-6.343		-5.613	-6.671	
	(7.191)		(7.297)	(7.433)	
gender				-5.122	
				(21.855)	
env prod	-21.753*	-19.049	-18.962	-22.415*	-24.409*
	(12.839)	(13.308)	(12.936)	(12.910)	(13.511)
appliance use			-5.739		-6.226
			(12.929)		(12.859)
switching off	7.349	6.575	6.797	7.040	6.460
	(6.730)	(6.561)	(7.118)	(6.710)	(6.981)
Constant	211.569*	128.655*	192.836**	170.471**	151.602**
	(110.429)	(71.090)	(74.900)	(0.594)	(0.592)

Observations	105	105	105	105	105
R-squared	0.13	0.13	0.12	0.12	0.11

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the regressions (Table 6), the variables, city, recycling behaviour and purchase of environmental products are significant. Rotterdam residents were found to be pursuing higher energy use, the same being the case of people who engage in higher recycling behaviour. This shows that H1 is supported. The case of higher recycling and higher energy use, could point towards rebound effect within the energy use. H11 was not supported, though an opposite effect was found and H12 was supported. However, the consumers who cared about purchasing environmentally friendly products were found to have lower energy consumption. None of the 'Values' were found to be significant, similar is the case of certain demographic variables. Nationality was found to be significant in one model with EU citizens having higher aggregate energy consumption, thus refuting H5. The variables efficacy and environmental identity have not been included in these models, as those rendered the regressions insignificant. Rest of the hypotheses were not supported by the models. The regressions with aggregate energy use have low R-squares pointing towards the amount of variation in energy consumption explained by the variables used in the regressions. Though several transformations were conducted and data improved, there was no significant improvement in explanatory power of the model. These included log transformations, taking robust models, checking for outliers and normal distributions. The chosen regressions are followed by regressions on self-reported energy behaviours of the consumers. These are also tested for the socio-demographic and socio-psychological variables and point out how the psychological variables better explain self-reported energy behaviour.

In the case of the regression with self-reported energy behaviour (Table 7), the explanatory power improved greatly with more variables significantly explaining the energy behaviour. These models have environmental identity, efficacy, recycling, use of environmental products, switching off and appliance use as significant predictors of energy behaviour. Environmental identity and efficacy which explain the behavioural control and attitudes show that, a rise in these factors align with higher self-reported positive energy behaviour. Pro-environmental Behaviour which was elicited through Switching off, appliance use, recycling etc. shows how higher pro-environmental behaviour in general is associated with higher positive energy behaviour. Thus, H9, H10, H12, H13 and H14 are all supported and found significant, though in opposite direction as these are in the context of self-reported energy behaviour. The EU citizens were found to have higher self-reported positive energy behaviour while higher education was found to lower it. H5 was refuted and H4 was supported by the findings. Other hypotheses were not supported in the models. Even in this case, none of the 'Values' were found to be significant in the regressions.

The following table 7 comprises of the results for regressions with self-reported energy behaviour as the dependent variable.

Table 7

Regression with Self-Reported Energy Behaviour as dependent variable

VARIABLES	(1) Model1	(2) Model2	(3) Model3	(4) Model4	(5) Model5
city	-0.254				-0.022
	(0.196)				(0.109)
nationality	-0.019	-0.215	-0.176	0.217**	0.202*
	(0.203)	(0.148)	(0.150)	(0.109)	(0.116)
age	0.033	0.0295		-0.0113	-0.009
	(0.028)	(0.0216)		(0.0208)	(0.021)
edu			-0.303*	-0.243	-0.239
			(0.178)	(0.168)	(0.173)
env idt	0.211*	0.0447	0.0390	0.0643	0.039
	(0.116)	(0.0936)	(0.0920)	(0.0634)	(0.068)
efficacy	0.336***	0.215***	0.199***	0.0419	
	(0.110)	(0.0785)	(0.0736)	(0.0564)	
recycling	0.157	0.0888	0.0958		0.051
	(0.098)	(0.0759)	(0.0755)		(0.055)
hedonic	-0.005				
	(0.082)				

egoistic	0.014				-0.025
	(0.072)				(0.039)
altruistic	-0.124				
	(0.113)				
biospheric	0.141	-0.0196			0.011
	(0.112)	(0.0563)			(0.039)
gender		-0.102	-0.124		
		(0.151)	(0.148)		
env prod		0.167*	0.177*	0.182***	0.183**
		(0.0955)	(0.0940)	(0.0674)	(0.0723)
appliance use		0.658***	0.648***		
		(0.0872)	(0.0867)		
switching off				0.504***	0.506***
				(0.0364)	(0.036)
Constant	0.4356	-1.539**	-0.746	1.451**	1.673***
	(0.9844)	(0.683)	(0.619)	(0.594)	(0.609)
Observations	105	105	105	105	105
R-squared	0.314	0.597	0.600	0.781	0.784

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The regressions with self-reported energy behaviour were found to be explaining the socio-psychological variables more than the measured energy use. This opens certain new findings on the impact of attitudes, norms and values possessed by an individual on his or her energy consumption through their perceptions on energy use. A closer look at the cases and more explications are provided in the Discussion.

5.2.2. Energy Time of Use

Inclusion of socio-psychological variables in analysing the energy time of use is novel to this study. In this regard, the study incorporates a linear mixed effects model with time order as the fixed effect impacting the participants' energy use over time. From the results, it can be verified that the time factor has a significant impact on energy use. The time factor is a variable capturing the time, as 2-hourly aggregates over 24 hours. The results show that the students have a steady increase in their electricity use from the afternoon till the midnight hours. Unlike regular households, student tenants do not have morning and evening peaks in energy use. The steady rise in electricity use is seen from, around 16.00 in the afternoon which remains high almost till 1 am in the morning. The factor of city was also found to be significant towards energy use where Rotterdam was found to have higher energy use. The random effect term of participants was dropped in the regressions. The regressions with time interaction effects were lower in significance and did not show significant time interaction with socio-psychological variables.

Table 8

Linear Mixed Effects Results for Energy Time of Use

Fixed Effects	Model 1	Model 2	Model 3	Model 4
Intercept	0.0416 (0.0605)	0.0049 (0.0590)	0.0454 (0.0575)	0.0246 (0.0373)
Time factor	0.0091*** (0.0014)	0.0091*** (0.0014)	0.0090*** (0.0014)	0.0091*** (0.0014)
City	0.0268* (0.0155)	0.0309* (0.0155)		0.0284* (0.0153)
EU Citizen				
Gender			0.0211 (0.0161)	
Biospheric Values		-0.0006 (0.0056)	0.0046 (0.0061)	
Environmental Identity	-0.0087 (0.0095)		-0.0078 (0.0097)	
Environmental Product	-0.0127 (0.0098)		-0.0134 (0.0104)	-0.0146 (0.0091)
Recycling	0.0073 (0.0079)	0.0031 (0.0078)	0.0035 (0.0081)	0.0061 (0.0076)
Appliance Use	0.0036 (0.0098)	-0.0006 (0.0098)		
Switching Off	0.0061 (0.0053)	0.0047 (0.0054)	0.0057 (0.0050)	0.0063 (0.0049)
Random Effects	Model 1	Model 2	Model 3	Model 4

Intercept Standard Deviation	0.0668	0.0679	0.0674	0.0664
Residual Standard Deviation	0.0433	0.0434	0.0434	0.0434
Model Fit Statistics	Model 1	Model 2	Model 3	Model 4
AIC	-1240.01	-1244.98	-1238.01	-1257.95
BIC	-1199.09	-1208.14	-1197.1	-12225.18
Log Likelihood	630.004	631.491	629.007	636.973

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The mixed effects model found no significant relationship between socio-psychological variables and energy time of use. Only hypotheses H1 and H15 were supported by the models with significance. The spread of energy use over time was thus not related to the demographic factors or psychological variables that have been considered. Since the study is an exploratory research investigating energy time of use in the integrative framework, there are certain limitations and overcoming those can improve the model.

Chapter 6. Discussion

In the Netherlands, built environment is the sector with maximum energy saving potential (ING, 2013). To manage energy demand and to realise the energy savings, particularly of electricity, the nation has to closely investigate and include residential energy consumption in its policies. Unlike previous studies which looked exclusively at the energy consumption aggregates, this research includes energy time of use using the basis of social psychology. Energy time of use, employed additionally with aggregate energy use sheds light on energy use patterns and possible energy saving measures for the residential buildings which do not pay per use. The data analysis brings forth interesting findings on the differences between actual energy use and reported energy behaviours. Certain behavioural variables have significant contribution towards energy consumption, whereas others do not. Moreover, the analysis of time of use shows how energy use patterns vary with behaviour, season and socio-demographic conditions.

The hypotheses based on the research objective were tested for both energy use and energy time use. Elaborating the same, this section delves into the findings and the discussions revolving around those. The study considers the sample of student tenants who are similar to renters. Renters have different energy use patterns and certain restrictions like inability to modify their dwellings which could affect their energy saving behaviour (Poruschi & Ambrey, 2016). As Davis (2012) points out, they have limited control over appliances that can be used, and this impacts their energy behaviours. This study aligns with those findings and locates limited relation between direct energy use and psychological factors among the tenants. Unlike previous studies, this study found that certain socio-psychological variables have significant impact on measured energy use, albeit the effect is weak. The limited explanatory power of the model with the measured electricity use underlines the findings by Abrahamse and Steg (2009) that psychological variables such as attitudes and perceived behavioural control did not have an impact on energy consumption. The models with self-reported energy behaviour as the dependent variable had better explanatory power. Nationality and education were found to impact the self-reported results. Moreover, attitude and perceived behavioural control were impacting energy behaviour and respondents with more pro-environmental behaviour were having responsible energy behaviour. This is aligned with the findings by Huebner at al. (2013) where self-reported habit strength was found to be related to self-reported energy consumption behaviours. Nevertheless, the results from the self-reported energy behaviour can be taken only with the caveat of a social desirability bias (Fisher, 1993). The impact of self-reported socio-psychological variables on energy use might be through other mediating variables or there could be other possible relations.

Socio-demographic variables were mostly insignificant except for the variable denoting the city of residence for regressions with direct energy use. This is in lines with the findings by Huebner et al. (2016), where only household size was found to be a significant predictor of energy consumption among socio-demographic factors. The results underline the findings by Poruschi and Ambrey (2016) regarding the characteristics specific to certain cities that lead to higher energy consumption among residents from those cities. The differences among cities could be also due to the different building characteristics and climatic conditions. The socio-demographic variables were significant in the regressions with self-reported energy behaviour, where residents with EU nationality and higher education scored high in terms of pro-environmental energy behaviour. The results from direct electricity use convey the importance of certain behavioural characteristics in eliciting direct energy consumption. This has implications for analysing socio-psychological variables more closely and improving the existing energy management systems. Energy use interventions targeting the psychological factors can realise better energy savings considering how the factors influence the energy use. The expected result of consumers with greater pro-environmental behaviour like switching off appliances and using environmental products showing prudent energy use, sheds light on the increase in understanding on sustainability and energy conservation.

Several studies have incorporated time use data to closely analyse electricity use patterns. Most of such studies have used simulations and arrives at the spread of activities and related electricity use. Torriti (2017a) provides a good case of time of use study and illustrates the activity –electricity use relation. This research also finds evidences supporting the findings by the author on time dependence of energy use during a day as well as seasonal dependences. The analysis of energy time of use presents a different picture for the student tenants. The daily activities start later and continue even after the midnight for many student respondents. Unlike the pattern for a regular household which has morning peaks and evening peaks which revolve around work, school and many other activities, students were found to have different patterns. Being the first study of its kind and considering the limited data available, the predictive model found no significant impact of socio-psychological variables for determining energy time of use. Time interaction effects were found insignificant pointing towards the weak relation between behavioural aspects and timing of energy use. Socio-demographic variables except city were found to be insignificant for predicting electricity time of use. The variation between cities in energy use can be attributed to the weather factors, the residents in The Hague include working youth, difference in the ownership of appliances and building characteristics. Nonetheless, other factors like age, gender or nationality was found to have no impact on energy use via time order.

The findings from energy time of use analysis and the electricity use patterns call for energy management in the student hotels focusing on reducing the evening peaks demands. EU policy makers have been working on ways to ease peak congestion which include rolling out of smart meters with constant feedback, imposition of time-of-use tariffs and promotion of smart appliances (Torriti, 2017b). The possible finding of rebound effect where consumers with high pro-environmental behaviour being less conscious is also to be considered in the energy savings initiatives. Rebound effect points out that an improvement in energy efficiency or management may save less energy than expected and backfire (Gillingham, 2015). An example is the consumer purchasing an energy efficient dishwasher and increasing the frequency of use considerably that there is net rise in her energy consumption. This was seen in the study in case of users involved in recycling behaviour having greater energy consumption. Nonetheless, it was found insignificant in the case of other pro-environmental behaviour related variables. It could be a case of model formulation as well not possible for generalisations. Another important economic rhetoric that arises in the case is the principal-agent problem that arises in rental market. It arises due to the conflicting interests on energy conservation and costs between tenants and landlords. This is latent in the context of energy use often and incentive programs as well as unit metering often brings out the cases. It calls for smart energy measures to circumvent the issue.

The findings yield some practical implications for energy use, energy time of use and energy management. Installing unit-metering for individual rooms and monthly electricity bills based on usage can promote more energy saving behaviours. As the evening peak demand tends to be similar in both student houses, getting more smart appliances as well as providing incentives for shifting the usage are possible options. Information campaigns highlighting prudent energy use and incentive schemes to save energy can promote gradual changes which could lead to consistent behavioural changes in the future. As psychological variables were found to have an impact on energy use, though weak influences; these channels can be used to leverage energy management and achieve responsible use among the student tenants.

Chapter 7. Conclusion

Energy Systems are among the most important technical systems that make human lives comfortable, innovations possible and economic progress attainable. It is an indicator of development of a society as well as a beacon of an economic system in technical progress. This study closely examined energy use and energy time of use among student tenants in two Dutch cities and brings out the impact of socio-psychological and demographic factors affecting the energy consumption. The study adds to the literature on energy time of use from the perspective of social psychology and suggests possible energy saving solutions for the field lab *The Student Hotel*.

The first chapter introduces the topic and the research questions. It highlights the importance of studying energy consumption in rented homes and in urban contexts. The section delves into the different aspects within energy use analyses and connects social psychology to the research objectives. The introductory section presents a picture of the energy use within the residential context and concludes by putting forth the research questions. The second chapter discusses the literature review and theoretical framework of the thesis. Different theoretical approaches are explicated and the befitting integrative model is chosen. The section provides an elaborate literature review and finds that ambiguous results in the literature call for more comprehensive analyses. This chapter concludes with the illustration of the theoretical framework and related variables. Based on literature review and theoretical review, appropriate variables are chosen for the study. Third chapter presents the field setting for the study and connects it to the empirical framework. Fourth chapter explains the empirical framework and connects the data analysis to the theoretical model. The section discusses the two methods used- linear regressions and linear mixed effects regressions. It concludes with presenting the methodology and paves way for the results. The subsequent chapter five presents the results which are arrived at. The section has an explorative analysis section which is followed by model testing. The section concludes with explanation of the hypothesis test results and the major findings. Chapter six is the discussion section which elaborates on the findings, associations to previous literature and the new insights from this thesis.

The results point towards a strong impact of psychological variables on self-reported energy behaviour, with a slightly weaker influence on direct energy consumption. The results underline what has been elicited in literature before about the limited influence of behavioural variables on direct energy use and adds certain novel findings. The analysis of energy time of use brings out the interesting energy use patterns that are prevalent among the student community. Though socio-psychological variables were not of significant influence on time of use, time order and city were significant factors determining the electricity consumption. This points towards more impact from underlying climatic factors, building characteristics and socio-economic characteristics of the tenants. The study is important for the pursuit of smart energy policies and prudent energy management in the *Student Hotels* considering the higher usages in the evenings. Adopting the right measures keeping in view the use patterns and user behaviour can realise the savings targets more effectively.

There are limitations to this study arising from the small sample that is being used as well as limited questions eliciting time of use, within the survey. There are also limitations arising from lack of time-variant factors which limits the choices in econometric methods. Despite the limitations, the study has attempted to undertake an exploratory analysis of energy use and energy time of use. Future studies can look at the influence of more building characteristics, climatic factors and more interaction variables. Inclusion of more mediating variables and information on appliances are plausible ways for improving the model. Building a more holistic techno-economic-behavioural model with more factors could lead to more robust findings. Big data techniques provide more possibilities for analyzing large amount of data and this can be used in the context of energy consumption analysis.

Managing energy consumption and ensuring prudent energy use are vital for a sustainable future. Keeping in view the global environmental problems, any measure that aims for a sustainable change can gradually lead to bigger gains. Energy management thus, has a central role in realising a sustainable future and smart energy choices are inevitable for initiating the transition to an energy secure, energy balanced, flexible and renewable energy based system.

“We do not fully understand the consequences of rising populations and increasing energy consumption on the interwoven fabric of atmosphere, water, land and life”.

Martin Rees

Chapter 8. References

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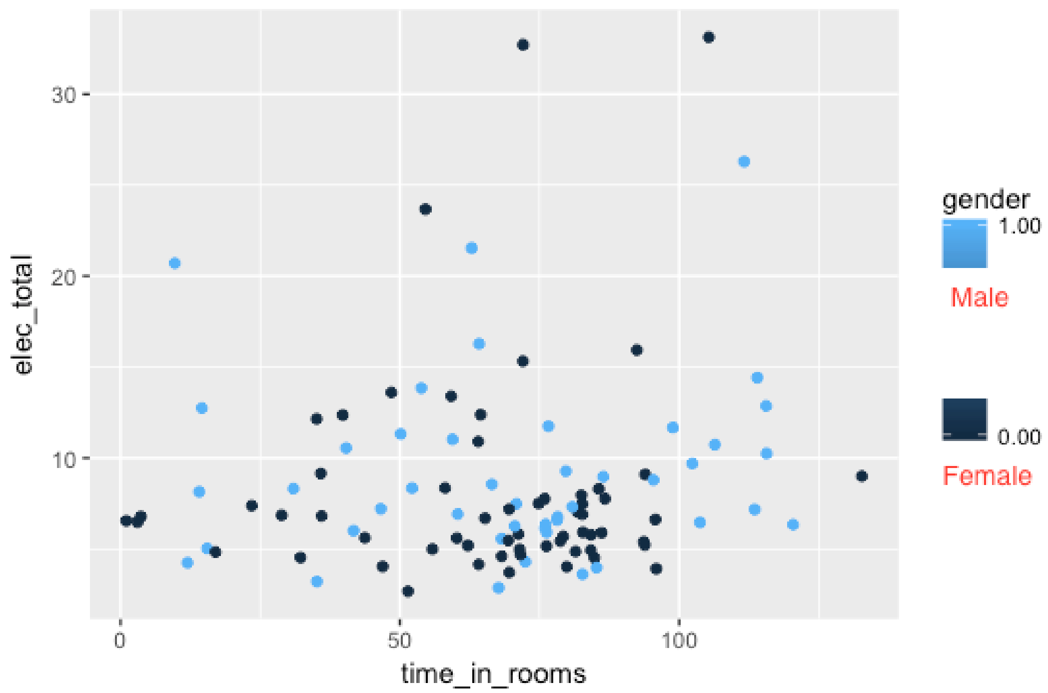
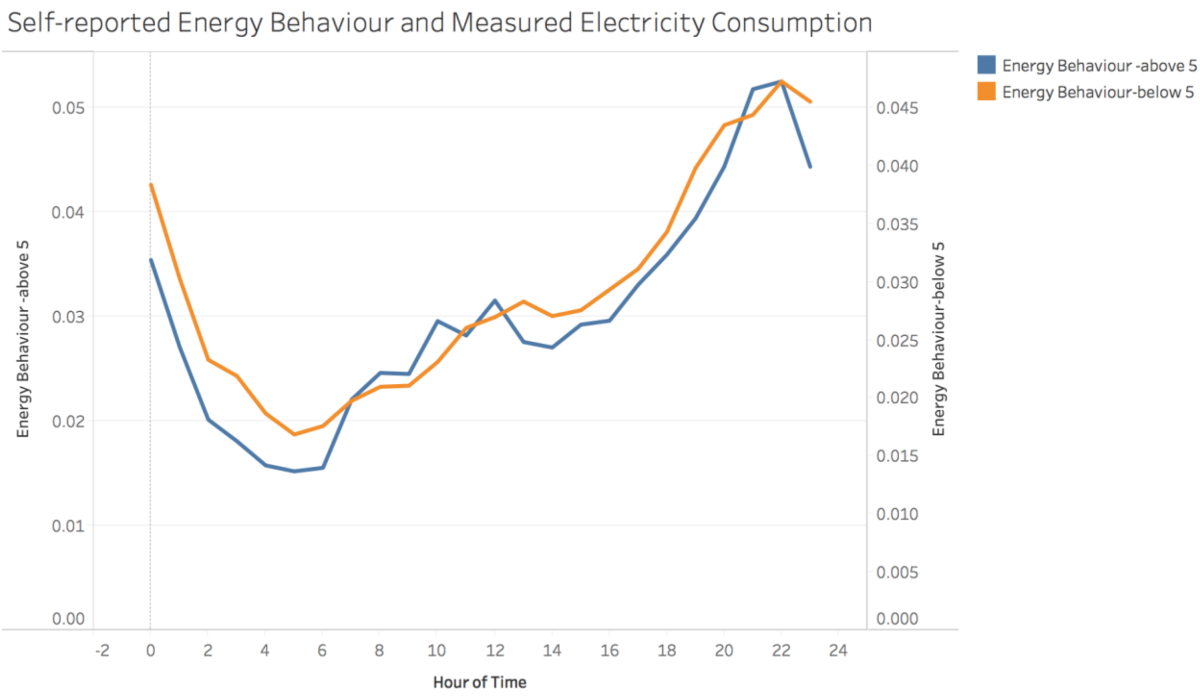
Appendices

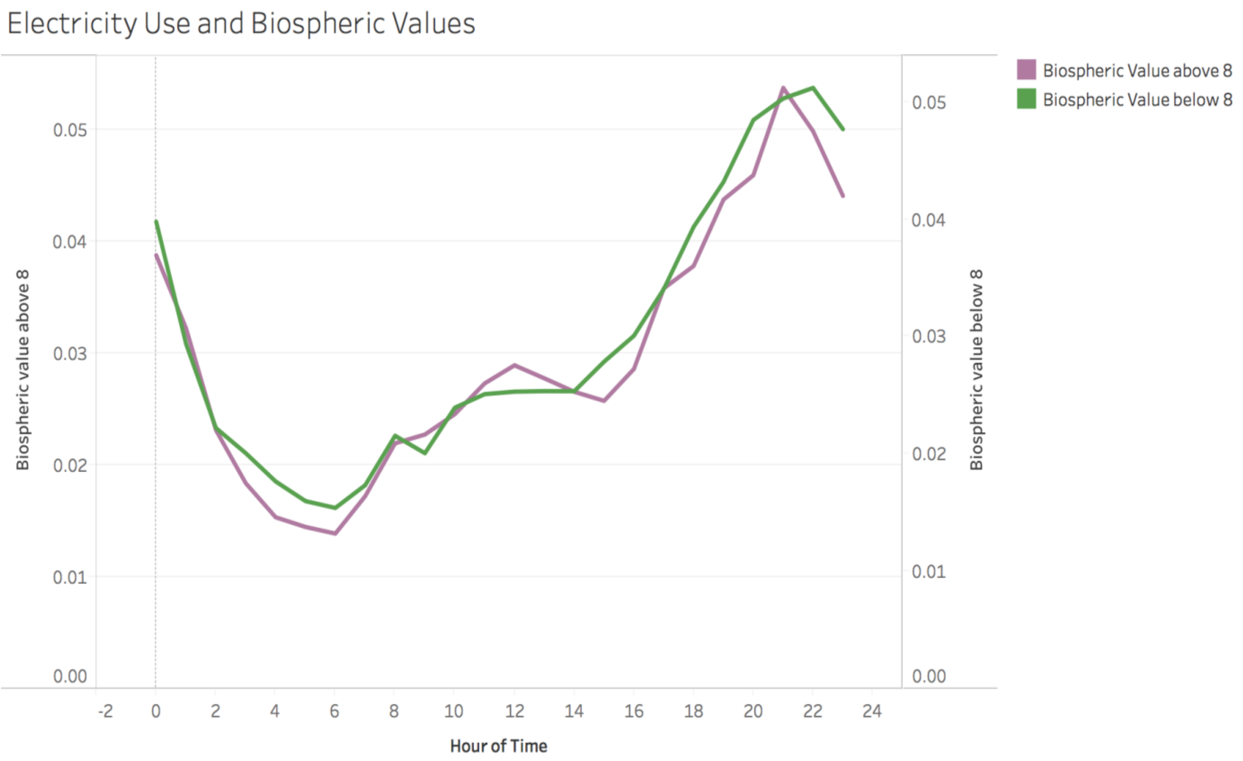
Appendix 1: Electricity Use versus Time Spent in Rooms- Based on gender



Appendix 2: Self-Reported Energy Behaviour versus Energy Use (kWh)



Appendix 3: Biospheric Values versus Energy Use (kWh)



Appendix 4: Partners in the Energy Behaviour Project