DOCTOR DISSERTATION

Determinant Impacts on Household Energy Consumption in Japan and Vietnam

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ACKNOWLEDGEMENTS

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Determinant Impacts on Household Energy Consumption in Japan and Vietnam

ABSTRACT

In the post-industrialization century, and with the impact of social crisis such as COVID-19 when more activities pour into the residential area leading to a significant change in the use of electrical appliances, which affect the household energy use, household energy tends to become the main share instead of the industrial sector. Japan and Vietnam belong to Asia-Pacific region where total energy end-use is expected to account for 52% in 2050. To overcome the urgent need on household energy saving, this study simultaneously assesses the multiple influences of household determinants, housing design, and physics characteristics on energy end-use. The proposed research herein first aims to investigate the effects of all influencing factors on household energy consumption and to evaluate their complex relationships under different situation. Hybrid modeling combing physics-based modeling and data-driven modeling is the state-of-the-art approach to be considered for energy forecast, while factor analysis has the potential for sorting the weight of factors. The crucial impacts of determinants on Energy End-Use (EEU) is well-presented to emerge ways optimize energy use in residential area. This approach can be an example for other regions where suitable energy policies should be provided to each locality with different environmental and social characteristics. Discussion on the final results imply cognitive changes for consumers where the visualization of energy efficiency optimization can be easily captured so that environmental sustainability will be closer than ever.

In Chapter 1, BACKGROUND AND PURPOSE OF THE STUDY. The research backgrounds of energy consumption in Japan and Vietnam are introduced in Chapter 1, which is including the current status and bottleneck of household energy end-use and related factors. Japan's electricity consumption is on a downward trend while Vietnam's is on an uptrend and the residential sector reveal the similar tendency. Electricity consumption in the household sector has been rapidly increasing and accounted for in residential area accounts for 27% in Japan and 36% in Vietnam. Recognizing the crucial role that energy efficiency plays in mitigating global environmental issues and greenhouse gases emissions, this study concentrates on the cause-effect of energy end-use in residential areas in Japan and Vietnam. The core concept is to apply the energy use optimization theory into reality. Thereby, sensitivity analysis of energy use behaviors has the potential to discuss in-depth the possibilities of adaptation in practice.

In Chapter 2, LITERATURE REVIEWS OF DETERMINANTS AND ITS IMPACT ON HOUSEHOLD EEU. The overview of these studies reveals that many prediction methodologies

and remarkable influential factors have been examined to get the holistic picture of Energy-related factors in the scale of building Energy consumption. However, a pellicular study for household Energy lifestyle is necessary and potential in developing countries. In a more concrete view, the residential factors and their linkage to household Energy use are displayed on a global background, which is an example of our granular case in the next section. From the research literature, it can be seen that Vietnamese households display comparable trends of Energy demand with other regions, however, more investigating data is required to signify the levels of influence, as well as identify specific Energy-saving solutions to cut down Energy use in the next generation. The current platform presents rich potentials for further exploration and analysis, mainly targeting the household impacts and occupant behaviors in the follow-up studies.

In Chapter 3, METHODOLOGY OF HYBRID METHOD AND PATH ANALYSIS. This Chapter is well-presented with three main approaches: investigation on household impact factors and household energy monitoring data, hybrid method combining data-driven and physics-based approach, path analysis using R-studio. These three main approaches are corresponding with chapter 4, chapter 5, chapter 6, and the application of physic-based only method (which is part of hybrid method) is used for Chapter 7. In general, Database derive from off-line survey, direct interview, technical drawing and energy monitoring in Japan and Vietnam support significant sources to the three approaches. The need of as much detailed as the energy data and much variety of the determinant data is reaffirmed. However, the limitation of databased can be improved by using Path analysis or Physic-based simulation only which is clarified in Chapter 6 and Chapter 7.

In Chapter 4, CORRELATION OF HOUSEHOLD AND HOUSING FACTOR WITH EEU IN JAPAN AND VIETNAM. The data resource derived mainly from statistical database and investigation in Japan and Vietnam. Accordingly, the crucial impacts of household characteristics on residential Electricity End-Use (EEU) have not been significantly paid attention. This section generalizes a detailed picture of distinct features of individual households such as family patterns, housing designs, occupancy rate (OCC), and occupant behaviors. Obtaining the Hourly Electricity Load (HEL) from the measurement and household surveys of an electric-only residential apartment in Japan, the authors perceived notable relationships among the household characteristics, OCC, and EEU. The study highlights the multi-dimensional influences of household attributes to emerge a holistic view of changing energy behavior through different case studies. The contribution of detailed HEL data facilitates sustainable lifestyles and raises awareness of energy-saving in residential apartments. From the database, this section first presents a panoramic view of Vietnamese and Japanese household energy studies in the context of the world household energy sector, pointing out that it is important to have an open-source database on household energy consumption as well as corresponding household factors, such as the number of family members, gross floor area, household income, appliance ownership, occupancy rates, and other elements related to the use of energy devices. The study emerges a detailed picture of Vietnamese and Japanese household energy consumption in its correlation with easy-to-approach causal variables regarding household factors. With increasing support from economic growth and the improvement of energy policy, exploratory researches can be further implemented in these two countries with many potentials.

In Chapter 5, SENSITIVITY ANALYSIS: INFLUENCE LEVELS OF VARIOUS IMPACT FACTORS CASE STUDY IN JAPAN. This section emphasizes the potential growth of combining model and energy monitor data toward energy forecast in the early design stage, with the supplement of occupancy and other available information regarding residential houses. With the integration of forwarding and inverse modeling methods, the sensitivity analysis using a multi-dimensional hybrid approach offers more improvements in the accuracy of energy prediction. The energy modeling and monitoring facilitate the estimation of energy use in each household and prompt resident behaviors with energy performance reports. This section exploits the reciprocal relationship between observed data and simulated data in residential areas, supplementing the mismatch correction of unobservable factors such as ACS, actual occupancy rates, and energy waste. Compared with the measured data, the correlation shows goodness-of-fit with the coefficient of determination reaches up to 100% probability of the simulated data. However, prediction of daily use shows higher accuracy in households with stable ACSs while fluctuating ACSs are more suitable for hourly usage anticipation. Overall, the Pearson correlation explains the proportion of variance in the energy models as follows: 75% on weekdays, 72% on Saturdays, and 76% on Sundays. Based on this result, the study proposes household energy efficiency solutions by comparing the impact of different household parameters on energy consumption. Especially, with lower levels of ACS in an acceptable comfort zone, 20% to 60% less heating energy can be achieved compared to the baseline of usage. This corresponds to 16% ~ 33% of the reduction for site energy and 13% ~25% for that of source energy. Larger household size, higher occupancy rate, lower thermal transmittance value for wall insulation, and smaller airflow rates can be more energy-efficient for household HVAC end-use as well as gross site and source energy.

In Chapter 6, PATH ANALYSIS: IMPACT OF HOUSEHOLD FACTORS AND HOUSING FACTORS IN VIETNAM

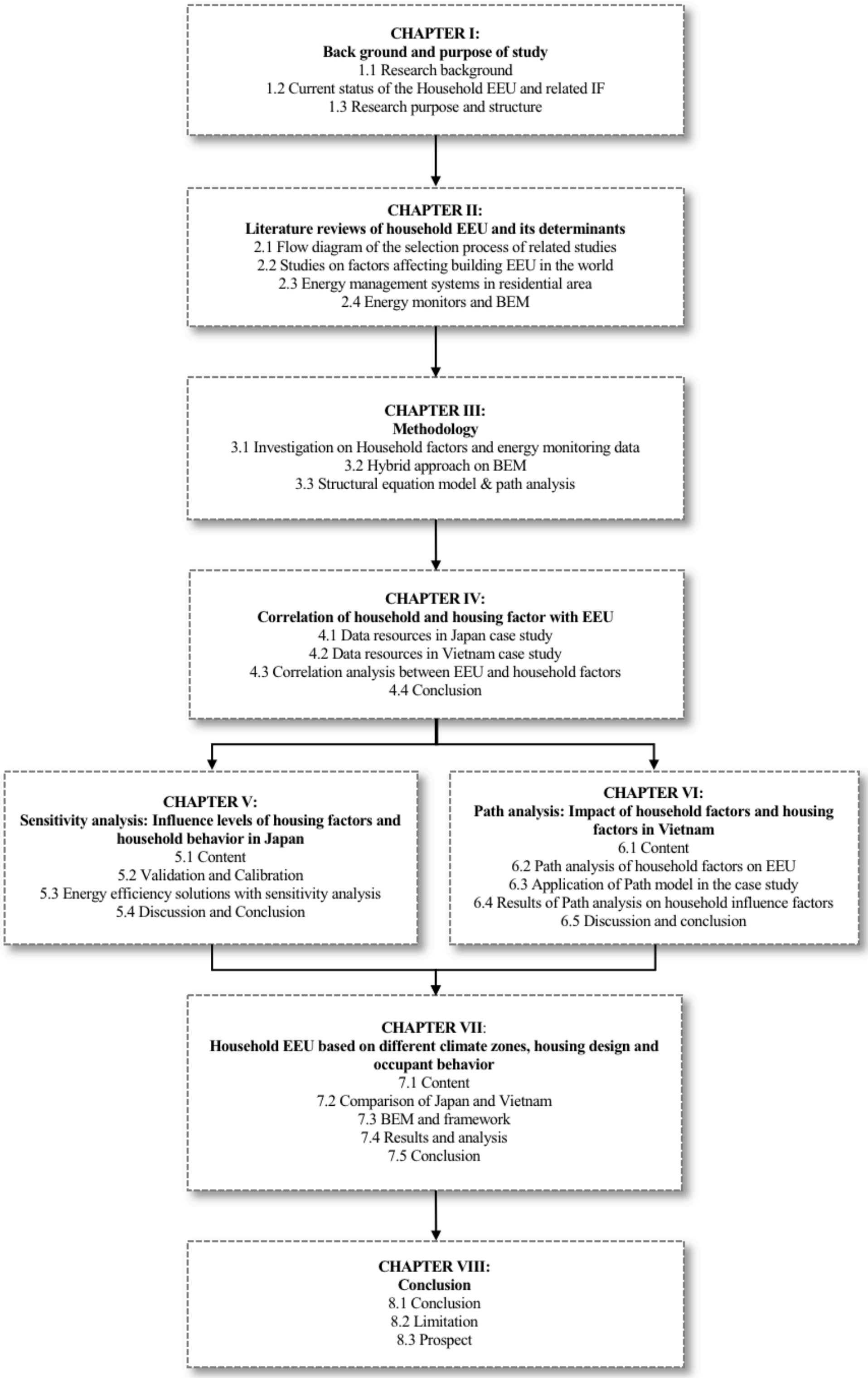
Vietnam remains a new case study with rare information including statistical energy data, as well as household surveys but it is also an opportunity to find a new method to analyze energy-related behaviors in residential buildings. We realized that the path model that only addresses the effects between observed variables was appropriate for this situation. Compared with the typical energy performance analysis which is better used to look at the relative variation of energy end-use by household categories instead of telling a specific influence number, this model can analyze the interactive relationships between the household factors and the energy consumption simultaneously, which enables more complex structures than multiple regression. The proposed SEM path analysis reveals better statistical findings on the correlations of variables and the influence levels of each household factor on the household energy end-use. While the TPP reveals a complex correlation of how various multi-unit household factors affect energy use on the same scale, the CM emphasizes the multi-dimensional influences of household attributes on the end-use and visualizes optimal options for energy-saving plans.

In Chapter 7, HOUSEHOLD ENERGY END-USE BASED ON DIFFERENT CLIMATE ZONES, HOUSING DESIGN AND OCCUPANT BEHAVIOR. The energy performance of a building is strictly dependent on the climatic conditions. The Heating Degree Days (HDD) and Cooling Degree Days (CDD) value index and can be used to evaluate. Comparing among 6 cities in Japan and Vietnam, an increase of EEU is corresponding with cities with greater latitudes in Japan, but decreasing with the increasing latitude number in Vietnam's cities. Major usage belongs to heating systems in Japan's cities while cooling use accounts for most of EEU in Vietnam due to high HDD in Japan and high CDD in Vietnam. Housing orientation is more important for cities in higher latitudes, and the South direction is recommended for designing bedroom's windows. Energy efficiency is clearer in VN cities than JP cities due to the significant saving for ACC and upto 50% energy saving could be achieved by changing ACS setpoint with low intensive usage within the thermal comfort standard. The comparison of energy use by geographical location shows that in the mild climate region with warm humid, cool humid, cold and very cold humid zones such as Japan (3A, 4A, 5A, 6A), household locations in greater latitudes tend to go with higher energy consumption due to the demand on heating system. However, in the hot humid zones such as Vietnam (0A, 1A, 2A), household locations in greater latitudes shows less energy consumption based on the need of cooling use). The North of Japan consumes more HVAC energy while the South of Vietnam spends more HVAC energy in residential houses.

In Chapter 8, CONCLUSION AND PROSPECT. A summarized of each Chapter is concluded.

TRAN LE NA 博士論文の構成

Structure of the Study: Determinant Impacts on Household Energy Consumption in Japan and Vietnam



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Chapter 1

BACKGROUND AND PURPOSE OF THE STUDY

CHAPTER ONE: BACKGROUND AND PURPOSE OF THE STUDY

1.1 Research background

1.1.1 The rapid growth of energy use in residential house

In recent decades, confronting the decline of ongoing environmental issues, energy efficiency has become a severe concern in the context of sustainable development over the world today. According to the International Energy Outlook 2019 [1], energy use in the building sector, including residential and commercial subsectors, accounted for 20% of global energy consumption in 2018, and was expected will increase by 22% by 2050. Household energy tends to become the main share instead of the industrial sector in the post-industrialization century [2]. The energy end-use (EEU) ratio of the appliances emphasizes that different cultures in different regions have carried out unique energy-related behaviors in residential needs depending on their national attributes, regional customs, and lifestyles [3]. Using detailed data of EEU, Lauretis et al. [4] assessed household energy consumption from the respective activities and explored various consumption patterns based on household compositions and housing features. Energy data, in general, has shown immense contributions to developing energy efficiency strategies such as benchmarking and policy-making.

Among different building subsectors, the residential buildings consist of around 15% to 25% of primary energy use in developed countries and a higher proportion in developing countries [5]. Compared to other developed countries, in 1988, Japan had low energy consumption per household, which were roughly one-half of that in France, the United Kingdom, and Germany, and about one-third of that in the United States (U.S.). In recent years, Japan's household energy consumption became closer to the average of European countries with an increase in household incomes [5]. According to the Ministry of Economy Trade and Industry Japan (METI), Japan household consumed 28% of final electricity consumption in 2017, increasing 2% from that of 2000 [6]. Among the five major countries of OECD countries (Japan, United Kingdom, United States, France, Germany), Japan has strengths on the demand side of reducing CO_2 emissions, especially on household sector efficiency [6]. D'Oca et al. cited that the energy demand of this sector tremendously relates to occupant behavior [7]. Besides, technology does not achieve energy-saving goals itself, but humans and their energy-related behavior must be included in energy performance efforts [8]. For that reason, it is necessary to implement thorough and detailed investigations to accomplish a comprehensive perception of various lifestyles and their complex interaction with the building energy [9]. Since the first commitment of the Kyoto Protocol concerning the reduction of greenhouse gasses was launch from 2008-2012 [10], electricity consumption started inclining to a slight downtrend. As a result, the term *smart community* was firstly emerged in Japan by Japan Structural Consultants Association (JSCA) [11]. Regarding the METI's plan for the adoption of the Paris Agreement 2015 United Nations Climate Change Conference, Japan Smart Community aims to reduce greenhouse gas emissions by 26% in 2030 and 80% in 2050 [12]. Accordingly, the household section's energy demand must decrease by 27% or 11.6 million kiloliters relatively [13].

Taking reference from the definition of Energy End-Use [14] [15], Electricity End-Use (EEU) is the electricity directly consumed by the users for services such as room temperature and light. Regarding residential EEU in different architecture categories, it proclaimed that residential apartments had used less energy than single-family detached houses [16]. To explain that, apartments have smaller walls and roofs' area that limits energy losses and gains. In contrast, detached houses are involved with ample floor space, which consumes more energy for heating, ventilation, and air conditioning (HVAC) [16]. Based on the data of Energy Efficiency in Buildings (EEB) in the U.S., an average apartment used about half the annual EEU of a detached house [16]. Although the larger sizes lead to lower energy per square meter, these studies manifested that apartments were likely to consume less EEU than detached houses. In Japan, after the establishment of JSCA and its strategy of Smart Communities in 4 cities, including Kitakyushu, many participants of the project are the residents living in recent-built apartments. According to The Statistics Bureau of Japan, dwellings are classified into four types of buildings: detached houses, apartments, tenement houses, and others [17]. Statistics in Table 1 indicate an increase of 7.7 million blocks from 1998 to 2018, accounting for a 40% growth rate. In 1998, apartments only accounted for 37.8% in total Japan dwelling and rose to 43.4% in 2018. Quoted from the report of Kanamori [18]: "A certain number of aged people had moved from detached houses to apartments from 2010", which explains the transition of the housing structure. According to the climb of housing demand, apartments can be the primary type of building construction in the next few decades of Japan instead of detached houses.

In Japan, Yoshiaki and Takashi [19] cited that the energy consumption in apartment houses is only 60% than that of detached houses, and the regional difference in energy consumption is smaller than detached houses. A survey of residential energy consumption in the U.S. in 2015 [20] also listed the different figures among house types, showing that over-5-floors apartment's EEU was only about 50% that of detached houses. These numbers emphasize the transition of residential house types from a detached house to an apartment in nearly future with development potentials in the context of energy-saving and sustainable energy conservation strategies. Also, Fig.1-5 displays that household EEU in apartments is lower than that in a detached house. There is no difference between the EEU in U.S. apartments and Japan apartments as a whole, and especially with the shares of water heater and space heating in particular [21] [22]. Many existing studies have explored the relationships between energy consumption and indirect factors, including household lifestyle and household characteristics [23] [4] [24] [25] [26]. However, it requires a more in-depth and thorough study focusing on activities of each household based on the multidimensional connections between energy use and occupancy, or energy use, and household features with a comprehensive evaluation.

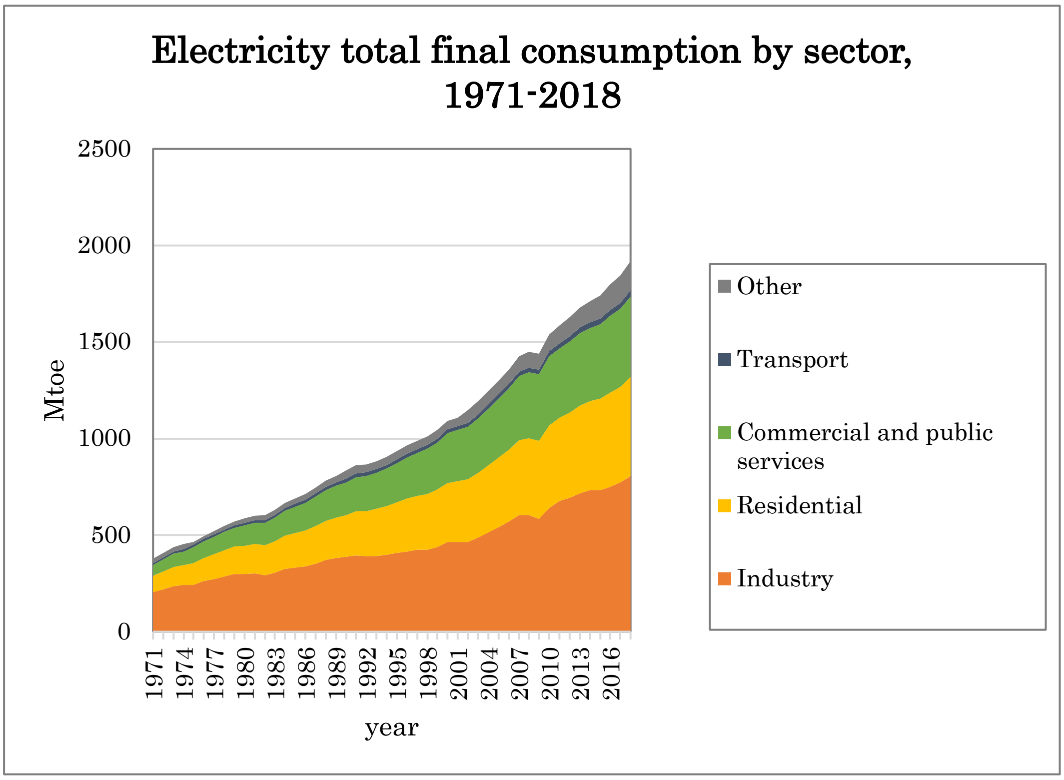

Fig. 1- 1. Electricity total final consumption by sector, 1971-2018, data by IEA [27]

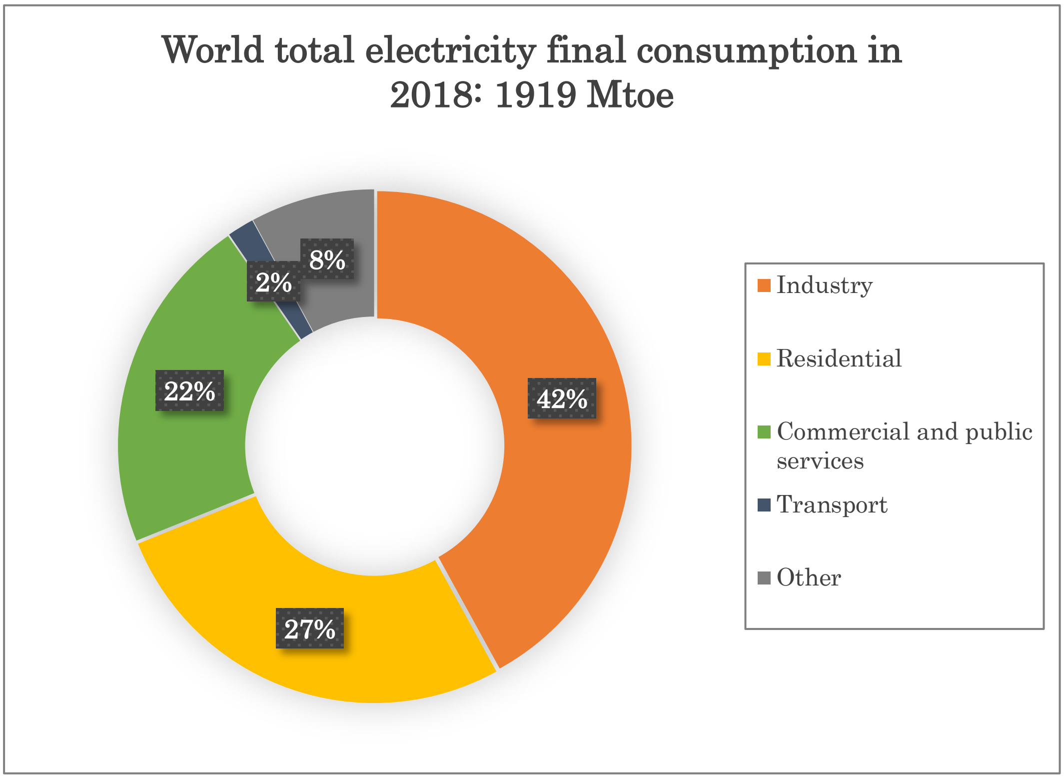

Fig. 1- 2. World total electricity final consumption in 2018 [27]

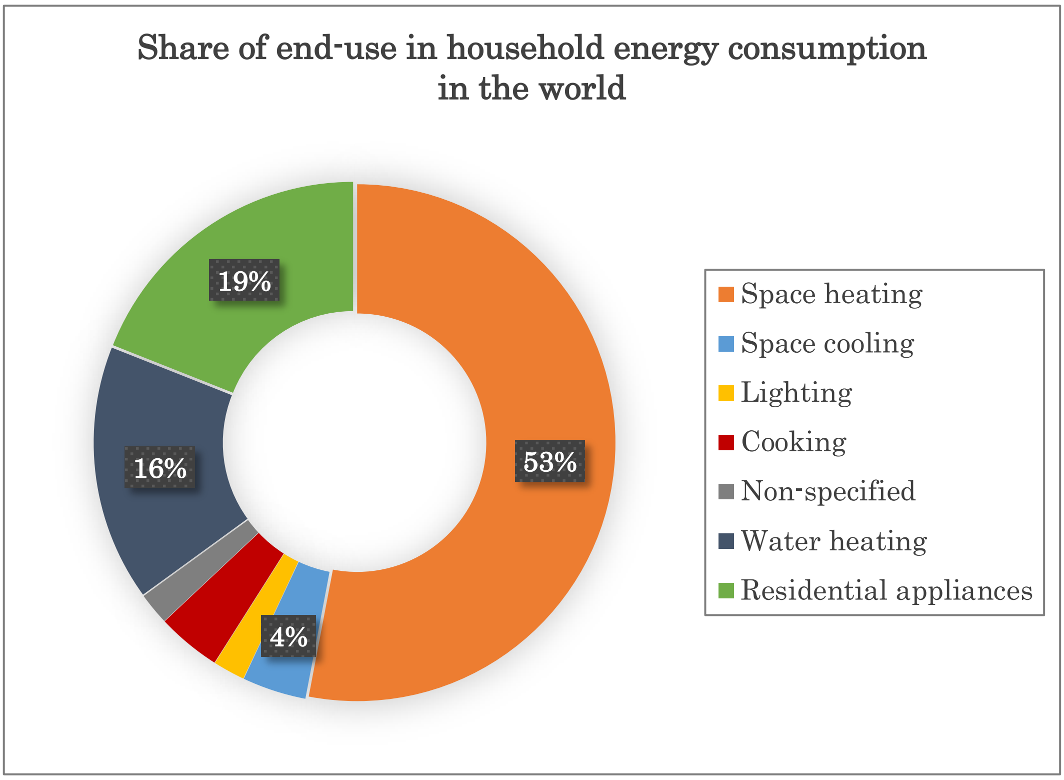

Fig. 1- 3. Share of end-use in household energy consumption in the world (IEA) [28]

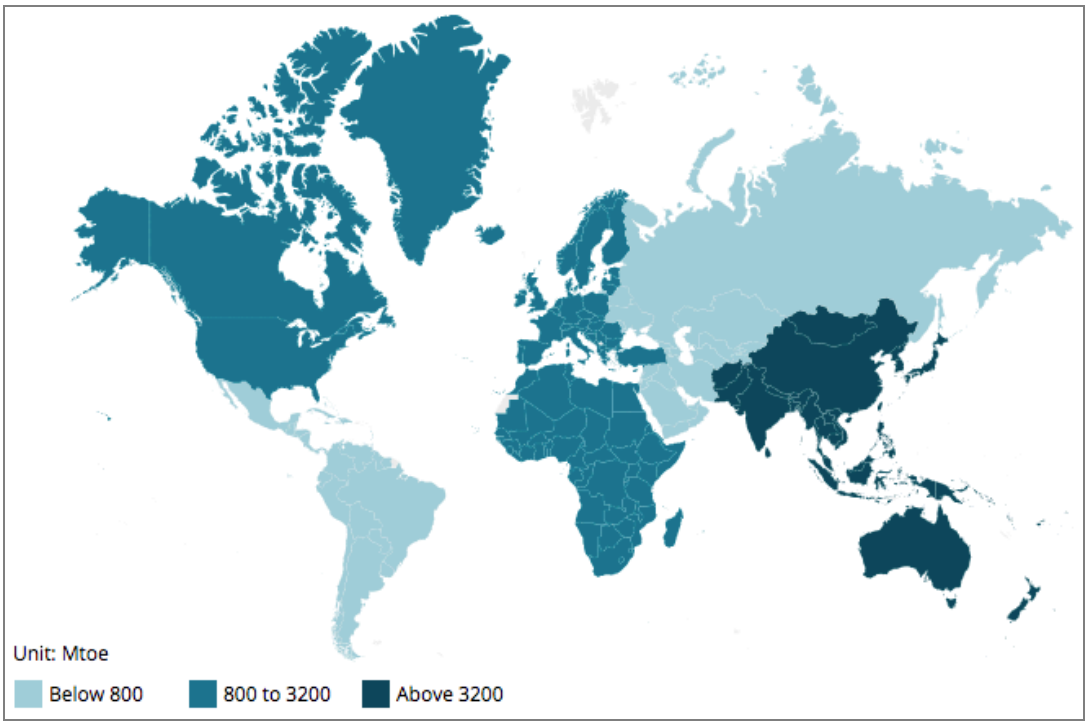

Fig. 1- 4. Forecast of total final energy consumption by region in 2050 [29]

Table 1- 1 Number (million building) and percentage of Japanese dwellings by types from 1998

to 2018 [17]

1998	2003	2008	2013	2018
25.3 (57.6%)	26.5 (56.5%)	27.4 (55.3%)	28.6 (54.9%)	28.8 (53.7%)
16.6 (37.8%)	18.7 (39.9%)	20.7 (41.8%)	22.1 (42.4%)	23.3 (43.5%)
1.8 (4.1%)	1.5 (3.2%)	1.3 (2.6%)	1.3 (2.5%)	1.4 (2.6%)
0.2 (0.5%)	0.2 (0.4%)	0.1 (0.2%)	0.1 (0.2%)	0.1 (0.2%)

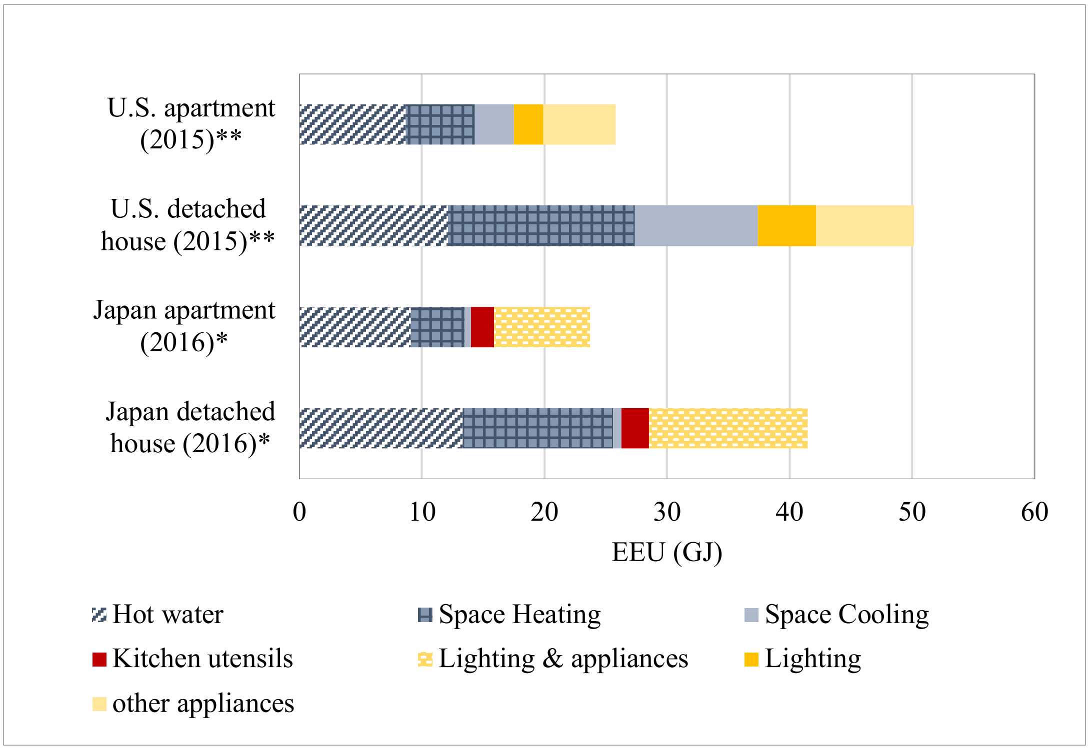

Fig. 1- 5. Household EEU shares by house types in U.S. and Japan

* The Energy Conservation Center, Japan [22]

** U.S Energy Information, 2015 [20]

1.1.2 Energy-related factors in residential houses

In residential areas, energy use is associated with important influencing factors such as weather, housing design, energy systems, and household economic level [30]. In the context of a growing population and global warming, this number is even higher due to the increase in comfort levels for space conditioning and hot water. Energy use for heating, ventilation, and cooling systems (HVAC), for instance, accounted for 50% of building energy consumption in the United States [30]. In the household sector, the HVAC system represented about 60 – 80% of EEU in most countries [31] (Fig. 1-6). Among them, households in European countries predominately require space heating while Japanese households prefer to use hot water the most in their homes. Studies [4] [7] [32] [24] [25] [26] [12] determined that the energy demand of this field is greatly linked to occupant behavior. For that reason, emerging applications that target energy-related behaviors of occupants and household characteristics are essential to optimize household end-use, under the orientation to minimize global environmental impacts.

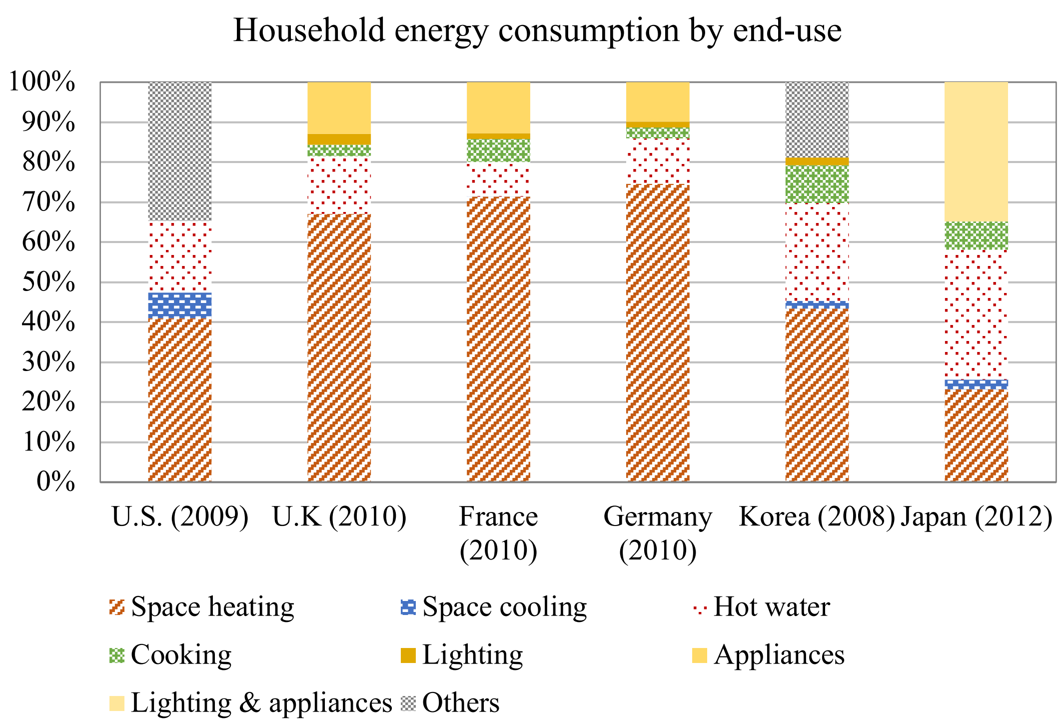

Fig. 1- 6. Shares of household energy consumption by end-use (Source: The Living Environment Planning Institute of Japan [31]).

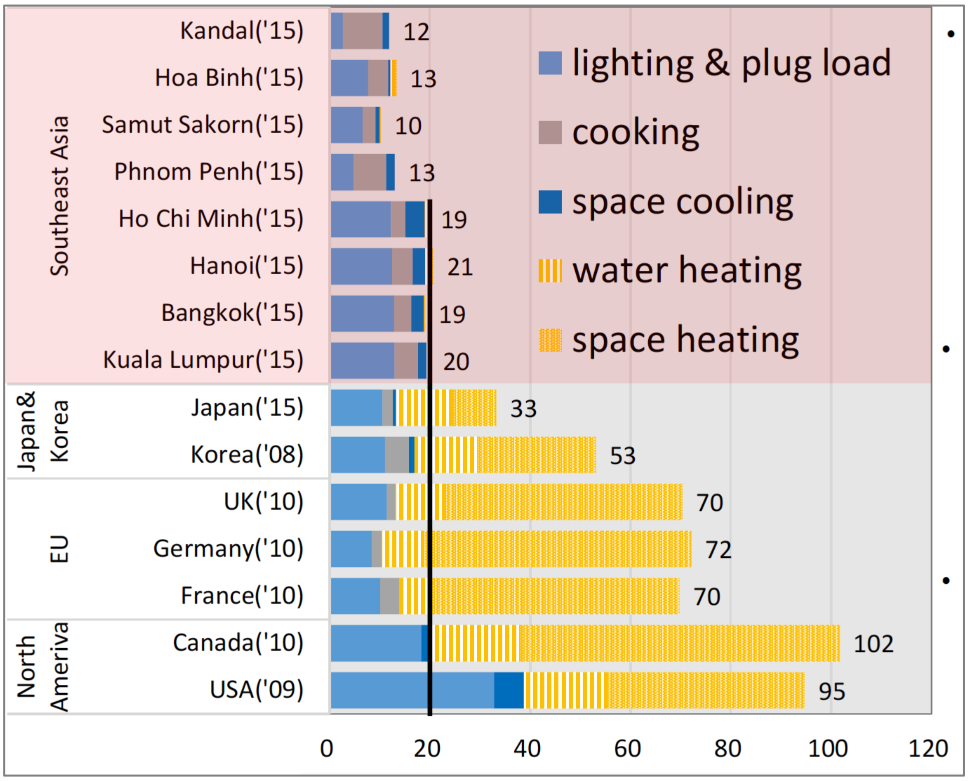

Fig. 1- 7. Household energy end-use in countries [33]

The approaches towards low-carbon emissions, resilience, and energy efficiency need to consider human factors [15]. For residential areas, energy consumption in the household sector is substantially related to household attributes and resident behavioral patterns [4]. And factors such as ownership and occupancy schedule also affect building energy, especially in the residential sectors that are associated with high levels of energy in construction and operations [34]. In addition to technological solutions depending on the economic status of residence, different approaches are proposed for energy efficiency strategies such as passive housing design and sustainable behavior patterns. In one example, a sensitivity analysis was applied to simulate a standard passive house model based on a detached house in Portugal [35]. The study stressed the role of dynamic simulations in designing energy reduction options for heating and cooling systems under a hybrid approach. Accordingly, thorough and detailed investigating data need to be conducted in conjunction with the sensitivity assessment of building energy modeling to facilitate a holistic understanding of sustainable lifestyles, optimal design options, and the complex interaction of these with the use of building energy [9].

1.2 Current status of the household energy end-use and related impact factors

1.2.1 Residential energy sector profile and related factors in Japan

1.2.2 Residential energy sector profile and related factors in Vietnam

Vietnam is one of the Southeast Asia countries with fast GDP growth in recent years, with an annual growth rate of 7% in 2019 [36]. With the robust development of the economy, the energy demand in Vietnam increases incessantly to meet the essential facilities and other domestic activities. Based on IEA data from the IEA (2018) – Key energy statistics [37], Vietnamese household electricity consumption has escalated by 139% in 10 years from 2008 to 2018 and the share of this sector was about 33% of total electricity consumption including other sectors such as industry 59%, commercial 5%, Agriculture/forestry 3% (Fig. 1). In Southeast Asia, Vietnam's household energy growth is even faster than that of Singapore, Indonesia, and Malaysia (Fig. 2). Along with the consumer demand, the average electricity consumption per capita of households doubled from 7% to 14% annually from 2000 to 2016 [38] – Calculated by ESCAP based on the data from International Energy Agency (IEA). Although the energy demand has insistently climbed up in recent decades, Vietnam is facing the risks of energy shortage due to a lack of corresponding development of technology and related policies. Before 2014, this country was a strong energy export in terms of different types of energy including electricity and crude oil. However, following the steps of industrialization in 2014, the escalation of energy imports found that the domestic supply was not enough to meet the current energy demand. This situation has appealed to serious concerns about energy security, energy conservation, and energy efficiency strategy, which have also been mentioned in many energy reports. In the Vietnam Energy Outlook Report 2019, investing in energy efficiency was considered to be much more cost-effective than building more power plant capacity, while the eco-friendly option can help cut CO_2 and mitigate dependence on energy imports. As stated in one of the targeted energy policies in Southeast Asian countries, electricity consumption in the building sector increased the most, where the use of household appliances and cooking equipment was expanded intensively [39]. For that reason, Politburo of Vietnam issued resolution No 55-NQ/TW in 2020 [40], stating that economical, efficient use of energy and environmental protection must be considered an essential national policy, and at the same time, diversification forms of energy such as renewable energy, clean energy should be applied.

The research topics on energy in general and household energy in Vietnam have been explored in the last decades and have received more attention from 2015 to the present. To account for the increase in energy consumption, the population growth and economic growth-oriented policies have become contributing causes to the rise in energy demand in Vietnam [41]. As demonstrated in a research paper on the energy reduction potential of zero-energy buildings in the Asia-Pacific region, economic development is the primary driver of energy demand [42]. Meanwhile, comparing Vietnam’s electricity usage intensity with 21 Asia-Pacific countries, one study used factor analysis of the economic and electricity indicators to denote that Vietnam had the highest intensity of electricity use, surpassing China and Mongolia [43]. To solve this issue, the article recommends shifting power diversification from the industrial sector to economic activities such as services and information technology. In line with this realization, a critical paper [44] discussed the need to focus on the collection, analysis, and management of energy data during the implementation of energy efficiency and conservation policies in Vietnam. These activities are familiar in the research topic in developed countries, however, they have not been fully explored in Vietnam and therefore possibly be an open field with great potentials for investigational research.

Among the different building sectors, the residential subsector is mainly of interest due to the considerable contribution of energy use and the accessibility to energy efficiency plans, for example, the improvement of environmental awareness and human behaviors. According to the Vietnam Energy outlook report 2017 [45], improving living conditions and population growth are the main causes of increasing household electricity consumption. An investigation conducted by the Institute of Energy shows that a 4-person household consumes around 1.8-2.5 kWh/day for hot water, representing 16-21% of daily electricity demand. This number is expected to grow faster during the transition from the conventional energy recourses for cooking such as natural gas, coal, biomass, to electrical appliances. Besides, the discount rate in the air conditioning market in Vietnam becomes more significant than those in developed countries [46], leading to more purchasing options with lower energy efficiency despite the energy-efficient air conditioning offer more energy-cost savings.

Based on the history of the global energy transition and the current development trend of the Vietnamese economy, household energy consumption has become an important aspect of the country's energy sector. Besides economic and social background, there are many factors that directly and indirectly affect the energy demand of households. It has been said that building energy use is related to different influencing factors such as building characteristics, operation and maintenance, occupant's activities, behaviors, and other environmental factors [47]. Among them, human-related factors including occupancy and behavior were considered as significant as the physical impacts. These interrelationships are more noticeable when evaluating the influence level of factors in a residential area, especially household aspects. Household energy use is correlated with many building features and human facets to generate a perception of household energy-related lifestyles. The adaptation of this correlation research in Vietnam is one of the pioneering steps to facilitate the necessity of impact factor analysis in the field of energy studies and energy efficiency strategy in the neighboring developing countries. Moving forward from the previous studies, the paper continues to review the current data sources on Vietnamese household energy in the background of global studies, at the same time, introduce the current research projects in this country, finally assess the impact of household factors on residential energy consumption based on household data. The study aims to explore different aspects of household energy-related styles in this developing country and contribute energy efficiency solutions for the upcoming energy planning phases.

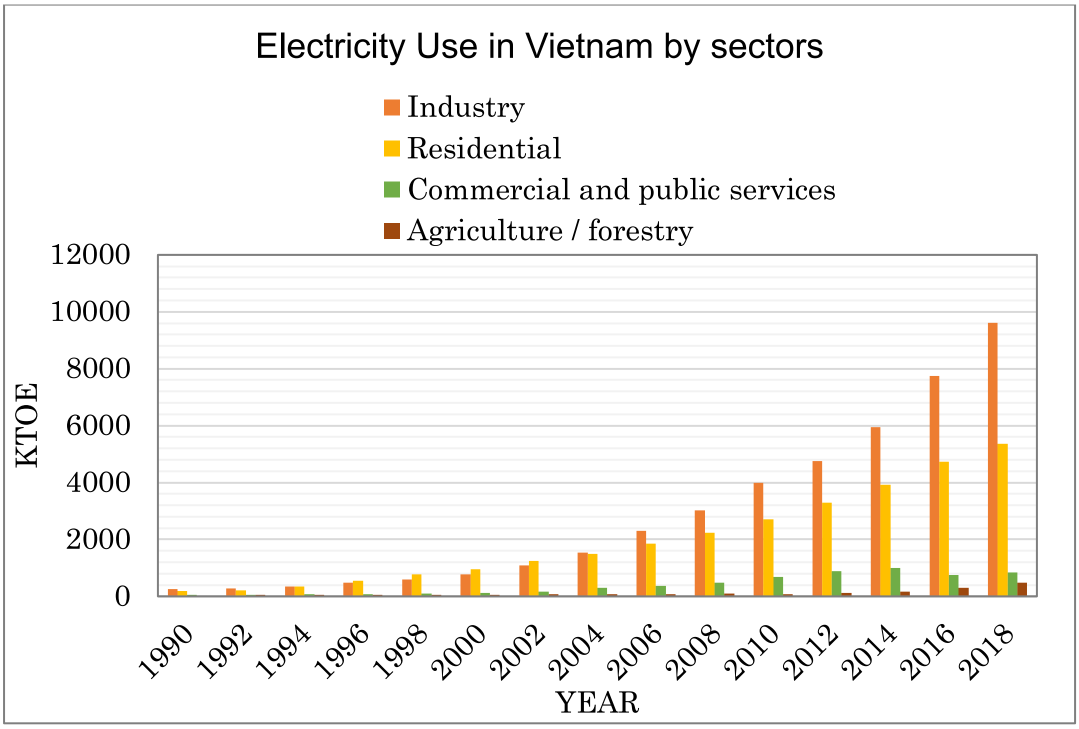

Fig. 1- 8. Electricity final consumption by sectors in Vietnam from 1990 to 2018 [49]

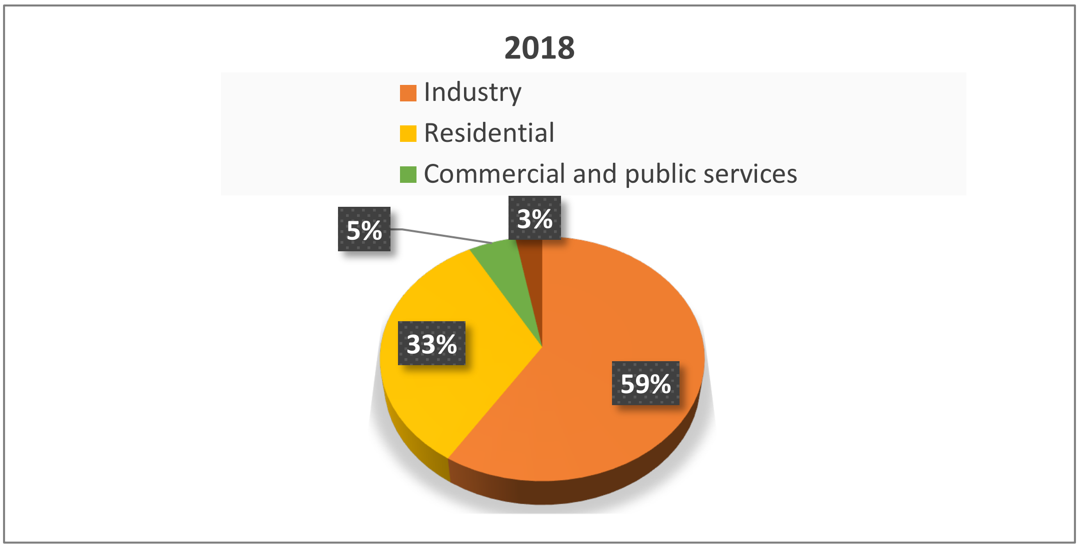

Fig. 1- 9. Shares of energy consumption by sectors in Vietnam 2018 [49]

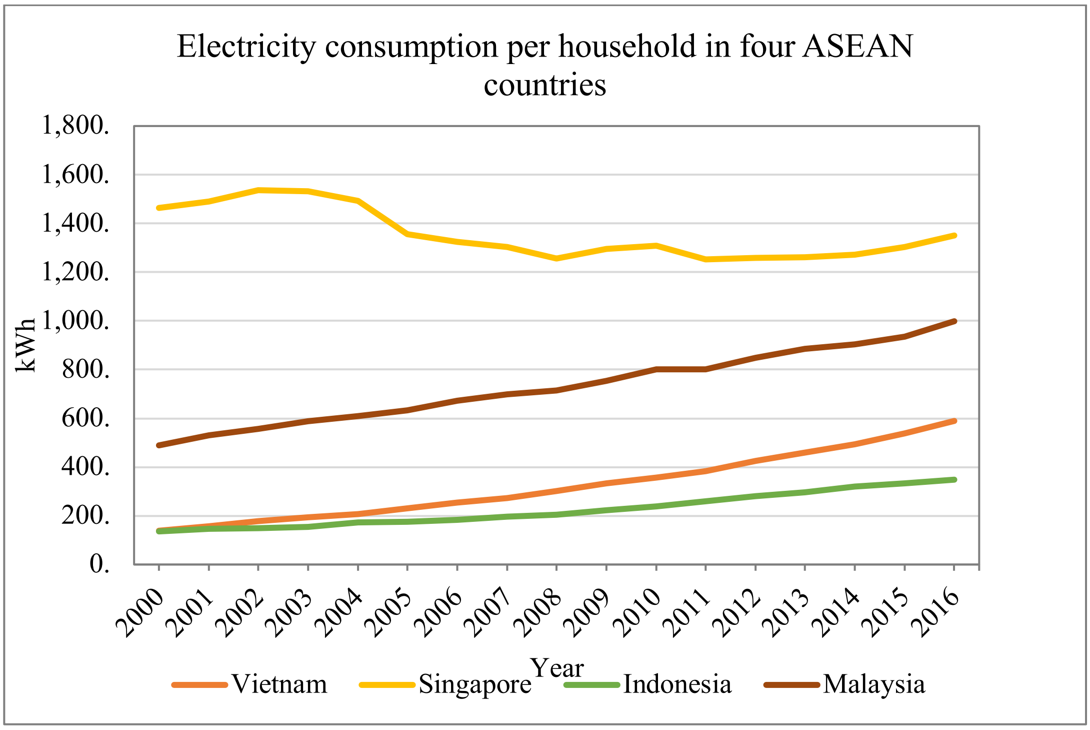

Fig. 1- 10. Electricity final consumption per household in four ASEAN countries: Vietnam, Singapore, Indonesia, and Malaysia from 2000 to 2016 [49]

1.3 Research purpose and structure

1.3.1 Research purpose

This study aims to investigate the residential apartments from a thoroughgoing picture of EEU while considering the vital impacts of lifestyle aspects. Based on the related reference and experience from previous studies, we develop a multi-aspect-based method of measurement, gathering information, and conducting surveys. Different facets of household characteristics and family activities were exploited fully to manifest the influences of various factors to household electricity consumption for the study area in a residential community in Japan. Hence, we discover the specific lifestyle of every participant in particular and discuss the role of household characteristics' approach to sustainable lifestyles and energy-saving behaviors in the residential area. This study is a continuation of the previous research on the relationships between household characteristics and electricity end-use in Japanese residential apartments [50], overcoming limitations of conventional survey and physics-based measurement methods. Regarding related topics, many existing studies have addressed the effects of indirect factors on energy consumption, including household lifestyle and household characteristics [2] [4] [25] [26], and energy data for commercial buildings and office buildings [51] [52] [53]. Recently, sensitivity analysis – an applicable method using for building energy consumption prediction and validation – is useful in assessing the relative impacts of various parameters in related studies [54] [55]. However, very few researches explore the potential of integrating energy monitoring and dynamic simulation for sensitivity analysis towards energy efficiency solutions in residential houses. To fill this gap, we need a call for a sensitivity approach examining a combination of the dataset from the household survey, actual energy consumption, and simulation. This study, therefore, analyzes influence levels of household parameters targeting the optimal energy-saving solutions of residential areas effectively.

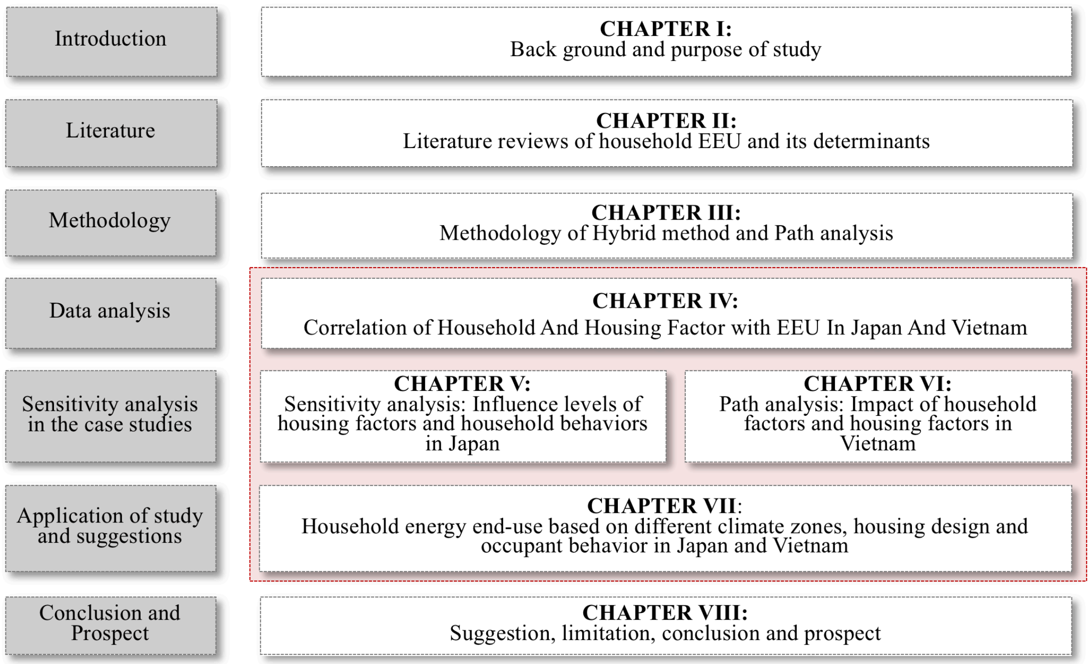

Fig. 1- 11. Chapter name and basic structure

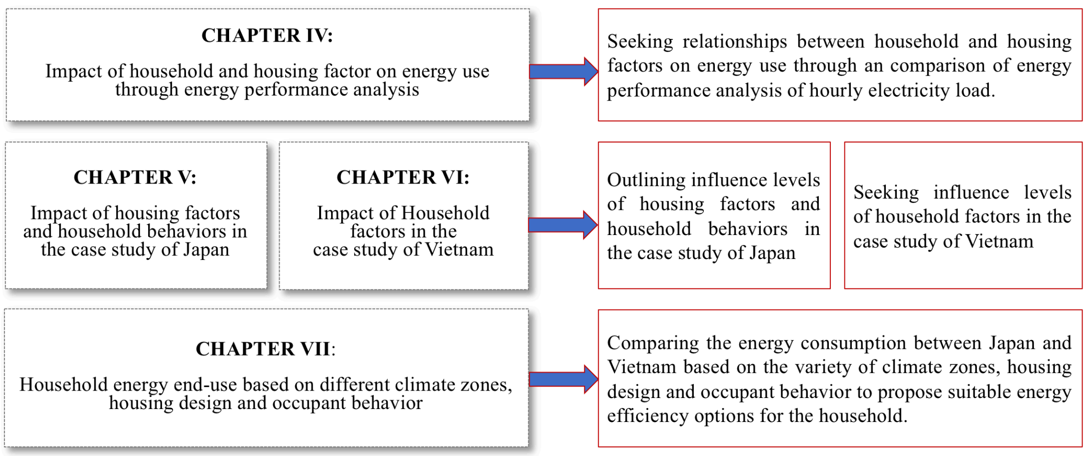

Fig. 1- 12. Research purpose

1.3.2. Research concept

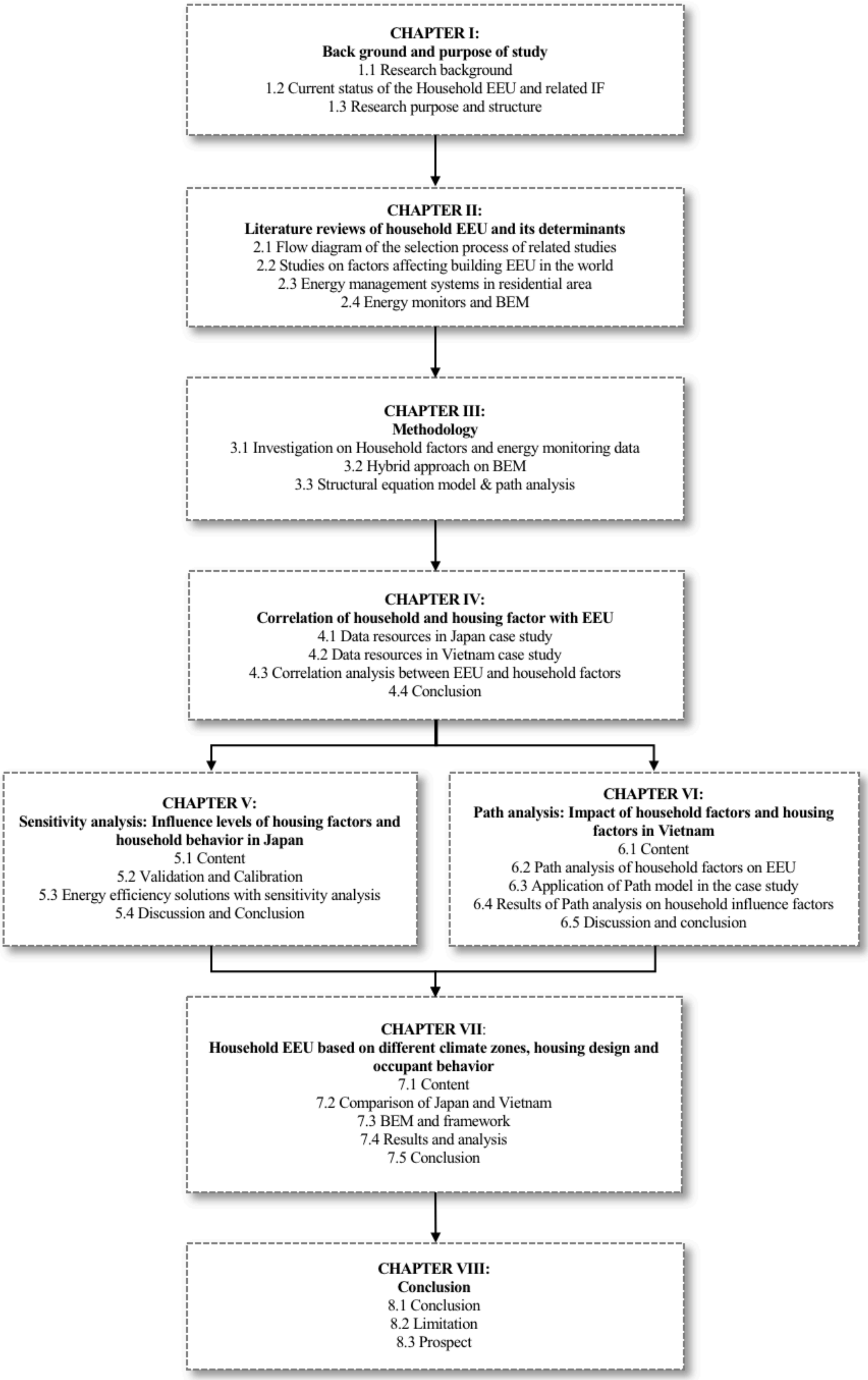

Fig. 1- 13. Brief chapter introduction

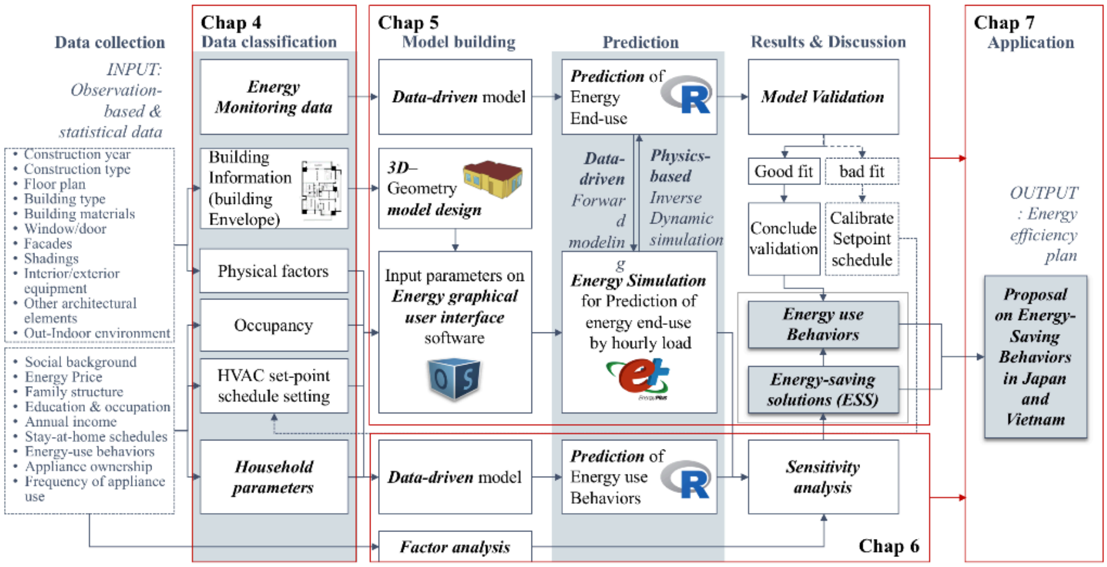

Fig. 1- 14. Research diagram

The chapter names and basic structure of this paper are shown in Fig 1-11. Besides, the brief introduction of chapters schematic is shown in Fig 1-13.

In Chapter 1, Research Background and Purpose of the Study:

Given the trend of household energy consumption in the background of intensive use of energy in the world in general and in Japan and Vietnam in particular, this chapter draws a picture of the impacts of determinants including physical factors and social factors on household energy consumption in these two countries. The transition of energy demand calls for consistent efforts of a research project regarding household energy use behaviors and other influenced factors. This is a pilot study following the largest ongoing global crisis to simultaneously assess the multiple influences of household factors, housing design, and social impacts on household energy end-use. The proposed research herein first aims to investigate the effects of all influencing factors on household energy consumption and to evaluate their complex relationships in order to create energy efficiency proposal for residential area.

In Chapter 2, Literature Reviews of Determinants and Its Impact on Household EEU

This Chapter provides a detailed review of the impact of various parameters on the household energy end-use and its multi-directional relationships. In the first section 2.1, a selection process was applied to filter studies related to the topic of energy consumption prediction and the impact of influence factors. Among 1623 results, A total of 40 articles with the specified research criteria were selected for review and analysis. These 40 articles meet the requirements to reflect in details ways of building Energy forecasts and Energy performance analysis or the impact levels of various factors in a comprehensive way. A review of studies in the same field was conducted in section 2.2 to show the distribution of determinants and its impact on EEU in general and household EEU in particular throughout the world. Section 2.3 mentioned about the theory of building energy management systems and section 2.4 described the application energy monitors and building energy modeling (BEM) as well as the limitation of current researches. The potential, urgency and novelty of this study is clearly seen after reviewing previous studies in the same field.

In Chapter 3, Methodology:

Three main approaches regarding three core chapter (chapter 4, chapter 5, chapter 6) will be presented in this chapter. The first section 3.1 carried out the process of investigation on household factors and household energy monitoring data in Japan and in Vietnam. The second sector 3.2 displayed the methodology of hybrid approach on BEM including the equations of data-driven models and the simulation process of the physics-based models on OpenStudio. In sector 3.3, Structural equation model and Path analysis is introduced with the application of model syntax using R language on R-studio as well as the detailed equations behind the calculation. Validation and Calibration is referred by model fit index which is also available on R-studio simulation and the mathematical formula.

In Chapter 4, Correlation of Household and Housing Factor with EEU In Japan And Vietnam

This section perceived an integrated methodology that accumulated two research methods: observation (on-site electricity measurement), surveys, and questionnaires for household characteristics. It inherited the experience derived from the previous research project, including pros and cons, to improve their findings of lifestyle factors that impacted electricity consumption, then propound a holistic picture of comparative analysis. Moreover, the results of OCC and HEL themselves can provide real observed data for building energy models or HEMS as a prediction method in future studies. Also, the section generalizes a detailed picture of differentiating characteristics of household energy demand and energy-related lifestyles such as household patterns, housing designs, number of stay-at-home days a week, and occupant behaviors in two case studies in Vietnam. As this is emerging for the study area, open-source databases and researches play a major role in the energy policy transition and environmental impacts. The content highlights the multi-dimensional influences of household attributes on the end-use to offer appropriate proposals for the energy-saving behaviors.

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In Chapter 5, Sensitivity Analysis: Influence Levels of Housing Factors and Household Behaviors in Japan

The energy forecast modeling has long been referred to as the function of estimating the energy consumption of a building and providing sustainable design options for energy-efficient policies. In addition to the existing conventional schemes for energy performance and energy simulation, there is the potential to connect steady-state energy modeling to energy monitoring data, along with household factors such as family size, housing design, and occupancy ratio to better understand hard-to-measure energy-related behaviors. This section introduces a multi-dimensional hybrid approach that combines multiple interactions between observation-based and simulation-based data using energy modeling's graphical interface software. The study underlines the diverse interactions among household characteristics, occupant schedules, and energy monitoring data, which are prospective to stimulate the application of building energy modeling in the early design stage and the optimization of energy efficiency in the operational phases.

In Chapter 6, Path analysis: Impact of household factors and housing factors in Vietnam

Energy consumption in the household sector has been rapidly increasing in Southeast Asia countries and Vietnam is no exception. Since its economic growth and corresponding energy demand become more significant, related research is expected to have many potentials to be explored, including the household energy sector. This study generalizes a detailed picture of differentiating characteristics of household energy demand and energy-related lifestyles such as household patterns, housing designs, number of stay-at-home days a week, and occupant behaviors in two case studies in Vietnam. As this is emerging for the study area, open-source databases and researches play a major role in the energy policy transition and environmental impacts. Path analysis is a recommended method for assessing the influence of various household factors on energy consumption in the residential area. The section highlights the multi-dimensional influences of household attributes on the end-use and emerges a holistic view of energy-related factor analysis to offer appropriate proposals for the energy-saving behaviors.

In Chapter 7, Household Energy End-Use Based on Different Climate Zones, Housing Design and Occupant Behavior

This Chapter will compare the prediction of energy consumption in two cases: Japan and Vietnam. For the sensitivity analysis, geographical location, housing floor plan, housing direction, and HVAC usage scenarios are considered impact factors to the energy consumption and OpenStudio will be the tool for dynamic simulation of the predicted models. We chosed two typical housing floor plans of apartments with the same area in Japan and Vietnam for the 3D-modeling. Eight orientations of housing models and 3 scenarios of HVAC energy use styles are examined to define the level of energy consumption in different cases. 20 cites in Japan and 20 cities in Vietnam are selected based of the different latitudes and climate zones and six cities out of them are simulated with detailed monthly energy performance. Results will show the sensitivity analysis of energy consumption by changing housing directions, housing floor plan, and HVAC usage behaviors in different latitudes and climate zones.

In Chapter 8, Conclusion and Prospect:

The conclusion of each Chapter is concluded.

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Chapter 2

LITERATURE REVIEWS OF DETERMINANTS AND ITS IMPACT ON HOUSEHOLD EEU

CHAPTER TWO: LITERATURE REVIEWS OF DETERMINANTS AND ITS IMPACT ON HOUSEHOLD EEU

Nomenclature

EFSD: Energy for Sustainable Development

EP: Energy Policy

JOCP: Journal of Cleaner Production

EPR: EPR

RSER: Renewable and Sustainable Energy Reviews

AE: AE

UP: Utilities Policy

JOBE: Journal of Building Engineering

EB: Energy & Buildings

RE: Renewable E

E: Energy

BE: Building and Environment

AIC: Automation in Construction

2.1 Flow diagram of the selection process of related studies

Building Energy consumption and its influential factors have attracted more attention in recent decades, and this broad spectrum mostly appears in developed countries. To better understand household factors and their association with global building Energy consumption, the research scope and distribution in previous papers were clarified, while the crucial factors are tracked in the following identification and clustering steps.

By using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA method [1]), previous literature can be aggregated systematically to evaluate the current state of our specific scheme in the research field. As shown in Fig. 2-1, there are four stages in the PRISMA selection diagram (identification, screening, eligibility, included) and four criteria in the review protocol (keywords, search fields, inclusion criteria, publication type). In the first phase, approximately 1623 journal articles and conference papers from research-searching websites (Science direct, Google scholars, Scopus) up to the time of the search (April 2021) were obtained. The main keywords to filter out articles are: “building”, “influence factors”, “E consumption”, and “prediction”. These keywords can cover the research questions about building Energy consumption and influencing factors without mixing up other field manuscripts that used keywords with similar meanings. Search engines picked up articles that include all of these keywords, so it could avoid leading to another research topic, e.g. transportation Energy consumption or building Energy supply, etc. Fields of the search were limited to studies regarding E, engineering, environmental science, and decision science to avoid mixing results with other subjects. For inclusion criteria, manuscripts referring to the residential area are sorted out to stress the focus on the literature of this research area. Once identified, duplicated records were removed while the main content in the titles and abstracts in the 1612 study works was screened for specific topic categories that are not relevant to the research topic. During the eligibility phase, we scanned all 90 selected manuscripts in full text and summarized the most relevant contents into the final paper collection. A total of 40 articles with the specified research criteria were selected for review and analysis. These 40 articles meet the requirements to reflect in details ways of building Energy forecasts and Energy performance analysis or the impact levels of various factors in a comprehensive way.

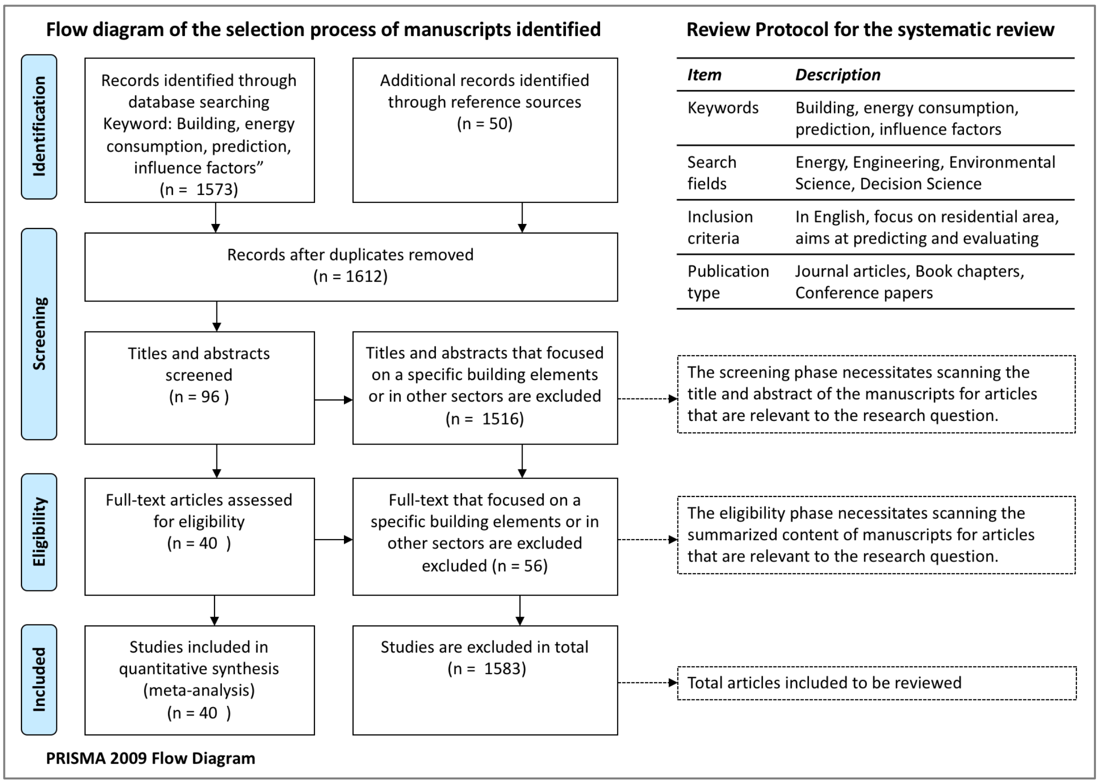

Fig. 2- 1. Flow diagram of the selection process of manuscripts identified. (PRISMA 2009 Flow Diagram *[1]*)

2.2 Studies on household factors and Energy use patterns

2.2.1 Studies on factors affecting building Energy end-use in the world

As a result of this review, most of the research was conducted in Europe, East Asia, and America, with a focus on developed countries. Within Asia, Japan and China are the two countries attracting more studies related to factors affecting building Energy use. As can be seen in Fig. 2-3, the first paper found on the lists was published in 1991 as the earliest record of the building Energy prediction based on residential factors. After that, the research topic was not of much interest until 2013 and received more attention from 2019 to 2020 and as well as in recent years. Regarding research scope, residential areas, despite being private living spaces, still attract working studies with 11 papers due to their practicality and variety of interaction and activities. In terms of methodologies, more than half of the listings adopted a data-driven approach while 15% of the profiles explored the application of the physics-based method. The hybrid method – a state-of-the-art approach that combines data-driven and physics-based methods – stands for the third option whereas the other multi-approaches are newly discovered in the field of building energy.

The second focus of this review is on the distribution of different influential factors in previous studies. In concrete, occupant-related factors appeared most frequently in six groups of major factors mentioned in 40 manuscripts. These major factors are occupant-related, building features, outdoor environment, equipment, operation and maintenance, outdoor environment, social factors, and pattern recognition. For the sub-factors of occupant-related factors, the assessment shows that occupant behavior is a significant factor to be considered in the occupant-related impacts of building Energy consumption (Fig. 5).

Compared with other sectors, residential area manifests more diversity in influence factors. The major factors and minor sub-factors mentioned in this research area are presented in Table 2-1. In particular, the first article by Takao Sawachi [2] discussed determinants that affected the use of residential air conditioners such as outdoor environment, thermal character, architecture, and residential properties. Among them, the location of the house is the factor that most affects the indispensability of air conditioners. Multidimensional effects are illustrated in a paper by Catalina et al [3], which asserts that climate conditions, building thermal insulations and air change rates have the highest impact; while human behavior provides more accuracy to the model. Architectural elements, for instance, light shelves, illuminance position, window length, floor area, etc. and social factors such as economy, urbanization rate, population, etc. were taken into account in these studies to develop design guidelines and energy policy for Energy efficiency buildings in the U.S [4] [5], Iran [6], and Italy [7]. Taniguchi-Matsuoka et al. provided a simulation model that considers the impacts of occupant behavior, equipment ownership, and building Energy efficiency in Japanese households to support solutions for policymaking regarding green Energy conservation in Japan. Their results discussed the possibility of overestimating the effect of high-efficiency lighting installations from the Japanese government [8]. Zhao et Magoulès [9] classified and summarized different approaches to predict building Energy consumption including engineering methods, statistical methods, and artificial intelligence methods. The proposed models address the complex questions of analyzing building Energy behaviors and influencing factors. The overview of these studies reveals that many prediction methodologies and remarkable influential factors have been examined to get the holistic picture of Energy-related factors in the scale of building Energy consumption. However, a pellicular study for household Energy lifestyle is necessary and potential in developing countries. In a more concrete view, the residential factors and their linkage to household Energy use are displayed on a global background, which is an example of our granular case in the next section.

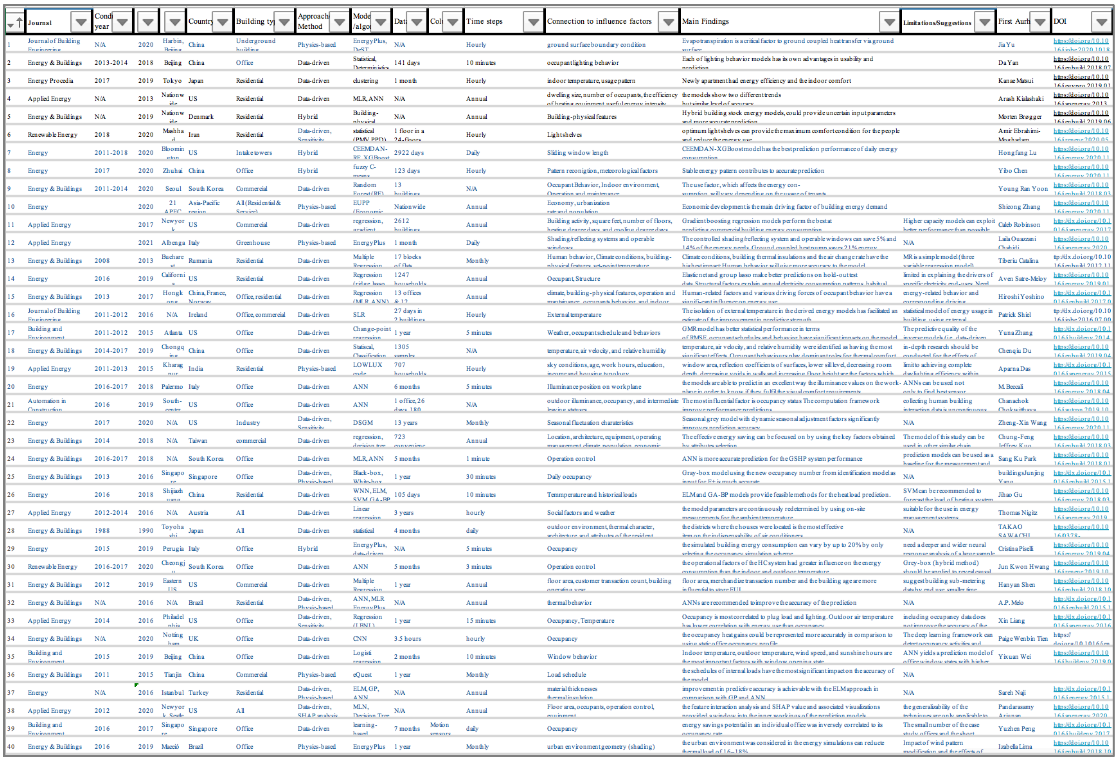

Fig. 2- 2. Excel file of summarization of full-text articles

Table 2- 1 Determinants in residential area studies

Major factors	**Minor sub-factors**
Climate conditions	Indoor temperature, outdoor temperature, sky conditions.
Social factors	Economy, urbanization rate and population.
Building features	Building-physical features, light shelves, building structure, material thicknesses, thermal insulation, dwelling size.
Equipment, operation, and maintenance	The efficiency of heating equipment, useful Energy intensity, historical loads, operation and maintenance, housing typology, setpoint temperature.
Occupant-related factors	Human behavior, number of occupants, usage pattern, occupant’s behavior, thermal behavior, occupant age, work hours, education, income.

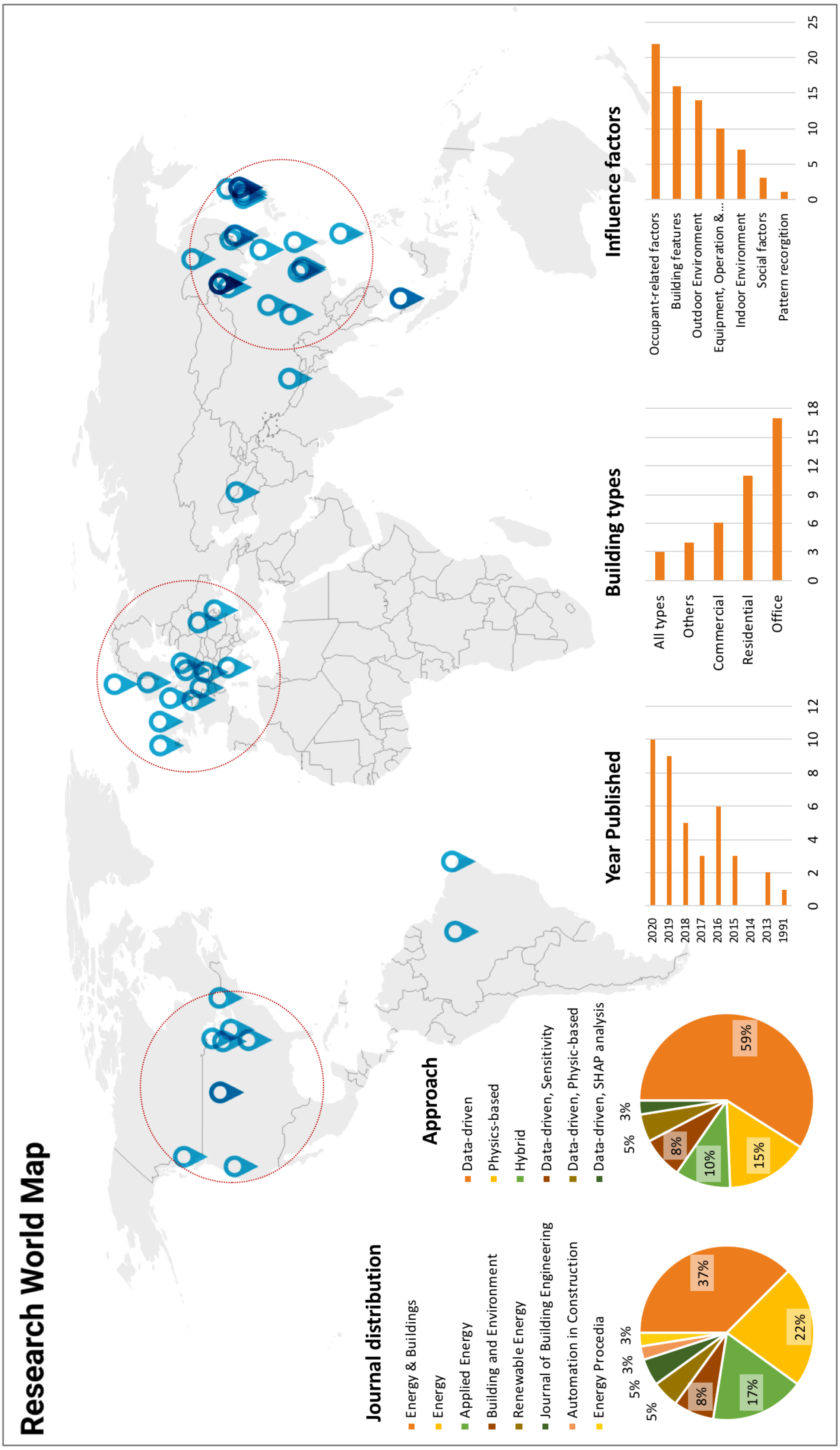

Fig. 2- 3. Research world map

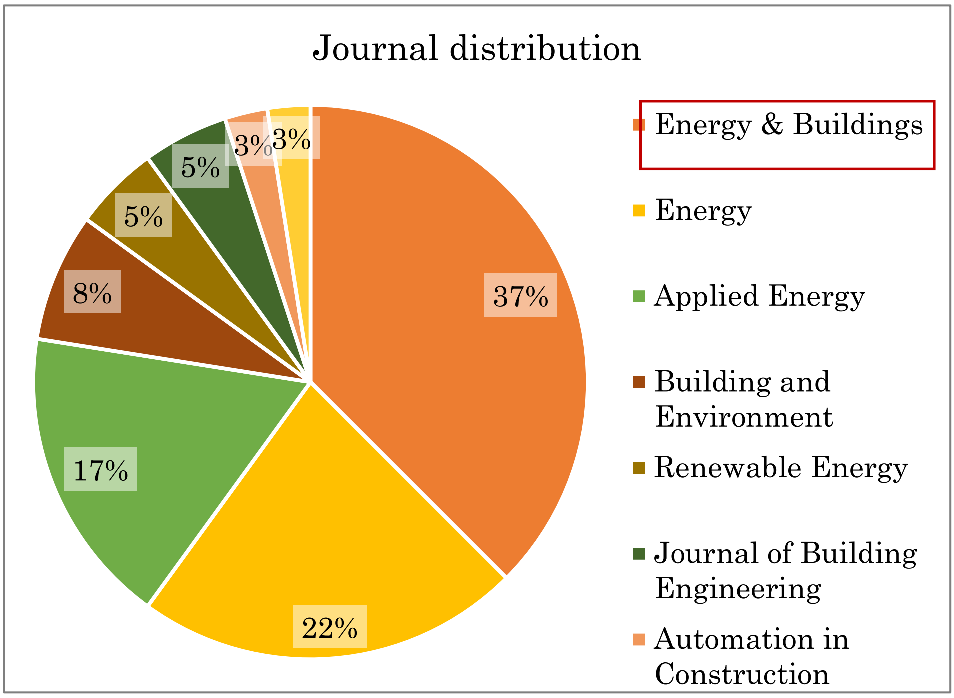

Fig. 2- 4. Distribution of journals

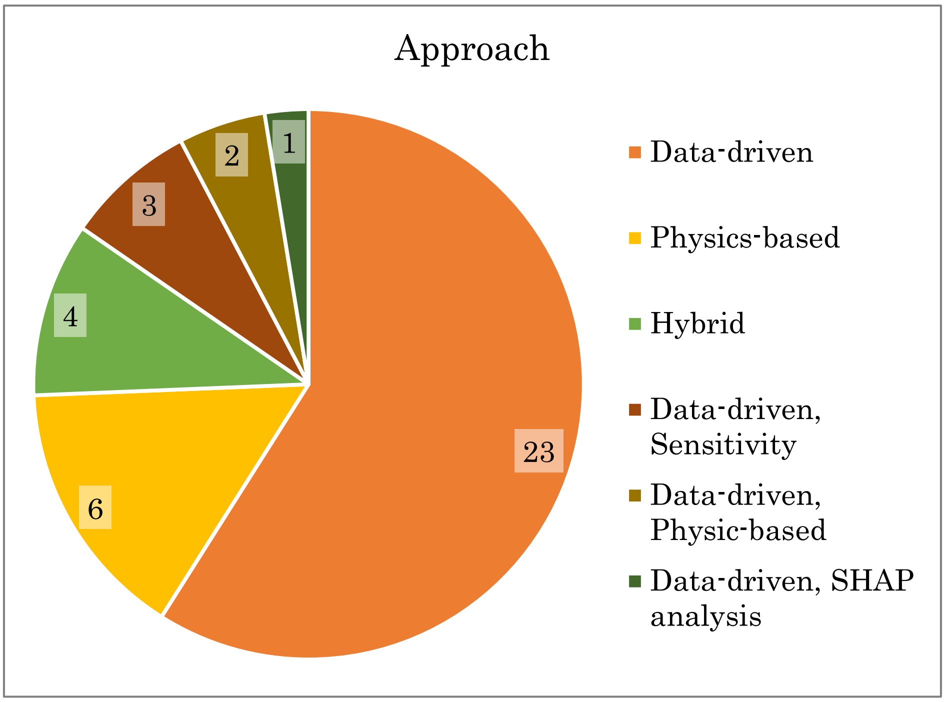

Fig. 2- 5. Distribution of method approached

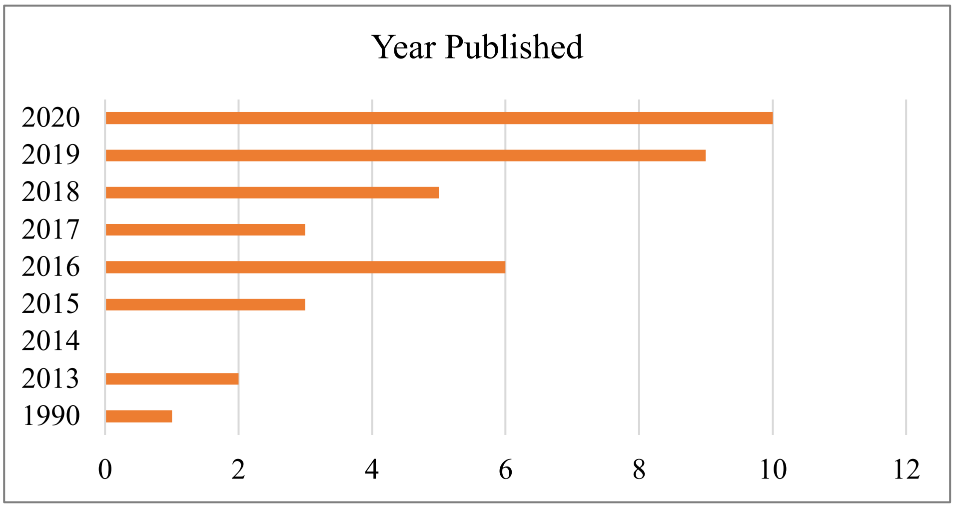

Fig. 2- 6. Year published of the articles

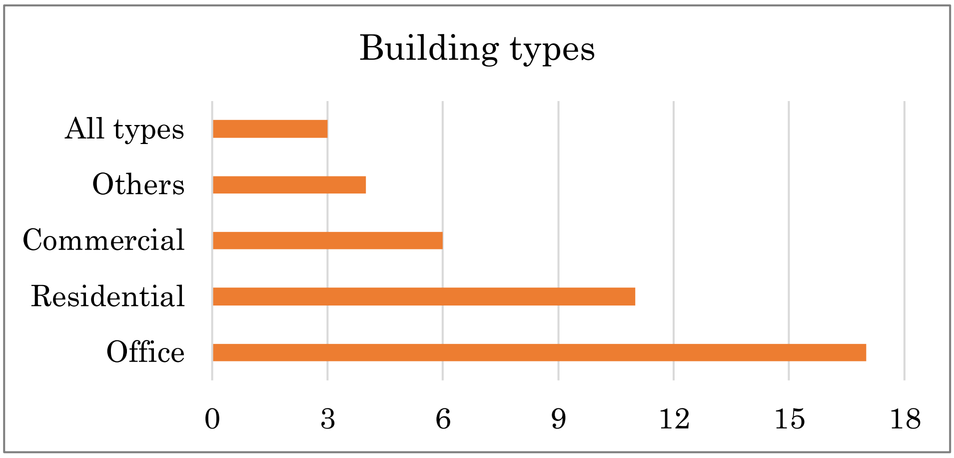

Fig. 2- 7. Building types

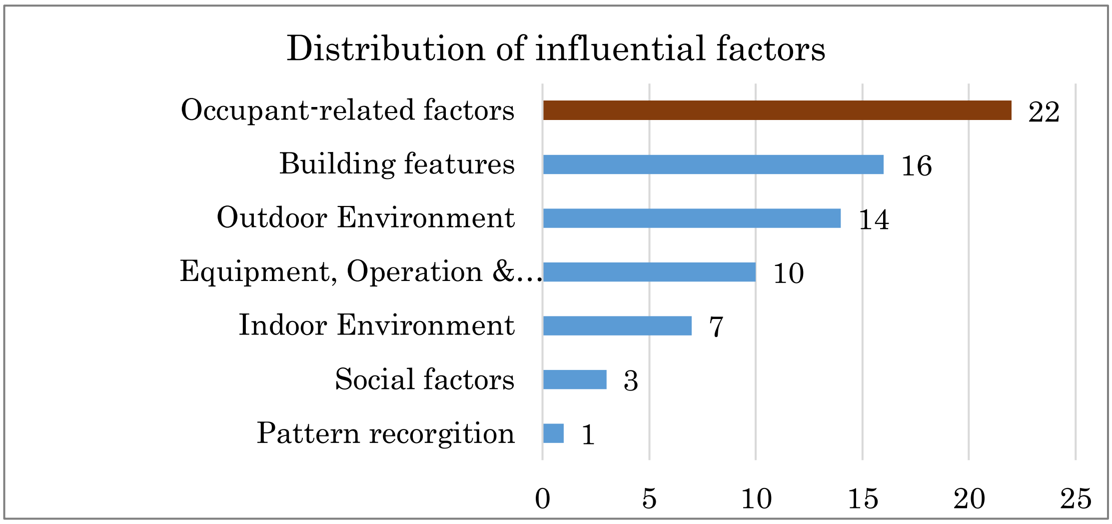

Fig. 2- 8. Distribution of influential factors in the previous studies

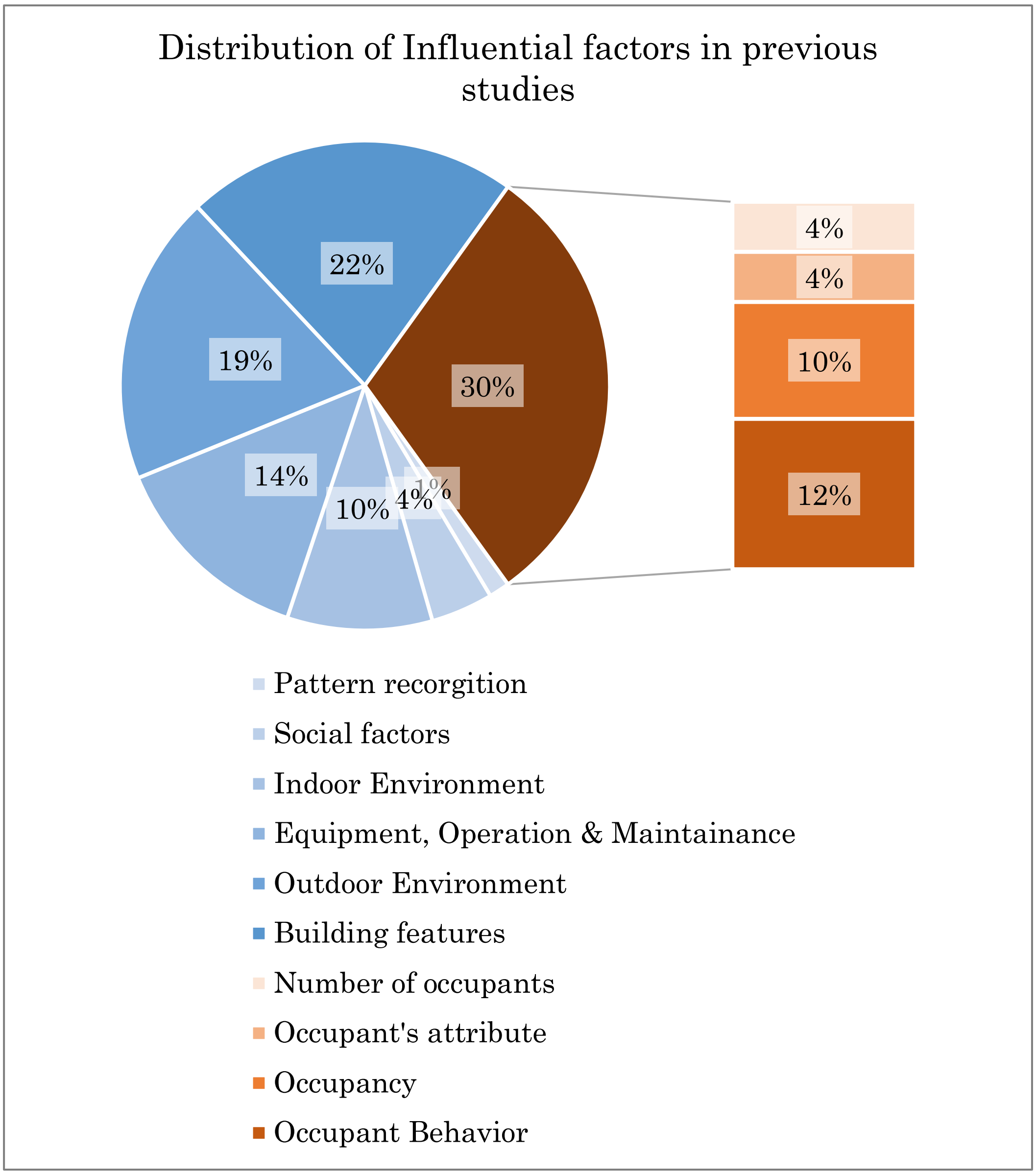

Fig. 2- 9. Distribution of influential factors in previous studies

2.2.2 Studies on factors affecting household Energy end-use in Vietnam

Building Energy is an emerging study in Vietnam, and the household Energy consumption sector is even rarer in the regional context. Up to now, around 20 articles have discussed building Energy in this country, including those on the supply side and end-user side. Regarding residential Energy consumption, we find several examples of studies that explain in detail household Energy use, household needs, and its relationships with influencing factors.

In general, the existing papers describe various effects of household features, mainly being driven by income, household size, housing parameters, and other social impacts. The topic was first explored in 1996, addressing the importance of household effects in urban and rural residents. In that study, income became a notable factor determining the quantity and structure of Energy use

[10]. Another paper also agrees that household income plays a vital role in affecting electricity consumption [11], meanwhile, household characteristics, such as the education level of the household head, household size, as well as the type of dwelling attributes, show pivotal influences to the gross end-use.

Given the weak performance regarding these indicators, Vietnam has highest Electricity Intensity (EI) among APEs followed by China and Mongolia. To reduce EI, Vietnam should consider diversifying away from the electricity-intensive industry sector toward economic activities such as service and information technology [12]. A Study in Vietnam reveals that household income is an important determinant of electricity consumption, and that this relationship is highly nonlinear with respect to income. Household characteristics, such as the education level of the household head, household size, as well as the type of housing (quality), are important factors that influence electricity consumption (Hyelim Son and Semee Yoon, 2020).

From the research literature, it can be seen that Vietnamese households display comparable trends of Energy demand with other regions, however, more investigating data is required to signify the levels of influence, as well as identify specific E-saving solutions to cut down Energy use in the next generation. The current platform presents rich potentials for further exploration and analysis, mainly targeting the household impacts and occupant behaviors in the follow-up studies.

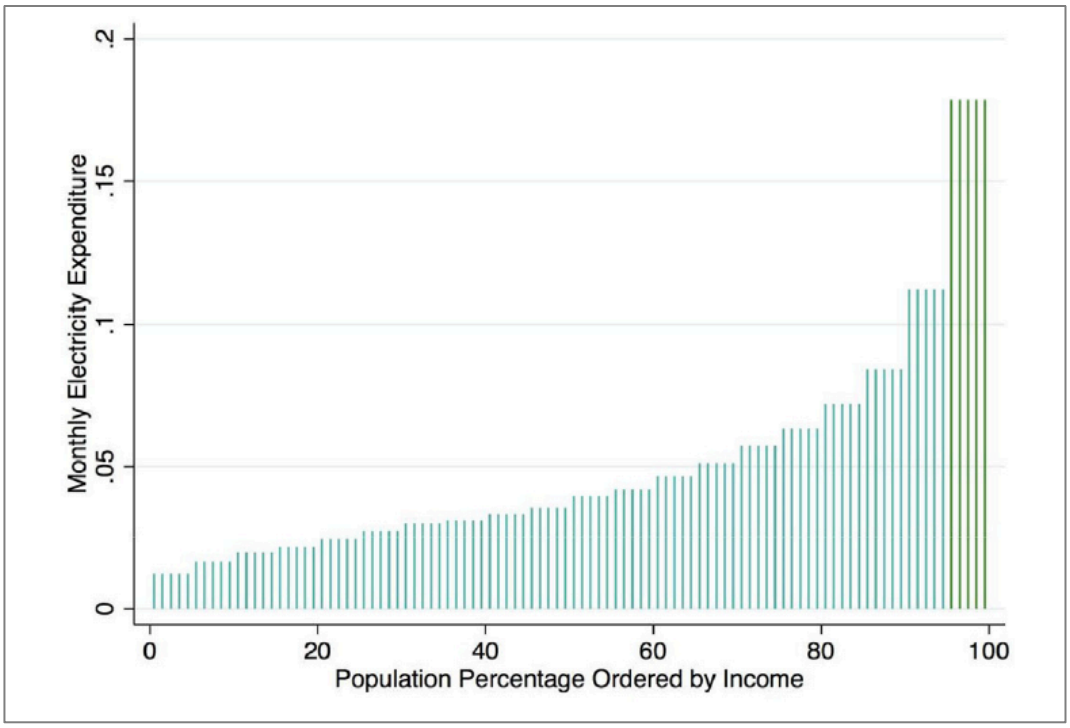

Fig. 2- 10. Monthly electricity expenditure share by income groups. Note: Monthly electricity expenditure and income levels are analyzed in real term. (*[12]*)

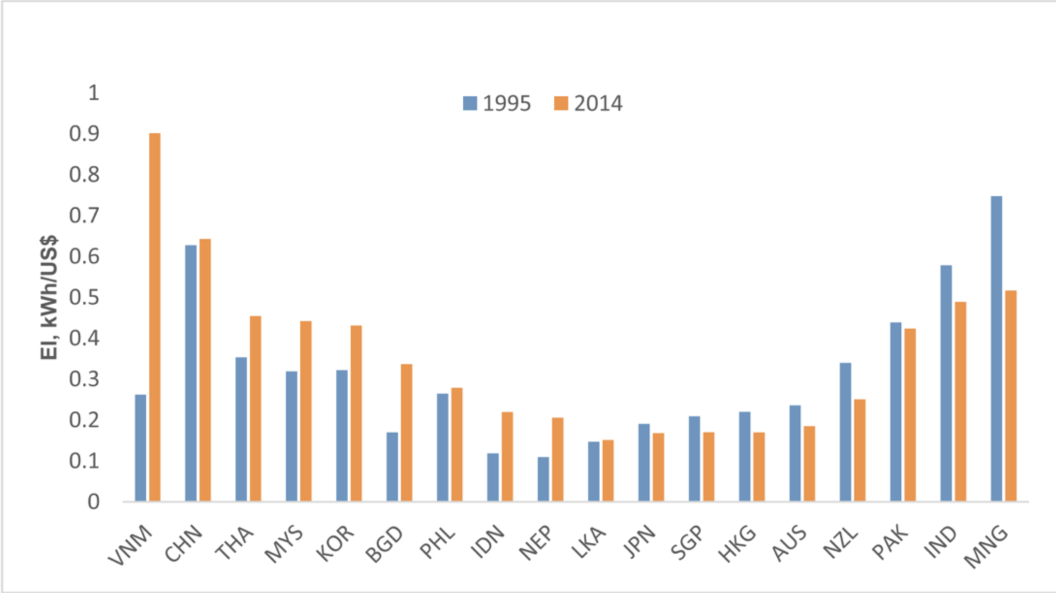

Fig. 3. Changes of *EI* in the Asia-Pacific from 1995 to 2014 (WB, 2015).

Fig. 2- 11. Changes of EI in the Asia-Pacific from 1995 to 2014 *[13]*

Table 2- 2 Energy consumption studies in Vietnam

No	Journal	Year	Title	Building type	Main finding	Ref
1	EFSD	2020	Reducing Energy poverty: Characteristics of household electricity use in Vietnam	Residential	Household income is an important determinant of electricity consumption, and this relationship is highly nonlinear with respect to income	Hy elim Son
2	EP	2019	Excessive electricity intensity of Vietnam: Evidence from a comparative study of Asia-Pacific countries	All	Vietnam has highest EI among APEs followed by China and Mongolia.	P.D. Hien [12]
3	EP	2011	Vietnam's Energy sector: A review of current Energy policies and strategies	All	The population growth and the government's determination to maintain high rates of economic growth will inevitably translate into	Tien Minh Do

					increased Energy demand	
4	JOCP	2017	Consumer valuations of Energy efficiency investments: The case of Vietnam's Air Conditioner market	All	discount rate in Vietnam's AC market is much higher (means lower value on Energy efficiency investment) than those in developed countries	Shigeru Matsumoto
5	EP	1996	Analysis of household Energy demand in Vietnam	Residential	Urban households use less Energy than rural households. With increase in income, households tend to utilize more electricity and less residue.	Nguyen Anh Tuan
6	EPR	2015	Analyses of Energy use and CO2 Emission in Residential Sector: Case Studies in Thailand and Vietnam	Residential	CO2 emissions in Vietnamese households will reach 79.12 million tons in the Demand-side management scenario and 81.53 million tons in the RE scenario in 2030.	Vu Thi Hong Thuy
7	RSER	2020	A critical review of Energy resources, policies and scientific studies towards a cleaner and more sustainable economy in Vietnam	All	Vietnam has abundant natural resources to develop renewable power; however, the economy is still small, lacking financial capacity, advanced technologies and human resources for rapid development of RE.	Duy Nong
8	EP	2019	E transition, poverty and inequality in Vietnam	All	Electricity poverty has decreased but E-cost poverty has increased. Energy inequality tends to decrease more significantly than income and consumption inequalities.	Trung Thanh Nguyen
9	AE	2021	A life cycle analysis techno-economic assessment framework	Residential	The cooling Energy demand in Vietnam is lowest among 6 ASEAN	Yanjie

			for evaluating future technology pathways – The residential air-conditioning example		countries	Li
10	UP	2019	The development and cost of RE resources in Vietnam	All	Vietnam has abundant natural resources, but a high vulnerability to climate change. the potential for growth in the use of non-hydro renewables is impeded by the low cost of hydropower.	Phuong Anh Nguyen
11	RSER	2015	A critical review on Energy Efficiency and Conservation policies and programs in Vietnam	All	More efforts of collection, analysis, and management of Energy data; capacity building during the implementation of Energy Efficiency and Conservation policies should be put forward	Nguyen Duc Luong
12	EP	2019	Potentials and opportunities for low carbon Energy transition in Vietnam: A policy analysis	All	Support a pathway towards low carbon development, policies need to include mechanisms that favor RE technology and also foster the mobilization of private investment or international cooperation	Caitlin Shem
13	EFSD	2013	The effects of internal migration on residential Energy consumption and CO2 emissions: A case study in Hanoi	Residential	rural-to-urban migration is shown to have a significant and negative influence on residential Energy consumption and CO2 emissions	Satoru Komatsu

Table 2- 3 Household Energy consumption studies in Vietnam

No	Year	Main keywords	Influence factors	Main finding	Authors
1	2020	E access, Household electricity expenditure, Inequality, determinants of electricity use.	Household characteristics, Housing characteristics. Income	Household income is an important determinant of electricity consumption, and the relationship between them is nonlinear.	Son et Yoon [11]
2	1996	Household, E	Income, climate, government policies, usage pattern, availability of resources	Urban households use less Energy than rural households. With higher income, households tend to consume more electricity and less residue.	Tuan et Lefevre [10]
3	2015	The residential sector, CO_2 emission, Energy use, LEAP model.	Emission factors	CO_2 emissions in Vietnamese households will reach 79.12 million tons in the demand-side management scenario in 2030.	Thuy et Limmee-chokchai [14]
4	2021	Life cycle analysis, Techno-economic, assessment, Energy systems modeling, Technology pathway, Residential air conditioning, Carbon	Refrigerant, electricity price	The cooling Energy demand in Vietnam is the lowest among the 6 ASEAN countries. Refrigerant replacement can be as important as Energy efficiency	Li et al. [15]

		abatement cost.		improvement.	
5	2013	Urbanization, Migration, Residential Energy consumption.	Immigration, household income, floor spaces, household size.	Rural-to-urban migration has been shown to have a significant negative effect on residential Energy consumption and CO_2 emissions.	Komatsu et al. [16]

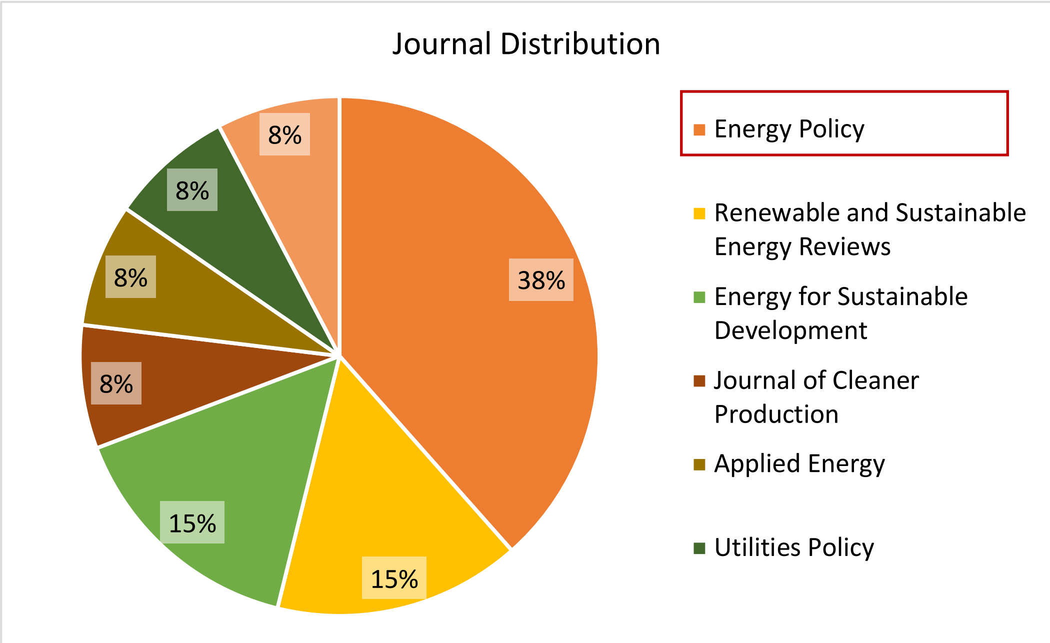

Fig. 2- 12 Journal Distribution of the articles

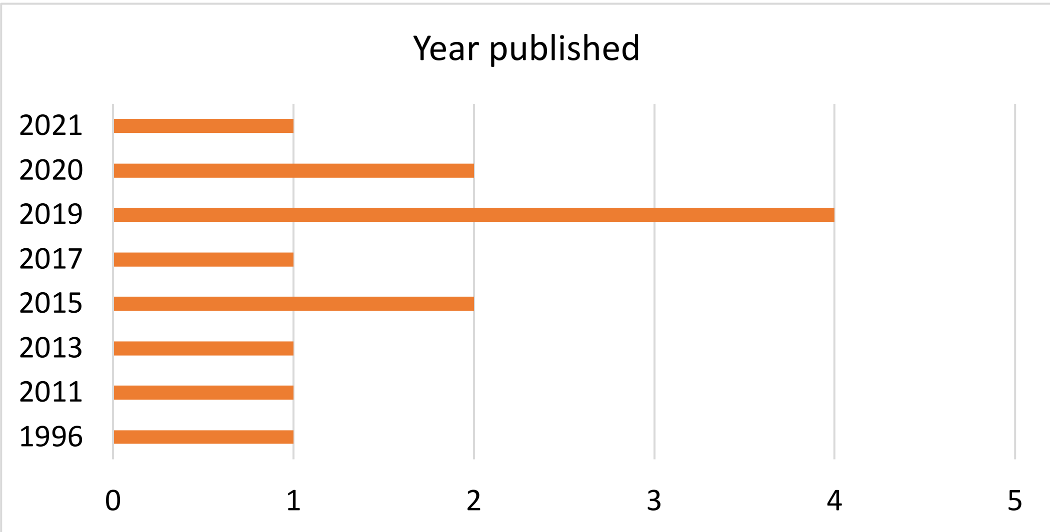

Fig. 2- 13 Year published of the articles

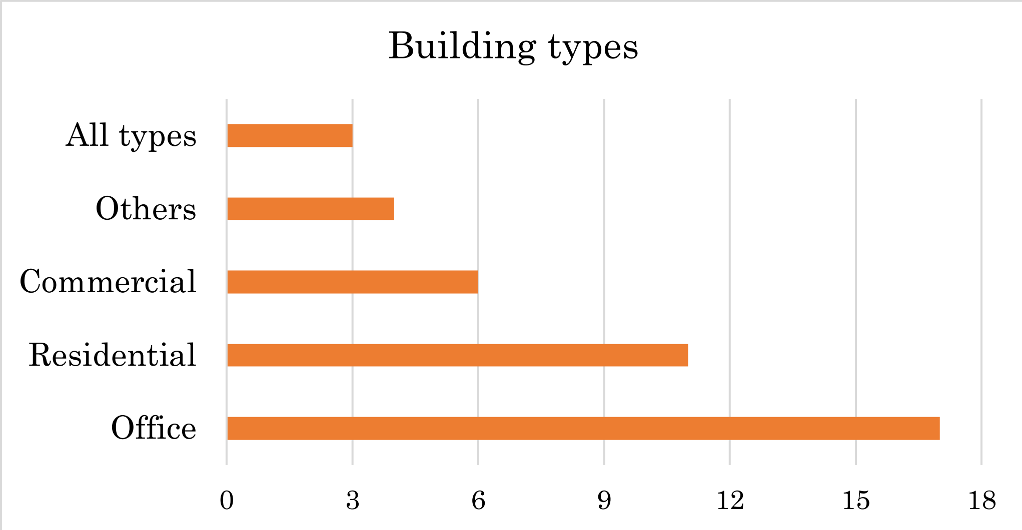

Fig. 2- 14 Building types in the article's research object

2.3 Energy Management Systems in Residential area

Residential lifestyle has a remarkable influence on Energy consumption and plays a crucial role in controlling Energy Management Systems (EMS). Ge and Hokao [17] pointed out that household's behavior had been controlled well by their preference. According to different performance levels of the building features, different behavioral patterns of the building occupants resulted as important variables in the variation of the building EEU [18]. Compared to other social factors of households, lifestyle factors that reflect social and behavioral patterns better account for consumption differences than income [19]. It seemed that city planning had greater possibilities of reducing heating and cooling Energy demand, while electricity consumption was more dependent on user behavior [20]. The book "E Efficiency in Buildings" [21] shows a vast difference in residential Energy use among regions. For instance, 70% of EEU in European households came from space heating, while only about 12% reported in Japan's household. More than 40% of EEU was used for domestic hot water in Japan, higher than Europe (12%), USA (20%), China (28%), and India (10%). Indian households did not use space heating but spent almost 65% EEU on cooking. These numbers proved that household Energy behavior and lifestyle vary in different cultures. In the same book, Japan's Energy consumption was radically lower because people only heated one room rather than the whole house, and developing countries' consumption increased as they become more and more wealthy. Besides, Japan's household consumption is half that of the United States, and about two-thirds that of Germany and other European countries [22]. Compared to other countries, the consumption of space heating in Japan was low while lighting and hot water usage were larger [22]. It means that different regions performed unique Energy use styles depending on their national attributes, regional customs, and particular lifestyles. Also, analyzing the residential lifestyle ask for a multidimensional view of household attributes on the local scale. Various studies have evaluated Energy use efficiency and ways to cut down Energy in residential areas in many countries. Abubakar et al. reviewed the application Intrusive Load Monitoring [23], which stressed the high expense of device installation at each load but more accurate than the Non-Intrusive Load Monitoring method. Both methods call for an EMS that can recognize as many kinds of loads as possible. Many estimation models of electricity consumption also applied based on household information and household Energy consumption database. EEU and Hourly Electricity load (HEL) were predicted by analyzing smart meter data to forecast in New South Wales, Australia [24], and by considering occupancy-related characteristics in Seoul, South Korea [25]. In Japan, Shiraki et al. [26] provided a comparison among engineering method, conditional demand analysis method (CDA), and hybrid method that could estimate seasonal fluctuation with high accuracy better than CDA. These papers recommended occupant behavior as an explanatory variable and distinct use of appliance depending on the Energy price policy. Also, A bottom-up and top-down approach adopted in Ghana reflecting demand factors such as GDP and appliance ownership [27], whereas a data mining-based prediction model was conducted to predict building thermal behaviors and estimated building's EEU in South Korea [28].

In terms of the applied methodology, the implementation of advanced technologies can enable E-saving behaviors, such as information communication technologies, and to build the EMS that has been using for several years. In the past few years, researchers utilized sensors for controlling home devices remotely, integrated history data of Energy use lifestyle for alerting inhabitant behaviors, and giving appropriate solutions to minimize Energy consumption. For example, a paper of Bibri [29] concentrated on big data applications in the context of sustainable cities to optimize Energy efficiency. Citations indicated that technology could facilitate awareness of reducing Energy waste in residential buildings in developed countries, and wasteful behavior can add one-third to a building's designed Energy performance, while conservation behavior can save a third [21]. In many smart communities, smart meters became an essential tool to perform individual appliance consumption that raises the inhabitant's awareness of their E-waste behaviors. Bhati et al. [30] found in the case studies, quoted that it is challenging to change E-saving behavioral patterns of consumers themselves. They claimed that smart technology and smart homes promoted users to control appliances actively and to save Energy with the help of artificial intelligence modules. Kavousian et al. [31] conducted a smart meter to determine the connection between residential electricity consumption and the influence of climate, building characteristics, ownerships, and occupant's behavior. A study by Sarah [32] signified that simple feedback demonstrated to cut down Energy use by up to 15% by using the meter or an associated display monitor.

Above all, existing studies have determined the essential impact of household attributes and lifestyle on residential EEU on a large scale such as neighborhood or city. These works of literature have laid the groundwork for the transition of Energy conservation with numerous state-of-the-art methods. Nevertheless, a few discussed specific cases at different days of a week, and most of the relevant works ignored the potential diversity of these small-scale units. In response to these concerns, it leads to calls for having a study concentrating on each household with distinct features that comprise of housing designs, family patterns, occupancy rate (OCC), residential lifestyles, and occupant behaviors. By evaluating their Energy use schedule in every home appliance such as air conditioning, electric water heater, or lighting equipment, we can gain HEL performance reports in every house. Obtained HEL reports can provide information for modifying residential lifestyle and suggesting recommendations to E-saving in apartments, thus depicted an in-depth project that enables detailed EEU and HEL data analysis in every residential house. Derived from studied works of literature, we propose a different view of E-related lifestyle in small-scale case studies providing an example of correlation analysis towards Energy conservation-related studies in general.

2.4 Energy monitors and building energy modeling (BEM)

A wide range of methods has been analyzed to conduct E-related evaluation and Energy efficiency solutions in detail. Accordingly, coordination between Energy monitoring data and building Energy modeling (BEM) was demonstrated to be complementary in many studies. BEM is the method of simulating and predicting the building Energy consumption to assess the Energy efficiency of the Energy system in the building sector [33]. The following review of the literature demonstrates interrelationships among household factors, architecture, and Energy consumption, as well as the Energy conservation results through the application of BEM before and post-occupation.

Ye et al. discussed applications of the Energy consumption database that includes survey data and simulation data sources for the use of Energy performance, Energy use predictions, and other policy-making analyses [34]. In this study, BEM creates a variety of samples based on observed data before modifying or calibrating to attain the results that the survey itself cannot improve. Swan and Ugursal [35] reviewed two BEM techniques in residential sectors: top-down approaches and bottom-up techniques, which highlights the role of statistical models in defining the identification of behaviors and end-uses, provides E-saving and Energy management policies during the growing technological period. Also, Kavgic et al. indicated specific benefits and limitations of these bottom-up and top-down modeling approaches [36]. An example of BEM in a residential area shows an impressive reduction in heating Energy after improving thermal insulation in building envelopes [33].

While the monitoring process provides information from measured Energy data, the Energy model is a computer simulation that calculates the Energy usage of a building based on the principle of building science. Energy simulation software tools are essential to assist building designers in minimizing Energy costs. The reviews of state-of-arts studies claimed that physics-based data itself cannot capture the variable building elements and human behaviors in their complexities but combining with data-driven and probabilistic methods [37]. Yang and Becerik-Gerber proposed a framework for modeling a personalized home-schedule for presenting long-term occupancy profile patterns [38]. The model was specified according to weekday and weekend occupancy ratios to evaluate the influence of detailed occupancy profiles on the application of Energy simulation. Also, the occupancy ratio becomes a decisive factor to show more accurate results than fixed design profiles; thus, it could be useful for Energy simulation for many purposes. Studied by Garcia and Zhu [39], building design models can transfer actual data into BEM tools to simulate building Energy end-use automatically instead of modifying them manually. Accordingly, compared to other simulation such as ESP-r, IDA ICE, IES, TRNSYS, EnergyPlus is relatively refined and applicable as the immerse connection with other design software, including 3D Google Sketchup. Using BEM methods through the works of EnergyPlus and OpenStudio for Energy conservation purposes shows high applicability in many studies [40] [41] [42] [43]. By integrating traditional physic-based investigation and data-driven analysis, these studies assess Energy consumption, E-related behavior, and Energy forecast. Li et al. [44] propose a new four-stage hybrid methodology for short-term prediction of Energy efficiency, showing reliable performance and clarify a diversity of influent factors that lead to dissimilar E-saving quotas. In EnergyPlus, the hybrid modeling method uses the inverse modeling to improve the accuracy of the building Energy simulation for existing buildings, adding measured data to solve uncertain model parameters [45]. For instance, people count is usually hard to measure in reality, which leads to simplification of occupancy schedule assumptions in the Energy model. The hybrid model introduces an approach to estimate the interior thermal mass, air infiltration rate, and people count with measured zone air parameters in EnergyPlus. In this study, integrating monitoring and modeling methods with the presence of household parameters such as occupancy, hourly electricity loads, and housing design in this area opens up a new look for a hybrid approach, a concise and accessible step during smart-oriented development of buildings and cities.

Since building information and modeling become a potential approach for sustainable and smart buildings in recent decades, Energy monitoring, survey data, and BEM can be grasped simultaneously to become a bottom-up and top-down approach for optimal Energy efficiency solutions. Also, BEM can cooperate with the architectural design plan and other occupant behavioral patterns for the shift from conventional buildings to smart buildings [46]. In this paper, after the validation and calibration of monitoring and modeling data, sensitivity analysis of household Energy consumption and influence parameters such as the number of people, occupancy rates, ACSs, occupant schedule, wall insulation, and ventilation is considered. Due to the complicated installation and high expense limit of electric meters and monitors, we propose to integrate monitoring data with Energy modeling in a multi-dimensional perspective, to analyze and predict the Energy performance in an interactive relationship loop, which has not been covered in previous works. In a laboratory context, the adoption of building information modeling that consists of Energy monitoring and BEM can drive building Energy conservation strategies from the early stage of a design concept or post-occupation evaluation.

Appendix

Table 2- 4 List of review articles

No	Journal	year	Country	Building type	Approach/ Method	Model /algorithm	Connection to influence factors	Main Findings	Reference
1	JOBE	2020	China	Underground building	Physics-based	EnergyPlus, DeST	ground surface boundary condition	Evapotranspiration is a critical factor to ground coupled heat transfer via ground surface	[47]
2	EB	2018	China	Office	Data-driven	Statistical, Deterministic, Hunt's, Wang's, Reinhart's model	occupant lighting behavior	Each of lighting behavior models has its own advantages in usability and prediction	[48]
3	EPR	2019	Japan	Residential	Data-driven	clustering	indoor temperature, usage pattern	Newly apartment had Energy efficiency and the indoor comfort	[49]
4	AE	2013	US	Residential	Data-driven	MLR, ANN	dwelling size, number of occupants, the efficiency of heating equipment, useful Energy intensity	the models show two different trends but similar level of accuracy	[50]
5	EB	2019	Denmark	Residential	Hybrid	Building-physical, Hybrid (MLR + Building physical)	Building-physical features	Hybrid building stock Energy models, could provide uncertain input parameters and more accurate prediction	[51]
6	RE	2020	Iran	Residential	Data-driven, Sensitivity	statistical (PMV, PPD)	Light shelves	optimum light shelves can provide the maximum comfort condition for the people and reduce the Energy use	[52]
7	E	2020	US	Intake towers	Hybrid	CEEMDAN-RF, XGBoost, CEEMDAN-XGBoost, RBFNN, PSO-SVM, LSSVM	Sliding window length	CEEMDAN-XGBoost model has the best prediction performance of daily Energy consumption	[53]
8	E	2020	China	Office	Hybrid	fuzzy C-means clustering, nonlinear regression	Pattern recognition, meteorological factors	Stable Energy pattern contributes to accurate prediction	[54]
9	EB	2020	South Korea	Commercial	Data-driven	Random Forest (RF) Gaussian regression (GR)	Occupant Behavior, Indoor environment, Operation and maintenance	The use factor, which affects the Energy consumption, will vary depending on the usage of tenants	[55]

10	E	2020	Asia-Pacific region	All (Residential & Service)	Physics-based	EUPP (Economic, Urbanization, Population and Purchasing power parity) model	Economy, urbanization rate and population	Economic development is the main driving factor of building Energy demand	[56]
11	AE	2017	US	Commercial	Data-driven	regression, gradient boosting regression models, and random forest regressor	Building activity, square feet, number of floors, heating degree days, and cooling degree days.	Gradient boosting regression models perform the best at predicting commercial building Energy consumption	[57]
12	AE	2021	Italy	Greenhouse	Physics-based	EnergyPlus	Shading/reflecting systems and operable windows	The controlled shading/reflecting system and operable windows can save 5% and 14% of the Energy needs. Ground coupled heat pump saves 21% E.	[58]
13	EB	2013	Rumania	Residential	Data-driven	Multiple Regression	Human behavior, Climate conditions, building-physical features, set-point temperature	Climate conditions, building thermal insulations and the air change rate have the highest impact; Human behavior will give more accuracy to the model.	[59]
14	E	2019	US	Residential	Data-driven	Regression (ridge, lasso, elastic net)	Occupant, Structure	Elastic net and group lasso make better predictions on hold-out test data. Structural factors explain annual electricity consumption patterns, habitual actions taken to save Energy in home	[60]
15	EB	2017	China, France, Norway, Belgium, Austria, Japan	Office, residential	Data-driven	Regression (MLR, ANN)	climate, building-physical features, operation and maintenance, occupant's behavior, and indoor environment	Human-related factors and various driving forces of occupant behavior have a significant influence on Energy use	[61]
16	JOBE	2016	Ireland	Office, commercial	Data-driven	SLR	External temperature	The isolation of external temperature in the derived Energy models has facilitated an estimate of the improvement in predictive strength	[62]
17	BE	2015	US	Office	Data-driven	Change-point regression, GPR, GMR, ANN	Weather, occupant schedule and behaviors	GMR model has better statistical performance in terms of RMSE. occupant schedules and behavior have significant impacts on the model prediction accuracy	[63]
18	EB	2019	China	Office	Data-driven	Statiscal, Classification tree, Sensitivity analysis	temperature, air velocity, and relative humidity	temperature, air velocity, and relative humidity were identified as having the most significant effects. Occupant behaviours play dominant roles for thermal comfort and Energy consumption.	[64]

19	AE	2015	India	Residential	Physics-based	LOWLUX code	sky conditions, age, work hours, education, income and housing typology.	window area, reflection coefficients of surfaces, lower sill level, decreasing room depth, decreasing voids in walls and increasing floor height are the factors which increase daylight factor	[65]
20	E	2018	Italy	Office	Data-driven	ANN	Illuminance position on work plane	the models are able to predict in an excellent way the illuminance values on the work-plane in order to know if they fulfil the visual comfort requirements	[7]
21	AIC	2019	US	Office	Data-driven	ANN	outdoor illuminance, occupancy, and intermediate leaving statuses.	The most influential factor is occupancy status The computation framework improve performance predictions	[66]
22	E	2020	US	Industry	Data-driven, Sensitivity	DSGM	Seasonal fluctuation characteristics	Seasonal grey model with dynamic seasonal adjustment factors significantly improves prediction accuracy.	[67]
23	EB	2018	Taiwan	commercial	Data-driven	regression, decision tree, clustering	Location, architecture, equipment, operating management, climate, population, economic income	The effective Energy saving can be focused on by using the key factors obtained by attributes selection.	[68]
24	EB	2018	South Korea	Office	Data-driven	MLR, ANN	Operation control	ANN is more accurate prediction for the GSHP system performance	[69]
25	EB	2016	Singapore	Office	Data-driven, Physic-based, Hybrid	Black-box, White-box, grey-box	Daily occupancy	Gray-box model using the new occupancy number from identification model as input for E+ is much accurate	[70]
26	E	2018	China	Residential	Data-driven	WNN, ELM, SVM, GA-BP	Temperature and historical loads	ELM and GA-BP models provide feasible methods for the heat load prediction.	[71]
27	AE	2016	Austria	All	Data-driven	Linear regression	Social factors and weather	the model parameters are continuously re-determined by using on-site measurements for the ambient temperature	[72]
28	EB	1991	Japan	All	Data-driven	statistical	outdoor environment, thermal character, architecture, and attributes of the resident.	the districts where the houses were located is the most effective item on the indispensability of air conditioners	[73]
29	E	2019	Italy	Office	Hybrid	EnergyPlus, data-driven occupancy, neutral response test	Occupancy	the simulated building Energy consumption can vary by up to 20% by only selecting the occupancy simulation scheme	[74]

30	RE	2020	South Korea	Office	Data-driven	ANN	Operation control	the operational factors of the HC system had greater influence on the Energy consumption than the indoor and outdoor temperature	[75]
31	EB	2019	US	Commercial	Data-driven	Multiple Regression	floor area, customer transaction count, building operating year	floor area, merchandize transaction number and the building age are more influential to store EUI	[76]
32	EB	2016	Brazil	Residential	Data-driven, Physic-based	ANN, MLR EnergyPlus	thermal behavior	ANNs are recommended to improve the accuracy of the prediction	[77]
33	AE	2016	US	Office	Data-driven, Sensitivity	Regression (LBNL)	Occupancy, Temperature	Occupancy is most correlated to plug load and lighting. Outdoor air temperature has lower correlation with Energy use than occupancy	[78]
34	EB	2020	UK	Office	Data-driven	CNN	Occupancy	the occupancy heat gains could be represented more accurately in comparison to using static office occupancy profile	[79]
35	BE	2019	China	Office	Data-driven	Logisti regression, Markov processes, ANN	Window behavior	Indoor temperature, outdoor temperature, wind speed, and sunshine hours are the most important factors with window opening state.	[80]
36	EB	2015	China	Commercial	Physics-based	eQuest	Load schedule	the schedules of internal loads have the most significant impact on the accuracy of the model	[81]
37	E	2016	Turkey	Residential	Data-driven, Physic-based	ELM, GP, ANN, EnergyPlus	material thicknesses thermal insulation	improvement in predictive accuracy is achievable with the ELM approach in comparison with GP and ANN	[82]
38	AE	2020	US	All	Data-driven, SHAP analysis	MLN, Decision Tree (XGBoost)	Floor area, occupants, operation control, equipment	the feature interaction analysis and SHAP value and associated visualizations provided a window into the inner workings of the prediction models.	[83]
39	BE	2017	Singapore	Office	Data-driven	learning-based demand-driven control	Occupancy	E savings potential in an individual office was inversely correlated to its occupancy rate	[84]
40	EB	2019	Brazil	Office	Physics-based	EnergyPlus	Urban environment geometry (shading)	the urban environment was considered in the Energy simulations can reduce thermal load of 16–18%	[85]

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Chapter 3

METHODOLOGY OF HYBRID METHOD

AND PATH ANALYSIS

CHAPTER THREE: METHODOLOGY OF HYBRID MODEL AND PATH ANALYSIS

3.1. Investigation on Household factors and energy monitoring data

3.1.1. Investigation in Japan Higashida Smart Community

This study investigated the electricity load of 12 residential houses in Higashida apartments and the response of their household's energy-related lifestyle by comparison analysis among different groups of household characteristics. The method examines interactive relationships among three aspects: EEU, Household characteristics, and occupant behavior based on the household's survey, OCC questionnaire, and real-time HEL measurement. From the exploratory analysis, we can determine the peculiar energy-related behaviors of the 12 households at the same time.

Smart Community signifies an efficient EMS of electricity that utterly uses information technology and enables a variety of services for power suppliers and demand-side users [1]. The smart community in Japan presently constituted by four representatives in four cities: Keihanna Eco-city, Yokohama Smart City, Toyota City Low-carbon Society, and Kitakyushu Smart Community. Our case study located in a 1.2 km^2 area in Higashida ward, Yahata district, Kitakyushu, which developed a project aiming to demonstrate a smart grid concentrating on energy-saving and environmentally friendly city. The project implemented the Home Energy Management System (HEMS) that transforms residents from energy consumers to energy producers to aware of their actions of energy-saving behavior. Dynamic pricing[1] and promoting programs were applied to influence the residents to change the energy-related lifestyle at home that efficiently reduces 20% of energy consumption, and the EMS introduced with storage batteries accounted for a peak cut effectively up to 49% energy saving [2].

According to Jianli Pan [3], it is easier to apply technologies to control or change the energy policy in small office buildings or home buildings. Therefore, we conducted our empirical research in Higashida apartments as a pivotal step for smart community projects in Kitakyushu. With the scale of 225 households in Higashida apartment, 12 households accepted with the proposal of energy monitor [2] installation. The data comprises of the EEU by house appliances and household OCC comparatively. Concentrating on this detailed energy consumption data and household information, we can evaluate a wide range of residential behaviors. After transmitting the report of the energy-saving strategy to 225 households in this community, 30 householders agreed to attend the meeting, and 15 householders decided to participate in the more in-depth research project which will implement in their own house. This paper analyzed the process during the two stages from 2016 to

[1] Dynamic pricing is setting where prices can be adjusted

[2] An electronic device measuring and gathering electricity use data

2018 in Fig.2. The first trial experiment of the project finished in 2016 with one energy monitor. In the second step, we installed two monitors and classified participants in groups of two households. The initial ideal pair grouping was assigned to households that showed similar family patterns and housing characteristics but different in OCC for evaluating the influence of occupant behaviors on their EEU. However, according to each household's privacy, only 12 participants decided to install the measurement equipment in their apartment. Also, grouping categories changed due to the schedule of each family. Accordingly, we moved our research orientation to a random grouping that objectively observed commons and differences of household characteristics as well as the recorded data of their EEU and HEL. Besides, the questionnaire regarding OCC or family member's information must be considered cautiously under the inhabitant's permission and building security management. For that reason, our measurement focused on the specific numbers of HEL, which were the advantages of this energy monitor, reflecting energy use activities in every household appliance while the location of appliances showed OCC in each room and finally carried out EEU schedule.

Considering a previous research in the same area from 2011 to 2014, Zheng et al. [4] grouped lifestyle patterns according to hierarchical clustering analysis and used monthly EEU from smart meters. Regarding their conclusion, larger floor area, bigger family size, higher annual income, more electrical appliances, and the existence of children of lifestyle would lead to more housing EEU. Also, it cited that smaller family size, lower annual income, fewer electrical appliances, and the existence of older people of lifestyle would cause less EEU. In this study, we examined those determinations again by recording the HEL from the energy monitor, with the corresponding time of OCC. Although the measurement only conducted on two available monitors and depended on participants' schedules, with the detailed information given to each household, this paper emerged benefits of pair comparison method and discussed more profound findings.

Fig. 3- 1. Higashida electric-only apartments, Kitakyushu, Japan. Photo: Google Earth [5].

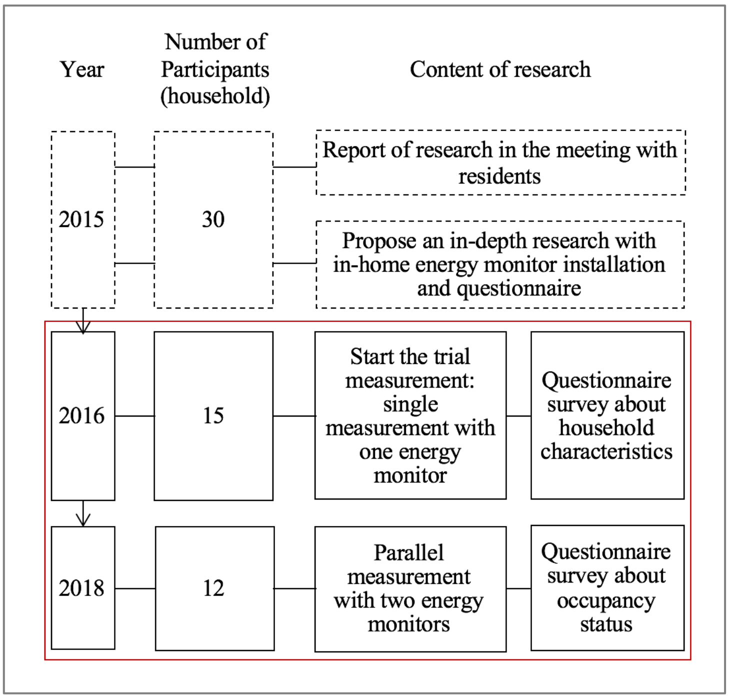

Fig. 3- 2. Research timeline

3.1.1.1 Investigation on household characteristics

A week survey was delivered to each of the participated families to question their family structure, OCC, and household characteristics. The use of questionnaires can be a simple way to assess any change in the behavior of end-users [6]. In our study, family attributes dedicated four sectors: Number of people in a family, and each person's information such as age, gender, and occupation. The questionnaire chiefly focused on the time they spent at home, specializing in three categories: Weekday, Saturday, and Sunday. This survey lasted in seven days and counted by hours. All categories of investigated information in the questionnaire are in Table 2. These delivered questions displayed the home-staying time of every member of families. Connecting to the EEU of house appliances in section 2.3, we can define their activities at home by time. It helped the study for predicting inhabitant behavior and their energy lifestyles at a specific time, hence providing suggestions for the further steps of residential energy-saving strategies. Besides, household characteristics, OCC, and housing characteristics were integrated as a platform for evaluating living conditions as well as residential features. For instance, drawing plans of the 12 houses provided to define house floor area, house window direction, number of rooms, and each room's dimensions.

Household surveys with household characteristics, housing design, and household activities are crucial aspects to perceive energy-related lifestyles in the most comprehensive and detailed portrayal. The building energy efficiency design is associated with many architectural design approaches, such as sustainable design approaches is a passive design or passive house. Passive concepts comprise significant facets: capitalizing on the potentials of the building site and optimizing the architectural design concept with different parameters such as natural lighting and ventilation or building geometry [7]. Regarding housing characteristics, we have gathered information on building elements and design that directly influence the end-use of energy. Overall, this apartment building belongs to a condominium complex built-in 2008 with 86 units on a total of 5 floors. The second block was built in 2009, has 139 units, locates in 13 stories, was leveled from West to East to increase south facades. This apartment has large balconies and patio access for natural light and ventilation. Regarding building type and layout plan, apartments in Japan refers to two types: low-rise apartments with few stories and mid-rise/high-rise apartments with multiple floors and elevators [8]. This selected apartment is the second type designed with genkan, living room, kitchen, tatami room, two or three bedrooms, bathroom, and toilet.

The properties are homes in the same apartment building constructed in 2009, using highly heat-insulating double glazing with heat-shielding effect and wood panel vinyl insulated wall to reduce cooling and heating load. All houses have the same structure and materials, are retrofitted with a high-efficiency water heater system (Eco-cute), CO_2 refrigerant heat pumps, which helps to reduce CO_2 emissions compared to conventional systems. These pivotal designs represent a transition from detached dwellings to modern apartments and condominiums in Japan with high energy efficiency and environmental-friendly approaches [9]. Based on research purposes, the selected household samples must meet the following criteria:

- Same housing construction with regards to materials, structure, and year built.
- The design floor plans and house directions are similar.
- Having a similar housing equipment system and using air conditioning (AC) for heating in winter with the temperature set point at 24°C.
- Willing to allow intrusiveness of energy monitors installed at home during the week.
- Willing to provide family patterns including the number of occupants, age, and gender of family members, under commitment confidentiality.
- Willing to record every member's "at-home and not-at-home" times 24 hours a day for seven days.

In sum, 12 households agreed to participate in the project with details of housing floor plans (see Appendix, Table A). While the previous research has explored correlation analyses between household characteristics and electricity end-use, this study overcame its limitations by focusing on the application of BEM to sensitivity analysis, which can stimulate replicable uses. The household survey method and housing description are listed in Table 1 and Table 2, respectively.

Table 3- 1 Household survey method

Categories	Sub-categories	Investigation methods
Household characteristics	Family pattern	Off-line survey
	Number of people	Off-line survey
	Age	Off-line survey
	Gender	Off-line survey
	Income	Off-line survey
Occupancy records	Weekday	Interview
	Saturday	Interview
	Sunday	Interview
Housing characteristics	House direction	Architectural technical drawing
	Floor plan	Architectural technical drawing
	Elevation	Architectural technical drawing
	Materials	Technical information
	Appliance	Off-line survey

3.1.1.2 Energy consumption measurement by energy monitor

In the Kitakyushu Smart Community, smart meters were implemented to connect HEMS within the Smart Grids of Higashida. A smart meter is a device that monitors a household's real-time EEU and can display real-time pricing in each household [10] Since smart meters only result in overall electricity consumption of participants in the Smart Community, we need another electronic equipment. In this study, we used Multi-circuit Energy Monitor manufactured by Panasonic, which can measure energy in every household appliance. This energy monitor recorded the EEU of appliances and stored the HEL data in an SD memory card for monitoring and energy performance reports. As an essential part of operating the Smart Grids, HEL can be measured in the most detailed level of energy consumption from daily and hourly data to minutely data, divided into every appliance in different spaces of a household. In Higashida apartments, Panasonic energy monitors were set up in 12 households for seven days under the security commitment and permit of the families (Fig. 3a-b). After seven days of metering, the source data was input to the laboratory's dataset for smart community research. Also, this energy monitor automatically classified and calculated the power consumption data (kW), before integrating them into CSV files. The dataset consists of 168 hours electricity load in 12 houses from 13/1/2018 to 28/2/2018. HEL data distributed into groups of electrical appliances according to the initial operation setting of the engineer. The setting process and related introduction guide are available on the equipment branch's website [11].

On the other hand, the fluctuation in household energy consumption depends considerably on how residents use lighting and electrical appliances such as televisions and refrigerators [12]. This founding emphasized the crucial role of defining frequent-used appliances in apartments and related influent factors to decrease residential EEU by changing human behavior and lifestyles. This paper assesses the electricity consumption levels based on its correlation with residential lifestyles such as and inhabitant habits and occupant behavior, ages, household structure, OCC, as well as house floor area, house direction, and equipment.

Table 3- 2 Household appliances ownership

Room	Electrical appliances
Living room	Air conditioning (for living room and kitchen), lighting equipment, television, living room outlet
Kitchen	Introduction cooking heater (IH heater), microwave, refrigerator, dishwasher, kitchen outlet
Bedroom	Air conditioner (parent's room), lighting equipment, bedroom outlets
Bathroom, Toilet	Electric water heater, washing machine, washlet[3], lighting equipment, bath heater (rare), bathroom outlet

[3] A toilet seat with a washer spray, a water heater and a heated seat **Invalid source specified.**.

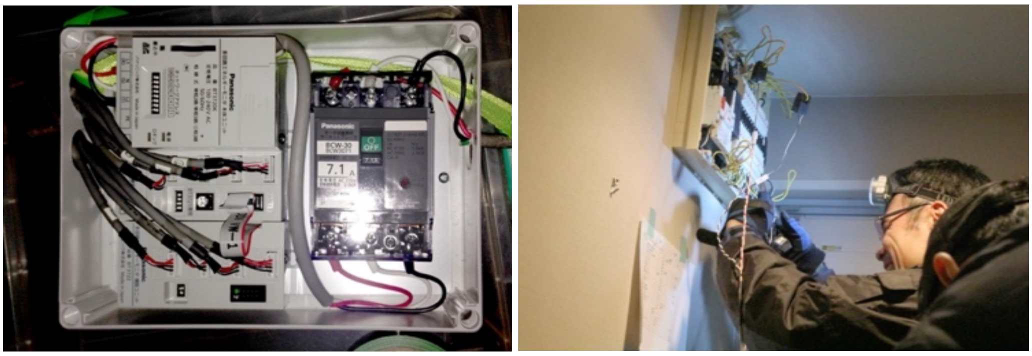

Fig. 3- 3a: Panasonic energy monitor (left). 3b: Installation in Higashida (right)

3.1.2. Research project on the household energy-related lifestyle in Vietnam

As for research on influencing factors and energy consumption impacts, the database plays an important role in the general and detailed analysis. Open data sources are popular in many regions, yet are still scarce to gather in Southeast Asia countries, especially for the household energy aspect of Vietnam. In recent years, several research projects have been emerging in this area, extending to a variety of field studies including energy-related subjects. For the residential area, we found a multinational research project in Southeast Asia, including Vietnam by the Building Energy Structure and Lifestyle database of Asia (BELDA). With support from the Japanese Government's Environment Research and Technology Development Fund, BELDA is chaired by the Institute for Living Environment Planning and Waseda University, in collaboration with Japanese universities and research Institutes in Asian countries. The project aims to provide a common database on the state of energy consumption in the consumer sector for emerging and developing countries in Southeast Asia, which are experiencing remarkable growth in the region [13]. The research started in 2015 and it will take the example of the data in Vietnam's two largest cities, conducted in the form of on-site measurement and survey in 2015 and 2016.

The database structure used in this paper involves two types: open-source data and raw data. Open-source data can be found online on the BELDA home page [13], which summarizes energy consumption and CO_2 emission according to the categorized groups of household factors and energy-related lifestyles. While this data source represents the overall trend of the total energy use and its correlation with household factors, the second data source provides detailed investigated household parameters and measurements. A total of 379 families participated in the project for two years from 2015 to 2016 in two cities: Hanoi and Ho Chi Minh. Each participant was invited to provide household characteristics such as the number of family members, monthly income, occupancy rate, house type, floor area, equipment ownership, and the permission to allow penetration of energy meter and electricity meter. The list of data is shown in Table 3 with four main categories and 11 items collected from the survey.

Table 3- 3 Description of the data categories

	Data categories	Subcategories	Units
1	Identification of Household	Household size	People
2		Monthly/Annual Income	Million VND
3		Frequency of Stay-at-Home	Day
4	Housing Characteristics	Gross floor area	m^2
5		House Type	Type
6	Home appliance ownership	Number of Air conditionings	Number
8		Year of manufacture (Air conditioning)	Year
10		Air conditioning setting point (Temperature)	T^o
11	Energy consumption	Cooking energy consumption (LPG)	MJ
12		Household electricity consumption (yearly)	MJ
13		Total energy consumption (yearly)	MJ
14		Energy saving-behaviors	Percentage

3.2. Hybrid approach on Building energy modeling BEM

The physic-based forward modeling approach takes input from weather data, building geometry, and building envelop, construction materials, equipment and operation schedules, and estimates the building heating and cooling load, and total building energy consumption based on those inputs.

The fundamental principles of the "Forward" models are based on the theory of heat transfer and thermodynamics, and have been developed for many years while "Data-Driven" models rely more on the data, assuming there is already a mathematical relationship between inputs (e.g. weather parameters) and outputs (e.g. total building energy consumptions).

Hybrid modeling approach integrates physics-based and data-driven modeling method. In EnergyPlus, Hybrid models combines steady-state modeling with monitoring data to utilize easily measurable zone air temperature, humidity ratio to solve hard-to measure zone parameters like: thermal mass (internal thermal mass), infiltration rate (velocity), zone people count (occupancy), with the aims to enhance current energy retrofit-practices, create user-friendly energy modeling environments, provides more accurate estimates of energy-saving at the same time.

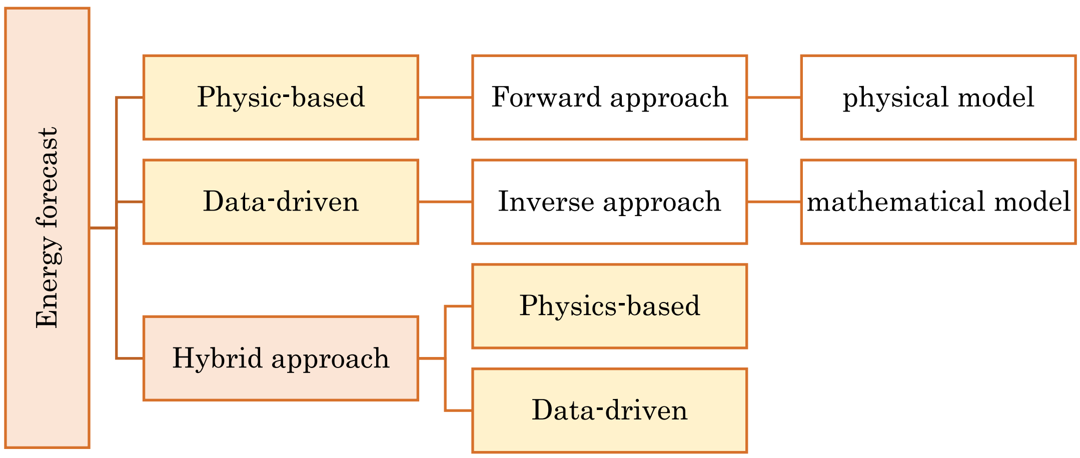

Fig. 3- 4. Methods for energy forecast

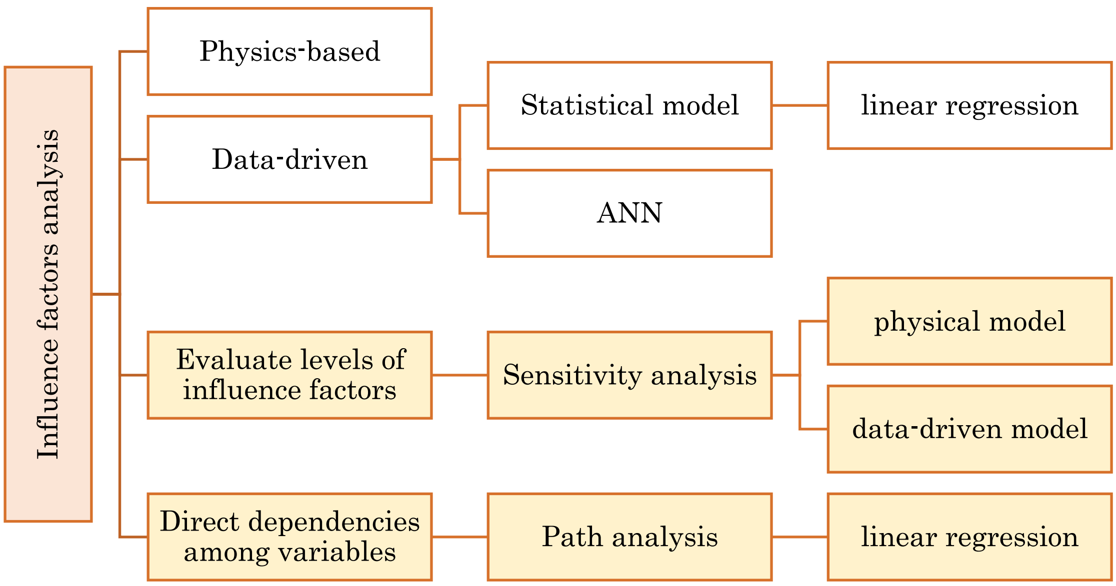

Fig. 3- 5. Methods to assess influence factors to energy consumption

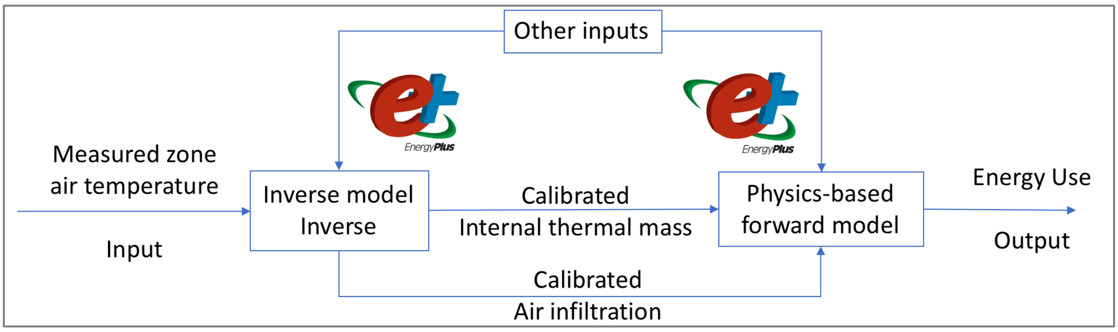

Fig. 3- 6. Hybrid approach in EnergyPlus [19]

3.2.1 Data-driven model

A Pearson correlation coefficient based on simple linear regression analysis are widely applied for evaluate the correlation among predicted data and observed data promoting mismatch correction in the modeling process. Ciualla and D'Amico [14] utilized Pearson coefficient to determine the relationship between heating and cooling energy demand with building and weather condition. Studies in the same field have been explored various energy model application using regression methods. Senatro et. Al [15] introduce regression model for energy demand projection to predict energy demand trends in end use sectors. The model that consists of linear regression has been validated by classical statistical tests with strong correlation of energy demand and other factors. Given a dependent variable y of p independent variables x, the simple linear regression introduces the relationship between variable y and variable X is written as follow. To perform the correction of energy model, assume the independent variable X is actual measured data and the dependent variable Y is modeling energy data, the linear regression model is written as equation (1) and predicted energy $\hat{y}$ become as equation (2).

$$y = \beta_0 + x\beta + \varepsilon(3)$$

$$\hat{y} = \beta_0 + x\beta \qquad (4)$$

Where

y is modeling energy use;

$\hat{y}$ is the predicted energy use;

x is the actual energy use;

β_0 is the intercept term;

β is the regression coefficient to be estimated;

ε is the error term or residual;

To evaluate how well the modeling data matches the actual data in this study, regression model presents coefficient of determination R squared which is an indicator represent goodness of fit of energy model (5). This value indicates the relationship between energy model and observed energy use by a scale 0 – 100%.

$$R^2 = \frac{(\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y}))^2}{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2} \quad (6)$$

Where R (multiple R) is coefficient of determination, x_i is equivalent to the value of x (energy consumption) in each i observation of the sample, $\bar{x}$ is the average of energy consumption, and y_i represents the modeling energy use for each i observation, $\bar{y}$ is the average of modeling energy use.

Besides a R squared, the goodness of fit of the model can be evaluated by a residual which is the error between the observed energy use y_i and the predicted energy data $\widehat{y_i}$. The residual in this regression can be calculated as follows:

$$\varepsilon = y_i - \widehat{y_i} \quad (7)$$

Linear regression analysis is applied to compare the correlation between modeling energy data and the actual measured data, forecast the energy consumption in each household based on the history of usage. The results of correlation analysis will be summarized with R squared value, coefficient of variable x, intercept and P-value.

3.2.2 Physics-base model

Based on the Energy use optimization process in Chapter I, we proposed a concept of applying survey data and housing design investigation for estimating energy end use and controlling energy-related behavior through the use of graphical interface software OpenStudio. The application of OpenStudio for connecting observed energy data and predicted energy consumption in Fig. 8.

In this step, all the input data was modified on OpenStudio's Interface in Fig.7. There are three main workflows: Resource (input data), energy management system, and Result (Fig.7). Resource data includes five tabs: Site (Weather, Live Cycle Cost, Utility Bills), Schedules (Occupancy, Activities, Heating and Cooling Schedules), Constructions (Materials and Construction standards), Loads, and Space Types. For the

Energy Management System (EMS), we insert information on the Facility tab, Spaces tab, Thermal zones tabs, and HVAC Systems. HVAC tab functions for design, inspect and edit cooling and heating systems such as air conditioning, water heating, and refrigerator. In this study, we concentrate primarily on the use of air conditioning in winter which is measured by thermal zone installation

(Fig. 9). In this case, there are two air conditioners in the house that placed in living room and parent's master room. Results shown in the final tabs "results" includes complete information related to building design, building location, weather condition, and energy consumption.

This application can help architects to inform energy decisions from the earliest phases in the design plan (Fig. 8) to the construction process and aims for minimizing energy use from changing three factors: Architecture, HVAC systems, time use. During the architectural model design process, we structure thermal zones simultaneously with the housing element's characteristics such as building type, building materials, and construction set. This step is a fundamental premise for the following setup in OpenStudio.

In this study, application of energy simulation solves the problems of limited data, which is restricted within one month due to the current measurement conditions and technology. EnergyPlus – and energy simulation analysis software – has the necessary tools to meet these requirements. With this simulation model, we create an architectural plan on the 3D design model (3D Sketchup) before inserting other input information into OpenStudio. After that, OpenStudio helps the researcher to analyze energy consumption based on their input conditions. This simulation mitigates the difficulties about time and expense during the investigation process. In the transition era from analog technology to digital technology, it becomes a premise for the movement of energy research from small data research to big data. The study processes a 6-steps programming energy model from input data to output and suggestion appropriate solutions.

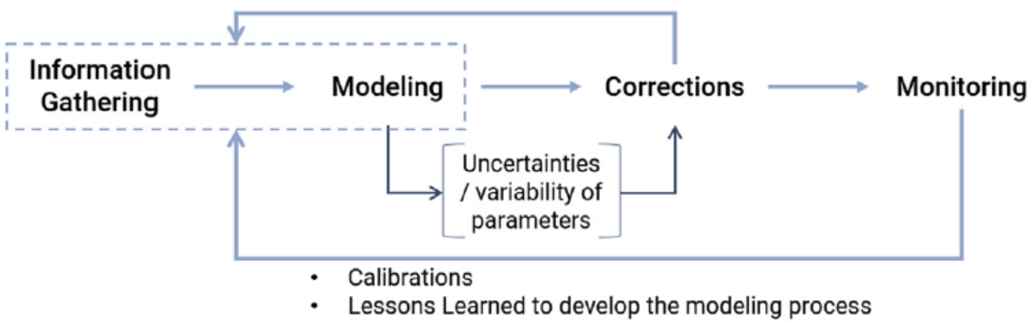

Fig. 3- 7. Building energy modeling (BEM) (Chang et al.)

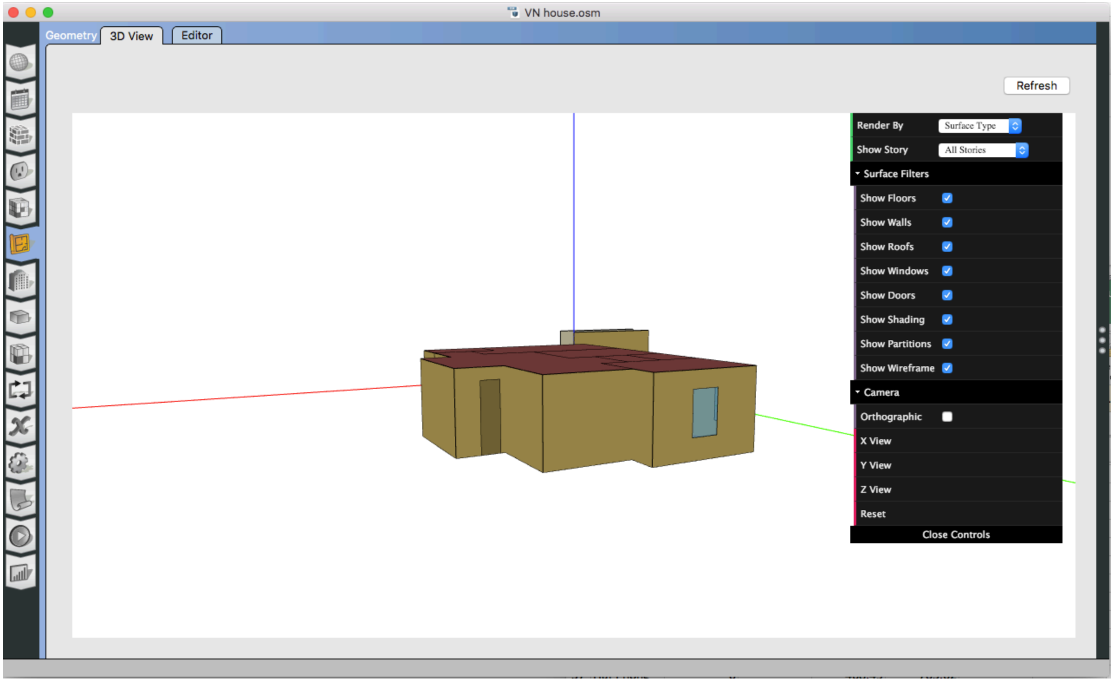

Fig. 3- 8. Open Studio Interface – 3D model

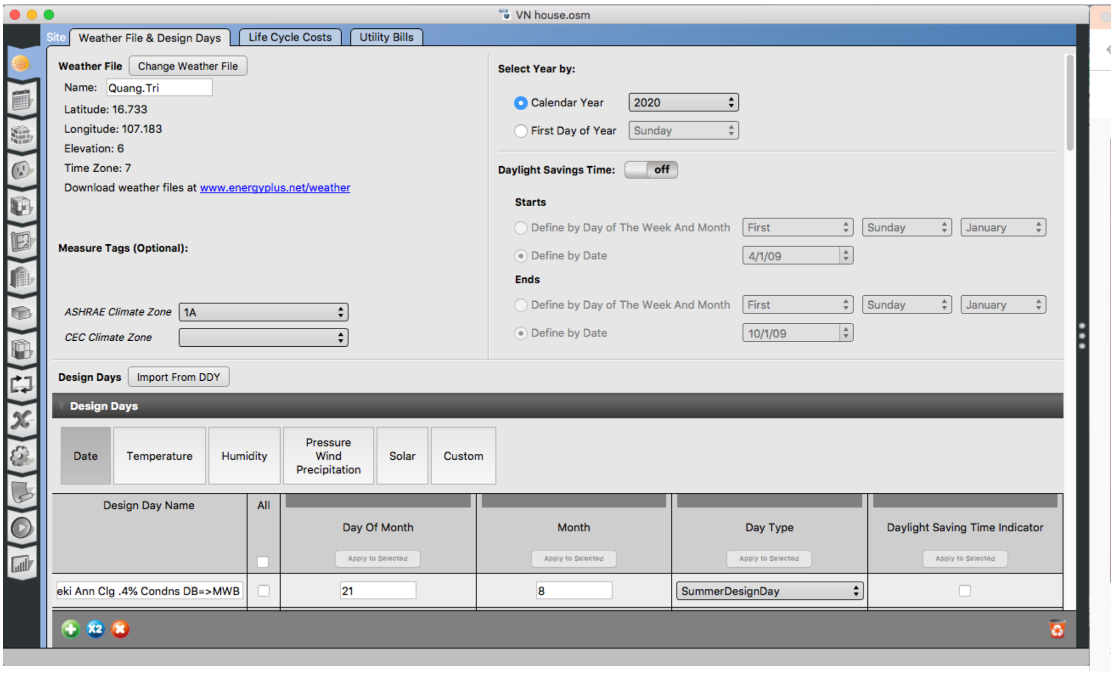

Fig. 3- 9. Open Studio Interface – Weather Files & Design Days

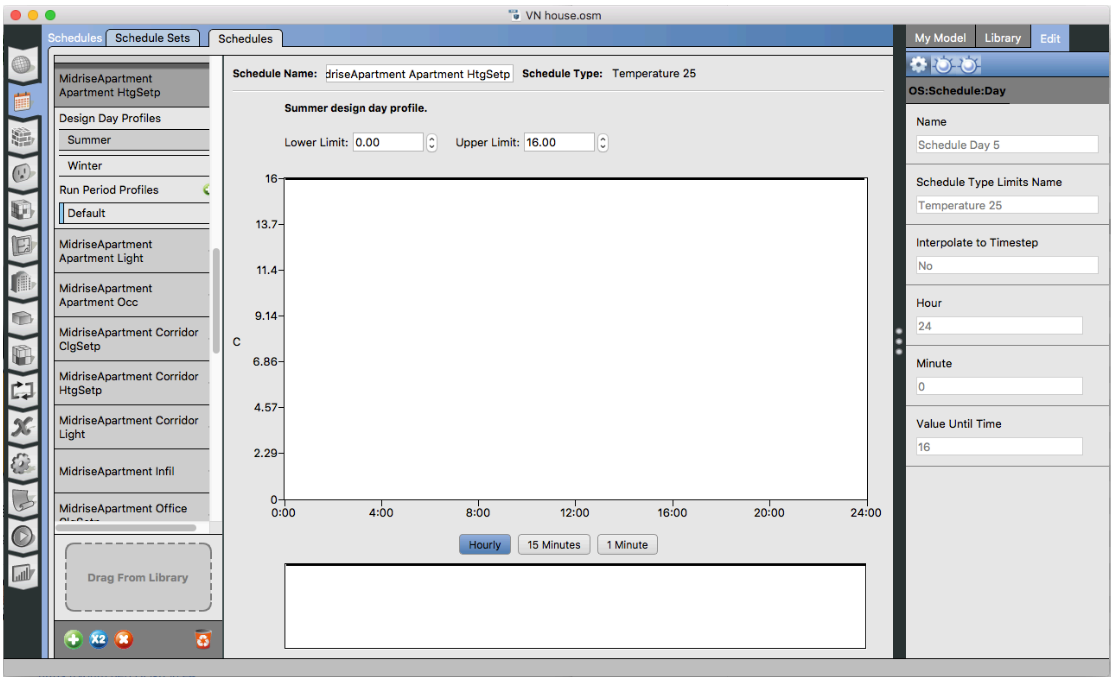

Fig. 3- 10. Open Studio Interface – Schedule

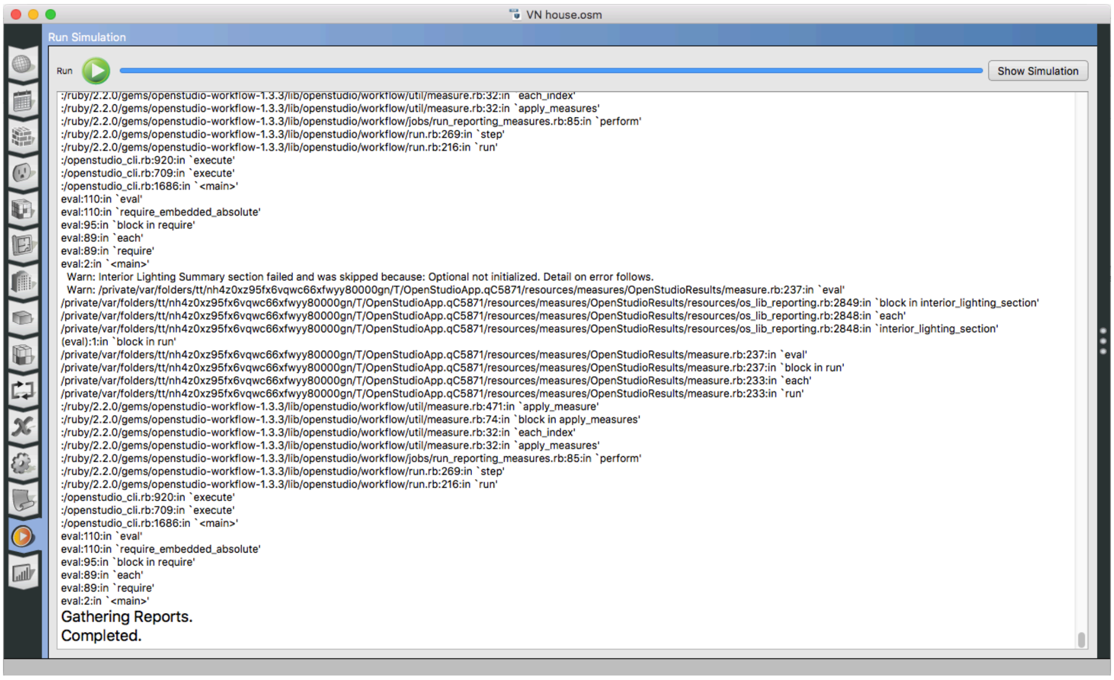

Fig. 3- 11. Open Studio Interface – Run Simulation

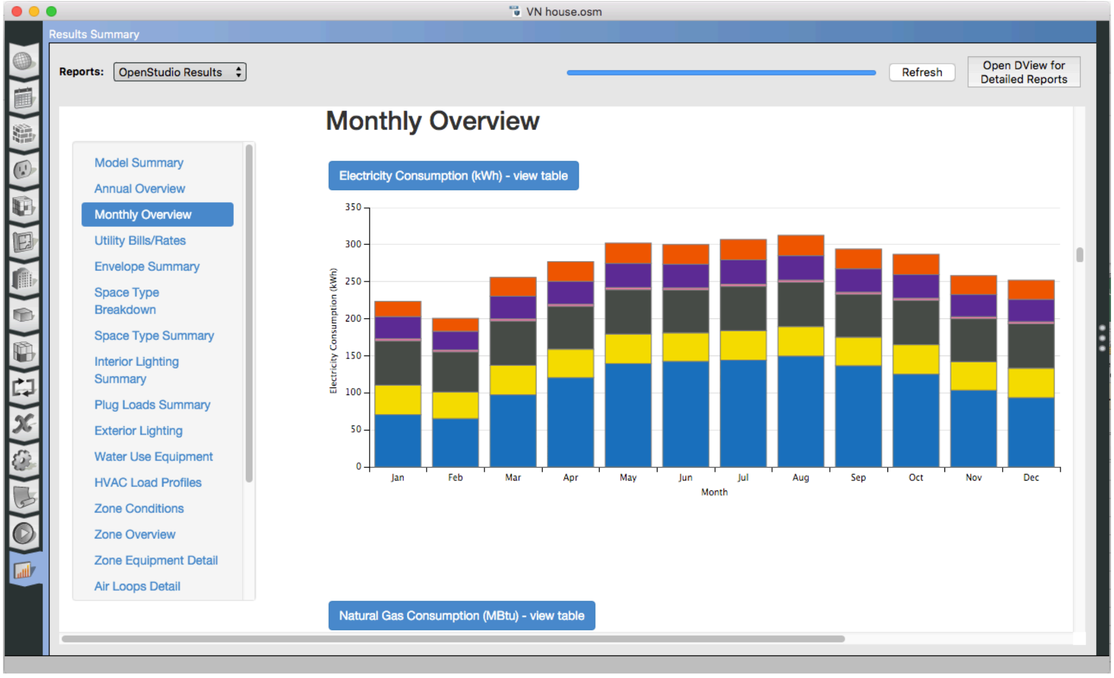

Fig. 3- 12. Open Studio Interface – Results

3.3.3 Sensitivity analysis

Beside traditional physic-based investigation and data-driven analysis, some studies applied combination of the two methodologies to assess energy consumption, energy-related behavior and energy forecast, which is known as Hybrid method. Li et al. [16] proposes a new four-stage hybrid methodology for short-term prediction of energy efficiency. This hybrid model shows reliable performance and clarify a variety of influent factors that lead to dissimilar energy saving quotas. Cai et al. [17] in their study, uses a hybrid method consisting bottom-up an top-down approach to simulate carbon emissions for building and transport sectors for low-carbon city management. Meanwhile, Dong et al. [18] enlightens improvements of coefficient of variance of hybrid modeling approach to single-family residential houses compared to data-driven model for short-term load forecasting.

In EnergyPlus, Hybrid modeling approach uses the inverse modeling method to improve the accuracy of the building energy simulation for existing buildings, which adds measured data to solve uncertain model parameters [19]. For instance, people count is usually hard to measure in reality, which result in simplification of occupancy schedule assumptions in energy modeling. The hybrid model introduces an approach estimate the zone level interior thermal masss, air infiltration rate, and people count with measured zone air parameters in EnergyPlus.

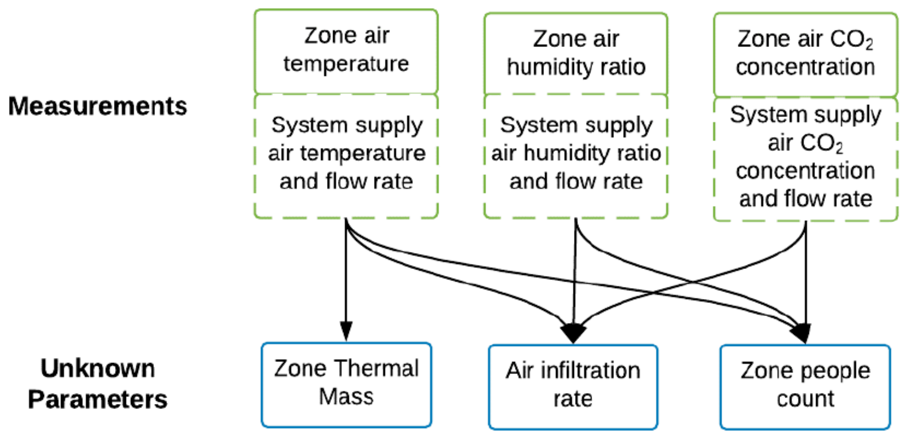

Fig. 3- 13. Schematic of hybrid method in EnergyPlus [19].

The hybrid model algorithms are built upon the physics-based zone air balance equations reformulated to solve a partially inverse problem. The hybrid model approach inverses the physics-based energy model, reformulating the heat, moisture, and CO2 balance algorithms with measured zone air temperature, humidity ratio, and CO2 concentration data (traditionally results/output of the physics-based model) to solve highly unknown parameters. The sum of zone loads and the provided air system energy equals the change in energy stored in the zone. Typically, the zone capacitance, C_z includes the zone air only when formulating energy balances for the zone air. The internal thermal mass, including furniture inside the house, is assumed to be in thermal equilibrium with the zone air m_{inf}, thus it is added in the zone heat capacitance, C_z. The infiltration airflow rate, changes for different conditions depending on outdoor temperature, wind speed, and HVAC system operations. The energy provided from systems to the zone is represented as Q_{sys}.

$$C_z \frac{dT_z}{dt} = \sum Q_i + \sum[h_i A_i(T_{si} - T_z)] + \sum[m_i C_i(T_{zi} - T_z)] + m_{inf}C_p(T_o - T_z) + Q_{sys} \quad (1)$$

$$C_z = V\rho_{air}C_pC_T \qquad (2)$$

Where ρ_{air} is Zone air density [kg/m^3]; V is Zone air volume [m3]; C_p is Zone air specific heat [kJ/kg · K]; T_z represents Zone air temperature at the current time step [K]; T_{zi} represents Nearby zone air temperature at the current time step [K]; T_o is Outdoor air temperature at the current time step [K]; t is Current time; $\sum Q_i$ is Sum of internal sensible heat gain; $\sum h_i A_i(T_{si} - T_z)$ represents Convective heat transfer from the zone surfaces [kW]; $\sum m_i C_i(T_{zi} - T_z)$ represents Heat transfer due to interzone air mixing [kW]; $m_{inf}C_p(T_o - T_z)$ becomes Heat transfer due to interzone air mixing [kW].

Regarding the general concept of transferring building information to BEM, we propose the application of a dynamic building energy model named EnergyPlus. EnergyPlus is a building simulation engine developed by the U.S. Department of Energy's (DOE) Building Technologies Office (BTO), and the National Renewable Energy Laboratory (NREL) [20]. It can calculate energy consumption, including heating and cooling energy use, lighting, and other electrical loads based on the building information [21]. Popular graphical interface software for applying EnergyPlus is known as OpenStudio – a collection of software tools that support building energy modeling using Energy Plus. Studies using OpenStudio for making energy performance, and energy-related behavioral analysis [22] [23] [24] demonstrated that OpenStudio graphical interface software and dynamic simulation software working behind – EnergyPlus – provide more accurate energy performance forecast and help architects or engineers with making decisions towards an optimal energy-efficiency design solution. The software cooperates with SketchUp to create OpenStudio plug-in in SketchUp extensions that analyze energy-related aspects of the SketchUp 3D modeling tool. This plug-in allows architects and researchers to directly integrating multiple functions in one Building Design Model and provide energy decisions from the earliest phases. In this way, we can utilize the double-way interactions between EnergyPlus – SketchUp to evaluate the correlations between a couple of different aspects: Energy – Architecture and Energy – Behavior. This interrelationship represents a reciprocal connection between energy use and other factors with the interpretation of BEM…. Inversely, residential energy consumption data can navigate ideas for designing house models and occupation schedule [25].

Regarding building energy modeling process, the study [7] determines three fundamental stages: (1) data collection and simulation; (2) data reevaluation or calibration; and (3) built evaluation. In response to the above-indicated opportunities and challenges, this paper provides a connection among three methods: on-site survey and questionnaire, observation-based energy monitoring, energy simulation for energy use forecast, and energy-saving solutions. The research process started from setting up an energy monitor and collecting data in the real site to deploying integrated data analysis and finally building a testing model based on collected data. Application of real-time energy monitoring can help for storing and managing energy-related building information [26] and reflecting energy-related activities through the corresponding occupancy data. In this paper, we suggest a research scheme drawing the interactive process to achieve energy use optimization by BEM.

The technique used to determine how the values of the independent variable will affect a particular dependent variable under a certain set of assumptions is defined as sensitivity analysis. Its use will depend on one or more input variables within specific boundaries, such as the effect of changes in household occupancy on household energy consumption. Sensitivity analysis works on the simple principle: Change the model and observe the behavior. [27]

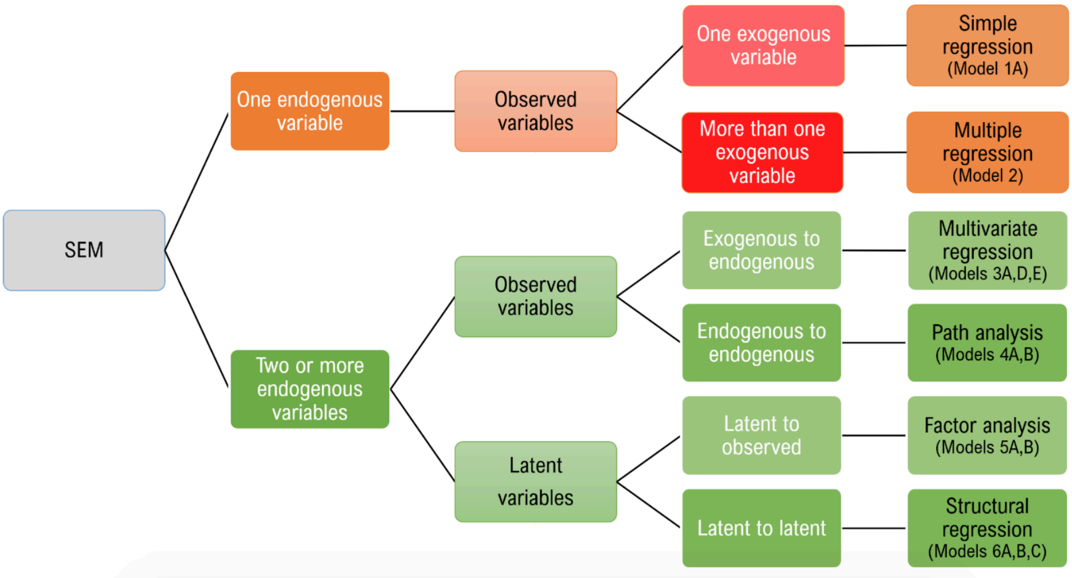

Fig. 3- 14. Structural Equation Models [27]

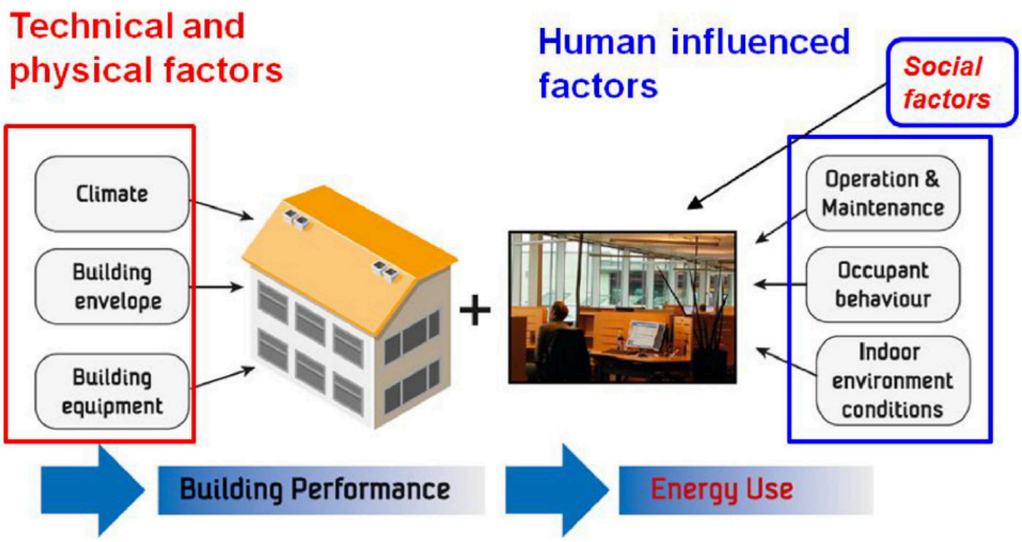

Fig. 3- 15. Six influencing factors on building energy use [28]

3.3. Structural equation model & Path analysis

3.3.1. Path model for household factors analysis

In previous research on energy-intensive lifestyle and energy-related effects, we examined the sensitivity analysis of household factors with a combination of energy monitoring and energy modeling in the case of apartments in Japan [28]. This hybrid approach assessed the influence of household factors such as household characteristics, housing design, and occupancy rates on energy consumption. Using sensitivity analysis for Energy-plus models, the results emphasized the significant impacts of household size, occupancy rate, thermal resistance on insulated walls, and airflow rate, on the end-use and the gross site or source energy. However, this approach applies to narrow-scale cases investigated across a few households and required specific data of hourly occupancy and detailed floor plans for three-dimensional visualization models. In this study, we expand the case study to Vietnamese households with a larger number of participants based on the generally available data, which is consistent with study areas in developing countries. Therefore, Path Analysis – a modeling approach of Structural Equation Modeling (SEM) is considered most applicable to the exploratory analysis in this study.

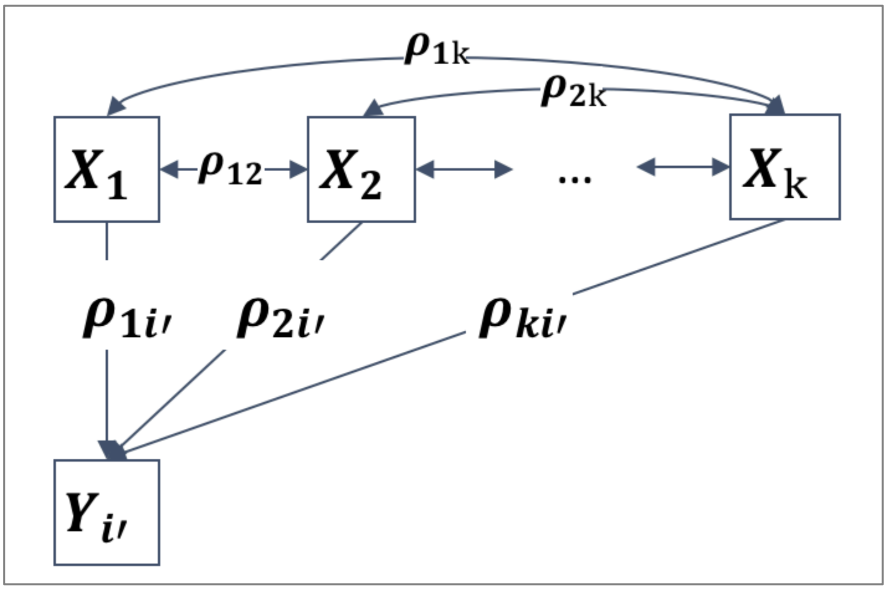

Fig. 3- 16. Path model strucutre

SEM is a broad statistical analysis technique (Data-driven) that combines factor analysis and multiple regression analysis to find structural relationships between variables. Path analysis was first developed by Sewall Wright [29]. This specific type of SEM investigates the direct and indirect relationship between a set of exogenous variables (independence, predictor, input) and endogenous variables (dependence, output). In the application of Path Analysis to the energy sectors, Gui et al. [30] evaluated six social factors, directly and indirectly, affect CO_2 emissions intensity: Six factors were included in the analysis: gross domestic product per capita, technology effect, energy price, industrial structure, energy structure, and foreign direct investment. According to the results of Path Analysis adoption in a residential area, the occupant's behavior or household Energy-Saving Option was identified as a crucial facet and strongly influenced by personal norms [31]. Among the various topics in SEM, the impact of two or more observed endogenous variables on the other endogenous and exogenous variables can be analyzed by Path analysis. Path analysis is a more general model in which all variables remain but endogenous variables are allowed to explain other endogenous variables [32]. Based on available sources and the scale of the case study, we selected three exogenous and five endogenous variables from existing household factors and energy use data in the survey. This Path analysis will focus on easy-to-seek aspects of household factors, such as monthly income, floor area, number of family members, number of operating AC, and number of stay-at-home days. These aspects have not been exploited in the previous studies, however, it is replicable and potentially scalable in similar cases. The structural equation describes the direct impact of the causal factor X_i on the outcome $Y_{i'}$, can be written as:

$$Y_{i'} = \varepsilon_{ii'} + \beta_{ii'} X_i \tag{1}$$

Where β_i stands for standardized coefficient and ε_i is the standardized residual.

The effect of the variable X_i on variables $Y_{i'}$ can be calculated as follows:

$$\rho_{ii'} = \beta_{ii'} \tag{2}$$

If there are k factors directly effect on Y. The correlation reflects the direct impact of k causal factorsX_i with $i \in [1, k]$ on the outcome $Y_{i'}$ can be expressed by the calculation below:

$$Y_{i'} = \varepsilon_{ii'} + \sum_{i=1}^{k} \beta_{ii'} X_i \tag{3}$$

Considering the total effect of the j^{th} factor X_j on Y, $j \in [1, k]$, if we multiply both sides of the structural equation by X_j, we get the normal equation:

$$X_j Y_{i'} = \varepsilon_{ii'} X_j + \sum_{i=1}^{k} \beta_{ii'} X_i X_j \tag{4}$$

Assuming that the residual ε_i is uncorrelated with all variables in the equation ($\rho_{\varepsilon_i X_j} = 0$), if we take the expectations of both sides [33], we can get the total effect of factor X_j on the outcome $Y_{i'}$ which is represented by $\rho_{ji'}$:

$$\rho_{ji'} = \rho_{\varepsilon_i X_j} + \sum_{i=1}^{k} \beta_{ii'} \rho_{ij} \tag{5}$$
$$= \sum_{i=1}^{k} \beta_{ii'} \rho_{ij}$$

Where ρ_{ij} stands for the correlation of factor X_i and factor X_j. If there are l indirect factorsX_z being correlated with factor X_i and X_j, ρ_{zi} implies the correlation between X_z and X_i, Equation (5) will be replaced by:

$$\rho_{ij} = \sum_{i=1}^{l} \beta_{zj}\rho_{zi} \tag{6}$$

From the calculation of Equations (5) and (6), the total effect of the factor X_j on the outcome $Y_{i\prime}$ in a multivariate multiple regression can be written as:

$$\rho_{ji\prime} = \sum_{i=1}^{k} \sum_{z=1}^{l} \beta_{ii\prime}\, \beta_{zj}\, \rho_{zi} \tag{7}$$

In the path diagram, ρ_{ij} represents the value of the correlation path between the independent variable X_j and dependent variable $Y_{i\prime}$ where X_j is the causal factor and $Y_{i\prime}$ is the outcome. The structural equation approach is more mathematical; while perhaps less intuitive, it is less prone to mistakes. Sewell Wright's Path diagram is based on these equations, however, is very diagram-oriented and is perhaps more intuitive to most people [33]. Therefore, a path diagram is an easy-to-approach tool to visualize the influence of household factors on energy use in residential areas.

3.3.2. Path model in R – LAVAAN SYTAX

Path analysis based on the path model is one of the structural equation models and to describe its differentiation with other SEM, the path model concerns effects only between the observed variables [34]. A variety of computational software that can simulate the Path model is SPSS, AMOS, R-Studio, etc. In this study, we introduce an approach of the LAVAAN (latent variable analysis) package in R-Studio, a free and open-source using R language to estimate a wide range of multivariate statistical models, including the path analysis [35]. In the LAVAAN package, models are set up using a concise and compact text-based syntax – a description of estimating model, which simplifies the multivariate regression modeling into the easy-to-use command in R-Studio. In particular, we examine how different household factors influence energy consumption in two types: Electricity use and cooking energy use. The model parameters can be analyzed and evaluated by the fit indices to meet the required goodness of fit, which is explained in section 4.2. In case these model indices do not match the acceptable threshold, the path models will be redesigned with syntax modifications to repeat the process until the final model achieves the criteria. With the available database, we finally figured out a structure of path diagram that best represents the relationships between household impact factors and energy consumption in the case study (shown in Fig. 14). The R-studio LAVAAN model syntax written for this path analysis is attached in the figure to be referred to.

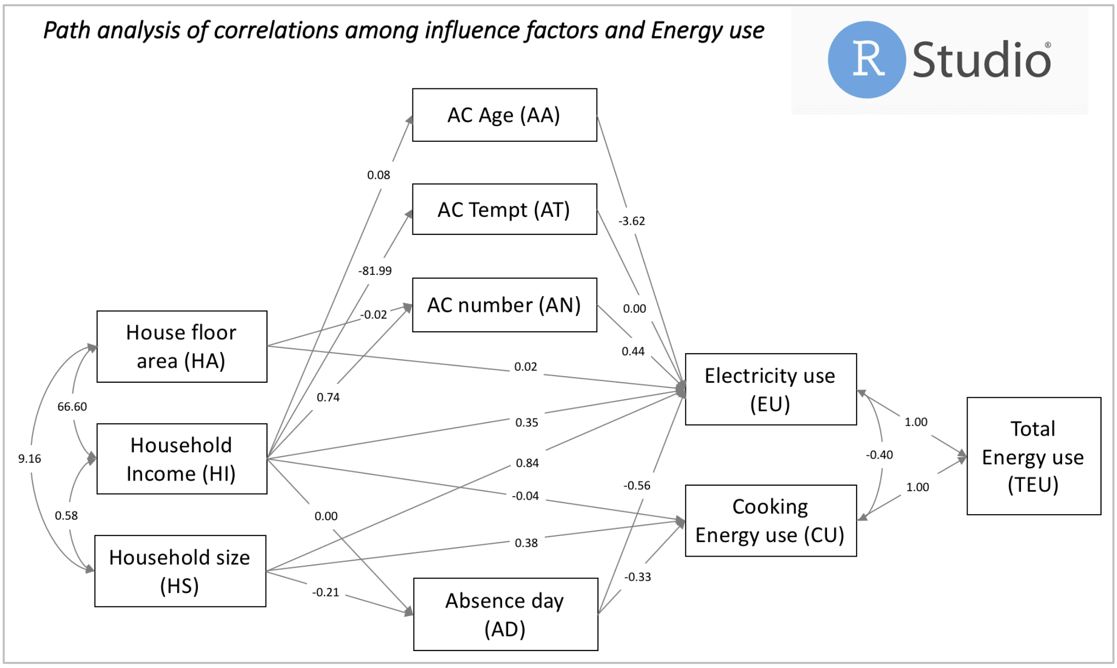

Fig. 3- 17 Path diagram

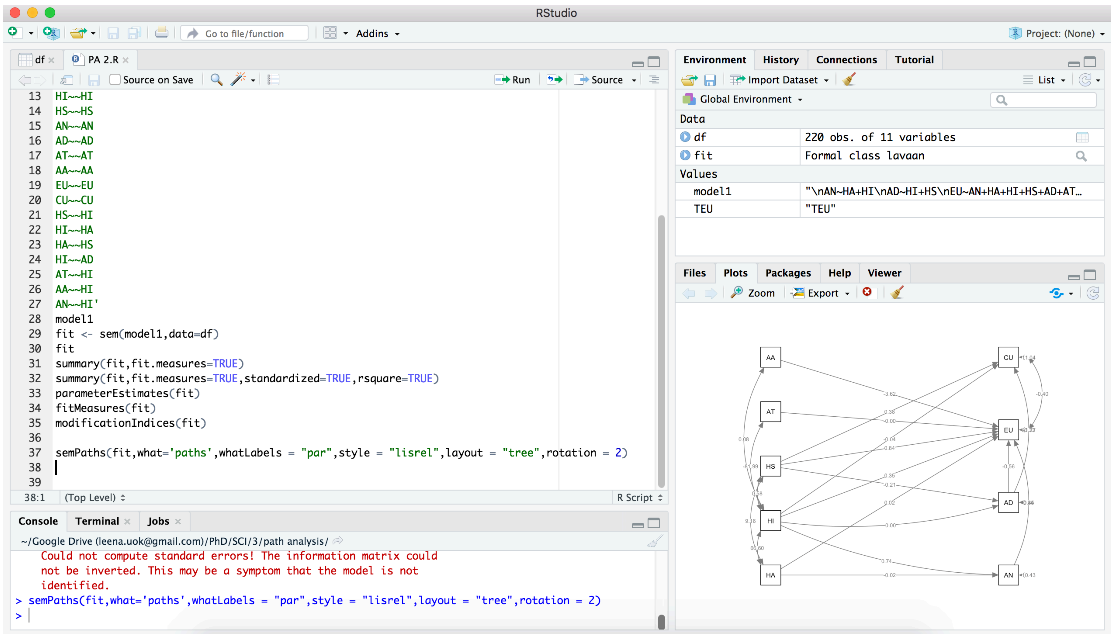

Fig. 3- 18 Path model syntax in R-studio

RESULTS:

lavaan 0.6-7 ended normally after 319 iterations

Estimator	ML	
Optimization method	NLMINB	
Number of free parameters	31	
	Used	Total
Number of observations	155	220
Model Test User Model:		
Test statistic	19.716	
Degrees of freedom	14	
P-value (Chi-square)	0.13	
Model Test Baseline Model:		
Test statistic	130.602	
Degrees of freedom	36	
P-value	0.000	
User Model versus Baseline Model:		
Comparative Fit Index (CFI)	0.940	
Tucker-Lewis Index (TLI)	0.845	
Loglikelihood and Information Criteria:		
Loglikelihood user model (H0)	-4362.977	
Loglikelihood unrestricted model (H1)	-4353.118	
Akaike (AIC)	8787.953	
Bayesian (BIC)	8882.300	
Sample-size adjusted Bayesian (BIC)	8784.177	
Root Mean Square Error of Approximation:		
RMSEA	0.051	
90 Percent confidence interval - lower	0.000	
90 Percent confidence interval - upper	0.100	
P-value RMSEA <= 0.05	0.438	
Standardized Root Mean Square Residual:		
SRMR	0.062	

Regressions:

	Estimate	Std.lv	Std.all
AN ~			
HA	-0.018	-0.018	-1.195
HI	0.736	0.736	5.025
AD ~			
HI	0.001	0.001	0.006
HS	-0.208	-0.208	-0.250
EU ~			
AN	0.439	0.439	0.031
HA	0.021	0.021	0.097
HI	0.350	0.350	0.171
HS	0.836	0.836	0.098
AD	-0.559	-0.559	-0.055
AT	-0.000	-0.000	-0.071
AA	-3.617	-3.617	-0.239
CU ~			
HI	-0.040	-0.040	-0.057
HS	0.378	0.378	0.128
AD	-0.325	-0.325	-0.092

Covariances:

	Estimate	Std.lv	Std.all
HI ~~			
HS	0.577	0.577	0.106
HA ~~			
HI	66.601	66.601	0.306
HS	9.164	9.164	0.175
.AD ~~			
HI	-0.079	-0.079	-0.018
HI ~~			
AT	-81.988	-81.988	-0.009
AA	0.082	0.082	0.027
.AN ~~			
HI	-14.368	-14.368	0.934
.EU ~~			
.CU	-0.400	-0.400	-0.013

Fig. 3- 19 Results in R-Studio

3.3.3. Model fit index

The degree to which the path model fits the observed data can be determined by a variety of indices commonly explained by: Chi-square, Confirmatory Factor Index (CFI), Tucker Lewis Index (TLI), Root Means Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR). The chi-square model is the chi-square statistic obtained from the maximum likelihood statistic (in LAVAAN, this is known as the Test Statistic for the Model Test User Model [32]), however, its sensitivity to discrepancies from expected values at a large sample size can be highly problematic [36], thus we cannot decide an acceptation or rejection for the model in this case. Alternatively, given the acceptable sample size (>200), four other indices are recommended to test the fit for accepting or rejecting the model [37] [38]. After the model evaluation procedure, a final decision is made when the model meets the baseline of close fit with the observed data sample. These baselines are briefly calculated using the criteria of four indicators below:

- CFI – The Comparative Fit Index – values can range between 0 and 1. The closer the CFI is to 1, the better the fit of the model (CFI values of 0.97 seem to be more realistic than the often-reported cutoff criterion of 0.95 for a good model fit [39]). The CFI is a popular fit index as a supplement to the model chi-square.

$$\mathrm{CFI} = 1 - \frac{\delta(\mathrm{User})}{\delta(\mathrm{Baseline})}$$

$$\delta = \mathrm{ts} - \mathrm{df}$$

where df denotes the Degrees of freedom for that particular model, ts is the Test statistics.

- TLI is known as the Tucker Lewis Index that also ranges between 0 and 1 with values greater than 0.90 indicating good fit. If the CFI and TLI are less than one, the CFI is always greater than the TLI [32].

$$\mathrm{TLI} = \frac{\mathrm{ts(baseline)/df} - \mathrm{ts(user)/df(user)}}{\mathrm{ts(baseline)/df(baseline)} - 1}$$

- RMSEA is the root mean square error of approximation. RMSEA defines δ as the non-centrality parameter which measures the degree of misspecification. A good model fit should have RMSEA value that ≤ 0.05 while a value between 0.05 and 0.08 is reasonable approximate fit and poor fit value is >= 0.10

$$\mathrm{RMSEA} = \sqrt{\frac{\delta}{\mathrm{df}(\mathrm{N}-1)}}$$

$$\delta = \mathrm{ts} - \mathrm{df}$$

where df is the Degrees of freedom for that particular model, ts means the Test statistics.

N is the total number of observations.

- SRMR is the Standardized Root Mean Square Residual, a measure of the mean absolute correlation residual, with smaller values suggesting good model fit [34]. The threshold of SRMR for concluding “acceptable fit” is <0.08 [40].
-

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Chapter 4

CORRELATION OF HOUSEHOLD AND HOUSING FACTOR WITH EEU IN JAPAN AND VIETNAM

CHAPTER FOUR: CORRELATION OF HOUSEHOLD AND HOUSING FACTOR WITH EEU

4.1. Data resources in Japan Case Study

4.1.1. Household characteristics and Social factors

Household characteristics given in Table 4, consisting of personal information: Age, gender, family position, family income. The investigation shows the number of family members who vary from two people to five people. The family structure defined by six age groups in table 5. The majority of families have one child to two children in the age group C2 and C3 (from 6-year-old to 15 years old). Parents' age were mostly in the working-age from 35 years old to 49 years old. This study classified the monthly income of a household in Higashida into four groups: Group 1: Less than 300 000 Japanese Yen (JPY); Group 2: 300,000 JPY to less than 500,000 JPY; Group 3: 500,000 to less than 700,000 JPY; and group 4: 700,000 or more. Overall, the household income in these families is above the average recorded income in Kitakyushu in 2018 was 397,445 JPY [1]. Shown in Table 4, a couple of elderly in house #4 who are 61 years old and 66 years old is positioned in a high-income group. The husband was still working as the Japanese working-age population has been getting older recently. Regarding the income statistics, families with high income seem to be older than most of the other families. As an example, family #4 and family #7 were the oldest family and had a relatively high income in Kitakyushu. At the same time, younger families who have parents less than 43 years old were likely to have a middle-income. In general, family income does not depend on family numbers. In terms of household OCC, the number of people staying at home varies considerably among each members' schedules in the family, which shown in Fig. 5. Even though the average OCC denotes 15.4 hours on a weekday, the fathers only resided 10 hours while mothers spent up to 21 hours a day at home. On Saturday and Sunday, fathers also took less time at home, which documented roughly 16 hours. In contrast, their wife kept an unchanging schedule in the whole week, which reached 21 hours a day. From this perception, it is possible to confirm that the women mostly become the primary occupant in the house. Besides, older children spent less time at home than younger children, not only on weekdays but also on the weekend. In brief, mothers were the inhabitants who have the most OCC at home, even on weekdays or weekends. The father needed to leave home more often than any other person in the family, followed by teenagers in group C3 were the members usually staying outside. Subsequently, small children in group C1 appeared at home more frequently than other elder children.

As regard to member OCC at home, the chart in Fig. 6 illustrates the total number of people who presented at home on a weekday in 12 households. With the sum of 44 people participating in our study, it documented that people started leaving for home at about 7 a.m. From 8:30, only mothers stayed at home in most of the families, which accounted for ten people. This number decreased to four people at ten and only two people when it was at noon. Children in group C2 whose age from 6 to 11 years old seemed to have a fixed schedule at school from 8 a.m. to 3 p.m. Depending on each person, back-home time deviated from 3 p.m. to 9 p.m. in most of the cases, the mothers inclined to be the first person going back after 1 p.m., while the following members were secondary students in group

Table 4- 1 Household information and architecture feature in 2018. SSE: South-southeast; S: South; S.W.: Southwest.

A1: adult age from 35 – 40; A2: adult age from 41 – 50 years old; A3: adult age more than 60 years old. C1: Children age less than six years old. C2: Children age from 6 – 11 years old. C2: Children age from 6 – 11 years old.

House #	Day start	Day end	Number of people	Age group						Housing characteristics		Income Group #
				Father	Mother	1st Child	2nd Child	3rd Child	4th Child	Floor area (m²)	Direction	
1	13/1/2018	19/1/2018	4	A2	A2	C2	C2	N/A	N/A	86.7	SSE	2
2	13/1/2018	19/1/2018	4	A2	A1	C2	C2	N/A	N/A	88.0	SSE	2
3	21/1/2018	27/1/2018	5	A1	A1	C3	C2	C1	N/A	104.5	SSE	3
4	21/1/2018	27/1/2018	2	A3	A3	N/A	N/A	N/A	N/A	83.5	S	4
5	29/1/2018	4/2/2018	3	A2	A2	C3	N/A	N/A	N/A	83.1	SSE	3
6	29/1/2	4/2/20	3	A2	A2	C2	N/	N/	N/	86.	SSE	3

	018	18						A	A	A 7		
7	6/2/2018	12/2/2018	4	A2	A2	C2	C2	N/A	N/A	104.8	SSE	4
8	6/2/2018	12/2/2018	4	A1	A1	C2	C1	N/A	N/A	75.3	S	2
9	14/2/2018	20/2/2018	4	A2	A1	C2	C2	N/A	N/A	99.0	SW	3
10	14/2/2018	20/2/2018	4	A2	A2	C2	C2	N/A	N/A	99.0	SW	3
11	22/2/2018	28/2/2018	3	A2	A2	C2	N/A	N/A	N/A	99.0	SW	3
12	22/2/2018	28/2/2018	5	N/A	A2	C3	C3	C3	C2	80.5	SSE	3

C3 from 12 to 15. The next group was primary students in group C2 and kindergarten group C1 who are less than five years old. Fathers were always the last persons presented at home from 5 p.m. to 9 p.m. These numbers explain why men become the person who spent less time at home, and most of the women in this study did not obtain a job outside but took care of housework in the family. On a weekday, the period of 5 hours around noontime from 10 a.m. to 3 p.m. was the lowest-OCC period when most of the people left home, including the mothers.

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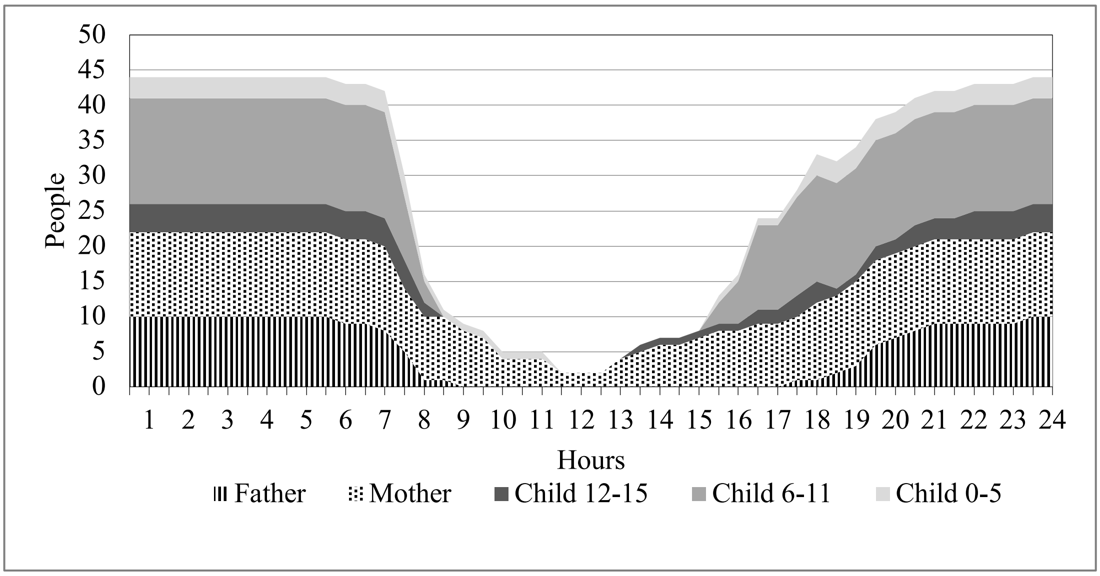

Fig. 4- 1. Total number of people stay at home by hours in one day

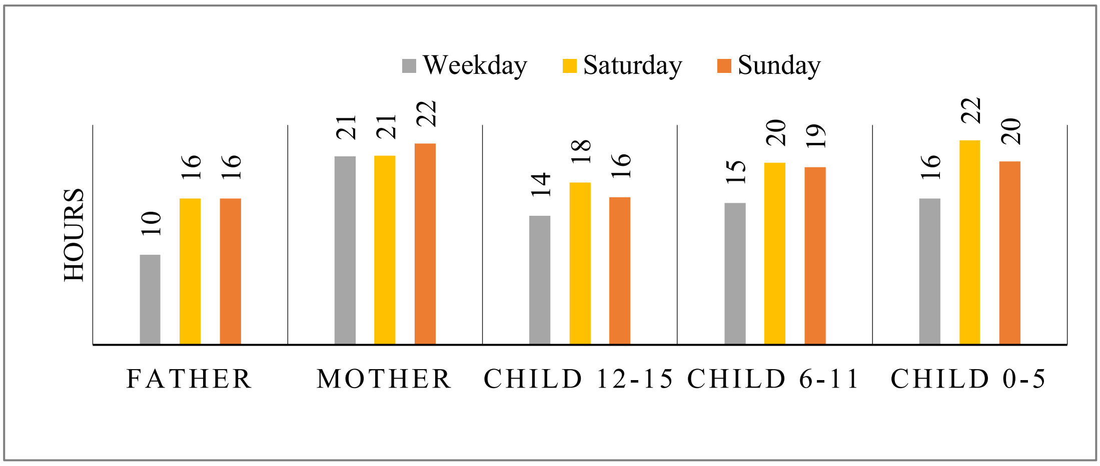

Fig. 4- 2. Occupancy time by family member's categories

4.1.2. Climate conditions and other physical parameters

Table 4- 2 Monthly mean air temperature in Kitakyushu in 2018 (ºC) [2]

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
-1.1	-1.1	5.2	12.4	16.5	21.1	27.2	25.8	20.6	14.9	9.1	2.8

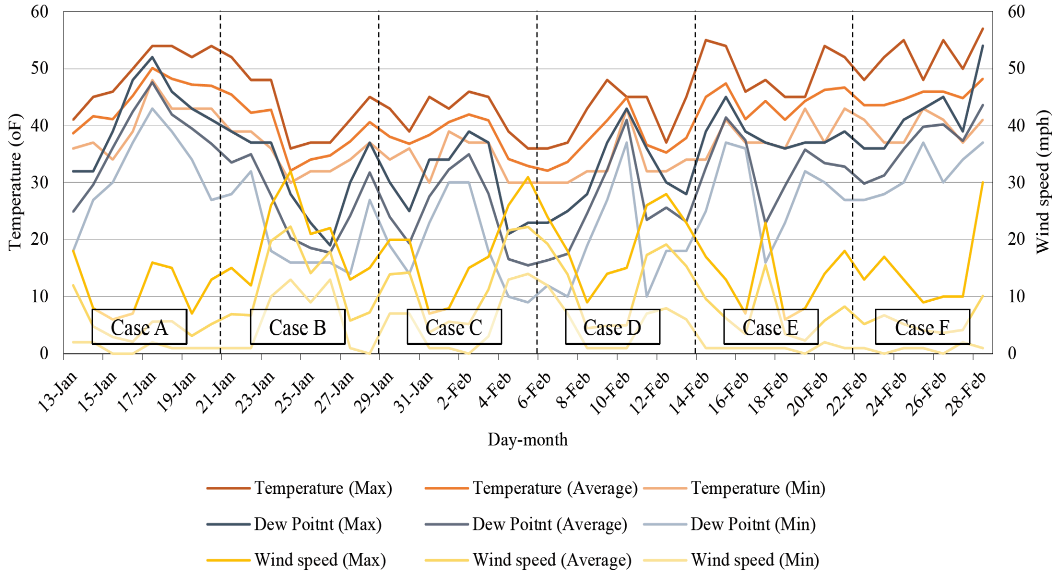

Fig. 4- 3. Physical environmental parameters: Temperature, Dew Point, Wind speed. Data source: [3]

4.2. Data sources in Vietnam Case Study

As for research on influencing factors and energy consumption impacts, the database plays an important role in the general and detailed analysis. Open data sources are popular in many regions, yet are still scarce to gather in Southeast Asia countries, especially for the household energy aspect of Vietnam. For the residential area, a multinational research project in Southeast Asia, including Vietnam by the Building Energy Structure and Lifestyle database of Asia (BELDA) provided a common database on the state of energy consumption in the consumer sector for emerging and developing countries in Southeast Asia, which are experiencing remarkable growth in the region [35]. The research started in 2015 and it will take the example of the data in Vietnam's two largest cities, conducted in the form of on-site measurement and surveys in 2015 and 2016. The database structure used in this paper involves two types: open-source data and raw data. Open-source data can be found online on the BELDA home page [35], which summarizes energy consumption and CO_2 emission according to the categorized groups of household factors and occupant behaviors. While this data source represents the overall trend of the total energy use and its correlation with household factors, the second data source provides detailed investigated household parameters and measurements. A total of 379 families participated in the project for two years from 2015 to 2016 in two cities: Hanoi and Ho Chi by using the snowball sampling method. It is a non-probability sampling technique in which the subsequent families will be recruited from the currently recruited families in the absence of statistical information, and also to prevent bias in the building location or type of construction. Each participant was invited to provide household characteristics such as the number of family members, monthly income, occupancy rate, house type, floor area, equipment ownership, and permission to allow penetration of the energy meter and electricity meter. The list of data is shown in Table 4-3 with four main categories and 11 items collected from the survey.

Table 4- 3. Description of the data categories

	Data categories	**Subcategories**	**Units**
1	Identification of Household	Household size	People
2		Monthly/Annual Income	Million VND
3		Frequency of Stay-at-Home[1]	Day
4	Housing Characteristics	Gross floor area	m^2
5		House Type	Type
6	Home appliance ownership	Number of AC	Number
8		Year of manufacture (AC)	Year
10		AC setting point (Temperature)	T^o
11	Energy consumption	Cooking energy consumption (LPG)	MJ
12		Household electricity consumption (yearly)	MJ

[1] Frequency of Stay-at-home: The number of days it takes for at least one household member to be home during the day. For example, five days of "Stay-at-home" means five days a week, this household is always home even during the day. However, zero days of "Stay-at-home" means no one is home during the day.

13	Total energy consumption (yearly)	MJ
14	Energy saving-behaviors[2]	Percentage

4.3. Correlation analysis between EEU and household factors

4.3.1 Correlation analysis in Japan case study

4.3.1.1 House floor area and energy consumption

In general, various number of EEU was easily noticed among 12 households. Most participants spent less than 250 kWh/week except house #7 with more than 300 kWh/week. On average, Fig. 4-5. shows that 60% of the electricity used in living rooms and tatami rooms came from merely 40% of total house spaces. Additionally, the kitchen, which representing cooking utensils, shared the same space with the living room and tatami room and consumed 18% despite its merely 9% of house space. This result proves a high OCC in shared spaces. In contrast, bedrooms, bathrooms, and toilets are spaces having less OCC. For instance, bedrooms contribute 38% of the home's area while using only 13% of the entire EEU. Generally, the demand energy has a more apparent correlation with the room's function and household device ownership than with the room size. Shared rooms seemed to get more usage priority at home, while private spaces were less often. For that is the use of space heating instead of central in most of the Japanese residents. Hence the heating consumption is closely related to the location of a room during the winter season.

Even though significant EEU denotes a manifest inclination toward shared spaces in Fig. 4-4, some exceptional cases are differing from the majority. For example, almost haft EEU of house #1 documented from bedrooms while the living room only consumed about a quarter. Also, the similarity happened in house #8 with 32% energy for the kitchen and 2% for bedrooms. In the meantime, house #10 spent 36% electricity on cooking activities in the kitchen while merely used electrical devices in bedrooms with 1% usage. In another case, the bathroom that is considered less energy consuming in every house rocketed abnormally in house #6 and house #8, reaching 39% in house #6 and 24% in house #8. Regarding these differences, it is necessary to investigate particular characteristics in each house to give concrete reasons and answer the question of reducing energy use by changing residential

[2] Calculated based on the scores of the questionnaire about energy-saving behavior in the survey (see Appendix)

behaviors or lifestyles for every household occupant.

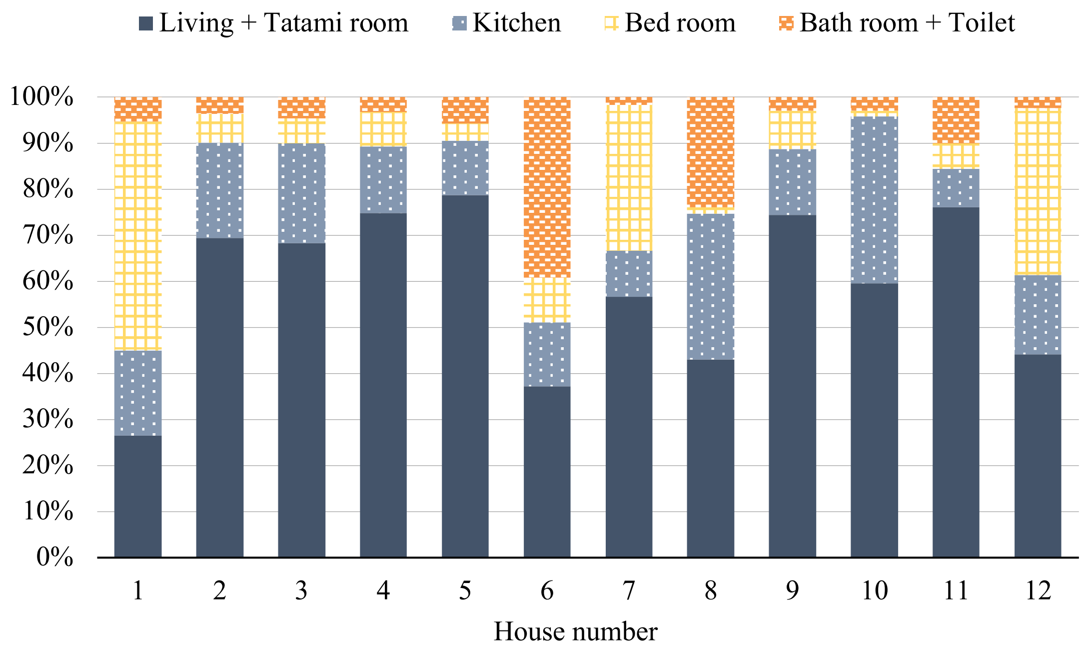

Fig. 4- 4. EEU distribution by room types in 12 households

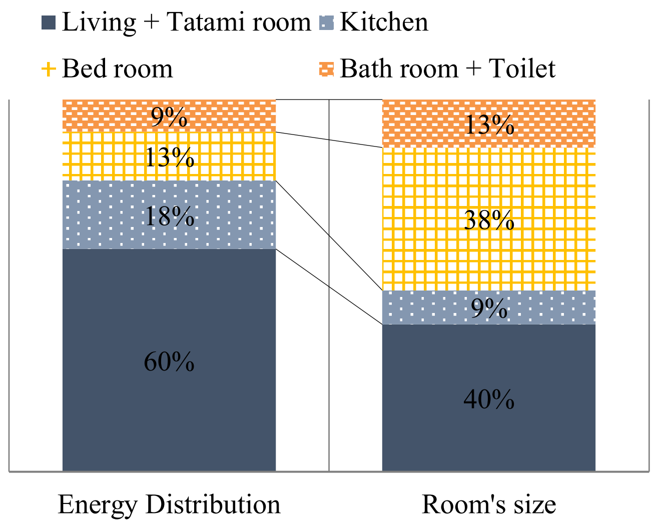

Fig. 4- 5. Room’s area and relative EEU

4.3.1.2 **House appliance and energy consumption**

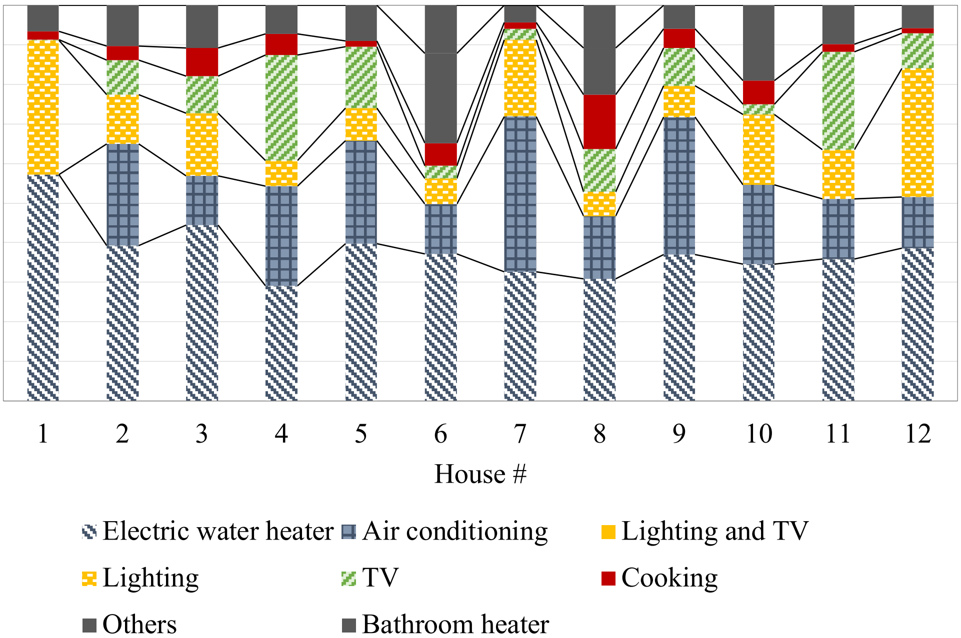

Fig. 4- 6. Shares of household EEU in Higashida

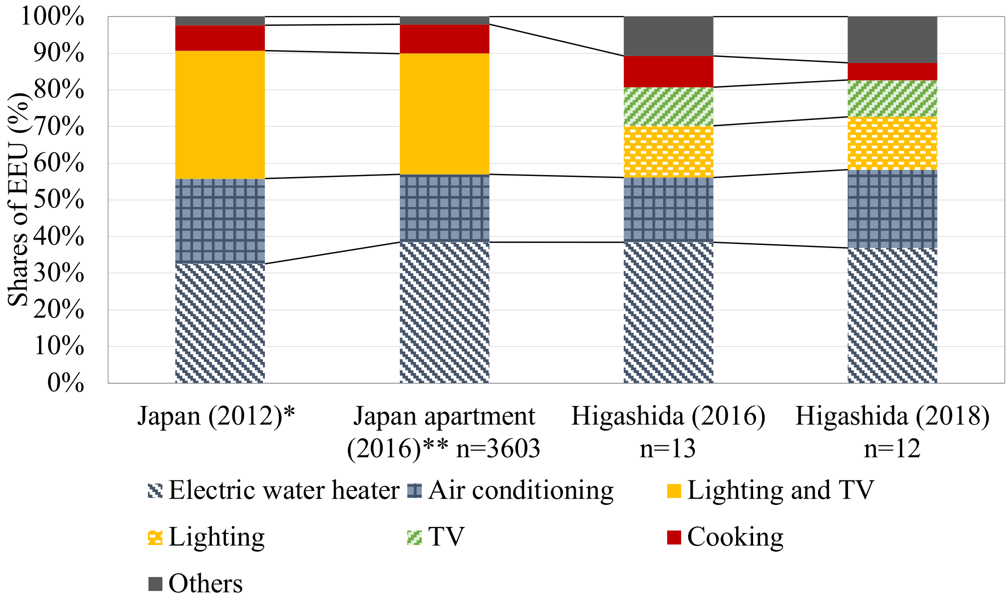

Fig. 4- 7. Shares of household EEU in Japan. * Ministry of Environment, Japan 2018 [28]. ** The Energy Conservation Center, Japan [51]

As Higashida apartments are electric-only multi-unit dwellings controlled by HEMS, all the house appliances were driven by electricity in the grids. In general, the most frequent-used appliances are Eco-cute water heater, air conditioning (in the living room and bedroom), led-light for lighting, refrigerator, I.H. heater, washing machine, toilet seat, kitchen outlets, and others. According to the share of the household appliance in Fig. 4-7, Electric water heater became the most leading EEU that stroked 38% in total consumption of 12 households. The following appliances that consumed considerable energy were air conditioning, which occupies 22%, lightings 15%, and 10% usage from televisions. While the electric water heater was regularly used at the sleeping time, the air conditioning was habitually switched on in the living room that reached 18% electricity load as the room seemed to be preferred mostly by family members during the daytime. Cooking utensils consumed the same amount of energy that takes 6% in total demand for household EEU while other appliances such as refrigerator, washing machines, and toilet seats are less consuming. On average, household EEU in this study reached about 27.3 kWh a day, increase by about 10.5% compared with that of the same time in 2013 accounted for nearly 24.7 kWh [4].

Has been cited by Nagakami and METI, most of the shares of household energy in Japan 2012 [5] reveal a similar number with the share of Japan's apartment in 2016 [6], and the previous research we conducted in Higashida in 2016's winter. Even though the amount of EEU increased after years, the average shares of appliances remained constant. Compared with Japan's figure, there is not much disparity in the use of air conditioning and water heater. In contrast, the share of EEU by appliances differed variously among houses even when they had the same measurement time. For example, house #7 showed the highest demand for air conditioning, while house #12 consumed lighting electricity as same as the use of the water heater. House #8's cooking utensils consumed significant electricity, while that of other houses only spend around 1%, and some other appliances caused the rocket to rise of EEU in house #6 and house #10. The ample diversity of EEU shares among participants proves the diversity of energy-style in different households again.

Overall, the heating system occupied nearly 60% of electricity consumption in Higashida apartments and Japan in general. Among the home devices, the electric water heater is the most electricity consuming that markedly affects the total consumption as well as hourly electricity usage. According to its indispensability in a Japanese home, the water heater was set up to work at night when most of the other equipment stopped working to balance with day time energy use in the grids. As for the customer's benefit, the price was lower at the same time, and hot water was ready for the whole day's activities in the morning. Therefore, this function eases convenience and appropriation for inhabitants. With the stability of consumption level, it could be called a small scale of the EMS.

4.3.1.3 Occupancy rates and energy consumption

Specific lifestyles in each family are unique due to their work and activities. Since the electric water heater is independent of daily occupant activities, in this section, we present EEU of non-water-heater appliances and indicate each house's OCC to analyze the difference between participant's energy styles.

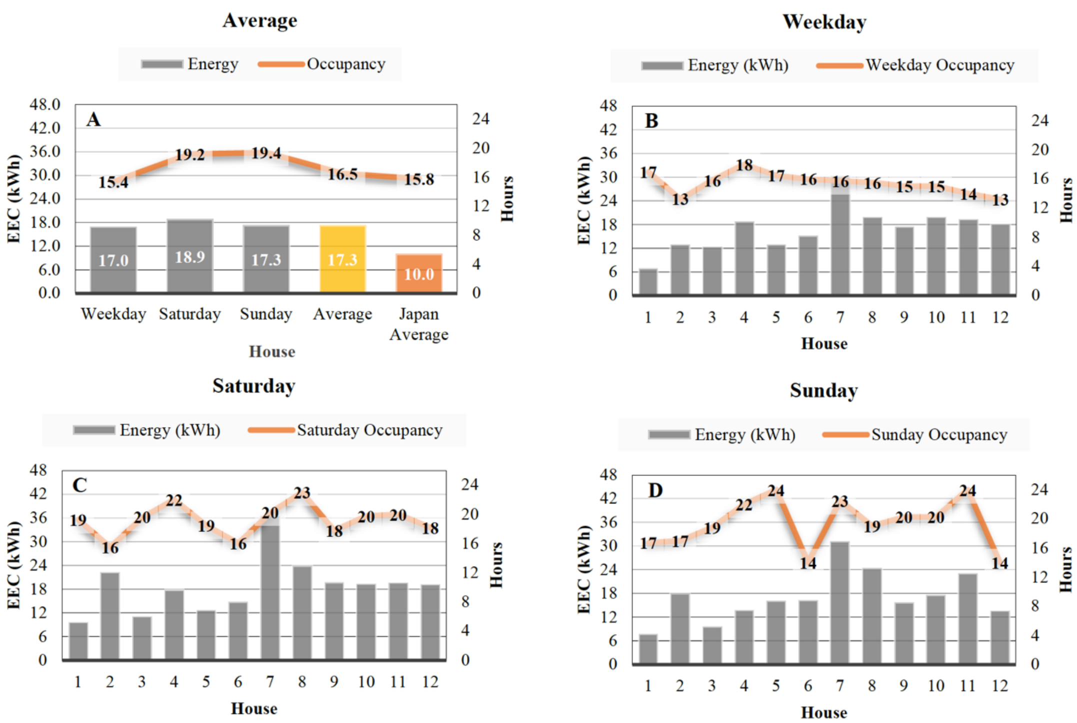

Fig. 4- 8. EEU of non-water-heater appliances and OCC in 12 households. A: Average EEU and OCC in one week. B: EEU and OCC on Weekday. C: EEU and OCC on Saturday, D: EEU and OCC on Sunday

First of all, the observed OCC illustrated that people spent averagely 16.5 hours a day while that of Japan household was 15.8 hours a day [7]. They stayed home15.4 hours on a weekday – four hours less than OCC on Saturday and Sunday that performed more than 19 hours (Fig.4-8-A). Even though the average occupant time on Saturday and Sunday was mostly the same, the total EEU in these two days varied differently. The number increased on Saturday, while Sunday's usage continually remained the same amount as weekday's number (Fig 4-8-A). Overall, the energy demand of people on a weekday, Sunday, and Saturday fluctuated between 17.3 kWh on average, clearly higher than the average of Japan's household electricity consumption in January 2013 with only about 10 kWh a day [8]. In the view of average OCC on a weekday in Fig. 4-8-B, most of the participants spent around 14 hours to 15 hours at home. House #4 had the most leading average OCC that peaked 18 hours, whereas the in-home time of people in house #2 lasted barely 13.25 hours on working days. The most compelling evidence is, house #4 included two elderlies who were more than 60 years old, whereas other families were younger with children in school age. Above all, observing from the indistinguishability among three categories demonstrate the steady variation of EEU in 12 households throughout their OCC.

Turn to Saturday and Sunday, the fluctuation of OCC denoted apparently in Fig. 4-8-C, D. Accordingly, the figure illustrates a different view of various lifestyles among 12 households according to a specific time on the weekend. It means that the trend of OCC performed more variously on Sunday and Saturday than on weekdays. Given a comparison between the highest and lowest number of OCC, weekday's figure displayed stability of occupancy among 12 houses. In contrast, Saturday's figure presented a deviation margin of 7 hours (16 hours to 23 hours), while Sunday's figure was likely to fluctuate apparently within 10 hours difference (14 hours to 24 hours). Despite the remarkable change in OCC from weekday to weekend, the electricity consumption in 12 houses presents unnoticeable differences by the total staying time but varies according to a different household. For instance, the figures below (Fig. 4-8-B, C, D) highlighted similar statistics of EEU in six houses (house #6, # 8, #9, #10, and #11) during the weekday, Saturday, and Sunday, while their OCC showed significant fluctuations differently among the three day-types in one week.

4.3.1.4 Household's activity based on energy performance report and occupancy investigation

This section aims to distinguish different energy styles on Weekday, Saturday, and Sunday in Fig. 4-9, and Fig. 4-10. Overall, the average hourly EEU shows apparent similarities and differences according to four periods: Period-1 occurred from midnight to early morning (1 a.m.– 5 a.m.), followed by period-2 in the morning (5 a.m.– 9 a.m.), period-3 designated in office and school time (9 a.m.– 3 p.m.), and period-4 from the afternoon till night (3 p.m.– 12 p.m.). In detail, energy usages in period-1 displayed a steady from weekdays to weekends, while there was significant differentiation in period-2 and period-3. In period-4, the line chart fluctuates slightly but not show an evident change. Connecting to the inhabitant lifestyle, we can state that participants tended to use the same amount of energy from 3 p.m.to 5 a.m. the next day (period-1 and period-4) during their whole week. Moreover, participants used the same amount of energy from 3 p.m.to 5 a.m. the next day (period-1 and period-4) during their whole week. Still, the remaining time manifests differentiation among weekdays, Saturday, and Sunday. On a weekday, they woke up earlier and conducted more activities that ended up with a surge in electricity load at 7 a.m., while this habit arose 5 hours later on the weekend at around noon. Energy consumption in three categories showed distinctive lifestyles. In period-1 and period-4, although OCC recorded 100%, HEL is different. HEL in period-4 was fluctuating around 1 kWh while it was double in period-1 at about 2 kWh for the use of water heater at midnight. At weekday noon, even only 5% of people stayed at home, EEU still got 0.5 kWh (20%) per family. The peak demand reported by different times in one day and different days in a week helps energy policies with reducing wasted energy.

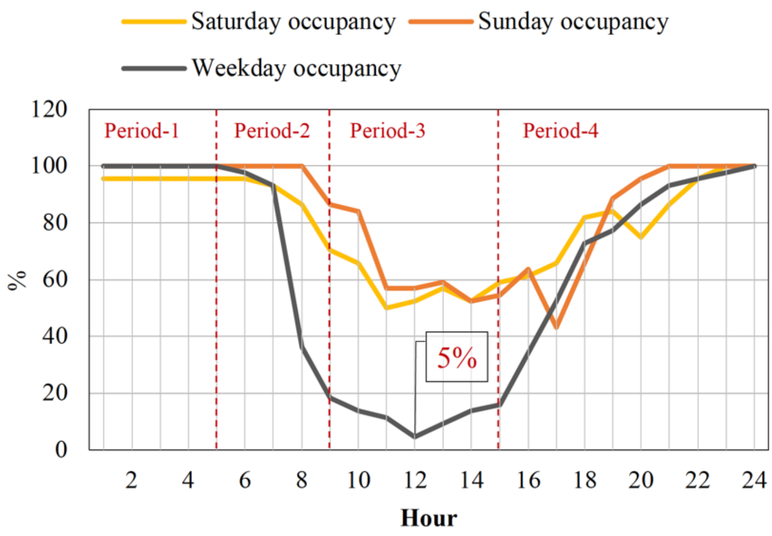

Fig. 4- 9. Average OCC by hour of 12 households (%)

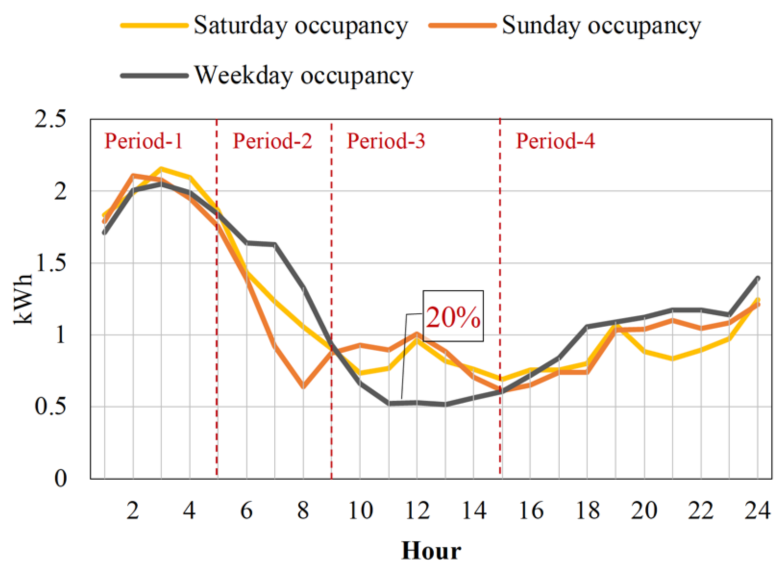

Fig. 4- 10. Average HEL of 12 households (kWh)

In summary, the average number of OCC did not reflect the relationship toward EEU. OCC on the weekend indicated a sharper fluctuation than on weekdays. Conversely, EEU depended remarkedly on each participant' s distinctness more than their daily OCC. Most of the participants drove their energy lifestyle steady despite various OCC status in one week. Thus, a household's characteristics significantly affect residential EEU.

4.4.1.5 Correlation plots

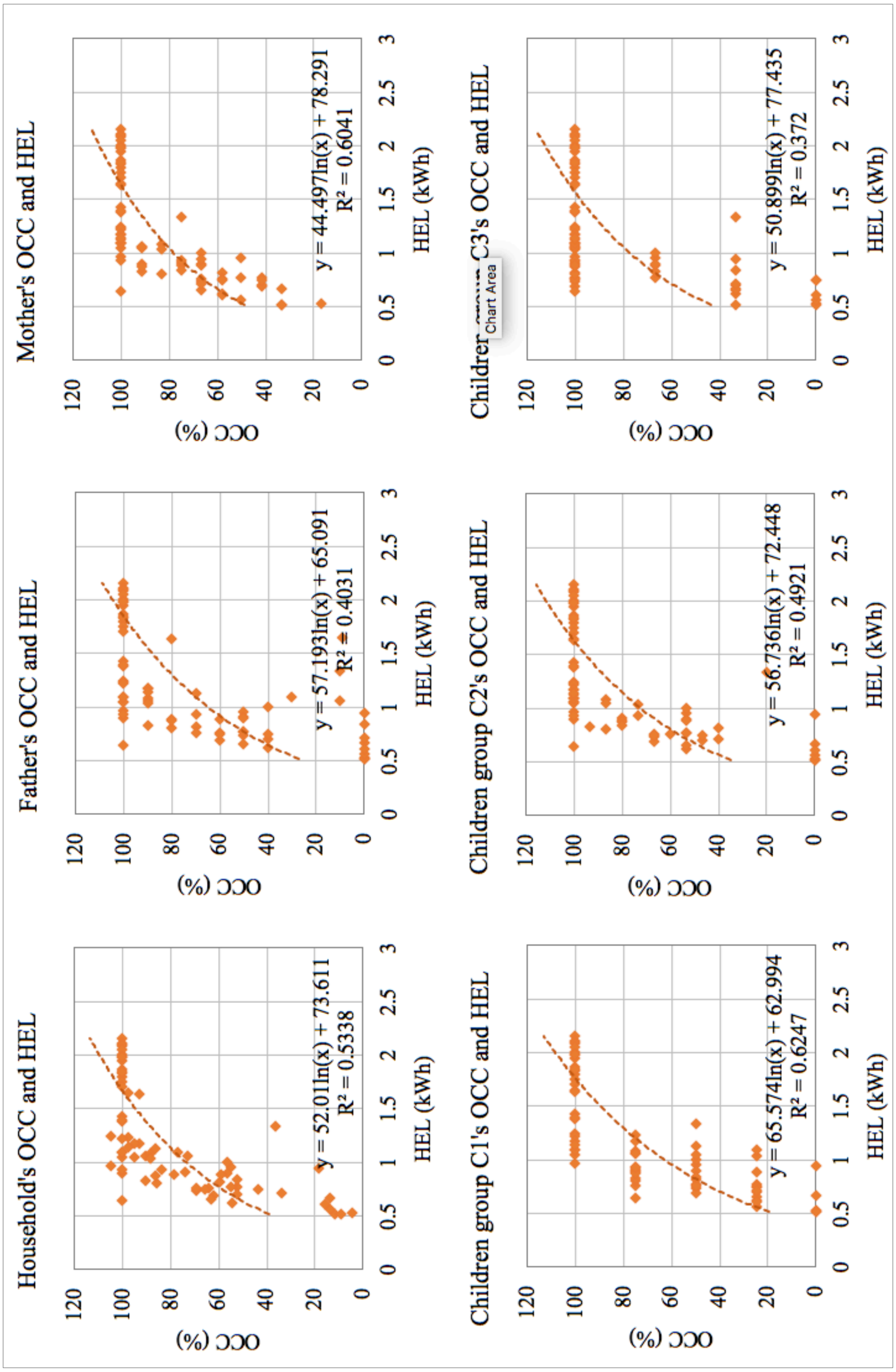

Fig. 4- 11. Correlation between HEL and household member's OCC

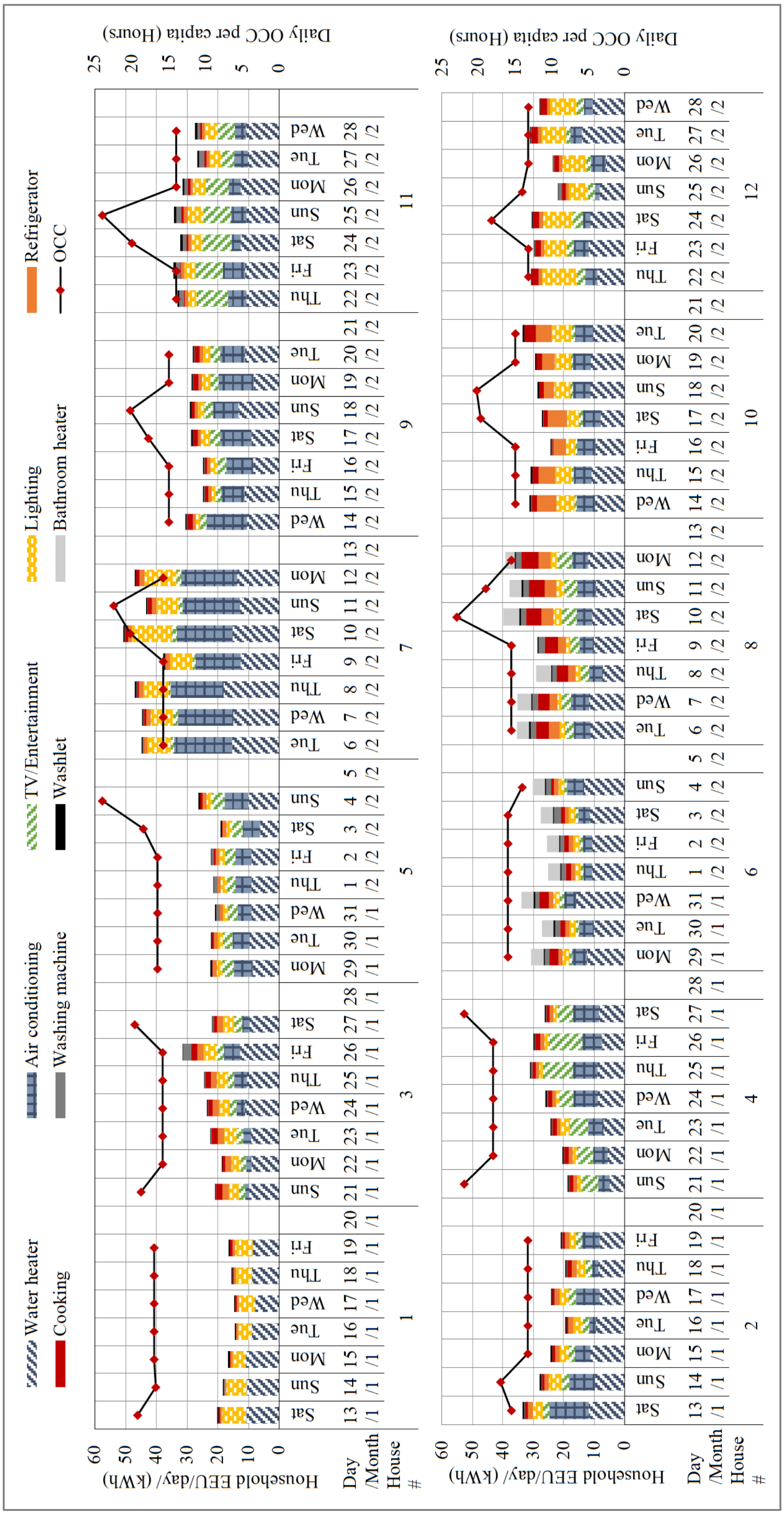

Fig. 4- 12. Average EEU and OCC in 12 houses

Taking the advantages of the residential survey, OCC, and HEL data in the residential apartments, this sector explored household characteristics' impact on residential building's EEU. Besides, it provided a methodology to examine how household electricity consumption response to occupant behavior and lifestyle. The given results argue in below points:

- Similar to Japan's household shares 2016 [28] and previous measurement 2012 in Higashida, electric water heater took the most EEU in residential houses at 38% in total; the following device was air conditioning with 22% of heating energy. A previous study in the same area indicated the peak of household EEU at 808 kWh in January 2012 and 768 kWh in 2013, due to the cold winter [39]. In this case, heating systems occupied 60% of the total EEU in the winter. To adapt to energy efficiency progress in the household sector [9], high-efficiency water heater systems (Eco-cute) should be applied widely, with regards to individual household demand. In the Global Energy Statistical Yearbook 2019, most of the electricity consumption growth of the residential sector in developed countries comes from the high demand for air conditioners [55]. Deng and Chen developed a smart HVAC control system by using physiological parameters, improved the occupants' thermal comfort, and coupling with occupant-based control to reduce up to 90% of heating loads [56]. With the development of the Residential EEU model, the deployment of new residential water heaters and P.V. systems can change the electricity load curve remarkably [57]. Given this point, the model for the temperature exchanges and water flows can be adjusted based on external temperatures [58]. Making a calculating tool for average usage of each household to automatically set up the working time of water heater is suggested since every family has their particular demand on the hot water, which is changeable every day.
- In these households, EEU related to the room's function and house appliance ownership than its floor area, and the distribution of HEL varies according to each household characteristic. About 60% of the HEL derived from living rooms and tatami rooms, which occupied approximately 40% in the gross house floor area. In contrast, bedrooms contributed 38% of the home's area while using only 13% of the total necessary electricity. The location of a device plays a vital role, since most Japanese households place air conditioning in shared rooms, leading to more energy use in this space, while private space usage was less often.
- In this 2018's observation, the household EEU is 10.5% higher than that of the previous records in the same area in 2012. Although the design surpasses the next-generation energy-saving standards in Japan [48], the EEU in these houses continues increasing. This number illustrated a high consumption among the citizen in this smart community due to individual demand. Despite the undifferentiated OCC, the EEU of non-water-heater

appliances on a weekday, Sunday, and Saturday fluctuated 17.3 kWh on average, much higher than that of Japan in 2013 [54], occupancy on the weekend (Saturday and Sunday) exhibited a sharper fluctuation than occupancy on a weekday. Participants' energy lifestyle stayed consistently despite various occupancy status in one week, interpreting that household characteristics are the foremost influence on EEU in residential houses.

- About family patterns, previous studies pointed out that households with retirees or homemakers and government employees generally consume more energy due to long hours spent at home [59], [19]. In this study, Japanese mothers inclinedly spent the most time at home around 21 hours a day while their husbands only stayed 10 hours at home on weekdays. Although the occupancy rate does not connect to the total EEU (see in Appendix -Fig. 4-12.), it shows a relative correlation with HEL (see in Appendix - Fig. 4-11.). OCC of the mother and small children have a better correlation with HEL than other members. It clarifies day time's EEU depends on the mother's activities who spend more time at home for cooking, entertainment, and laundry. In consequence, it is a crucial point for household energy-saving strategies in aging population countries and the cultures having a high number of housewives in households.
- Detailed performance indicated the peak use of self-controlled appliances, which explicates inhabitants should change their energy-related behavior during those periods. In this community, the average peak time was between 7 a.m. and 8 a.m. or 7 p.m. and 9 p.m. based on the HEL performance. These numbers help the policymakers to mitigate energy demand during peak hours by applying dynamic pricing or setting the limit of monthly usage by prepaid energy meters [60]. The use of electricity prepayment meter reported satisfied feedbacks with energy-saving and improving household energy behavior [61]. Also, a motif-based association rule mining and clustering technique can help smart meter to determine the energy use patterns of the consumers [62].
- High-income families were more carefree on electricity consumption in cases A, B, and D. As average income increased by an aged group of households [63], this factor affected to energy use lifestyle. Affluential families are inclined to have higher energy consumption [59]. Also, in Japan, households with higher income and aged families consumed higher electricity [64]. Back to our observation, households with the oldest head over 60 years old or with the highest income are the top users of energy due to the EEU/capita. In contrast, households with a young head less than 40 years old consumed the least EEU/capita.
- When comparing among households with the same family size and floor area, households with higher income and high occupancy due to the presence of elderly or

housewife would spend more EEU. connection with the same study area in the previous citation, Zheng et al. [39] asserted that larger floor area, bigger family size, higher annual income, more electrical appliances, and the existence of children of lifestyle would lead to more household EEU. In this study, we would argue that floor area, family size, family generation, income, and occupancy impact to household EEU multi-dimensionally in different situations.

Above all, assuming with the same thermal condition inside houses, the given study about household characteristics and the EEU in 12 households demonstrates three indirect factors mainly affecting the energy consumption of residential houses: Household income, household's head age, and occupancy status of the mother. Meanwhile, the house area and house direction merely have a little impact on total energy use. It is worth mentioning that number of people in the family, even though it does not affect clearly to gross EEU, enlightening the efficiency level of saving energy use per capita. Depending on the specific habitual energy-style of every household member, the EEU and the HEL by appliances differ apparently in every household, thus lead to the need for comprehensive policies with multi-aspect-based studies and proper tools to detect detailed data of household characteristics, including occupancy status and occupant behaviors.

4.3.2 Correlation analysis in Vietnam case study

4.3.2.1 Energy performance analysis

Table 4-4 describes the general statistics on the dwelling samples in Hanoi and Ho Chi Minh City during the survey year. In this case study, the number of household members increased slightly by 2% in Hanoi and decreased by 4% in Ho Chi Minh after one year. However, gross household income in both cities spiked by more than 100%. Accordingly, the number of daytime absences increased significantly, in other words, these families tended to stay home less often than in the previous year. In terms of housing factors, most of the buildings are detached houses with a wide range of floor space, considerably increased from 88 m^2 to 124 m^2 in Hanoi and from 79 m^2 to 147 m^2 in Ho Chi Minh within a year. Growing up with monthly income and floor space trends, the average number of wall-mounted ACs escalated rapidly, reaching 38% in Hanoi and 113% in Ho Chi Minh city. Most households in the samples have been equipped with two ACs since 2016, especially in Hanoi. Along with the rise of air conditioning (AC) service demand, the cooling AC setpoint increased by 2.1 ^{o} C in Hanoi and 0.4 ^{o} C in Ho Chi Minh, indicating a remarkable change in energy-saving consciousness. According to the recommendation of the Vietnam Electricity company (EVN), setting the cooling AC temperature from 26 ^{o} C to 28 ^{o} C is suitable for household indoor thermal comfort and energy efficiency in summer [9]. A survey on Vietnamese indoor thermal comfort indicated that more than 90% of residents considered room temperatures ranging from 24 ^{o}C to 29 ^{o}C to be thermally comfortable [10], which is a little higher than the standard (23 ^{o}C – 26 ^{o}C) by ISO-7730:2005 [11]. In a study of human thermal comfort in Hanoi, it was found that the citizens could adapt to the outdoor environment, which in turn can drive human behaviors, and improve the dependence on AC systems with energy-saving setting modes [12]. In addition, although household occupancy or the time spent at home increased, cooking energy use decreased significantly in both cities' samples due to the growth of food services. In consequence, when aggregating the total electricity consumption in Hanoi's participants, results show a notable reduction of 1163.9 MJ, while those in Ho Chi Minh enhanced by 1381.7 MJ. The average of household energy end-use by four main services in four cases is presented in Fig.4-14.

Table 4- 4. Description of database

City Name	**Hanoi**		**Ho Chi Minh**	
Survey year	**2015**	**2016**	**2015**	**2016**
Number of household members	4.3	4.4	4.7	4.5
Household monthly income	7.2	16.5	6.5	13.4
Weekday daytime presence days 1: 5-7 days, 2: 3-4 days, 3: 1-2 days, 4: 0 days	1.6	2.4	1.1	1.7
Total floor area of the house	88.2	124.1	79.1	147.3
House type 1: Detached house, 2: Meeting, 3: Shophouse "	1.0	1.0	1.0	1.1
Number of air-conditioning wall-mounted air conditioners (all households)	1.6	2.2	0.8	1.7

ACS (1st unit: set temperature)	25.4	27.5	25.6	26.0
Cooking (LPG): MJ / household/year	4225.2	3356.4	2918.9	4130.2
Electricity: MJ / household/year	16571.9	14908.0	16487.0	17868.7
Energy: MJ / household/year	20643.5	16346.3	19405.9	20567.0

Different household factors will have a lot of impacts on the energy consumption by end-use. Aside from the fact that lighting and plug load accounts for major consumption in this case, according to Fig. 4-15, larger households show higher energy use of AC lighting load and plug load in each case, even though some figures differ with the floor areas equal to or greater than 200 m^2 due to the small number of census records. The significant changes displayed for household sizes in Fig. 4-16 are largely influenced by lighting usage and plug load. It can be expected that monthly income contributes a coefficient that is positively correlated with total energy use (shown in Fig. 4-17). Even so, an upward trend in income is proved with the use of AC, lighting, and plugs, whereas the opposite drift is seen in some cases: Hanoi (2015) and Ho Chi Minh (2016). As for occupancy, the survey of home-presence shows negligible effects on energy consumption trends in these cases, while the number of wall-mounted ACs and their operating time in a day outperforms the propensity to the end-use (Fig. 4-18 and Fig. 4-19). Concerning the indirect impact factor, human behavior is considered an essential facet affecting the direct operation of home devices including time use, setpoint, usage intensity, equipment maintenance, and choices of energy-efficient appliances. In this case, the implementation of energy-saving behaviors has been established in the project and thus gives the results in Fig. 4-20. An increase in energy-saving behaviors of approximately 10% is manifested in the cases in Hanoi and Ho Chi Minh after one year. Although participants in Hanoi showed a greater decrease in average energy use, the high percentage group implementing energy-saving behaviors in Ho Chi Minh in 2016 (80-100%) demonstrated significant efficiency, reducing 5 GJ compared to those in 2015 and more than 10 GJ saving compared to households that only applied 20-39% energy efficiency in the same year.

In summary, among the various influencing factors, the increase in the number of family members and the number of AC seems to be more pronounced with increasing energy use, while other factors show different tendencies due to the small scale of participants.

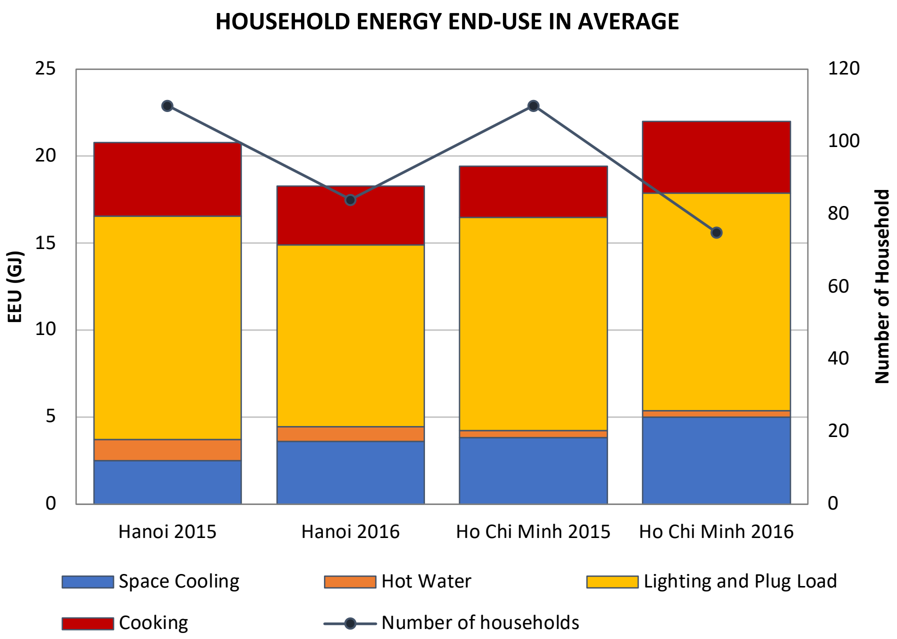

Fig. 4- 13. Household energy consumption by End-use – case in Hanoi and Ho Chi Minh

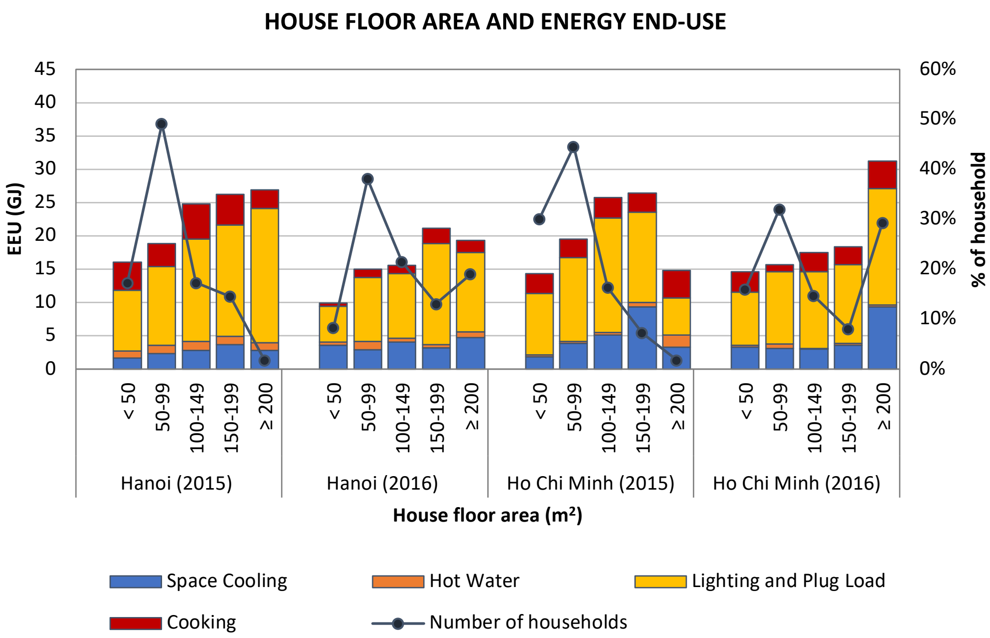

Fig. 4- 14. Energy consumption by End-use and floor area – case in Hanoi and Ho Chi Minh

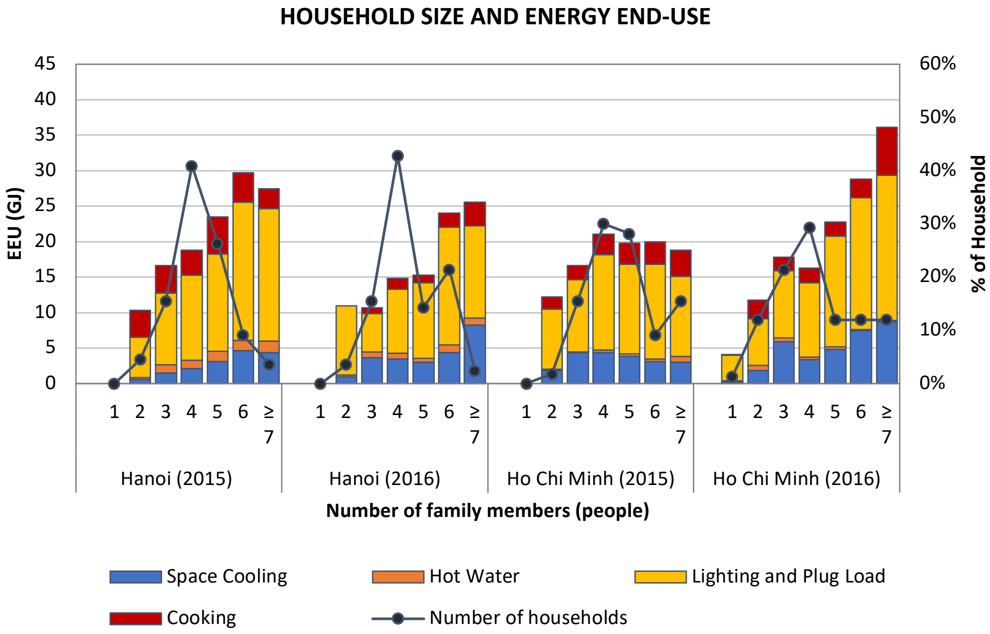

Fig. 4- 15. Energy consumption by End-use and Household size – case in Hanoi and Ho Chi Minh

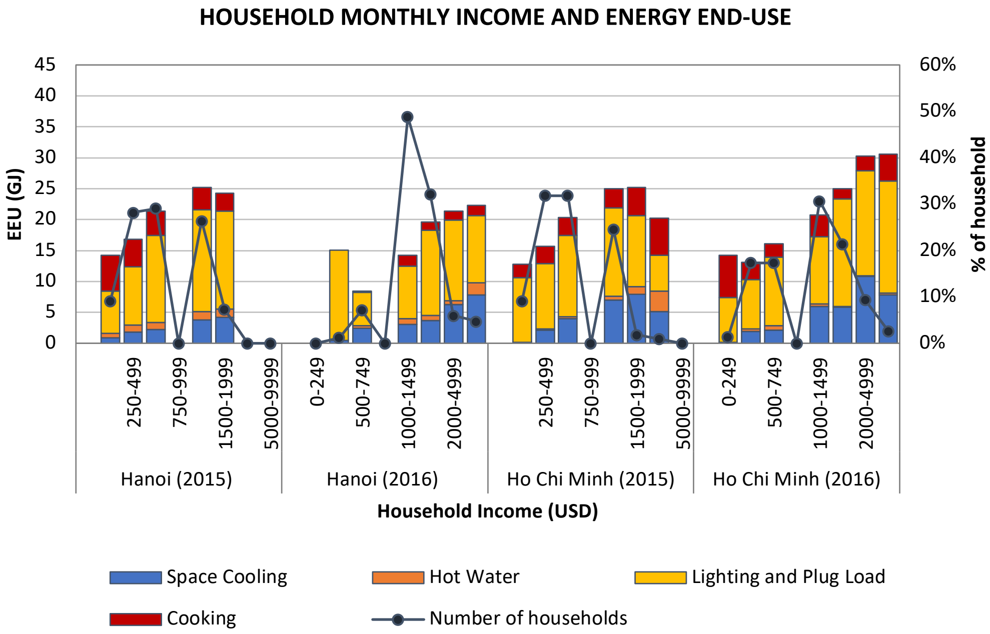

Fig. 4- 16. Energy consumption by End-use and monthly income – case in Hanoi and Ho Chi Min

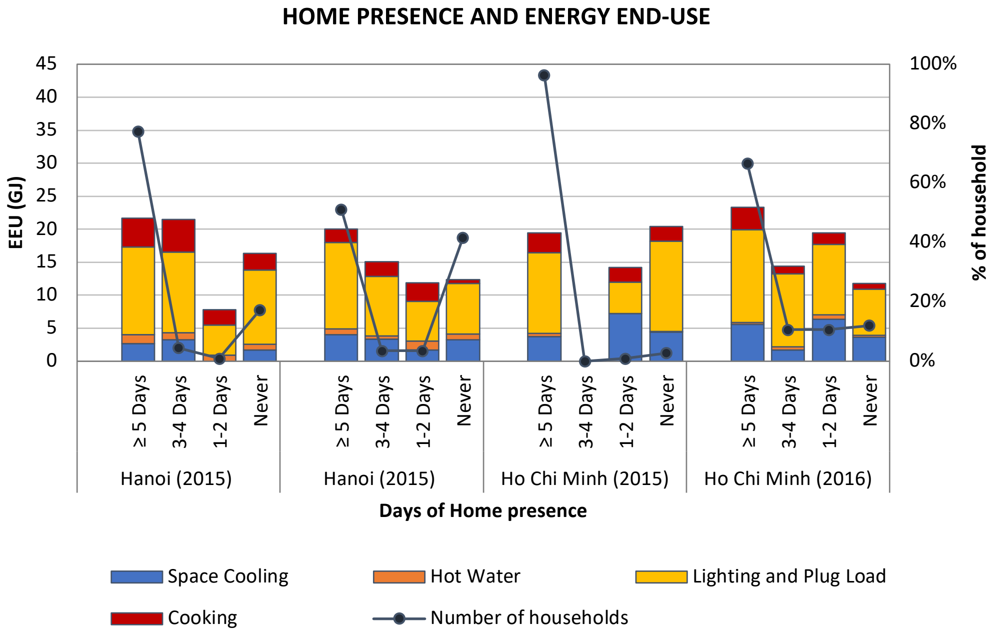

Fig. 4- 17. Energy consumption by End-use and home presence – case in Hanoi and Ho Chi Minh

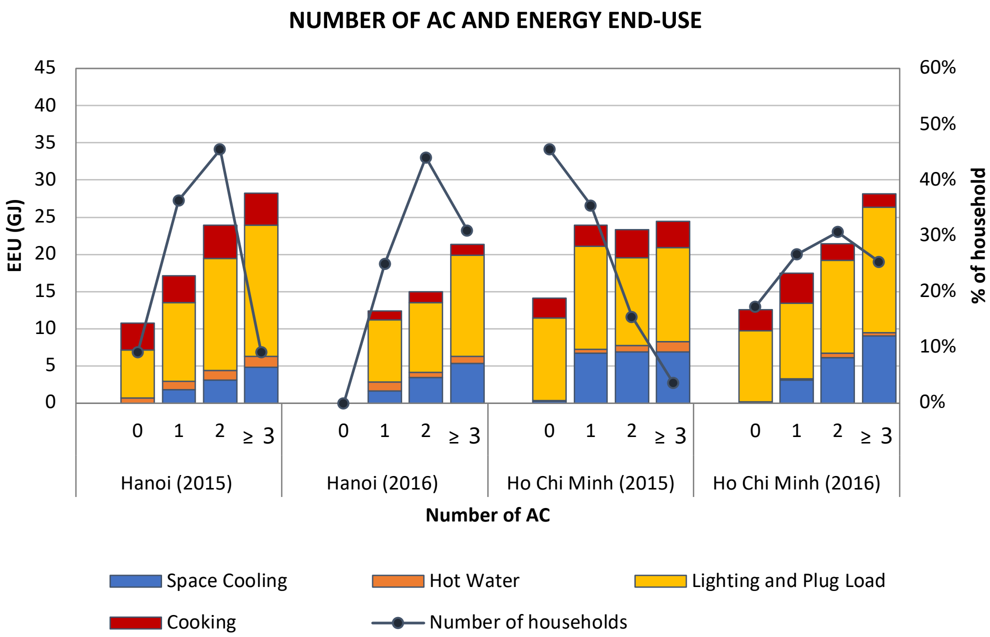

Fig. 4- 18. Energy End-use and number of wall-mounted AC – case in Hanoi and Ho Chi Minh

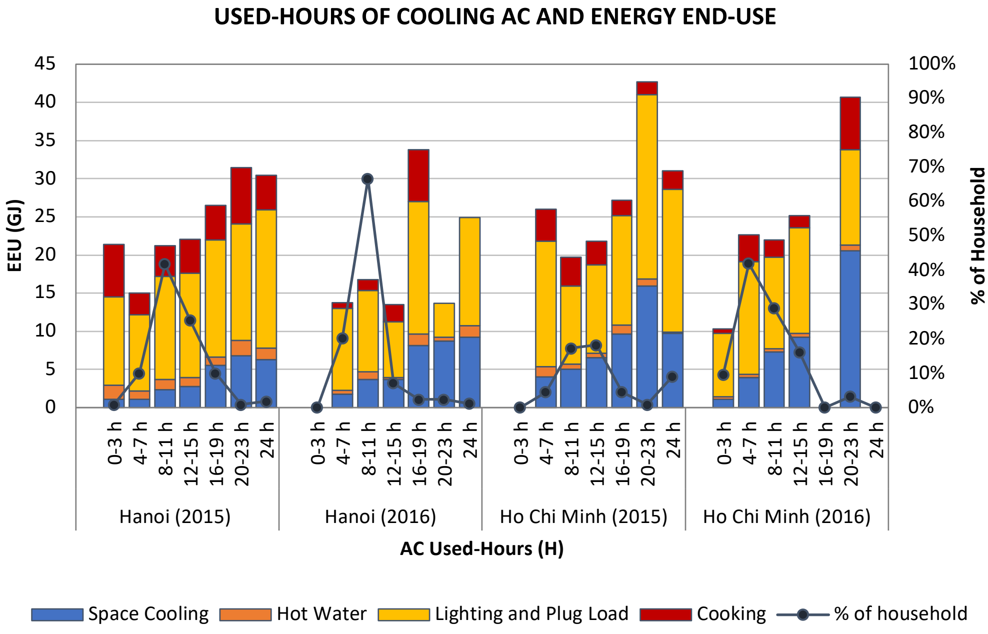

Fig. 4- 19. Energy consumption by End-use and used-hours of cooling AC – case in Hanoi and Ho Chi Minh

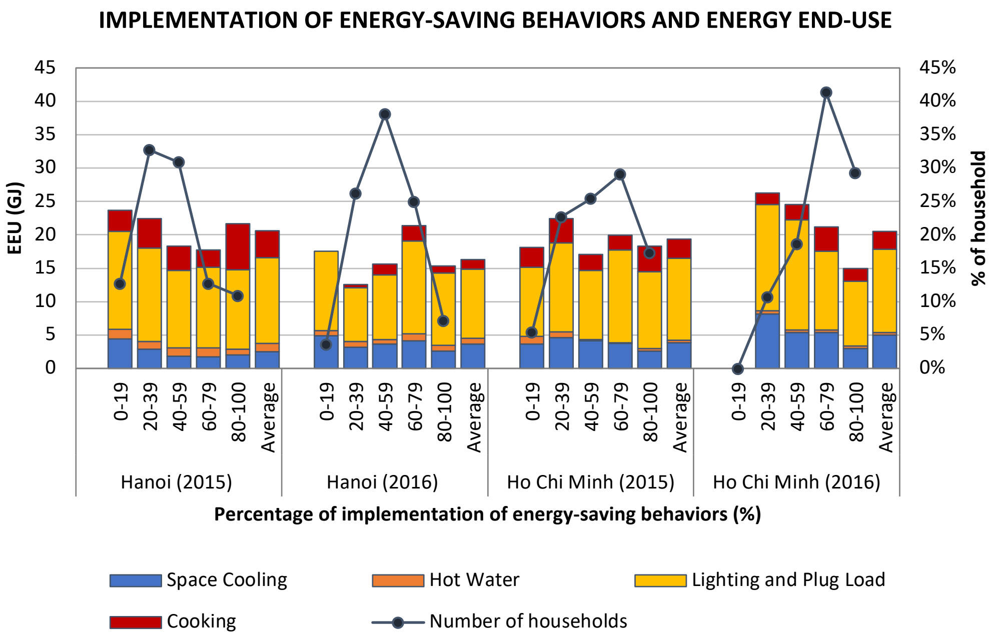

Fig. 4- 20. Energy consumption by End-use and Energy-saving behaviors – case in Hanoi and Ho Chi Minh

4.3.2.2 Correlation analysis

Vietnam has had several remarkable research works in the field of household energy, however, the number of articles and other records is still sparse compared to the global average. Most of the current work is concentrating on reviewing household energy overview, energy policies, energy-saving plans, and energy-related programs, indicating that household energy, in particular, will grow faster in recent years and call for more efforts toward implementing renewable energy or cutting CO_2 emission. This study first pointed out that it is important to have an open-source database on household energy consumption as well as corresponding household factors, such as the number of family members, gross floor area, household income, appliance ownership, occupancy rates, and other elements related to the use of energy devices. The lack of large-scale data causes limited access to the usage-pattern analysis, sensitivity analysis, or energy forecast, which are crucial for researchers and policymakers to apply statistical approaches and energy-saving implementation. Regarding the significant impact of occupant-related factors, of which occupant behavior is one of the most frequent causes, this paper highlights the indispensable role of household characteristics and that an analysis of these easy-to-approach factors concerning household energy is compelling and applicable in the case study. Using linear regression, Pearson correlation coefficient reflects that among 4 determinants, number of AC and floor area have higher impacts on EEU while the correlation of income with EEU in Vietnamese household is the most inconsiderable (Fig. 4-22)

The relationship between household factors and energy consumption by end-use is clarified in the case study of this paper, using the energy performance analysis integrating multiple factors based on the open-source database, and implementing SEM path analysis based on the raw database. For energy performance analysis, the combination of causal factors and usage outcome indicate unpredictable trends, illustrating the household size and the number of AC are more considerably related to energy use than other factors. Nevertheless, because the number of participants is not uniform across the studied cases, this method is better used to look at the relative variation of energy end-use by household categories instead of telling a specific influence number. Alternatively, the proposed SEM path analysis reveals better statistical findings on the correlations of variables and the influence levels of each household factor on the household energy end-use.

4.4 Conclusion

The section underlines the multidimensional influences of household characteristics on energy end-use and energy-related lifestyle to emerge a holistic view of changing energy behavior through different case studies. From that exploratory analysis, we would claim that with a more detailed approach, the study can propose more precise solutions given to every single family. Concerning the "2015 Energy Conservation Rationalization Promotion Infrastructure Development Project" by METI and "Japan's first large-scale experiment demonstrated the energy-saving effect of consumer behavior change 2016" by Living Environment Planning Institute [65], energy consumption performance report could successfully save 1.2% energy two months after sending the report to the households. Therefore, a detailed dataset presenting EEU, HEL, and OCC of households can carry out appropriate recommendations and increase the energy-saving effect ratio [66]. In brief, energy-saving strategies must consider an in-depth approach to the behavioral patterns and habitual activities of each household.

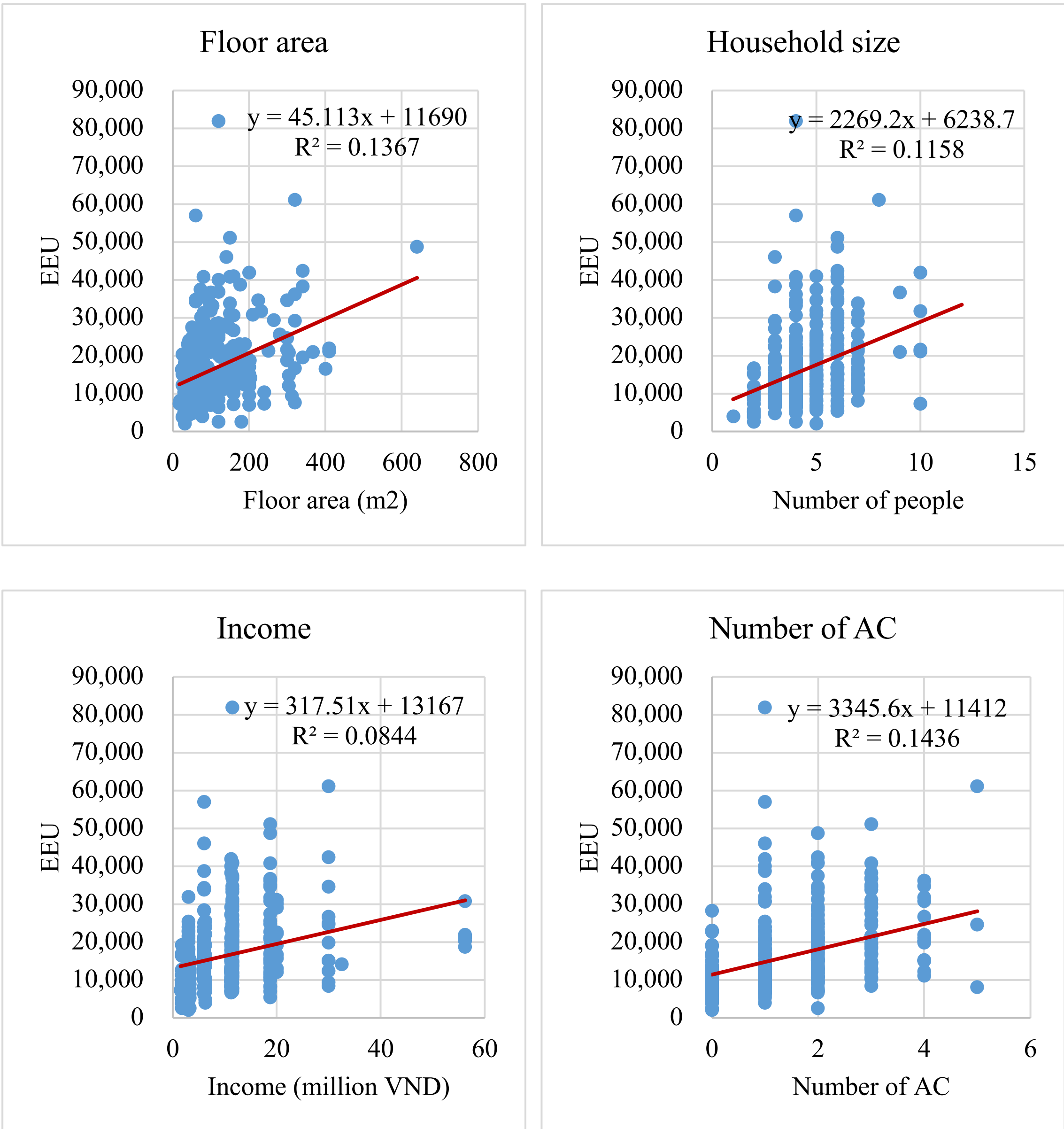

Fig. 4- 21. Correlation between household and housing factor with EEU

Based on the correlation analysis in this study, we can claim that household behaviors have a crucial influence on residential EEU and HEL. Detailed HEL data reveals a noticeable waste of energy due to corresponding OCC information and specific characteristics of each household related to their energy lifestyle. In our study, the electric water heater becomes an indispensable appliance every day in the winter season as a unique custom in Japanese households. Different families with different backgrounds have disparate habits and inclination of energy use; thus, the energy-saving solution must be specified distinctly due to their habits or lifestyles.

This section perceived an integrated methodology that accumulated two research methods: observation (on-site electricity measurement), surveys, and questionnaires for household characteristics. It inherited the experience derived from the previous research project, including pros and cons, to improve their findings of lifestyle factors that impacted electricity consumption, then propound a holistic picture of comparative analysis. Moreover, the results of OCC and HEL themselves can provide real observed data for building energy models or HEMS as a prediction method in future studies. There are two limitations to this methodology. The first one is the number of available energy monitors. The second restriction is household privacy, which limits the research scale to a few participants, and shortens the measurement time. Besides, the questionnaire regarding OCC or family member's information must be considered cautiously under the inhabitant's permission and building security management. Therefore, future studies should involve more comprehensive technologies to strengthen measurement time and provide long-term observation process. In doing so, the correlation findings of EEU and household characteristics can be further exploited comprehensively.

The section suggested an example for future studies about energy-related lifestyle in Japan in particular and other Asian countries in general. Energy consumption per household in Southeast Asian countries is lower compared to that of Japan [67], due to the use of space heating and water heating. However, the consumption in urban areas except for the heat demand is the top level of the world regarding the need for space cooling, lighting, and other plug loads. There are several relevant kinds of research in these areas [68] [69]. Still, none of these studies conduct the energy consumption rate among household HEL, as well as household occupancy on different days of a week. Studies in these countries could carry out different images of regional and cultural impact on residential energy consumption and widen our understanding of energy-related behavior in the field. According to the rapid rise of urbanization in developing countries, this study contributed a practical experience to empirical studies and facilitated an energy-saving strategy in a residential area. In the next step, we will simulate energy consumption in the energy models based on the observed data and given results for predicting energy-saving solutions, and further study will explore in the context of surrounding regions to widen more understanding regarding EEU and household characteristics.

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Chapter 5

SENSITIVITY ANALYSIS: INFLUENCE LEVELS OF HOUSING FACTORS AND HOUSEHOLD BEHAVIORS IN JAPAN

CHAPTER V: SENSITIVITY ANALYSIS: INFLUENCE LEVELS OF VARIOUS IMPACT FACTORS CASE STUDY IN JAPAN

5.1 Content

5.1.1 Schematic process of sensitivity analysis

During the building energy modeling process, research [1] identified three principal phases: (1) data collection and simulation, (2) data reevaluation or calibration, and (3) built evaluation. In response to the above-indicated opportunities and challenges, this paper provides reciprocal relationships among three methods: (1) on-site survey and questionnaire, (2) observation-based energy monitoring, and (3) energy simulation with sensitivity analysis. The process started from setting up an energy monitor and collecting on-site data to deploying integrated data analysis and ending up with a BEM phase based on the collected data. Real-time energy monitoring can help store and manage energy-related building information [2] and reflect energy-related activities through the respective occupancy data. The paper proposes an energy-optimization concept that plots the reciprocal interaction from survey data and monitoring data to energy simulation, as visualized in Fig.5-1.

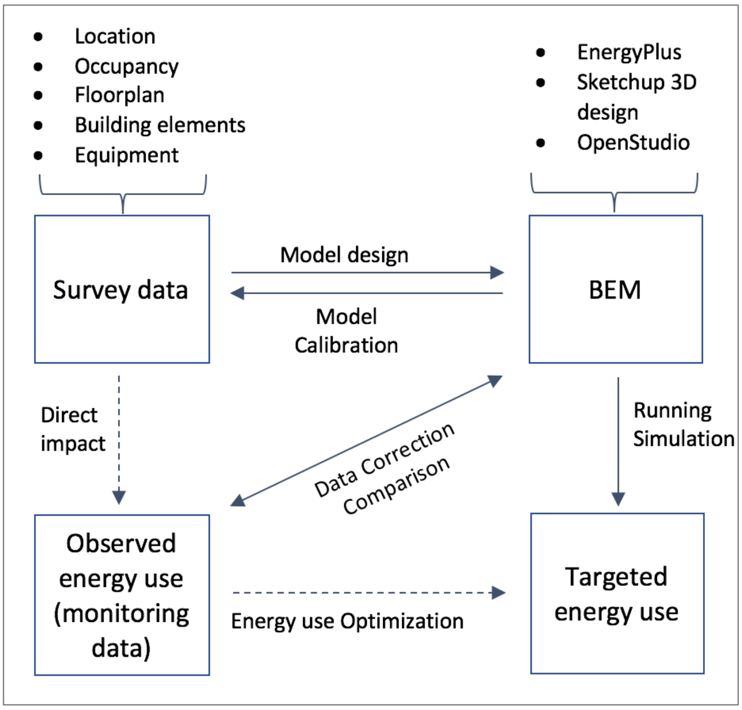


Fig. 5- 1. Energy use optimization concept

Continuing the energy use optimization process, proposed energy monitoring and modeling for energy consumption prediction evolve into the final step: a sensitivity analysis. The schematic diagram of this study, shown in Fig. 5-2, describes the combination of the physics-based and data-driven method from measured monitoring data and the background information to the validation and calibration process. The final results aim to identify energy-related behaviors and evaluate the impact of different parameters on the EEU as well as the gross site & source energy. To find the implied occupant activities behind the EEU, the modeling calibration loop on the air conditioning setpoints (ACSs) replicates until the simulation results match the observed data. The diagram includes two primary approaches toward the optimal energy efficiency solutions. The first approach is to compare the determination of coefficient between observation-based monitoring data and predicted energy use from conducting energy simulation, based on weather information and other survey data. The second approach is energy modeling, which uses variable household input parameters under respective standards, to run dynamic simulation EnergyPlus. This stage assesses the influence levels of impact factors toward final end-use, under the sensitivity analysis.

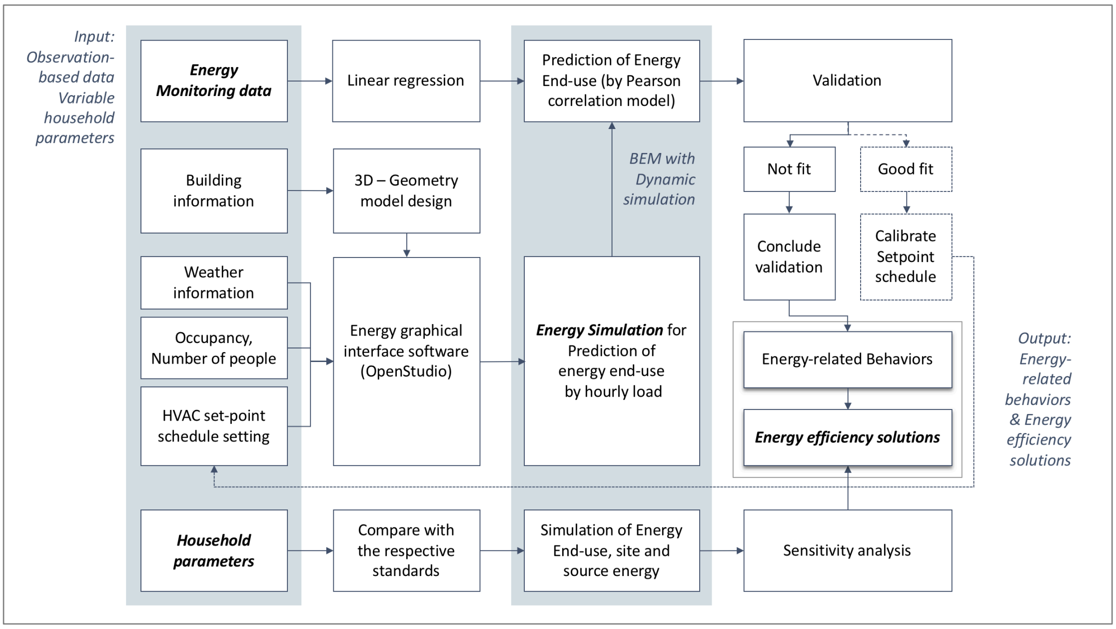


Fig. 5- 2. Research scheme

Fig. 5-1 The distribution of research area in Japan

5.1.2 Observation-based energy consumption data by energy monitors

The performance of observed data sheds light on the vital role of combining energy monitoring and occupancy status survey. Regarding the energy management systems, a building equipped with sensors and meters, triggered by changes in the environment and human activities, sensory information can be used to adjust the building model in real-time automatically [3]. While the smart meter information provides energy consumption of the entire building yearly or monthly, energy monitors can record the minute electricity load of the appliances in each house. The monitoring raw dataset in this study contained 120960 rows of data for minute loads and 2016 rows of data for hourly loads for twelve homes. Each row shows the energy consumption of AC, lighting, TVs, and other home appliances. To conduct energy modeling, validation, and calibration, we selected hourly load data and categorized them by weekdays, Saturdays and Sundays. Since the installation of energy monitor in households is time-consuming, costly, and limits the number of participants, the hybrid approach proposed in the following sections can simultaneously apply gathered observation-based EEU with dynamic simulation, analyze the household usage based on input parameters such as weather conditions, house design, people activities.

5.1.3 Building Energy simulation

During the energy modeling phase, housing simulation data links to Energy Plus for energy analysis. EnergyPlus is a building simulation tool developed by the U.S. Department of Energy, Building Technologies Office, and the National Renewable Energy Laboratory [4]. It calculates energy consumption, including heating and cooling energy use, lighting, and other electrical loads based on the building information [5]. Graphical interface software for applying EnergyPlus is OpenStudio – a set of software tools that support building energy modeling using Energy Plus. This software allows users to simultaneously add-on and modifies both architectural models such as height, floor plan layout, windows, doors, materials, and energy systems such as thermal zone, lighting, heating, and cooling systems. In this phase, all the input data was modified on OpenStudio Interface with three main workflows: Resource, setting and calibration, and simulation results. This study focuses on AC usage by installing thermal zones in the living room and the parent's master room, respectively. The end-stage results display complete information related to building design, building location, weather conditions, and energy consumption.

5.2. Validation and Calibration

5.2.1 Occupancy and Energy consumption

The relationship between observed energy monitoring data and EEU simulation data is an essential part of the validation and calibration process before the prediction of energy consumption. Previously, occupancy rate data showed a great impact on the precision and accuracy of building energy model performance [6]. At the same time, observed data from real-time energy monitor can detail the total energy consumption and the hourly load of the devices over selected periods. When comparing hourly load with the corresponding occupancy records, significant loss of wasted energy can be shown during the noontime when no one was at home in each house [7]. For a total of 36 energy models, the data presents actual AC heating energy consumption and relative occupancy of twelve houses on weekdays, Saturdays, and Sundays, including house 1 not using AC full time. According to Fig. 5-4, the fluctuations in hourly energy consumption do not appear to have a strong relationship with the number of people staying at home. It can illustrate some energy-related behaviors during different times in a day. For example, energy use soars in the morning before all the family members leave home. The hourly load increase can be found around 6 a.m. on weekdays and one or two hours later on weekends. More energy waste is found at noon on weekdays due to the greater gap between heating load and occupancy rate in Fig. 5-4. In some statistics reports and studies in Japan, the energy use was deeply dependent on the appearance of the wives or elderlies at home or family income ([8] [9] [10] [11]). These factors also affect the shares of EEU with unpredictable behaviors and lifestyles. In general, AC accounts for a large amount of energy ranging from 19% to 56% on weekdays (See Appendix, Fig. A2). A previous study in this area [7] indicates that ACs took 22 % of total household electricity consumption in 2018. Although the use of other appliances is related to personal needs and activities, the operation of ACs can be better controlled to avoid energy waste.

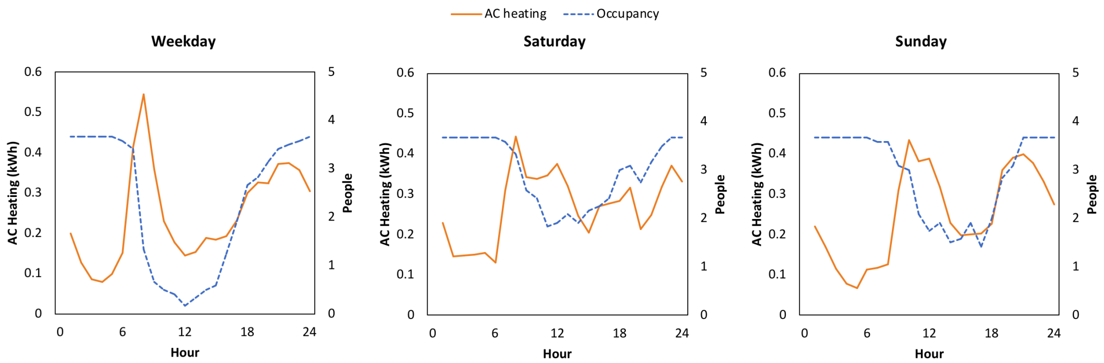


Fig. 5- 3. Occupancy and hourly load in average

5.2.2 Air conditioning setpoint and occupant's schedule

This section examines an interrelationship between energy consumption and energy-related behavior through ACSs and occupant schedules. The purpose of this approach is to predict energy-related behaviors based on the similarities and differences between energy simulation and observation-based monitoring data. When setting up the model, housing design, household characteristics, outdoor weather conditions are the input parameters according to the survey, while the heating ACS is flexibly changed to match the measured energy data. Multiple modeling tests with different ACSs were applied until their results well perform the goodness-of-fit between modeling data and observed data. Consequently, this best-fit model carried out an immeasurable schedule of the ACS that includes AC operating times and hourly set temperatures. The overview demonstrates that the occupant's schedules can enable a relative forecast of the ACSs EEU trends. An example in Fig. 5-5 shows a close relationship between occupancy and ACS on weekdays, Saturdays, and Sundays. However, the detailed results show various routines using ACs despite a fixed at-home schedule. Specifically, households No. 5-7-9-10-11 seemed to turn on the ACs despite being away from home for a short-time while households No. 2-3-6-8-12 paid attention to turn it off. Additionally, four houses (No. 5-4-10-11) fully used ACs 24-hours/day, whereas the remaining houses partially used at certain hours of the day.

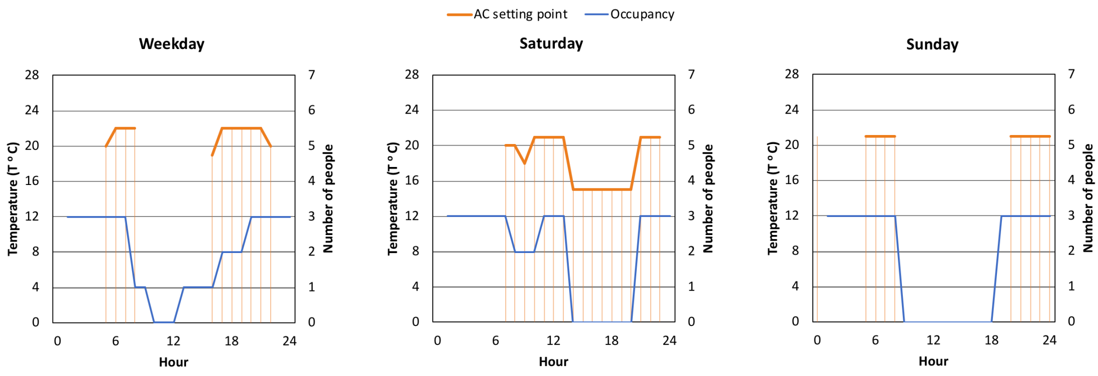


Fig. 5- 4. Household occupancy and predicted ACSs

5.2.3 Air conditioning load from monitoring and modeling

From the initial input of housing design, household characteristics, and operation, end-use energy was simulated by OpenStudio based on EnergyPlus calculations. The results of the energy model and the comparison with the actual energy of household samples are shown in Fig. 5-6 as an example of house 6, and the total performance of 36 cases are provided in the Appendix section – Fig. A4 to Fig. A6. Generally, daily use forecast seems more accurate in households with stable ACS while fluctuating ACS is better estimated for hourly usage. A brief summarization of the twelve samples is indicated in table 5-1, showing similarities and differences between actual energy use and simulation energy performance. In general, most of the peak times for heating load are around 6 a.m. to 9 a.m. that reached from 0.31 kWh to 1 kWh. The trivial despair between the real performance and the peak and lowest time use predictions is evident in this figure. According to the specified setpoint in Table 5-1, the modeling presents accurate numbers of peaks with a small error of 0.00 to 0.11 kWh, whereas the total modeled day uses show significant differences. To explain, the energy consumption estimated in the model is based on fundamental heat balance principles depending on the environment, schedule, and energy systems factors [12]. Since the occupant's lifestyle is an aperiodic element, a household occupancy survey can merely capture the general presence status, while numerous activities directly affect the end use at home. These influential factors do not match any fixed rules that EnergyPlus can simulate, but the energy performance itself presents a precise picture of energy use patterns. The difference between simulated and observed energy use demonstrates that the unforeseen activities of the occupants caused an increase or decrease in indoor temperature during certain times. For example, energy model prediction in house 7 gives an exact peak number at 9 AM, however, actual data shows higher consumption. Considering household background in Table 2, this family has the highest income, identified as of major influence on energy-related lifestyle in the previous paper [7]. The coefficient of determination of the samples in the next section will show the goodness-of-fit between the monitoring and modeling data.

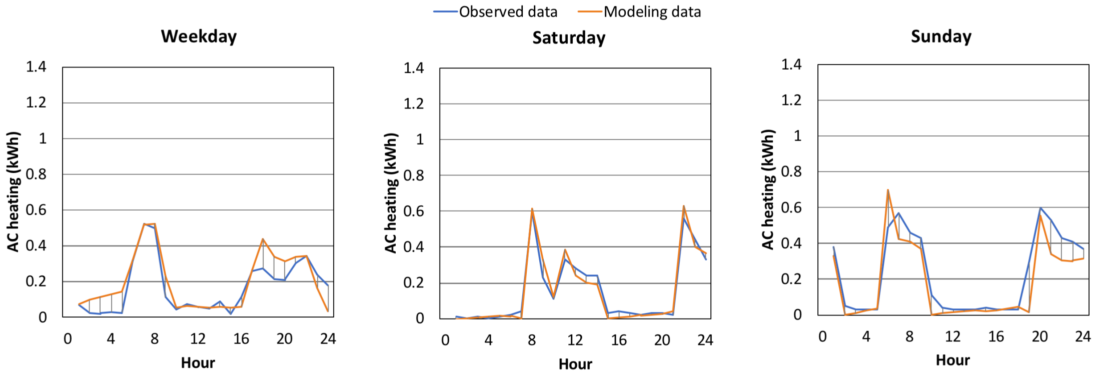


Fig. 5- 5. Heating AC hourly load of actual energy consumption and modeling use

Table 5- 1 Regression results

House #	Actual peak time (hour)	Modeling peak time (hour)	Actual peak use (kWh)	Modeling peak use (kWh)	Actual day use (kWh)	Modeling day use (kWh)	Peak use deviation (kWh)	Day use deviation (kWh)
1	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
2	7	7	1.00	1.03	4.59	6.89	+ 0.03	+ 2.30
3	8	8	0.40	0.51	2.86	3.03	+ 0.11	+ 0.17
4	7	7	0.48	0.52	6.35	5.33	+ 0.04	- 1.02
5	8	7	0.68	0.70	6.15	4.68	+ 0.02	- 1.47
6	7	7	0.52	0.52	4.09	4.78	0.00	+ 0.69
7	9	9	1.37	1.28	17.67	9.28	- 0.09	- 8.39
8	8	8	0.36	0.41	5.31	4.67	+ 0.05	- 0.64
9	8	8	1.01	0.99	9.79	7.31	- 0.02	- 2.48

10	18	10	0.26	0.27	5.87	5.24	0.01	-0.63
11	6	6	0.39	0.48	4.69	5.00	+ 0.09	+ 0.31
12	23	1	0.31	0.35	0.40	0.35	+0.04	- 0.05

5.2.4 Correlation analysis of monitoring and modeling data

Based on a simple linear regression analysis, the Pearson correlation coefficient is widely used to evaluate the correlation between predicted data and observed data that promotes mismatch correction in the modeling process. Ciulla and D'Amico [13] applied the Pearson coefficient to determine the relationship between the HVAC energy demand with the weather and building conditions. Studies in the same field have been explored in various energy modeling applications by regression methods. Senatro et al. [14] introduced a regression model forecasting energy demand trends in end-use sectors.

Classical statistical tests with strong correlations of energy demand and other factors give proof of the linear regression models. As an application for energy modeling data and the actual measured data, this model predicts the energy consumption in each household based on the history of use. The summarized results of correlation analysis are in Table 5-2 with the R-squared value, the coefficient of variable x, and the P-value of all cases were less than 0.05. To perform the goodness-of-fit of the model, Fig. 5-7 displayed the corresponding equation and R-square of Pearson correlation, while Fig. 8 shows how well the model fits into the real data by observing the residuals. The coefficient of determination provides a scale ranging from 72% on Saturdays, to 75% on weekdays, and 76% on Sundays. Most of the models manifest a high correlation coefficient such as house 12 with R = 0.95 on a weekday, R = 0.99 on Saturday and R = 1.00 on Sunday. However, the coefficient of the electricity load in the household that set the AC in a very stable low setpoint is lowest in house 10, because this case might not reflect a significant change in heat balance despite the impact of occupant schedules. The residual stochastic patterns in Fig. 5-8 scattered around zero elucidates a good fit of the model, except for house 2 and 7 due to their high amount of actual hourly load. These cases also account for the unanticipated energy-related activities that steady-state models and occupancy data cannot comprehensively simulate. In sum, the energy model in this study performs a relatively good matching between monitoring measurement and the energy model by combining the Linear regression model and EnergyPlus. Details clarify that the best fit performs in house 3, 6, 9, 11, and 12.

In the next section, a house sample with a good fit and typical pattern is in use to simulate energy variability after applying energy-saving proposals. Since house 9 represent the typical housing type (a), standardized family pattern in the area, and a stable setpoint, it is suitable to be selected out of twelve as a sample to apply energy-behavioral changes options through calibrating and modifying household parameter as well as virtual behavioral changes in simulation.

Table 5- 2 Regression results: Pearson Correlation Coefficient (R) and R^2. The numbers are rounded to two decimal places

Observation	**Weekday**		**Saturday**		**Sunday**	
	R	**R^2**	**R**	**R^2**	**R**	**R^2**
House 1	N/A	N/A	N/A	N/A	N/A	N/A
House 2	0.86	0.743	0.82	0.67	0.94	0.89
House 3	0.87	0.76	0.98	0.96	0.99	0.98
House 4	0.77	0.59	0.90	0.82	0.93	0.87
House 5	0.85	0.72	0.96	0.92	0.90	0.81
House 6	0.90	0.81	0.98	0.97	0.92	0.84
House 7	0.88	0.77	0.59	0.35	0.70	0.50
House 8	0.70	0.50	0.84	0.70	0.00	0.00
House 9	0.88	0.78	0.93	0.86	0.79	0.62
House 10	-0.12	0.01	0.05	0.00	0.15	0.02
House 11	0.83	0.70	0.98	0.97	0.93	0.87
House 12	0.95	0.90	0.99	0.99	1.00	1.00

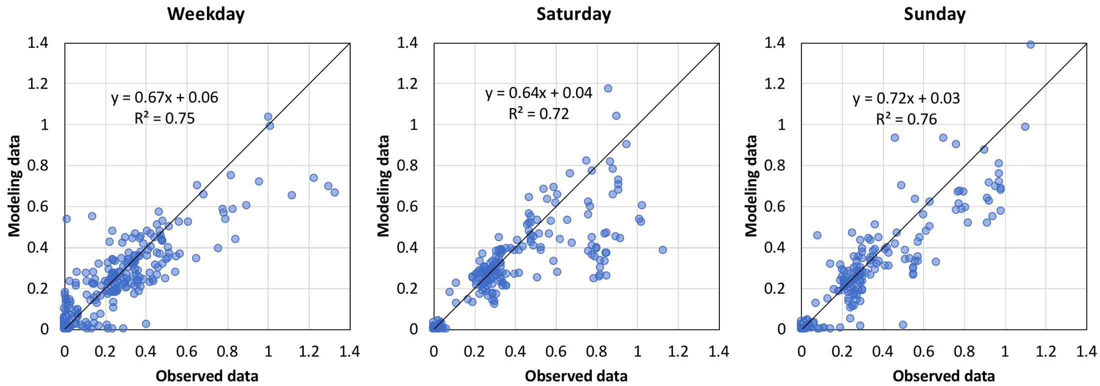


Fig. 5- 6. Correlation between AC load monitoring and modeling data

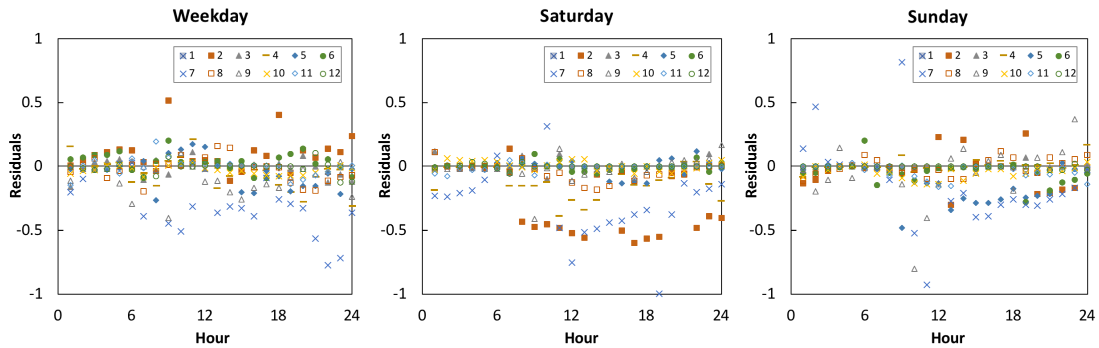


Fig. 5- 7. Residuals between AC load monitoring and modeling data

5.3 Energy efficiency solutions with sensitivity analysis

5.3.1. Observed data Housing elements analysis

Among twelve houses, we selected house 9 for sensitivity analysis due to its typical residential features. According to data in Table 2, the 99 m^2 floor area is classified in the middle-size group and oriented mainly toward the southwest. The family pattern consists of 4 people, father, mother, and two children who go to primary school and secondary school. Their total monthly income ranged from JPY 500.000 to JPY 700.000, considered above average compared to the 2018 Kitakyushu median income of JPY 397,445 [15]. In terms of energy use, 36% of the total consumption is for AC. The measurement time is from February 14th to February 21st, 2018. Regarding the thermal environment, this period is the coldest time of the year in Japan, with temperatures ranging from 0 ^{o} C and 13 ^{o} C, relative humidity 38% to 93%, and average wind speed 0 m/s to 10.3 m/s [16]. Fig.

9 shows the observed energy use that reached a total of 16 kWh and about 60% occupancy ratio in a day.

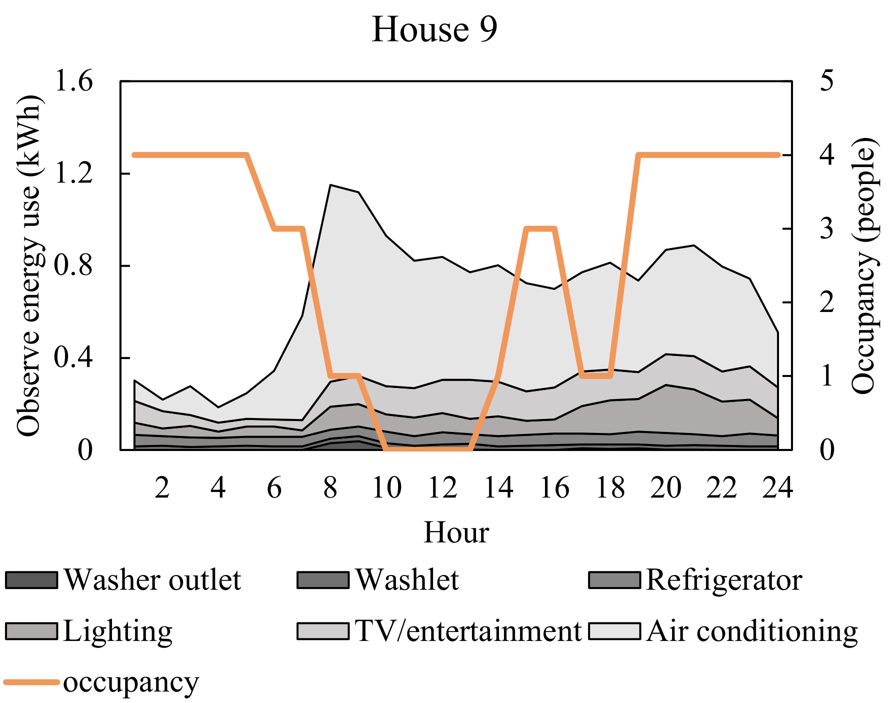


Fig. 5- 8. Observed hourly energy use and occupancy in house 9.

The floor plan is one of the indispensable inputs for energy modeling. The design in Fig. 5-10 shows typical styles with a shared living-kitchen and a tatami room (Japanese-style room with matting floor), three western-style bedrooms, and a bathroom with a separate toilet. From the built-in 3D housing model, the summary result calculates the ratio of the window area and the wall area in each housing direction (Table 5-3). For instance, with a total wall area of 130.89 m^2 and a window opening area of 11.31 m^2 shown in the house model, the gross window-to-wall ratio results in 8.64% of the total. Meanwhile, this ratio reaches 18.19 % in the southern facade while the northern and western surface accounts for 5.73% and 7.65%, respectively. No windows records were found on the eastern facades. These numbers indicate that thermal loss can be maximum on the south side and minimum on the east side with regards to design choices. The housing layout explains a typical pattern in Japan's houses as the south-facing façade can facilitate a comfortable indoor environment. The simulation results contribute to the assessment of housing design and its correlation with household energy consumption.

Table 5- 3 Results of the envelope's architectural elements

Architectural elements	Total	North 315° – 45°	East 45° – 135°	South 135° – 225°	West 225° – 315°
Gross Wall Area (m^2)	130.89	38.74	26.71	38.74	26.71
Above Ground Wall Area (m^2)	130.89	38.74	26.71	38.74	26.71
Window Opening Area (m^2)	11.31	2.22	0.00	7.04	2.04
Gross Window – Wall Ratio (%)	8.64	5.73	0.00	18.19	7.65
Above Ground Ratio Window – Wall (%)	8.64	5.73	0.00	18.19	7.65

Fig. 5- 9. House floor plan

For the modeling process, the integrated Sketchup – OpenStudio model visualized in Fig. 5-11 structure housing zones according to the floor plan in Fig. 5-10, in which master bedroom, living room, kitchen, and tatami room were selected to install the thermal zone function. These are spaces where the two ACs are located in the apartment.

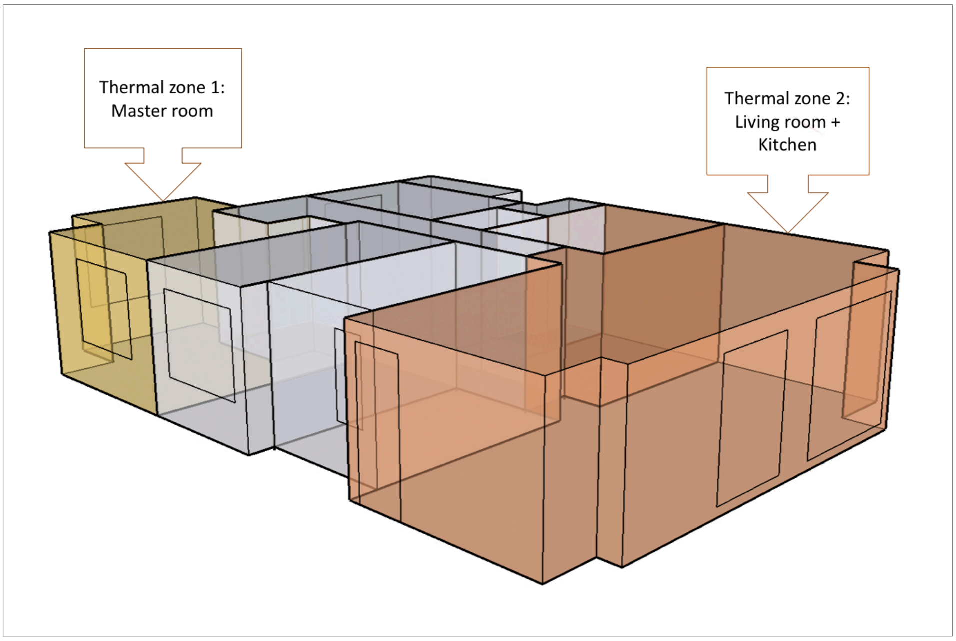


Fig. 5- 10. Energy Model: Heating and Cooling Thermal Zone

5.3.2. Household and housing parameters

Household energy consumption is not only associated with housing design, household characteristics, and appliances but also many factors such as occupancy rates, people behavior, and thermal comfort. Personal habits can cause unnoticed heat loss that we technically cannot measure. Accordingly, energy-saving potentials were estimated to be in the range of 10% - 20% for residential buildings with the changes in occupant behavior [17]. General influencing factors such as building occupant rates, weather elements, and lighting parameters are in use for sensitivity analysis of residential energy consumption [18] [19]. It has been proved to be useful when supplementing sensitivity analysis to assess uncertainty with better predictive building energy efficiency for heating and cooling [20]. In this section, five selected household parameters varying from household parameters (R-value of wall insulation and airflow changes) to occupant status (number of people, occupancy rate, and ACSs) are taken into consideration with sensitivity analysis. The model house is considered a baseline household, consisting of 4 people in the family, occupancy rate 60% on a weekday, R-value (R) = 2.4 $m^2K\cdot W^{-1}$, ventilation rate 1.2 ACH, and ACS is rated "high" according to the classification of levels in Table 5-6. These parameters were obtained from the initial survey.

Table 5- 4 Description of influencing household factors and indicators of the model house

Influence factors	Unit	Description	Model House
Number of people	People	Number of household members in the range from 1 person (single household) to 6 people	4
Occupancy rate	Percentage (%)	Percentage of occupancy at home in 24 hours	60%
Wall insulation R-Value	$m^2K \cdot W^{-1}$	Thermal resistance measured by the proportion of Thickness (m) and Conductivity value ($m^2 \cdot K/W$)	2.4
Air changes rate	ACH	Air changes per hour (ACH) measure air volume added or removed in a space in one hour.	1.2
ACS level	Level	Heating and cooling temperature setpoint by levels: Low, Middle-Low, Middle, Middle-high, High	High

5.3.3 Sensitivity analysis: Application of energy modeling

5.3.3.1 Number of people

The number of people not only influences the use of an electrical appliance but also contribute to the consumption of heating and cooling energy. In EnergyPlus, the "number of people" is in function to simulate the effect of the occupant on the spatial conditions [21]. Performance simulation models provide variation in energy use across six types of household. Given similar household conditions and other settings, the increasing number of household size exhibits growth in EEU for space cooling and a significant decrease for space heating (Fig. 5-12). In a year sum, the site and source energy slightly level down in larger-size families.

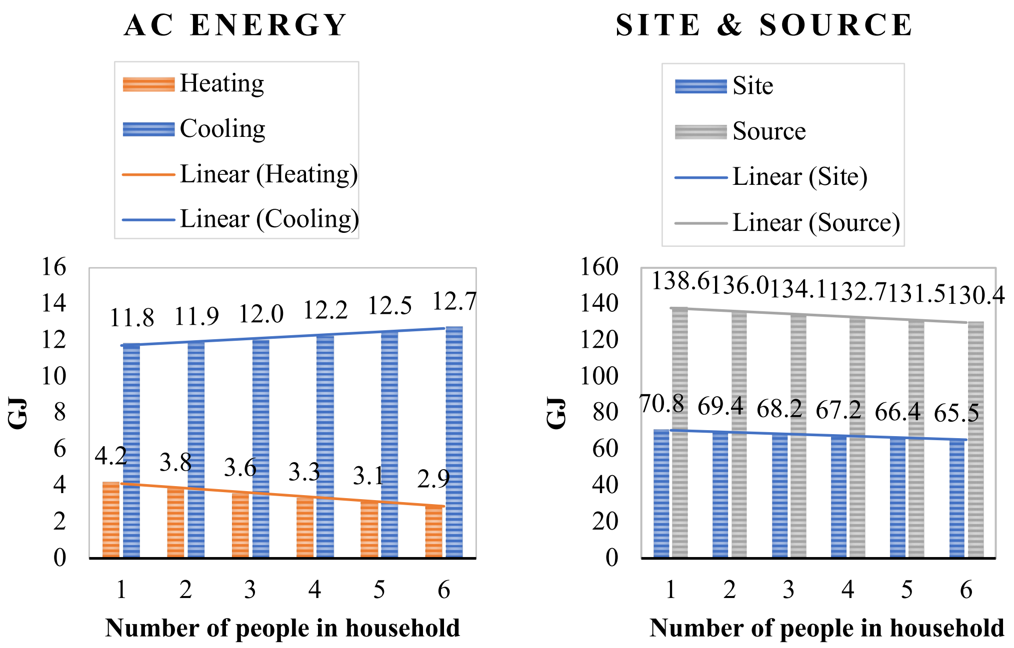


Fig. 5- 11. Predicted energy use by a variable number of people

5.3.3.2 Occupancy rate

While the number of people determines the maximum number of occupants staying at home during a day, occupancy rates reflect proportions of these residents who are home-present at a certain time. The designed occupancy schedule can build occupancy rate (percentage) in 24 hours according to the real home-occupied schedule for energy prediction and lifestyle evaluation. Results show that the percentage of occupancy rate at home can engender air cooling energy in summer but reduce air heating energy in winter (Fig. 5-13). With the same schedule throughout the year, the gross site and source energy will remain unchanged. Hence, to save HVAC energy, high occupancy in winter is recommended, while the opposite applies to the summer schedule. This behavioral factor, however, is related to the variable schedule of household activities. Having been stressed in a previous study [7], families with different backgrounds show specific daily routines and lifestyles, so the energy efficiency plan should be applied distinctly following their household characteristics. The occupancy rate in house 9 was 60% during the investigating period, and during winter, this factor can lead to a total of 3.3 GJ of AC heating.

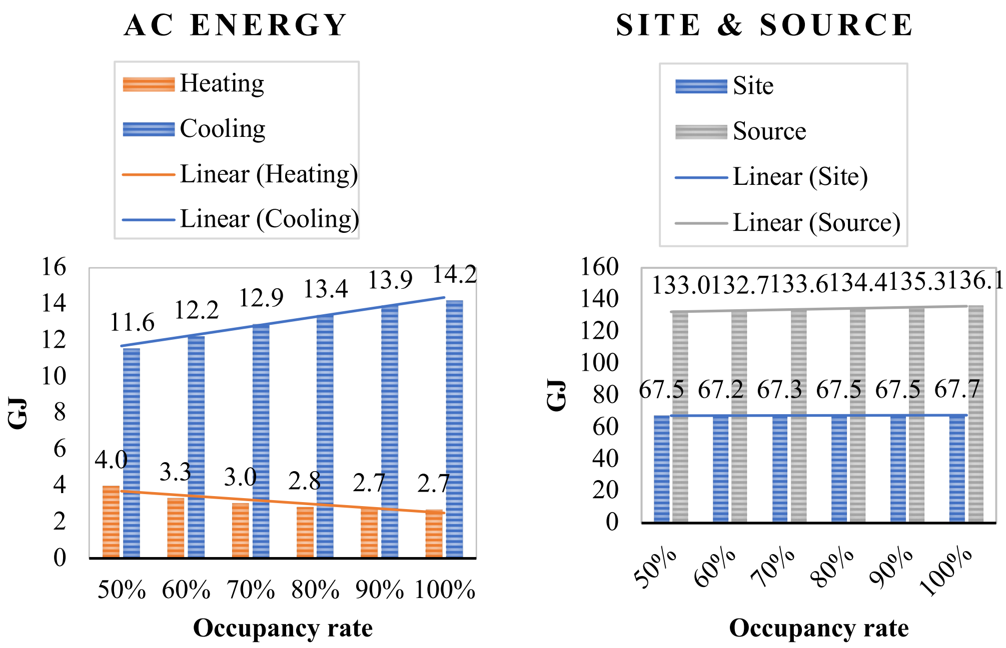


Fig. 5- 12. Predicted energy use by variable occupancy percentage

5.3.3.3 Materials

Materials play an important role in controlling thermal transmission through various ways to improve the insulation of the wall. This factor is usually concerned with the housing structure during the construction. However, thermal properties can be retrofitted with energy-saving measures in different areas. For example, solid insulation walls have been tested to reduce heating transfer coefficient by 11% (+6% / -7%) [22]. Meanwhile, vacuum insulation panels were predicted to cut heating consumption by 12.5% [23], and even 46% when applied to a building without insulating walls. As shown in Fig. 14, energy use decreases with higher thermal resistance or R-values, especially for $0.8 < R < 2.4$. When $R > 2.4$, energy use slowly falls an inconsiderable amount, however, with a climb in material cost. Compared to the model without insulated walls, the retrofitted model with R of approximately 0.8 is efficient for energy saving in this case. That is, the model house's wall insulation is close to the ideal value. Cited by Yuan et al. [24], a reflectivity of 0.6 and insulation thickness of 50 mm is the recommendation for buildings in Fukuoka, Japan. The calculation for R-value in this sector is written in the following equation:

$$R = \frac{d}{C} \tag{1}$$

Where R is the thermal resistance of Wall Insulation $m^2K{\cdot}W^{-1}$, d is the thickness of the wall insulation layer (m), and C displays the Thermal Conductivity value $m^2K{\cdot}W^{-1}$

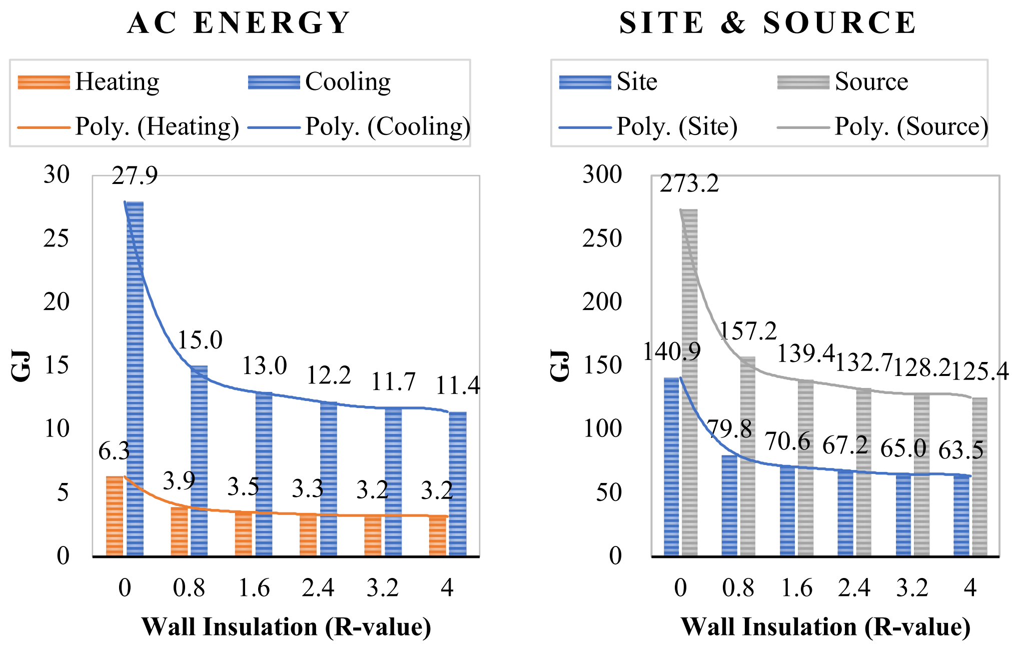


Fig. 5- 13. Predicted energy use by wall insulation R ($m^2K{\cdot}W^{-1}$)

5.3.3.4 Air change flow

Air change flow or ventilation is a crucial factor affecting building energy consumption. To simulate airflow, the infiltration model that defines the unwanted flow of air from the outdoor environment into a thermal zone, directly impact HVAC energy consumption [12]. This calculation applies to spaces with AC full-operating system. In this simulation result, higher infiltration results in greater AC energy use (Fig. 5-15). The figure illustrates that energy consumption increases around 10% of the cooling and 6% of the heating when the ventilation rate rises 0.3 ACH-step (ACH = air changes per hour). At the same time, site and source energy manifest the same escalation, respectively.

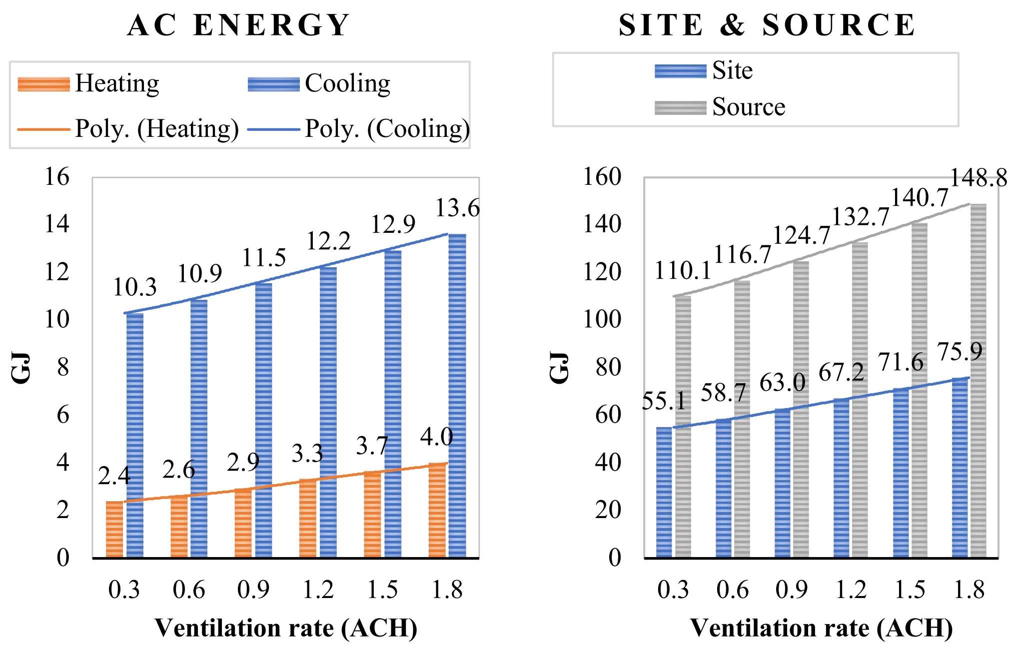


Fig. 5- 14. Predicted energy use by air change flows rate (ventilation rate)

5.3.3.5 Air conditioning setpoints based on energy use pattern and indoor thermal comfort

The usage pattern of the ACS is one of the critical factors, that directly influences indoor temperature and the number of household energy use. Different levels of energy performance have been introduced in the paper of Barthelmes et al. [25], specified three comfort levels based on temperature values recommended for residential buildings that refer to comfort categories described in EN15251 [26]. Other standards have been reviewed in the Predicted Mean Vote approach and the adaptive approach for indoor thermal comfort [27], which formed the basis of the ASHARE 55 standard. A quick calculation tool based on this standard – CBE Thermal Comfort [28] is applied to determine groups of energy use patterns due to the levels of thermal comfort. For example, in our case, assuming winter thermal conditions with metabolic rate 1 Met, typical winter cloth 1.0 clo (1 clo = 0.155 $m^2K.W^{-1}$), average relative humidity 66.7% (as referred to Table 5-5), and indoor airspeed 0.1 m/s, the operative indoor temperature for the comfort zone should vary between 21 ^oC to 24 ^oC (according to the CBE tool). In contrast, a typical operative temperature in summer should change between 24 ^oC to 27 ^oC. The groups of ACS in Table 5-6 ranges from Mid-low to High which represents the level of energy use pattern in the comfort zone, and Low represents the highest energy-saving pattern below the thermal comfort.

In this model, reheat heating and cooling is applied to supply variable air setpoint temperature in each timestep. The setpoint temperature formula is as follows:

$$T_{set} = T_z + Q_z/(C_{p,air} \times m_z) \quad (2)$$

Where, T_z is the control zone temperature, Q_z is the zone load (> 0 for heating, < 0 for cooling), m_z is the zone supply air mass flow rate, and $C_{p,air}$ is the specific heat of air [29].

In this part, T_{set} for AC cooling and heating setpoint represents usage patterns, which can reveal an energy-related behavior is high-consuming or not. The simulation results in Fig. 5-16 reveal noticeable energy efficiency in heating consumption with a higher level of ACS while cooling energy is almost equal at the lower four levels. The end use of heating energy considerably varies based on the setpoint change, whereas that of cooling energy increases dramatically when the AC temperature at 24 °C. These numbers account for mild weather conditions in Japan's summer but harsher-colder in winter, requiring deeper attention during this season.

Table 5- 5. Climate condition

Outdoor temp (°C)			Relative Humidity (%)			Wind speed (m/s)		
Max	Mean	Min	Max	Mean	Min	Max	Mean	Min
9.9	7.0	3.6	82.8	66.7	50.9	5.9	3.1	0.4

Table 5- 6. Classification of ACS levels

ACS	Low	Mid low	Average	Mid-high	High
T_{set} for AC Cooling (degree C)	28	27	26	25	24
T_{set} for AC Heating (degree C)	20	21	22	23	24

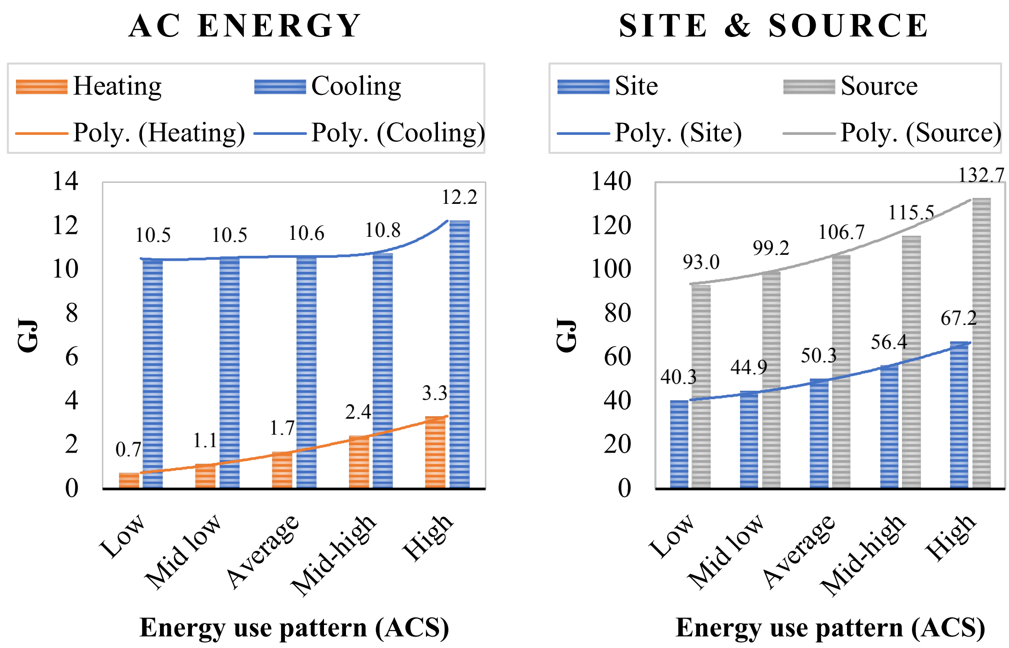


Fig. 5- 15. Predicted energy use by HVAC energy use pattern

5.4. Discussion and Conclusion

In summary, with the integration of forwarding and inverse modeling methods, the sensitivity analysis using a multi-dimensional hybrid approach offers more improvements in the accuracy of energy prediction. The energy modeling and monitoring facilitate the estimation of energy use in each household and prompt resident behaviors with energy performance reports. This study exploits the reciprocal relationship between observed data and simulated data in residential areas, supplementing the mismatch correction of unobservable factors such as ACS, actual occupancy rates, and energy waste. Applications of bench-marking and prepaid meter among neighborhood areas can help to limit the over-consuming actions based on the gap between household occupancy and hourly load.

Compared with the measured data, the correlation shows goodness-of-fit with the coefficient of determination reaches up to 100% probability of the simulated data. However, prediction of daily use shows higher accuracy in households with stable ACSs while fluctuating ACSs are more suitable for hourly usage anticipation. Overall, the Pearson correlation explains the proportion of variance in the energy models as follows: 75% on weekdays, 72% on Saturdays, and 76% on Sundays.

Based on this result, the study proposes household energy efficiency solutions by comparing the impact of different household parameters on energy consumption. The simulation illustrates a greater influence of HVAC setting points or ACSs on energy saving than the other four indicated factors (Fig. 5-17 and Fig. 5-18). Especially, with lower levels of ACS in an acceptable comfort zone, 20% to 60% less heating energy can be achieved compared to the baseline of usage. This corresponds to 16% ~ 33% of the reduction for site energy and 13% ~25% for that of source energy. Larger household size, higher occupancy rate, lower thermal transmittance value for wall insulation, and smaller airflow rates can be more energy-efficient for household HVAC end-use as well as gross site and source energy.

The limitation of this method is that the energy modeling has limited library resources and needs more upgrades to simulate unanticipated behavioral factors. The mismatch correction between actual data and predicted data calls for different approaches to improve the accuracy such as data-driven and hybrid methods. More attention needs to be drawn to the hybrid approach that integrates energy simulation with data analysis and architectural model design in their multi-dimensional interactions to perceive various aspects of the energy-related lifestyle. Example techniques such as mobile-internet-based occupancy data [6] prove to facilitate the building energy simulation and mitigate model distortion during the calibration process.

This paper emphasizes the potential growth of combining model and energy monitor data toward energy forecast in the early design stage, with the supplement of occupancy and other available information regarding residential houses. The sensitivity analysis underlines diverse solutions for researchers and engineers for future studies on energy-related impact assessment, moreover, shed light on visualizing energy saving suggestions in the operational phase with many significant prospects.

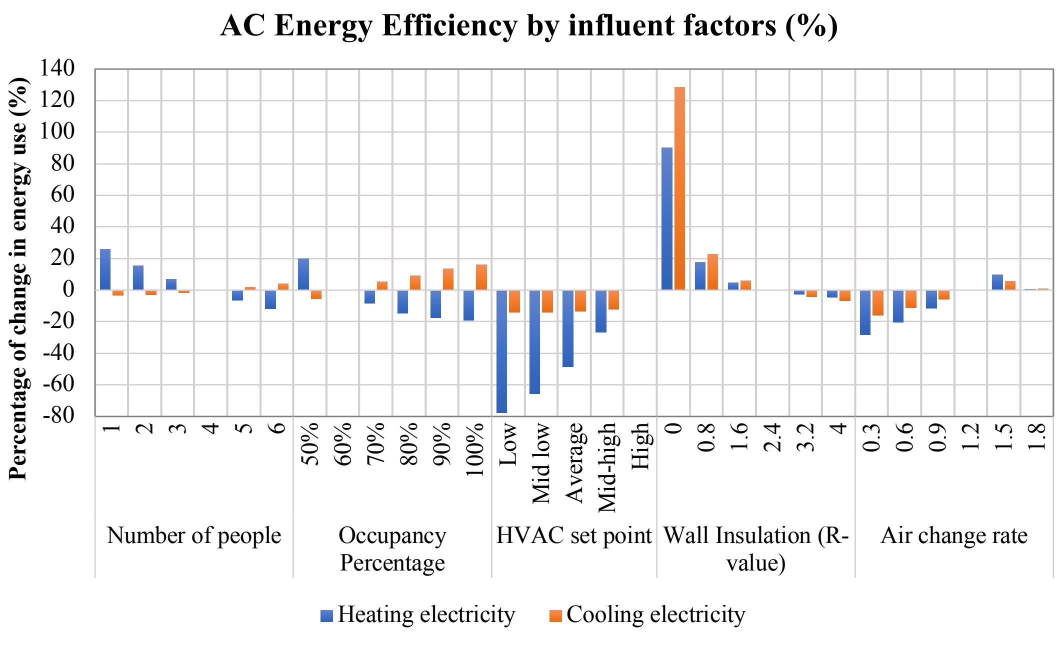


Fig. 5- 16. The percentage of end-use energy saving by variable household factors

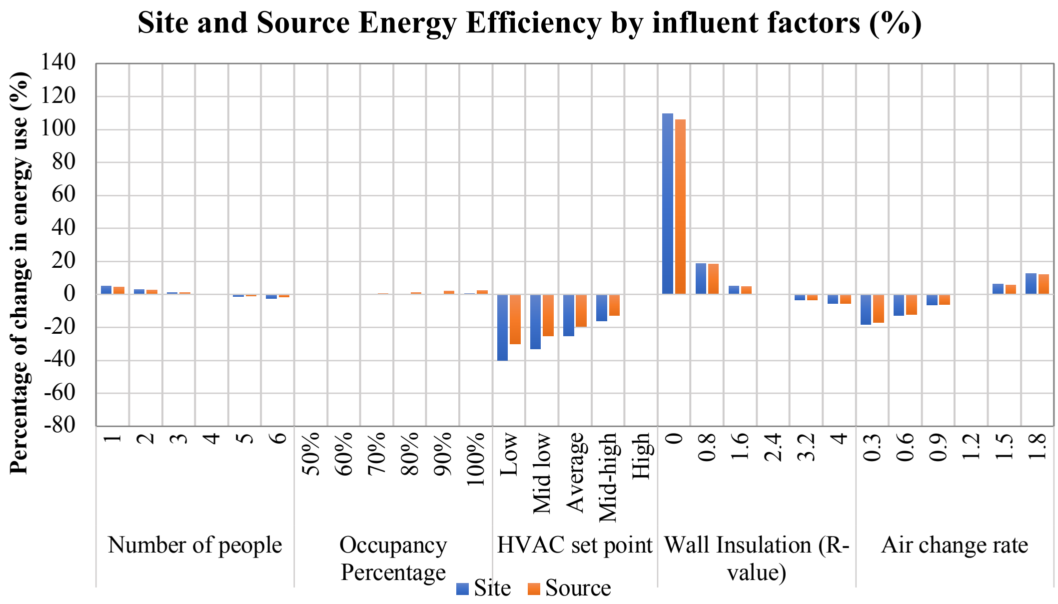


Fig. 5- 17. The percentage of the site and source energy saving by variable household factors

Appendix

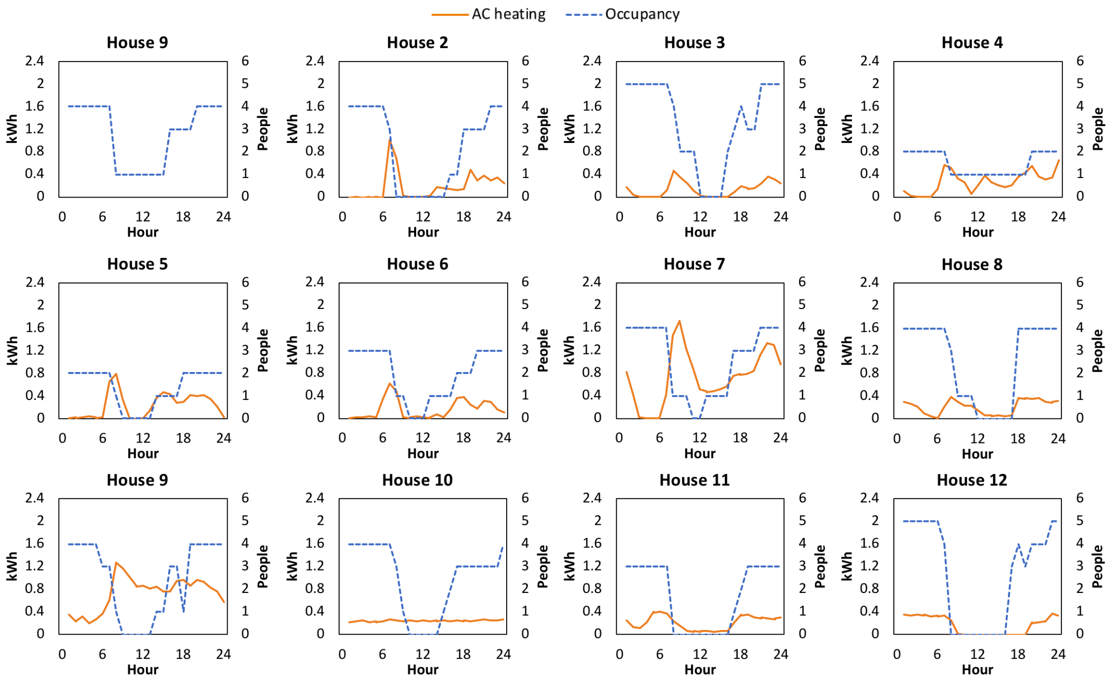


Fig. A1. Occupancy and hourly load on weekday.

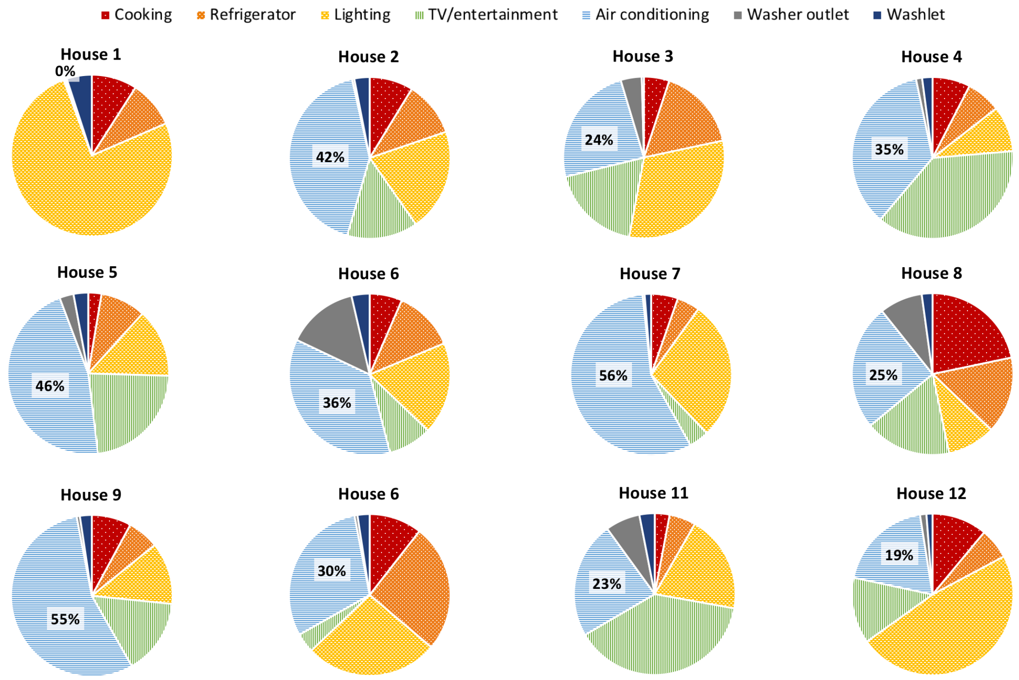


Fig. A2. Share of energy use on weekdays (%)

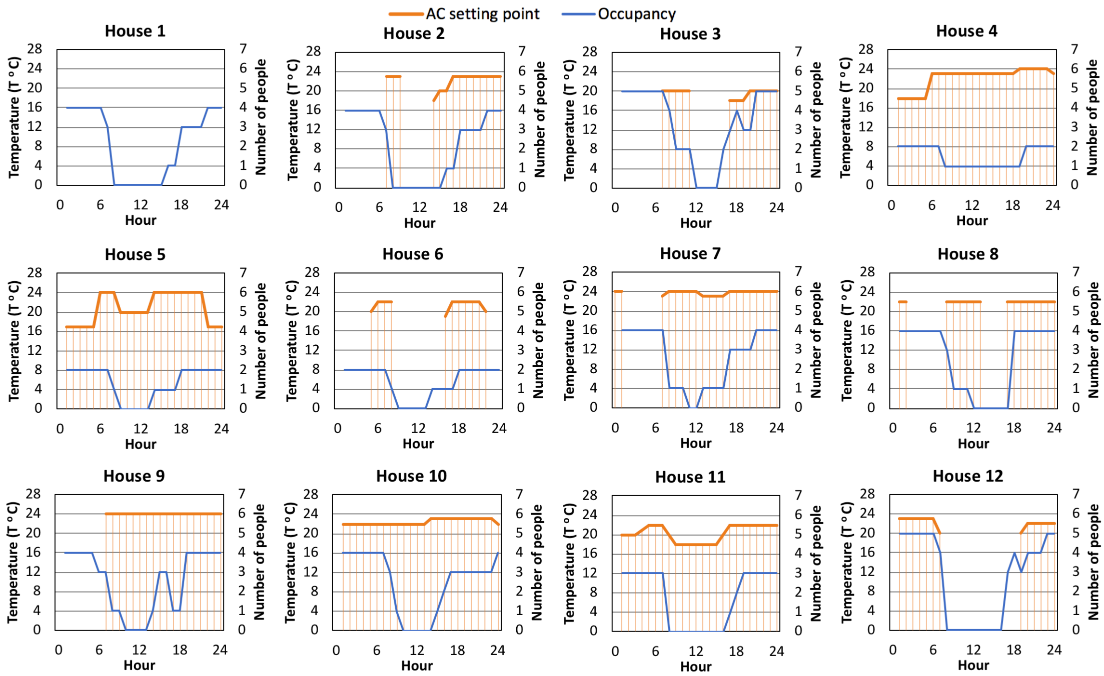


Fig. A3. Household occupancy and predicted air-conditioning set point on weekdays

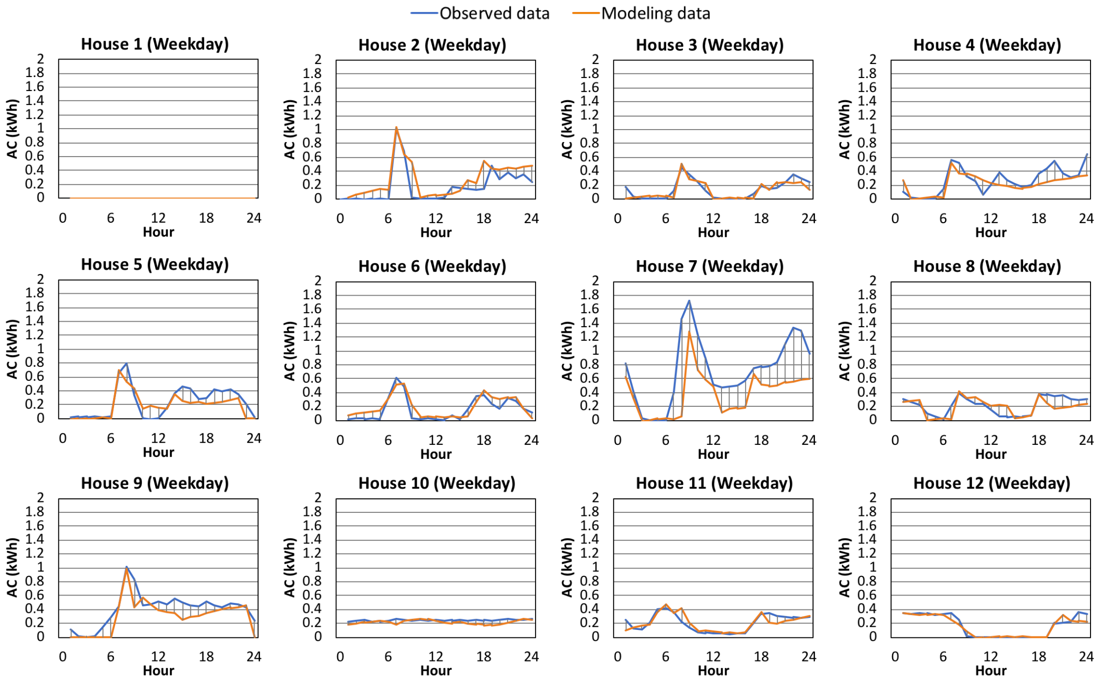


Fig. A4. AC heating load of actual and predicted energy consumption on weekdays

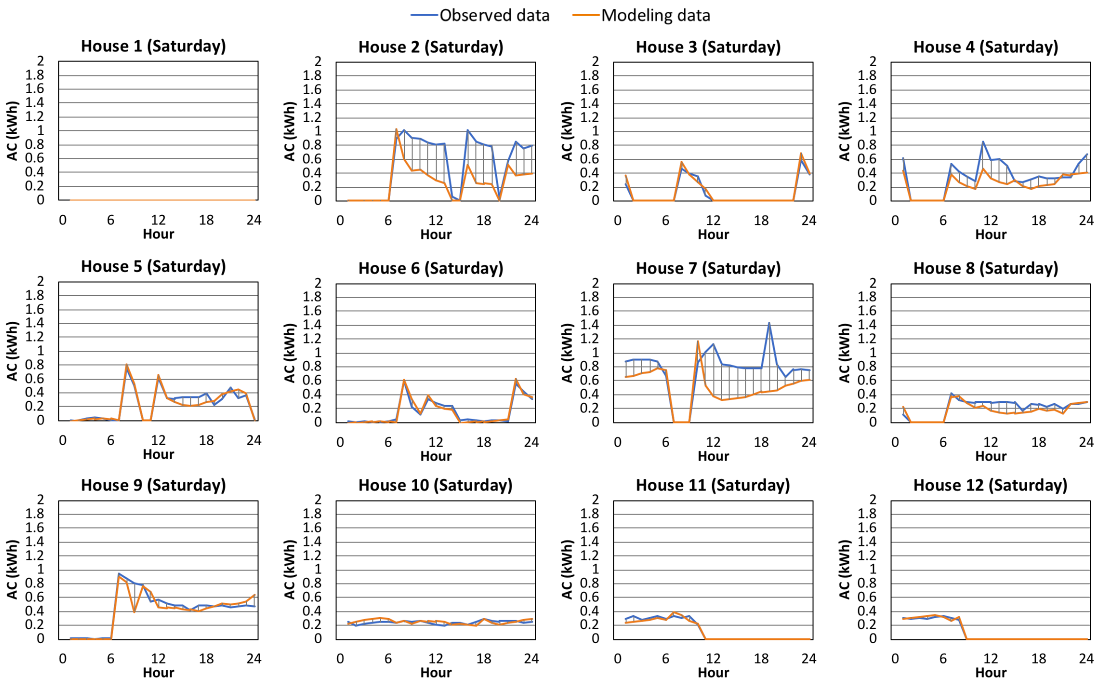


Fig. A5. AC heating load of actual and predicted energy consumption on Saturday

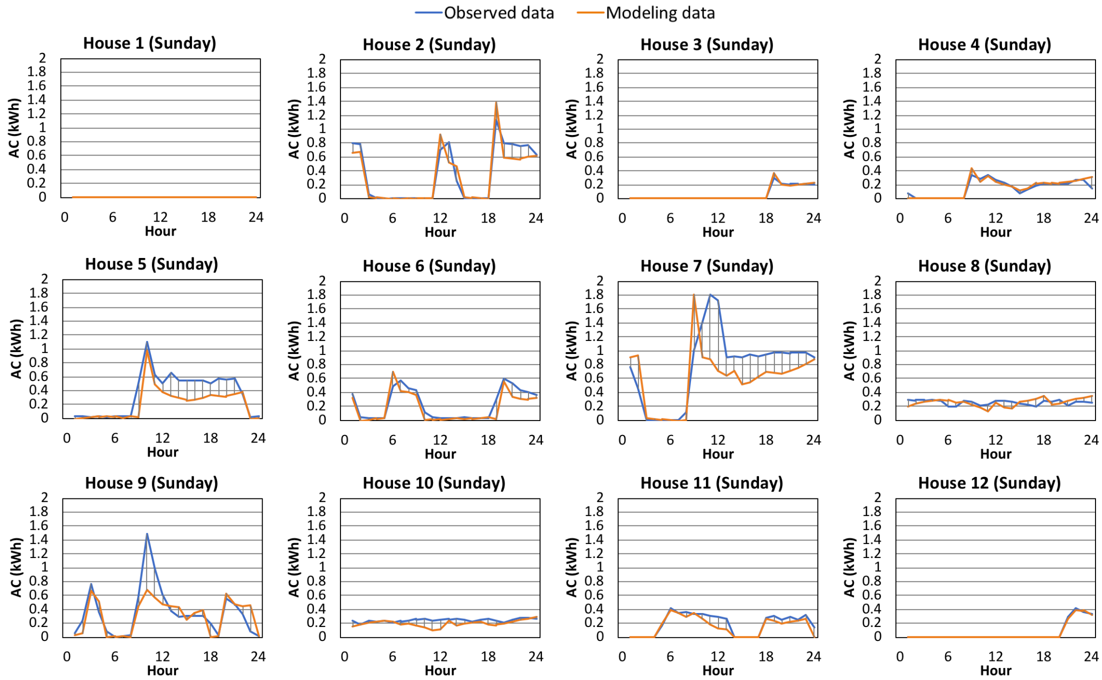
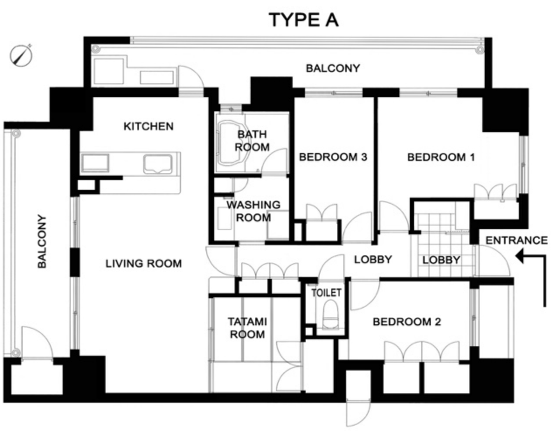
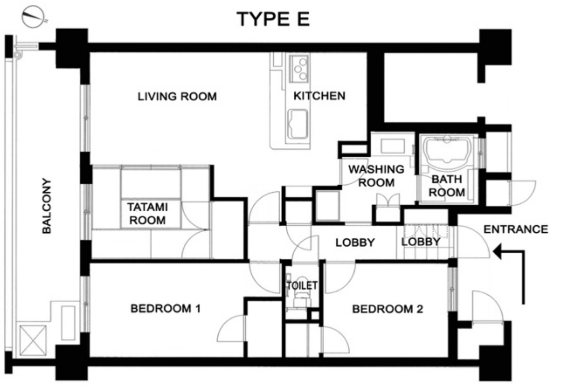


Fig. A6. AC heating load of actual and predicted energy consumption and on Sunday

Table A1. House’s information by types.

	House type: A Year built: 2009 Direction: southwest Height: 2.5 m Floor area: 98.98 m^2

<table>
<tr>
<td>
</td>
<td>House type: E

Year built: 2009

Direction: south-southeast

Height: 2.5 m

Floor area: 80.46 m^2</td>
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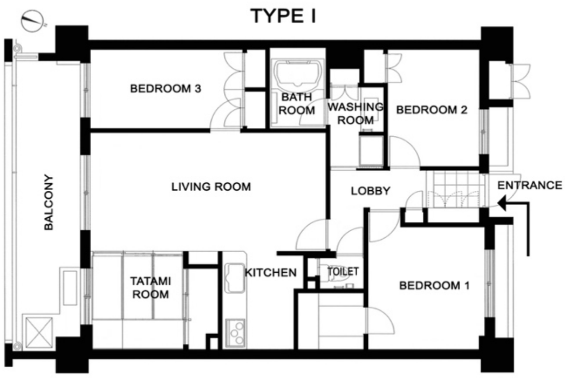
<td>
</td>
<td>House type: I

Year built: 2009

Direction: south-southeast

Height: 2.5 m

Floor area: 87.98 m^2</td>
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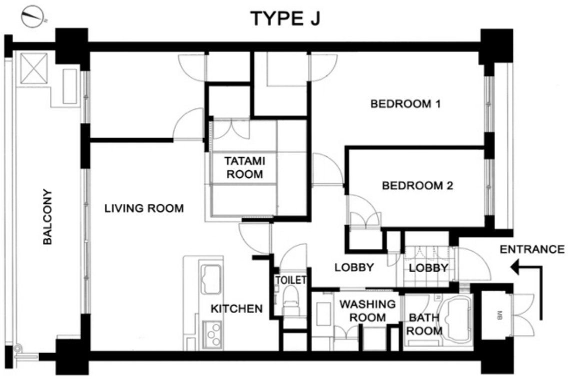
<td>
</td>
<td>House type: J

Year built: 2009

Direction: south-southeast

Height: 2.5 m

Floor area: 86.68 m^2</td>
</tr>
</table>

	House type: K Year built: 2009 Direction: south-southeast Height: 2.5 m Floor area: 104.78 m^2

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Chapter 6

PATH ANALYSIS: IMPACT OF HOUSEHOLD FACTORS AND HOUSING FACTORS IN VIETNAM

CHAPTER 6: HOUSEHOLD ENERGY-RELATED PATH ANALYSIS AND ITS APPLICATION IN THE CASE STUDY OF VIETNAM

Abbreviation	**Explanation**
AC	Air conditioner
ACH	Air change per hour
AD	Frequency of absence days at home
AN	Number of Air conditioners
BELDA	Building Energy Structure and Lifestyle database of Asia
CM	Correlation Matrix
CU	Cooking energy use
ESCAP	The Economic and Social Commission for Asia and the Pacific
EU	Electricity use
HA	Housing floor area
HI	Household monthly income
HS	Household size
IEA	International Energy Agency
LPG	Liquefied petroleum gas
SEM	Structural Equation Modeling
TEU	Total energy use
TPP	Tree Plot Path

6.1 Content

Energy consumption in the household sector has been rapidly increasing in Southeast Asia countries and Vietnam is no exception. Since its economic growth and corresponding energy demand become more significant, related research is expected to have many potentials to be explored, including the household energy sector. This study generalizes a detailed picture of differentiating characteristics of household energy demand and energy-related lifestyles such as household patterns, housing designs, number of stay-at-home days a week, and occupant behaviors in two case studies in Vietnam. Path analysis is applied to illustrate a complex structure of how household factors with different multi-unit impacts energy use on the same scale. The direct and indirect correlations between household factors and energy use can be clarified by graphical visualization of Tree Plot Path and Correlation Matrix. The results of the regression path and correlation matrix shed light on the “influence level” of direct and indirect factors, where household size, housing floor area, and the number of air conditioning significantly affect total energy consumption in the case study. The use of cooking utensils is significantly proportional to the occupancy of people at home while non-cooking electricity consumption derives from the number of air conditioning. By adapting to different environmental and social characteristics, this concise and easily modified model syntax shows the levels of household impacts to offer appropriate scenarios for household energy-saving policies in areas with hard-to-reach statistical data such as Vietnam and other developing countries in the region.

This is a replication work of sensitivity analysis that focuses on factors affecting household energy end-use, extending to another case study following the case study in Japan in earlier papers [1] [2]. After perceiving the potentials and challenges of the social and economic circumstances in this country, we introduce the essentiality of research projects and related works addressing the energy use patterns. An insightful investigation of two cities in Vietnam is dissected with detailed data on household energy consumption, household characteristics, housing features, and occupant-related factors. In the final stage, a path analysis that examines the influence levels of these household factors on energy consumption is applied to explore different perspectives on household factors in the case study and thus explain how to determine the appropriate approach for sensitivity analysis or relevant studies with a given available database. This study examines two case studies where household size, income, housing floor area, occupancy, and the number of AC are considered to be the influence factors on energy consumption. The purpose of this study is to provide an analysis of the energy efficiency of the Vietnamese households, meanwhile assessing the impact of household easy-to-approach factors on energy use in areas with limited access to statistical data. A concise and modifiable model syntax is designed targeting tailored solutions for household changes to contribute to energy-saving behavioral changes in developing countries.

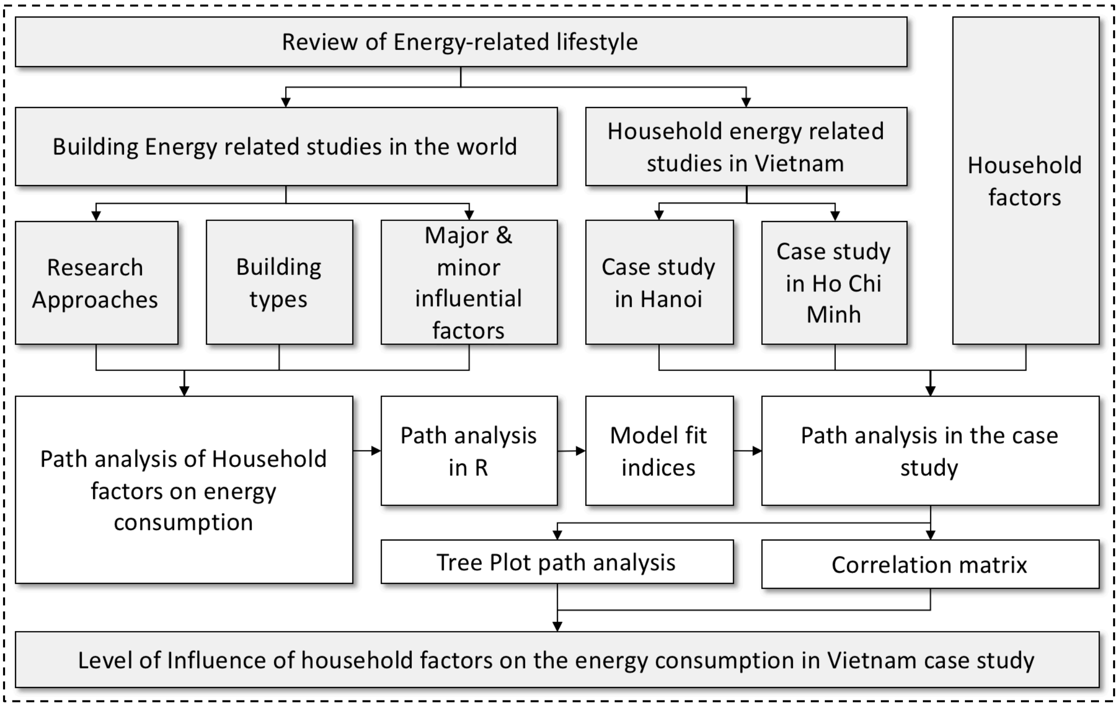

Fig. 6-1 Research flow

6.2. Path analysis of household factors on EEU

6.2.1. Structural equation modeling

In previous research on energy-intensive lifestyle and energy-related effects, we examined the sensitivity analysis of household factors with a combination of energy monitoring and energy modeling in the case of apartments in Japan [2]. This hybrid approach assessed the influence of household factors such as household characteristics, housing design, and occupancy rates on energy consumption. Using sensitivity analysis for Energy-plus models, the results emphasized the significant impacts of household size, occupancy rate, thermal resistance on insulated walls, and airflow rate, on the end-use and the gross site or source energy. However, this approach applies to narrow-scale cases investigated across a few households and required specific data of hourly occupancy and detailed floor plans for three-dimensional visualization models. In this study, we expand the case study to Vietnamese households with a larger number of participants based on the generally available data, which is consistent with study areas in developing countries. Therefore, Path Analysis – a modeling approach of Structural Equation Modeling (SEM) is considered most applicable to the exploratory analysis in this study.

SEM is a broad statistical analysis technique (Data-driven) that combines factor analysis and multiple regression analysis to finds structural relationships between variables. Path analysis was first developed by Sewall Wright [3]. This specific type of SEM investigates the direct and indirect relationship between a set of exogenous variables (independence, predictor, input) and endogenous variables (dependence, output). On the application of Path Analysis to the energy sectors, Gui et al. [4] evaluated six social factors, directly and indirectly, affect CO_2 emissions intensity: Six factors were included in the analysis: gross domestic product per capita, technology effect, energy price, industrial structure, energy structure, and foreign direct investment. According to the results of Path Analysis adoption in a residential area, the occupant's behavior or household Energy-Saving Option was identified as a crucial facet and strongly influenced by personal norms [5]. Among the various topics in SEM, the impact from two or more observed endogenous variables on the other endogenous and exogenous variables can be analyzed by Path analysis. Path analysis is a more general model in which all variables remain but endogenous variables are allowed to explain other endogenous variables [6]. Based on available sources and the scale of the case study, we selected three exogenous and five endogenous variables from existing household factors and energy use data in the survey. This Path analysis will focus on easy-to-seek aspects of household factors, such as monthly income, floor area, number of family members, number of operating ACs, and number of stay-at-home days. These aspects have not been exploited in the previous studies, however, it is replicable and potentially scalable in the similar cases.

6.2.2. Equation behind Path analysis

The structural equation describes the direct impact of the causal factor X_i on the outcome $Y_{i'}$ can be written as:

$$Y_{i'} = \varepsilon_{ii'} + \beta_{ii'} X_i \tag{1}$$

Where β_i stands for standardized coefficient and ε_i is the standardized residual.

The effect of the variable X_i on variables $Y_{i'}$ can be calculated as follows:

$$\rho_{ii'} = \beta_{ii'} \tag{2}$$

If there are k factors directly effect on Y. The correlation reflects the direct impact of k causal factorsX_i with $i \in [1, k]$ on the outcome $Y_{i'}$ can be expressed by the calculation below:

$$Y_{i'} = \varepsilon_{ii'} + \sum_{i=1}^{k} \beta_{ii'} X_i \tag{3}$$

Considering the total effect of the j^{th} factor X_j on Y, $j \in [1, k]$, if we multiply both sides of the structural equation by X_j, we get the normal equation:

$$X_j Y_{i'} = \varepsilon_{ii'} X_j + \sum_{i=1}^{k} \beta_{ii'} X_i X_j \tag{4}$$

Assuming that the residual ε_i is uncorrelated with all variables in the equation ($\rho_{\varepsilon_i X_j}$ = 0), if we take the expectations of both sides [7], we can get the total effect of factor X_j on the outcome $Y_{i'}$ which is represented by $\rho_{ji'}$:

$$\rho_{ji'} = \rho_{\varepsilon_i X_j} + \sum_{i=1}^{k} \beta_{ii'} \rho_{ij} \tag{5}$$

$$= \sum_{i=1}^{k} \beta_{ii'} \rho_{ij}$$

Where ρ_{ij} stands for the correlation of factor X_i and factor X_j. If there are l indirect factorsX_z being correlated with factor X_i and X_j, ρ_{zi} implies the correlation between X_z and X_i, Equation (5) will be replaced by:

$$\rho_{ij} = \sum_{i=1}^{l} \beta_{zj} \rho_{zi} \tag{6}$$

From the calculation of Equations (5) and (6), the total effect of the factor X_j on the outcome $Y_{i'}$ in a multivariate multiple regression can be written as:

$$\rho_{ji'} = \sum_{i=1}^{k} \sum_{z=1}^{l} \beta_{ii'} \, \beta_{zj} \, \rho_{zi} \tag{7}$$

In the path diagram, ρ_{ij} represents the value of the correlation path between the independent variable X_j and dependent variable $Y_{i'}$ where X_j is the causal factor and $Y_{i'}$ is the outcome. The structural equation approach is more mathematical; while perhaps less intuitive, it is less prone to mistakes. Sewell Wright's Path diagram is based on these equations, however, is very diagram-oriented and is perhaps more intuitive to most people [7]. Therefore, a path diagram is an easy-to-approach tool to visualize the influence of household factors on energy use in residential areas.

6.3 Application of Path model in the case study

6.3.1 Path analysis in R – LAVAAN model syntax

Path analysis based on the path model is one of the structural equation models and to describe its differentiation with other SEM, the path model concerns effects only between the observed variables [8]. A variety of computational software that can simulate the Path model is SPSS, AMOS, R-Studio, etc. In this study, we introduce an approach of the LAVAAN (latent variable analysis) package in R-Studio, a free and open-source using R language to estimate a wide range of multivariate statistical models, including the path analysis [9]. In the LAVAAN package, models are set up using a concise and compact text-based syntax – a description of estimating model, which simplifies the multivariate regression modeling into the easy-to-use command in R-Studio. In particular, we examine how different household factors influence energy consumption in two types: Electricity use and cooking energy use. The model parameters can be analyzed and evaluated by the fit indices to meet the required goodness of fit, which is explained in section 6.3.2. In case these model indices do not match the acceptable threshold, the path models will be redesigned with syntax modifications to repeat the process until the final model achieves the criteria. With the available database, we finally figured out a structure of path diagram that best represents the relationships between household impact factors and energy consumption in the case study. The R-studio LAVAAN model syntax written for this path analysis is attached in the figure to be referred to.

Path analysis is a model where not only exogenous variables predict endogenous variables, but endogenous variables can simultaneously affect other endogenous variables in the path relationship. Hence, the path can analyze the interactive relationships which are suitable for more complex models than multiple regression [10]. In this model, household income (HI), house floor area (HA), and household size (HS) are the exogenous variables that directly and indirectly impact electricity use (EU) and cooking energy use (CU). Meanwhile, total energy use (TEU) is the final endogenous variable to be affected. The number of AC (AN) and the number of absent days from home (AD) although effect to energy consumption, are influenced by other factors. In this case, AN and AD can be both causal variables and outcome variables concurrently. We assume that AN is related to HI, HA, and HS when AD is affected by HI and HS. All factors mentioned in this case (HI, HA, HS, AN, AD) directly impact on EU when CU is explained by HI, HA, HS and AD because AN has no linkage with the cooking activities. The covariance paths considered in the case perform the correlations between HI and HA, HS and HA, HI and HS, EU and CU. The modeling outputs are summarized in Table 6-1 showing the simulation parameters and the calculated fit indices.

Table 6- 1 Definition of factors

SEM Factors	Factors in the case study	Abbreviation	Units
Exogenous variables	House floor area	HA	M^2
	Household income	HI	Million VND
	Household size (number of family members)	HS	People
Endogenous variables	Number of AC	AN	Number
	Home-presence day	AD	Day
	Electricity use	EU	GJ
	Cooking energy use	CU	GJ
	Total energy use	TEU	GJ

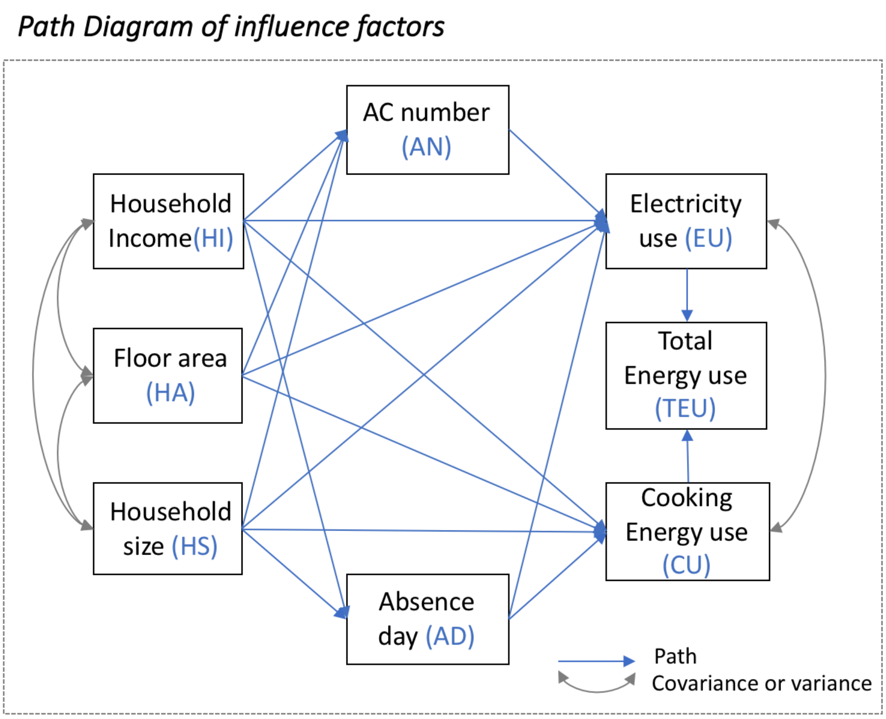

Fig. 6- 1. Path diagram

Lavaan model syntax

```
model <- ‘
#equation where AN is predicted by HA, HI and HS
AN~HA+HI+HS
#equation where AD is predicted by HI and HS
AD~HI+HS
#equation where EU is predicted by AN, HA, HI, HS
and AD
EU~AN+HA+HI+HS+AD
#equation where CU is predicted by HA, HI, HS and AD
CU~HA+HI+HS+AD
#equation where TEU is the sum of CU and EU
TEU~1*CU+1*EU
# estimating the covariances of the exogenous
variables HA, HI and HS
HA~~HI+HS
HI~~HS
#estimating the covariance of residuals for EU and
CU
EU~~CU ’
Model
# Fit the model to the data
fit <- sem(model, data=data)
```

Fig. 6- 2. Model syntax (conversion to LAVAAN)

Table 6- 2 Simulation parameters

Modeling method:	Estimator	ML
	Optimization method	NLMINB
	Number of free parameters	26
	Number of observations	436
Model Test User Model:	Test statistic	14.862
	Degrees of freedom	10
	P-value (Chi-square)	0.137
Model Test Baseline Model:	Test statistic m	5560.635

	Degrees of freedom	28
	P-value	0.000
User Model versus Baseline Model:	Comparative Fit Index (CFI)	0.999
	Tucker-Lewis Index (TLI)	0.998
Root Mean Square Error of Approximation:	RMSEA	0.033
	90 Percent confidence interval - lower	0.000
	90 Percent confidence interval - upper	0.067
	P-value RMSEA <= 0.05	0.762
Standardized Root Mean Square Residual:	SRMR	0.018

6.3.2 Model fit indices

The degree to which the path model fits the observed data can be determined by a variety of indices commonly explained by: Chi-square, Confirmatory Factor Index (CFI), Tucker Lewis Index (TLI), Root Means Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR). The chi-square model is the chi-square statistic obtained from the maximum likelihood statistic (in LAVAAN, this is known as the Test Statistic for the Model Test User Model [6]), however, its sensitivity to discrepancies from expected values at large sample size can be highly problematic [11], thus we cannot decide an acceptation or rejection for the model in this case. Alternatively, given the acceptable sample size (>200), four other indices are recommended to test the fit for accepting or rejecting the model [12] [13]. After the model evaluation procedure, a final decision is made when the model meets the baseline of close fit with the observed data sample. These baselines are briefly calculated using the criteria of four indicators below:

- CFI – The Comparative Fit Index – values can range between 0 to 1. The closer the CFI is to 1, the better the model fits (CFI values of 0.97 seem to be more realistic than the often-reported cutoff criterion of 0.95 for a good model fit [14]). The CFI is a popular fit index as a supplement to the chi-square model. The formula of CFI is

$$\mathrm{CFI} = 1 - \frac{\delta(\mathrm{User})}{\delta(\mathrm{Baseline})} \tag{8}$$

$$\delta = \mathrm{ts} - \mathrm{df} \tag{9}$$

where df denotes the Degrees of freedom for that particular model, ts is the Test statistics.

- TLI known as the Tucker Lewis Index also ranges between 0 to 1 with values greater than 0.90 indicating a good fit. If the CFI and TLI are less than one, then the CFI is always greater than the TLI [6]. TLI index is calculated as follows:

$$\mathrm{TLI} = \frac{\mathrm{ts(baseline)/df - ts(user)/df(user)}}{\mathrm{ts(baseline)/df(baseline)} - 1} \tag{10}$$

- RMSEA is the Root Mean Square Error of Approximation. RMSEA defines δ as the non-central parameter that measures the degree of misspecification. A good model fit should have an RMSEA value that ≤ 0.05 while a value between 0.05 and 0.08 is a reasonably approximate fit and a poor fit value is >= 0.10. RMSEA is expressed as follows:

$$\mathrm{RMSEA} = \sqrt{\frac{\delta}{\mathrm{df}(\mathrm{N}-1)}} \tag{11}$$

$$\delta = \mathrm{ts} - \mathrm{df} \tag{12}$$

where df is the Degrees of freedom for that particular model, ts means the Test statistics.

N is the total number of observations.

- SRMR is the Standardized Root Mean Square Residual, a measure of the mean absolute correlation residual, with smaller values revealing a good model fit [8]. The threshold of SRMR to conclude an “acceptable fit” is <0.08 [15]. SRMR can be written as:

$$\mathrm{SRMR} = \sqrt{\frac{2}{N(N+1)}\sum_{i=1}^{N}\sum_{j=1}^{i}\left[\frac{(s_{ij} - \sigma_{ij}}{s_{ii}s_{jj}}\right]^2} \tag{13}$$

Where N denotes the number of observations, s_{ij} stands for the sample covariance between variable i and j or sample correlation matrix, and σ_{ij} represents implied correlation matrix.

6.4 Results of Path analysis on household influencing factors

6.4.1 Tree Plot Path analysis

The detailed results of the path model are shown in table 6-2 to manifest the relationship between the variables using the path standardized coefficient of regression and covariance outputs. There are five major parameters to be considered: Coefficient or regression coefficient estimate, standard error (Std. Err), test statistics (z-value), p-value (P (>|z|)), and standardized coefficient (Stt. all) or β. Of those, the standardized coefficients were estimated to signify the direct and indirect effects in the consecutive multiple regressions when other parameters were used to perform the inferential analysis [16]. In multiple regression analysis, standardized coefficient or standardization of the coefficient is to explain which of the independent variables has a stronger influence on the dependent variables despite having different units of measure. For path analysis, the standardized coefficients allow researchers to compare the relative magnitude of the effects of different explanatory variables in the path model by adjusting for standard deviations such that all the variables have the same standard deviations [17]. In our path diagram, since there are many units of measure for the variables, we decided to convey the "effect size" based on the calculation of standardized coefficients and using P-value as an indicator to assess the correlation between causal variables and the outcomes.

According to the regression results in table 5-3, in general, floor area, number of AC, and household size have a positive effect while the number of days absent shows a negative effect on household electricity consumption. Among them, the number of AC, that have a standardized coefficient β of 0.254, contributes the most significant impact on electricity use. It is interesting to notice that household income (with p-value > 0.1) in this case is not correlated with the electricity use but has a negative correlation with cooking energy (with a β = -0.198 and p-value < 0.001). Since total energy use equals the sum of cooking energy and electricity use, the coefficients are estimated to be 1, while β indicates a higher amount of electricity consumed in the gross end-use.

To visualize the relationship between each factor and the outcomes, a plot path diagram (Tree Plot Path -TPP) was created with concise and easy-to-imagine parameters shown in Fig. 6-3.

The value of the paths stands for the standardized coefficients β between couples of variables. In this graph, we classified the relationship paths into six types. "Positive paths" and "negative paths" indicate the standardized coefficients to compare the effect between directly-impact variables. "Positive covariance" and "negative covariance" display how two factors vary together, while the "variance" presents how a single factor varies. Only one special variable TEU or "total energy use" is not predicted, instead, it is a fixed factor equal to the sum of electricity use and cooking energy use, so the pattern of TEU's path is different from other paths. In addition to the color of positive and negative parameters, the strength of the effect is determined by the size and the shade of color of the lines. Considering the direct impact, the number of AC is the greatest influencing factor on electricity use with $\beta_{\text{AC EU}}$ = 0.25. Household income, even though having a trivial impact on electricity use ($\beta_{\text{HI EU}}$ = 0.04), significantly affects the use of cooking ($\beta_{\text{HI CU}}$ = -0.20). An increase in floor area and household size possibly leads to a rise in cooking energy usage ($\beta_{\text{HA CU}}$ = 0.13, $\beta_{\text{HS CU}}$ = 0.15), whereas higher monthly income and fewer days at home can reduce cooking services ($\beta_{\text{HI CU}}$ = -0.20, $\beta_{\text{AD CU}}$ = -0.15). The TPP analysis (given by the Tree plot in Fig. 6-3) demonstrates a complex structure of how different multi-unit household factors impact energy consumption on the same scale. Through the visualization of TPP, every factor can drive the outcome in direct and indirect ways, meaning that the degree of influence can be dynamically perceived through the other intermediate elements.

Table 6- 3 Regression results

Path		Coefficient	Stt. Err	z-value	P (>|z|)	Stt. all (β)	Correlation
AN~							
	HA	0.021	0.007	3.278	0.001**	0.152	Yes
	HI	0.055	0.006	9.350	0.000***	0.437	Yes
	HS	0.047	0.031	1.515	0.130	0.063	No
AD~							
	HI	0.035	0.006	5.528	0.000***	0.253	Yes
	HS	-0.269	0.038	-7.138	0.000***	-0.327	Yes

EU~							
	AN	2.228	0.422	5.273	0.000***	0.254	Yes
	HA	0.248	0.058	4.252	0.000***	0.201	Yes
	HI	0.041	0.058	0.704	0.482	0.037	No
	HS	1.497	0.293	5.109	0.000***	0.225	Yes
	AD	-1.281	0.350	-3.657	0.000***	-0.159	Yes
CU~							
	HI	-0.083	0.023	-3.617	0.000***	-0.198	Yes
	HS	0.376	0.125	2.996	0.003**	0.149	Yes
	AD	-0.471	0.150	-3.137	0.002**	-0.154	Yes
	HA	0.058	0.025	2.366	0.018*	0.125	Yes
TEU~							
	CU	1.000	-	-	-	0.899	-
	EU	1.000	-	-	-	0.340	-

Sig. codes: ***p < 0.001, **p < 0.01, *p < 0.05, p < 0.1

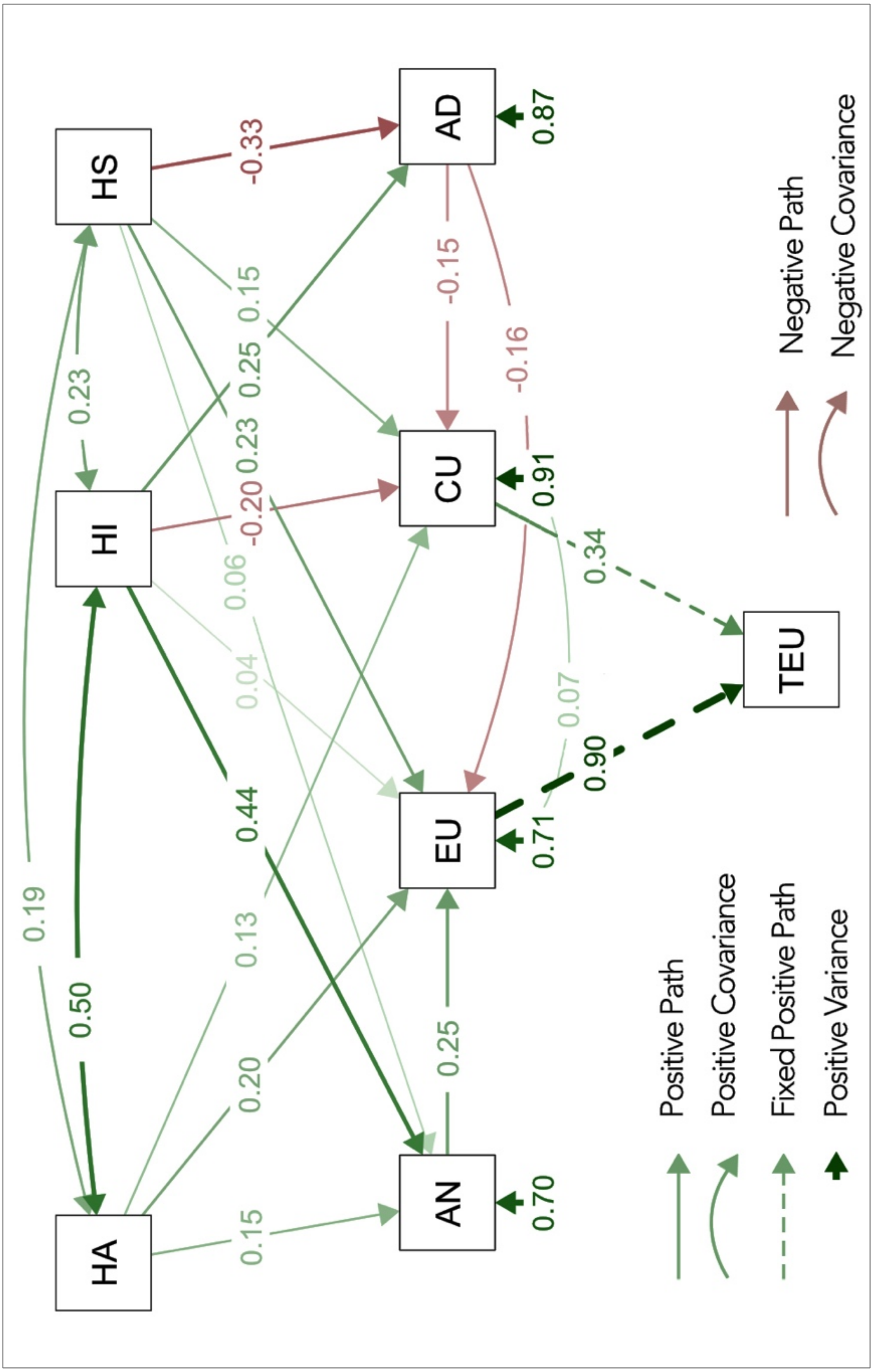

Fig. 6- 3. The Tree plot path analysis of the structural equation model

6.4.2 Correlation Matrix

Regarding the correlation analysis between variables or variances, the correlation matrix is a plot matrix of standardized coefficients between each independent variable and the dependent variable. These values are also known as path coefficients – a type of linear regression weights to inspect the possible causal connection between variables in the SEM approach [18]. Similar to the Tree plot path analysis, the standardized coefficients in the correlation matrix are unitless and refer to the standard deviations of the outcome variables, so a comparison of relative effects between a couple of variables can be expressed. The correlation matrix is shown in Fig. 6-6 in levels of color gradient from red (representing absolute $\beta = 1$) to green (as absolute $\beta = 0$). Among the predictors in this figure, the household income has a strong effect on floor area and number of ACs (with β equal to 0.53 and 0.54, respectively). Meanwhile, the number of days absent is nearly uncorrelated with these two factors (similar to those predicted in the path model in Fig. 6-3). Regarding the explanatory variables, electricity use gets the highest effect from the number of AC and the lowest effect from days of absence. At the same time, cooking energy use mainly increases despite a decrease in the family's absence and probably remains stable despite the vary of floor area or number of AC. Total energy use reflects a greater correlation with household size although it is mainly counted from electricity use, explaining the complex relationships between the variables. This graphical analysis, although showing merely a single correlation between each factor, reaffirms the reliability of the path model, and implies multi-dimensional impacts between all household factors as well as the indirect influence on household energy consumption.

Table 6- 4 Standardize coefficient β and correlation ρ

X_i	$\rho_{X_i\,HS}$	$\rho_{X_i\,HI}$	$\rho_{X_i\,AD}$	$\rho_{X_i\,HA}$	$\rho_{X_i\,AC}$	$\rho_{X_i\,EU}$	$\rho_{X_i\,CU}$	$\rho_{X_i\,TEU}$	$\beta_{X_i\,EU}$	$\beta_{X_i\,CU}$
X_{HS}	1	.24	-.27	.19	.19	.36	.17	**.38**	.23	.15
X_{HI}	.24	1	.18	.50	.53	.29	-.13	.22	.04	**-.20**
X_{AD}	-.27	.18	1	-.001	.002	-.21	**-.23**	-.26	-.16	-.15
X_{HA}	.19	.50	-.001	1	.38	.36	.006	.34	.20	.13
X_{AC}	.19	.53	.002	.38	1	**.39**	-.001	.35	**.44**	N/A

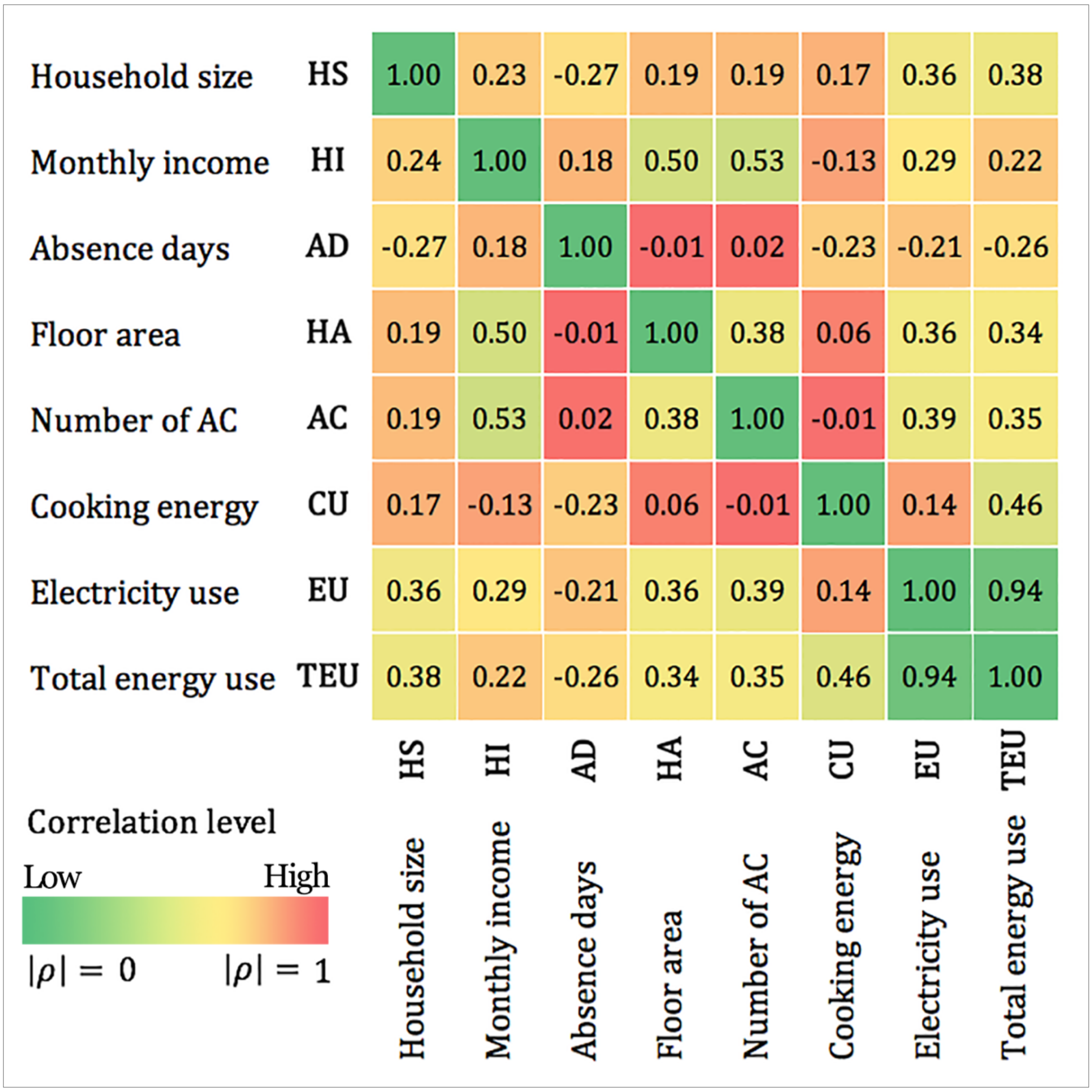

Fig. 6- 4. Correlation matrix

6.5 Discussion

Vietnam has had several remarkable research works in the field of household energy, however, the number of articles and other records is still sparse compared to the global average. Most of the current work is concentrating on reviewing household energy overview, energy policies, energy-saving plans, and energy-related programs, indicating that household energy, in particular, will grow faster in recent years and call for more efforts toward implementing renewable energy or cutting CO_2 emission. This study first pointed out that it is important to have an open-source database on household energy consumption as well as corresponding household factors, such as the number of family members, gross floor area, household income, appliance ownership, occupancy rates, and other elements related to the use of energy devices. The lack of large-scale data causes limited access to the usage-pattern analysis, sensitivity analysis, or energy forecast, which are crucial for researchers and policymakers to apply statistical approaches and energy-saving implementation. Regarding the significant impact of occupant-related factors, of which occupant behavior is one of the most frequent causes, this paper highlights the indispensable role of household characteristics and that an analysis of these easy-to-approach factors concerning household energy is compelling and applicable in the case study.

The relationship between household factors and energy consumption by end-use is clarified, using the energy performance analysis integrating multiple factors based on the open-source database, and implementing SEM path analysis based on the raw database. For energy performance analysis used in the original study [11], the combination of causal factors and usage outcome indicate unpredictable trends, which is better used to look at the detailed fluctuation of energy end-use by household categories and energy use behaviors by household characteristics instead of telling a specific influence number. Alternatively, the proposed SEM path analysis reveals better statistical findings on the correlations of variables and the influence levels of each household factor on the household energy end-use.

The results of TPP and CM show the effect size of direct and indirect factors, which clearly explain the multi-dimensional impact on energy consumption in the path analysis. The use of cooking utensils is significantly proportional to the occupancy of people at home while non-cooking electricity consumption derives from the number of AC. From direct effect in TPP, among five factors, AC is the most important determinant for electricity use while HI better reflect the frequent use of cooking service. Considering the total effect in CM (direct and indirect effects), HS is the major impact on total energy consumption including electricity use and cooking use, and monthly income shows the most negligible effects. This notion means if we consider the holistic impact of all factors with their complex relationships among them, population is the first and foremost cause of household energy consumption. The outcome argue with the conclusion of previous papers in which household income is considered to be a major influence on household energy use in Vietnam ([28] [29]). However, because household size and floor area are invariable behavioral determinants, reducing number of AC is a recommended option to be first considered. The finding is consistent with research works of Vietnam and other case studies that emphasizes the effect of household size [58] [59] [60] and number of appliances including AC [33] [58] [61]. Therefore, household size, floor area, and the number of AC need to be considered more rigorously to reduce total energy consumption in the residential area, especially those that tend to increase in population and decrease in AC price. Household size should be controlled under the government direction of energy-saving policies such as: population balance in urban region while floor area is minimized by architects with optimal functional design. This suggestion will also solve the problems in previous studies in section 2 regarding mitigating the impact of population and mitigation issues in Vietnam on residential energy [30] [31]. As for behavioral changes at home, adjusting the number of AC is a priority in energy-saving solutions. In line with AC market in Vietnam, an article [33] stresses on increasing AC price and encourage high energy-efficiency items, whilst another recommends refrigerant replacement for reducing AC cooling energy [35]. Contributing to the discussion in the original study [11] and earlier replication study [16] where AC setpoint is under high consideration, it underlines the essential role of reducing AC operation time and adjusting AC setpoint to ease the intensity of use. Also, natural ventilation is highly recommended as an alternative of AC cooling in this country due to the character of hot-humid climate in this country.

6.6 Conclusion and prospects

Vietnam remains a new case study with rare information including statistical energy data, as well as household surveys and the path model that only addresses the effects between observed variables was appropriate for this situation. Since each factor impacts the outcome in direct and indirect ways, the level of influence can be dynamically perceived through the intermediate factors. Conclusion can be summarized in the following points:

- Compared with the typical energy performance analysis, this model can analyze the interactive relationships between the household factors and the energy consumption simultaneously, which enables more complex structures than multiple regression.

- While the TPP reveals a complex correlation of how various multi-unit household factors affect energy use on the same scale, the CM emphasizes the and visualizes optimal options for energy-saving plans. multi-dimensional influences of household attributes on the end-use

- Among five factors, household size is the major determinant while monthly income shows the most negligible effects on total energy use. The use of cooking utensils is significantly proportional to the occupancy of people at home while non-cooking electricity consumption derives from the number of air conditioners.

- Although many parameters affect energy usage, the path model only addresses the effects between observed variables in the database is a user-friendly model. If more data is contributed, variables can be added to the path diagram based on the main structure introduced in this conceptual model.

After experiencing the impacts of lockdown and work-from-home policies during Covid-19, more efforts on household energy use behaviors should be concerned. Future related studies may refer to the correlations and impact levels in this case study or extend the results with deeper approaches in a different context of social factors. Because the introduced path diagram using model syntax in R is customizable, modifiable, concise and applicable to datasets containing variables with different units, emerging case studies, or developing countries where hard-to-reach energy data and household surveys can apply the same method as adjusting for variables in the path model. This approach can be an example for other regions where suitable energy policies should be provided to each locality with different environmental and social characteristics.

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Appendix

Table 6- 5 Covariances parameters of the path model

	Estimate	Std. Err	z-value	P (>|z|)	Std. all
HA~HI	31.808	3.417	9.309	0.000***	0.498
HA~HS	2.057	0.517	3.892	0.000***	0.194
HI~HS	2.693	0.581	4.637	0.000***	0.228
EU~CU	1.886	1.267	1.489	0.137	0.072

Sig. codes: ***p < 0.001, **p < 0.01, *p < 0.05, p < 0.1

Table 6- 6 Variances parameters of the path model

	Estimate	Std. Err	z-value	P (>|z|)	Std. all

. AN	0.787	0.053	14.765	0.000***	0.700
. AD	1.151	0.078	14.765	0.000***	0.867
. EU	61.546	4.168	14.765	0.000***	0.711
. CU	11.310	0.776	14.765	0.000***	0.909
. TEU	0.001	0.000	14.765	0.000***	0.000
. HA	57.188	3.873	14.765	0.000***	1.000
. HI	71.314	4.830	14.765	0.000***	1.000
. HS	1.961	0.133	14.765	0.000***	1.000

Sig. codes: ***p < 0.001, **p < 0.01, *p < 0.05, p < 0.1

Table 6- 7 Participant's questionnaire and answers about the implementation of energy-saving behaviors

Questionnaire			Answer		
Please select the answers that best describe your household's attitudes and actions regarding energy consumption. If you have multiple units, please answer about those that you use most frequently. If you are unable to answer because you do not own the particular home electronic or for another reason, please answer "not applicable."			YES, we do this	NO, we don't do this	Not applicable
Television sets	(a)	Reduce the brightness of the television	1	0	0
	(b)	Switch off the power of the television when not using	1	0	0
Refrigerators	(c)	Do not leave the refrigerator door open	1	0	0

	(d)	Try not to put too many things in the refrigerator	1	0	0
Air conditioner	(e)	Refrain from using the air conditioner	1	0	0
	(f)	Keep the temperature setting of the air conditioner higher than the comfortable level	1	0	0
Lighting	(g)	Try to turn lights off when leaving a location, even for a short time	1	0	0
Shower	(h)	Use a water-saving showerhead	1	0	0
	(i)	Shorten the time of using showers	1	0	0
	(j)	Try to take cold instead of hot showers	1	0	0
Home electronics	(k)	Reduce the number of times to run the washing machines	1	0	0
	(l)	Try not to use the keep-warm function of the electric rice cooker	1	0	0
	(m)	Turn off the power of the PC or switch to low-power mode when not in use	1	0	0
Cooking	(n)	Fill pots and kettles with the optimal amount of water whe	1	0	0

	n boiling

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Chapter 7

HOUSEHOLD ENERGY END-USE BASED ON DIFFERENT CLIMATE ZONES, HOUSING DESIGN AND OCCUPANT BEHAVIOR

CHAPTER VII: HOUSEHOLD ENERGY END-USE BASED ON DIFFERENT CLIMATE ZONES, HOUSING DESIGN AND OCCUPANT BEHAVIOR

7.1 Research contents

Energy consumption in the household sector has been rapidly increasing in Japan and Vietnam. Accordingly, the crucial impacts of household characteristics on residential Electricity End-Use (EEU) have not been significantly paid attention. This Chapter will compare the prediction of energy consumption in two cases: Japan and Vietnam. For the sensitivity analysis, geographical location, housing floor plan, housing direction, and HVAC usage scenarios are considered impact factors to the energy consumption and OpenStudio will be the tool for dynamic simulation of the predicted models. We chosed two typical housing floor plans of apartments with the same area in Japan and Vietnam for the 3D-modeling. Eight orientations of housing models and 3 scenarios of HVAC energy use styles are examined to define the level of energy consumption in different cases. 20 cites in Japan and 20 cities in Vietnam are selected based of the different latitudes and climate zones and six cities out of them are simulated with detailed monthly energy performance. Results will show the sensitivity analysis of energy consumption by changing housing directions, housing floor plan, and HVAC usage behaviors in different latitudes and climate zones. The study highlights the multi-dimensional influences of household attributes to emerge a holistic view of changing energy behavior through different case studies.

7.2. Comparison of Japan and Vietnam

7.2.1. Background of household energy consumption in Japan and Vietnam

Over the last decade, Japan made substantial progress in implementing its vision of an efficient, resilient and sustainable energy system. The country's strong innovation and technology base will play a vital role in developing the technologies needed to achieve its ambitions of achieving carbon-neutrality by 2050 [3]. Japanese electricity consumption has performed a stable growth throughout 19 years and even slightly decreased since 2010 (Fig. 7-2). The share of electricity consumption has changed significantly where the use of industrial energy decreased and commercial need increased. Residential electricity has not much difference due to the slow growth of population. According to the FY2019 Energy Supply and Demand Report by The Agency for Natural Resources and Energy (ANRE) [2], the household sector shows a decrease on a year-on-year basis, due to the impact of the colder summer, warmer winter, and other factors. A breakdown by sector on a year-on-year basis shows that final energy consumption decreased 0.8% in the household sector. In terms of electricity consumption on a year-on-year basis, the household sector shows a decrease by 3.8% and the business sector also shows a decrease by 1.3%.

Based on the energy report of IEA [2], in recent years, Viet Nam has increased its non-hydro renewable capacity targets in its power development plan, from 9.4% to 21% of total installed capacity in 2030, and decreased the share of coal-fired capacity from 52% to 43%. The parabolic growth of total electricity consumption increases exponentially from 1990 to 2019 which results in a rise of 33.8 times after 19 years (Fig. 7-3). Even though main distribution of electricity consumption shifted from residential area to industrial area, significant share of industrial electricity use is apparent in Vietnam. Comparing with Electricity consumption in Japan, Vietnamese electricity consumption increase more faster in recent years due to its rocketed development of economy. However, the intense of electricity demand are still significant in Japan where the average consumption per capita in Japan is equal to the average use of three people in Vietnam (Fig. 7-1). A concrete number is displayed in Fig. 7-4 and Fig. 7.5 where Japanese household presents consistent demand on residential energy consumption while Vietnamese household usage accelerated sharply during 6 years from 2010 to 2016. In 2010, household electricity consumption per capita in Japan to household electricity consumption per capita in Vietnam is 14 times but in 2016, the proportion decreased to about 3 times. These data illustrate that Vietnamese household in particular has potentials to have higher demand on energy services and with many similarities and differences about physical characteristics between two countries, which will be presented in section 7.2.2, a comparison study is way to emerge multi-dimensional insights about the impacts of household factors on saving household energy consumption.

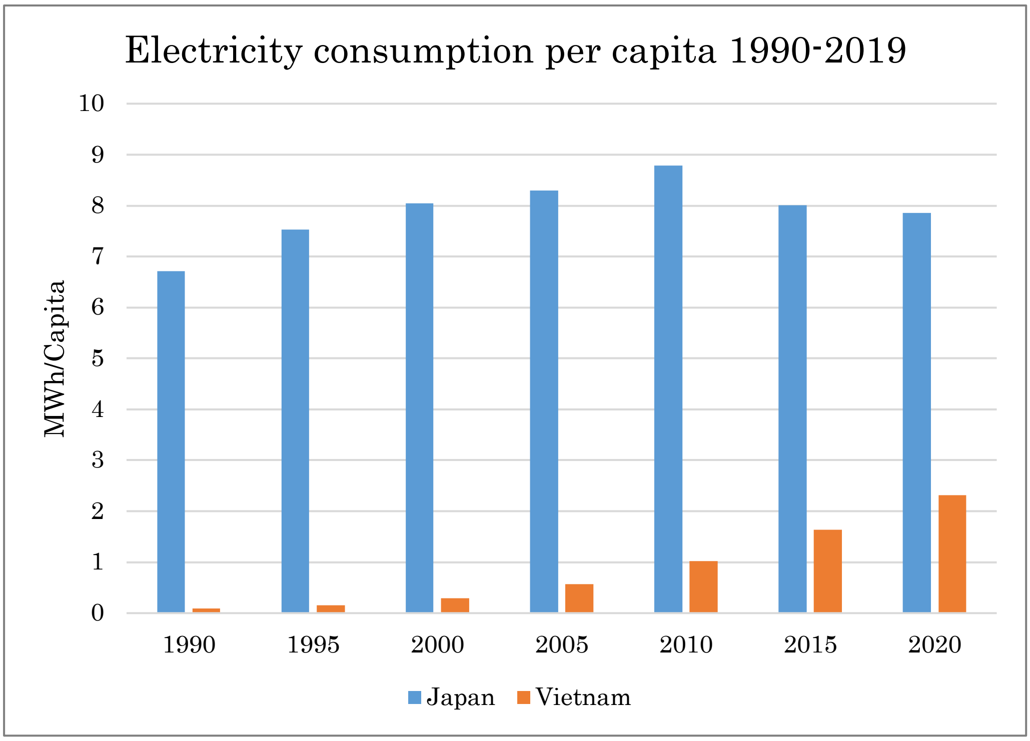

Fig. 7- 1. Electricity consumption per capita in Japan and Vietnam, 1990-2019

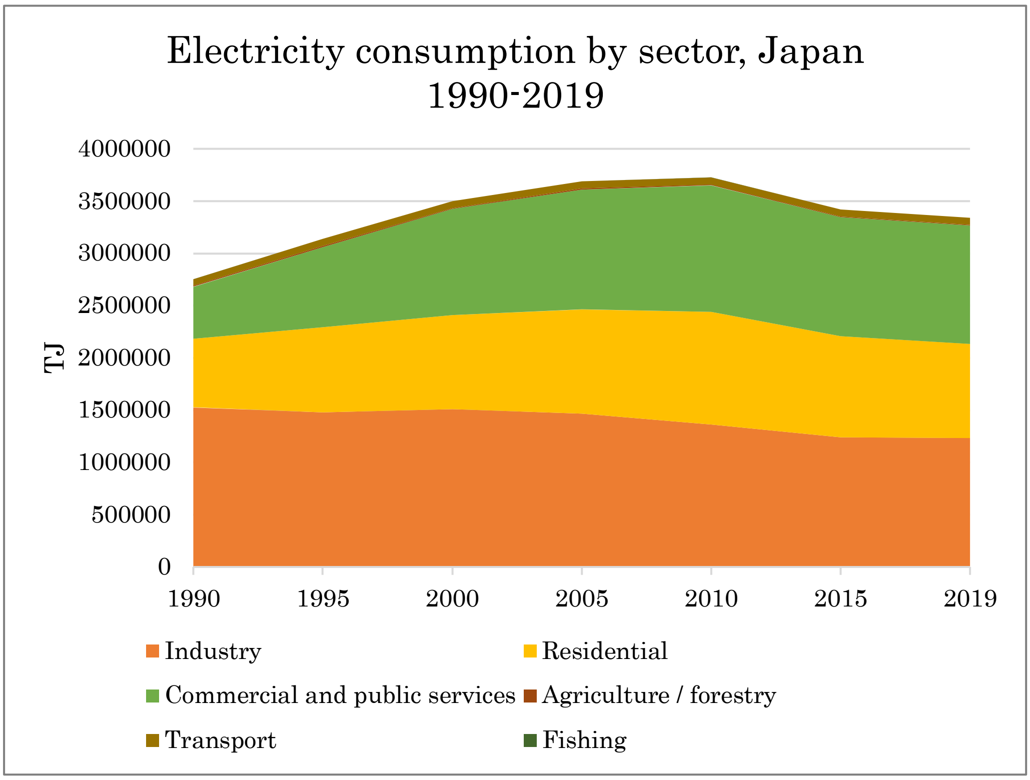

Fig. 7- 2. Electricity consumption by sector in Japan from 1990 to 2019 [1]

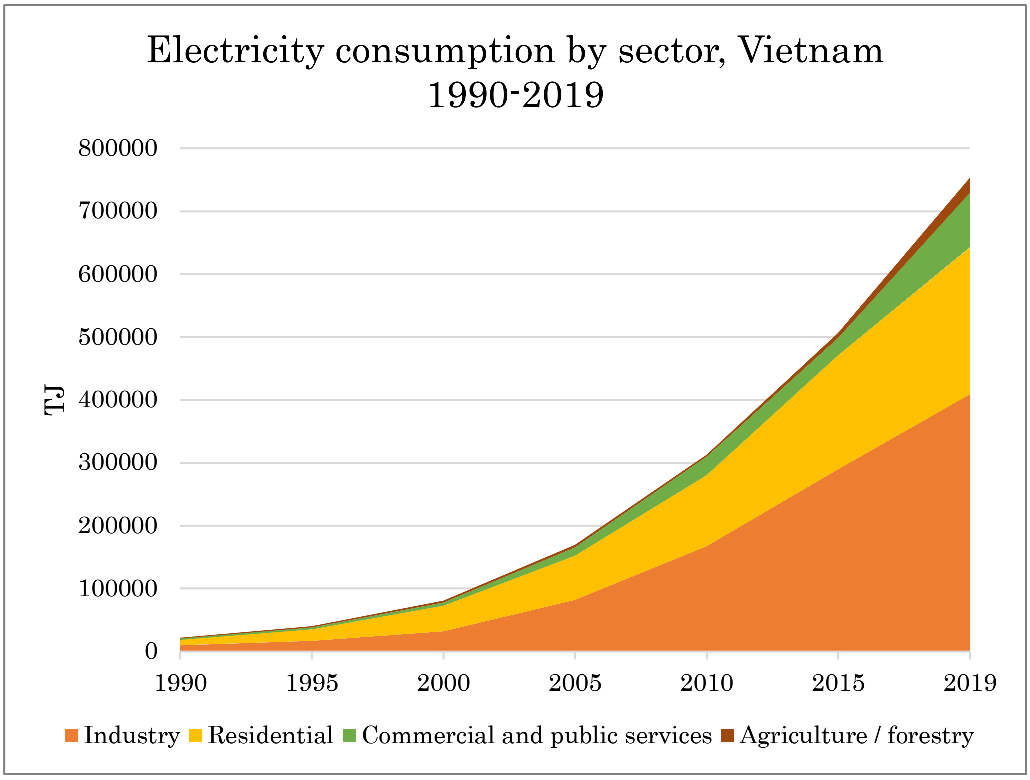

Fig. 7- 3. Electricity consumption by sector in Vietnam from 1990 to 2019 [1]

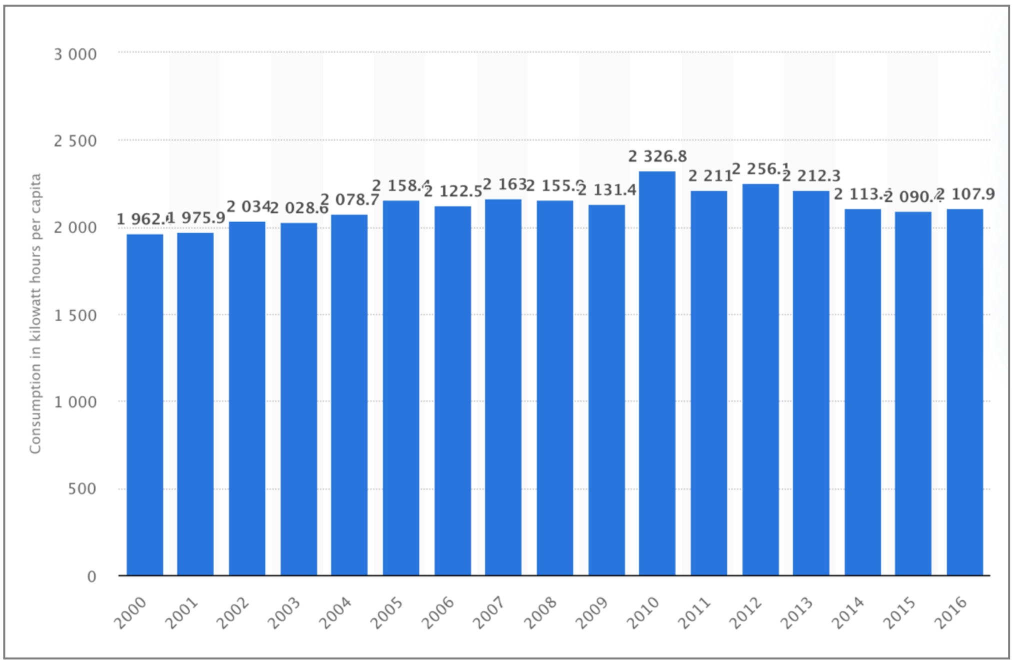

Fig. 7- 4. Annual household consumption in Japan 2000 – 2016 [6]

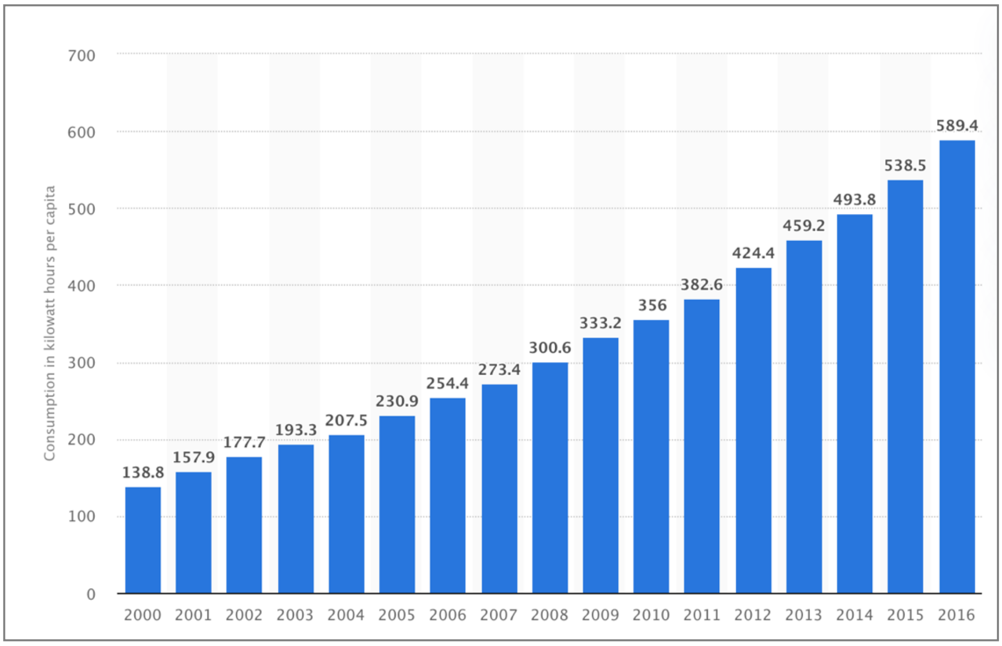

Fig. 7- 5. Annual household cconsumption in Vietnam 2000 - 2016 [6]

C7.2.2. Comparison on physics characteristics between Japan and Vietnam

Takao Sawachi [2] discussed determinants that affected the use of residential air conditioners such as outdoor environment, thermal character, architecture, and residential properties. Among them, the location of the house is the factor that most affects the indispensability of air conditioners.

According to Japan Meteorological Agency [8], Japan has four distinct seasons with a climate ranging from subarctic in the north to subtropical in the south. Conditions are different between the Pacific side and the Sea of Japan side. Northern Japan has warm summers and very cold winters with heavy snow on the Sea of Japan side and in mountainous areas. Eastern Japan has hot and humid summers and cold winters with very heavy snow on the Sea of Japan side and in mountainous areas. Western Japan has very hot and humid summers (with temperatures sometimes reaching 35°C or above) and moderate cold winters. Okinawa and Amami have a subtropical oceanic climate. These areas have hot and humid summers and mild winters. Vietnam has both a tropical climate zone and a temperate climate zone, with all of the country experiencing the effects of the annual monsoon. Rainy seasons correspond to monsoon circulations, which bring heavy rainfall in the north and south from May to October, and in the central regions from September to January. In the northern regions, average temperatures range from 22–27.5°C in summer to 15–20°C in winter, while the southern areas have a narrower range of 28–29°C in summer to 26–27°C in winter [9].

"Heating degree days": HDD 16, are a measure of how much (in degrees), for 12 months (year 2020), outside air temperature was lower than 16°C (base temperature). They are used for calculations relating to the energy consumption required to heat buildings. "Cooling degree days": CDD 26, are a measure of how much (in degrees), for 12 months (year 2020), outside air temperature was higher than 26°C (base temperature). They are used for calculations relating to the energy consumption required to cool buildings. According to D'Amico et al. [1] The energy performance of a building is strictly dependent on the climatic conditions. The Heating Degree Days value for each considered location represents the most important climate severity index and can be used to evaluate the building energy performance. With $\mathrm{H_i}$, $\mathrm{C_i}$ denotes average HDD and average CDD of month $\mathrm{i^{th}}$, $\mathrm{T_i}$ represents the temperature of month $\mathrm{i^{th}}$ in degree C and $\mathrm{T_{HB}}$ is the base temperature of HDD and $\mathrm{T_{CB}}$ is the base temperature of CDD.

$$\mathrm{HDD} = \sum_{\mathrm{i=1}}^{12} \mathrm{H_i}$$

$$\begin{cases} \mathrm{H_i = T_{HB} - T_i \ (if\ T_i < T_{HB})} \\ \mathrm{H_i = 0 \ (if\ T_i > T_{HB})} \end{cases}$$

$$\mathrm{CDD} = \sum_{\mathrm{i=1}}^{365} \mathrm{C_i}$$

$$\begin{cases} \mathrm{C_i = T_i - T_{CB} \ (if\ T_i > T_{CB})} \\ \mathrm{C_i = 0 \ (if\ T_i < T_{CB})} \end{cases}$$

Results on HDD and CDD in 6 cities in Japan and Vietnam is shown in Table 7-1 and Table 7-2 with detailed geographical information. Climate zone and climate characteristics. Climate zone can be referred in Asia Climate zones map by ASHARE [10]. Cities with the higher latitude reveals higher HDD and lower CDD.

Table 7- 1. Heating degree days and Cooling degree days in Vietnam. Weather data calculated by Degree Days.net [4],

Cities	Latitude (° N)	Longti-tude (° N)	Climate zone code	Climate characteristics	Heating degree days (HDD 16)	Cooling degree days (CDD 26)
Ca Mau	9.2	105.2	0A	Extremely Hot Humid	0	820
Rach Gia	10.0	105.9	0A	Extremely Hot Humid	0	-
Can Tho	10.0	105.7	0A	Extremely Hot Humid	0	-
Ho Chi Minh	10.8	106.7	0A	Extremely Hot Humid	0	956.5
Phan Thiet	10.9	108.1	0A	Extremely Hot Humid	0	716.3
Buon Ma Thuot	12.7	108.1	1A	Very Hot Humid	0	-
Nha Trang	12.3	109.2	0A	Extremely Hot Humid	0	721.9
Quy Nhon	13.8	109.2	0A	Extremely Hot Humid	0	796.6
Pleiku	14.0	108.0	2A	Hot Humid	0	193.7
Da Nang	16.0	108.2	1A	Very Hot Humid	0	779
Quang Tri	16.7	107.2	1A	Very Hot Humid	0	-
Dong Hoi	17.5	106.6	1A	Very Hot Humid	0	-
Thanh Hoa	19.8	105.8	1A	Very Hot Humid	0	594.9
Hanoi	21.02	105.8	2A	Hot Humid	82.2	633.9
Hai Phong	20.8	106.6	1A	Very Hot Humid	119.9	497.2
Son La	21.3	103.9	2A	Hot Humid	121.2	271.1
Mong Cai	21.5	108.0	2A	Hot Humid	279.2	-
Lang Son	21.8	106.8	2A	Hot Humid		378.6
Lao Cai	22.5	104.0	1A	Very Hot Humid	367.8	0.3

Cao Bang	22.7	106.3	2A	Hot Humid	1303.9	428.8

Table 7- 2. Heating degree days and Cooling degree days in Japan. Weather data calculated by Degree Days.net [4]

Cities	Latitude (^{o} N)	Longti-tude	Climate zone code	Climate characteristics	Heating degree days (HDD 16)	Cooling degree days (CDD 26)
Naha	26.2	127.7	2A	Hot Humid	27.5	358.9
Kagoshima	31.6	130.6	3A	Warm Humid	642.9	220.4
Nagasaki	32.7	129.9	3A	Warm Humid	867.8	148.4
Fukuoka	33.6	130.5	3A	Warm Humid	1019.5	175.3
Kochi	33.6	133.6	3A	Warm Humid	932.9	154.4
Kitakyushu	33.8	131.0	3A	Warm Humid	966.7	115.9
Hiroshima	34.4	132.5	3A	Warm Humid	1127.1	177
Osaka	34.7	235.5	3A	Warm Humid	1011.7	211.4
Nagoya	35.3	136.9	3A	Warm Humid	1174.3	191.8
Tokyo	35.7	139.8	3A	Warm Humid	1126.1	138.7
Matsumoto	36.3	138.0	4A	Mixed Humid	2122.7	90.5
Onahama	37.0	140.9	4A	Mixed Humid	2064.6	43.5
Niigata	37.9	139.0	4A	Mixed Humid	1655.4	100.7
Sendai	38.3	140.9	4A	Mixed Humid	1772.2	57.9
Akita	39.7	140.1	4A	Mixed Humid	2110.5	78.8
Aomori	40.8	140.8	5A	Cool Humid	2399.9	39.4
Sapporo	43.1	141.3	5A	Cool Humid	2806.9	36.3
Nemuro	43.3	145.6	6A	Cold Humid	3322.4	1.8
Asahikawa	43.8	142.4	6A	Cold Humid	3488.2	49.4

Wakkanai	45.4	141.7	6A	Cold Humid	3315.6	4.4

7.3. Building energy modeling and framework

7.3.1. Building energy modeling

7.3.1.1 Weather file map

The weather data used for energy simulation are EPW files derived from different sources which was uploaded in weather files maps [4] and climate/weather data sources [12]. In this dataset, An EPW file can be divided into two parts, headers and weather data. The first eight lines of a standard EPW file are normally headers which contains data of location, design conditions, typical/extreme periods, ground temperatures, holidays/daylight savings, data periods and other comments. There are 35 variables in the core weather data [13]: dry bulb temperature, dew point temperature, relative humidity, atmospheric pressure, horizontal infrared radiation intensity from sky, direct normal radiation, diffuse horizontal radiation, wind direction, wind speed, present weather observation, present weather codes, snow depth, liquid precipitation depth.

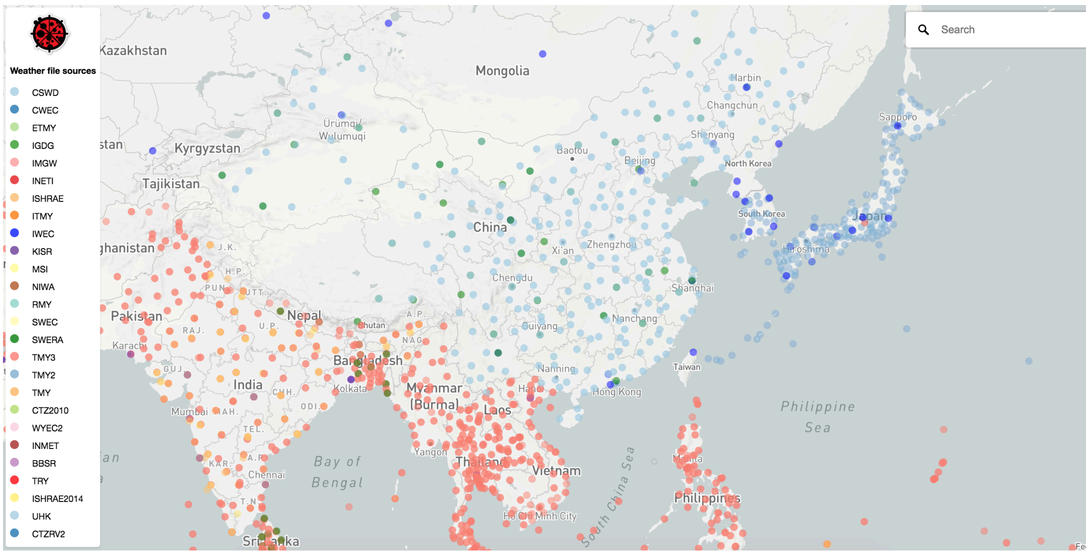

Fig. 7- 6. Weather files map [4]

7.3.1.2. House floor plan in two case studies

The selected floor plan of two models A and B in Japan and Vietnam (Fig. 7-8 a, b) is based on the typical real apartment floor plan in Kitakyushu (Japan) and Ho Chi Minh city (Vietnam). These two designs have the same floor area and three bedrooms. However, there are still difference in the direction of the main facades where JP VN house balcony is facing to the south and southeast while VN house balcony is facing to the north and west. In JP house, three bedrooms are located in the north while common space (including kitchen, living room and dining room) is in the south of the apartment. In contrast, VN house's bedrooms are located in the west and the common room was designed to be in the west of building. JP house has a lobby connecting the entrance to living room when JP house's entrance directly connects to the living room and kitchen. There is more toilet in VN house (three) while storages occupy more spaces in JP house's bedrooms. The 3D energy models were built by OpenStudio Plugin on Sketchup before exporting to EnergyPlus simulation to predict the energy consumption and other output parameters (Fig. 7-9 a, b).

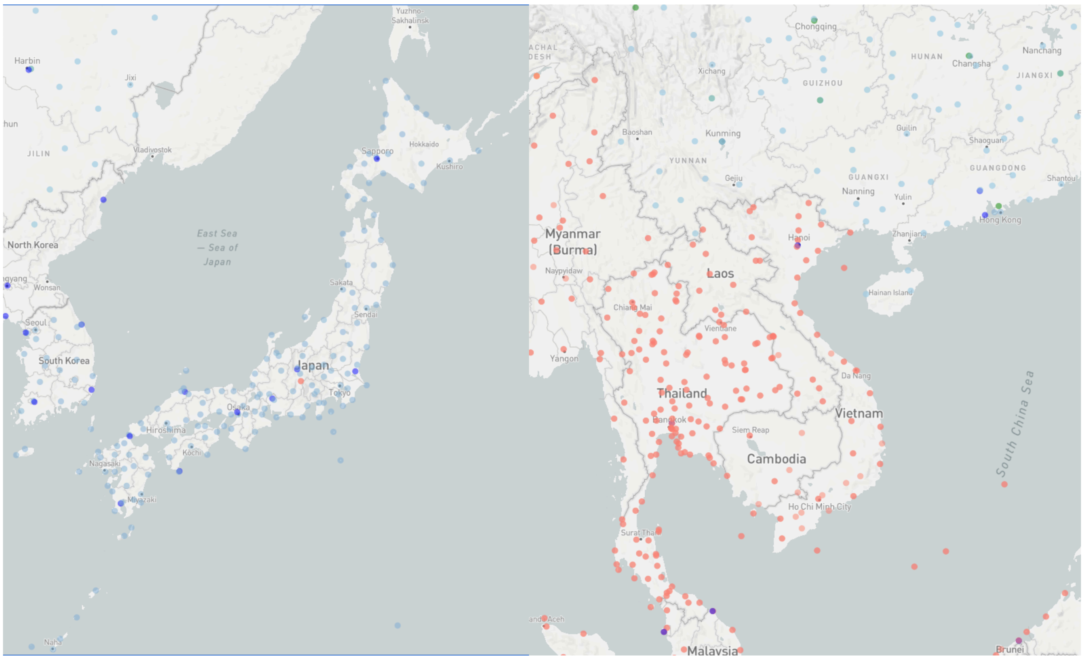

Fig. 7- 7. Location of the housing models. JP house (left) in Japan, VN house (right) in Vietnam

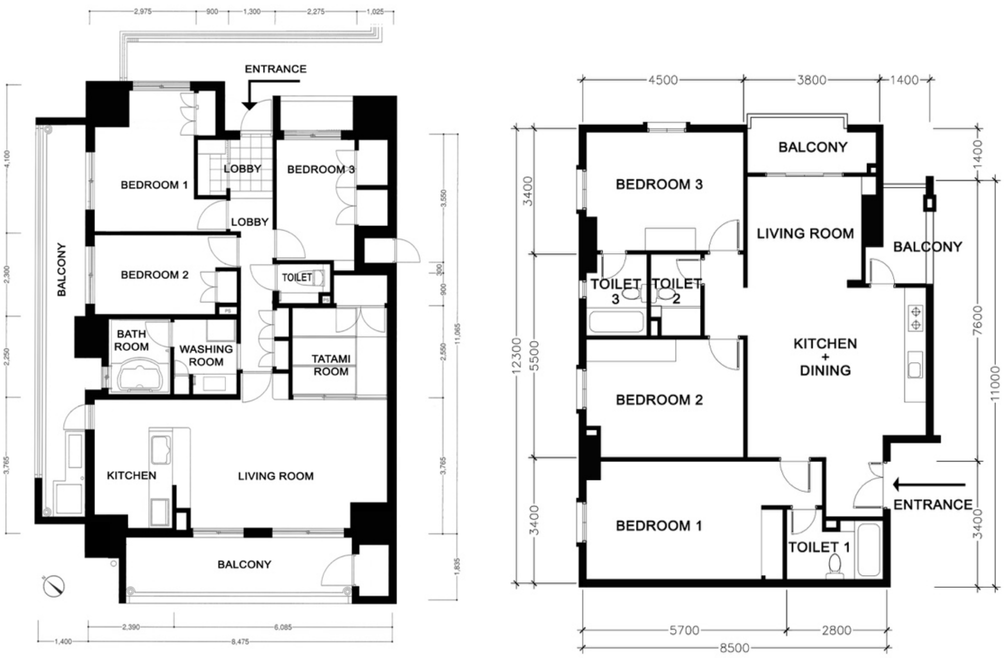

Fig. 7- 8. a) Housing floor plan A (house in Japan), b) Housing floor plan B (house in Vietnam)

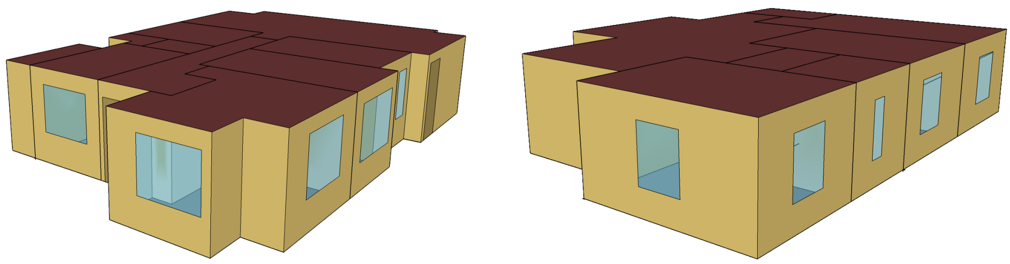

Fig. 7- 9. a) 3D-EnergyPlus model A (house in Japan), b) 3D-EnergyPlus model B (house in Vietnam)

7.3.2. Framework

The structure of this section is following as Fig. 7-10 including 4 steps of energy simulation and energy modeling analysis before the final conclusion of the comparison study. In the first step, we built two energy models on 3D Sketchup to represent two housing style in Japan and in Vietnam. In the second step, annual energy consumption and monthly energy consumption of the two houses style will be simulated in 6 cities in Japan and Vietnam. The next step is the comparison study where total energy consumption will be put together to analyze and compare by locations, housing orientation, and energy use scenarios. The energy comparison map will expand the locations to 40 cities (20 cities in Japan and 20 cities in Vietnam) to display the difference of energy consumption by regions in two countries. Discussion can be made after considering sensitivity of influencing factors which cause the difference among energy consumption in the simulated models.

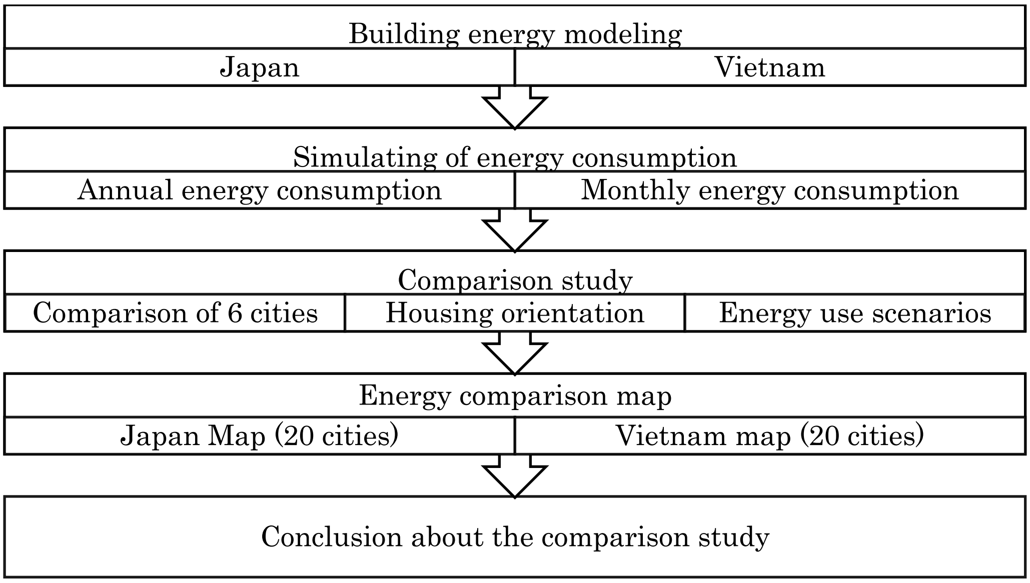

Fig. 7- 10. Framework

7.4. Results and analysis

7.4.1 Comparison study

7.4.1.1. Results of the annual energy consumption in 6 cities of Japan and Vietnam

The results of annual energy consumption in 6 cases shows that VN house style consumes more energy if it locates in Japan and vice versa, JP house styles need more energy use if it locates in VN, however, this number is smaller compared to the difference between two housing styles in Japan. An increase of energy use is corresponding with cities with greater latitudes in Japan, but decreasing with the increasing latitude number in Vietnam's cities. According to Fig. 7-11, major usage belongs to heating systems in Japan's cities while cooling use accounts for most of energy consumption in Vietnam due to the high average temperature and high CDD in Vietnam.

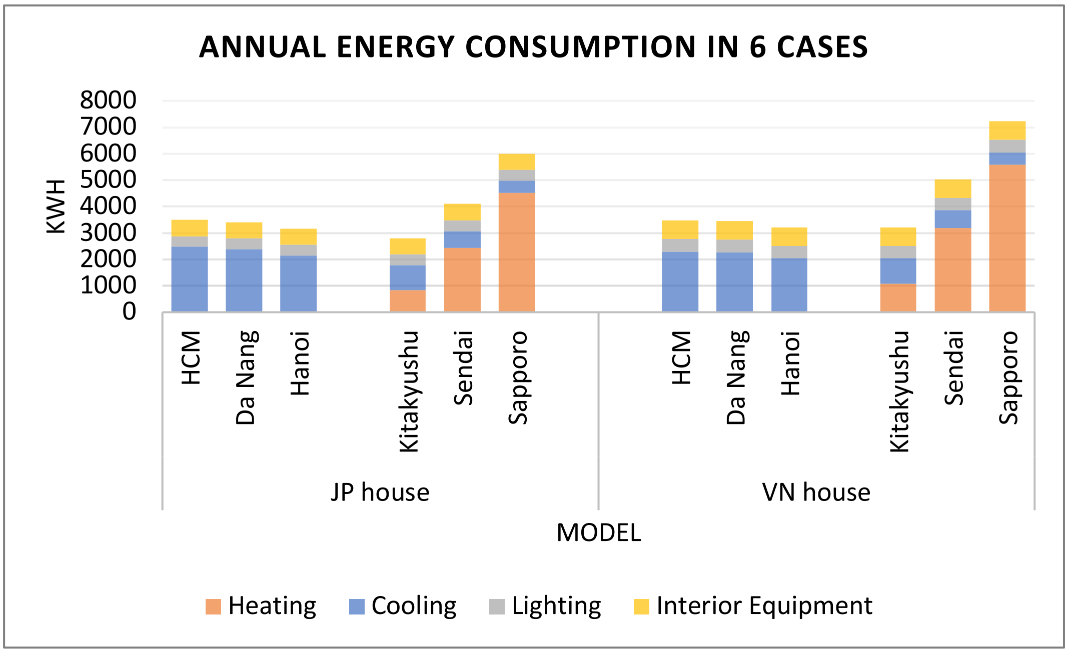

Fig. 7- 11. Annual energy consumption in 6 cases

7.4.1.2. Results of monthly energy consumption in 6 areas

Results shows that monthly energy consumption in Ho Chi Minh and Da Nang is stable throughout the year that is less than 400 kWh and the monthly energy consumption is Hanoi is higher in summer and lower in winter due to the need of cooling air conditioning. Heating usage is only found in January of Hanoi with very negligible amount. In Japan, even though the peak cooling energy use in summer reveal the same among three cities, the heating energy use in winter is significant different from Kitakyushu to Sapporo, especially in January.

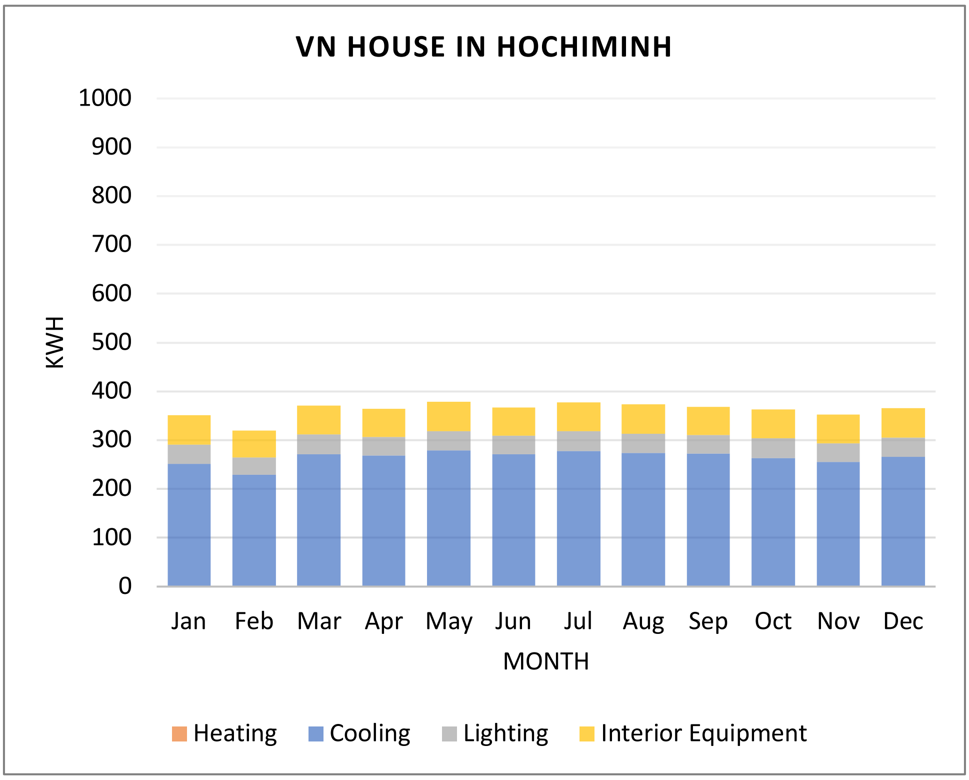

Fig. 7- 12. Monthly energy consumption of VN house in Ho Chi Minh

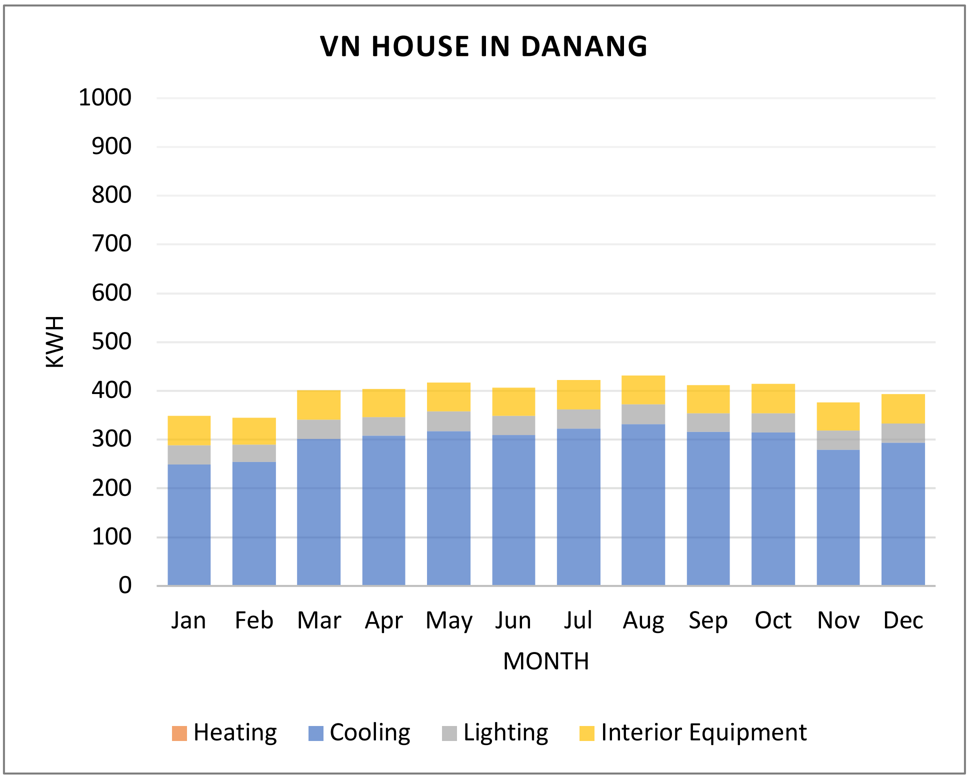

Fig. 7- 13. Monthly energy consumption of VN house in Da Nang

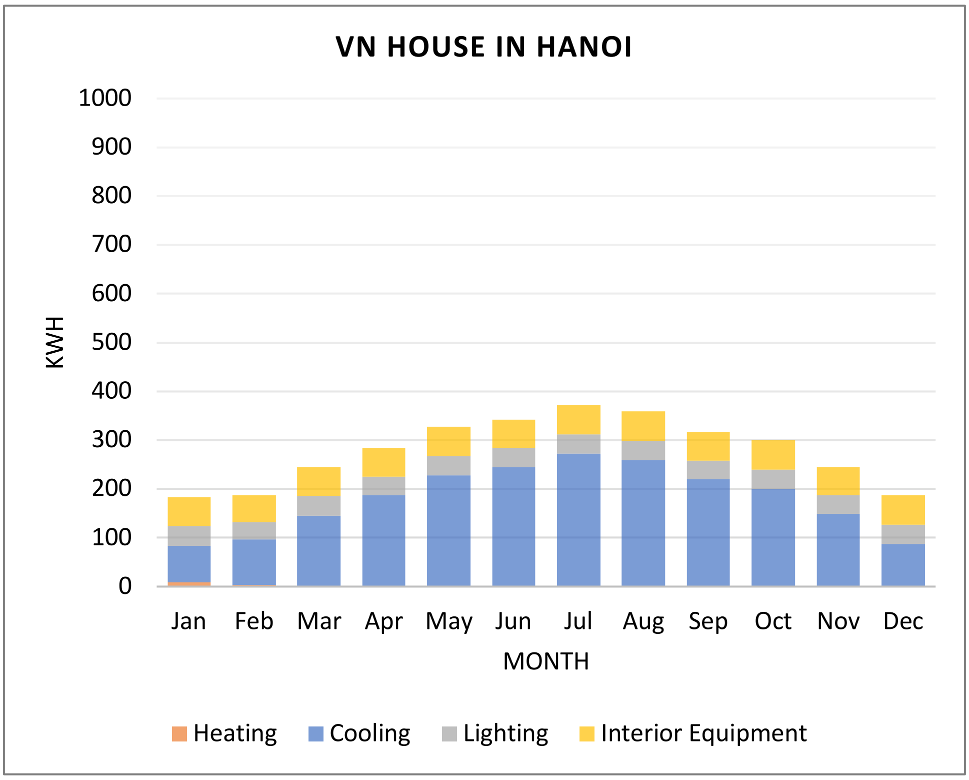

Fig. 7- 14. Monthly energy consumption of VN house in Da Nang

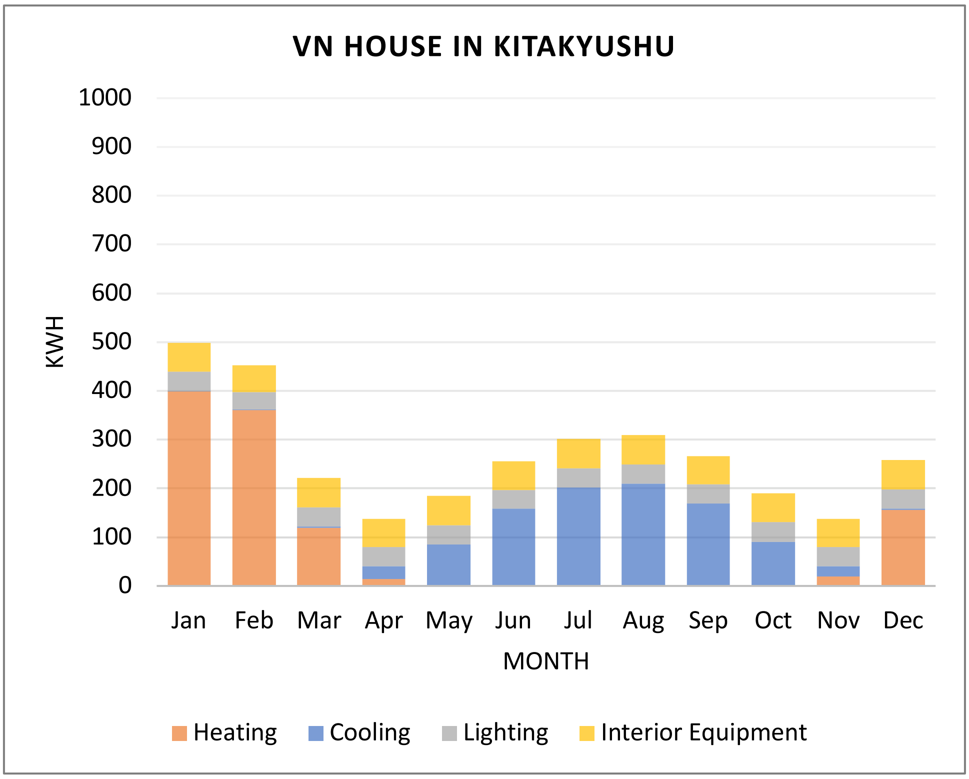

Fig. 7- 15. Monthly energy consumption of VN house in Kitakyushu

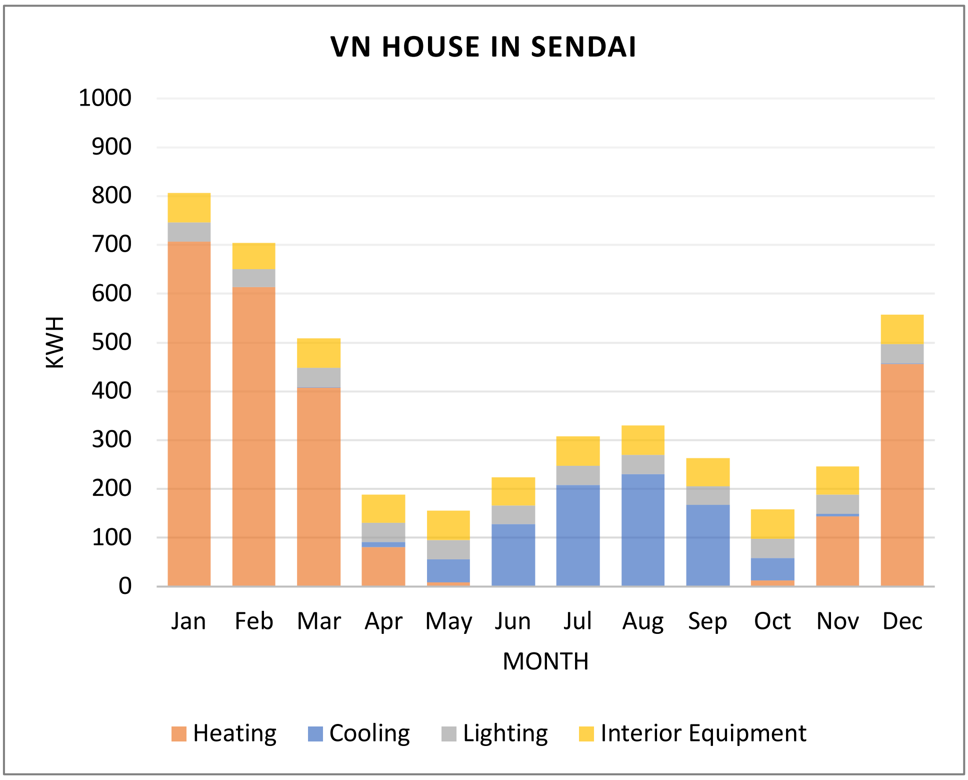

Fig. 7- 16. Monthly energy consumption of VN house in Sendai

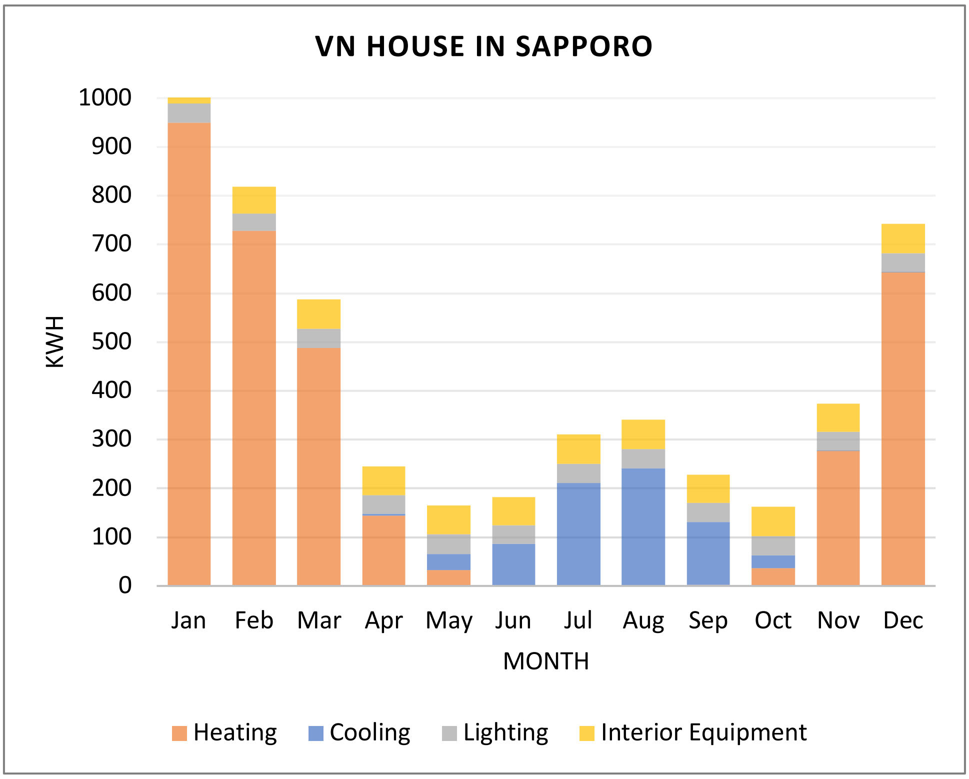

Fig. 7- 17. Monthly energy consumption of VN house in Sapporo

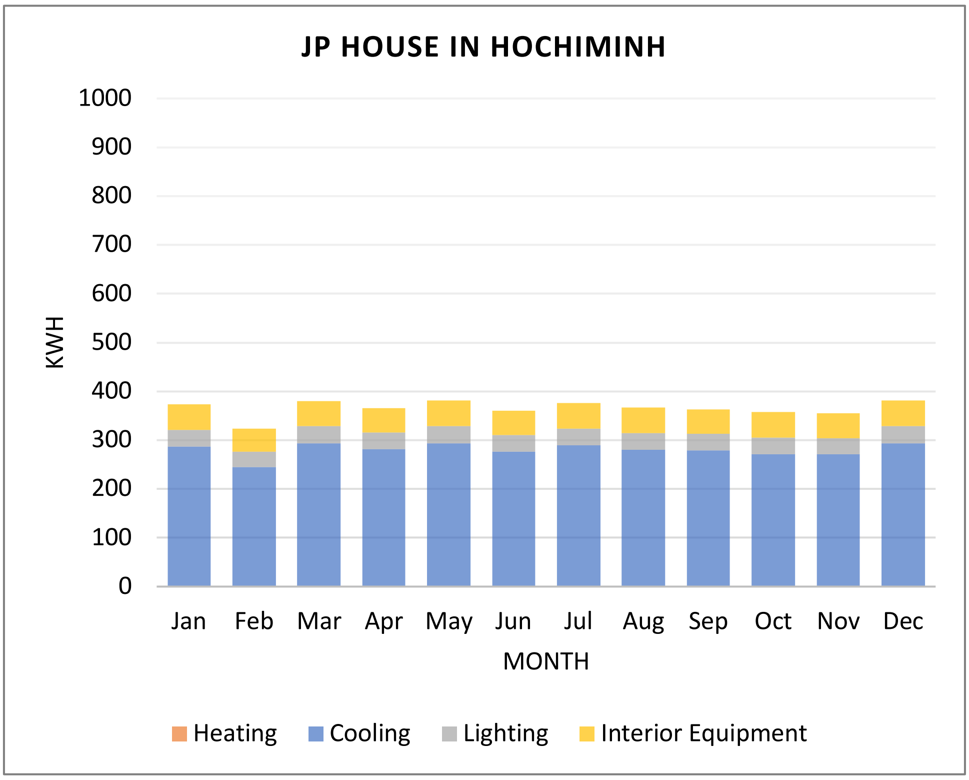

Fig. 7- 18. Monthly energy consumption of JP house in Ho Chi Minh

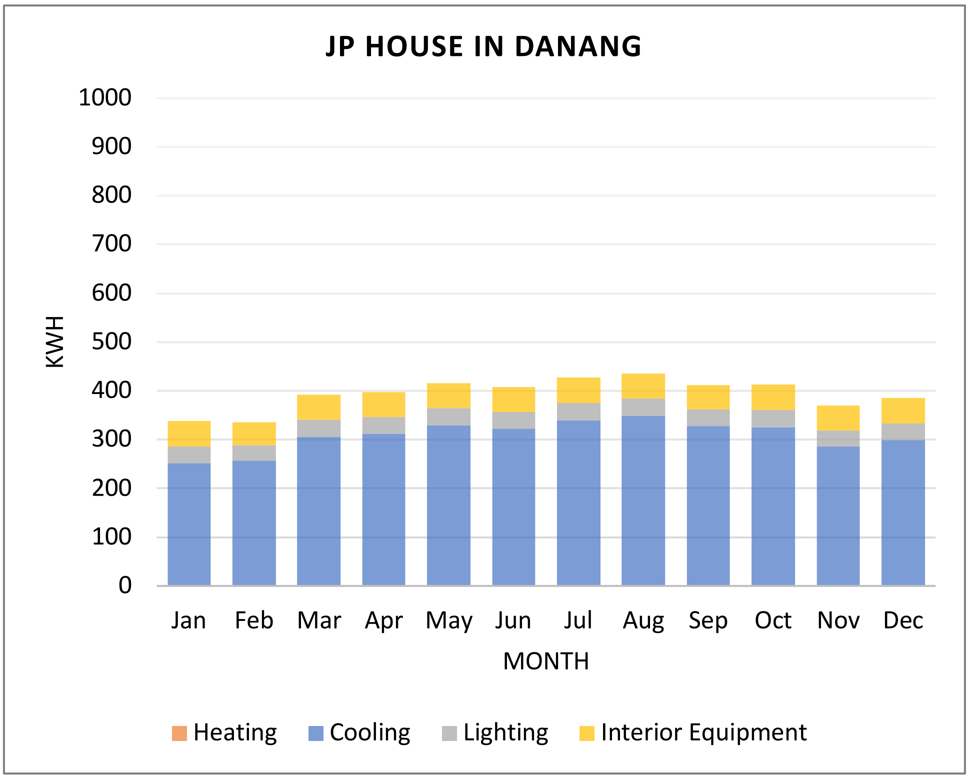

Fig. 7- 19. Monthly energy consumption of JP house in Da Nang

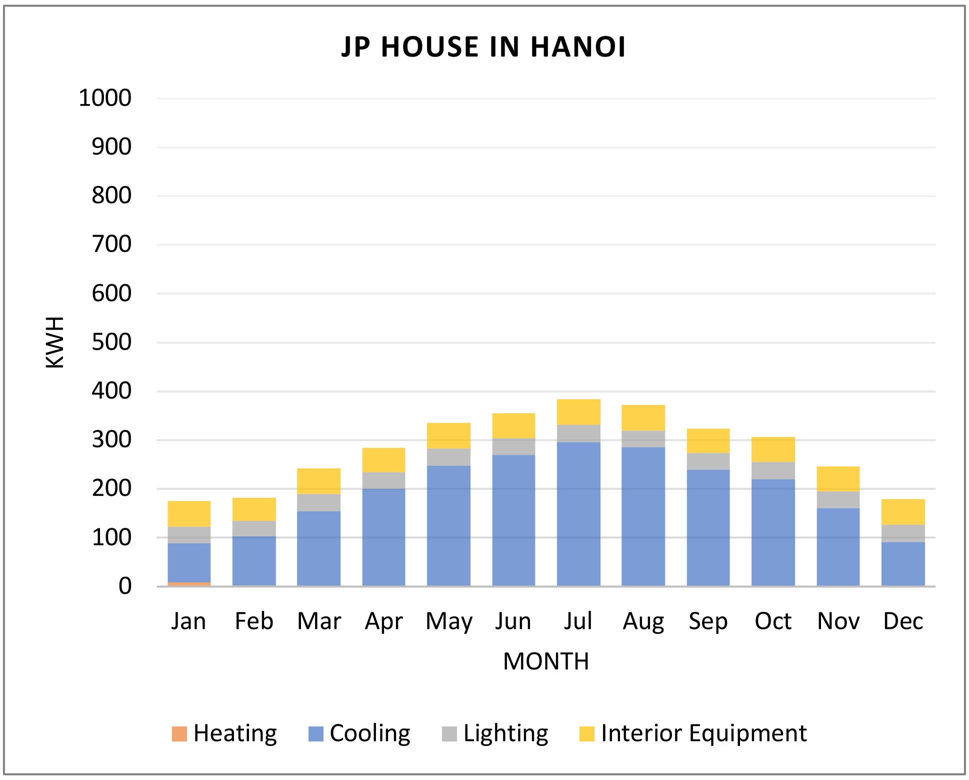

Fig. 7- 20. Monthly energy consumption of JP house in Hanoi

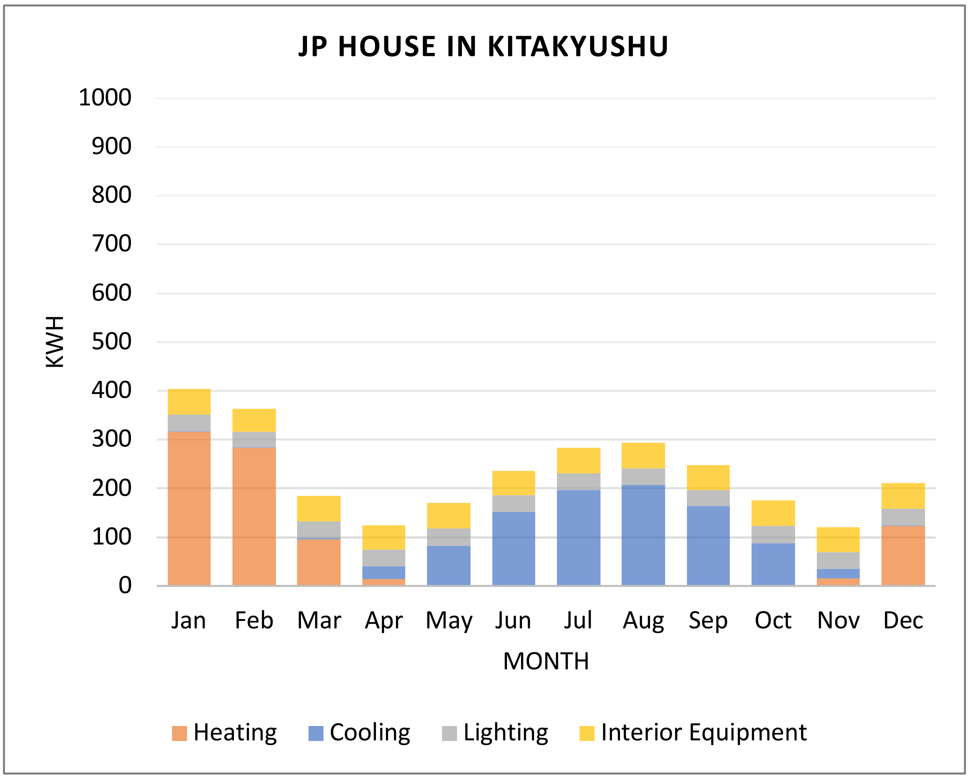

Fig. 7- 21. Monthly energy consumption of JP house in Kitakyushu

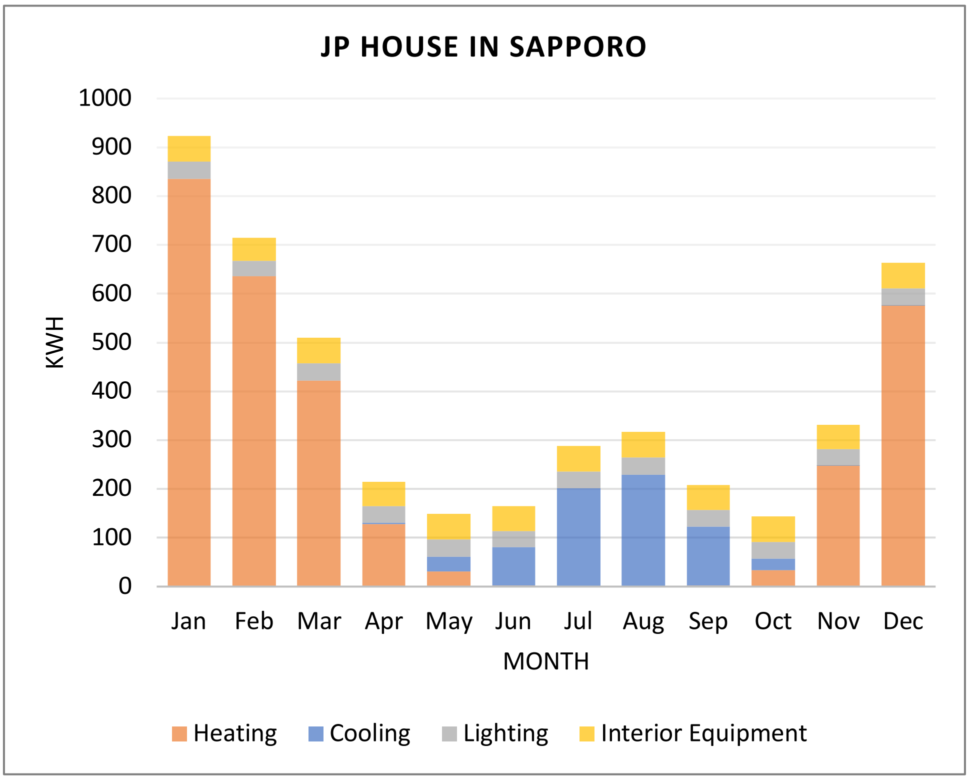

Fig. 7- 22. Monthly energy consumption of JP house in Sapporo

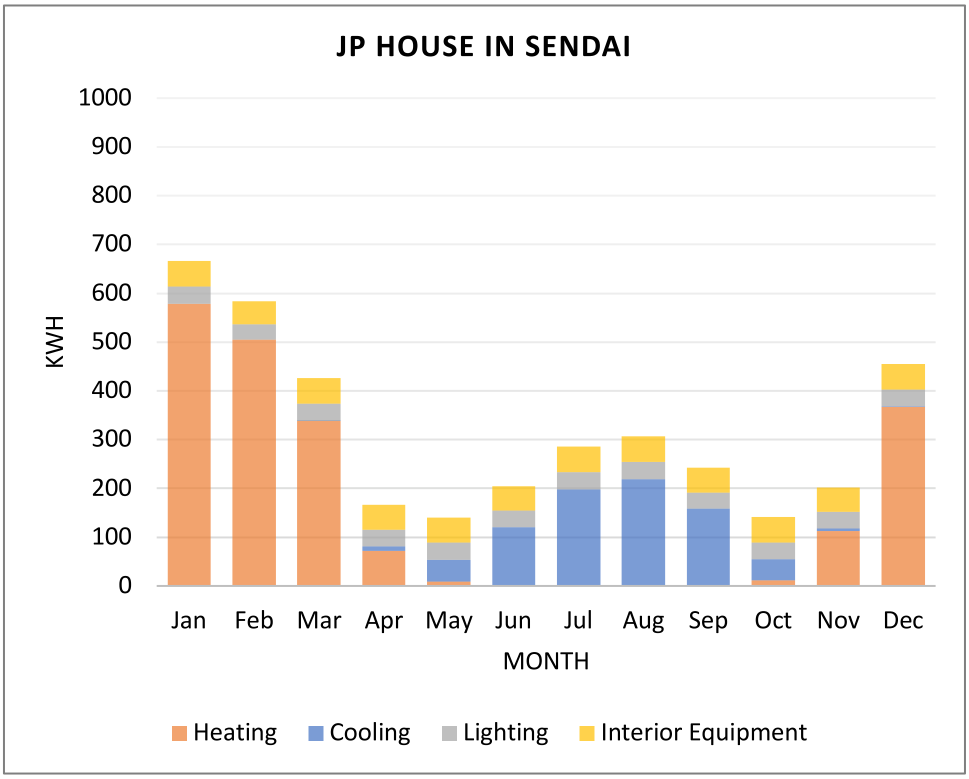

Fig. 7- 23. Monthly energy consumption of JP house in Sendai

7.4.1.3 Comparison of Energy use modeling by orientation

This section examines the variant performance of annual energy use when changing the direction of a house. The first selected housing model is JP house which is assumed to be sited in Kitakyushu and the second housing model is VN house in Ho Chi Minh. Both of two models have a same designated energy use pattern. The only variable parameter among them are housing direction that is modified in 3D energy models. We chose 8 directions of the main facades: North (0 degree), Northeast (45 degree), East (90 degree), Southeast (135 degree), South (180 degree), Southwest (225 degree), West (270 degree), Northwest (315 degree). Results in Fig. 7-24 shows that the energy consumption of JP house in Kitakyushu reach the peak when the living room direction face to the west and bedroom's window main direction face to the East. When this model turns the living room direction to the West and Bedroom's window main direction to the South, energy consumption can achieve the most saving status. However, the energy results of modeling in VN house in Ho Chi Minh seems to be fixed with all the directions. This finding can be explained by the stable condition of climate in Ho Chi Minh and the cold winter in Kitakyushu. Therefore, housing orientation is more important for cities in higher latitudes, and the South direction is recommended for designing bedroom's windows.

Table 7- 3 Model orientations

Model location	Degree	Direction	Living room direction	Bedroom's window main direction
Kitakyushu	0	North	South	North
	45	Northeast	Southwest	Northeast
	90	**East**	**West**	**East**
	135	Southeast	Northwest	Southeast
	180	**South**	**North**	**South**
	225	Southwest	Northeast	Southwest
	270	West	East	West
	315	Northwest	Southeast	Northwest
Ho Chi Minh	0	North	North	West
	45	Northeast	Northeast	Northwest
	90	East	East	North
	135	Southeast	Southeast	Northeast
	180	South	South	East
	225	Southwest	Southwest	Southeast
	270	West	West	South
	315	Northwest	Northwest	Southwest

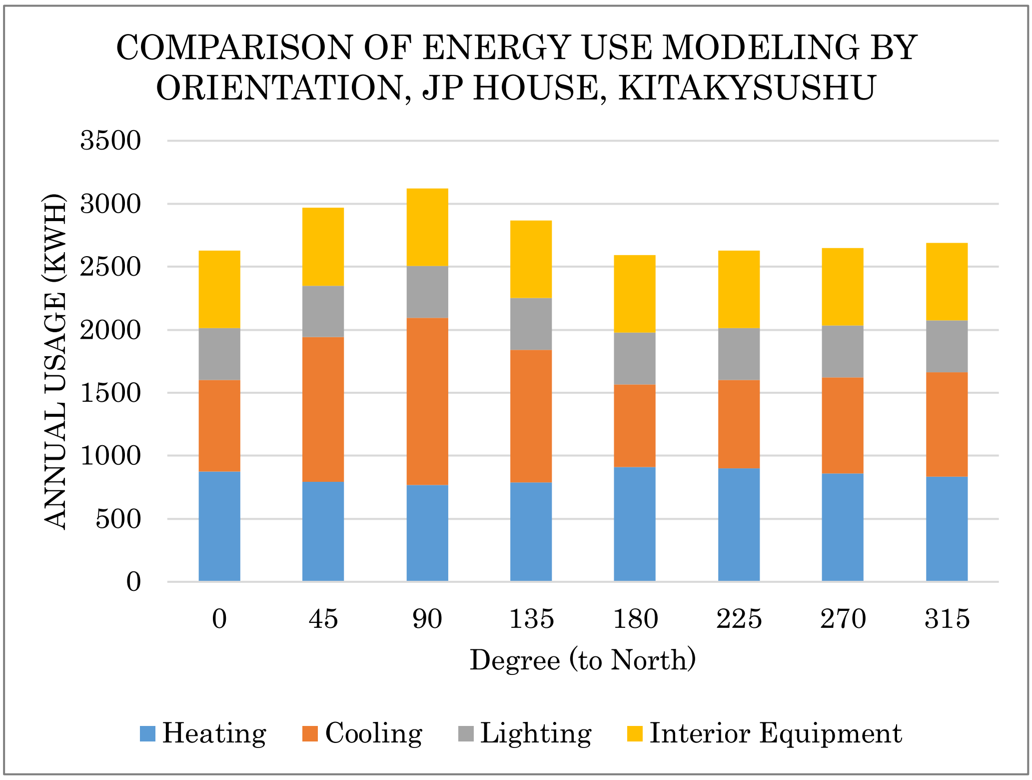

Fig. 7- 24. Comparison of energy use modeling by orientation, JP house Kitakyushu.

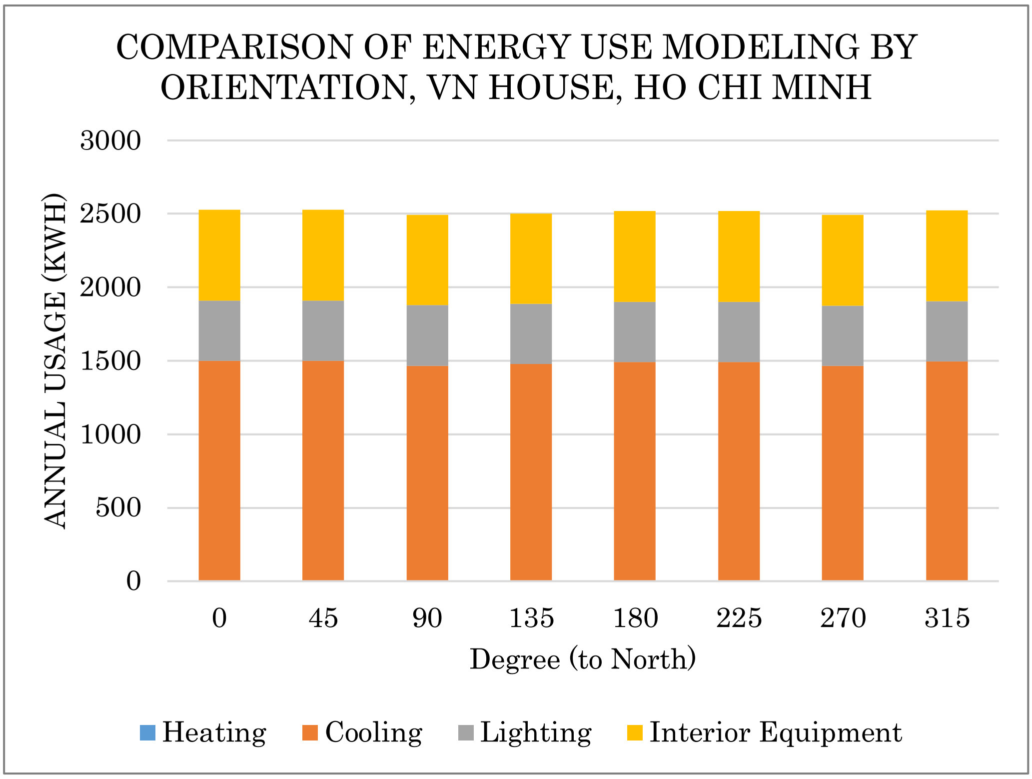

Fig. 7- 25. Comparison of energy use modeling by orientation, VN house, Ho Chi Minh.

7.4.2.4. Application of three setting modes (patterns) representing different energy use intensities (usage styles)

Study in previous section have shown the sensitivity analysis on air conditioning setpoint mode by comparing different levels of air conditioning temperature setpoint. In this section, three levels of air conditioning use are classified and compared among cities in Japan and Vietnam. The setpoint is designated depending on average air temperature relating human thermal comfort (complies with ASHRAE Standard 55-2020 [14]). For the acceptable air temperature in summer, 28^{o} C or lower is consider comfortable while 16^{o} C or higher temperature is acceptable in winter with thicker clothes. The scenarios are classified in Table 7-3 where three levels of energy usage: High intensity, middle intensity and low intensity are specified with cooling setpoint and heating setpoint of air conditioning in the context of thermal comfort.

After applying these scenarios on the energy modelling, results of energy performance are displayed in Fig. 7-26 and Fig. 7-27.

Table 7- 4 Scenarios of energy usage

Scenario A: **High intensity of energy usage**	**Scenario B:** **Middle intensity of energy usage**	**Scenario C:** **Low intensity of energy usage**
1. Cooling: setpoint **24^{o} C**	**1. Cooling:** setpoint **26^{o} C**	**1. Cooling:** setpoint **28^{o} C**
Cooling set on if indoor temp is:	Cooling set on if indoor temp is:	Cooling set on if indoor temp is:
- **> 24^{o} C** in Summer	- **> 26^{o} C** in Summer	- **>28^{o} C** in Summer
- **>24^{o} C** in Winter	- **>26^{o} C** in Winter	- **>28^{o} C** in Winter
2. Heating: setpoint **20^{o} C**	**2. Heating:** setpoint **18^{o} C**	**2. Heating:** setpoint **16^{o} C**
Heating set on if indoor temp is:	Heating set on if indoor temp is:	Heating set on if indoor temp is:
- **<20^{o} C** in Summer	- **<18^{o} C** in Summer	- **<16^{o} C** in Summer
- **<20^{o} C** in Winter	- **<18^{o} C** in Winter	- **<16^{o} C** in Winter

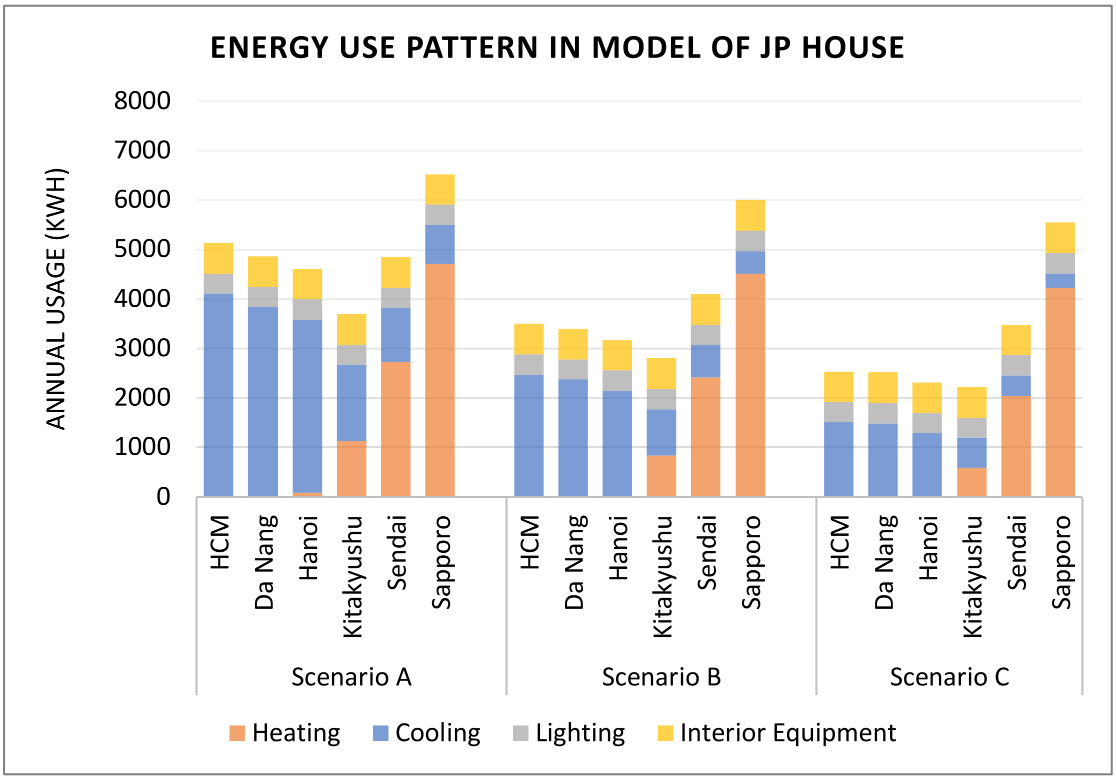

Fig. 7- 26. Energy use pattern in model of Japanese house

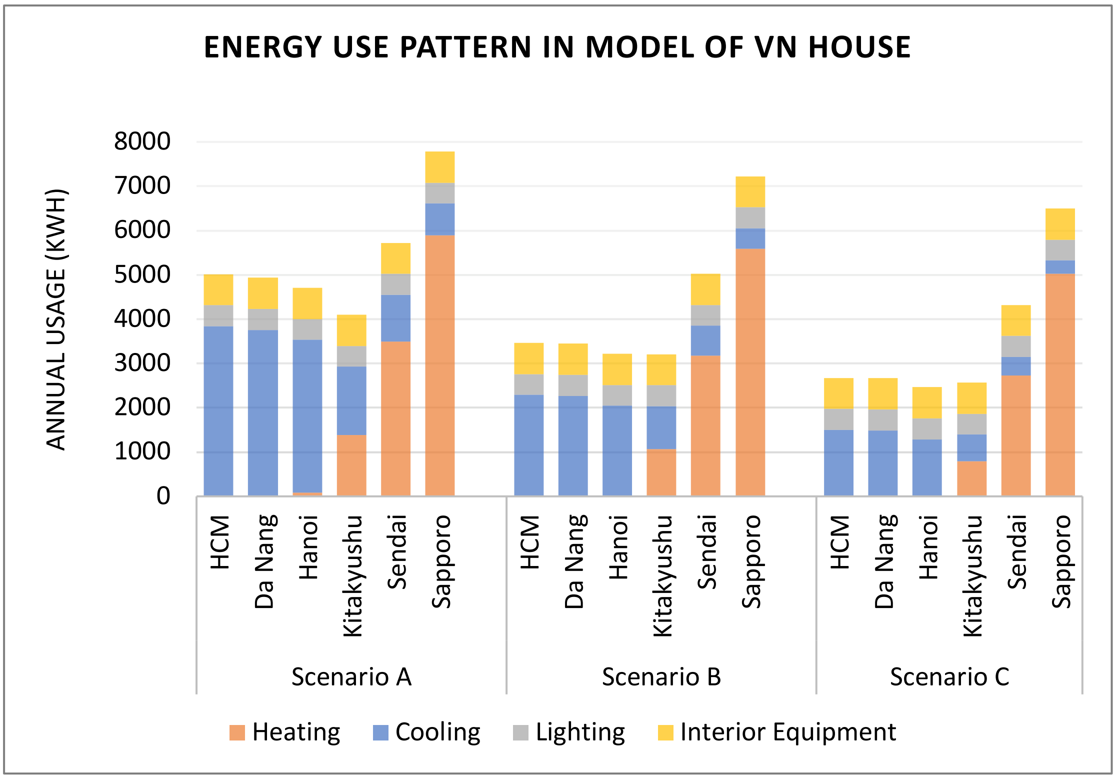

Fig. 7- 27. Energy use pattern in model of Vietnamese

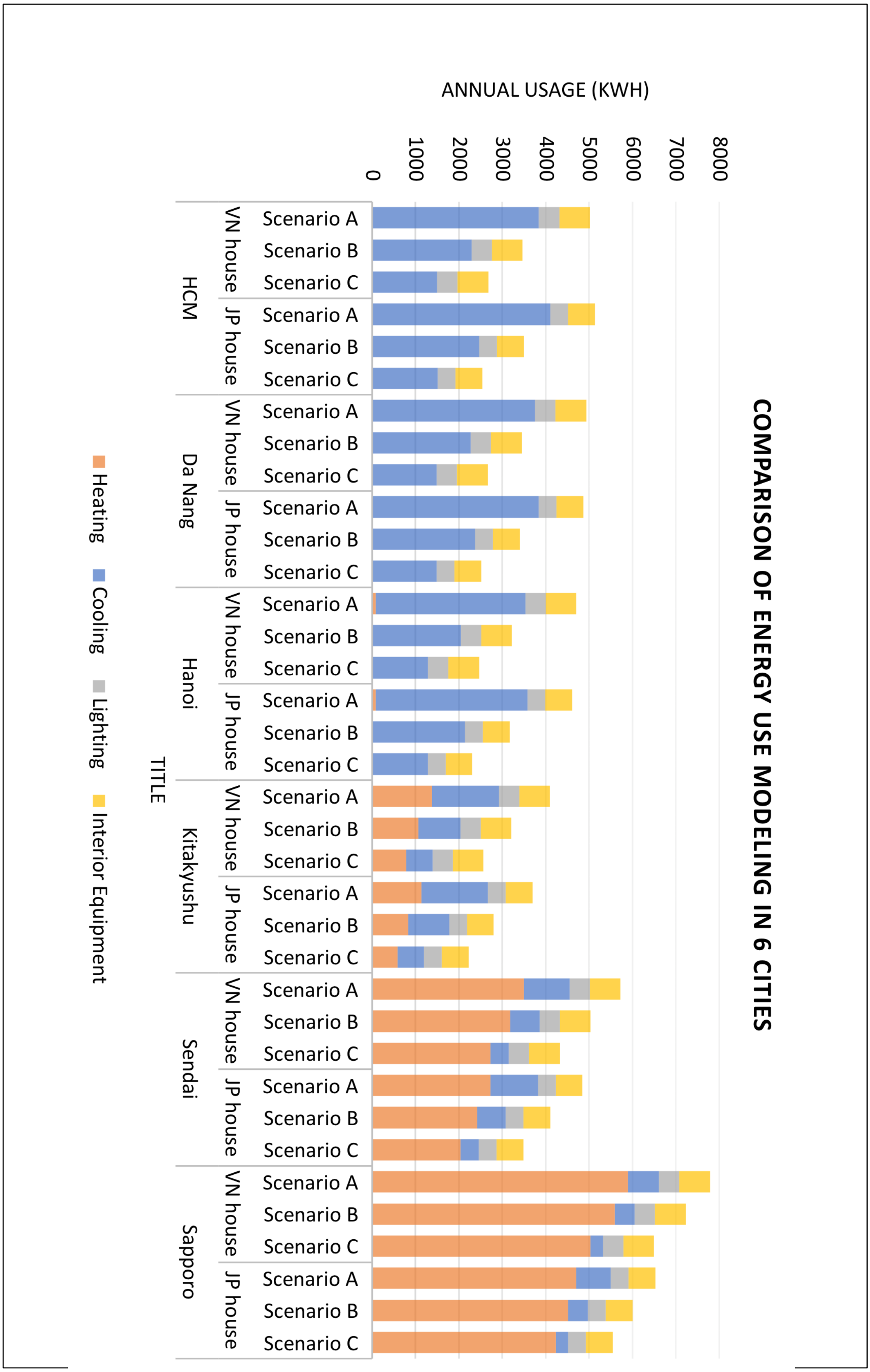

Fig. 7- 28. Comparison of energy use modeling in 6 cities of Japan and Vietnam

7.4.2. Energy consumption by geographical location

7.4.2.1 Comparison of Energy consumption in 40 cities in Japan and Vietnam

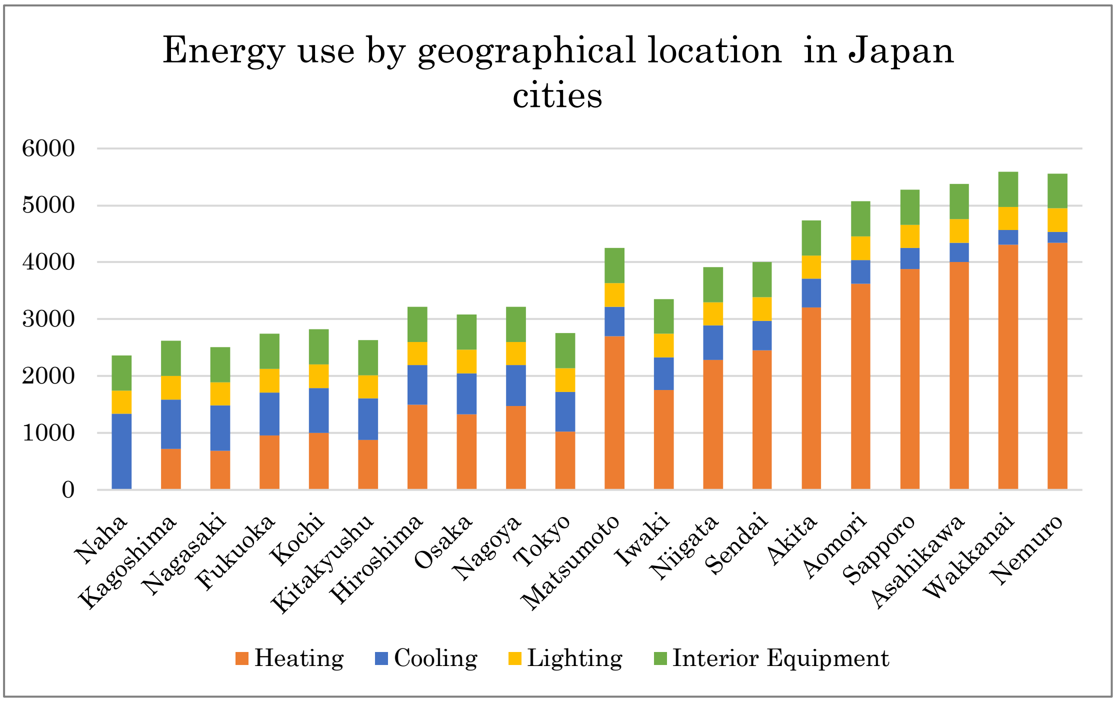

Fig. 7- 29. Energy use by geographical location in Japan

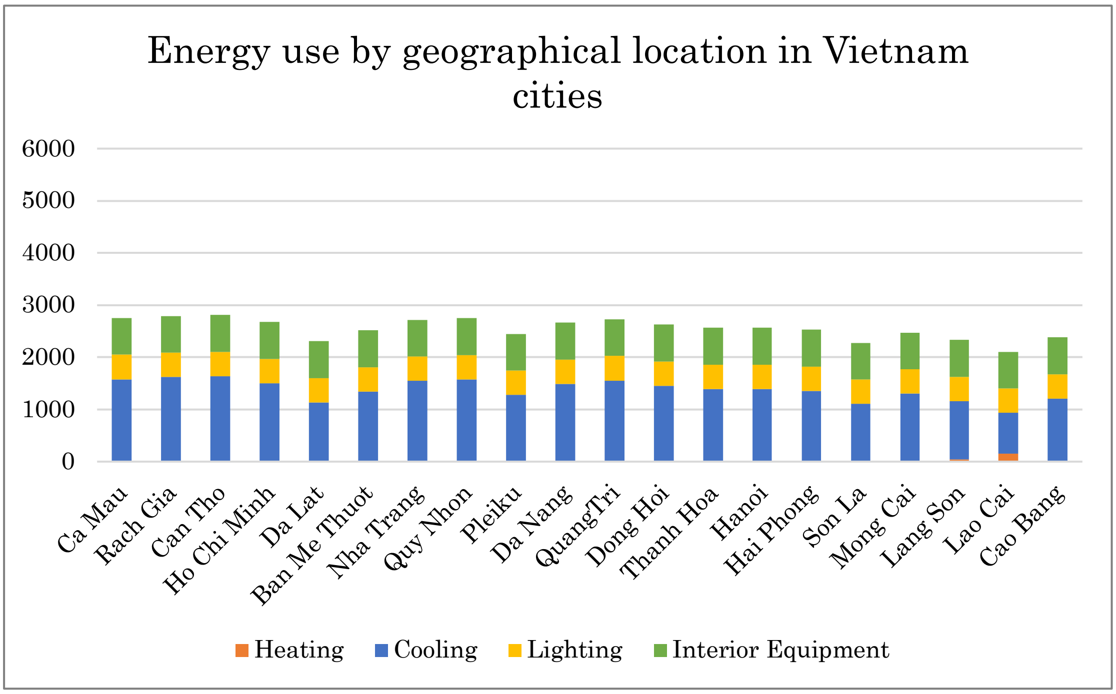

Fig. 7- 30. Energy use by geographical location in Vietnam

The comparison of energy use by geographical location shows that in the mild climate region with warm humid, cool humid, cold and very cold humid zones such as Japan (3A, 4A, 5A, 6A), household locations in greater latitudes tend to go with higher energy consumption due to the demand on heating system. However, in the hot humid zones such as Vietnam (0A, 1A, 2A), household locations in greater latitudes shows less energy consumption based on the need of cooling use). The North of Japan consumes more HVAC energy while the South of Vietnam spends more HVAC energy in residential houses.

7.4.2.2. Correlation between energy modeling HVAC and HDD, CDD

To see the relationship between HDD and heating energy consumption, correlation plot was drawn from the modeling data of 20 cities in Japan (Fig. 7-31) and 20 cities in Vietnam (Fig. 7-32). Results indicate that the heating modeling is better proportional and fitted with the HDD (at the setpoint 16) where R^2 equal to 0.95. Therefore, we can use linear regression using observed data from HDD for predicting heating use and cooling use in these cases.

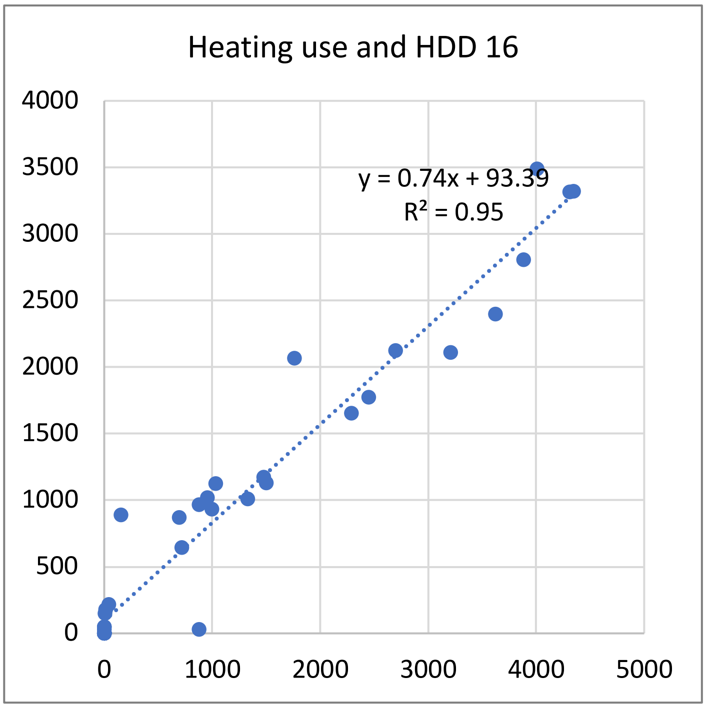

Fig. 7- 31. Correlation between heating consumption and HDD

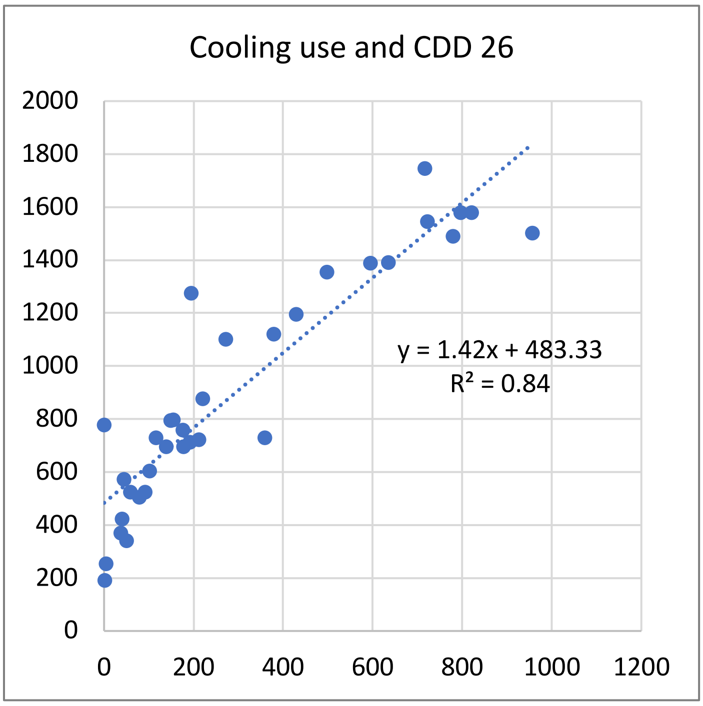

Fig. 7- 32. Correlation between Cooling consumption and CDD

7.5. Conclusion

In conclusion, the energy performance of a building is strictly dependent on the climatic conditions. The Heating Degree Days (HDD) and Cooling Degree Days (CDD) value index and can be used to evaluate. Comparing among 6 cities in Japan and Vietnam, an increase of EEU is corresponding with cities with greater latitudes in Japan, but decreasing with the increasing latitude number in Vietnam's cities. Major usage belongs to heating systems in Japan's cities while cooling use accounts for most of EEU in Vietnam due to high HDD in Japan and high CDD in Vietnam.

Regarding the impact of housing orientation, EEU of JP house in Kitakyushu reach the peak when the living room direction face to the west and bedroom's direction face to the East. When this model turns the living room direction to the West and Bedroom's window main direction to the South, energy consumption can achieve the most saving status. The energy results of modeling in VN house in Ho Chi Minh seems to be fixed with all the directions. This finding can be explained by the stable condition of climate in Ho Chi Minh and the cold winter in Kitakyushu. Therefore, housing orientation is more important for cities in higher latitudes, and the South direction is recommended for designing bedroom's windows.

In terms of energy use pattern related to ACS, the setpoint is designated depending on average air temperature relating human thermal comfort. The scenarios of three levels of energy usage results in differentiate energy-saving probabilities by regions. It indicates that comparing to Scenario A, Scenario C perform the lowest EEU which saving around 50% in VN's cities and 14%

to 50% in JP's cities. Energy efficiency is clearer in VN cities than JP cities due to the significant saving for ACC. Scenario C in JP house in Kitakyushu presents lowest EEU while Scenario A in VN house if located in Sapporo accounts for highest EEU.

The comparison of energy use by geographical location shows that in the mild climate region with warm humid, cool humid, cold and very cold humid zones such as Japan (3A, 4A, 5A, 6A), household locations in greater latitudes tend to go with higher energy consumption due to the demand on heating system. However, in the hot humid zones such as Vietnam (0A, 1A, 2A), household locations in greater latitudes shows less energy consumption based on the need of cooling use). The North of Japan consumes more HVAC energy while the South of Vietnam spends more HVAC energy in residential houses.

In terms of the relationship between HDD and heating energy consumption, correlation plot was drawn from the modeling data of 20 cities in Japan and 20 cities in Vietnam. Results indicate that the heating modeling is better proportional and fitted with the HDD (at the setpoint 16) where R^2 equal to 0.95. using observed. Therefore, we can use linear regression data from HDD for predicting heating use and cooling use in these cases.

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Chapter 8

CONCLUSION AND PROSPECT

CHAPTER EIGHT: CONCLUSION AND PROSPECT

8.1 Conclusion

In the post-industrialization century, and with the impact of social crisis such as COVID-19 when more activities pour into the residential area leading to a significant change in the use of electrical appliances, which affect the household energy use, household energy tends to become the main share instead of the industrial sector. Japan and Vietnam belong to Asia-Pacific region where total energy end-use is expected to account for 52% in 2050. To overcome the urgent need on household energy saving, this study simultaneously assesses the multiple influences of household determinants, housing design, and physics characteristics on energy end-use. The proposed research herein first aims to investigate the effects of all influencing factors on household energy consumption and to evaluate their complex relationships under different situation. Hybrid modeling combing physics-based modeling and data-driven modeling is the state-of-the-art approach to be considered for energy forecast, while factor analysis has the potential for sorting the weight of factors. The crucial impacts of determinants on Energy End-Use (EEU) is well-presented to emerge ways optimize energy use in residential area. This approach can be an example for other regions where suitable energy policies should be provided to each locality with different environmental and social characteristics. Discussion on the final results imply cognitive changes for consumers where the visualization of energy efficiency optimization can be easily captured so that environmental sustainability will be closer than ever.

The main works and results can be summarized as follows:

In Chapter 1, RESEARCH BACKGROUND AND PURPOSE OF THE STUDY. The research backgrounds of energy consumption in Japan and Vietnam are introduced in Chapter 1, which is including the current status and bottleneck of household energy end-use and related factors. Japan's electricity consumption is on a downward trend while Vietnam's is on an uptrend and the residential sector reveal the similar tendency. Electricity consumption in the household sector has been rapidly increasing and accounted for in residential area accounts for 27% in Japan and 36% in Vietnam. Recognizing the crucial role that energy efficiency plays in mitigating global environmental issues and greenhouse gases emissions, this study concentrates on the cause-effect of energy end-use in residential areas in Japan and Vietnam. The core concept is to apply the energy use optimization theory into reality. Thereby, sensitivity analysis of energy use behaviors has the potential to discuss in-depth the possibilities of adaptation in practice.

In Chapter 2, LITERATURE REVIEWS OF DETERMINANTS AND ITS IMPACT ON HOUSEHOLD EEU. The overview of these studies reveals that many prediction methodologies and remarkable influential factors have been examined to get the holistic picture of Energy-related factors in the scale of building Energy consumption. However, a pellicular study for household Energy lifestyle is necessary and potential in developing countries. In a more concrete view, the residential factors and their linkage to household Energy use are displayed on a global background, which is an example of our granular case in the next section. From the research literature, it can be seen that Vietnamese households display comparable trends of Energy demand with other regions, however, more investigating data is required to signify the levels of influence, as well as identify specific Energy-saving solutions to cut down Energy use in the next generation. The current platform presents rich potentials for further exploration and analysis, mainly targeting the household impacts and occupant behaviors in the follow-up studies.

In Chapter 3, METHODOLOGY. This Chapter is well-presented with three main approaches: investigation on household impact factors and household energy monitoring data, hybrid method combining data-driven and physics-based approach, path analysis using R-studio. These three main approaches are corresponding with chapter 4, chapter 5, chapter 6, and the application of physic-based only method (which is part of hybrid method) is used for Chapter 7. In general, Database derive from off-line survey, direct interview, technical drawing and energy monitoring in Japan and Vietnam support significant sources to the three approaches. The need of as much detailed as the energy data and much variety of the determinant data is reaffirmed. However, the limitation of databased can be improved by using Path analysis or Physic-based simulation only which is clarified in Chapter 6 and Chapter 7.

In Chapter 4, CORRELATION OF HOUSEHOLD AND HOUSING FACTOR WITH EEU IN JAPAN AND VIETNAM. The data resource derived mainly from statistical database and investigation in Japan and Vietnam. Accordingly, the crucial impacts of household characteristics on residential Electricity End-Use (EEU) have not been significantly paid attention. This section generalizes a detailed picture of distinct features of individual households such as family patterns, housing designs, occupancy rate (OCC), and occupant behaviors. Obtaining the Hourly Electricity Load (HEL) from the measurement and household surveys of an electric-only residential apartment in Japan, the authors perceived notable relationships among the household characteristics, OCC, and EEU. The study highlights the multi-dimensional influences of household attributes to emerge a holistic view of changing energy behavior through different case studies. The contribution of detailed HEL data facilitates sustainable lifestyles and raises awareness of energy-saving in residential apartments. From the database, this section first presents a panoramic view of Vietnamese and Japanese household energy studies in the context of the world household energy sector, pointing out that it is important to have an open-source database on household energy consumption as well as corresponding household factors, such as the number of family members, gross floor area, household income, appliance ownership, occupancy rates, and other elements related to the use of energy devices. The study emerges a detailed picture of Vietnamese and Japanese household energy consumption in its correlation with easy-to-approach causal variables regarding household factors. With increasing support from economic growth and the improvement of energy policy, exploratory researches can be further implemented in these two countries with many potentials.

In Chapter 5, SENSITIVITY ANALYSIS: INFLUENCE LEVELS OF VARIOUS IMPACT FACTORS CASE STUDY IN JAPAN. This section emphasizes the potential growth of combining model and energy monitor data toward energy forecast in the early design stage, with the supplement of occupancy and other available information regarding residential houses. With the integration of forwarding and inverse modeling methods, the sensitivity analysis using a multi-dimensional hybrid approach offers more improvements in the accuracy of energy prediction. The energy modeling and monitoring facilitate the estimation of energy use in each household and prompt resident behaviors with energy performance reports. This section exploits the reciprocal relationship between observed data and simulated data in residential areas, supplementing the mismatch correction of unobservable factors such as ACS, actual occupancy rates, and energy waste. Compared with the measured data, the correlation shows goodness-of-fit with the coefficient of determination reaches up to 100% probability of the simulated data. However, prediction of daily use shows higher accuracy in households with stable ACSs while fluctuating ACSs are more suitable for hourly usage anticipation. Overall, the Pearson correlation explains the proportion of variance in the energy models as follows: 75% on weekdays, 72% on Saturdays, and 76% on Sundays. Based on this result, the study proposes household energy efficiency solutions by comparing the impact of different household parameters on energy consumption. Especially, with lower levels of ACS in an acceptable comfort zone, 20% to 60% less heating energy can be achieved compared to the baseline of usage. This corresponds to 16% ~ 33% of the reduction for site energy and 13% ~25% for that of source energy. Larger household size, higher occupancy rate, lower thermal transmittance value for wall insulation, and smaller airflow rates can be more energy-efficient for household HVAC end-use as well as gross site and source energy.

In Chapter 6, PATH ANALYSIS: IMPACT OF HOUSEHOLD FACTORS AND HOUSING FACTORS IN VIETNAM

Vietnam remains a new case study with rare information including statistical energy data, as well as household surveys but it is also an opportunity to find a new method to analyze energy-related behaviors in residential buildings. We realized that the path model that only addresses the effects between observed variables was appropriate for this situation. Compared with the typical energy performance analysis which is better used to look at the relative variation of energy end-use by household categories instead of telling a specific influence number, this model can analyze the interactive relationships between the household factors and the energy consumption simultaneously, which enables more complex structures than multiple regression. The proposed SEM path analysis reveals better statistical findings on the correlations of variables and the influence levels of each household factor on the household energy end-use. While the TPP reveals a complex correlation of how various multi-unit household factors affect energy use on the same scale, the CM emphasizes the multi-dimensional influences of household attributes on the end-use and visualizes optimal options for energy-saving plans.

In Chapter 7, HOUSEHOLD ENERGY END-USE BASED ON DIFFERENT CLIMATE ZONES, HOUSING DESIGN AND OCCUPANT BEHAVIOR. The energy performance of a building is strictly dependent on the climatic conditions. The Heating Degree Days (HDD) and Cooling Degree Days (CDD) value index and can be used to evaluate. Comparing among 6 cities in Japan and Vietnam, an increase of EEU is corresponding with cities with greater latitudes in Japan, but decreasing with the increasing latitude number in Vietnam's cities. Major usage belongs to heating systems in Japan's cities while cooling use accounts for most of EEU in Vietnam due to high HDD in Japan and high CDD in Vietnam. Housing orientation is more important for cities in higher latitudes, and the South direction is recommended for designing bedroom's windows. Energy efficiency is clearer in VN cities than JP cities due to the significant saving for ACC and upto 50% energy saving could be achieved by changing ACS setpoint with low intensive usage within the thermal comfort standard. The comparison of energy use by geographical location shows that in the mild climate region with warm humid, cool humid, cold and very cold humid zones such as Japan (3A, 4A, 5A, 6A), household locations in greater latitudes tend to go with higher energy consumption due to the demand on heating system. However, in the hot humid zones such as Vietnam (0A, 1A, 2A), household locations in greater latitudes shows less energy consumption based on the need of cooling use). The North of Japan consumes more HVAC energy while the South of Vietnam spends more HVAC energy in residential houses.

In Chapter 8, CONCLUSION AND PROSPECT. A summarized of each Chapter is concluded.

8.2. Limitation

The limitation of this method is that the energy modeling has limited library resources and needs more upgrades to simulate unanticipated behavioral factors. The mismatch correction between actual data and predicted data calls for different approaches to improve the accuracy such as data-driven and hybrid methods. More attention needs to be drawn to the hybrid approach that integrates energy simulation with data analysis and architectural model design in their multi-dimensional interactions to perceive various aspects of the energy-related lifestyle. Example techniques such as mobile-internet-based occupancy data [6] prove to facilitate the building energy simulation and mitigate model distortion during the calibration process. There are two limitations related to the monitoring method. The first one is the number of available energy monitors. The second restriction is household privacy, which limits the research scale to a few participants, and shortens the measurement time. Besides, the questionnaire regarding OCC or family member's information must be considered cautiously under the inhabitant's permission and building security management. Therefore, future studies should involve more comprehensive technologies to strengthen measurement time and provide long-term observation process. In doing so, the correlation findings of EEU and household characteristics can be further exploited comprehensively.

8.3. Prospect

From the impacts of lockdown and work-from-home policies during COVID-19, more activities pour into the residential area leading to a significant change in the use of electrical appliances, which affect the household energy end-use. In this respect, the increase in energy demand and the transition of energy use patterns call for consistent efforts of a research project and comprehensive strategy regarding household energy use behaviors and other influenced factors. This is a pilot study following the largest ongoing global crisis to simultaneously assess the multiple influences of household factors, housing design, and social impacts on household energy end-use. From this research, we proposed energy-saving solutions and oriented methodologies for residential areas in Japan and Vietnam.

The initial study began with applying energy monitors and household surveys, determining the contribution of hourly load data to analyze household energy-related lifestyles. Different families with different backgrounds have disparate habits and inclination of energy use style, so the energy-saving solution must be specified distinctly due to their household characteristics. In the second study, the sensitivity analysis using a multi-dimensional hybrid approach offers more improvements in the accuracy of energy prediction. This study exploits the reciprocal relationship between observed data and simulated data in residential areas. The energy modeling and monitoring facilitate the estimation of energy use in each household and prompt resident behaviors with energy performance reports. These research works have laid a platform to form the basic method for further replication of the study more completely and concisely.

Regarding the urgent topic of the COVID-19 pandemic, many studies have begun to focus on energy security, while several articles have explored the impacts of social-distancing policies on household energy use. To compare pre-lockdown and post-lockdown, previous studies illustrated the influence of COVID-19 on household energy consumption in the many countries in which household behaviors are the main factor. However, an empirical research on this topic is unprecedented while other crucial elements such as housing design, household characteristics, and social characteristics remain unexplored. Recognizing the crucial role that household energy efficiency plays in mitigating global environmental issues and greenhouse gases emissions, this study particularly concentrates on the cause-effect of energy end-use in residential areas in countries being severely affected after the pandemic. The core concept is to apply the energy use optimization theory into reality by transferring the research achievements into ***Empirical Proposal on Energy-Saving Behaviors (EPESB)*** in residential areas to observe the effect of before and after the implementation of EPESB. In this respect, a holistic sensitivity analysis on occupant behaviors and the factors indicated has the potential to discuss in-depth the possibilities of adaptation in practice.

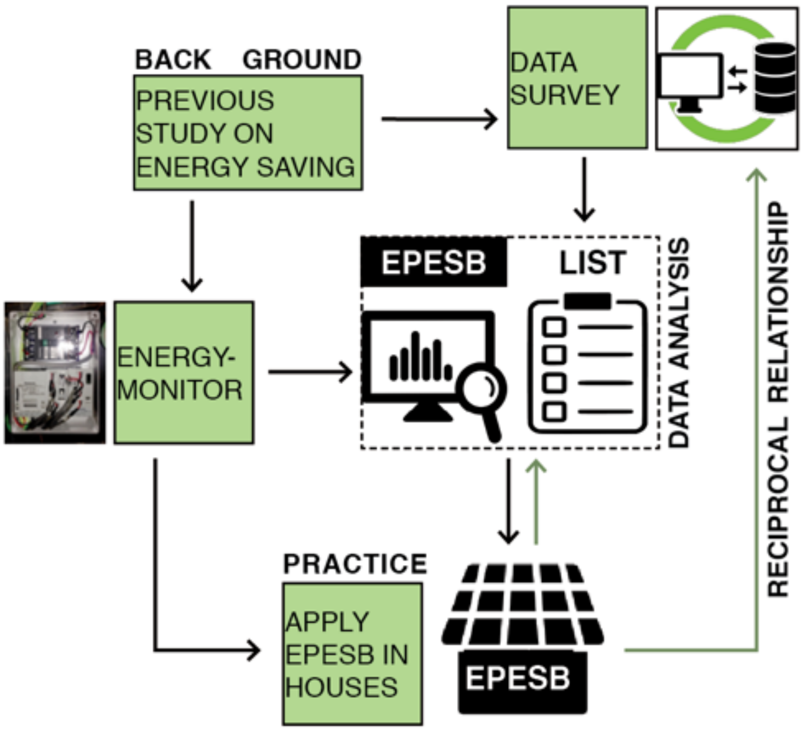

Fig. 8- 1 Prospect of study