ABSTRACT

Title of Dissertation: OCCUPANT BEHAVIOR IN BUILDING ENERGY MANAGEMENT: BEHAVIORAL CHARACTERIZATION, INTERVENTION AND FORECASTING

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With the advent of the climate change and global warming, there is a need to adopt a diversified approach to address climate change; this is especially the case of promoting building energy conservation. This dissertation is one of the first studies that focuses on the occupant behavior in the building energy conservation, in particular three dimensions. First, this study aims to propose a behavior-based model that investigates impact of renters' rebound effect on building retrofit saving amount and to design the shared saving scheme among major stakeholders during their decision-making process. With demonstration of a real retrofitting project in a university campus, the rebound effect was identified to significantly extend the payback period of retrofit contracts and such the prolonged duration is partially determined by renters'

risk attitudes towards monetary incentives. Second, the study compares two message delivering means, paper-based (e.g. stickers) versus instant messaging tool (e.g. WeChat), as a platform for sharing energy-saving information and promoting occupant energy conservation in China. It was found that WeChat is the most effective intervention in reducing energy consumption, but the effects are short-lived. Using stickers, comparatively, produces more sustained results with long-term engagement of households. The changes in certain occupant energy behaviors are also correlated with individuals' perception of responsibility and quality of life to explain the heterogeneity of individual behaviors. Third, the study examines the interaction effect between occupant personality, energy behavior and intervention strategies with algorithms that can identify the optimal intervention strategy tailored for each household. This is followed by an improved Support Vector Regression (SVR) model that is capable of predicting household electricity consumption under optimal intervention strategies according to occupant behavior and personality traits. The proposed intervention lead to an average reduction of 12.1% in monthly household energy consumption compared with conventional behavioral interventions. The methods and algorithms developed from this study are pioneer works providing implications to measure the influence of occupant behaviors on energy saving amounts, to enrich and diversify behavioral intervention strategies, and to design incentives, programs and policies that effectively regulate occupant behaviors, collectively contributing to the demand-side energy management in buildings.

OCCUPANT BEHAVIOR IN BUILDING ENERGY MANAGEMENT: BEHAVIORAL CHARACTERIZATION, INTERVENTION AND FORECASTING

by

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Preface

This dissertation is served as an introduction to the emerging discussion of occupant behavior in the building energy management. The purpose of this dissertation is to explore, exam, assess and quantify the impact of occupant behaviors in the building energy management. Reading this dissertation will provide you an overall understanding of occupant behavioral characteristics and their influence on building energy consumption and building operations. Several key issues have been discussed in the dissertation such as what are means of communication can be used to intervene occupant behavior and how to examine the effectiveness of each means in reducing household energy consumption. Moreover, how to design a tailored intervention strategy based on the personality of each occupant so as to maximize the potential of energy saving through the change of behavior with the support from a machine learning tool of predication. These questions are well illustrated by examples from real-world cases and experiments with the findings that could be interested by academic scholars, policy makers and professionals in the energy and building sectors. The study is expected to offer novel ideas, methods and techniques in the arena of energy behavior and to recognize the great potential of behavioral energy saving in the future.

Dedication

This dissertation is dedicated to my families.

Acknowledgements

First and foremost, I would like to thank my advisor, Dr. Qingbin Cui for offering me the opportunity to study in the United States and to fully engage me with a variety of academic, research and educational activities. His guidance and recommendation over the past years not only help me to complete my doctoral studies but also broaden my vision and perspectives for the preparation of future academic career. I would like to thank Dr. Miroslaw Skibniewski, Dr. Gregory Baecher, Dr. Edward Lemay and Dr. Meina Liu for agreeing to serve on my dissertation committee and for taking time out of their busy schedules to review this dissertation and to provide constructive comments. I would like to thank all faculty members in the Project Management Center for Excellence for their enlightening teaching and motivations during course works, and my fellow classmates, members and friends for the collaborations, discussion and mutual support. I would also like to thank my families for their continuous support for my long journey of study.

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List of Abbreviations

AI	Artificial Intelligence
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
ATUD	American time use data
BIC	Bayesian information criterion
BPNN	Back-Propagation Neural Networks
BU	Building
Capex	Capital Expenditures
CDD	Cooling Degree Days
CFLs	Compact Fluorescent Lamps
CO_2	Carbon Dioxide
DE	Differential Evolution
DEMO	Demographic
DT	Decision Tree
EB	Energy Behavior
EEMD	Ensemble Empirical Mode Decomposition
ESCO	Energy Service Company
ESPC	Energy Saving Performance Contract
FOA	Fly Optimization Algorithm
GA	Genetic Algorithm
GDP	Gross Domestic Product

GRNN	General Regression Neural Network
HDD	Heating Degree Days
IN	Intervention
LASSO	least absolute shrinkage and selection operator
LEDs	Light-Emitting Diodes
LSSVR	Least Squares Support Vector Regression
MAPE	Mean Absolute Percentage Error
NBSC	National Bureau of Statistics of China
NEAC	National Energy Administration of China
NPV	Net Present Value
O&M	Operation and Maintenance
PE1	Extraversion
PE2	Agreeableness
PE3	Conscientiousness
PE4	Neuroticism
PE5	Openness
PSO	Particle Swarm Optimization
QOL	Quality of Life
RBF	Radial Basis Function
RBFNN	Radial Basis Function Neural Network
RICCOW	Responsibility, Incentive, Capacity, Capability, Opportunity and Willingness
SARIMA	Seasonal Autoregressive Integrated Moving Average
SVR	Support Vector Regression

Chapter 1: Introduction

1.1 Research Objective and Thesis Structure

Over the past decades, there are more buildings been retrofitted to energy efficiency by using energy saving performance contracts (ESPCs). ESPC is an approach of debt finance which use the future savings to secure the installment of the upfront investment. This method has been widely adopted in the industry because owners can save large amount of upfront investment, capture energy savings over the long term, and achieve corporate social responsibility and energy efficiency goals. Energy saving companies (ESCOs), who provides this kind of services, also benefits much for this contractual arrangement because they can quickly engage with the clients by providing an integrated energy service solution, opening new business opportunities, and transforming the industry from the role of "technical contractors" into "service providers" in the new era of service economic. However, the success of such a business model is subjected to a key assumption that the energy savings in the long-term future must to be precisely predictable and controlled as scheduled. Because capital lenders require a stringent condition of protection when loaning the capital for such a long-term contract with uncertainties. Variations in the energy savings create uncertainties of loan payment and further escalate the risk of business default. Hence, a robust forecast of energy savings in the future is critical to the success of the execution of the ESPCs project.

In the review of pertinent literature on energy consumption forecast in energy retrofitting projects, most projects have large variances of the energy consumption between actual and expected energy retrofitting (e.g. lighting efficiency in Schleich et al. (2014)). More and more literature concluded that the energy consumption is not only influenced by the technical specifications of the energy retrofitting equipment, appliances and hardware, but is more influenced by the occupant behavior and their psychological and social norms (Schultz et al., 2015). In some case, the influence of occupant behavior contributes much more significant variances on the energy consumption than the technical perspective (Zhao et al., 2017). For instance, due to the existence of occupant rebound effect, occupant may use more energy after the retrofit than what they used to consume prior to the retrofit. Occupants may turn on light for longer time or use new appliances. In another way, occupant behavior changes the baseline demand of the energy consumption, making the predication of future energy savings unrealistic. Such significant influence of occupant behavior has been gradually recognized and measured by recent studies, yet lacking systematic evaluation and examination, especially on such an effect on energy contract design and optimization. Hence, the dissertation mainly focuses on the influence of user behavior on building energy management in particular three dimensions: energy behavior in energy retrofit, intervention of energy behavior, and behavior-based energy use forecasting. Each of the theme is described as follows and the dissertation framework is shown in Figure 1.1.

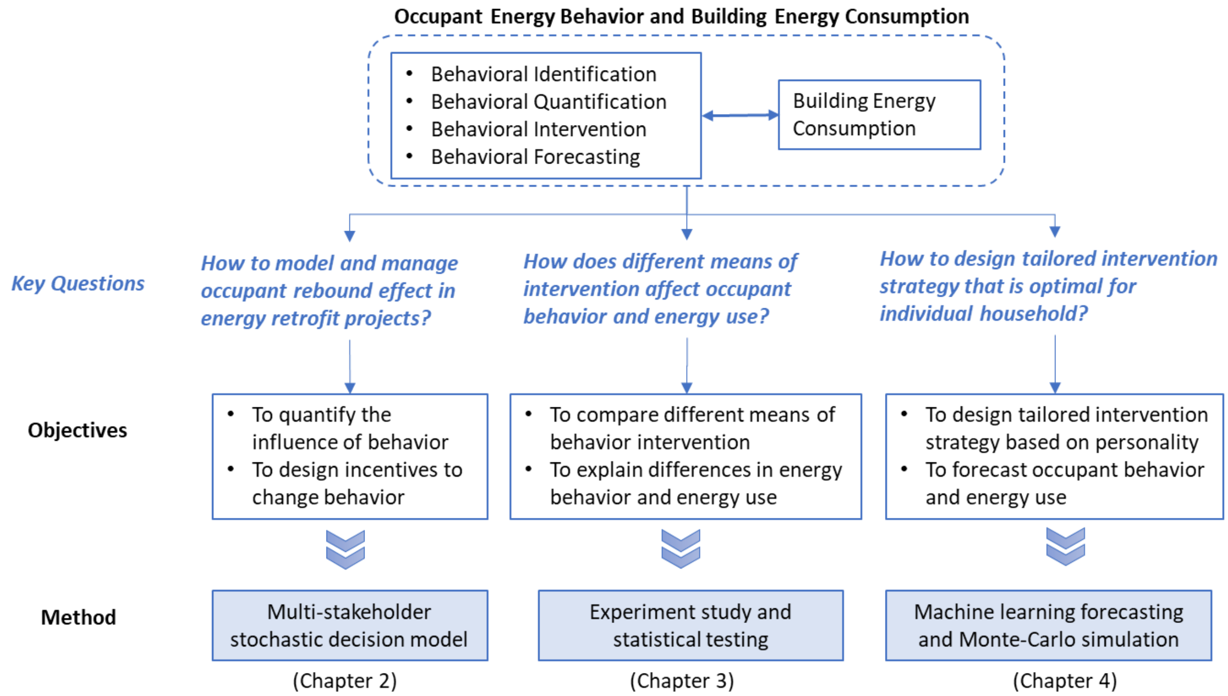


Figure 1.1 Dissertation Framework and Key Research Questions

Chapter 2 introduces a novel decision-making model that considers the occupant behavior in the design of ESPC contract, and by using the model to assist the contract design and decision-making process among building stakeholders. Previous decision-making of ESPC only deals with the duo-relationship between the owners and the ESCOs and ignores the occupant behavior (e.g. rebound effect) and its influence on the long-term energy saving. When occupants show higher rebound effect, they use more energy after the retrofit, hence the total energy savings will be reduced, subsequently influencing the contract terms and duration. The proposed model innovatively incorporate occupant behavior (i.e. rebound effect) as additional variables that mediate the relationship between owners and ESCOs. Occupant rebound effect has been examined with largely variations to change the actual energy savings and consequentially to increase the payback period of ESPCs contract duration for up to 4 years. The study further tested the heterogeneity of occupants regarding their risk attitudes and expected rates of return towards shard monetary incentives and explained their differences in determining the energy consumption. The results showed a significant distinction among different demographic groups. In the scenario when 30% of energy savings are shared to occupants, sensitive occupants who care much about split monetary savings would quickly behave in a more conservative way (with a lower rebound effect) than insensitive occupants who are not motivated by monetary incentives. A result of additional 9% saving on energy consumption was observed from the former group than the later, consequentially shortening the contract period by 1 year. The implications of the findings on the forecast of long-term energy consumption and on the practical design of ESPC have also been discussed in the end of the Chapter 2, with special contribution to the contract theory by incorporating occupant behaviors, monetary incentive design and negotiation strategies into the energy contract assessment in energy retrofit projects.

Followed by understanding the importance of occupant behavior and its influence to building energy management, the next key questions are to examine whether these occupant behaviors can be changed? And what are the effect strategies that can nudge occupants and intervene their behavior to the desired and more energy conservative pattern in buildings. The research on user behavior intervention has been studied for decades from perspectives of different knowledge domains such as behavior economics, consumer behavior research, psychological behavior, and social behaviors. However, the research on intervening occupant behavior, especially energy use behavior has not been studied until the last decade. Previous studies have focused on the areas such as message framing of energy consumption information (Khashe et al., 2016), provision of normative feedback on energy consumption (Komatsu and Nishio, 2015), and psychological theory of pro-environmental behaviors (Pichert and Katsikopoulos, 2008).

Provided the promising results from above studies, it is interesting to note that occupants would always response differently with varying resultant behaviors even when intervened by the same strategy. For instance, by providing the normative energy consumption information to college students via social platform, the variations of users' energy saving amount could be a few times (Delmas and Lessem, 2014). This can be explained by the differences in an individual's personality, perception and understanding of the information, hence an individual would respond with his or her own approach and behave differently though received the similar information. The effectiveness of behavior intervention is a complex process that is influenced by lots of factors such as the means of communication, quality of life, individual's perception to responsibility and pro-environmental attitude. Identifying and quantifying these factors would help to discover the underlying mechanism that promotes occupant energy conservation behavior and to further provide tailored intervention strategies to individuals for maximum energy savings. Among all potential factors, the means of intervention, quality of life and personal traits are to be considered as the most important factors that haven't been fully examined yet. Hence, the means of intervention and its effectiveness has been focused on the Chapter 3 and the use of personality traits for understanding and forecasting energy behavior is to be examined in Chapter 4.

In Chapter 3, the objective is to examine different means of information conveying and their effectiveness in intervening occupant energy behavior in residential buildings. Two sets of intervention strategies, namely paper-based messages and electronic-based instant message, were designed to disseminate energy use tips to residences in a few communities in the city of Hangzhou, China. In addition to means of delivery, incorporating residents' demographics, quality of life (QoL) standard, and RICCOW factors has also been recorded and evaluated using a questionnaire, and tested for its effectiveness to change occupant energy behavior. After analysis of results from a few months of experiment, the WeChat group recorded the most reduction (that is, 225.63 kWh). However, it was also observed that the results of WeChat were not as consistent as the Sticker group – its effect diminished toward the end of the study and the reductions in several testing periods were not significant. In addition, three RICCOW factors that were found to correlate with certain energy behaviors. For instance, the action to keep windows and doors closed when the air-conditioner is switched on was found to be correlated with a willingness (the RICCOW factor of "willingness") to set and achieve specific consumption targets and having an opportunity to commit to energy saving. These results show promising effect of employing online platform (e.g. WeChat) to engage households energy conservative behavior over large areas, such as mega cities. Meanwhile, it also demonstrates the practical implication of optimizing energy savings by customizing tailored energy information and delivery to individuals based on the demographics of user groups, their life style, and purpose of the intervention.

By knowing the importance of tailored information delivery and its influence on energy savings, it is essential to know who saving more than others and what are the characteristics of this group of people. Hence, in Chapter 4, an individual's personality traits has been carefully examined to explore the underlying relationship between one's personality traits and responsive energy behavior after the intervention. The objectives of Chapter 4 are two-folded. The first is to find certain personality traits, specifically Big Five Personality Trait, that significantly affect an individual's response to different intervention strategies. The second objective is to incorporate these identified personality traits to predict household electricity consumption based on the improved machine learning technic, in particular the Support Vector Regression (SVR) model. The proposed model is composed of key predictors such as personality traits, energy behaviors, occupant demographics, building features, weather indicators, historical monthly consumption, as well as the interaction effect between the energy behavior and all other predictors mentioned above. The model was trained and tested by electricity consumption data collected from 166 households during year 2015-2016. The selected model (R^2=0.6428) confirmed 18 key predictors in the use of GA-RBF-SVR technique that exhibits the best performance on next-month prediction with lowest error (measured by mean absolute percentage error, MAPE= 8.48-9.34%).

The model was then used to determine the best-fit intervention strategy for each household and subsequently to simulate the maximum electricity savings under that intervention strategy. Predicted energy consumption of 10,000 households were simulated by using the Monte Carlo method with the results illustrated in a 3D surface plot. On average, the optimized intervention strategies enable an additional 12.1% reduction in monthly electricity consumption than real experimental intervention. Among five intervention strategies, the intervention strategy of WeChat with feedback and without feedback achieved the highest (15.97%) and second highest (15.43%) electricity savings compared to other strategies. Based on the combinations of two specific personality traits (i.e. extraversion and conscientiousness), five types of intervention have also been analyzed and featured as occupants respond very distinctively to the optimized interventions. In particular, the resident type $\mathrm{E^LC^H}$ with a high rate of conscientiousness while low rate of extraversion has a small-to-moderate saving potential, while type E^LC^L residents who are disorganized and introverted showed polarized behaviors to either save a lot when intervened by the WeChat with feedback or save little. These findings expand the theory of tailored behavioral intervention strategies and are especially essential to be employed for effective design of energy feedback system in large-scale engagement of energy efficient buildings.

In a nut shell, the relationship of chapters in the dissertation is shown in Figure 1.2. Chapter 2 conceives the importance of occupant behavior in the building energy management by discovering its influence on long term energy consumption and the design of energy retrofitting contract. After understanding the importance of occupant behavior, Chapter 3 studies how to change and intervene occupant behavior toward a more conservative patter and tested the effectiveness of different information conveying means in nudging user energy behavior. From the experimental results in which users are observed to behave differently to the same intervention, Chapter 4 investigates how an individual's personality influence one's change of energy behavior and then final energy consumption. Based on the machine learning algorithm and Monte-Carlo simulation, the proposed model can tailor the best-fit intervention strategy based on both individual's personalities and other characteristics to achieve the full potential of energy savings for residential households. Three parts collectively contribute to the perceiving, intervening, modeling and simulating the occupant behavior in the building energy management.

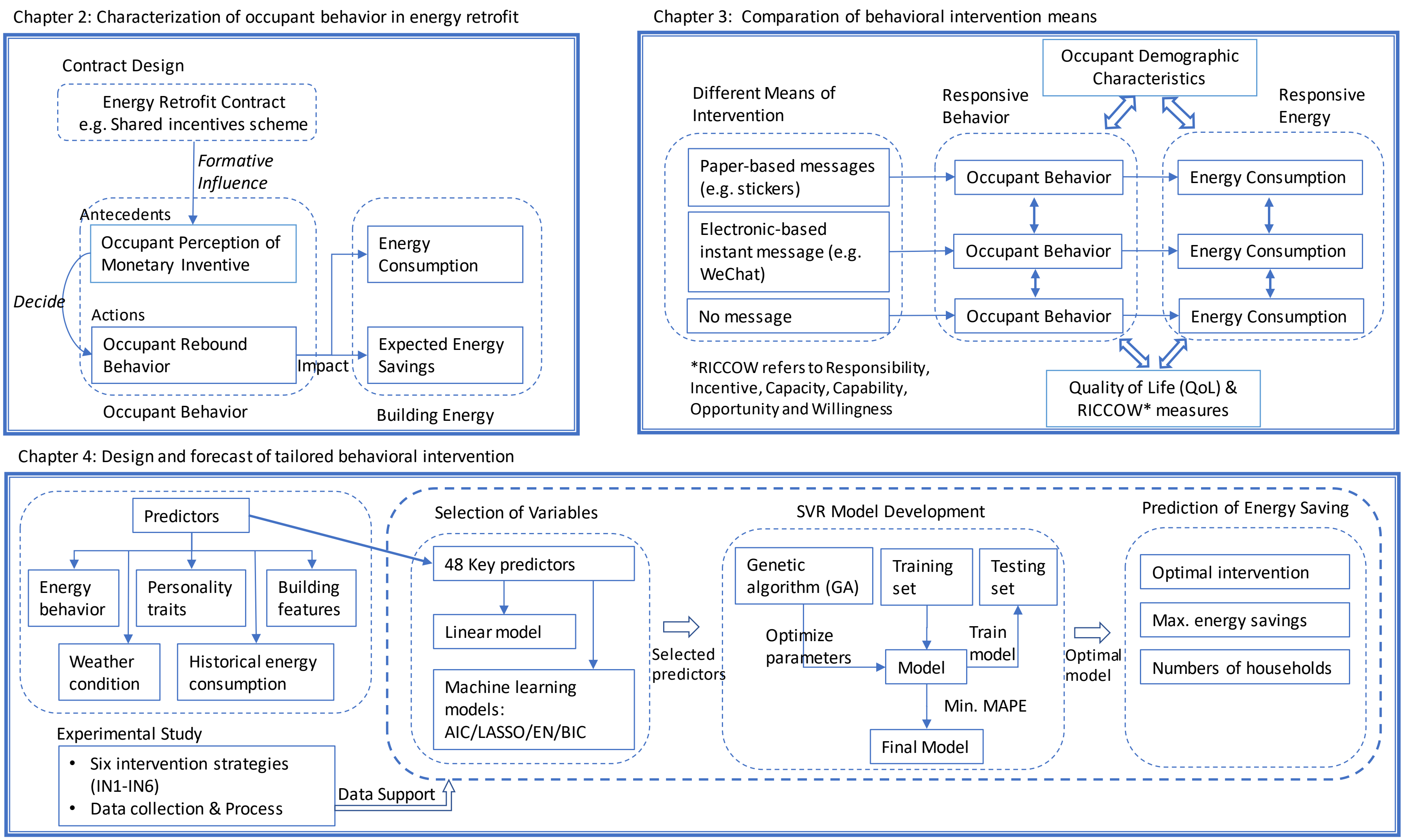


Figure 1.2 Summary of Key Elements in the Dissertation

1.2 Research Contribution

The research contribution of this dissertation is multi-perspective and summarized into three aspects.

First and foremost, the rebound effect was reported to negatively impact on the performance of energy retrofit and prolong the contract period, but it has yet to be considered in the energy retrofit contract. The approach proposed in Chapter 2, fills the knowledge gap by quantifying the level of impact caused by occupant rebound effect on the building expected energy saving amount and subsequently determining the optimal contract including contract duration and shared incentive scheme between owners and renters. The method of studying the effect of the shared saving scheme on mitigating the renters' rebound effect has also programmed into the decision model of ESPC contract assessment that enables a joint energy efficiency and maximum savings collectively from both owners and renters. Such the decision-making method is of the first in the literature to provide holistic assessment of occupant rebound effect in the design of building energy retrofit contract.

Another key contribution is to be the first in the literature that investigates and compares the effectiveness of using instant messaging platform (e.g. WeChat) and stickers for promotion of energy saving in households in China. It is also the first study in which a set of occupant lifestyle factors, such as Quality of Life (QoL) and RICCOW factors (responsibility, incentive, capacity, capability, opportunity and willingness), have been examined to correlate building occupants with their self-reported energy behavior and energy consumption. The results unveil that the instant message is the most effective in reducing monthly consumption, but effects are short-lived. In contrast, using stickers as a mean of engaging households produces more sustained results. These results provided preliminary evidence in the local context that an integrated intervention approach, in which different modes of engaging households based on the nature and the purpose of messages, is a preferred strategy with a higher chance of success in motivating behavioral change. The combination of messaging delivery means and the personality acceptance on the intervention are especially important for rolling out energy policies and large-scale energy programs that aims to create a sustainable society through the change of use behavior.

The last but not the least contribution of this study is the development of a predictive tool that is able to select the optimal intervention strategy and to predict the maximum of electricity savings potential for each household, with identified subsets of all characteristic variables of households. This model is the first kind in the literature because it examined and incorporated the interaction effect between occupants' energy use behaviors and other selected variables such as households' demographic factors and personality traits into the energy forecasting. The algorithm outperformed conventional methods and shed light on the future design of tailored behavioral intervention strategy and on the demand-side energy management for building individuals.

Chapter 2: Occupant Behavior in Building Energy Retrofitting[1]

Abstract

Energy Saving Performance Contracts (ESPCs) are a business model that aims to promote building energy efficiency through retrofitting with minimal or zero upfront costs for owners. Many studies show that occupants tend to use more energy than expected after retrofits (referred as rebound effect), which results in underestimated retrofitting costs. However, end users' energy-using behaviors and their relationship to the ESPCs decision-making process have seldom been studied. This study aims to propose such a behavior-based model to assist the contract decision-making among the major stakeholders in a building's retrofit, including building owners, Energy Service Companies (ESCOs), and renters. The proposed model incorporates renters' rebound effect and investigates the impact that major variables have on the rebound effect. To validate and evaluate the performance of the proposed model, a real retrofitting project in Maryland, United States, was examined. The results show that the rebound effect can significantly increase the payback period of ESPCs contracts by up to 4 years and the contract duration is significantly affected by renters' risk attitudes. The proposed model and findings can help ESCOs and building owners predict more accurate energy saving amounts and design proper retrofitting contracts.

2.1 Introduction

Building energy retrofit has become an emerging strategy in globally promoting sustainable development and building energy conservation. It improves building energy efficiency

[1] This chapter is revised based on the published article: LU, Y., ZHANG, N. and CHEN, J. "A behavior-based decision-making model for energy performance contracting in building retrofit." *Energy and Buildings* 156 (2017): 315-326.

and reduces energy bills for building owners in the long run, and it also has the environmental benefits of reducing greenhouse gas emissions and polluted waste. However, due to high upfront capital expenditures (Capex), most building owners are reluctant to invest in energy retrofit projects. Energy Saving Performance Contracts (ESPCs) is an alternative financing mechanism recommended by Energy Service Companies (ESCOs) to compensate an owner's initial investment with long-term savings from operations and maintenance (O&M) cost and energy bills. Increasingly more owners are adopting this model, seeking higher future economic benefits.

In a typical ESPCs process, ESCOs initiate an energy audit for an existing building and assess its energy savings potential. Then, ESCOs negotiate with building owners on the terms of the ESPCs contract duration and profit-sharing plans. ESCOs usually invest the initial retrofitting Capex, reimburse the investment, and earn profits from the saved energy cost until the contract expires. From the perspective of ESCOs, a longer contract is preferred to avoid cash flow uncertainty, while building owners prefer a shorter contract for fewer payments. Therefore, the duration of a contract reflects both parties' risk exposure and crucial to the success of the ESPCs project (Yik and Lee, 2004). However, in practice, it is difficult for ESCOs and building owners to estimate and determine proper the contract duration due to the uncertainties and risks over the long contract period. This issue was identified as the major market barrier for the adoption of ESPCs (Ghosh et al., 2011). Therefore, both parties are motivated to develop rigorous models to assist their decision-making. The tradition method is to select a fixed contract duration based on historical projects but such approach apparently not reliable given the uniqueness of each project (Hanaoka and Palapus, 2012, Zhang, 2011).

Many researchers have proposed several theatrical models to determining contract duration. For example, Deng et al. (2014) proposed a pioneer model to help ESCOs determine contract duration based on building characteristics, saving potential, and ESPCs contract clauses. However, several researchers found that the uncertainty in the occupants' behavior amplified the potential risks and undermined the profitability of retrofit projects. In Hertwich's study, the researchers discovered the "rebound effect", which suggests some occupants take a behavioral or other systematic response that may offset the benefits from the retrofit Hertwich (2005). In the same research, Hertwich proposed using an index to quantify the response effect. For example, one proposed retrofit intends to save 20% energy by updating LED lightbulbs, but it results in a 15% consumption reduction. Then, the rebound effect can be measured by the marginal difference as 25% (that is, [20%–15%]/20%). The "missing" 5% energy savings can be attributed to the changed occupant behaviors. Some occupants may realize LED lights are more energy efficient, so they use lights more often or for longer durations than before. Given the "rebound effect", the actual project energy savings are lower than the expectation and affect the breakeven contract duration. Thus, this study aims to develop a behavior-based decision-making model that incorporates renters' behavior for the building energy retrofit. The model should be comprehensive and objective for all involved parties (owners, renters, and ESCOs), and able to incorporate various contract considerations, such as duration, stakeholder benefits, risk allocation and renters' behavior. The contract duration in this model is determined under the condition in which owners maximize their energy savings while ECSOs make profits, collectively promoting the success of ESPCs.

The rest of this study is organized as follows: Section 2 reviews the literature on ESPCs studies, rebound effect, and energy incentive strategies. Section 3 introduces the structure of the proposed model. Section 4 examines a real case study to demonstrate and justify the model. Section

5 reports and discusses the results of the sensitivity analysis on major model parameters. Finally, Section 6 concludes this study and suggests avenues for future research.

2.2 Literature Review

2.2.1 Definition and Classification of ESPCs

ESPCs or Energy Performance Contracting (EPC) are a market mechanism and financing tool (Xu et al., 2011) that encourages building owners to conduct energy retrofits. ESCOs will undertake financial and performance risks for building owners; in return, ESCOs get paid with future cost savings (Himanen et al., 2007, Marino et al., 2011). Baechler (2011) divided ESPCs into four categories based on the risk allocation and financing structure: guaranteed savings, shared savings, no guaranteed savings, and chauffauge (also known as utility purchase agreements).

(1) In guaranteed savings contracts, ESCOs have to assume project performance risk since the Capex is paid by building owners. In this type of contract, ESCOs are hired by building owners to execute energy retrofits and satisfy the savings targets required by the building owners. If the actual savings are lower than the guaranteed amount, ESCOs have to compensate the owners' loss. Conversely, when the cost savings are higher than initially set, building owners will pay extra to ECSOs (Dreessen, 2003). Guaranteed savings contracts are suitable for those building owners who can finance the initial capital investment by themselves, and such contracts can potentially maximize the building owners' revenue.

(2) In shared savings contracts, ESCOs undertake both financial and performance risks as ESCOs not only provide the Capex, but also guarantee the project performance. In return, ESCOs take a share from energy savings during the contract period. Xu (2012) suggested

that, in shared savings contracts, ESCOs actually undertake all major risks — such as performance, investment, technical, and market risks — leaving almost “zero risk” for owners.

(3) No guaranteed savings contracts are a type of contract that is similar to traditional retrofitting contracts. ESCOs are paid a fixed fee by building owners for their services, such as energy audit, design and construction management, and commissioning. After retrofits finished, ESCOs are not involved in sharing the benefits, and there are no guarantees on energy cost savings (Baechler, 2011).

(4) The word “chauffauge” comes from French, meaning “heating,” and it represents another type of ESPCs where building owners purchase the services (heating, air-conditioning, lighting, etc.) for an agreed-upon rate and period of time from ESCOs. ESCOs are in charge of the building facility operation and maintenance (O&M).

Among the above four categories, guaranteed saving contracts and shared saving contracts are most commonly used methods in commercial buildings.

2.2.2 Market, Challenges, and Decision-making of ESPCs

In recent years, ESPCs have been wildly studied all over the world regarding their market trends and acceptance (Goldman et al., 2002, Marino et al., 2011, Vine, 2005). Bertoldi et al. (2006) analyzed the development and current statue of the ESCOs industry in the EU and suggested some long-term strategies and legislation measures to promote the application of ESPCSs in less developed countries. Goldman et al. (2005) empirically studied the US ESCOs market and concluded that policy support is crucial to the adoption of ESPCs. Xu and Chan (2013) analyzed successful factors in implementing ESPCs in China’s building energy retrofit market.

Meanwhile, researchers also explored the barriers to adopting ESPCs. Bhattacharjee et al. (2010) categorized a total of 21 barriers into four types — market barriers, institutional barriers, financial barriers, and technological barriers — and identified that the most challenging obstacles to the market acceptance of ESPCs were project complexity and long contract periods. Ghosh et al. (2011) ranked the importance of those barriers and found that the biggest barrier was building owners' lack of knowledge about ESPCs. To overcome these barriers, Pätäri and Sinkkonen (2014) developed an efficient business strategy for the ESCOs industry based on the Hamel business model.

Comparting with other traditional energy retrofit contracts, ESPCs are preferable for their advantages in flexible Capex sources, contract integrity, risk sharing, and potential penetration into the energy efficiency market (H2PC, 2014, Himanen et al., 2007, MDA, 2014). Coleman et al. (2014) concluded that ESPCs yield substantial benefits and higher realization rates compared to conventional bid to specification contracts when proper financial structure and fund sources are selected. Therefore, the success of ESPCs highly relies on the decision-making related to risks and benefits allocation. In addition, ESPCs projects often involve numerous uncertainties, such as energy price fluctuations, unknown building energy consumption patterns, and varying O&M cost. Therefore, various models have been developed to handle uncertainties in ESPCs projects. For example, Pantaleo et al. (2014) established an ESPCs model to simulate the resultant process of energy savings for biomass heating and combined heat and power (CHP) generation. Jackson (2010) used a risk management decision tool, Value-at-Risk, to quantify the project risks and associated financial returns. Deng et al. (2014) proposed a decision-making model that helps ESCOs select optimal contract periods and improve their competitiveness and profitability of winning an ESPCs tender.

2.2.3 Users' Behaviors, Rebound Effect, and Shared Incentives

Users' energy behaviors significantly impact the outcomes of energy retrofits, especially in rented buildings where renters pay a lump-sum space rent (Delmas and Lessem, 2014, BCA, 2014). In such scenarios, renters have no economic incentive to save energy or may use more energy after the energy retrofit. Fouquet and Pearson (2011) found that users may overuse lighting resources or are less motivated to switch lights off when they know that lighting efficiency has been increased. Such energy consumption increases after retrofits are regarded as the rebound effect (Berkhout et al., 2000).

The rebound effect was first introduced as a result of Jevons' paradox when efficiency gains were realized to be associated with increasing demand and consumption (Jevons, 1906). Theoretically, the rebound effect is defined as the ratio of difference between estimated savings and actual savings to estimate savings (Madlener and Alcott, 2009). For instance, a zero rebound effect indicates the actual savings are equal to estimated savings; when the rebound effect ratio is greater than zero, the actual savings is less than the predicted savings. In other words, the greater the value of the rebound effect ratio, the less cost savings that can be realized. The rebound effect can be categorized as direct rebound effect, indirect rebound effect, economy-wide rebound effect, and transformation effect (Greening et al., 2000). This study mainly focuses on direct rebound effect, which is the major consideration in rented properties. The rebound effect has been widely observed in a variety of fields and results in significant losses. Bentzen (2004) found that the US manufacturing industry suffered a 24% loss from 1949 to 1999 due to the rebound effect. There is also an estimated 19% of rebound effect in the US aviation industry, according to a simulation experiment of passengers and airline behavior (Evans and Schäfer, 2013). The rebound effect shows up in the transportation industry as well; for example, the direct rebound effect was estimated to be 42.1% and 57%–67% for the fuel efficiency improvement in German personal transportation (Frondel et al., 2007).

The rebound effect also exists in building energy efficiency and facility management. González (2010) showed that the rebound effect of household energy efficiency in Catalonia (Spain) was about 35% in the short term and 49% in the long term. After analyzing the residential energy consumption of 48 states during the period from 1995 to 2011, Orea et al. estimated the average rebound effect was from 56%–80%, using the energy demand frontier models (Orea et al., 2015). Schwarz and Taylor explored the impact of increased insulation on wintertime thermostat settings and found the rebound effect was around 1%–3% (Schwarz and Taylor, 1995). Another study in Austria on space heating also reported a 20%–30% rebound effect based on a time series and cross-sectional analysis (Haas and Biermayr, 2000). Dubin et al. estimated the rebound effect on space cooling was around 13% during the non-summer months and 1%–2% during peak summer months in the US (Dubin et al., 1986). Schleich et al. studied the direct rebound effect of replacing lighting with more efficient compact fluorescent lamps (CFLs) and light-emitting diodes (LEDs), and observed a rebound effect of 3%–6% (Schleich et al., 2014).

To mitigate the rebound effect in building retrofit and cultivate residents' energy conservation behaviors, green lease and green lease toolkits have been developed to outline the responsibility and proper practices of building owner and renters (Transformation, March 2016). These green lease toolkits aim to help both parties develop appropriate and economically feasible profit-sharing mechanisms (Toolkit, June 2014). The Building and Construction Authority of Singapore, for example, has developed green lease toolkits that are suitable to local geography and a humanistic environment. Successful applications of green lease toolkits suggest that the shared incentives could prevent renters from inappropriate energy-using behaviors (Delmas and Lessem, 2014). Inspired by the green lease, the shared incentives, particularly shared financial incentives, can substantially influence discrete behavior at the individual level (Stern, 1999).

ESPCs projects also yield a considerable rebound effect; however, few studies have been conducted. In a typical shared saving contract, the rebound effect could undermine the potential energy savings and result in contract changes and renegotiation. Proper ESPCs decision-making models that consider the rebound effect help makers assess the risks and develop robust, profitable ESPCs contracts and avoid over-optimistic saving estimations. Therefore, this study intends to integrate the rebound effect into the existing decision model and propose a quantitative optimization model to reconcile the profit-sharing mechanisms among ESCOs, building owners, and renters in energy retrofit projects.

2.3. Model Establishment

This section illustrates the structure of the proposed ESPCs decision model that incorporates rebound effect and shared incentives in order to make the optimal decision for the ESPC contract terms and conditions. Figure 2.1 shows the framework of the model and its key elements. Component ① estimates the project energy-saving potential and required investments, such as Capex and O&M cost. Component ② analyzes the users' behaviors and the rebound effect that impacts project energy savings and possible profit share among owners. Component ③ aims to maximize the owner's benefits and determines the contract period based on all parties' net present value (NPV) under the impact of the rebound effect.

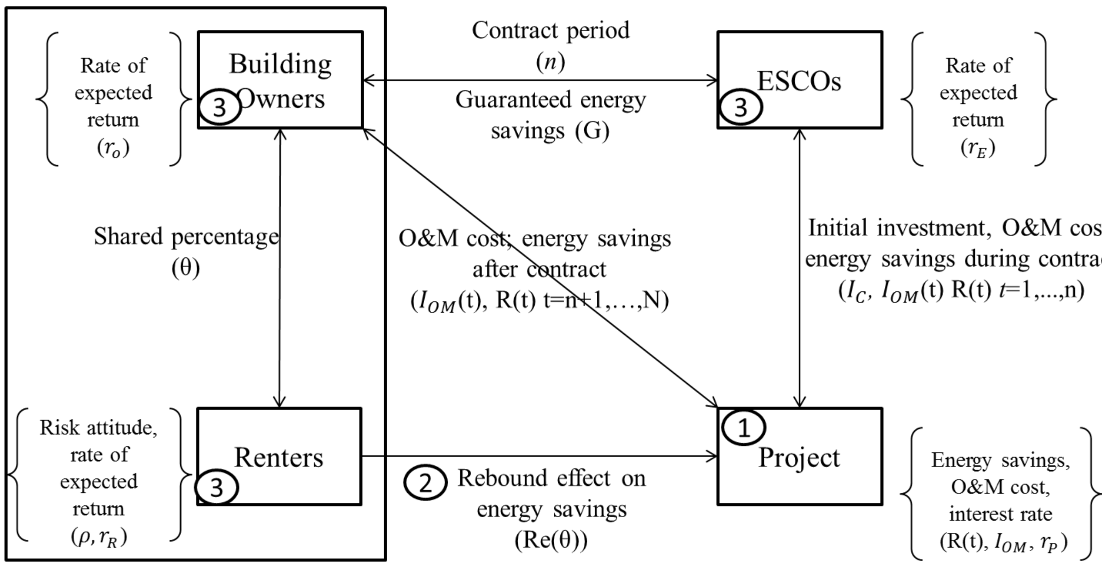


Figure 2.1 Framework of Behavior-based Decision-Making Model

2.3.1 Project Investment and Savings

In the proposed ESPCs model, total project investment through the project lifetime (N) consists of two parts: Capex (I_C) and O&M cost $(I_{OM}(t))$. Capex is provided by ESCOs at the beginning of the project; O&M cost is covered by ESCOs during the contract period (n), thereafter borne by building owners till the year of N. The investment decision $(I(t))$ in an energy retrofit project can be expressed as Equation (2.1):

$$
\begin{gathered}
I(t) = I_E(t) + I_O(t) \\
I_E(t) = \begin{cases} I_C & t = 0 \\ I_{OM}(t) & t = 1, \dots, n \end{cases} \\
I_O(t) = I_{OM}(t) \qquad t = n+1, \dots, N
\end{gathered} \tag{2.1}
$$

Where, $I_E(t)$ represents the investment made by ESCOs, which consists the Capex I_C at the beginning of the project and O&M cost ($I_{OM}(t)$) generated during the contract duration, $I_O(t)$ is the O&M cost ($I_{OM}(t)$) spent by owners after the contract yet within the project lifetime (N). Capex is a one-time decision variable and determined by the project nature, such as the size, age, and condition of a building.

Once determined, Capex will positively affect retrofit efficiency, annual O&M cost, and energy saving potential, since a higher Capex (I_C) is likely to gain better energy performance by using advanced technologies that also demand relatively high cost in maintenance, O&M cost ($I_{OM}(t)$). O&M costs often are modelled as a stochastic variable, which follow uniform distribution in public-private-partnership projects (Ng et al., 2007) and normal distribution in build-operate-transfer projects (Shen and Wu, 2005). In building retrofit projects, the O&M cost depends on various uncertain factors, such as equipment failures and breakdowns, labor cost for qualified professionals, inflated utility costs, and uncertain HVAC operation hours due to climate conditions and customer demand. These factors vary in different situations and should be dynamically modelled. In several recent studies, O&M costs of retrofit projects in Maryland, United States were modeled as a stochastic process (i.e. GBM process) to reflect the randomness and statistical nature of uncertainties (Deng et al., 2014, Dufresne, 2001). Thus, stochastic model was adopted in this study for it is closer to reality. Specifically, the uncertainties in this study are modeled as geometric Brownian motion (GBM). GBM is a well-established stochastic process model has been proven effective in cost related processes with uncertainties, such as stock price, oil price, and traffic volumes.

Three major parameters — initial value, drift, and volatility — are used to define the GBM process model. Initial value sets the baseline of the process; drift indicates the overall trend of the process; and volatility determines the variance of the process. In this study, the annual increment of O&M costs is measured by δ, and the stochastic uncertainties in the O&M costs are measured by the GBM with no drift effect. The O&M cost ($I_{OM}(t)$) in year t, then can be represented in Equation (2.2) and Equation (2.3).

$$I_{OM}(t) = \delta^{t-1}H(t) \tag{2.2}$$

$$H(t) = I_C H_0 e^{-\frac{\sigma_{H_i}^2}{2}t+\sigma_{H_i}\epsilon_H\sqrt{t}} \tag{2.3}$$

Where, δ describes the change of the O&M cost over project lifetime. When $\delta > 1$, the O&M cost increases annually. $H(t)$ is the quantitative form of the GBM process; σ_{H_i} is the volatility derived from historical data of annual O&M cost; and ϵ_H is the random error. Both Capex I_C and H_O determine the initial value of the O&M cost.

Project energy savings $\hat{R}(t)$ equals to energy saving quantity $Q(t)$ multiplied by the energy market price $P_E(t)$ at year t, shown as Equation (2.4). In the simulation process, I use $\hat{R}(t)$ to estimate the actual energy savings $R(t)$.

$$\hat{R}(t) = Q(t)P_E(t) \qquad t = 1, 2, \dots, N \tag{2.4}$$

Similar to O&M cost, the future energy price also can be modeled as a stochastic process. Equation (2.5) represents the GBM model for future energy price ($P_E(t)$) with the annual price drift effect α_{Et}, the annual price volatility effect σ_{Et}, and the initial energy price P_{EO}. These values are derived from historical energy prices.

$$P_E(t) = P_{EO}e^{\left(\alpha_{Et}-\frac{\sigma_{Et}^2}{2}\right)t+\sigma_{Et}\epsilon_P\sqrt{t}} \tag{2.5}$$

Actual energy saving quantity $Q(t)$ depends on a project's energy saving potential ($K(t)$), equipment deterioration ($f(t)$), and rebound effect multiplier ($Re(\theta)$), as shown in Equation (2.6). $K(t)$ is determined by the initial retrofit investment (I_C) and the investment coefficient K_0. The initial saving amount is $I_C K_0$, and its value subjects to a yearly random variation that is modeled by the GBM process with no drift effect, as shown in Equation (2.7). $f(t)$ decreases from year 1 afterward, for equipment deteriorates annually. The deterioration of the facilities and/or equipment across the project lifetime is a common problem that has been widely discussed in the literature, such as degradation in solar photovoltaic panels (Meyer and Van Dyk, 2004) and in HVAC equipment (Wang, 2014). It follows a performance degradation pattern described in Equation (2.8) (Heo et al., 2012, Carrico and Riemer, 2011). $f(t)$ is ranged from 1 to 0 during the project economic lifetime (N).

$$Q(t) = f(t)Re(\theta)K(t) \qquad t = 1, \dots, N \tag{2.6}$$

$$K(t) = I_C K_0 e^{-\frac{\sigma_{K_t}^2}{2}t+\sigma_{K_t}\epsilon_K\sqrt{t}} \tag{2.7}$$

$$f(t) = \frac{\log(N + 1 - t)}{\log(N)} \qquad t = 1, \dots, N \tag{2.8}$$

Where, K_0 is a coefficient that represents a project's potential energy savings per unit of initial investment of retrofit. For example, when $K_0 > 0$, higher investments can save more energy. σ_{Kt} is a volatility coefficient, and ϵ_K is the random error.

2.3.2 The Influence of Users' Behaviors

The rebound effect results in the actual energy saving amount possibly being less than the expected value, particularly the rented properties that only require renters to pay a lump-sum bill. The proposed model designed a percentage split (θ) of energy savings so that the renters can receive some portion of energy saving benefits as incentives for more energy efficient behavior. θ is a percentage (ranging from 0.5 to 1) to present the energy saving benefits that building owners can keep. When $\theta = 1$, owners keep all energy savings, and the renters receive no incentive. When θ decreases, more benefits are allocated to building residents. When $\theta = 0.5$, renters and owners equally share the savings.

The rebound effect $(\overline{Re}\,(\theta))$ is defined as a function of θ. $Re(\theta)$ is the rebound effect multiplier and defined as $Re(\theta) = 1 - \overline{Re}\,(\theta)$. For example, for a given specific θ^*, if the rebound effect $(\overline{Re}\,(\theta^*))$ is 14%, then the rebound effect multiplier $(Re(\theta^*))$ is 86%, indicating 86% of estimated energy saving potential can be realized. The calculation of $Re(\theta)$ follows the standard utility function $(U(\theta))$ that has been widely used to quantify human behavior and decisions, as shown in Equation (2.9).

$$U(\theta) = a + b\, exp\left(-\frac{\theta}{\rho}\right) \quad \rho < 0 \tag{2.9}$$

Where, ρ is the risk tolerance to determine the curvature in the utility function. ρ can be used to differentiate risk attitudes of various renters with individual differences. ρ in this model is negative, given the common renters' attitude to shared savings is risk adverse. The greater the value of $|\rho|$, the closer a renter is to risk neutral. a and b are constants to define the boundary conditions of $U(\theta)$.

In this study, the maximal rebound effect is defined as $\max\left(\overline{Re}\,(\theta = 1)\right) = \phi$. When building owners share no energy saving benefits with renters, renters' rebound effect would reach the highest ϕ, while the multiplier $Re(\theta = 1)$ would have a minimum value of $1 - \phi$. After normalizing the boundary of x and y axes (x was rescaled from original scope (0, 100) to a new scope (0.5, 1); y was rescaled from original scope (0, 1) to (1-ϕ, 1)), $Re(\theta)$ can then be defined as Equation (2.10).

$$\begin{cases} Re(\theta) = a + b \exp\left(-\dfrac{200 * \theta - 100}{\rho}\right) \\ a = 1 - \dfrac{1}{1 - e^{-\frac{100}{\rho}}}\phi, \quad b = \dfrac{1}{1 - e^{-\frac{100}{\rho}}}\phi \end{cases} \tag{2.10}$$

2.3.3 Benefits Sharing in ESPCs

In the model, I assume the success of the ESPCs project depends on an energy saving benefits allocation strategy. An ideal allocation strategy would not only establish the trust among involved parties, thus promoting the success of the project, but also potentially increase the total energy savings amount. During the contract, the annual energy savings is shared by owners and ESCOs based on the (estimated) guaranteed annual energy savings (G) and actual annual energy savings ($R(t)$). In a specific year during the contract, if the actual energy savings $R(t)$ is less or equal to G, owners keep αG as their savings, where α denotes the owner's revenue-sharing percentage. When $R(t)$ is larger than G, building owners would obtain the saving of αG, plus an additional shared saving of $(R(t) - G)\beta$, where β denotes the owner's excess revenue beyond the savings guarantee. When β is much larger than α, owners obtain more savings when a project over-performs ($R(t) > G$) than underperforms ($R(t) < G$). This guarantee policy is set to encourage ESCOs to provide a precise estimation of the guaranteed savings.

Meanwhile, renters' behaviors would also influence the annual energy savings ($R(t)$) with the rebound effect. As mentioned in previous paragraphs, both the rebound effect and the actual energy savings ($R(t)$) are functions of shared percentage θ. If owners are willing to share $1 - \theta$ percentage of their annual savings ($\alpha G + \max[0, \beta(R(t) - G)]$) with renters, the actual energy savings ($R(t)$) could be higher due to the reduced rebound effect. Such sharing contracts can last for as long as the entire building's service life. Revenues for ESCOs, renters, and owners are formulated by Equations (2.11), (2.12) and (2.13).

$$R_E(t) = \begin{cases} 0 & t = 0 \\ R(t) - \alpha G - \max[0, \beta(R(t) - G)] & t = 1,2,\dots,n \\ 0 & t = n+1, n+2, \dots, N \end{cases} \tag{2.11}$$

$$R_R(t) = \begin{cases} 0 & t = 0 \\ (1-\theta)(\alpha G + \max[0, \beta(R(t) - G)]) & t = 1,2,\dots,N \end{cases} \tag{2.12}$$

$$R_O(t) = \begin{cases} 0 & t = 0 \\ \theta(\alpha G + \max[0, \beta(R(t) - G)]) & t = 1,2, \dots, n \\ R(t) - R_R & t = n+1, n+2, \dots, N \end{cases} \tag{2.13}$$

Monetary benefit of the ESPCs contract is represented as NPV of all parties. r_R, r_O, and r_E are the expected rates of return for renters, building owners, and ESCOs, respectively, and r_P is the overall project's interest rate. Since ESCOs undertake both the financial and performance risks of the project, their expected rate of return is often higher than owners ($r_E > r_O$). NPVs of the above objects, with respect to the contract period n, are calculated in Equations (2.14) to (2.17).

$$NPV_R = \sum_{t=1}^{N} \frac{R_R(t)}{(1 + r_R)^t} = \sum_{t=1}^{N} \frac{(1 - \theta)(\alpha G + \max[0, \beta(R(t) - G)])}{(1 + r_R)^t} \tag{2.14}$$

$$NPV_O = \sum_{t=0}^{N} \frac{R_R(t) - I_{OM}(t)}{(1 + r_0)^t}$$

$$= \begin{cases} 0 & , n = 0 \\ \displaystyle\sum_{t=1}^{n} \frac{\theta(\alpha G + \max[0, \beta(R(t) - G)])}{(1 + r_0)^t} + \sum_{t=n+1}^{N} \frac{[R(t) - R_R(t)] - I_{OM}(t)}{(1 + r_0)^t} & , n = 1,2, \dots \end{cases} \tag{2.15}$$

$$NPV_E = \sum_{t=0}^{n} \frac{R_E(t) - I_{OM}(t)}{(1 + r_E)^t}$$

$$= \begin{cases} -I_C & , n = 0 \\ \displaystyle\sum_{t=1}^{n} \frac{R(t) - \alpha G - \max[0, \beta(R(t) - G)] - I_t}{(1 + r_E)^t} & , n = 1,2, \dots, N \end{cases} \tag{2.16}$$

$$NPV_P = \sum_{t=0}^{N} \frac{R(t) - I_t}{(1 + r_P)^t} \tag{2.17}$$

Length of contract period (n) serves as the key decision variable in the ESPCs negotiation process. Thus, an optimized model was developed to facilitate the decision for main stakeholders in a project. The model is expected to find the optimal contract period (n^*) that maximizes owners' NPV, and the formation subjects to the condition that ESCOs should make a positive profit ($NPV_E \geq 0$), shown in Equation (2.18).

$$n^* = \arg\max(NPV_0)\,, \quad subject\ to\ \ NPV_E \geq 0 \tag{2.18}$$

2.4. Case Study

Data from a real energy retrofit project on the University of Maryland campus was collected to validate the proposed ESPCs decision model. The applicability of the same data set has already been tested in Deng et al. (2014) work. In the project, each individual school, regardless of its energy consumption, pays a standard O&M fee to the university based on factors such as available classroom spaces, numbers of registered students, or tuition fees. In the building, residents did not receive any monetary incentive to save energy after the energy retrofit. This is a typical scenario in rental properties, as noted in the aforementioned discussion, where the tenants pay a fixed fee to an owner based on the rented area regardless of the energy consumption. Therefore, this building energy retrofit project was examined as a case study with the proposed ESPCs model that involves both owners (university) and renters (schools).

2.4.1 Data Collection and Calculation of relevant coefficients

The initial values of the variables in our model are listed in Table 2.1. The first variable group (S/N 1-8) includes the parameters of the GBM processes, which were aggregated from the real project data, such as energy price and O&M cost. The second variable group (S/N 9-20) contains the parameters related to the ESPCs contract terms and conditions that can vary for the sensitivity analysis.

Gillingham et al. (2016) reported that the maximum rebound effect ϕ in a household electricity retrofit project ranges from 5% to 30% (considering both short- and long-term effect). This model adopts Gillingham et al.'s conclusion; the initial value of ϕ is set as the median (15%). The choice of initial value of risk attitude ρ is based on the averaged policy, given there are four candidates in the original utility function ($\rho = -10, -20, -50, -100$) (Kirkwood, 1997). The initial value of θ is temporarily set as 100% to reflect the maximum influence of the rebound effect on ESPCs project's contract period and energy savings. The sensitivity analysis for the range of each variable will be discussed in Section 2.5.

The detailed calculation process is shown as follows. The source of Data is abstracted from the internal energy audit report from ESCOs.

Table 2.1 Parameters and Initial Values Used in the EPC Decision Making Model

S/N	Parameters	Symbols	Values
1	Volatility of the O&M cost coefficient	σ_H	0.25
2	Volatility of the energy saving amount coefficient	σ_K	0.01
3	Energy price drift effect	α_E	0.0523
4	Energy price volatility effect	σ_E	0.0856

5	O&M trend index*	δ	1.025
6	Initial value of the O&M cost coefficient*	H_0	0.0036
7	Initial value of the energy saving amount coefficient*	K_0	0.0043
8	Initial value of the energy price*	P_{E0}	22.82 $/Btu
9	Economic lifetime of the energy efficiency system	N	25 years
10	Capital cost of the energy efficiency investment	Ic	$20,668,991
11	Annual energy cost savings guarantee	G	$3,000,000
12	Owners' expected revenue share within the guarantee	α	5%
13	Owners' excess revenue share beyond the guarantee	β	20%
14	Owners' expected rate of return*	r_O	3.10%
15	Renters' expected rate of return*	r_R	3.10%
16	Project interest rate*	r_P	3.10%
17	ESCOs' expected rate of return*	r_E	6%
18	Owners' expected revenue share with Renters	θ	100%
19	Maximum renters' rebound effect	ϕ	15%
20	Risk attitude of renters	ρ	-20

**Note: 1. values of parameters are partially derived from Deng et al. (2014), while those with star (*) were adjusted or newly collected based on the project documents or relative background information.*

(1) *Calculation of initial value of O&M cost coefficient (H_0) and O&M trend index (δ)*

The initial value of O&M cost is calculated by $H_0 * \mathrm{I_C}$ from the historical data. O&M cost can be retrieved from the project document (shown in Table 2.2) and I_C is a known, hence:

$$H_0 * I_C = 73{,}894 \rightarrow H_0 = 0.0036 \tag{2.19}$$

Table 2.2 Expected O&M Cost and Expected Energy Savings of the Selected Case

Year/ i	O&M cost (USD)	Saving amount (Btu)
2009/ 1	73,849	79,750
2010/ 2	75,914	85,000
2011/ 3	78,042	87,500
…..	…...	……
2021/ 13	103,162	82,250

O&M trend index δ indicates the annual change in O&M cost. δ is also calculated based on the historical project raw data, as follows:

$$\delta_i = C_{O\&M}^{i+1}, i = 1, \ldots, 12 \tag{2.20}$$

$$\delta = \frac{\Sigma\delta_i}{12} = 1.025 \tag{2.21}$$

(2) Calculation of Initial value of the energy saving amount coefficient (K_0)

The annual energy saving amounts at the first four years show an increasing tendency, the project saving potential increase gradually until reach its maximum. This result consistent with the projects in practices, since retrofit projects normally take years to finish. In the model, the project is assumed to be finished in the first fiscal year. Based on such assumption, energy saving amount at the end of the first year reaches the highest value of 89,000Btu. Then the benefits gradually decrease along with the facility depreciation. Hence the coefficient of initial value of energy saving amount K_0 can be calculated as

$$K_0 * I_C = 8.9 * 10^4 \;\rightarrow\; K_0 = 0.0043 \tag{2.22}$$

(3) Calculation of initial value of the energy price (P_{E0})

As the selected project started at 2008, the value of energy price at 2008 was set as initial energy price in case study. P_{E0} is assumed the mean value of energy prices of residential sector and commercial sector at the time being. The energy price in 2008 is 23.14 USD per Btu for residential sector and 22.49 for the commercial sector.

$$P_{E0} = \frac{23.14+22.49}{2} = 22.82 \quad (2.23)$$

(4) Calculation of expected rates of returns (r_R, r_O, r_E)

The expected rate of return of the Owners is assigned as the 30-year Treasury Yield Curve Rates where $r_O = 0.031$. The rate of return of renters is assumed the same with owners. The expected rate of return for ESCOs is based on the average operating margin that derived from financial statement of the energy retrofit companies, as $r_E = 0.06$.

2.4.2 Calculation and Results Analysis

A Monte Carlo simulation was performed with Mathworks Matlab R2016a to simulate different project scenarios (each scenario has 25,000 trials). The final results were aggregated by averaging the results of all trials. For energy investment (Capex I_C and O&M cost $I_{OM}(t)$) and annual energy savings $\hat{R}(t)$, a sample scenario and the averaged result of the 25,000 scenarios were plotted in Figure 2.2 as an illustration.

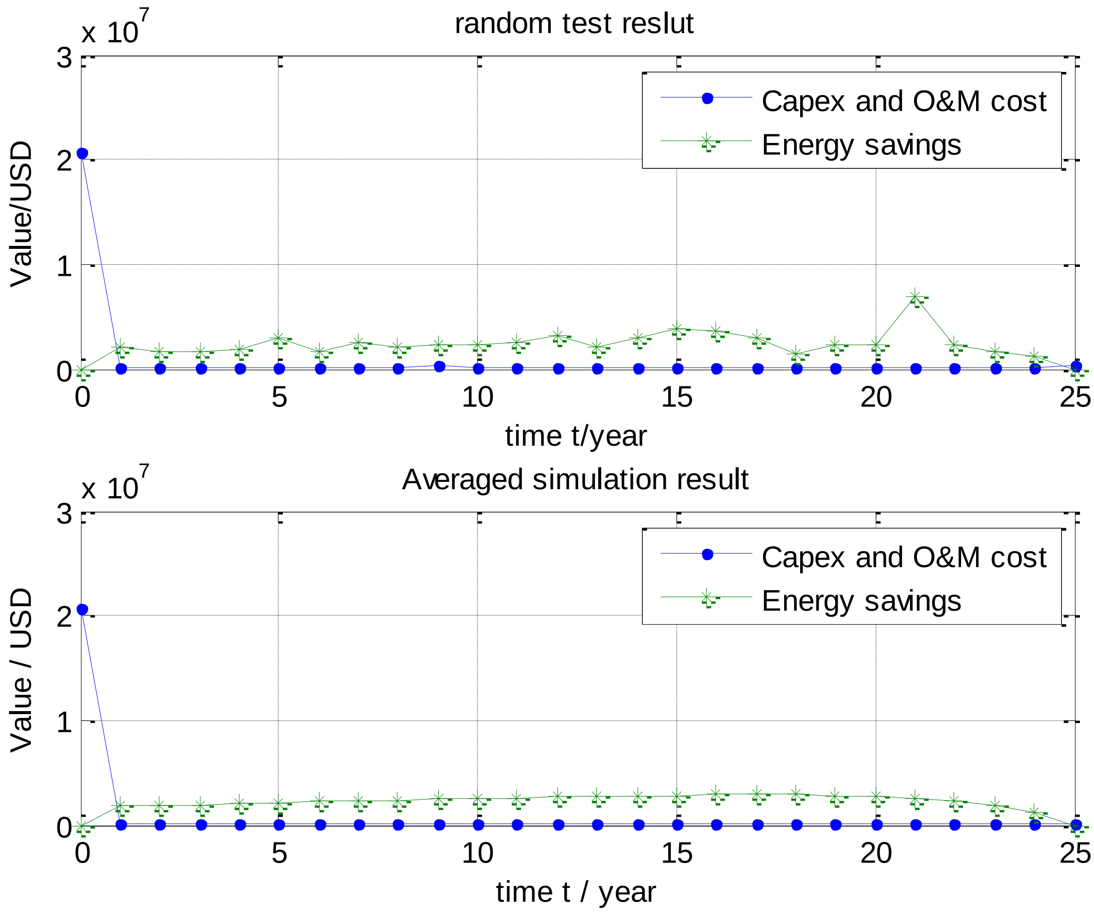


Figure 2.2 Random and Average Results for Cash Flow of Cost Savings and Costs

After obtaining annual energy savings and O&M cost, the project's revenue (NPV) can be calculated and split among stakeholders according to the sharing strategy. Figure 2.3 shows the NPVs of four parties (project, owners, ESCOs, and renters) at different contract periods. For instance, when the contract period is set as 15 years, the NPVs of each stakeholder are -1.1 million USD for ESCOs, 13.7 million USD for owners, 0 for renters, and 17.2 million USD for the project. It can be observed that NPVs of both the project and renters remain unchanged in different contract periods, because a project's NPV only relates to its total investment and energy savings, while renters' NPV is influenced by the shared percentage θ with owners, regardless of the contract period.

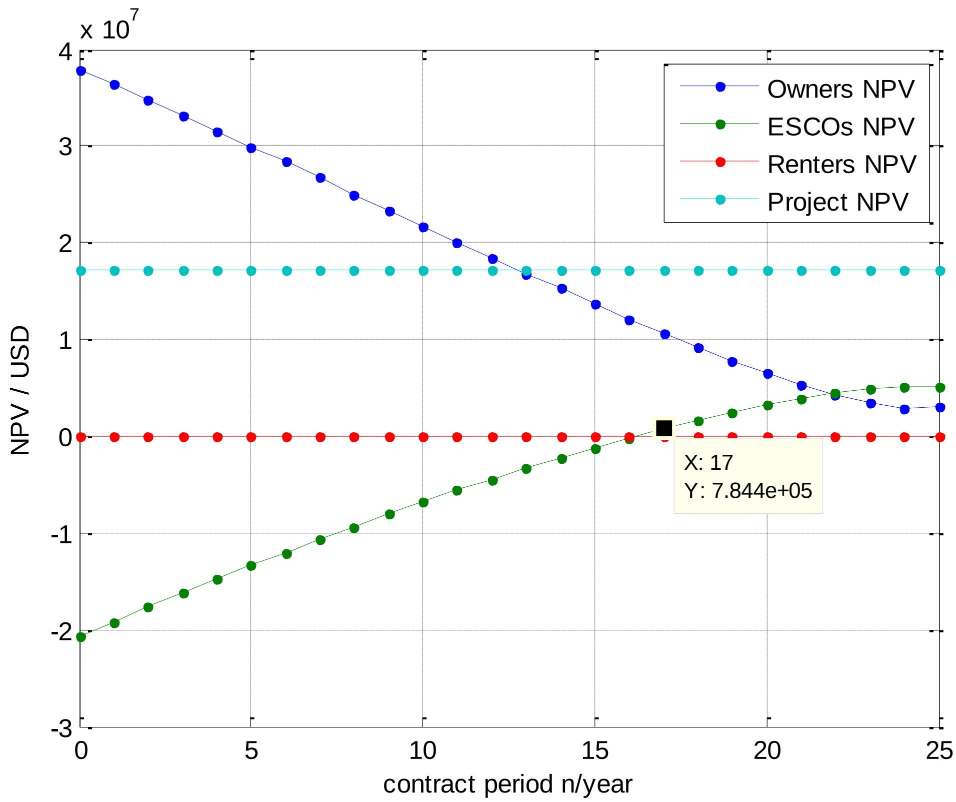


Figure 2.3 NPVs of Four Objects at Different Contract Periods

The trends of building owners and ESCOs are monotonically increasing along with the contract periods. A longer contract period results in a larger NPV for ESCOs since they have the benefit sharing for a longer period and vice versa. The optimal contract period for owners is determined as 17 years, when the NPV of ESCOs first breaks even (larger than 0), which results in a 5-year (41.7%) longer contract (Deng et al., 2014). In this case, the sharing percentage (θ) was initially set to 100%, reflecting no energy saving shared by renters, and their rebound effect is up to 15%. As a result, only 85% of estimated energy savings can be achieved so that a longer period is needed to recover the loss of the rebound effect.

2.5. Results and Discussion

To identify the optimal contract period, this section discusses the sensitivity of key factors from three perspectives: first, the dynamic relationship between the shared percentage (θ) and optimal contract period (n^*); second, an analysis of different risk attitudes (ρ) of renters; third, an examination of the sensitivity of other ESPCs-related variables.

2.5.1 Multilateral Sharing Mechanism

In order to find the optimal θ for both ESCOs and owners, 51 independent simulation trials traverse θ from 0.5 to 1 with a step size of 0.01. The overall project energy savings and the NPVs of relevant stakeholders were calculated for each θ. The premise of acceptable contract period and sharing percentage should have $NPV_E \geq 0$. Figures 2.4 and 2.5, respectively, show the NPVs of both ESCOs and owners at different a θ and the contract periods.

Figure 2.4 shows the positive NPV of ESCOs at available contract periods from 13 to 17 years. For each contract period, the NPV of ESCOs will decrease as θ increases. Taking 14 years of contract period, for instance, if the sharing percentage is greater than 0.9 (say 0.91), the NVP of ESCOs will drop below zero, and ESCOs are not willing to bid the project due to the predicable loss. Alternatively, a longer contract period should guarantee that θ equals or is greater than 0.91 to satisfy an ESCO's requirement. For ESCOs, the highest NPV (1.25 Million USD) can be achieved at $\theta = 0.58$ and $n = 14$. When a contract is 14 years, the θ can range from 0.58 to 0.9, and its corresponding renters' rebound effect would range from 0.12% to 5.5%.

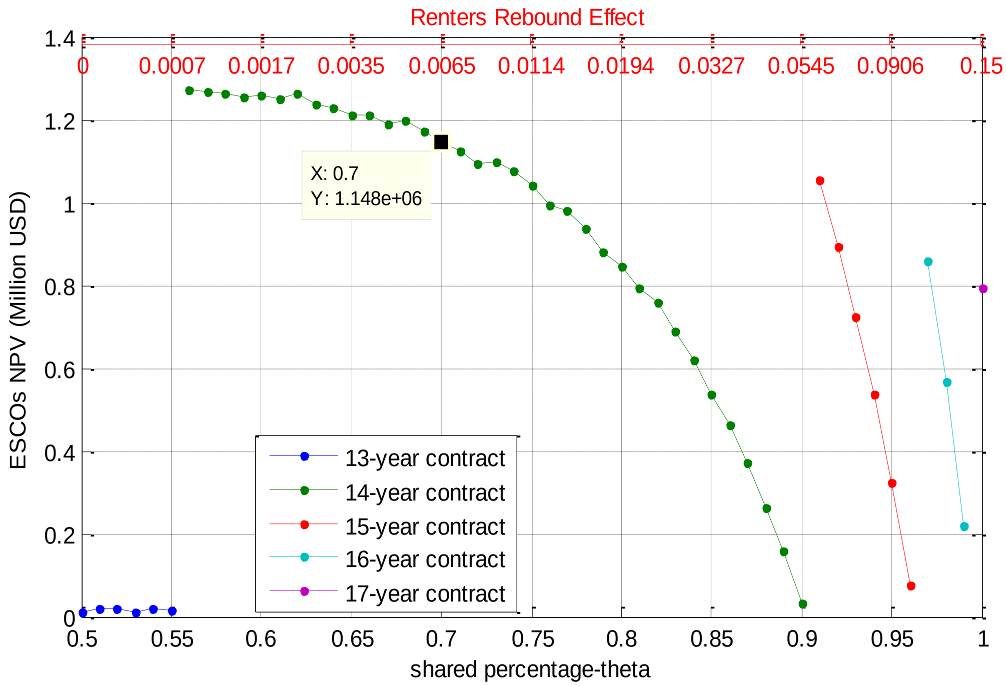


Figure 2.4 NPV of ESCOs at Different Sharing Percentage and Contract Periods When NPV of ESCOs is Positive

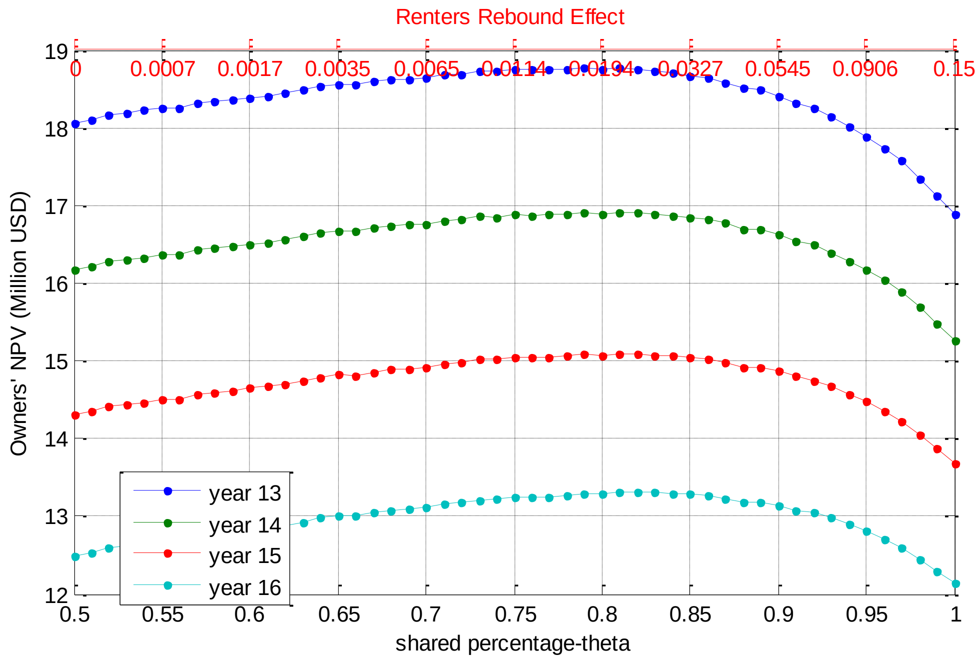


Figure 2.5 NPV of Building Owners at Different Contract Periods and Sharing Percentages

In Figure 2.5, contract period is the dominate variable for owners' NPV. Among different contract periods, the 13-year contract generates the highest NPV. Along with the contract period increases, the owners' NPV decreases since ECSOs will be locked in the sharing contract for a long time. For a given contract period, the owners' NPV follows the concave function of the shared percentage (θ). When θ increases from 0.5 to 0.81, owners' NPV keeps growing since sharing the benefits can mitigate the rebound effect to some extent (0-2.2%). The owners' NPV reaches its highest value when θ equals to 0.81. Thereafter, NPV starts to decrease when θ is greater than 0.81. As a result, considerable rebound effect (2.2%–15%) can be observed and sabotages the actual energy savings. It is noticeable that NPV generated with shared strategy ($\theta \in [0.5,1)$) is always greater than that without sharing ($\theta = 1$), indicating that shared incentive is an effective tool to promote renters' energy conservation behaviors.

For the ESPCs negotiation between ESCOs and owners shown in Figure 2.6, the priority is to determine the contract period (n) and then to determine the shared percentage (θ) because the former is more sensitive for both parties' NPV. Figure 2.6 shows the negotiation process between ESCOs and owners. The acceptable contract period for both parties ranges from 14 to 16 years. A 13-year contract is feasible due to the zero NPV. Therefore, the minimum accepted contract length for ESCOs is 14 years. Comparing to the NPV of a 13-year contract, the owner's cash flow decreases by 10.1% in a 14-year contract, by 19.1% in a 15-year contract, and by 30.3% in a 16-year contract. Hence, a 14-year contract is the equilibrium for both parties.

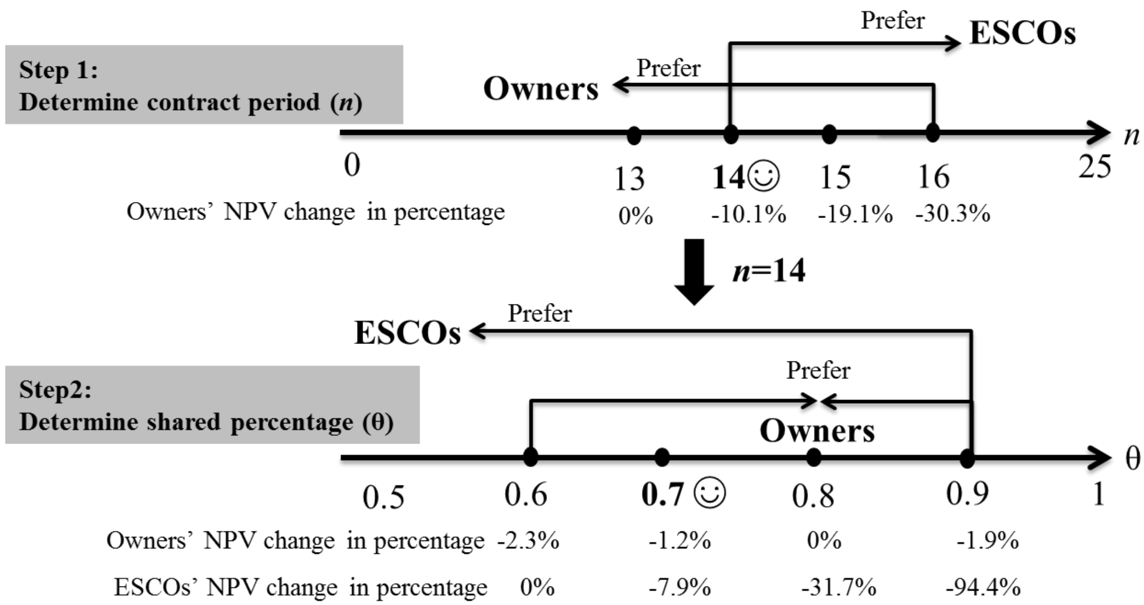


Figure 2.6 Negotiation Process on Contract Period and Shared Percentage

Agreeing upon a 14-year ($n = 14$) contract, ESCOs and owners have the negotiable shared percentage (θ) from 0.6 to 0.8. To compromise the benefits of both parties, the average θ of 0.7 can be assigned. Figure 2.7 shows the results of NVPs of four objects when setting $n = 14$ and shared percentage $\theta = 0.7$.

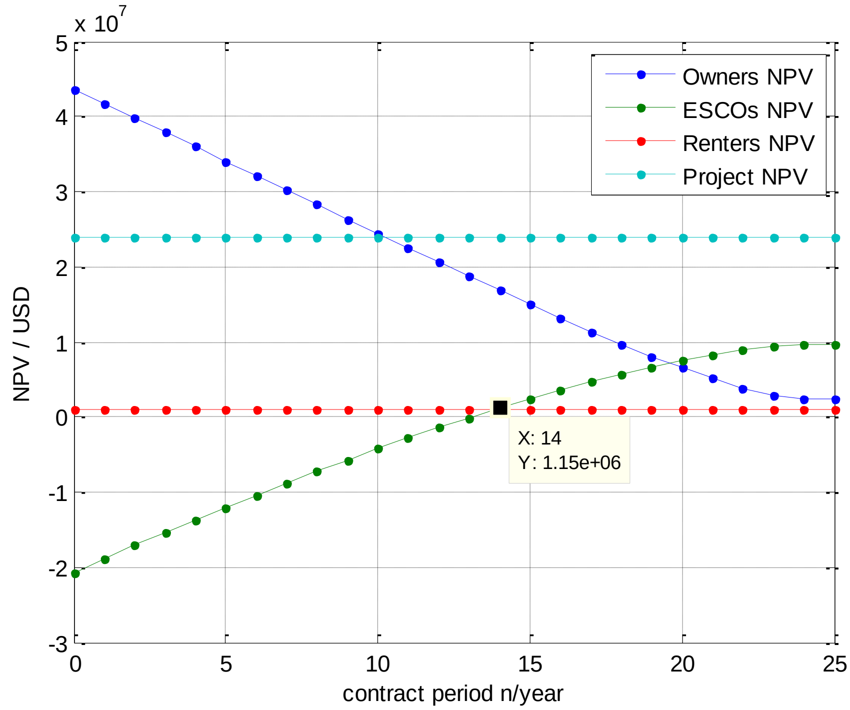
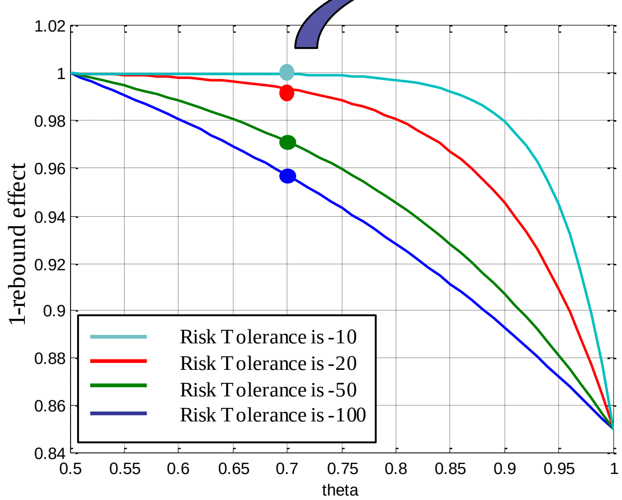


Figure 2.7 NPVs of Four Objects at Different Contract Periods When Sharing Percentage Is 0.7

The truncation on contract length is a win-win result for both parties and will effectively promote ESPCs project bidding and proper risk allocation. The overall project NPV is also increased by 39.5%, from 17.2 million USD (when $\theta = 1$) to 24.0 million USD (when $\theta = 0.7$). For owners, even though they share part of saving benefits to renters, their life cycle NPV still increased by 58.5% from 10.6 million USD (when $n = 17$ and $\theta = 1$) to 16.8 million USD (when $n = 14$, $\theta = 0.7$). For ESCOs, the new shared percentage not only raises their NPV by 46.8%, from 0.79 million USD (when $n = 17$, $\theta = 1$) to 1.16 million USD (when $n = 14$, $\theta = 0.7$), but also increases their competitiveness through a shorter contract period. Therefore, a sophisticated design of contract period and associated shared percentage are crucial to enabling a successful ESPCs project.

2.5.2 Risk Attitude

Risk attitude (ρ) reflects the renters' energy conservation behavior response to incentives and affects their rebound effect ($\overline{Re}(\theta)$). For example, sensitive renters (i.e., schools with tight budgets), presented by the shallow curve ($\rho = -10$) in Figure 2.8, are more easily motivated by shared incentives and therefore change their behavior with a lower rebound effect. The other type of renters (i.e., schools with abundant budgets) may not be sensitive to shared incentives, and they (as "insensitive renters") can be represented as the steep curve ($\rho = -100$) in Figure 2.8. Their rebound effect changes proportionally according to the savings allocated to them.



Risk attitude	NPV of Project (million USD)	Change in percentage	Contract period
ρ=-10	$24.19	9.06%	13
ρ=-20	$23.85	7.53%	14
ρ=-50	$22.84	2.98%	14
ρ=-100	$22.18	0%	14

Figure 2.8 Curves of Risk Tolerances

As indicated in Figure 2.8, when the sharing percentage is fixed (i.e., 0.7), renters with different attitudes can yield different actual savings and result in different projects' NPVs and contract periods. For example, the sensitive renter ($\rho = -10$) resulted in the 9.06% increment of a project's NPV compared to the insensitive renter ($\rho = -100$) and in a 1-year decrease in contract period (from 14 years to 13 years).

2.5.3 Other Influencing Factors

The sensitivity analysis of variables can help decision makers deepen the understanding of performance-based contracts and better position themselves in negotiating ESPCs contracts. In order to measure and compare the impact of each variable, sensitivity coefficients (β_P, β_C) were introduced to normalize their respective impacts on project NPV and optimal contract period. Sensitivity coefficient (β) is calculated by $\beta = \frac{|Y_{max}-Y_{min}|/Y_{baseline}}{X_{max}-X_{min}}$. The greater the value of a coefficient, the higher impact that a parameter would have on the ESPCs contract value and period. Table 2.3 summarizes the result of sensitive analysis for key variables.

Regarding the project NPV, initial investment (I_C) and maximum rebound effect (ϕ) are key variables that most significantly impact project NPV. Capex (I_C) is linearly correlated with energy saving potential, O&M cost, and the project NPV (β_P of Capex=1.00). Compared with initial investment, the maximum rebound effect (ϕ) has limited influence on project NPV because the NPV is explicitly determined by the actual rebound effect and dependent on both ϕ and shared percentage (θ). For example, when the maximum renters' rebound effect (ϕ) is set to 5%, due to the shared incentive applied on renters (shared percentage $= 0.7$), the actual renters' rebound effect is only 0.22% (retrieved from Equation (2.10)).

Another significant factor ($\beta_C = 0.5$) is the ESCOs' expected rate of return r_E, which represents a company's operating income on an investment over a period of time. The choice of expected rates of return (r_E) should be determined carefully by ESCOs based on their needs. A 50% increase of r_E from its original value of $r_E = 0.09$ will result in the minimum acceptable contract period to be stretched to 18 years. An additional 4 years is vital for a tender decision on a new project.

Table 2.3 Sensitive Analysis Results for Key Project Parameters

Parameter	Percentage change Adjusted value		NPV of Project		Optimal contract period (n*)	
	Percentage change	Adjusted value	In millions USD	β_P	In years	β_C
I_c	-50%	$10,334,496	11.96	1.00	14	/
	-20%	$16,535,193	19.09		14	
	0	$20,668,991	23.88		14	
	+20%	$24,802,789	28.62		14	
	+50%	$31,003,487	35.88		14	
G	-83%	500,000	23.89	/	16	0.08
	-75%	1,000,000	23.87		15	
	0	3,000,000	23.88		14	
	+75%	5,000,000	23.89		14	
	+83%	5,500,000	23.90		14	
α	-80%	0.01	23.88	/	13	0.08
	-40%	0.03	23.85		13	
	0	0.05	23.87		14	
	+40%	0.07	23.89		14	
	+80%	0.09	23.79		14	
β	-75%	0.05	23.97	/	13	0.05
	-25%	0.15	23.90		14	
	0	0.20	23.89		14	
	+25%	0.25	23.91		14	
	+75%	0.35	23.90		14	
r_E	-50%	0.03	23.91	/	11	0.50
	-17%	0.05	23.88		13	
	0	0.06	23.89		14	
	+17%	0.07	23.87		15	

	+50%	0.09	23.89		18	
ϕ	-66%	5%	24.03	0.01	14	/
	-33%	10%	24.00		14	
	0	15%	23.92		14	
	+33%	20%	23.81		14	
	+66%	25%	23.67		14	

The guaranteed energy sharing clauses, such as sharing percentages (α, β) and guaranteed savings (G), can cause changes to the optimal contract period. Sharing percentages (α, β) indicate the distribution of energy saving benefits between ESCOs and building owners. A low sharing percentage (α, β) means ESCOs share less from owners. A better-agreed-upon sharing percentage could encourage ESCOs to accept a shorter contract period. For example, ESCOs may offer a 13-year contract when setting α to 0.01 or β to 0.05. However, the value of guaranteed savings (G) needs to be designed carefully to avoid over- or under-estimation. When G is largely lower than the actual savings (under-promise scenario), ESCOs would offer a large portion of savings amount to owners. When sharing percentage β for extra savings $(R_t - G)$ is large (much higher than α), the ESCOs have to extend the contract for a longer period to recover the initial investment. For instance, when G decreases to 500,000 USD, the contract period under this case will increase to 16 years. On the contrary, when G is over-estimated, ESCOs must compensate the saving shortage $(G - R_t)$ to owners based on the contract terms, causing an even longer contract period. In some extreme cases, such as when G is increased by 125%, the corresponding contract period will increase up to 15 years.

2.6. Conclusion

This study introduces a behavior-based decision-making model for evaluating and designing ESPCs contracts in rented properties. Renters' rebound effect, a significant but frequently ignored phenomenon, is incorporated in this model to better estimate potential energy savings. The result shows that renters' rebound effect would cause up to a 4-year difference of acceptable ESPCs contract length in the case study (17-year contract with 15% rebound effect, 13-year contract without rebound). In order to mitigate and eliminate renters' rebound effect, a shared incentive strategy between owners and renters was proposed. The major associated variables with rebound effect were discussed to assess their impacts on the profitability and duration of ESPCs projects, such as renters' risk attitudes (ρ), expected rates of return (r_R, r_O, r_E), and sharing strategy variables (G, α, β).

This proposed research contributes to the body of knowledge in two aspects. First, it incorporates renters' energy rebound effect into ESPCs contract assessment for rented properties. The rebound effect was found to dominantly determine the contract period in this result. Second, the shared saving scheme proposed in the decision model enables a feasible incentive to mitigate the renters' rebound effect. The results suggest the effectiveness of shared saving strategies in jointly achieving energy efficiency from both owners and renters.

However, the study has two limitations that can be studied in the future. First, the rebound effect used in this study was estimated purely based on referred literature rather than direct experimental data. The rebound effect varies among various regions, projects, or users. Future works could focus on quantifying the magnitude of the rebound effect for different types of projects. Second, the stochastic process used in this model makes it difficult to simulate or forecast an event with a small probability and macro factors. For example, the energy price is presented by a stochastic process based on historical data, but such a process is unable to forecast a sudden drop, such as the global oil price decrease in 2015. Further studies could incorporate discrete events into the simulation model.

Chapter 3: Means of Intervention for Occupant Energy Behavior

Abstract

With the advent of the Paris Climate Agreement and China ratifying it recently, there is a need to adopt a diversified approach to address climate change; this is especially the case of promoting residential energy conservation. This study is one of the first household energy intervention studies that focuses on the comparison of two message delivering means, paper-based versus instant messaging tool, as a platform for sharing energy-saving tips and engaging households to save energy in China. Conducted in several communities in Hangzhou, Zhejiang Province of China, the effectiveness of using a widely used application known as WeChat in promoting household energy conservation is compared with that of using stickers. It was found that WeChat is the most effective is reducing monthly consumption but the effects are short-lived. Comparatively, using stickers as a mean of engaging households produces more sustained results in terms of energy savings. This study also provides evidence to correlate the changes in energy consumption behavior with personal perception of one's responsibility and quality of life. That is, certain behavior can be triggered if residents are willing to impose energy ration in their households, or are given more opportunities in the form of local programs that enable them to have more practices in energy conservation.

3.1. Introduction

China is presently regarded as a country with "transition economy", whereby this transition brings a huge change to people in terms of their shared values, consumer behavior, standards of living and other socio-demographic indicators. Over the past decades, the electricity consumption in China has been surging across various sectors, especially for the residential sector which has the highest consumption in overall, as compared to Service & Commercial, Agriculture & Forestry sector (Davidson, 2014). The National Bureau of Statistics of China (NBSC) found a drastic gain of energy use over the last 10 years at annual growth rate of 10.78% on average (NBSC, 2017). The World Energy Issues Monitor 2016 (Frei et al., 2017) also showed noted that the average electricity consumption of electrified household and electricity consumption for electrical appliances and lighting rise by 1% over the last 10 years, leading to a drastic increase of 3.5% of carbon dioxide (CO_2) emissions in households between 1990 to 2014. This highlights the significance of utilization of electrical appliances to household energy consumption.

With the drastic growing trend in China's electricity consumption, it is of critical importance to study the efficacy of energy conservation initiatives and programs. While a variety of legislations and incentive schemes have been introduced to improve energy efficiency and conservation, the effectiveness of the programs and efforts has not generated significant impact to household energy conservation. The electricity consumption across all sectors, in particular, residential sector, is still largely dependent on the residents, regarding their education levels, intrinsic motivation and user behavior that lead to difference on the energy conservation (Schroer, 2008).

This study was thus conducted to find out how household energy intervention methods can be effective in encouraging Chinese households to save electricity consumption. Specifically, the key research objectives are: 1) to evaluate and compare the effectiveness of various antecedent intervention methods (that is, intervention without feedback), with respect to self-reported energy consumption behavior and amount of electricity used; and 2) to find the relationship between various human behavioral and psychological factors, energy consumption behavior and electricity consumption.

3.2 Literature Review

3.2.1 Intervention Methods, Contents and Conveying Means

Intervention methods can be divided into two types: antecedent and consequence. Antecedent intervention is introduced before the act of using energy so as to engage energy-saving behavior through knowledge-strengthening information. Consequence intervention occurs after the act of energy use so as to provide resultant information that reinforce the energy behavior (for example, providing feedback on historical energy consumption). Intervention to conserve household energy exert considerable influence when a combination of tailored information, goal setting, and feedback has been employed. The scope of this research is focused on antecedent intervention (tailored information) on direct energy.

The effectiveness of providing feedback to intervene residents' behaviors is various and depended on different factors such as customized information and frequency of delivery. The individual intervention, in which the information of a resident's energy consumption in the current period compared to the amount in the previous period, can generate significant energy reductions about 5-12% (Dietz et al., 2009, Jain et al. 2012). Studies also found that residents who received comparative feedback of their energy use in relation to peers' consumption tend to show more energy-saving manners than those who received only individual feedback (Shen et al. 2016), because the comparative feedback generate motivational effect that encourages participants to save more energy. Similarly, Delmas and Lessem tested the efficacy of detailed private and public information on electricity conservation in an unique field experiment context in university residence halls (Delmas and Lessem, 2014). Private information that contains energy usage information was delivered through an online dashboard coupled with weekly emails, while public information was presented in the form of posters that publicly rated rooms as above or below averages energy users additionally. They concluded their study that while private information alone was ineffective, a combination of public and private information motivated a 20% reduction in electricity consumption. The competition orientation created by such an intervention strategy can lead to continuous savings even after the intervention (Siero et al. 1996, Abrahamse et al. 2007). For residents living in a well-connected social network so they can effectively communicate among their peers, the intervention-induced energy savings are suggested to be higher (Nilsson et al. 2015).

Another often raised debate with the feedback intervention is to determine the impact of delivering method of the feedback in reducing energy consumption. A Sweden study that included more than 2000 households evaluated the effects of the different ways of presenting feedback used for different intervention groups (Vassileva et al., 2012). Emails become popular in many behavior intervention studies (Asensio and Delmas, 2015, Carrico and Riemer, 2011, Gulbinas and Taylor, 2014, Jain et al., 2013). Jain et al. employed weekly eco-feedback emails in their experiments to examine the impact that information representation has on energy consumption behavior by comparing the effectiveness of direct energy feedback versus feedback represented as environmental externality (Jain et al., 2013). They revealed that information representation has a statistically significant impact on the energy consumption behavior of uses. However, the experiment that provides paper-based manual feedback on energy conservation suggested no significant effect on reducing energy use (Katzev et al. 1980), and this result aligns with other studies (Kua and Wong 2012). Websites or in-home display that have used by relatively high income families can provide easy and instant access to energy information that reflects residents' energy behavior (Vassileva et al. 2013). Web-based feedback resulted in being the most effective compare to direct display and paper-based and achieved approximately 15% electricity savings (Vassileva et al., 2012). A recent research stated that counselling is more powerful in residents' energy conservation (He and Kua 2013).

Given uncertain impact by various delivery methods, it is essential to compare and to choose optimal delivery methods as part of the energy intervention for achieving maximum conservation. In the non-residential building context, Gulbinas and Taylor developed an eco-feedback system in a novel 9-week system study and demonstrated that the organizational network dynamics can significantly affect energy conservation among commercial building occupants (Gulbinas and Taylor, 2014). Weekly emails and stickers were used to remind employers to increase the engagement of the energy management systems. Carrico and Riemer also selected to use monthly group-level feedback emails and peer education to test different energy conservation motivations in the workplace, in addition to the usage of a series of four postcards in the early information campaign (Carrico and Riemer, 2011). The results showed that feedback and peer education resulted in a 7% and 4% energy reduction, respectively (Carrico and Riemer, 2011). In a most recent famous experiment that evidenced environment and health-based information strategies outperform monetary savings in driving residential behavior change, informational messages were delivered via a specialized, consumer-friendly website and weekly accessible emails by personal computer and portable electronic devices (Asensio and Delmas, 2015).

3.2.2. Behavior Intervention in China

Most of past energy behavior related studies in China are based on survey, interview and qualitative inquires. Diansu et al. (2010) conducted surveys and interviews of 600 households in

Liaoning Province; they investigated the relationship between electricity consumption and household lifestyle, and evaluated the potential to improving occupants' behavior in reducing electricity consumption through energy saving education. Wang et al. (2011) studied residents' willingness and behavioral characteristics in saving electricity; they found that economic benefits, policy and social norms, and past experience positively influenced behavior, but physical discomfort negatively influenced such behavior. They concluded that additional and sustainable administrative interventions in electricity marker need to be initiated with government support. Hori et al. (2013) conducted a survey of energy-saving behavior of residents in five Asian cities, including Dalian and Chongqing. They discovered that global warming consciousness, environmental behavior, and social interaction significantly improve energy-saving behavior. Income and age have weaker but positive effects on energy-saving behavior, while social interaction has strongly linkage. They then suggested using community program to modify such behavior.

In their study on Tianjin residents, Xu et al. (2013) found little behavioral change in response to the provisions of monetary incentive, billing-method reform, or metering of heating energy use in individual apartments. Their findings hinted that innovative energy policies, technology upgrades, and education would be needed to promote behavioral changes towards additional savings. Yue et al. (2013) studied 638 households across 6 cities in Jiangsu Province; using an internet survey to study three types of energy-saving behavior and four dimensions of influencing factors – including socio-demographics, energy-saving awareness, behavioral ability, and situational factors. In studying commercial building users in Beijing, Zhang et al. (2013) found that personal norm positively influences employee electricity-saving behavior. In addition, awareness of consequences, ascription of responsibility, and organizational electricity saving programs positively influence personal norm.

In an interesting study on the effect of metering, Ling et al. (2014) quantitatively analyzed the arousal effect of electricity metering policy on occupancy energy-saving behavior. They found that energy-saving rate in the heating season increased significantly from 4.11% in 2008–2009 to 10.27% in 2011–2012, as a result of the metering policy. Chen (2016) conducted one of the few studies on Taiwan; the author argued that extended Theory of Planned Behavior model offers better prediction of one's intention to engage in energy conservation. The findings imply that one's intention to engage in energy savings and carbon reduction is mostly influenced by one's own moral obligation, instead of one's perceived behavioral control. Ma et al. (2016) assessed the impact of culture (6 factors) on the effectiveness of eco-feedback technologies in shaping occupants' energy consumption behavior within the dormitory of Tongji University. They suggested that eco-feedback technologies should be tailored to specific cultural context to improve their effectiveness in building energy conservation. Finally, Ding et al. (2017) investigated 187 individuals in Jiangsu Province and found whether there is any urban-rural and regional differences in the energy-saving behavior of residents. They found evidence that urban residents tend to engage in more energy-saving activities. The most important influencing factor is different and dependent on where these residents live.

Only a few of these studies adopted empirical interventions and that included energy-saving education (Ouyang and Hokao, 2009), changes to energy pricing (Ling et al., 2014) and eco-feedback (Ma et al., 2014). Ouyang and Hokao (2009) examined the effectiveness of education on changing residents' behavior by comparing the energy bill for one month (July) between two consecutive years. Ma et al. (2016) studied the effectiveness of eco-feedback for users from different cultural background but within a campus environment, whereas Ling et al. (2014) conducted a natural experiment in which the regional government reformed the heart-metering price, and resulting in a significant change of occupancy behavior changes in associated areas.

Central to all intervention related studies are the nature of the information and the ways by which it is conveyed to households. Although stickers and leaflets were implemented in several studies (including Thondhlana and Kua, 2015), such intervention method has not been applied to China yet. With the advent of various social media and instant communication platforms, it becomes imperative for us to examine their effectiveness in promoting energy-saving behavior.

WeChat is an instant messaging service in China that was first released in 2011. It is one of the largest messaging applications by more than a billion created accounts and 700 million active users in 2016. WeChat is available on most of current smartphone systems, such as iPhone and Android, as well as a web-based client. It comprises of a variety of functions including text, voice and video messaging, broadcast (one-to-many) messaging, sharing of photographs and videos (known as "Moments"), and also social networking services that are similar to those provided by Facebook and Instagram. Based on a recent national survey (Penguin Intelligence, 2016), WeChat is the most popular smartphone application for Chinese citizens and its users show very high customer loyalty – that is, 94% of WeChat users utilize the application daily, with about 55% of these users spending over 1 hour daily using its services. Such a critical mass of daily users and stable user habit provides an opportunity to study its effectiveness in engaging and promoting energy-saving behavior in households.

3.2.3 Other influencing factors

It is important for household intervention studies to carefully consider how residents' quality of life and views towards their lifestyle determine their energy consumption behavior. This understanding will inform the design of intervention methods that can be implemented to change residents' energy consumption behavior, without compromising their demands for their expected lifestyle. Examples of interpretation and correlation of changes in energy behavior and consumption according to personal values and worldviews include studies by Chelleri et al. (2016), He and Kua (2013), Kua and Wong (2012), and Thondhlana and Kua (2015). Although some of these studies were carried for predominantly Chinese community in Singapore, such correlation studies carried out on China has not been done before. Most of these studies utilizes the quality of life (QOL) variables proposed by Poortinga et al. (2004). QOL is closely link with users behavior in determining natural resources consumption, however one of the key weaknesses of these QOL variables is that to conduct survey of these 22 variables is not always easy. To complement these variables, Kua (2016) proposed the 6-factor system known as RICCOW, which stands Responsibility, Incentive, Capacity, Capability, Opportunity and Willingness. In the context of this study, understanding one's RICCOW means

(a) Knowing one's sense of *responsibility* to save energy;

(b) Knowing the types of *incentive* that will encourage him/her to be more *willing* to save energy;

(c) Knowing how to increase his/her *capability* and *capacity* to save energy; and

(d) Providing appropriate *opportunities* for him/her to save energy.

The relationships between these RICCOW factors and the Theory of Planned Behavior is shown in Figure 3.1, in which the shaded boxes are the main stages in determining pro-environmental behavior according to conventional Theory of Planned Behavior. Posited between "intention" and "pro-environmental behavior" are so-called "context provision factors" that provide the context for "intention transformation factors" – willingness and capacity to save energy

– to take effect, either positively or negatively (Kua, 2016). In short, for intention to lead to pro-environmental behavior, households must be provided with "opportunities" to practice these pro-environmental behaviors. When opportunities are present, they must also be "willing" and have the "capacity" to practice this behavior. Willingness can be enhanced by having adequate and appropriate "capabilities" and "incentives". The more households feel responsible toward, the more likely that they will be willing to practice it.

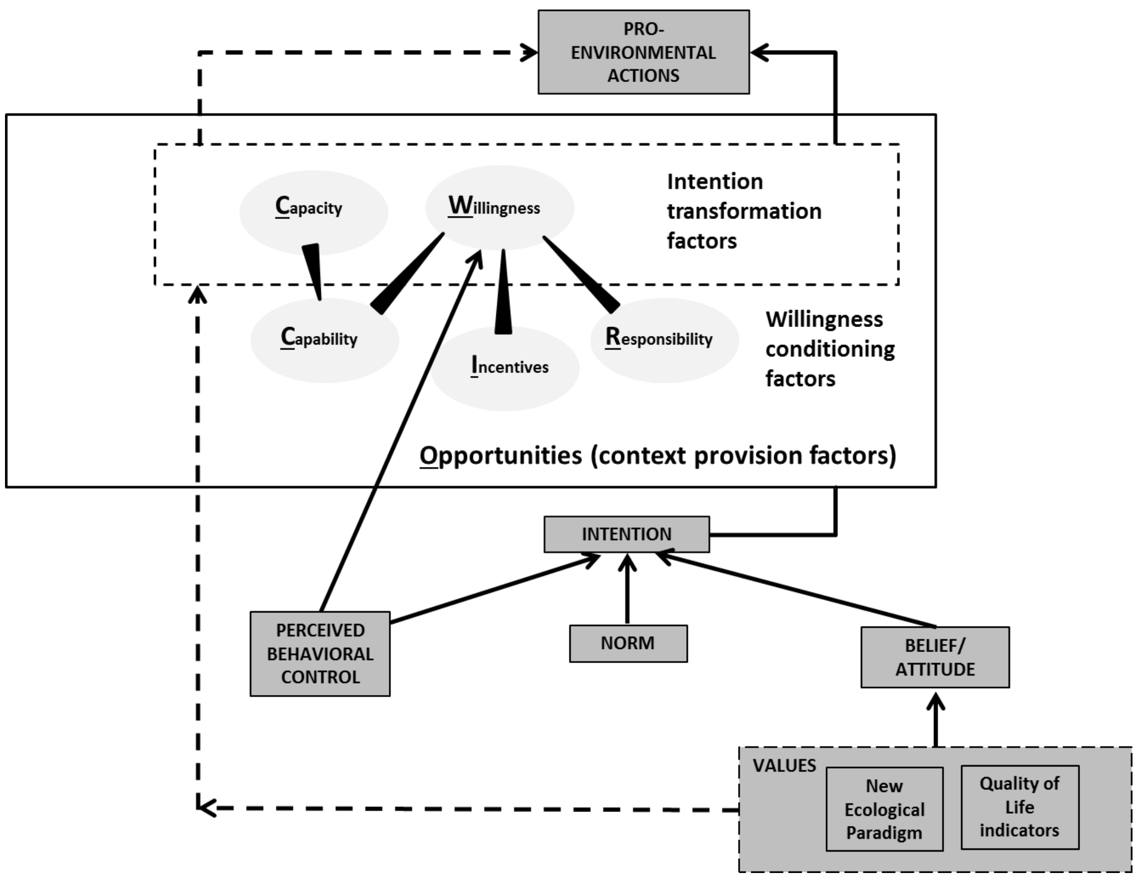


Figure 3.1 The RICCOW Model Proposed by Kua (2016)

3.3. Research Methodology

This study focused on households in two residential communities (Changmu and Qinfeng communities) in Jianggan District of Hangzhou, Zhejiang Province, China. Hangzhou is one of the low-carbon pilot cities selected by China's administration. With prospective social and political environment, the result of this study in Hangzhou would significantly impacts on policy-making of local government, and even on energy behavior conservation policies in China. During the sampling process, a population of 120 households were chosen from these two communities and they were divided into three categories – the Sticker, "WeChat" and Control groups, with 40 samples per group. It is worth to note that two residential communities (Changmu and Qinfeng) were both ordinary residential communities in the same district where residents share similar demographic statistics and living habits without significant difference. Table 3.1 provides the details for each of these three group. A sample of energy saving tips is shown in Figure 3.2.

The overall sequence of the intervention process is shown in Figure 3.3. In summary, only direct energy consumption of electricity was studied. The study began in January 2016 and ended in June 2016. Participants were notified for the commencement of the energy-savings campaign on 15th January 2016. Although the actual intervention starts in April, the consumption data for the earlier months were collected to exam possible existence of the Hawthorne effect. As electricity consumption is likely influenced by varying weather conditions, the daily forecasted weather information from the year of 2015 to July 2016 were also retrieved from Hangzhou Meteorological Bureau. They were used during data analysis to uncover possible anomalies in energy consumption data due to changes in weather conditions.

Table 3.1 Details of Treatment and Location of the Three Experimental Groups

Types of Intervention	Community	Sample Sizes	Description of intervention methods
Stickers	Changmu community (Linli, Dong Yuan, Xi Yuan residential complexes)	40	A list of energy-saving tips is shown in the stickers, and it was distributed to the targeted households once every month. Households were encouraged to paste the stickers on the fridge as a form of reminder and for creating awareness regularly. The Chinese and English versions of the sticker designs are shown in Figures 3.2.
WeChat (instant messaging platform)	Qinfeng community (Mingzhu residential complexes)	40	WeChat is the most common social chatting platform that is widely used in China. Upon selected to be part of this intervention group, households were asked for the WeChat IDs of as many of the household members as possible. WeChat messages that contain energy-savings tips and reminders (the same information as printed in stickers) were sent to the targeted households twice a month.
Control (without intervention)	Changmu community (Dong Yuan, Xi Yuan residential complexes)	40	The control group was not given any intervention.

Save energy. Make your effort.

5 energy saving tips:
1. Use a fan instead of an air-conditioner to keep cool
2. Choose energy efficient light bulbs
3. Switch off main power (when not in use)
4. Set AC cooling temperature $26^{o}C$ or above
5. Select energy efficiency labelled appliance

More tips:
1. Use more natural light
2. Shut the contains or blinds
3. Boil water before necessary use
4. Turn on air-conditioner one hour before sleep
5. Use a fan instead of an air-conditioner before sleep
6. Keep the refrigerator away from heat sources
7. Do not overfill the refrigerator
8. Turn off the set-top box when you are not watching TV

Figure 3.2 Energy-Saving Tips (in Chinese) and Translation in English

<u>January 2016</u>
- Notification of residents of the study (on 15th January).
- Collection of electricity bills.

➡

<u>February and March 2016</u>
- Conducting of survey A and B.
- Collection of electricity bills.

➡

<u>April, May and June 2016</u>
- Conducting of survey B.
- In June, survey A was *also* conducted for the second time in this study.
- Implementation of intervention, if applicable.
- Collection of electricity bills.

Figure 3.3 Sequence of the Interventions Over the 6-Month Experiment Period

Participants were then approached in February to answer a questionnaire (that is, survey A, shown in Appendix A) that recorded any changes in self-reported energy consumption behavior.

The survey questionnaire was adapted from He and Kua (2013), in which they conducted an experiment of energy saving behavior intervention in Singapore. Aside from questions on the possession of the appliances (e.g. number of air-condition, fridges and washers), the behavior survey is grouped by sets of operation behaviors on the air-conditioner, refrigerator, lighting and home electronics. More precisely, the respondents are asked questions relating to the use of the appliance, in terms of the frequency and/or the way they use it. Demographic, QOL and RICCOW factors were recorded and evaluated using a second questionnaire (survey B, shown in Appendix B); any correlations among these various factors and the self-reported behavioral changes (taken from responses to Appendix A) were evaluated. Demographic profiles of households were recorded; this include household members' age, households' size, income, education level, housing type and so on; all these are the basic yet essential factors which might influence the results of the study. Such information allowed us to evaluate any correlation between them and any reduction in electricity consumption. The second questionnaire (Appendix B, Part 2 and 3) was designed based on the QOL factors proposed by Poortinga et al., (2004) and RICCOW factors proposed by Kua (2016). Subsequently, all interventions were given from April to June 2016.

Six kinds of quantitative/qualitative analyses were performed on the data collected. They are

i. Correlation between demographic factors and energy consumption/energy behavioral scores,
ii. Differences in energy behavioral scores between treatment and control groups; that is, differences between Sticker group's average score and control group's average score were found. The statistical significance of such differences were evaluated.

iii. Differences in monthly energy consumption between treatment and control groups; that is, differences between Sticker group's average consumption and control group's average consumption were found. The statistical significance of such differences were evaluated.

iv. Correlation between energy behavioral scores and QOL/RICCOW factors,

v. Correlation between energy consumption and QOL/RICCOW factors, and

vi. Correlation between energy behavioral scores and energy consumptions.

The Shapiro-Wilk's test was used to determine whether the obtained data set is normally distributed. If the condition of normality is not met, non-parametric statistical methods were employed for the aforementioned six types of tests.

3.4. Results

A total of 116 out of the intended 120 households completed the entire study. As shown in Table 3.2, 56 of them lives in economically affordable housing, with majority of the households having 3 to 4 family members each. The household sample distribution shows that over 22% of household occupants belong either to Generation Z (those born in the range from mid-1990s to early 2000s), Generation Y (those born in the 1980s and early 1990s) or baby boomers (those born between 1946 and 1964). Above 50% of the households receive education level up to university degree. Majority of the households has also indicated a total monthly income between 5,000¥ (Chinese Yuan) and 15,000¥. This distribution may potentially influence households' self-reported energy behavioral scores and electricity consumption monthly.

Table 3.2 Characteristics of Households Involved in This Study

Demographics	Range	Numbers	Percent (%)
Housing Type	Commercial	38	32.76
	Economically affordable housing	56	48.27
	Low-rent housing	None	None
	Resettlement housing	22	18.97
Age groups	< 27 years old	81	22.63
	27 - 34 years old	71	19.83
	35 - 45 years old	43	12.01
	46 - 59 years old	83	23.18
	> 59 years old	80	22.35
Number of members per household	1 – 2 members	30	26.09
	3 – 4 members	59	51.30
	5 – 6 members	22	19.13
	7 – 8 members	4	3.48
Education Level	Below Primary School	2	1.74
	Primary School	None	None
	Junior School	9	7.83
	Senior High School (Technical Secondary, Vocational, and Technical School)	26	22.61
	Diploma (Higher Vocational School)	14	12.17
	Degree	59	51.30
	Postgraduate and above	5	4.35
Income Level	Below 5,000¥	28	24.56
	Between 5,000¥ and 10,000¥	43	37.72
	Between 10,000¥ to 15,000¥	24	21.05
	Between 15,000¥ to 20,000¥	11	9.65
	Between 20,000¥ to 25,000¥	4	3.51
	More than 25,000¥	4	3.51

3.4.1 Changes in Energy Behavior

Using Shapiro-Wilk's test, it was found that the energy behavior scores were not normally distributed. Therefore, the non-parametric Kruskal-Wallis test was used to determine whether there was any significant difference in energy behavior scores amongst the three groups for the months of April, May and June. The results are shown in Table 3.3.

Table 3.3 Different Energy Behaviors Between the Treatment and Control Groups

Energy Behavior Types	Between Groups	Significance Level
1. Refrigerator that is not overloaded.	Stickers and Control	0.038
2. Use automatic time-off switch when possible, for example, after going to bed at night.	WeChat and Control	0.047
3. Regularly check the air-conditioners and clean air filter timely.	WeChat and Control	0.015
4. Frequency of using the washer in a week	WeChat and Control	0.020
5. Switch off the top boxes (of all home electronic devices) when they are not in use?	Stickers and Control	0.011
	WeChat and Control	0.001
6. Turn on the electric water warmer only when necessary. Turn it off and unplug it when it is not in use.	Stickers and Control	0.000
	WeChat and Control	0.000

Note: These results are based on Kruskal-Wallis tests performed on the scores recorded by households in the different treatment and control groups in the energy behavioral survey (Appendices A and B).

Table 3.3 shows that Kruskal-Wallis test found significant difference between the treatment and control groups for only six out of the 29 recommended energy behaviors. Overall, WeChat was found to be more effective than stickers in modifying behavior, because the WeChat group recorded improvements in more types of energy behavior than the Sticker group. Specifically, households in the WeChat group reduced the weekly frequency of using washers, increased the use of automatic timer switch, and more regularly checked and cleaned their air-conditioners. On the other hand, stickers were found to be more effective in reminding residents not to overload their refrigerator and turn off their electric warmers.

3.4.2 Changes in Energy Consumptions

The Shapiro-Wilk's test was applied to determine whether the energy consumption data collected was normally distributed. It was found that the data distribution was skewed and kurtosed (outside ± 2.58), and hence it was concluded that the distribution was not normal. Overall, no significant correlation was found between the demographical factors and energy consumption.

The key results between the intervention and energy consumption are shown in Table 3.4. As mentioned earlier, this study was introduced to all households on 15th January 2016. Although the treatments were only administered in the middle of April, there were significant changes between February and January in all groups. This seems to imply that Hawthorne effect was present; that is, there is an improvement in energy saving purely from an awareness of being observed. However, the annual Chinese New Year was celebrated in the month of February, and the fact that majority of the household members were not at home most of the time could be the key reason that there were significant reductions in electricity consumption from January to February.

Table 3.4 Reductions in Electricity Consumption of Treatment and Control Groups

Groups		**Difference in energy consumption between two months (in kWh)**					
		February and January	**March and February**	**April and March**	**May and April**	**June and May**	**June and January**
Sticker	Mean	85.51	42.69	46.28	12.28	-28.46	158.30
	Significance (2-tailed)	0.00	0.00	0.00	0.02	0.01	0.00
WeChat	Mean	228.39	11.71	35.42	1.92	-51.81	225.63
	Significance (2-tailed)	0.00	0.31	0.00	0.57	0.00	0.00
Control	Mean	114.97	36.28	43.82	0.90	-17.79	178.17
	Significance (2-tailed)	0.00	0.00	0.00	0.83	0.00	0.00

Note: Positive values refer to reductions in consumption from the previous month.

The significant reduction between March and April for the Sticker and Control groups may also indicate the presence of Hawthorne effect; however, changes in the weather in Hangzhou between these two months might be the likely reason. Specifically, the total heating degree day in March was 172.9, whereas that in April was only 14.7. That is, the significant change in weather condition across two months might have contributed to the reduction in electricity consumption (for heating), other than (or instead of) the Hawthorne effect. Similarly, the hot weather exerted influence in June and caused a universal energy increase for all groups between May and June by using more cooling devices. As shown in Table 3.4, consumption reductions were present and significant for all months in the Sticker group, which was the most consistent of all groups.

However, across the six-month study, Sticker group recorded the least reduction (that is, 158.30 kWh).

Over the entire study, the WeChat group recorded the most reduction (that is, 225.63 kWh), compared to Sticker and Control group (158.3 kWh and 178.17 kWh respectively). WeChat messages were sent out to the residents twice every month, and so residents experienced a higher frequency of reminder about energy-saving tips than the sticker group. Hence, it is reasonable to expect that residents might be more likely to act by reducing their electricity consumption in a timely reinforced feedback. However, it was also observed that the results of WeChat were not as consistent as the Sticker group – its effect diminished toward the end of the study and the reduction in the period June-and-May decayed in a great amount (-51.81 kWh). Possible reasons for these findings are presented in Section 3.5.

3.4.3 Correlating Energy Behavior and Consumption with Quality-of-Life and RICCOW Factors

The non-parametric Spearman's rho correlation coefficient test was used to determine whether there is significant correlation between human values/psychological factors and changes in energy behavior. Table 3.5 shows the several variables that are significantly correlated to the energy behavior traits. Out of the 32 QOL and RICCOW variables, only 11 variables were found to significantly correlate with the self-reported energy behavior change. Specifically, most number of households in the Sticker group showed significant changes in the following behavioral traits:

- *Covering up container lids before storing liquid in refrigerator, and this was found to correlate with QOL factors of "importance of comfort in daily life", "good environmental quality", "having sufficient self-esteem and personal identity", "having sufficient personal time", "feel safe" and "live with spirituality".*

- *Keeping the doors and windows closed when air-conditioner is switched on, and this was found to correlate with RICCOW factors of "having strict electricity consumption plan to control budget and conserve energy".*

One can conclude from Table 3.5 that RICCOW factors complement the QOL factors reasonably well, because there are three RICCOW factors that were found to correlate with behavioral traits that do not correlate with any of the 22 QOL factors. However, no significant correlation was found between any QOL or RICCOW factor with the monthly electricity consumption.

3.4.4 Correlation between Behavioral Change and Consumption

The last type of analysis done was identifying any significant correlation between the electricity consumption data and self-reported energy behavior scores. The finding revealed that only one behavior trait has statistically significant correlation with electricity consumption ($p = 0.031$, two-tailed) – the behavior trait of drying clothes under sunlight. In other words, those who practiced drying clothes under natural sunlight, instead of doing so with clothes dryer whenever possible, were also likely found to reduce more electricity consumption.

Table 3.5 Variables That are Significantly Correlated to the Energy Behavior Traits

Treatment group	Behaviors with significant difference between a treatment and control groups	Human values or psychological factors that are significant to the behavioral trait	Significance (2-tailed)
Sticker group	○ Store liquids in the refrigerator after covering it up	– Comfort Level: Having a comfortable and easy daily life	0.002
		– Environment Quality: Having access to clean air, water and soil. Having and maintaining a good environmental quality.	0.007
		– Self-esteem/ Personal Identity: Having sufficient self-respect and being able to develop one's own identity	0.003
		– Leisure Time: Having enough time after work and household work and being able to spend this time satisfactorily.	0.002
		– Safety: Being safe at home and in the streets. Being able to avoid accidents and being protected against criminality.	0.006
		– Spiritual/Religion freedom: Being able to live a life with an emphasis on spirituality and/or with your own religious persuasion.	0.008
	○ Keep windows and doors closed when the air-conditioner is switched on.	– Strict electricity consumption plan (family plans a cut-off point for electricity consumption, which cannot be exceeded every month) help to conserve energy.	0.008
		– Having such energy-saving activity as an opportunity.	0.004
	○ Turn lights off when nobody is in the room.	– Health: Being in good health, access to adequate health care.	0.009

	○ Use task lighting for activities requiring small amount of focus light (for example, only turn reading lamps on and turn the other lights off).	– The higher the education level of family members, the stronger the intention to conserve energy.	0.006
	○ Turn off home appliances (for example, television) not in use instead of leaving on standby.	– Social Recognition: Being appreciated and respected by others.	0.009
	○ Unplug chargers or off the switch when appliances not in use.	– Freedom: Freedom and control over the course of one's life, to be able to decide for yourself, what you do, when and how.	0.01
		– Living Condition: Having nice possessions in and around the house.	0.004
		– Income: Having enough money to buy and to do the thing necessary and pleasing.	0.001
	○ Set the thermostat below 20^{o}C (or turn off air-conditioner) during winter; Set the thermostat above 26^{o}C during summer	– Environment Quality: Having access to clean air, water and soil. Having and maintaining a good environmental quality.	0.008

WeChat group	○ Keep windows and doors closed when the air-conditioner is switched on.	– Having such energy-saving activity as an opportunity.	0.004
	○ Allow some space all around the fridge.	– Safety: Being safe at home and in the streets. Being able to avoid accidents and being protected against criminality.	0.007
		– Comfort Level: Having a comfortable and easy daily life.	0.001
	○ Store liquids in the refrigerator after covering it up.	– Environment quality: Having access to clean air, water and soil. Having and maintaining a good environmental quality.	0.002
		– Self-esteem/ Personal Identity: Having sufficient self-respect and being able to develop one's own identity.	0.003
		– Safety: Being safe at home and in the streets. Being able to avoid accidents and being protected against criminality.	0.006
	○ Turn lights off when nobody is in the room.	– Health: Being in good health, access to adequate health care.	0.003
		– Environment quality: Having access to clean air, water and soil. Having and maintaining a good environmental quality.	0.004
	○ Unplug chargers or off the switch when appliances not in use.	– Income: Having enough money to buy and to do the thing necessary and pleasing.	0.000

3.5. Discussion of Findings

Described in Section 3.4.1, WeChat was the most effective in triggering significant behavioral changes than using stickers. Although the WeChat group recorded the most energy savings between June and January (that is, 225.63 kWh), the amount of saving decreased through the months – from 228.39 kWh (between February and January) to 35.42 kWh (between April and March). The messages that were sent to residents via WeChat were not varied throughout the study; therefore, the fact that respondents might have gotten used to receiving similar (albeit more regular) messages to the extent that they might not pay as much attention to these messages over a longer period of time. In other words, the effectiveness in using instant messaging platform, such as WeChat, was short-lived.

It was observed that even the control group recorded significant reductions as well. Although this group was informed about the energy saving study, they were neither informed that they were the control nor the nature of the other treatment groups; therefore, it is likely that they had considered themselves as being "treated" and the information given to them about the study was the treatment itself. The decreased sharply – from 114.97 kWh (between February and January) to 43.82 kWh (between April and March). This decrease is expected because without additional treatment, the effect of merely receiving information about this study itself is unlikely to sustain.

Although the 22 QOL factors proposed by Poortinga et al. (2004) were widely used for correlating energy behavior and consumption with personal values or worldviews, results of the present study clearly indicated that the 22 QOL factors are insufficient to describe all the observations. Three RICCOW factors correlate with several behavioral traits that QOL factors are unable to correlate with. Specifically, the action to keep windows and doors closed when the air-conditioner is switched on was found to be correlated with a willingness (the RICCOW factor of "willingness") to set and achieve specific consumption targets and having an opportunity to commit to energy saving. People who believe that higher education (leads to the RICCOW factor of "capacity") to save energy also commit more to using task lighting. However, it is worth noting that although the notion that higher educational level of family members leads to stronger intention to save energy has a significant influence on the increased use of task lighting, statistical analyses proved that educational level is not correlated with any improvement in behavioral traits.

Finally, although data on energy consumption and behavior congruently show the advantage of using the WeChat treatment, the correlation of these variables with QOL or RICCOW showed very different results. Firstly, these results reflect the complexity and difficulty involved in linking psychological or social factors to behavior and, even more so, actual reductions in electricity consumptions. Secondly, while changing energy behavior has been an aspiring target for many similar studies in the past and ongoing energy policies around the world, it is worth pointing out that not all pro-environmental behavior will lead to eventual energy reduction (even without considering the infamous rebound effect). One of the reasons is that existing physical problems in buildings may negate effects of energy-saving behavior. A good example is electrical appliances that are not energy efficient. Even though improvement in energy behavior may not lead to actual savings, they should still be promoted by using different policies because if the right sets of conditions were presented or provided in the future – for example, more energy efficient appliances are made available or better wall insulations are installed – these actions will likely lead to actual energy savings.

3.6. Conclusion

This study is likely to be the first in the literature that investigates and compares the effectiveness of using instant messaging platform and stickers for promotion of energy saving in households in China. It is also the first study in which a set of RICCOW factors was used to correlate participants with their self-reported energy behavior and energy consumption. It was found that WeChat is the most effective is reducing monthly consumption, but effects are short-lived. In contrast, using stickers as a mean of engaging households produces more sustained results. This study also provides evidence that not all changes in energy consumption behavior can be readily correlated with personal perception of quality of life. Additionally, certain behavior can be triggered if residents are willing to impose energy ration in their households, or are given more opportunities that enable them to have more practices in energy conservation.

As the Paris Climate Agreement enters into effect and China ratifying it ahead of the G20 Summit in September 2016, climate change mitigation efforts worldwide should more widely embrace the use of creative household intervention methods for a more diversified approach to address climate change. Therefore, more studies are needed to fully understand the acceptability and effectiveness of various intervention methods to the highly diversified populace of China. Another future study is to consider residents' interconnected social network and its effect in influencing the people's energy behavior, because people are social oriented and they are likely to be changed after interacting with a close relative or friend. Meanwhile, long term investigation about the decay effect and rebound effect of intervention is also imperative and can bring significant value to the field. It is hoped that the results will spur more future studies that target on the use of pervasive social media platforms as a mean of engaging a country that will continue to play a very crucial role in deciding the eventual success of climate change strategies in meeting our common global mitigation goal.

Chapter 4: Occupant Personality, Behavior and Energy Use Forecasting[1]

Abstract

Household electricity consumption influenced by various behavioral intervention strategies is difficult to predict due to the uncertainty arises from involved human behaviors and their responses to intervention. Based on an energy conservation experiment conducted in Hangzhou, China, the study aims to develop an improved Support Vector Regression (SVR) model that is capable of predicting household electricity consumption under multiple intervention strategies. The proposed model incorporates personality traits into the consumption prediction. This study firstly proposes a variable selection approach to determine the best subset of consumption predictors using Akaike Information Criterion (AIC). 18 of the 48 initial variables have been considered as the critical predictors, including energy behaviors, personality traits, demographic/building features, weather indicators and the historical monthly consumption in this research. Furthermore, this research also introduces the interaction effect between the energy behavior and all other predictors mentioned above to the SVR prediction model which applies Gaussian radial basis function (RBF) optimized by genetic algorithm (GA) as the kernel function. The results show that the proposed model achieves high accuracy and robust performance on the next-month prediction and time-series forecasting. More importantly, the improved SVR model is able to select the optimal intervention strategy and to predict the maximum electricity savings for each household. The proposed optimized intervention strategies enable the households to achieve an average reduction of 12.1% in monthly electricity consumption compared with the conventional behavioral intervention.

[1] The abridged vision of this Chapter was previously presented in the 9th International Conference on Applied Energy, ICAE2017, 21-24 August 2017, Cardiff, UK.

Moreover, through performing Monte Carlo simulation to explore the relationship between personality traits, the best-fit intervention strategies and the maximum electricity savings, the study also identifies five types of households with different combinations of extraversion and conscientiousness that respond differently to the optimized interventions. The findings of this study contribute to the residential demand-side energy management by enriching and diversifying personalized behavioral intervention strategies.

4.1 Introduction

The residential sector is considered as the key sector for energy saving potentials in China. In 2015, residential buildings contributed to 13.1% of the electricity use (NEAC, 2016), and this amount of consumption continued to quickly expand by 10.8% in 2016 (NEAC, 2017). Recent research reveals that other than innovative energy-efficient technology, occupant behavior driven energy reductions could also be a promising strategy to tackle this problem (Khosrowpour et al., 2016b). Since household energy-related behavior itself can significantly bear on energy use (Schakib-Ekbatan et al., 2015), there is plenty of room in energy conservation in buildings through introducing multiple behavioral intervention strategies to change occupant behaviors (Stern, 2011).

As existing studies seldom considered and quantified the impacts of occupant behaviors and other personal characteristics on household electricity consumption, the effectiveness of behavioral interventions may not be assessed and predicted accurately (Steg, 2008, Martinaitis et al., 2015). In particular, for residents with heterogeneous characteristics, there is a growing need to identify key energy behaviors, in order to predict the household energy consumption accurately through different intervention strategies (Huebner et al., 2013, Huebner et al., 2016). However, the energy-related behaviors cannot be easily measured, due to the influence from a wide range of factors such as personalities and situated contexts (Gatersleben et al., 2002). Moreover, although the majority of behavioral intervention studies have focused on conducting statistical analysis of a field and/or on laboratory experiment (Chen et al., 2017a, Pichert and Katsikopoulos, 2008) or carrying out a system simulation experiment (Anderson and Lee, 2016), the impacts of different delivering method of electricity usage feedback are still unclear. In addition, previous research on the linkage between personal characteristics (such as openness to suggestion) and the intervention effects rarely explained why a uniform intervention may have different impacts on occupants with different personality traits (Shen and Cui, 2015, Shen et al., 2015). That is, personality being a fundamental construct of our attitudes, values and beliefs, may be a significant predictor of the energy behavior and energy consumption (Milfont and Sibley, 2012). With this in mind, the study starts with the following questions: What is the impact of the interaction between occupant behaviors, and personality traits as well as interventions on household electricity consumption? How to predict household energy consumption by considering occupant behaviors and their personality traits under multiple behavioral intervention strategies? Can the intervention strategies be better designed to achieve the maximal household electricity savings?

Therefore, this study aims to 1) propose an optimal Support Vector Regression (SVR) model for accurately predicting household consumption under multiple intervention strategies, 2) choose the best-fit intervention strategy that can generate the maximum electricity savings for every single household, and 3) clarify the relationship between residents' responses to intervention strategies and their personality traits. To achieve it, a variable selection approach was adopted to determine the optimal set of household electricity consumption predictors that include energy-related behaviors, personality traits, demographic variables, building features and weather data.

Then, the interaction effect between behaviors and other variables has also been introduced to predict households' electricity consumption. The data supporting SVR model development are collected from an energy conservation experiment conducted to infer the effects of feedback via different delivered methods including paper, mobile application and face-to-face interactions on household monthly electricity consumption in Hangzhou, China. Last but not least, Monte Carlo method is employed to simulate the profiles of households to examine the effects of personality traits on concerted intervention strategies.

The structure of this chapter is as follows. Section 4.2 describes the recent literature pertinent to behavioral interventions in terms of energy conservation and the variables used in predicting energy consumption by the machine learning. Section 4.3 presents the experiment design and data collection. Section 4.4 explains the methodology adopted in this study and the SVR modelling process. Section 4.5 describes the results of electricity savings prediction from the proposed SVR model. Section 4.6 designs the optimal intervention strategy for maximum electricity saving based on different personality traits of extraversion and conscientiousness. Section 4.7 concludes this research with both practical and policy implications.

4.2 Literature review

4.2.1 Behavioral Intervention Strategies for Energy Conservation

Intervention strategies in energy conservation domain have been divided into two categories, respectively informational strategies (e.g. information, feedback, education) and structural strategies (e.g. services, price policies) (Steg, 2008). Several studies (Bowles, 2008, Wolak, 2011) proved that structural strategies which mainly focused on changing contextual factors, such as providing incentives or disincentives, are not able to lead the residents' pro-environmental behaviors to a favorable movement due to “crowding out” intrinsic motivation to save energy (Frederiks et al., 2015). With regard to the information-based strategies, traditional education programs and media campaigns which simply distribute pro-environmental information to the public do not necessarily trigger durable behavior change due to the attitude-action gap (Frederiks et al., 2015, Asensio and Delmas, 2015). Moreover, the energy-saving tips are one of the powerful and commonly used strategies which often coupled with other types of intervention strategies. The provision of information tips could significantly enhance the effectiveness of intervention when delivered with other information, such as energy audits (Corradi et al., 2013), while others (Delmas et al., 2013) argued it only offered marginal effect in persuading residents to change behaviors. Focusing on energy-use feedback intervention which contributes to the change of residents’ behaviors, its effectiveness has been tested in a multitude of field experiment studies (Schultz et al., 2015, Nilsson et al., 2014, Lynham et al., 2016). By delivering residents the messages including the amount of energy consumption and comparison to the previous period, the feedback approach can generate moderate and robust reductions at range of 5-12% in energy usage (Dietz et al., 2009, Jain et al., 2012). Compared with participants in individual feedback group, those who received comparative feedback tend to show more energy-saving manners (Shen et al., 2016). This is due to the fact that the motivational effect of comparative feedback was straightforward and encouraged participants to save more energy. The competition orientation created by this strategy led to continuous savings even after the intervention (Siero et al., 1996, Abrahamse et al., 2007). Besides, the interconnected social network among groups and participants could promote the communication between them, leading to energy savings higher than the ones receiving comparative feedback (Nilsson et al., 2015).

An often-raised debate with the feedback intervention is that whether the combination of descriptive and injunctive norm messages may help to reduce the boomerang effect. Schultz et al. (2007) confirmed the effect of the combined normative messages in eliminating the boomerang effect, Anderson et al. (2017) did not support this idea since they found no significant energy savings generated from the messages. The reason behind is that the personally designed handwritten message caused a stronger sense of social pressure and concern. However, there is a scarcity of research on the impact of delivering method of the feedback in reducing energy consumption. The experiment conducted by Katzev et al. (1980), revealed the negligible impact of paper-based manual feedback (given every three days) on energy conservation. This was in line with other studies that also indicated no significant effect of feedback in reducing energy consumption (Kua and Wong, 2012). A recent research explored the effectiveness of counselling in behavioral intervention and found that counselling is more powerful in energy conservation when employed with pamphlets and stickers (He and Kua, 2013). Besides, websites or in-home display that were usually used by households with higher income provided convenient and simultaneous access to instant information reflecting their energy behavior (Vassileva et al., 2013). Provided the uncertain impact of various message delivery methods, it is essential to recommend appropriate interventions as part of the energy policy for achieving maximum conservation. Thus in this study, the effectiveness of the following behavioral intervention strategies have been examined: home energy reports containing only feedback, and the reports containing feedback and energy-saving tips. The ways of disseminating reports to the households, including through paper, mobile application and face-to-face consultation have also been investigated in the study respectively.

4.2.2 Machine Learning Techniques for Energy Consumption Prediction

Literature is rich in adopting traditional machine learning techniques to model and forecast energy consumption. A series of approaches including Multiple Linear Regression (MLR) (Bianco et al., 2009), Decision Tree (DT) (Tso and Yau, 2007), Artificial Neural Network (ANN) (González and Zamarreno, 2005), SVR (Jung et al., 2015) and others (Robinson et al., 2017) have been proposed by incorporating varied variables for accurate energy consumption prediction. MLR is a commonly used linear technique and served as a benchmark of prediction performance. Among the machine learning models, it has the merits of being easy to interpret and computationally efficient (Fumo and Biswas, 2015). However, the poor accuracy of prediction precludes it from dealing with modeling nonlinearity (Wang and Srinivasan, 2017). DT is one of the most popular intelligence algorithms in last decades (Yu et al., 2010). However, it suffers from severe probability influence, which leads to poor reproducibility in prediction accuracy (Østergård et al., 2018). With regard to ANN, several studies adopted this intelligence technique to predict energy consumption in buildings (Kalogirou and Bojic, 2000, Neto and Fiorelli, 2008, Wong et al., 2010) since it can capture nonlinearity and consider a three-layer neural network to obtain relatively high prediction accuracy of a continuous function described by Kromogol's theorem (Wang et al., 2012). Nevertheless, there are many problems with ANN models, such as the difficulty of controlling multiple variables, the high probability of overfitting and the uncertain solutions (Chou and Ngo, 2016).

With the predominant generalization, SVR is especially capable of dealing with complex and nonlinear relationships and has reliable predictive ability for limited sample size (Chia et al., 2015). Therefore, it has been widely proved to be a more accurate energy consumption prediction tool compared with the methods above (Massana et al., 2015, Chou and Bui, 2014). Zhu et al. (Zhu et al., 2015) proposed an SVR approach with the false neighbor's filtered-SVR local predictor that took the specific individual behaviors of different days into account. By removing the false neighbors, the new algorithm was able to optimize the original local predictors for the natural gas demand forecasting. In a study of nuclear energy consumption forecasting (Tang et al., 2012), least squares support vector regression (LSSVR) and ensemble empirical mode decomposition (EEMD) have been employed to decompose the original data into several intrinsic model functions (IMFs) and then to predict each of those generated functions separately. The research however did not consider various factors that might have influence on nuclear energy consumption as it only performed a univariate time series analysis. It is worth to note that a dominant step of SVR model is to choose the suitable kernel function since different kernel types may result in different predictive performance. To achieve better prediction accuracy, the optimal individual kernel-based SVR model (Chen et al., 2017b) and hybrid kernel-based SVR model (Che and Wang, 2014) have both been discussed in energy consumption prediction. In addition, another challenge for SVR modelling in energy consumption prediction is the selection of SVR parameters. It is worth mentioning that several methods including differential evolution (DE) algorithm (Wang et al., 2012), particle swarm optimization (PSO) (Yang et al., 2016) and other hybrid algorithms (Jung et al., 2015) were utilized to select parameters of SVR model in different research contexts. Recently, Cao and Wu (2016) carried out the fruit fly optimization algorithm (FOA) to select the parameters of SVR model, and further optimized the performance of the model by incorporating the seasonal index adjustment. Their results demonstrated that the proposed hybrid SVR model performed better than seasonal ARIMA (SARIMA), back-propagation neural networks (BPNN) and other conventional SVR models in predictive accuracy. Since the majority of research have admitted that SVR is a robust and effective approach to predict energy consumption, it is adopted as the algorithm to predict household electricity consumption under multiple behavioral intervention strategies in this research.

4.2.3 Energy Consumption Predictors in Machine Learning Techniques

4.2.3.1 Variables of Occupant Behavior

Owning to complex and intertwined occupant behaviors, current predictive approaches in residential buildings yield unsatisfactory accuracy when compared with commercial buildings. Burger and Moura (2015) discussed an ensemble learning method that potentially forecast the electricity demand across building use-types. The results revealed that the forecasts for residential buildings yielded a mediocre result with a mean absolute percent error of only 55.8%, much lower than the forecasts for commercial buildings with a mean absolute percent error of 7.5%. Thereby, an increasing number of researchers have begun to probe into the human behavior-based electricity prediction in residential buildings. However, such studies on the development of energy forecasting models considered the impact of human behaviors are still in the beginning stages. Wang et al. (2016b) proposed artificial intelligence (AI) models to predict the hourly electricity use in residential space heating. Comparing with the prediction performance of BPNN, radial basis function neural network (RBFNN) and general regression neural network (GRNN), their study demonstrated that the SVR was better than the rest of the models. More importantly, they also evaluated the effect of dynamic occupant behaviors on the prediction ability of the AI models. Based on the American time use data (ATUD), Diao et al. (2017) identified and classified the residents' behaviors to propose a more accurate energy demand and consumption prediction model that integrates k-modes clustering and demographic-based probability neural networks. As a result, 10 behavior patterns had been recognized according to their demographic profiles including their ages, genders, occupations and lifestyles. However, most of these studies assumed static behavior patterns, but ignored the dynamic change of behavior due to interventions. Virote and Neves-Silva (2012) developed a Markov stochastic model based on the measured building performance data which was able to simulate the occupant behavioral patterns and to predict the energy consumption in different buildings. Focused on the lighting system of the buildings, their results illustrated that the occupant behaviors should be considered as vital variables in the patterns analysis of energy consumption within a building. Similarly, Wang and Ding (2015) also proposed an occupant-based energy consumption prediction model by adopting stochastic methods including Polynomial and Markov chain–Monte Carlo methods. Given the case studies of three different types if office buildings, the model analyzed the relationship between building energy consumption and occupant behaviors. The error rate of the prediction was below 5%, but the estimates of overtime work rate and the consumption of the lighting system were not particularly accurate. Taking occupant actions and presence into account, Wang et al. (2016a) showed their approach of generating stochastic occupancy profiles that can accurately predict the energy usage. Their research also elaborated the impacts of occupancy variables on energy consumption under different scenarios. In addition to the electricity consumption prediction, Zhu et al. (2015) came up with a customer behavior based SVR model that could achieve higher accuracy in the natural gas demand prediction, suggesting that behaviors have a significant influence on the forecasting performance.

4.2.3.2 Building features, household characteristics and other variables

Besides the impact of occupant behavior, the electricity consumption of buildings has also been influenced by other vital input parameters. It is noted that comparing with using all available data, only a subset of data that achieve a higher accuracy to predict energy consumption in buildings (Paudel et al., 2017). Some researches especially paid more attention on exploring the effect of those variables on the predictive performance of machine learning approach. They found that, for residential building electricity consumption, historical energy consumption data was rated as the most important variable that should be employed in general (Chou and Ngo, 2016). The building features including the building orientation, building use, size and morphology (Tsanas and Xifara, 2012, Kontokosta and Tull, 2017), have emerged as the vital predictors. What's more, the weather variables including the outdoor temperature, solar radiation and solar gain on wall have also been identified as powerful variables to predict electricity consumption with fair accuracy (Biswas et al., 2016, Paudel et al., 2017). Nevertheless, even without regard to the outdoor temperature, the machine learning approaches focusing on the electricity usage forecasting of households could still offer accurate and reliable results (Paudel et al., 2017). Furthermore, Candanedo et al. (2017) underscored the importance of involving the data from the kitchen, living room and laundry to predict household energy consumption. When considering the home appliance consumption, numbers of occupants and house size as the input variables, the error rate of the predicting average and maximum consumption are 4.2% and 18.1% respectively, while the error rate of the hourly forecasting energy demand could be amongst 10% to 23.5% (Rodrigues et al., 2014).

Meanwhile, there are evidences showing that the demographic factors are capable of improving the prediction efficiency of energy consumption. For example, Bianco et al. (2009) investigated the annual electricity consumption in residential and non-residential building in Italy during the year of 1970-2007, and developed single and multiple regression models for electricity usage prediction. The results showed that the economic and demographic factors including gross domestic product (GDP) and population could be effectively used to predict the electricity consumption. Likewise, using regression model and ANN, the energy consumption in Turkey has been modelled and predicted based on economic and demographic variables (such as GDP, population and employment) (Kankal et al., 2011). Yet this type of investigation was often based on the idea of aggregating the data at national level rather than individual level due to personal privacy preservation (Mathew et al., 2015). As the building features and climate data are mainly accessible to the public, they have been heavily discussed when developing robust prediction model of energy consumption, while household energy behavior and individual characteristics are rarely explored (Williams and Gomez, 2016). Khosrowpour et al. suggested that the prediction model could be much improved by adding more information related to demographic information, occupant behavior data and appliance energy-use disaggregation (Khosrowpour et al., 2016a). Existing knowledge have discussed the effects of demographic characteristics on personal preference of energy efficient technology. For instance, Yue et al. (2013) pointed out that the middle-aged residents tend to invest in energy efficient products instead of engaging in energy saving programs. Urban and Ščasný (2012) found out that households with higher income are less likely to care about the environment issues, but tend to invest in green products. On the other hand, there remains a lack of discussion on energy consumption prediction under different interventions by incorporating the interaction between occupant behavior and other variables, although the interaction has been proved to have significant effects on energy conservation. Thus, for accurate electricity prediction, the occupant energy behavior, demographic profile, building features, weather condition, the interaction between behavior and other variables are introduced to the model in this study.

4.2.3.3 Personality traits and energy conservation

Personality traits, as the most fundamental aspect of the heterogeneity of people can lead to different pro-environmental behaviors (Stern et al., 2016). However, to the best of existing knowledge, the electricity consumption prediction has been scarcely investigated from occupants' personality perspective. Some researchers began to examine the relationship between personality and pro-environmental behaviors based on the dominant theory of personality, the Big Five Personality Traits (McCrae and Costa Jr, 1997, Khashe et al., 2016, Schweiker et al., 2016, Hirsh, 2010, Milfont and Sibley, 2012). The theory classified the personality into five basic traits, namely extraversion, neuroticism, openness, agreeableness and conscientiousness. In terms of the light setting system in office building, neuroticism has been identified as the only personality trait that has an impact on the participants lighting adjustments (Heydarian et al., 2016). They revealed that the high neurotic person tends to keep the initial setting if the setting has maximum simulated daylight available. Similarly, Komatsu and Nishio (2015) studied the effects of normative messages on motivation for change in electricity conservation and found that the personality is one of the triggers. But the results demonstrated that the normative messages provision was especially effective for people with high extraversion and agreeableness. Openness appears to be the driver to improve the energy saving performance when integrated in the intervention strategy design for energy conservation in the residential sector (Shen et al., 2015). Interestingly, other research showed that conscientiousness and agreeableness were the only two traits that could impact on the electricity conservation behaviors (Milfont and Sibley, 2012). Given such various results, the underlying mechanism of how personality traits have influenced on the resident's energy conservation behaviors and their consequently electricity consumption have been inconclusive, thus more attention should be devoted to this research area.

4.3 Data Collection and Processing

4.3.1 Experimental Design

To facilitate the understanding the intertwined relationship among occupant personality, energy intervention, and energy saving potentials, the electricity conservation experiment was conducted in Hangzhou, a capital of Zhejiang Province in east China, to collect real data and true effect for the analysis. The city was as one of the low-carbon pilot cities by China's government demonstration programs and has also been picked up as the host for 2016's Group of Twenty (G20) summit. With prospective social and political environment, the study in Hangzhou would have significant impacts on policy-making of local government and communities, with great potential of influencing energy behavior conservation policies in China. It is worth to note that the experiment location, two residential communities (Changmu and Qinfeng) in Jianggan District were both ordinary residential communities where residents share similar demographic statistics and living habits as in Hangzhou city.

The home energy report with feedback and energy saving tips was adopted as the main intervention strategy in this study. Three types of energy report delivery, including through paper, mobile application and face-to-face interactions, were also tested in the experiment. These elements were integrated in the design process and come up with five treatment groups and one control group. Before any types of intervention could be delivered, all of the households in the selected communities had been randomly assigned to the six groups (see Table 4.1).

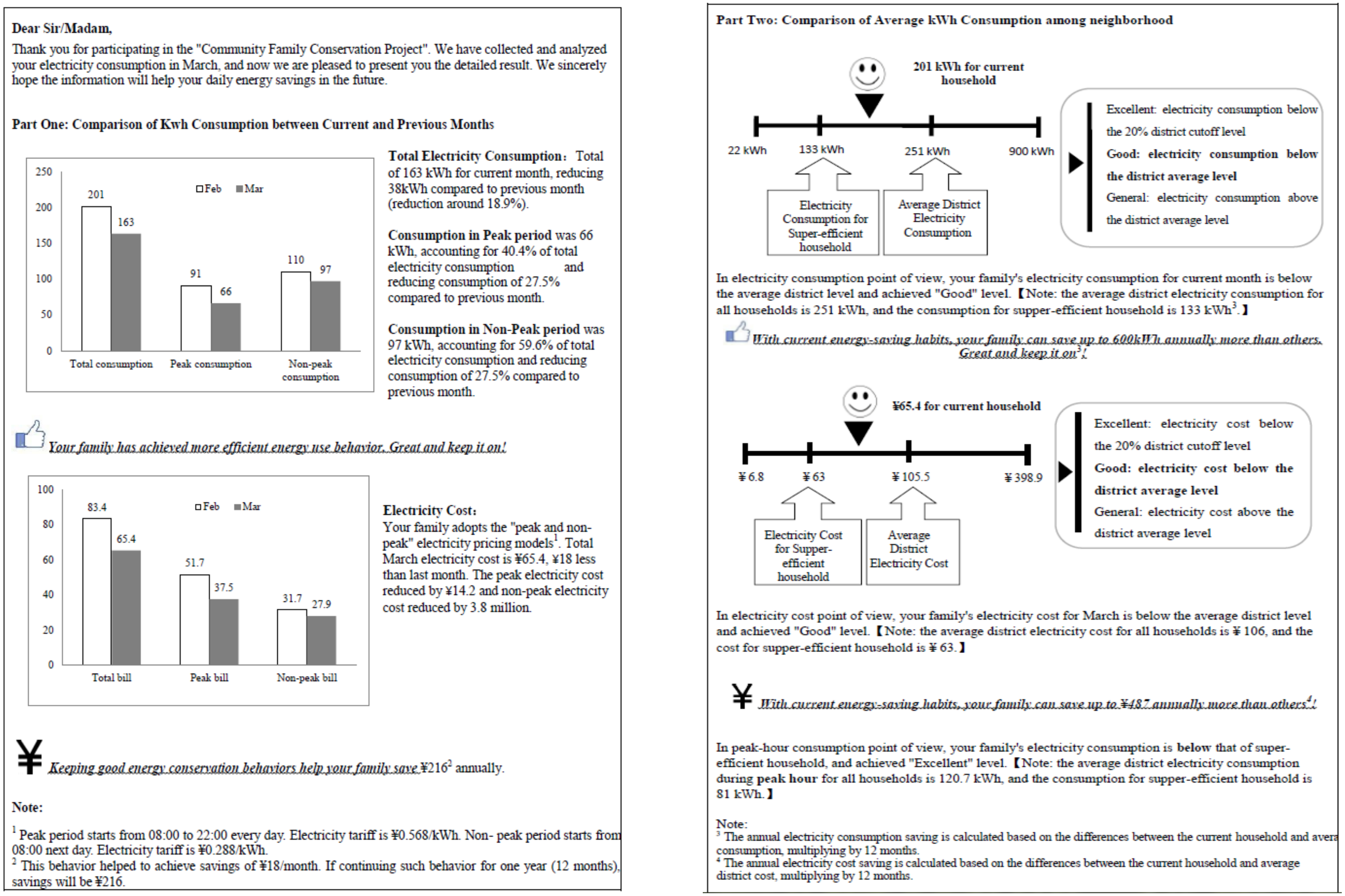
Table 4.1 Experiment Group Design

Group	Intervention					
	Sticker (Paper)		WeChat (Mobile App)		Consultation (Face-to-Face)	
	Feedback	Energy saving tips	Feedback	Energy saving tips	Feedback	Energy saving tips
1	✓	✓				
2		✓				
3			✓	✓		
4				✓		
5					✓	✓
6(control)						

More specifically, both treatment group 1 and group 2 received paper energy saving tips such as leaflet/sticker, while only group 1 received monthly feedback in paper format. Treatment group 3 and 4 received online energy saving tips through WeChat which is a leading social platform in China, whereas only group 3 received online feedback through WeChat on a monthly basis. Treatment group 5 received both the paper stickers and the feedback via monthly face-to-face consultation. The provision of feedback and energy saving tips were not separated in group 5 because during face-to-face interactions, interviewers frequently had to answer enquiries from respondents and the answers provided some degree of feedback to these respondents. Group 6, the control group, did not receive any interventions or feedback. With the exception of receiving the home energy reports, treatment households were not intervened differently than control households. All interventions were carried out monthly from April to June 2016. This process produced, therefore, three months of consumption data (May, June, July 2016) that can be used to train the prediction model. This is because, for example, the April energy consumption data produced the May home energy reports, and the impact of those reports was reflected in the May consumption data. In addition, to retrieve households' information, the questionnaires consisting energy saving behaviors, big five personality traits, demographic profile and building features, were given to all of the participants from February to June 2016 (see Appendix C all questionnaires).

4.3.2 Description of the Interventions

The experiment involved delivering monthly feedback on household energy consumption and evaluated performance to households in the treatment groups 1, 3 and 5, while delivering energy-saving tips to all five treatment groups on a monthly basis. In the energy feedback reports, household electricity consumption between two consecutive months in both peak and non-peak hours are compared in both numbers and figures (see Figure 4.1). The consumed electricity in the latter month was calculated in dollars and compared with that in the previous month. The electricity consumption presented in the reports are in kilowatt-hour (kWh), and the electricity cost are in Chinese currency Yuan (¥). The reports also include the normative feedback and compare the previous month's electricity consumption of a household to the consumption of super-efficient nearby households and the average district electricity consumption in the neighborhood. In addition, the reports show electricity cost of all households as well as indicate the minimum and maximum amount of monthly kWh consumption in the neighborhood. Households could thus know their comparative ranks in terms of energy consumption and monetary savings in the neighborhoods. The reports also provided comments on the household's performance in past month.



Dear Sir/Madam,

Thank you for participating in the "Community Family Conservation Project". We have collected and analyzed your electricity consumption in March, and now we are pleased to present you the detailed result. We sincerely hope the information will help your daily energy savings in the future.

Part One: Comparison of Kwh Consumption between Current and Previous Months

Total Electricity Consumption：Total of 163 kWh for current month, reducing 38kWh compared to previous month (reduction around 18.9%).

Consumption in Peak period was 66 kWh, accounting for 40.4% of total electricity consumption and reducing consumption of 27.5% compared to previous month.

Consumption in Non-Peak period was 97 kWh, accounting for 59.6% of total electricity consumption and reducing consumption of 27.5% compared to previous month.

Your family has achieved more efficient energy use behavior. Great and keep it on!

Electricity Cost:
Your family adopts the "peak and non-peak" electricity pricing models[1]. Total March electricity cost is ¥65.4, ¥18 less than last month. The peak electricity cost reduced by ¥14.2 and non-peak electricity cost reduced by 3.8 million.

¥ *Keeping good energy conservation behaviors help your family save* ¥216[2] annually.

Note:

[1] Peak period starts from 08:00 to 22:00 every day. Electricity tariff is ¥0.568/kWh. Non- peak period starts from 08:00 next day. Electricity tariff is ¥0.288/kWh.
[2] This behavior helped to achieve savings of ¥18/month. If continuing such behavior for one year (12 months), savings will be ¥216.

Part Two: Comparison of Average kWh Consumption among neighborhood

In electricity consumption point of view, your family's electricity consumption for current month is below the average district level and achieved "Good" level. 【Note: the average district electricity consumption for all households is 251 kWh, and the consumption for supper-efficient household is 133 kWh[3].】

With current energy-saving habits, your family can save up to 600kWh annually more than others. Great and keep it on[3]!

In electricity cost point of view, your family's electricity cost for March is below the average district level and achieved "Good" level. 【Note: the average district electricity cost for all households is ¥106, and the cost for supper-efficient household is ¥63.】

¥ *With current energy-saving habits, your family can save up to ¥487 annually more than others[4]!*

In peak-hour consumption point of view, your family's electricity consumption is **below** that of super-efficient household, and achieved "Excellent" level. 【Note: the average district electricity consumption during **peak hour** for all households is 120.7 kWh, and the consumption for supper-efficient household is 81 kWh.】

Note:
[3] The annual electricity consumption saving is calculated based on the differences between the current household and avera consumption, multiplying by 12 months.
[4] The annual electricity cost saving is calculated based on the differences between the current household and average district cost, multiplying by 12 months.

Figure 4.1 A Sample of Feedback Report

The energy-savings tips illustrated five common approaches to reduce electricity consumption with pictures (see Figure 4.2). They mainly covered the use of major appliances, e.g., air-conditioning, fridge, lighting and TV top box. The pictures were used to help households understand and absorb information in a quick and straightforward way. For the continuity that kept those tips as reminder, households were more likely to replace new stickers/leaflets when old ones were tore out or lost.

Save energy. Make your effort.

5 energy saving tips:

1. Use a fan instead of an air-conditioner to keep cool
2. Choose energy efficient light bulbs
3. Switch off main power (when not in use)
4. Set AC cooling temperature 26ºC or above
5. Select energy efficiency labelled appliance

More tips:

1. Use more natural light
2. Shut the contains or blinds
3. Boil water before necessary use
4. Turn on air-conditioner one hour before sleep
5. Use a fan instead of an air-conditioner before sleep
6. Keep the refrigerator away from heat sources
7. Do not overfill the refrigerator
8. Turn off the set-top box when you are not watching TV

Figure 4.2 Energy-Saving Tips (in Chinese) and Translation in English

4.3.3 Data Collection and Processing

In this study, 240 households were initially targeted at 40 samples per group. As an anticipated attrition in participated households, there were 235 households remaining in the end of the experiment. However, not all of them could be used in this research. For example, 46 households gave incomplete answers of the demographic survey. 10 households provided no personality data. As a result, 179 households remained as eligible for further analysis.

With regard to the survey of household energy saving behaviors, 19 questions were drafted and sent to the households monthly from February to June, 2016. The survey questionnaire was adapted from He and Kua (2013), in which they conducted an experiment of energy saving behavior intervention in Singapore. Aside from questions on the possession of the appliances (e.g. number of air-condition, fridges and washers), the behavior survey is grouped by the switch or setting operation behaviors on the air-conditioner, refrigerator, lighting and home electronics. More precisely, the respondents are asked questions relating to the use of the appliance, in terms of the frequency and/or the way they use it. Note that during the collection of the behaviors survey data, small pieces of information were found missing because the households forgot to answer some questions in a certain month. Therefore, in order to pre-process the missing values, the data interpolation method was adopted to fill in the data. For instance, when there is a missing number of operation behaviors in a particular month, the average value of the responses in the previous month and the next month is employed to fill the missing value.

As for the demographic variables, several data trimming steps were performed prior to analysis. Since both the age and gender of all family members were collected, the age of the household is calculated as the average of age for each family member, and the gender is represented by the ratio of males to the household. Besides, the retrofit year is calculated as the difference between 2016 and the year the house was retrofit. As shown in Appendix C, regarding the big five personality traits inventory (Gosling et al., 2003), 10 questions were used to assess the personality of the subject households with each of the trait (that is, extraversion, agreeableness, conscientiousness, neuroticism and openness to experience) calculated as the average value of two items. Among them, items 1, 3, 4, 5 and 7 are reverse-scored and calculated by subtracting 6 from each reverse-scored item and taking the absolute value.

Considering the influence of varying weather conditions on electricity consumption, the daily weather information from the year of 2015 to July 2016 was retrieved from Hangzhou Meteorological Bureau. For this research, the Heating Degree Days (HDD) (below 18℃) and Cooling Degree Days (CDD) (above 26℃) calculations were made on a monthly basis.

Monthly electricity consumption data in kWh of the subject households during the year of 2015 and 2016 were collected from a local utility company, or through the electricity bill sent by the residents from February to August 2016. Some households with the electricity usage data contained blanks or zero were filtered out in the study. In addition, households with the monthly electricity consumption less than 20 kWh were also considered unrealistic and were filtered out subsequently. The selected predictors from February to June 2016 are used for SVR model training. Eventually, the electricity consumption data collected from 166 households which also provided valid questionnaire responses are qualified for training the prediction model since other variables are also collected in this period. To validate the model, the monthly electricity consumption from February to April 2015 is used are as the testing dataset for evaluating the performance of prediction.

4.4 Development of the Prediction Model

According to the discussion in literature review, SVR model is considered as an effective approach to predict energy consumption in the residential sector, so that it has been adopted in this research. The following is the proposed SVR modelling process in three steps (see Figure 4.3).

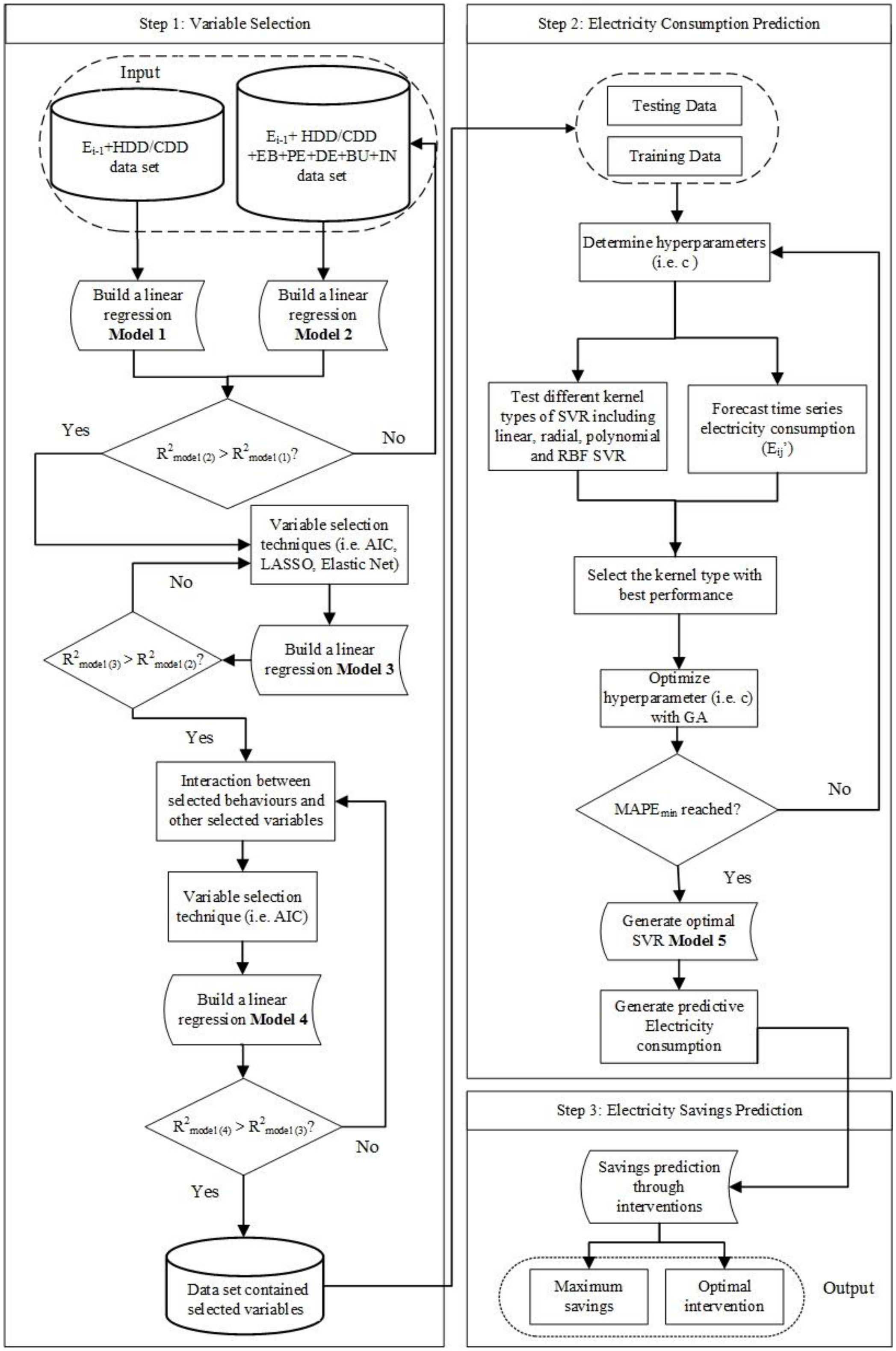


Figure 4.3 Flow Chart in Developing an Optimal SVR Prediction Model

4.4.1 Step 1: Variable Selection Using Akaike Information Criterion (AIC)

As not all identified variables are necessary for building an accurate predictive model, screening the most adequate subset of the variables should be conducted as the first step. We begin with a basic linear regression Model 1 that directly uses the consumption data of the previous month and the weather data in the current month to predict the electricity consumption. However, as such few factors that potentially being insufficient for the accurate prediction, all variables collected from the Hangzhou experiment (i.e. energy behaviors, personality traits, types of interventions, demographic factors, building features and weather indicators) were added to form Model 2. Model 1 and Model 2 are formulated as follows,

Model 1:

$$E_{ij} = \alpha + \beta_{1,1} * E_{(i-1)j} + \beta_{2,1} * HDD_i + \beta_{3,1} * CDD_i + \varepsilon_{ij} \tag{4.1}$$

Model 2:

$$\begin{aligned} E_{ij} = \alpha + \beta_{1,2} * EB + \beta_{2,2} * BU + \beta_{3,2} * DE + \beta_{4,2} * PE + \beta_{5,2} * IN + \beta_{6,2} * E_{(i-1)j} \\ + \beta_{7,2} * HDD_i + \beta_{8,2} * CDD_i + \varepsilon_{ij} \end{aligned} \tag{4.2}$$

where E_{ij} denotes the electricity consumption of the j^{th} household in the i^{th} month, $\beta_{a,b}$ is the a^{th} vector coefficient of the b^{th} model, EB, BU, DE, PE, IN, $E_{(i-1)j}$, HDD_i and CDD_i are the vectors of independent variables including energy behaviors, building feature, demographic factors, personality traits, intervention variables, the consumption in the last month and weather respectively, α denotes the intercept, and ε_{ij} is the error term. The types of variables are listed in

Appendix A and all ordinal variables involved are coded as continuous in the models. Thus, Model 2 initially comprises of 48 predictors to forecast the electricity usage in the i^{th} month. It is well known that when adding more variables to the model, the increase in goodness-of-fit of the model (measured by adjusted R-squared) is considered as the evidence that the model has been improved by adding new input variables rather than by chance (Jovanović et al., 2015). That is, if the added predictors in Model 2 does not significantly increase the adjusted R-squared, the existing variables should not remain in the model. The process will return to the starting point by collecting more meaningful candidates of predictors. It is repeated until Model 2 has more predictive power than Model 1 based on the adjusted R-squared value assessing, the feature selection process is then executed to extract a critical set of predictors to avoid overfitting. The commonly used feature selection criterions (that is, AIC, LASSO[1], Elastic Net and BIC) are applied to eliminate the variables with the poor capability to represent the majority of the predictors. Coupled with feature selection techniques, the adjusted R-squared is extensively used to guide the selection of alternative models (Liu et al., 2011). Here the adjusted R-squared is a measure of whether a model has been much improved by removing useless variables. Both AIC and BIC can effectively trade-off between the accuracy of prediction and the parsimoniousness of the model (Ardakani and Ardehali, 2014), while AIC has its own merits in the domain of energy consumption forecasting (Sari and Soytas, 2004, Sagaert et al., 2018). LASSO performs better especially for large datasets (Kuha, 2004), while Elastic Net has a great advantage in fast calculation and good regression performance by combining the ridge and LASSO penalties (Tibshirani, 2011). However, among

[1] LASSO stands for least absolute shrinkage and selection operator; BIC stands for Bayesian information criterion.

the above techniques, opinions are divided over to which the best techniques should be used (Zou and Hastie, 2005). Therefore, four of them have been adopted in the study.

In the later stage of the study (Section 4.4.1), AIC has been identified as the most proper method due to its relatively higher adjusted R-squared value compared with the ones performed by other methods. AIC can be defined mathematically as follows:

$$AIC = 2k - \ln(L) \tag{4.3}$$

where k denotes the number of parameters to be estimated, and L is the likelihood function. AIC is capable to measure the quality of fit data with the purpose of avoiding overfitting through removing the least significant predictors. In the AIC method, it assumes that the error of the model obeys a normal distribution and the most ideal model is featured by the lowest AIC value (Yang et al., 2017). The variables survived the AIC procedure are the key predictors that can be used to construct Model 3. If the goodness-of-fit of Model 3 (measured by adjusted R-squared value) is larger than that of Model 2, the next move can be proceeded. In addition to the selected variables, as the interaction between household energy behaviors and other variables may have significant influence on household monthly electricity consumption, the interactions between selected behavior variables and other variables that have been previously identified in Model 3, along with those variables selected above, need to go through AIC again. When re-running the AIC, the updated combinations of predictors and interactions are considered to establish the Model 4. Therefore, if the adjusted R-squared value has been much improved, Model 4 that contains the updated predictors as well as the interactions between behaviors and other predictors, can be considered as the proper model that improves the overall predictive performance.

4.4.2 Step 2: SVR Model Development

In step 2, a SVR model is built using the predictors identified in the above step. SVR, being one of the most commonly used machine learning algorithms, is effective in capturing nonlinearity. Developed by Vapnik in 1995, it has been adapted from support vector machine (SVM) algorithm to solve a regression problem. Given a regression problem with a training data set,

$$S = \left\{(x_i, y_i), \ldots, (x_k, y_k) \middle| x_i \in R^{\xi}, y_i \in R\right\} \tag{4.4}$$

SVR aims to find an optimal function that has the minimal required precision from the actual target for all of the training data and at the same time holds the highest possible flatness, as expressed in Equation (4.5):

$$f(x) = \langle w, \varphi(x) \rangle + b \tag{4.5}$$

where $\langle \cdot,\cdot \rangle$ indicates the dot product, w denotes a parameter vector, b is the constant term, and $\varphi(x)$ denotes the nonlinear kernel functions. After using the Lagrange multipliers to nonlinearly map data into a higher dimensional feature space, Equation (4.5) can then be updated as follows:

$$\begin{gathered} f(x) = \sum_{i=1}^{\xi} \left(\alpha_i - \alpha_i^*\right) \left\langle \varphi(x) \cdot \varphi(x_i) \right\rangle + b \\ \textit{subject to} \;\; 0 \le \alpha_i, \alpha_i^* \le C \end{gathered} \tag{4.6}$$

where α_i and α_i^* denote the Lagrange multipliers, C is the cost hyperparameter that controls the trade-off between penalizing the slack variables and maintaining the flatness of the vector of w, the vector inner product $\langle \varphi(x) \cdot \varphi(x_i) \rangle$ represents mapping data from the input space to the feature space. To simplify the mapping process (Tang et al., 2012), it can be replaced by the genetic kernel function $K(x, x_i)$, hence the Equation (4.6) is adapted as follows:

$$f\left(x\right)=\sum_{i=1}^{\xi}\left(\alpha_i-\alpha_i^*\right)K\left(x,x_i\right)+b \tag{4.7}$$

where the parameters are estimated by satisfying the following conditions:

$$\begin{cases} \min(\frac{1}{2}\sum_{i,j=1}^{\xi}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)K(x_i,x_j)+\varepsilon\sum_{i=1}^{\xi}(\alpha_i-\alpha_i^*)-\sum_{i=1}^{l}y_i(\alpha_i-\alpha_i^*)) \\ \sum_{i=1}^{\xi}(\alpha_i-\alpha_i^*)=0 \end{cases} \tag{4.8}$$

Equation (4.7) is a general function of SVR kernel that can be calculated by different forms. With respect to SVR kernels, a series of alternative SVR kernels including linear, radial, polynomial and Gaussian radial basis function (RBF) kernels are widely used in the domain of energy consumption forecasting. For instance, Kavaklioglu (2011) adopted radial kernel function to handle the electricity consumption prediction of Turkey until 2026 using the data from 1975 to 2006. Radial basis function has been used to forecast northeast electricity demand of China (Wang et al., 2009). Besides, linear, Gaussian and polynomial kernels are proven to have comparable accuracy for short-term wind speed forecasting (Zhou et al., 2011). In this study, these four types of nonlinear kernel functions including linear, radial, polynomial and RBF have been adopted as candidates for the kernel functions.

In this case, after selecting the critical predictors in step 1, the extracted data from updated database is split into a training set with the consumption data in the i^{th} month this year (e.g. February 2016), and a testing set with the data in corresponding period last year (e.g. February 2015). It is worth noting that in this study, only those families with similar consumption in 2015 were selected for model testing since they are assumed to follow the behavior patterns in the same time period in 2016. By computing the percentage of differences between the consumption of 2015 and 2016 expressed as Equation (4.9), the households with a difference smaller than 10% has been chosen as the testing set

$$Difference = \left| \frac{E_{2015ij} - E_{2016ij}}{E_{2015ij}} \right| \times 100\% \tag{4.9}$$

where E_{2015ij} denotes the electricity consumption of the j^{th} household in the i^{th} month 2015, and E_{2016ij} is the electricity consumption of the j^{th} household in the i^{th} month 2016. Note that a difference smaller than 10% is considered as the criterion of data selection because it represents the behaviors of households did not change too much in a particular month between year 2015 and 2016. Thus, in this way, such two sets of data can be compared. To further optimize the prediction outcomes, the SVR hyperparameters (i.e., the cost C) is tuned. Moreover, among the results calculated by different kernel types above, the most proper type is determined by the mean absolute percentage error (MAPE). The MAPE equation presents as follows:

$$MAPE = \frac{1}{d} \sum_{d=1}^{d} \left| \frac{E_{ij} - E_{ij}'}{E_{ij}} \right| \times 100\% \tag{4.10}$$

where E_{ij}' represents the predicted value, E_{ij} represents the actual value, and d represents the number of data samples. The performances of different kernel types are also assessed by MAPE in a time-series consumption forecasting. Assessing the performance of time-series forecasting shows advantages in many aspects. On one hand, it allows us to manifest the prediction power and capability of the proposed model in the following months instead of just in the next month. On the other hand, it provides a summary of the constant efficiency and accuracy of the proposed model over other models. In particular, the aforementioned procedure has been repeated 30 times, and the results of MAPE are averaged. As this validation technique has been widely used in maintaining the reliability of the proposed model (Forrest, 1993), it is employed in both training and testing processes in this study.

Besides, with respect to choose the proper hyperparameter of SVR model, it would be too difficult for us to manually test all possibilities of parameter values. Hence in this case, the genetic algorithm (GA) has been adopted as the parameter optimization method. Inspired by natural selection and biological evolution, GA has been often used to solve optimization problems (Forrest, 1993). Specifically, the algorithm uses a set of solutions selected from the initial candidates to generate the next generation solutions following the steps of crossover and mutation. That is, the candidates whose performance are closed to the optimal cases are combined with each other and then mutate to generate the optimal solutions, otherwise they will be eliminated.

In this study, the hyperparameter of the cost C in Equation (4.6) has been set to a wide range of values. Subjected to minimize the MAPE of the SVR model, GA can select the proper value of the cost C automatically. This procedure is able to save calculation efforts and achieve the optimal performance of SVR in a short time.

Followed by these processes, the Model 5 can be generated as the most suitable SVR model for the prediction of household electricity consumption. Eventually, Model 5 has been developed as the most suitable and accurate SVR model for household electricity consumption prediction.

4.4.3 Step 3: Electricity Savings Prediction

In stage 3, the output data in stage 2 (i.e. predictive results of $IN_1 - IN_6$) were taken as inputs to calculate the maximum electricity savings for each household respectively during the treatment months. For every household, the maximum electricity savings are the differences between the minimum predictive consumption under a certain intervention and the consumption under the control condition. It is worth mentioning that the electricity savings are identified by comparing with the consumption from no treatment. Thus, for the family who cannot save any electricity under interventions (use more than they did under the control condition), the electricity savings is viewed as zero. By doing this, the process is able to customize the optimal intervention strategy for every single household. Thus,

$$S_j' = \max\left[\frac{\sum_{i=p}^{q}(E_{mij}' - E_{zij}')}{T}\right] \tag{4.11}$$

where S_j' represents the maximum average electricity savings through the optimal intervention for the j^{th} household of T month, T is the period of the intervention from the p^{th} month (the starting time of the intervention) to the q^{th} month (the ending time of the intervention), E_{mij}' denotes the predictive consumption value of the j^{th} household in the i^{th} month ($i = \{p, p+1, ..., q\}$) through the control condition m, E_{zij}' is the predictive consumption value of the j^{th} household in the i^{th} month through the z^{th} intervention, $z = \{n, m\}$, n=1,2,…5. Notably, if $\left[\frac{\sum_{i=p}^{q}(E_{mij}' - E_{zij}')}{T}\right] < 0$ for a subject household, then the control condition (i.e. no treatment) is more suitable for the subject as the electricity consumption is higher in all interventions (from IN_1 to IN_5) than in control condition m, and $S_j' = 0$. Given Equation (4.11), each household is suggested with an optimal intervention strategy. Thus the new population setting of the intervention groups is able to achieve substantial electricity savings over the Hangzhou experiment setting.

Furthermore, the model is also able to suggest the predictive proportion of households grouped into each of the optimal intervention strategies. According to Equation (4.11), each household is provided with the new optimal intervention strategy. Equation (4.12) calculates the predictive proportion of households grouped into each of the optimal intervention strategies as follows,

$$Percentage_z = \frac{R_z}{R} \tag{4.12}$$

where R_z denotes the population of households that suggested with IN_z, IN_z is the optimal intervention strategy for which Equation (4.11) holds, and R is the total numbers of households.

4.5 Results

The results generated from the previous three steps of SVR prediction model development are demonstrated as follows. All data processing and analysis is performed in RStudio 1.0.143.

4.5.1 Variable Selection

To select the most appropriate independent variables for the household electricity consumption prediction, four models considering different variables have been built and tested. Table 4.3 lists all the critical predictors identified by the process of variable selection process. In the basic model, Model 1, the monthly electricity consumption is predicted by the weather factors comprise HDD, CDD, and the electricity consumption in the previous month. Model 2 includes the direct effects of all 48 independent variables on electricity consumption. Meanwhile the MAPE value is decreased to 27.27% from 28.66% of Model 1. Through the variable selection process, Model 3 and Model 4 are then built as follows,

Model 3:

$$\begin{aligned} E_{ij} &= \alpha + \beta_{1,3} * EB + \beta_{2,3} * BU + \beta_{3,3} * DE + \beta_{4,3} * PE + \beta_{5,3} * IN + \beta_{6,3} * E_{(i-1)j} \\ &\quad + \beta_{7,3} * HDD_i + \beta_{8,3} * CDD_i + \varepsilon_{ij} \end{aligned} \tag{4.13}$$

Model 4:

$$\begin{aligned} E_{ij} &= \alpha + \beta_{1,4} * BU + \beta_{2,4} * DE + \beta_{3,4} * PE + \beta_{4,4} * IN + \beta_{5,4} * EB * (BU + PE \\ &\quad + IN + E_{(i-1)j} + HDD_i + CDD_i) + \beta_{6,4} * E_{(i-1)j} + \beta_{7,4} * HDD_i + \beta_{8,4} * CDD_i + \varepsilon_{ij} \end{aligned} \tag{4.14}$$

In Model 3, the irrelevant variables have been eliminated, so the AIC method achieved a higher R-square value (0.6507) compared with other feature selection techniques (see Table 4.2). As a result, 18 independent variables were considered as appropriate to build Model 3. It contains five energy behavior variables, five building feature variables, two demographic variables, two personality variables, the intervention variables, along with the weather factors and the consumption in the last month. The interactions between the energy behaviors and the rest of the variables were added, then re-run the process of AIC to build Model 4 that includes 18 independent variables and 30 interaction variables. Among the 18 independent variables, the five behavior variables that were previously identified in Model 3 are no longer exist as individual variables, in which only their interactions with the rest of the variables are considered. R-square value is obtained as high as 0.6857 for Model 4.

Thus, 18 critical predictors (listed in Table 4.3) have been identified by the variable selection process. Specifically, this process identified five critical energy behaviors related to the air-conditioner, fridge and lighting; two personality traits of extraversion (PE_1) and conscientiousness (PE_3); two demographic factors including the number of family members and average age; five building features including house size, house age, the frequency of cooking, the number of air-conditioners and fridges. Besides, six types of strategies (including 5 interventions and 1 control condition), weather indicators and the last month electricity consumption have been selected as the significant predictors of household electricity consumption. It is to be noted that the interaction effects between the selected behaviors and other predictors are also extracted as the key predictors since they contribute to optimizing the performance of the prediction.

Table 4.2 The Goodness-of-fit of the Models

	Model 2	Model 3				Model 4
		AIC	BIC	LASSO	Elastic Net	
R-square	0.6428	0.6507	0.6135	0.6236	0.6133	0.6857

Table 4.3 The Selected Predictors for the Models

Attribute	Predictor	Model 1	Model 2	Model 3	Model 4
Energy behaviours	EB_ac_temp (EB_1)		✓[a]		
	EB_ac_power (EB_2)		✓		
	EB_ac_clean (EB_3)		✓		
	EB_ac_close (EB_4)		✓	✓	✓*[b]

	EB_ac_occu (EB_5)	✓		
	EB_fridge_outside (EB_6)	✓		
	EB_fridge_inside (EB_7)	✓		
	EB_fridge_food (EB_8)	✓	✓	✓*
	EB_fridge_liquid (EB_9)	✓	✓	✓*
	EB_light_day (EB_{10})	✓		
	EB_light_occu (EB_{11})	✓	✓	✓*
	EB_light_focus (EB_{12})	✓	✓	✓*
	EB_app_off (EB_{13})	✓		
	EB_app_nouse1 (EB_{14})	✓		
	EB_comp_save (EB_{15})	✓		
	EB_app_unplug (EB_{16})	✓		
Personality traits	Extraversion (PE_1)	✓	✓	✓
	Agreeableness (PE_2)	✓		
	Conscientiousness (PE_3)	✓	✓	✓*
	Neuroticism (PE_4)	✓		
	Openness (PE_5)	✓		
Demographic factors	DEMO_residents (DE_1)	✓	✓	✓
	DEMO_age (DE_2)	✓	✓	✓*
	DEMO_resident_gen (DE_3)	✓		
	DEMO_income (DE_4)	✓		
	DEMO_owner_edulvl (DE_5)	✓		
	DEMO_residen_tedulvl (DE_6)	✓		
	DEMO_highest_edulvl_no (DE_7)	✓		
	DEMO_religion (DE_8)	✓		
	DEMO_occup(DE_9)	✓		
Building features	Demo_floor (BU_1)	✓		
	Demo_direction (BU_2)	✓		
	BU_house_age (BU_3)	✓	✓	✓*
	Demo_retrofit_date (BU_4)	✓		

	Demo_rent (BU_5)		✓		
	BU_Cooking (BU_6)		✓	✓	✓*
	Demo_living_rom (BU_7)		✓		
	Demo_bedroom (BU_8)		✓		
	Demo_study_room (BU_9)		✓		
	BU_area (BU_{10})		✓	✓	✓*
	Demo_home_type (BU_{11})		✓		
	BU_ac_num (BU_{12})		✓	✓	✓
	BU_fridge_num (BU_{13})		✓	✓	✓
	EB_washer_num (BU_{14})		✓		
Intervention	IN_1, IN_2, IN_3, IN_4, IN_5, IN_6		✓	✓	✓
Weather	HDD	✓	✓	✓	✓
	CDD	✓	✓	✓	✓
Last month consumption	$E_{i-1,j}$	✓	✓	✓	✓
Interaction between behaviors and others	EB_4* BU_6, EB_4* DE_1, EB_4* PE_3, EB_4* IN_3, EB_4* IN_4, EB_4* $E_{i-1,j}$, EB_8* BU_{10}, EB_8* BU_3, EB_8* DE_1, EB_8* PE_1, EB_8* IN_2, EB_8* IN_4, EB_8* $E_{i-1,j}$, EB_8* HDD, EB_9* BU_{10}, EB_9* BU_3, EB_9* DE_1, EB_9* CDD, EB_{11}* BU_3, EB_{11}*DE_2, EB_{11}* PE_1, EB_{11}* IN_3, EB_{11}* $E_{i-1,j}$, EB_{11}* HDD, EB_{11}* CDD, EB_{12}* BU_6, EB_{12}* PE_1, EB_{12}* PE_3, EB_{12}* HDD, EB_{12}* CDD				✓

Note: a) "✓" represents the variables included in the model individually; b) "*" represents the variables only included in the model when they have the interactive effects with other variables.

4.5.2 SVR Model Performance

For developing an improved SVR model to predict household electricity consumption more accurately, Table 4.4 presents the accuracy percentage assessed using MAPEs of different SVR kernels with the 18 variables and 30 interaction variables corresponding to Model 4. All of the MAPE values in Table 4.4 are obtained from 30 times experiments. It can be seen from Table 4.6 that among four types of SVR kernel (i.e. linear, Radial, polynomial and RBF kernels), the predictive performance of linear regression model measured in training data with the highest MAPE value of 28.11%, whereas Radial SVR model with the lowest of 7.25%. However, in terms of the predictive performance measured in both training data and testing data, Radial SVR has significantly increased MAPE value from 7.25% (for training data) to 25.13% (for testing data), while RBF kernel has marginally increased the value from 9.56% (for training data) to 10.47% (for testing data). The results indicate that Radial SVR model is not able to prevent over-fitting in training data for this case, which eventually leads to the significant high MAPE value in testing data. Thus, RBF SVR is the best performing SVR kernel overall, due to the significantly lower value of MAPE than the rest of the kernels.

In terms of the time-series forecasting, RBF kernel also provides more accurate results than other models. Here the electricity consumption in January 2016 and all of the selected predictors in February were considered as the inputs to conduct the SVR forecasting for the experiment period. The criteria to select the best performing model is the lowest MAPE values for the first month and the lowest range of MAPE value during the whole testing period. Although the radial kernel has the minimum MAPE value (6.87%) in February, it shows poor performance from March to June (MAPE range from 45.79% to 68.30%). The result demonstrates that radial SVR does not hold the stability of prediction in a time-series forecasting. Instead, as RBF SVR yield a relatively lower MAPE value (11.54%) in the first month and a robust performance in a time-series forecasting (MAPE range from 26.67% to 36.60%) from March to June, it was then employed to perform the hyperparameter optimization using GA. The result demonstrates that GA-RBF-SVR model exhibits the best performance on next-month prediction with MAPE of 8.48% and 9.34% using training data and testing data respectively, along with the minimum MAPE value (range from 6.95% to 36.14%) during the testing period. Therefore, the GA-RBF-SVR model is selected for household electricity consumption prediction.

Table 4.4 Performance of SVR on the Household Energy Consumption Forecasting Measured by Mean Absolute Percentage Error (MAPE; %)

Model	Next-month prediction		Time-series forecasting				
	Training data	Testing data	February	March	April	May	June
OLS Regression	28.11	22.75	36.22	35.28	44.54	40.88	38.41
Linear SVR	26.13	18.85	38.77	34.86	42.37	35.58	34.68
Radial SVR	7.25	25.13	6.87	52.15	68.30	59.68	45.79
Polynomial SVR	14.57	13.68	16.83	31.32	46.04	41.68	54.37
RBF SVR	9.56	10.47	11.54	26.67	36.60	33.47	35.56
GA RBF SVR	8.48	9.34	6.95	25.47	36.14	27.85	29.97

4.5.3 Electricity Savings Prediction

According to Equation (4.11), the training dataset is used to compute the predictive electricity savings under each intervention strategy for each household during the experiment period (from February to June 2016). In order to set the baseline for comparing with the results of the prediction model, the effects of each intervention strategy was also calculated in the field experiment in Hangzhou. Specifically, as can be seen from Figure 4.4, the left one demonstrates the calculated results of the field experiment, and the right pie chart in Figure 4.4 illustrates the optimized prediction results using the proposed model. The thickness of the inner ring of both pie charts shows the variation of the electricity saving percentage (%) with maximum electricity savings (kWh) presented in brackets. In addition, the length of the outer ring represents the household proportion (%) under each intervention strategy from IN_1 to IN_6).

In Hangzhou field experiment, the effect of each intervention is evaluated by comparing with the control group. Notably, since the calculation serves as a benchmark for comparison with the optimized prediction results using the proposed method, there is no additional control variables. As shown in the left pie chart in Figure 4.4, it reveals that the strategy of sticker without feedback (IN_2) has the highest electricity savings (5.55%) during the period. The rest of the experiment groups actually increase in the electricity consumption by 2% (4.32kWh), 7.52% (15.93kWh), 10.1% (24.17kWh) and 8.10% (17.15kWh) for sticker with feedback (IN_1), WeChat with feedback (IN_3), WeChat without feedback (IN_4) and consultation (IN_5) respectively. However, for the optimized prediction results based on the proposed model, in the right pie chart in Figure 4.4, the WeChat intervention strategies (IN_3 and IN_4) show the highest savings during the experiment period with the savings of 15.97% (33.81 kWh) for IN_3 (with feedback), and the second highest savings of 15.43% (32.68 kWh) for IN_4 (non-feedback). The consultation strategy (IN_5) is the third highest savings with an average monthly reduction of 14.9% (31.55 kWh). Comparatively, the sticker strategies (IN_1 and IN_2) present the lowest values in electricity savings during the period with 10.87% (23.02 kWh) and 10.74% (22.75 kWh) respectively. It is important to note that the feedback strategy leads no more additional reduction than non-feedback intervention in electricity consumption, indicating that feedback may only generate marginal impact in electricity conservation when occupants already received optimal interventions.

With regard to the household proportion under each interventions, as shown in the outer ring of the right pie chart in Figure 4.4, the WeChat feedback strategy achieves the largest share (40.5%) of the households according to Equation (4.12). In other words, 40.5% of the households can reduce more electricity consumption when choosing the WeChat feedback strategy than any other strategies. The consultant intervention achieves a relatively lower percentage of 14.5% in households. IN_1, IN_2 and IN_4 present even smaller shares of 6.4%, 6.9% and 4.6% respectively. There are 27.1% of the households that belong to the control condition, indicating they are insensitive to any intervention strategies. Thus, the new population setting of the optimal intervention groups based on the prediction model is supposed to save massive energy comparing with the original experiment setting shown in the left pie chart in Figure 4.4.

4.6 Discussion

In this section I first discuss the results of electricity savings prediction with optimal intervention strategies, followed by investigating the relationship between personality traits and each intervention strategy. As can be seen from Figure 4.4, the results of prediction model and field experiment are different in all aspects, i.e. the electricity savings and the households proportion under each intervention strategy (from IN_1 to IN_6).

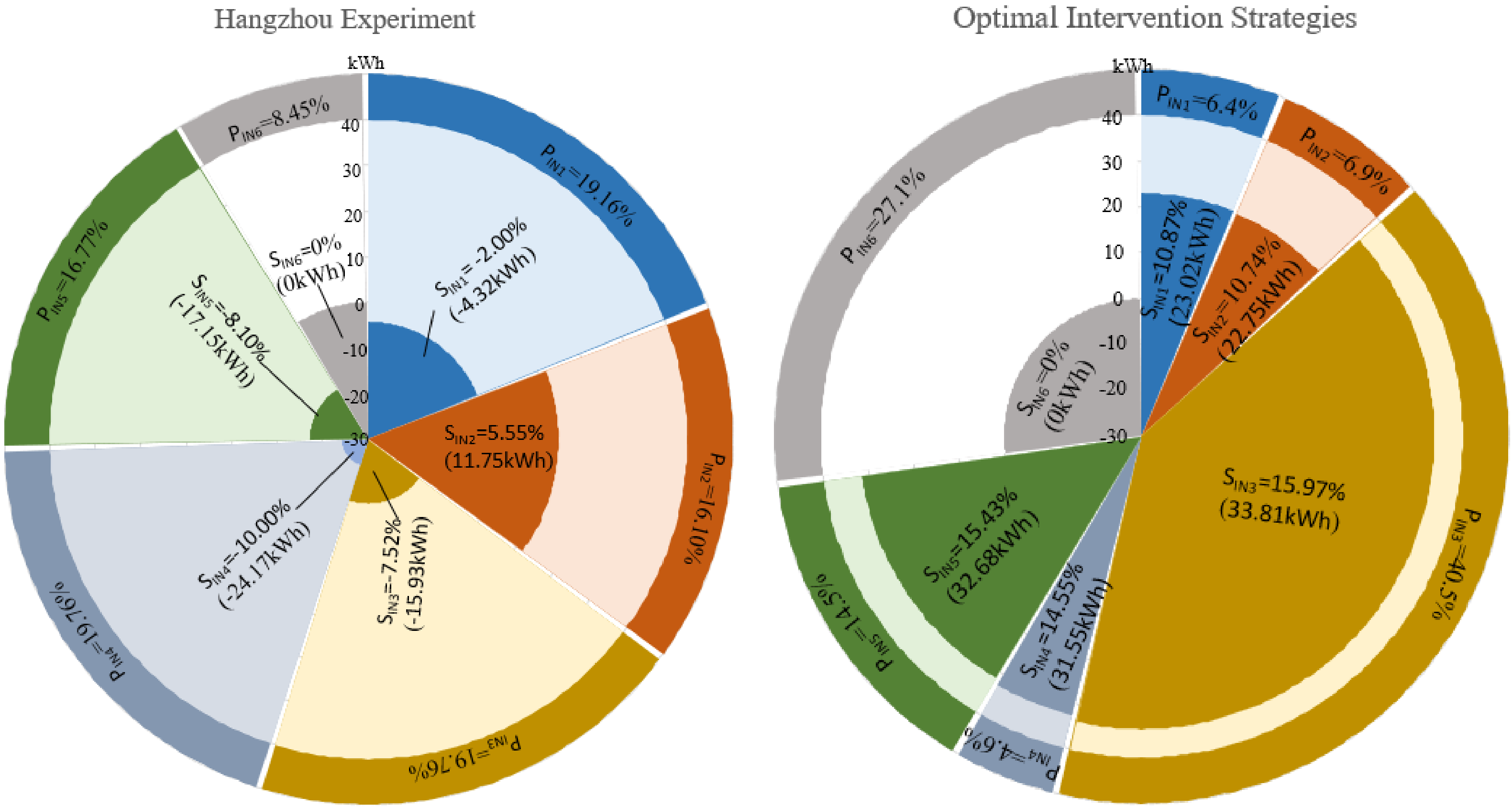


Figure 4.4 A comparison of Electricity Savings Between Field Experiment (Left) and the Optimal Strategies (Right)

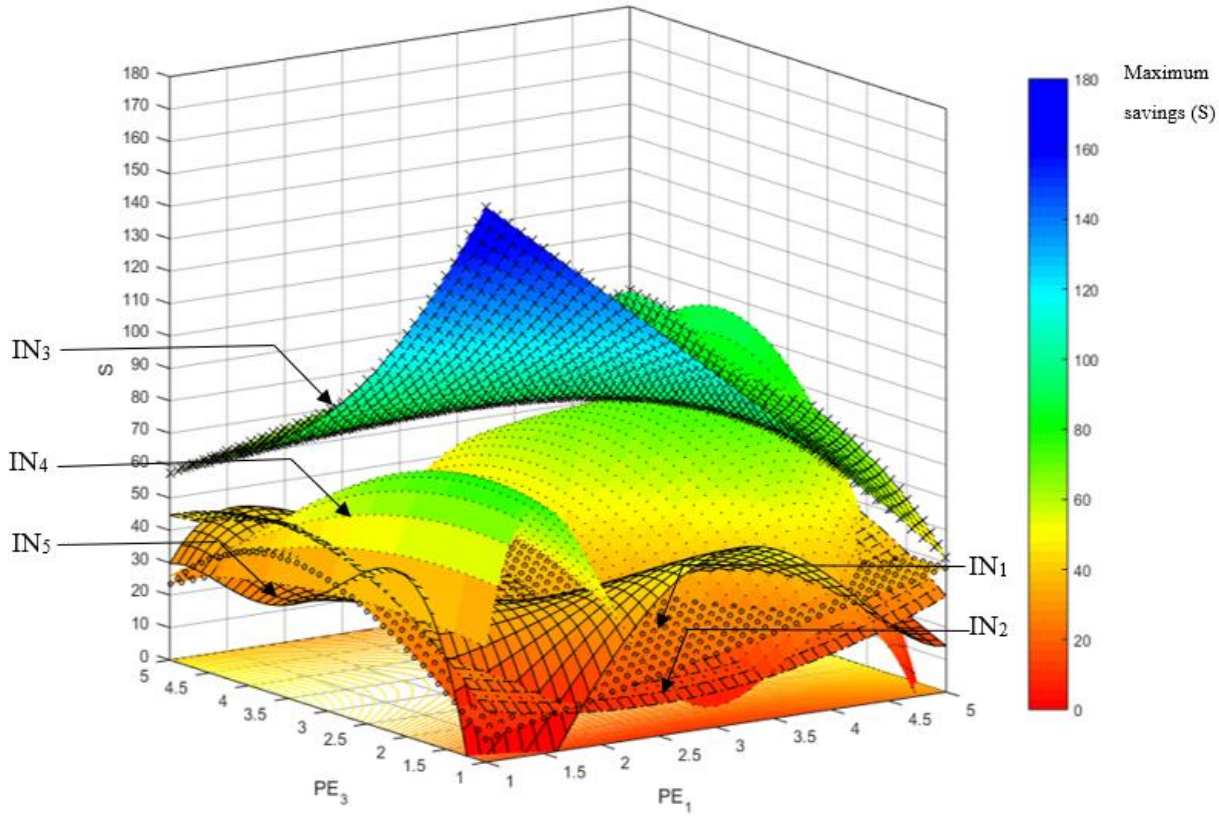
Note: P stands for household proportion (%) illustrated as the length of the outer ring. S is the electricity saving percentage (%) illustrated as the thickness of the inner ring. The saving percentage is relative to the control condition. IN_1 to IN_6 represent each intervention strategy.

In the Hangzhou field experiment (left in Figure 4.4), households were equally assigned into intervention groups without considering their own characteristics and backgrounds, resulting in the assigned intervention strategy might not be the optimal choice for them. In the optimized strategy (right in Figure 4.4), the percentage of households in WeChat with feedback has significantly increased from 19.76% to 40.5%, while the shares of other ineffective intervention strategies have dramatically decreased, such as sticker with/without feedback (decreasing from 19.16% to 6.4%, and from 16.10% to 6.9% respectively) and WeChat without feedback and consultation (decreasing from 19.76% to 4.6%. In addition, the results of optimized model illustrate the households in all treatment groups and control group can reach the maximum average electricity savings of 12.10% with the most appropriate treatment strategy for each of them, comparing to the maximum of 5.55% in the original experiment. Interestingly, the optimization results suggest that WeChat feedback intervention indicates the highest reduction in electricity consumption along with the largest percentage in households. This conclusion illustrates that the optimization results provided by the proposed model have much improved the effect on the households as a whole.

Yet it is still difficult to observe and understand all of variability in the prediction results, especially the influence by different types of personalities, since the GA RBF SVR model is a black box containing both apparent independent variables and hidden rules. Thus, in order to obtain an overview of the relationships among the maximum electricity savings (S), the personality traits of extraversion (PE_1) and conscientiousness (PE_3), and optimal intervention strategies, the Monte Carlo simulation of 10,000 households was run according to their distribution of each variable. As a result, a comprehensive three-dimensional plot is illustrated in Figure 4.5, in which each surface stands for the effectiveness of the feedback intervention to different personalities.

The surface graph is plotted using the calculated maximum electricity savings ($S \geq 0$) as vertical axis, and the rate of the personality traits of extraversion ($1 \leq PE_1 \leq 5$) and conscientiousness ($1 \leq PE_3 \leq 5$). As can be seen in Figure 4.5, the five surfaces which signify the optimal choice of intervention strategy for a household with different personality traits, are IN_3, IN_4, IN_5, IN_1, IN_2 from the top to the bottom respectively. This corresponds with the results observed in the previous analyses. For example, the predicated electricity savings in the group of WeChat with feedback (i.e., IN_3) are more than the savings by other intervention strategies for all kinds of people. More detailed explanations for each of the surfaces (intervention methods) are provided in the following section.

From the observation presented in Figure 4.5, the simulated households can be grouped into two types owing to different combinations of their personality traits of extraversion (PE1) and conscientiousness (PE3), with the optimal intervention strategies (IN1-IN5) presented in five surfaces respectively. The details for each surface are subsequently shown in the following Figures 4.6-4.10. Specifically, for the households with $PE_1<1.38$ and $PE_3>4.88$ ($E^L C^H$ residents; low score in extraversion while high score in conscientiousness), the electricity savings range is from 42.82kWh to 57.79kWh. This represents the smallest range of electricity savings in the Figure 4.5, indicating that people who feel a strong sense of moral obligation (high conscientiousness) while introverted (low extraversion) can save energy, though with a small-to-moderate amount, regardless intervention strategies.



○ Sticker w/ Feedback (IN_1) -. Sticker w/o Feedback (IN_2) × WeChat w/ Feedback (IN_3)
· WeChat w/o Feedback (IN_4) □ Consultation (IN_5)

Figure 4.5 The Relationship Between the Maximum Electricity Savings, the Personality Traits, and the Optimal Intervention Strategies

Note: Personality traits include extraversion (PE1) and conscientiousness (PE3); Strategies (IN1-IN5) are presented in five surfaces respectively.

For the households with PE_1<1.62 and PE_3<1.24 (E^LC^L residents; low score in both extraversion and conscientiousness), the electricity savings range from 0 to 171.4kWh, and this represents the largest potential savings. Such phenomenon illustrates that those who are disorganized (low conscientiousness) and quite introverted (low extraversion) can show wide differences in savings – some may show significant energy saving, while others show little. This result suggests that although these residents may rarely care about the environment, they show varying receptivity when intervened by WeChat feedback. For these types of residents, provision of online information is effective to help them improve their energy saving behaviors.

4.6.1 Surface 1: WeChat with Feedback Intervention (IN3)

Figure 4.6 shows the maximum predicted electricity savings (S) when the optimal intervention strategy for households is WeChat with feedback (IN_3), which depends on the two of personality traits (PE_1 and PE_3). It can be noticed from Figure 4.6b that the savings range from 41.59 kWh to 171.4 kWh if the WeChat with feedback intervention is selected as the best choice for these households. Specifically, the electricity savings reach a maximum of 171.4 kWh when PE_1=1 and PE_3=1, while the predictive savings reach a minimum of 41.59 kWh when PE_1=5 and PE_3=1. As shown in Figure 4.6b, the surface is mainly symmetric around the diagonal line PE_1=PE_3. The maximum predicted electricity savings decreases when either extraversion or conscientiousness grows, suggesting that people scoring low in extraversion and conscientiousness respond more actively to the intervention strategy IN_3 (that is, WeChat with feedback) by reducing more energy. In other words, households who tend to be introverted and unconscientious can save most electricity through the use of WeChat with feedback. This can be explained that introverted people may preferred to be communicated via personal platform (e.g. WeChat) which provides a private and intimate environment to deliver the message rather than a shared or public announcement. Regarding unconscientious occupants, providing feedback is suggested as an effective approach to develop their awareness towards energy conservation and further to facilitate the change of energy behavior.

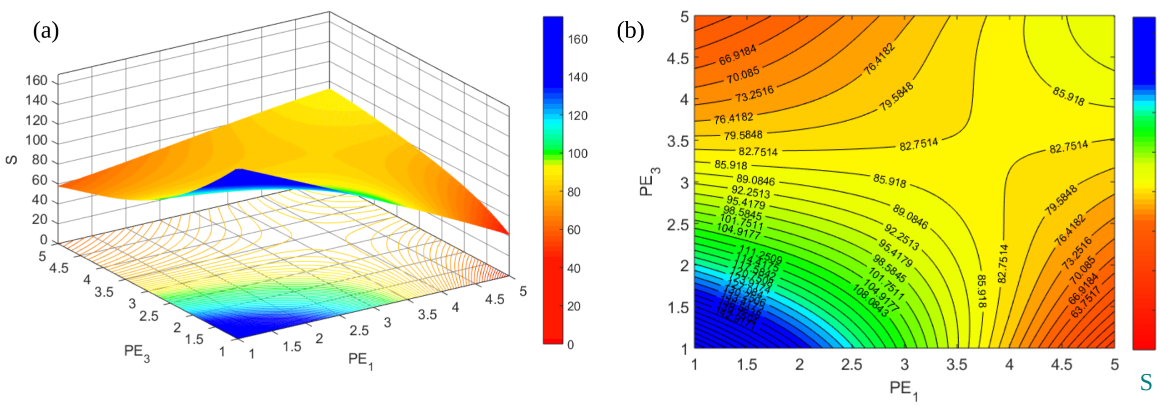


Figure 4.6 Extraversion (PE_1) and Conscientiousness (PE_3) Map with the Optimal Intervention Strategy (WeChat with Feedback) a) 3-D Surface Plot; b) Top View of the Surface

4.6.2 Surface 2: WeChat without Feedback Intervention (IN4)

Figure 4.7 shows the surface plot with the maximum predicted electricity savings (S) when the optimal intervention strategy for households is WeChat without feedback (IN_4), which depends on the two of personality traits (PE_1 and PE_3). The maximum electricity savings is achieved (S=96.03 kWh) when PE_1=5 (extremely high extraversion) and PE_3=3.84 (high conscientiousness) – that is, $E^H C^H$ residents – for which the surface descends toward the periphery. The results illustrate that extraverts and responsible households, for whom intervention with WeChat without feedback is suitable, have a potential to save more electricity than other types of residents; this suggests that they can be strongly influenced even by the saving tips alone offered via WeChat as they are always being mindful of the environment around them. However, households with PE_1>4.72 and PE_3<1.5 can barely save electricity (S=0) even when intervened by WeChat without feedback as the best choice, let alone other intervention strategies.

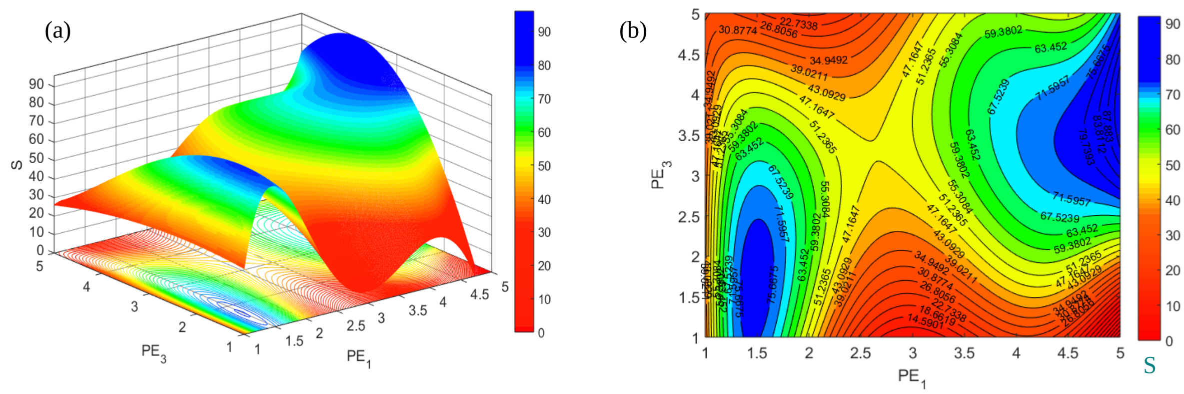


Figure 4.7 Extraversion (PE_1) and conscientiousness (PE_3) Map with The Optimal Intervention Strategies (WeChat without Feedback) a) 3-D Surface Plot; b) Top View of the Surface

4.6.3 Surface 3: Consultation Intervention (IN5)

As can be seen from Figure 4.8, when the consultation (IN_5) is selected as the optimal intervention strategy for households, the maximum predicted electricity savings (S) depend on two personality traits (PE_1 and PE_3). The range of the electricity savings is from 54.3 kWh (PE_1=3.2 and PE_3=1) to 0 (PE_1<1.62 and PE_3<1.24). There are two types of households – $E^M C^L$ and $E^L C^M$ (PE_1=3.2 and PE_3=1, PE_1=1 and PE_3=2.24 respectively) – who are capable of saving significantly more energy, suggesting that consultation is probably the ideal intervention strategy for those who are ambiversion but unconscientious, or are introversion and relatively unconscientious. However, people who are less outgoing and extremely unconscientious tend to disregard all types of feedback and energy saving tips even in the face-to-face intervention, because they focus more on themselves instead of the environment around them.

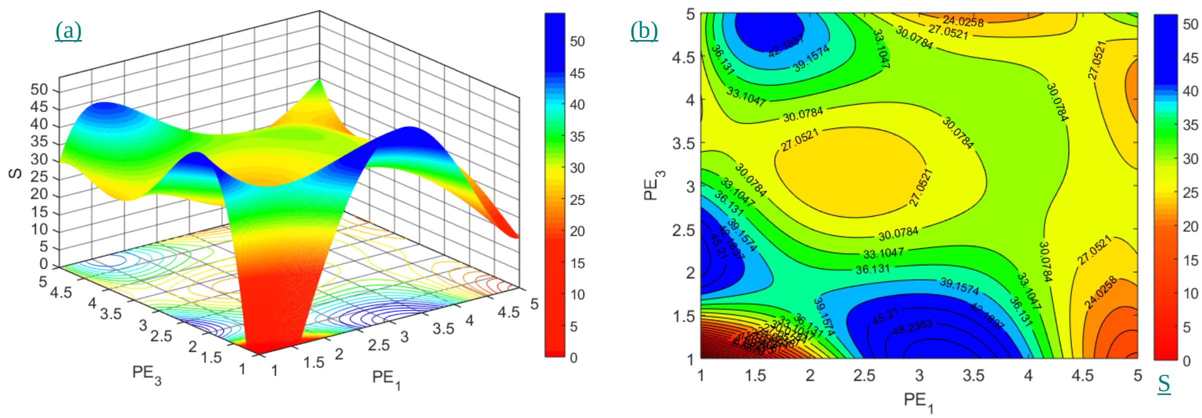


Figure 4.8 Extraversion (PE_1) and Conscientiousness (PE_3) Map with the Optimal Intervention Strategies (Consultation). a) 3-D Surface Plot; b) Top View of the Surface.

4.6.4 Surface 4 and 5: Sticker with Feedback Intervention (IN1) and Sticker without Feedback Intervention (IN2)

Figure 4.9 and Figure 4.10 indicate surface plots with the maximum predicted electricity savings (S) for personality traits (PE_1 and PE_3) when the optimal intervention strategy for households is sticker with feedback intervention (IN_1) and sticker without feedback intervention (IN_2) respectively. The amount of maximum predicted savings through the intervention of sticker with feedback (9.83 kWh - 53.04 kWh) is slightly larger than the amount of savings by the intervention of sticker without feedback (7.17kWh - 43.62kWh).

With respect to sticker with feedback intervention, as shown in Figure 4.9b, the surface is almost vertically symmetric around the line PE_3=3.5 with the two peak values of savings at 53.04 kWh (PE_1=5 and PE_3=3.16) and 52.85 kWh (PE_1=1 and PE_3=3.72). In terms of the sticker without feedback intervention in Figure 4.10b, the further the value of PE_3 is away from PE_3=3.7, the smaller of electricity potential savings are achieved by the households. That is, people with moderate level of conscientiousness can achieve more electricity savings than other types of people when the sticker without feedback intervention is employed, regardless of their level of extraversion.

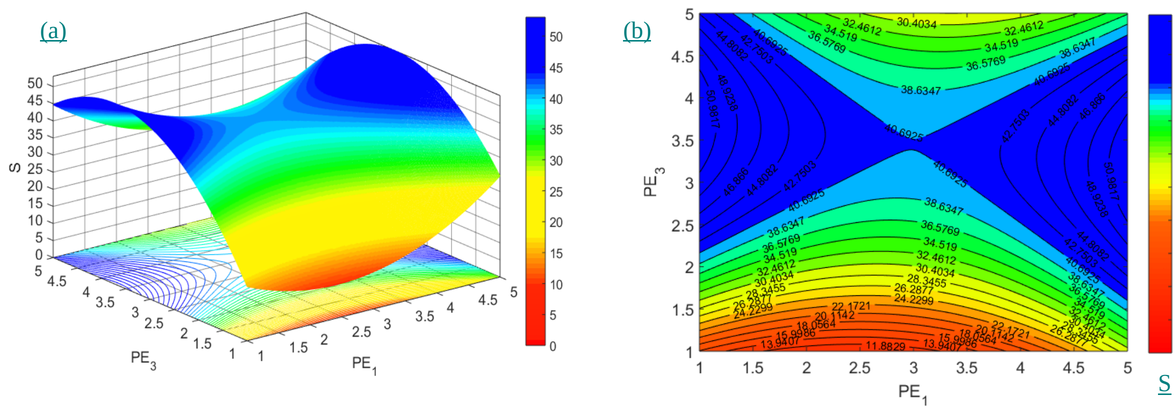


Figure 4.9 Extraversion (PE1) and Conscientiousness (PE3) Map with the Optimal Intervention Strategies (IN1). a) 3-D Surface Plot; b) Top View of the Surface.

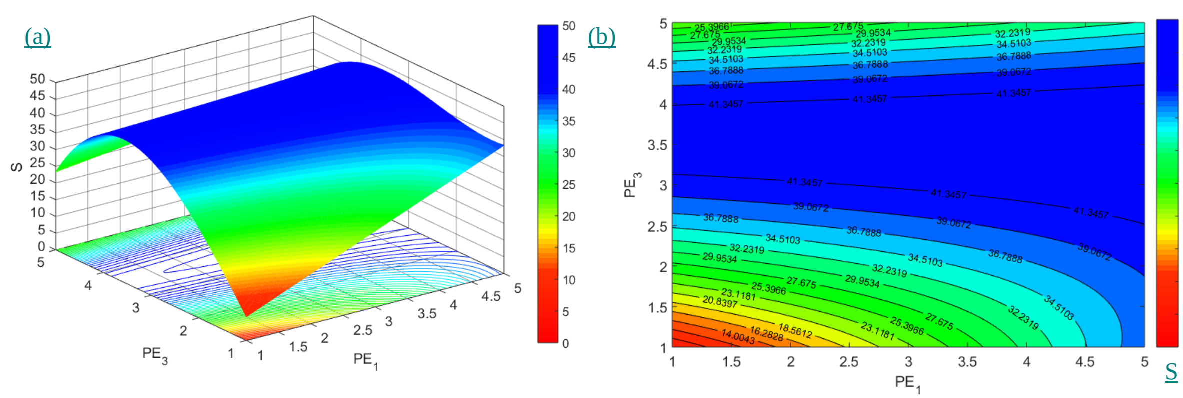


Figure 4.10 Extraversion (PE1) and Conscientiousness (PE3) Map with the Optimal Intervention Strategies (IN2). a) 3-D Surface Plot; b) Top View of the Surface.

4.7 Conclusion

Occupant personality and behavior greatly influence the selection of optimal energy intervention strategy and result in large variances of household energy forecasting. Therefore, it is critical to understand interweaved relationship among occupant behaviors, their personality traits, and suitable behavioral intervention strategies, so as to accurately predict energy consumption under the best-fit intervention strategy.

Based on an experiment conducted in Hangzhou, China, this study has proposed a variable selection approach that determines the optimal set of variables in predicting household electricity consumption. Among the initial 48 variables, 18 of them have been considered as the critical predictors including energy behaviors, personality trait, demographic information, building features and weather indicators in this research. Moreover, the prediction was further improved by introducing the interaction effect between the selected five behavior predictors and other variables in a GA RBF SVR model that incorporates occupant personality, behaviors, and intervention strategies to predict household electricity consumption. The result shows that the proposed model exhibits the best and robust performance in both next-month prediction and time-series forecasting. Therefore, the proposed model is able to act as a decision-making tool to choose the most appropriate intervention strategy for an individual household and to accurately predict the electricity savings under the selected intervention strategy. It is also of high practical value, since the heterogeneous effects of intervention strategies on individuals are the thorny problems for policymakers and behavioral researchers. The proposed model can also be adopted to forecast the energy consumption related to occupant behaviors in residential buildings and potentially in commercial buildings. By considering the individual profiles and their own characteristics, especially occupant behaviors and personalities, it is possible to tailor the interventions to achieve the full potential of energy savings.

According to the proposed approach, the best-fit strategy for each of the households was calculated in all experiment groups. This personality-based customized strategy generated from the improved SVR model can overall lead to an additional 12.1% reduction in household energy consumption than the real experiment setting. Specifically, the result demonstrated that the intervention strategy of WeChat with feedback and without feedback achieved the highest (15.97%) and second highest (15.43%) electricity savings compared to other strategies, followed by the consultation strategy (14.9%). The sticker strategies showed the smallest reduction in electricity consumption during the experiment period. Importantly, all of the feedback interventions (IN_1, IN_3 and IN_5) presented a slightly more electricity savings comparing to non-feedback interventions (IN_2 and IN_4).

Besides, two personality traits− extraversion and conscientiousness−out of Big Five personality test, have been identified with significant influence in responding energy intervention. To examine their effects on the maximum predictive electricity savings, 10,000 households was simulated by using the Monte Carlo method and illustrated the results in a 3D surface plot, in which the predicted maximum energy savings in WeChat with feedback condition was much more than any other intervention strategies, reinforcing the previous predictive results.

Further, five types of people (that is, E^LC^H, E^LC^L, E^HC^H, E^MC^L and E^LC^M) were identified based on their combination of extraversion and conscientiousness that response very distinctively to the optimized intervention strategy. The plot presented that the resident type $\mathrm{E^LC^H}$ with a high rate of conscientiousness while low rate of extraversion has a small-to-moderate saving potential. Nevertheless, type E^LC^L residents who are disorganized and introverted showed polarized behaviors that they could either save massive electricity consumption when intervened by the WeChat with feedback or save little.

The first contribution of this study is the development of a predictive tool that is able to select the optimal intervention strategy and to predict the maximum of electricity savings potential for each household, with identified subsets of all characteristic variables of households. Furthermore, the interaction effect between occupants' energy use behaviors and other selected variables such as households' demographic factors and personality traits are examined and incorporated in the household energy prediction model. Last but not least, the results shed light on the design of personality-based behavioral intervention strategy with considerable energy savings in the residential community, enlightening a customized approach for demand-side energy management.

Given the contributions above, this study has three limitations that require for the future study. First, this study is a crucially preliminary step in the domain of electricity savings forecasting under multiple intervention strategies by considering energy behaviors, personality traits and the interaction effects between variables. Although the results are valid in the proposed approach, whether a household can persist in behaving in an energy-efficient lifestyle over a longer period of time is still under debate. Further study is thus suggested to focus on examining whether the energy behaviors of residents with different characteristics (e.g., personality traits, age) decay or relapse when intervention is terminated, and tailoring intervention strategies based on psychological methods to tackle this issue. Second, the current work was conducted in one city of China, however, residents' behaviors and living habits may be different in other cities or countries. To generalize the prediction model, it needs to be applied to and tuned by different places with various scales and culture. Last but not least, the prediction model is developed by monthly household consumption in this research. To further improve the accuracy of the proposed model, future work should use high resolution data (i.e. minute-based energy data) to calibrate the model and to reduce the estimate error.

Chapter 5: Conclusion

5.1 Major Findings and Novelty

This dissertation evaluates the occupant behavior and its influence on the building energy management in three effects: 1) influencing of occupant behavior on the performance of energy retrofit, 2) change of occupant energy behavior via messaging intervention, and 3) incorporation of occupant personality characteristics in behavior intervention and energy forecast models. The main findings are summarized as follows.

In Chapter 2, this study introduces an occupant behavior-based decision-making model for evaluating and designing ESPCs contracts in building energy retrofit. Renters' rebound effect, a significant but frequently ignored phenomenon, is incorporated in this model to better estimate potential energy savings. The result shows that renters' rebound effect is a significant variable that would cause up to a 4-year difference of acceptable ESPCs contract length in the case study of University of Maryland campus (17-year contract with 15% rebound effect, 13-year contract without rebound). In order to mitigate and eliminate renters' rebound effect, a shared incentive strategy between owners and renters was proposed. It is noticeable that NPV generated with shared strategy ($\theta \in [0.5,1)$) is always greater than that without sharing ($\theta = 1$), indicating that shared incentive is an effective tool to promote renters' energy conservation behaviors. Key associated variables with rebound effect were also discussed to assess their impacts on the profitability and duration of ESPCs projects, such as renters' risk attitudes (ρ), expected rates of return (r_R, r_O, r_E), and sharing strategy variables (G, α, β). The results suggested that the sensitive renters ($\rho = -10$) whose behavior can be motivated by monetary incentives are likely to save more energy during sharing split program and resulted in the 9.06% increment of a project's NPV compared to the insensitive renter ($\rho = -100$) and in a 1-year decrease in contract period (from 14 years to 13 years). The ESCO's choice of expected rates of return (r_E) must be determined with discretion as an increase of r_E (i.e. a 50% increase from original value of 9%) will substantially stretch the acceptable contract period from 14 years to 18 years and lose bidding advantage in a highly competitive energy efficiency market.

The determination of sharing strategy variables (G, α, β) is even more complicated considering the intertwined relationship and responsive behaviors among owners, ESCOs and occupants. The value of guaranteed savings (G) needs to be designed within a dedicated zone to avoid over- or under-estimation. When G is largely lower than the actual savings (R_t) (under-estimated scenario), the extra savings amount $(R_t - G)$ is high. Because an owner's sharing percentage beyond the guarantee ($\beta = 20\%$) is much higher than an owners' sharing percentage within the guarantee ($\alpha = 5\%$), the ESCOs have to split a large portion of extra savings ($\beta * (R_t - G)$) to owners and hence recover less from the extra savings. Consequently, ESCOs have to extend the contract for a longer period to recover the initial investment. For instance, when G decreases to 500,000 USD, the contract period under this case will increase to 16 years. On the contrary, when G is over-estimated and higher than actual savings, ESCOs must compensate the saving shortage $(G - R_t)$ to owners based on the contract terms, causing an even longer contract period. In a case when G is increased by 125%, the corresponding contract period will increase up to 15 years. The contract negotiation between ESCOs and owners has also been discussion with interactive process and key determining variables including the contract period (n) and the shared percentage (θ).

These results provide convincing evidences to quantify and evaluate the influence of occupant behavior, i.e. the renters' energy rebound effect, as a key specification on determining the contract assessment of ESPCs. To effectively mitigate the renters' rebound effect, the optimal design of shared saving scheme needs to be carefully considered to create joint energy savings from both owners and renters. Such sharing strategies offer theoretical implications for contractual design that improve building energy efficiency in various applications, such as ESPC, green lease and smart grid implementation in the future.

In Chapter 3, both paper-based leaflet messages and electronic-based instant messages (i.e. WeChat) were comparatively studied with different sets of intervention strategies in residential communities. The results show that the effectiveness of intervention strategies depends on both the way the messages are delivered and the frequency of delivery. WeChat was the most effective in triggering significant behavioral changes than using stickers. Although the WeChat group recorded the most energy savings between June and January (that is, 225.63 kWh), the amount of saving decreased through the months afterwards. In other words, the effectiveness in using instant messaging platform, such as WeChat, was short-lived. Comparatively, paper-based delivering method (e.g. sticker) is not as effective as WeChat but suitable to promote persistence of intervention effect in the long-term effect. Among the 22 quality of life (QoL) and RICCOW factors, the action to keep windows and doors closed when the air-conditioner is switched on was found to be correlated with a willingness (the RICCOW factor of "willingness") to set and achieve specific consumption targets and having an opportunity to commit to energy saving. People who believe that higher education (leads to the RICCOW factor of "capacity") to save energy also commit more to using task lighting. Overall, although data on energy consumption and behavior congruently show the advantage of using the WeChat treatment, the correlation of these variables with QOL or RICCOW showed very different results, reflecting the complexity and difficulty involved in linking psychological or social factors to self-report energy behaviors.

This chapter expands previous efforts of occupant behavior intervention by differentiating interventions accordingly to occupant life styles and psychological perceptions. The results showed that the effectiveness of occupant intervention strategies depends on both the information messages contained and the means the messages are delivered. When the feedback is tailored to individuals and communicated in a suitable means, it provides additional value and persuasive power in changing occupant behavior. The findings also enhance the message framing theory in their applications in the energy efficiency communication by considering different message delivering means and the nature of message recipients.

Chapter 4 examined the occupant personality traits (e.g. Big Five Personality Traits) in determining the best intervention strategies that can change their energy use behavior. Based on these selected personality traits and other critical predictors, an improved Support Vector Regression (SVR) model has been developed to predict household electricity consumption under multiple intervention strategies. The model includes 18 critical predictors such as personality trait, energy behaviors, demographic information, building features and weather conditions, and the interaction effect among themselves. Out of five candidate SVR models, the GA-RBF-SVR model was selected the optimal model for household electricity consumption prediction as it exhibits the best performance on next-month prediction with MAPE of 8.48% and 9.34% using training data and testing data respectively, along with the minimum MAPE value during the testing period. According to the proposed approach, the best-fit strategy for each of the households was recommended and such a personality-based customized strategy generated from the improved

SVR model can overall lead to an additional 12.1% reduction in household energy consumption than the real experiment setting.

Specifically, the result demonstrated that the intervention strategy of WeChat with feedback and without feedback achieved the highest (15.97%) and second highest (15.43%) electricity savings compared to other strategies, more than any other intervention strategies. Importantly, all of the feedback intervention groups (e.g. IN_1, IN_3 and IN_5) presented a slightly more electricity savings comparing to non-feedback intervention groups (e.g. IN_2 and IN_4). It is worth noting that this result is similar but slightly different from the result in Chapter 3 in which the WeChat intervention (without eco-feedback) achieved the highest saving. This is because in Chapter 3, only two interventions, WeChat (without eco-feedback) and sticker (without eco-feedback) were compared. Another reason is that the method used in Chapter 4 is the hypothetical optimal saving amount provided that the personality traits of the household occupants are known and they are also provided with best-fit intervention strategies. In other words, the optimal saving amount from Chapter 4 (hypothetical value) are much higher than the actual results in Chapter 3. Such differences reinforce the key point that is there is a huge potential to improve the energy saving amount by properly tailoring and designing the customized intervention strategies based on occupant preferences and characteristics.

Additionally, two personality traits− extraversion (E) and conscientiousness (C)−out of Big Five personality test, have been identified with significant influence in responding energy intervention. Based on the combination of these two traits in either high or low level, five types of people (that is, E^LC^H, E^LC^L, E^HC^H, E^MC^L and E^LC^M) and their response to multiple intervention strategies were simulated by using the Monte Carlo method with the results plotted in 3D surface diagram. The plot presented that the resident type $\mathrm{E^LC^H}$ with a high rate of conscientiousness (C) while low rate of extraversion (E) has a small-to-moderate saving potential. Nevertheless, type $E^L C^L$ residents who are disorganized and introverted showed polarized behaviors that they could either save massive electricity consumption when intervened by the WeChat with feedback or save little.

The predictive model developed from this chapter is able to select the optimal intervention strategy and to predict the maximum of electricity savings potential for each household, with identified subsets of all personality traits of household occupants. This model expanded the existing theory on household energy prediction by highlighting the interaction effect between occupants' energy use behaviors and other selected variables such as personality traits and households' demographic factors. The results shed light on the design of personality-based behavioral intervention strategy with considerable energy savings in the residential community, enlightening a customized approach for demand-side energy management.

5.2 Managerial and Policy Implications

Behavior-based studies conducted in this dissertation provide new perspectives for the demand-side energy management and also offer innovative principles to regulate and govern user energy behaviors in the building sector. These results shed light on the design of tailored behavioral intervention strategy with considerable energy savings in the residential community, enlightening a customized approach for demand-side energy management. These key results also provided preliminary evidence that an integrated intervention approach, in which different modes of engaging households based on the nature and the purpose of messages, is a preferred strategy with a higher chance of success in motivating behavioral change. Policymakers may consider the use of social messaging platforms such as WeChat as a social information sharing platform that quickly engage households to an energy conservation program. After a short period of time (about two months, as indicated by this present study), more sustaining methods, such as stickers, can be introduced to maintain the initial "momentum" of energy-saving behavior initiated by the WeChat method.

As indicated by the results, households in general welcome more such opportunities to attempt to save energy; the fact that WeChat is a very widely used platform makes it very suitable to be employed for such a study. Also, using widely popular social platform is a way of providing more opportunities for households to engage in energy saving programs. The challenge in such programs may lie in two areas: 1) knowing how to keep the messages (conveyed through the social media platform) engaging and interesting, so that they can have more lasting effects on behavior; and 2) knowing when to introduce a more sustaining and long-lasting form of sharing information and engaging households (that is, by using methods such as stickers). In other words, an effective household engagement program or policy depends on not just the effectiveness of each phase (in which different method is employed) but also on the transition from one phase to another.

The fact that WeChat is a very widely used platform makes it very suitable to be employed over large areas, such as mega cities. Although some households indicated that having a strict energy ration in their households help them to save energy, formalizing this across all families is impossible in the near future. Unless in times of serious energy shortage, energy rationing is never a preferred policy strategy. In spite of this, energy rationing may be implemented as either an educational activity in schools or as an encouraged activity for the public. An example of the latter is the World Wildlife Fund's Earth Hour, which is a global celebration where people switch off their lights for one hour as a way to save energy in a concerted effort to mitigate climate change. This activity has created a strong following around the world and many companies and organizations are supporting this activity annually. Similarly, an annual energy rationing challenge may be started in conjunction with the annual Earth Day to engage firms and households to embark on actions that consciously cut back on unnecessary usage.

Finally, before formally incorporating the results of these studies into local energy policies or programs, it is essential for policymakers to fully understand how providing users with feedback while using the methods in this study can cause any changes to the results, in both short- and long-term. As any intervention may lead to ripple effect, meaning not only the direct response (first-tiered) expected by the intervention, but also generating additional second-tiered effects, such as rebound effect, decay effect and spillover effect. These second-tiered effects may improve (e.g. spill-over effect) or deteriorate (e.g. rebound effect) the overall efficacy of the energy policies in different phases. For instance, when comparing two kinds of intervention between monetary feedback venue environmental feedback to promote energy conservation, the immediate effect may evolve and change when the rebound effect or spillover effect kicks in, and subsequently it will change the overall effective of the intervention. Conducting a pilot study to fully aware of all responsive behaviors to a target policy and studying phase-in behavior changes with multi-faceted implications are key to the long-term success in engaging energy end users and will be undertook by the author in the future studies.

Appendices

Appendix A: Survey Questionnaire of Household Energy-Saving Behavior

Each family is approached to answer the following questionnaire to report energy saving behavior in each month during the experiment. The measurement of scale is noted in the end of the table.

Air-Conditioner
A． Possession [a]
1. Set the thermostat below 20 ^{o}C (or turn off air-conditioner) during winter; Set the thermostat above 26 C during summer [b]
2. Use automatic time-off switch when possible, e.g. after going to bed at night. [b]
3. Regularly check the air-conditioners and clean air filter timely. [c]
4. Keep windows and doors closed when the air-conditioner is switched on. [b]
5. Turn off air-conditioners when nobody at home. [b]
Refrigerator
B. Possession [a]
6. Allow some space all around the fridge. [d]
7. Refrigerator that is not overloaded. [e]
8. Cool down hot food before storing in fridge. [b]
9. Store liquids in the refrigerator after covering it up. [b]
Water Heater
C. Possession [a]
10. Heat enough water without too much unused. [f]

11. For an instantaneous type of heater, switch it on before shower and turn off after use. For a storage type of heater, switch it on about 45 minutes before shower, and turn it off after use. [b]
Bathroom Master
D. Possession [a] 12. Switch it on before shower and turn off after use. [b]
Lighting
13.Turn lights on during daytime. [b] 14. Turn lights off when nobody is in the room. [b] 15. Use task lighting for activities requiring small amount of focus light. (e.g. only turn reading lamps on and turn the other lights off). [b]
Home Electronics(E.g. Computers, TVs, etc.)
16. Turn off home appliances (e.g. TV) not in use instead of leaving on standby. [b] 17. Switch top boxes and routers off when not in use. (e.g. overnight) [b] 18. Allow computer to be on energy-saving mode (e.g. hibernation mode after 10- 15 min and completely off after 30 minutes. [b] 19. Unplug chargers or off the switch when appliances not in use. [b]
Electric Water Warmer
E. Possession [a] 20. Turn it on only when necessary. Turn it off and unplug when it is not in use. [b]
Clothes Dyer (Not Washing Machine)
F. Possession [a]

21. Dry laundry under natural sunlight instead using clothes dryer whenever possible. [b]
Heating Appliances (During Winter) **Electric Heating Blanket**
A. Possession [a] 1. Turn the blanket on only before going to bed and turn it off after the bed gets warm. [b]
Heating Appliances (E.g. electric heater, electric fan, oil filled radiator, etc.)
B. Possession [a] 2. Turn the heating appliances off when the room is warm instead of leaving them on. [b] 3. Average duration of using heating appliances every day.
Floor Heating
C. Possession [a] 4. Set the heating temperature between 18 to 20℃ 5.Close the windows and doors when the floor heating is in use. 6. Lower down the heating temperature instead turning it off when no one is at home for a short period of time (e.g. out for grocery) 7. Turn the floor heating off when no one is at home for long period of time. 8. Regularly check, clean and maintain the floor heating equipment.

Note:

a. Yes/No. If yes, how many?

b. Five-scale measurement: never, rarely (1-2 days/month), sometimes (1-2 days/week), usually (3-4 days/week), always (everyday).

c. Five-scale measurement: never, once/7-10 years, once/4-6 years, Once/2-3 years, Once within 2 years.

d. Five-scale measurement: no space (0-2cm), a little space(2-5cm), relative small space (5-7cm), small space (7-8cm), enough space (> 10cm).

e. Five-scale measurement: no space; full of storage, almost full of storage(2/3), plenty food but not full of storage(1/2), little storage(1/3), almost no storage.

f. Five-scale measurement: everyday too much unused hot water, many days too much unused hot water, sometimes too much unused hot water, usually not too much unused hot water, everyday not too much unused hot water.

g. Five-scale measurement: plenty (>10 hours), many (5-10 hours), average (3-5 hours), several (2-3 hours), very few (< 1hour).

Appendix B: Survey Questionnaire of Household Information

Part 1. Households Demographics

Housing Information 1) Floor level ______ 2) Orientation: North-south/East-west 3) Age of your house (since built until now): ________ years 4) The latest renovation completed in year _______ month______ 5) Usage: A. Rent B. Self-owned 6) Cook at home using kitchen appliances (e.g. induction cooker) A. Never B. Occasionally C. Usually D. Always 7) Your house includes _______ living rooms, ______ bedrooms, _____ study rooms 8) Usable floor area: ____ _meter square 9) House type: A. Commercial B. Economically affordable housing C. Low-rent housing D. Resettlement housing
Household Information 10) The number of family members (including yourself): _________, and their ages and gender. 11) Total monthly income (After tax): ( ) A. below 5000 RMB B. 5000-10000 RMB C. 10000-15000 RMB D. 15000-20000 RMB E. 20000-25000 RMB F. Above 25000 RMB 12) Education level of the house owner:( ) A. Never been to primary school B. Primary School C. Junior School D. Senior High School (Technical Secondary school, vocational school, technical school, etc.) E. Diploma (Higher vocational school) F. Degree G. Postgraduate and above 13) The highest level of education of family member who stays most of the time at home: ( )

A. Never been to primary school B. Primary School C. Junior School D. Senior High School (Technical Secondary school, vocational school, technical school, etc.) E. Diploma (Higher vocational school) F. Degree G. Postgraduate and above

14) The highest education level among the family members: ( )

A. Never been to primary school B. Primary School C. Junior School D. Senior High School (Technical Secondary school, vocational school, technical school, etc.) E. Diploma (Higher vocational school) F. Degree G. Postgraduate and above

15) Nationality: ( )

A. Chinese B. Minority, please specify: ______

16) Occupation: ( )

A．Government Organizations B．Enterprise C．Institutions D．Social group, district/village community n E. Self-employed F. Army G. Others, please specify:__________

Part 2. Household Quality of Life (QOL)

Rate the importance of the following aspects to your family based on the most appropriate answer. (Measured by five scales: 1 = Unimportant; 2 = Slightly important; 3 =Important; 4 =Very important; 5 =Critical.)

1) Aesthetic: Being able to enjoy the beauty of nature and culture.

2) Challenge: Having challenges and experiencing pleasant and exciting things in life.

3) Life Experience: Having a varied life, experiencing many things as possible.

4) Comfort Level: Having a comfortable and easy daily life.

5) Education: Having the chance to get a good education and to gain general knowledge.

6) Environment Quality: Having access to clean air, water and soil. Having and maintaining a good environmental quality.

7) Freedom: Freedom and control over the course of one's life, to be able to decide for yourself, what you do, when and how.

8) Health: Being in good health, access to adequate health care.

9) Self-esteem/ Personal Identity: Having sufficient self-respect and being able to develop one's own identity.

10) Leisure Time: Having enough time after work and household work and being able to spend this time satisfactorily.

11) Living Condition: Having nice possessions in and around the house.

12) Income: Having enough money to buy and to do the thing necessary and pleasing.

13) Biodiversity: To enjoy natural landscapes, parks and forests. Assurance of the continued existence of plants and animals and maintaining biodiversity.

14) Friend and family: Having an intimate relation, a stable family life and good family relationships.

15) Privacy: Having opportunities to be yourself, do your own things, a place of your own

16) Safety: Being safe at home and in the streets. Being able to avoid accidents and being protected against criminality.

17) Care and love: Feeling attended to and cared for by others.

18) Social Justice: Feeling attended to and cared for by others.

19) Social connection: Having good relationships with friends, colleagues, neighbors.

20) Spiritual/Religion freedom: Being able to live a life with an emphasis on spirituality and/or with your own religious persuasion.

21) Social Recognition: Being appreciated and respected by others.

22) Work: Having or being able to find a job and being able to fulfill it as pleasantly as possible.

Part 3. Individual Energy-saving Responsibility (RICCOW)

Please read the following item carefully and select the most appropriate answer. (measured by five scales: the measurement scale ranges from: completely not, occasionally/somewhat, depends, most of the time, always.)

1) You should be responsible for the energy savings 2) Material Incentives (E.g. monetary incentive, prizes and other material rewards) help to develop the energy-saving habit. 3) The current material incentives are adequate. 4) Non-material incentives (recognize and commend the model energy-saving family in the whole district) help to develop the energy-saving habit. 5) The current non-material incentives are adequate. 6) Mastering some energy-saving knowledge and skills help to conserve energy. 7) Strict electricity consumption plan (family plans a cut-off point for electricity consumption, which cannot be exceeded every month) help to conserve energy. 8) The higher the education level of family members, the stronger the intention to conserve energy. 9) Willing to participate in the energy-saving activities within community, company and organizations. 10) Having such energy-saving activity.

Appendix C: Description of the Attributes and Variables Used in the Experiment and the Simulation

Survey Name	Attribute	Numbers of Items	Variable Name	Variable type	Item	Collection Period	Frequency
Demographics Survey	Demographic Profile	9	DEMO_residents (DE_1)	Continuous	Number of family members.	February, 2016	Once
			DEMO_age (DE_2)	Continuous	Average age of all family members.		
			Demo_resident_gen (DE_3)	Continuous	Ratio of males to the household.		
			Demo_income (DE_4)	Ordinary	Total monthly income (After tax). [a]		
			Demo_owner_edulvl (DE_5)	Ordinary	Education level of the house owner. [b]		
			Demo_residen_tedulvl (DE_6)	Ordinary	The highest level of education of family member who stays most of the time at home. [b]		
			Demo_highest_edulvl_no (DE_7)	Ordinary	The highest education level among the family members. [b]		
			Demo_religion (DE_8)	Categorical	Nationality: 0. Others(DE_{8a}) 1. Han(DE_{8b})		
			Demo_occup(DE_9)	Categorical	Occupation: 1. Government organizations(DE_{9a}) 2. Enterprise(DE_{9b}) 3. Institutions(DE_{9c}) 4. Social group(DE_{9d}) 5. Self-employed(DE_{9e}) 6. Army(DE_{9f}) 7. Others(DE_{9g})		

	Building features	11	Demo_floor (BU_1)	Continuous	Floor level.		
			Demo_direction (BU_2)	Categorical	Orientation: North-south (BU_{2a})/East-west(BU_{2b})		
			Demo_house_age (BU_3)	Continuous	Age of your house (since built until now)		
			Demo_retrofit_date (BU_4)	Ordinary	The latest renovation completed in year ______ month_____.		
			Demo_rent (BU_5)	Categorical	Usage: 1. Rent(BU_{5a}) 2. Self-owned(BU_{5b})		
			Demo_cooking (BU_6)	Ordinary	Cook at home using kitchen appliances (e.g. induction cooker). [c]		
			Demo_living_rom (BU_7)	Continuous	Your house includes _____living rooms		
			Demo_bedroom (BU_8)	Continuous	Your house includes ____bedroom		
			Demo_study_room (BU_9)	Continuous	Your house includes _____study rooms		
			Demo_area (BU_{10})	Continuous	Usable floor area: ______meter square		
			Demo_home_type (BU_{11})	Categorical	House type: 1. Commercial (BU_{11a})2. Economically affordable housing(BU_{11b}) 3. Low-rent housing(BU_{11c}) 4. Resettlement housing(BU_{11d})		
Energy Behaviour Survey (adapted from He & Kua [19])	Building feature	3	EB_ac_num (BU_{12})	Continuous	The number of air conditions.	February to June, 2016	Monthly
			EB_fridge_num (BU_{13})	Continuous	The number of fridges.		
			EB_washer_num (BU_{14})	Continuous	The number of washers.		
	Energy Behaviour	16	EB_ac_temp (EB_1)	Ordinary	Set the thermostat below 20°C (or turn off air-conditioner) during winter; Set the thermostat above 26°C during summer. [c]		

and Kua and Wong [18])	EB_ac_power (EB_2)	Ordinary	Use automatic time-off switch when possible. e.g. after going to bed at night. [c]
	EB_ac_clean (EB_3)	Ordinary	Regularly check the air-conditioners and clean air filter timely. [c]
	EB_ac_close (EB_4)	Ordinary	Keep windows and doors closed when the air-conditioner is switched on. [c]
	EB_ac_occu (EB_5)	Ordinary	Turn off air-conditioners when nobody at home. [c]
	EB_fridge_outside (EB_6)	Ordinary	Allow some space all around the fridge. [c]
	EB_fridge_inside (EB_7)	Ordinary	Refrigerator that is not overloaded. [c]
	EB_fridge_food (EB_8)	Ordinary	Cool down hot food before storing in fridge. [c]
	EB_fridge_liquid (EB_9)	Ordinary	Store liquids in the refrigerator after covering it up. [c]
	EB_light_day (EB_{10})	Ordinary	Turn lights on during daytime. [c]
	EB_light_occu (EB_{11})	Ordinary	Turn lights off when nobody is the room. [c]
	EB_light_focus (EB_{12})	Ordinary	Use task lighting for activities requiting small amount of focus light. (e.g. only turn reading lamps on and turn the other lights off). [c]
	EB_app_off (EB_{13})	Ordinary	Turn off home application (e.g. TV) not in use instead of leaving on standby. [c]
	EB_app_nouse1 (EB_{14})	Ordinary	Switch top boxes and routers off when not in use. (e.g. overnight). [c]

			EB_comp_save (EB_{15})	Ordinary	Allow computer to be on energy-saving mode (e.g. hibernation mode after 10-15 min and completely off after 30 minutes. [c]		
			EB_app_unplug (EB_{16})	Ordinary	Unplug chargers or off the switch when appliances not in use. [c]		
Big Five Personality Traits Inventory (BFI-10) [51]	Personali ty	10	Extraversion (PE_1)	Ordinary	Extraversion is measured by two survey items as follows: 1. I see myself as someone who is reserved. [h] 6. I see myself as someone who is outgoing and sociable. [h]	July, 2016	Once
			Agreeableness (PE_2)	Ordinary	Agreeableness is measured by two survey items as follows: 2. I see myself as someone who is generally trusting. [h] 7. I see myself as someone who tends to find fault with others. [h]		
			Conscientiousness (PE_3)	Ordinary	Conscientiousness is measured by two survey items as follows: 3. I see myself as someone who tends to be lazy. [h] 8. I see myself as someone who does a thorough job. [h]		

	Neuroticism (PE_4)	Ordinary	Neuroticism is measured by two survey items as follows: 4. I see myself as someone who is relaxed, handless stress well. [h] 9. I see myself as someone who gets nervous easily. [h]
	Openness (PE_5)	Ordinary	Openness is measured by two survey items as follows: 5. I see myself as someone who has few artistic interests. [h] 10. I see myself as someone who has an active imagination. [h]
Intervention	IN_1	Categorical	Leaflet/Stickers with feedback group
	IN_2		Leaflet/Stickers without feedback group
	IN_3		WeChat with feedback group
	IN_4		WeChat without feedback group
	IN_5		Consultation group
	IN_6		Control group
Last month consumption	Last_month ($E_{i-1,j}$)	Continuous	Electricity consumption of the subject household in the last month (kWh).
Weather	HDD	Continuous	Heating Degree Days (°C·d).

CDD	Continuous	Cooling Degree Days (°C·d).

Note:

a. Below 5000RMB, 5000-10000RMB,10000-15000RMB, 15000-20000RMB, 20000-25000RMB, Above 25000RMB.

b. Never been to primary school, Primary school, Junior school, Senior school, Diploma, Degree, Postgraduate and above.

c. Never, Rarely, Sometimes, Usually, Always.

d. Never, Once/7-10 years, Once/4-6 years, Once/2-3 years, Once within 2 years.

e. Everyday too much unused hot water, Many days too much unused hot water, Sometimes too much unused hot water, Usually not too much unused hot water, Everyday not too much unused hot water.

f. Plenty>10 hours, Many (5-10 hours), Average (3-5 hours), Several (2-3 hours), Very few (< 1hour).

g. Full load, 2/3 load, 1/2 load, 1/3 load, Minimal load.

h. Disagree strongly, Disagree a little, Neither agree nor disagree, Agree a little, Agree strongly.

Glossary

A. Parameters and initial values used in the EPC decision making model (Chapter 2).

S/N	Parameters	Symbols	Current Values
1	Volatility of the O&M cost coefficient	σ_H	0.25
2	Volatility of the energy saving amount coefficient	σ_K	0.01
3	Energy price drift effect	α_E	0.0523
4	Energy price volatility effect	σ_E	0.0856
5	O&M trend index*	δ	1.025
6	Initial value of the O&M cost coefficient*	H_0	0.0036
7	Initial value of the energy saving amount coefficient*	K_0	0.0043
8	Initial value of the energy price*	P_{E0}	22.82 $/Btu
9	Economic lifetime of the energy efficiency system	N	25 years
10	Capital cost of the energy efficiency investment	Ic	$20,668,991
11	Annual energy cost savings guarantee	G	$3,000,000
12	Owners' expected revenue share within the guarantee	α	5%
13	Owners' excess revenue share beyond the guarantee	β	20%
14	Owners' expected rate of return*	r_O	3.10%
15	Renters' expected rate of return*	r_R	3.10%
16	Project interest rate*	r_P	3.10%
17	ESCOs' expected rate of return*	r_E	6%
18	Owners' expected revenue share with Renters	θ	100%
19	Maximum renters' rebound effect	ϕ	15%
20	Risk attitude of renters	ρ	-20

**Note: 1. values of parameters are partially derived from Deng et al. (2014), while those with star (*) were adjusted or newly collected based on the project documents or relative background information.*

B. Parameters and the explanation used in the energy forecasting model (Chapter 4).

S/N	Parameters	Symbols
1	Electricity consumption (kwh) of the j^{th} household in the i^{th} month	E_{ij}
2	Predicted value of E_{ij}	E_{ij}'
3	The a^{th} vector coefficient of the b^{th} model	$\beta_{\mathrm{a},b}$
4	Vector of energy behaviors	EB
5	Vector of building features	BU
6	Vector of demographic factors	DE
7	Vector of personality traits	PE
8	Vector of intervention variables	IN
9	Vector of heating degree days	HDD_i
10	Vector of cooling degree days	CDD_i
11	Intercept	α
12	Error term	ε_{ij}
13	Number of parameters to be estimated	k
14	Likelihood function	L
15	Parameter vector	w
16	Constant term	b
17	Nonlinear kernel functions	$\varphi(x)$
18	Lagrange multiplier	α_i
19	Cost hyperparameter	C
20	Number of data samples	d
21	Starting time of the intervention	p
22	Ending time of the intervention	q
23	Period of the intervention from the p^{th} month to the q^{th} month	T

24	Maximum average electricity savings through the optimal intervention for the j^{th} household of T month	S_j'
25	No treatment condition	m
26	Population of households that suggested with optimal intervention	R_z
27	Total number of households	R
28	Personality trait of extraversion	PE_1
29	Personality trait of agreeableness	PE_2
30	Personality trait of conscientiousness	PE_3
31	Personality trait of neuroticism	PE_4
32	Personality trait of openness	PE_5
33	Intervention strategy of leaflet/stickers with feedback	IN_1
34	Intervention strategy of leaflet/stickers without feedback	IN_2
35	Intervention strategy of WeChat with feedback	IN_3
36	Intervention strategy of WeChat without feedback	IN_4
37	Intervention strategy of Consultation with feedback	IN_5
38	No intervention	IN_6

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