Master’s Thesis of City Planning

Forecasting Building Energy Demand in Seoul Under Different Climate and Development Scenarios using LSTM

기후변화 및 도시발전 시나리오를 활용한 LSTM
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Abstract

Alongside the rising global consensus to take more proactive measures to tackle climate change, Seoul Metropolitan Government (SMG) pledged 2050 carbon neutrality and submitted the Climate Action Plan to C40 in 2021. As 74.8% of the total Greenhouse gas emission from Seoul accounts for the building sector, meeting this goal heavily depends on cutting down building energy consumption by designing an energy-efficient urban environment. However, no investigation has been made to examine whether the current highest-level statutory plan of Seoul, <2030 Seoul Plan>, aligns with the 2050 carbon neutrality goal. Against such a backdrop, this research was conducted to forecast Seoul's building energy consumption in the years 2030 and 2050 as an attempt to provide an evaluation of the 2050 carbon neutrality goal. For the prediction, Long Short-term Memory (LSTM) networks were constructed using historical data from 2010 to 2019. In order to account for the inherently uncertain nature of the future, the scenario analysis method was used in the forecasting process. Four scenario combinations were applied to forecast building energy consumption in 2030, considering two climate change scenarios, two socioeconomic scenarios, and a baseline urban development scenario based on the 2030 Seoul Plan. For forecasting in 2050, twelve scenario combinations were employed, replacing the baseline urban development scenario with three different urban development assumptions. The results showed that the LSTM models accurately depicted the residential and commercial building energy consumption patterns, with acceptable CV(RMSE) values of less than 15%. The LSTM models also outperformed traditional statistical method, ARIMA, in predicting future energy consumption in the building sector. The results of the energy consumption forecast indicated that by 2050, the electricity consumption in the residential sector would range from 14,049,562 MWh to 14,462,569 MWh. The most significant factors affecting residential building energy consumption are socioeconomic conditions, followed by urban form and climate. In the commercial sector, the forecast of electricity consumption by 2050 ranges from 25,808,064 MWh to 28,024,238 MWh. The most significant factor affecting commercial energy consumption is urban development, followed by socioeconomic conditions. Scaling up urban forests is expected to reduce commercial energy consumption by 10.9 to 12.2%. The evaluation results of the 2050 carbon neutrality goal indicate that none of the 12 scenarios come close to reaching the 2030 interim target or achieving the 2050 goal of carbon neutrality. Nevertheless, the study found that energy transition measures, combined with increased urban forests, can significantly cut down building sector carbon emissions.

Keywords: Building Energy Prediction, Deep Learning, LSTM, 2050 Carbon Neutrality, Scenario Analysis

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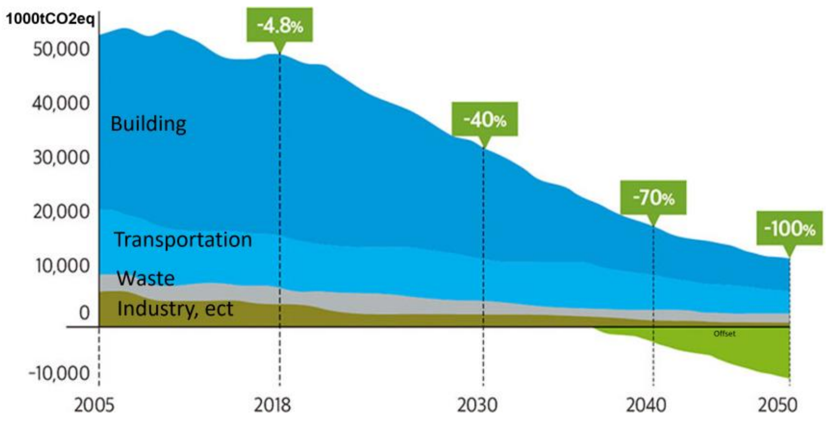
I. Introduction

1. Research Background

Under the current climate regime, which consists of the UNFCCC (1992), the Tokyo Protocol (1997), and the Paris Agreement (2015), taking actions and committing resources to limit climate change has become not just a moral mandate but a legal obligation. The Paris Agreement, the most effective and legally binding of all, states that the goal is to limit global warming well below 2, and preferably 1.5°C compared to the pre-industrial level (UNFCCC, 2015). The International Panel on Climate Change (IPCC) is projecting that the goal is only possible when global carbon neutrality is achieved by the year 2050 (IPCC, 2018). In response to this global consensus, Seoul Metropolitan Government(SMG) pledged to achieve carbon neutrality by 2050 in the 2018 Global Climate Action Summit, which made it the very first Korean municipality to join the 2050 carbon neutrality goal (서울특별시, 2021b). Referring to the Climate Action Plan (CAP) that SMG submitted to C40 in 2021, SMG is planning to reduce total Greenhouse Gas (GHG) emissions by 40% level compared to 2008 until 2030, and reach carbon neutrality by 2050, as shown in [Figure 1]. For 74.8% of Seoul's GHG was emitted from the building sector in 2020 (서울특별시, 2021a), meeting this goal heavily relies on cutting down building energy consumption through designing energy-efficient urban environments. However, <2030 Seoul Plan>, the highest-level statutory plan of Seoul, was established in 2014 without carbon neutrality in consideration nor careful inspections of the potential impact it may have on climate change. Thus, there is a crucial need to examine whether the 2050 carbon neutrality goal aligns with SMG's current urban development plans.



[Figure 1] SMG Greenhouse Gas reduction trajectory to achieve 2050 Carbon Neutrality (서울특별시, 2021b)

2. Motivation

Forecasting building energy consumption is crucial in determining the effectiveness and feasibility of current mitigation efforts. In order to forecast future energy consumption in a comprehensive manner, it is vital to accommodate today's trends. The identification of factors that could potentially influence building energy consumption has been thoroughly investigated in the literature. As much as the level of climate change can be affected by building energy consumption, the inverse relationship is also possible. Higher energy demand in buildings to adjust to the hotter and more extreme climatic conditions may result in a vicious circle of CO2 emissions (Ciancio et al., 2020). Socioeconomic factors are also crucial determinants of building energy consumption. Currently, South Korea is facing gradual changes in socioeconomic aspects - a sharp decrease in the total population, a rapid increase in the elderly population, and an economic slowdown are the most prominent ones (Park & Yun, 2022). However, research on predicting urban-scale building energy consumption, with consideration of various influencing factors in climatic and socioeconomic categories, was hard to find. Moreover, few studies have used a scenario-based framework to account for the uncertainties of future conditions in their predictions.

3. Research Aims

As an attempt to fill in the literature gap, this research's primary aim is to forecast the electricity consumption of residential and commercial buildings in future Seoul through the years 2030 and 2050 under different assumptions on future. It is important to note that the purpose of such forecasting does not lie in probing the uninvestigated relationship between factors, but rather in examining how future energy use will change, assuming the current trends persist. The secondary aim of this research is to examine how energy consumption in building sectors would change when applying various urban planning measures. The results of this study will provide insights for urban planners and policymakers to deal with the predictable range of the future. In particular, this research is essential for policymakers because estimating the building energy consumption in the year 2030 can provide an interim evaluation of the 2050 carbon neutrality plan that the SMG pledged. It is also helpful for urban planners, as the results of this research can suggest concrete urban form regulations and land use plans for the year 2050 as a guideline to achieve carbon neutrality.

This study seeks answers to the following research question to serve the research purposes: Considering the impact of climate change, socioeconomic shifts, and urban development, how will building energy consumption change in Seoul in 2030 and 2050?

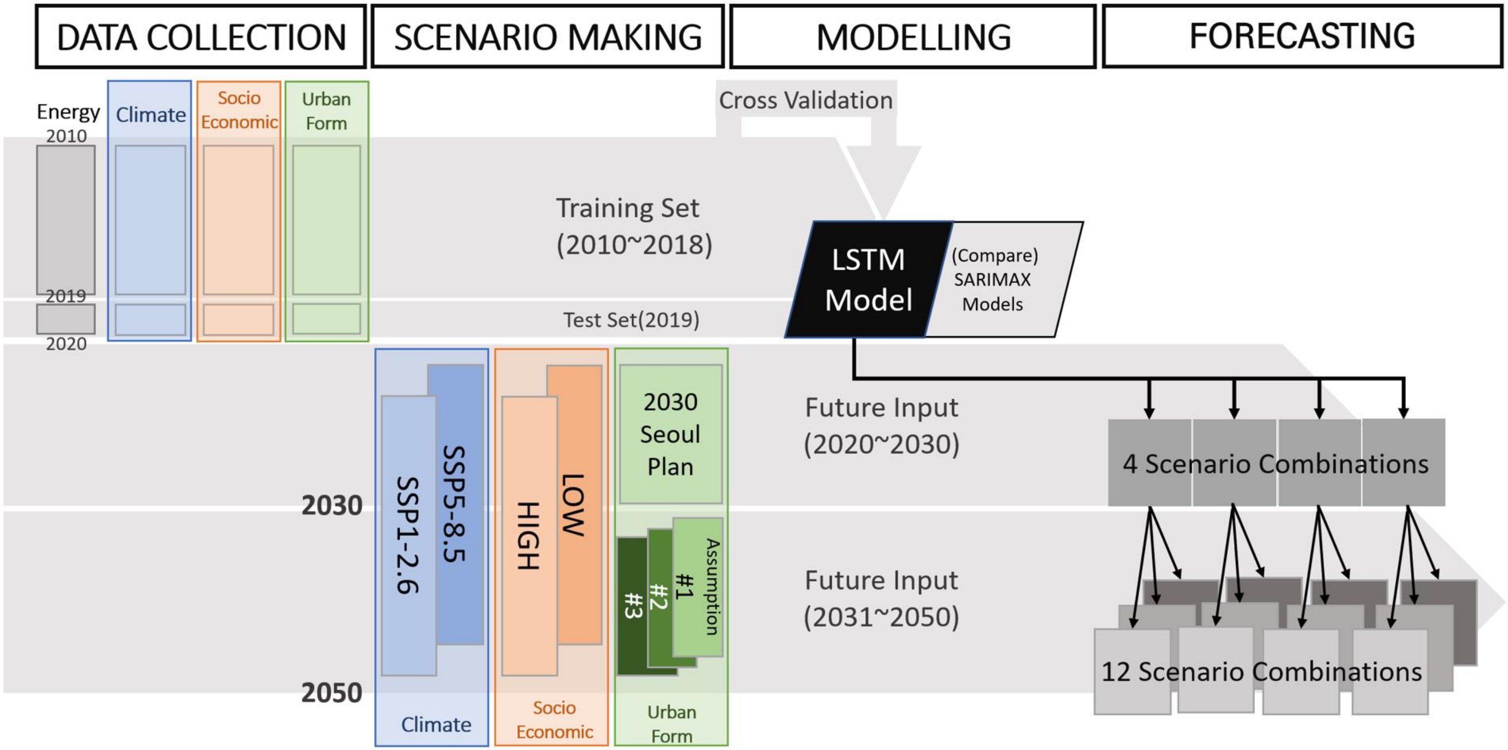
4. Data and Methodology

Residential and commercial energy consumption in 25 gu-s in the years 2030 and 2050 were forecasted, considering various factors from climatic, socioeconomic, and urban form categories. With the ongoing electrification tendency in Seoul, only electricity consumption among primary energy sources was examined (SMG, 2020).

To make the predictions, Long Short-Term Memory (LSTM) neural networks were used as a prediction method. As a type of machine learning technique, LSTM can effectively handle non-linear relationship between dependent and independent variables. Additionally, unlike classical statistics models, LSTM can handle autocorrelations in time series data without complex assumptions. Such characteristic of LSTM enables the researcher to extract as much information as possible from 10 years of panel data consisting of 25 gu, two building sectors, and nine features for forecasting future energy consumption. Fifty LSTM models were constructed in total, corresponding to two dependent variables – residential and commercial electricity consumption and 25 gu in Seoul. The prediction accuracy of the LSTM models was evaluated by comparing the RMSE values with the ARIMA models.

In order to address the inherent unpredictability of the future, different sets of scenarios were employed in the forecasting process. Specifically, four sets of scenario combinations were used to project the building energy consumption in 2030, based on two climate change scenarios, two socioeconomic scenarios, and one urban development scenario. For forecasting in 2050, a total of twelve sets of scenarios were used, based on two climate change scenarios, two socioeconomic scenarios, and three urban development assumptions.

The research consists of four major stages as show in [Figure 2]. In the data collection stage, historical data from 2010 to 2019 in the four categories – energy, climatic, socioeconomic and urban form were collected to be used as input for LSTM model construction. In the next scenario making stage, scenarios for 2030 and 2050 were created and future values of independent variables were generated corresponding to each scenario. In the modelling stage, fifty LSTM models were built using the historical data collected in the first stage. With the exact same data, twenty-five ARIMA models to predict residential electricity consumption in 25 gu were constructed at the same time, to be used as a comparison purpose. Finally, in the forecasting stage, future values of dependent variables were used as input to the constructed LSTM models, to forecast building energy consumption under four different scenarios combinations in 2030 and twelve combinations in 2050.



[Figure 2] Flow chart of building energy consumption forecast under different scenario combination

II. Literature Review

This section investigates the reasoning behind the choices of independent variables, dependent variables and forecasting method by reviewing previous literature on building energy consumption. Literature was explored in two aspects, one being explanative and the other being predictive, following the categorization presented by Nakata et al., (Nakata et al., 2010). In the paper, it is suggested that the researchers aiming to contribute to energy system design should construct models to serve either two purposes: "explain, or predict and/or control the actual situation of energy systems". Researches using the "explaining" models are categorized as explanatory studies on building energy consumption and covered in the first part of this section. The studies presented "predict and/or control" models are reviewed in the second part as prediction studies. The third part summaries the reviewed works, and point out the limitation from the literature to identify the contribution of this research.

1. Explanatory Study on Building Energy Consumption

Over the past years, many scholars from various disciplines have explored the influencing factors of building energy consumption. The variables identified in the previous explanatory studies can be categorized into three groups - climatic influence, socioeconomic determinants, and urban form and land use factors.

1) Climatic Influence

Several studies on climatic influence on building energy and electricity consumption were found. Such researches have mainly focused on electricity consumption changes caused by heating and cooling behaviors inside the buildings in the research scope (Fan et al., 2019). Due to the non-linear relationship between temperature and energy consumption, researchers often replaced temperature values with a set of new derived variables such as Cooling Degree Days(CDD) and Heating Degree Days (HDD) to conduct quantitative and numerical analysis (Ang et al., 2017). Unlike most existing studies focusing on a single sector of the buildings, or treating energy from all types of buildings as a whole, Moral-Carcedo et al,. explored residential, service and industrial sector separately (Moral-Carcedo & Perez-Garcia, 2015). The paper provides that the sectoral difference in terms of temperature effects on electricity has been found to be significant, the highest sensitivity being firms in the service sector.

2) Socioeconomic Determinants

Sarwar et al. investigated the relationship among economic growth, electricity consumption, and total population using panel data from 157 countries of 1960 to 2014, and concluded there was a significant correlation among all the studied variables (Shahbaz et al., 2017). Demographic variables are particularly investigated often in the literature. Brounen et al. examined gas and electricity consumption of more than 300,000 households and concluded that the aging population will significantly increase the future demand for residential sector building energy (Brounen et al., 2012).

3) Urban form and Land Use Factors

Chen et al. investigated 231 communities in Tainan city, Taiwan to examined the relationships between urban density, community layout, and land use factors and household electricity consumption simultaneously, along with building characteristics and demographic (Chen et al., 2018). From the result, the literature indicated that the urban form factors such as greater population density, greater urban canyon narrowness, greater percentages of vacant space are associated with lower household electricity consumption.

2. Prediction of Building Energy Consumption

1) Prediction Scale

The field where the building energy consumption prediction work has most frequently been investigated is the architecture engineering field, the main focus point being on building optimization. Somu et al., investigated the use of deep learning models to predict future energy consumption of four floor building in Indian Institute of Technology Bombay, India using a minute frequency data from 2017 to 2019 (Somu et al., 2021). The literature used short, high-frequency data to build models, and then predicted the short-term future by profiling energy consumption patterns. Larger scales of building energy prediction research were less likely to be found. (Gassar & Cha, 2020; Somu et al., 2021; 공동석 et al., 2010).

However, with the recent rising importance of carbon neutrality goal, scholars in the urban planning field have started to explore the future change of building energy consumption considering upcoming changes. Zuo et al., conducted a research to identify 30 provinces in China's carbon peak using LSTM-STRIPAT model, and assessed the drivers of the carbon emissions in different regions (Zuo et al., 2020). Liu et al., investigated the long-term monthly electricity demand in Hong Kong under future climatic and socioeconomic changes by the year 2100 using six machine learning models (Liu et al., 2021). Also, Zheng's research team has come up with a study exploring the climate change impacts on electricity demands in Guangzhou, China by the year 2095 (Zheng et al., 2020).

2) Dependent and Independent Variables

Studies of building energy prediction utilize the results from the explanatory studies to examine the future changes of energy consumption. Studies which examined the effects of climate change on building energy largely focused on the residential building sector, analyzing the changes in electricity demand caused by heating and cooling behaviors (Fan et al., 2019). Huang's study extended the analysis to commercial buildings and examined residential and commercial building energy use in the United States at the state level (Huang & Gurney, 2017). The conclusion indicated that at the end of the century, energy demand in some parts of the US the energy demand in two types of buildings is going to increase by more than 50%. Lee et al. forecasted residential building energy consumptions from cooling and heating, with consideration of climate change as well as the socioeconomic shifts in future Korea using the year 2010 to predict the year 2050 (이미진 et al., 2015). The result indicated that the cooling energy demand is going to increase significantly, while demand for heating will decrease. Jeong et al. conducted scenario research to present the ways in which the building sector in Korea can reach carbon neutrality by 2050. Presented scenarios were: Obligatory zero energy building scenario, Green remodeling scenario, high energy efficiency technology – infrastructure supply scenario, building energy information infrastructure and behavioral improvement scenario, and low CO2 energy source scenario. but the analysis was limited to apartment buildings and no prediction model was employed. (정영선 et al., 2021)

3) Prediction Methods

There are several ways to categorize the prediction models used in building energy forecast studies. Somu et al., defined them as Engineering methods, statistical methods, and artificial intelligence methods (Somu et al., 2021). Amasyali & El-Gohary reviewed researches on data-driven building energy consumption prediction, and concluded that two main approaches have been taken for building energy consumption prediction, one being “physical modelling approach”, and the other one being “energy analysis” (Amasyali & El-Gohary, 2018). The researches belonging to the first category utilizes software such as EnergyPlus, eQuest, and Ecotect to calculate building energy consumption. In Korean context, scenario analysis is often employed.

[Table 1] Large-scale building energy consumption prediction study with multiple independent variables

Reference	Forecast Methods	Dependent Variables	Independent Variables	Modelling (t unit)	Predict (t unit)	Site (level)
(D'Agostino et al., 2022)	simulation	Residential electricity	Climatic	2004-2018 (hourly)	~ 2060 (hourly)	Milan (building)
(Liu et al., 2021)	Machine learning	Residential, Commercial Electricity	Climatic, Socio-economic	2003-2008 (monthly)	~2100 (monthly)	Hongkong (city)
(Zheng et al., 2020)	Statistics	Total, Residential electricity	Climatic, Socio-economic (GDP)	2004-2015 (monthly)	~2100 (monthly)	Guangzhou (city)
(Fan et al., 2019)	Statistics	Electricity consumption	Climatic, Socio-Economic	1995-2016	~2100	30 Province in China (Province)
(Ang et al., 2017)	Statistics	Electricity in residential, commercial, industrial sector	Climatic	1990-2015 (monthly)	-	Singapore Hong Kong (City)
(Gunay, 2016)	Machine learning	Gross electricity consumption	Climatic, Socio-economic	1975-2013 (yearly)	2028	Turkey (national)
(Bilgili et al., 2012)	Machine learning	Residential, Industrial Electricity	Socio-economic	1990-2003 (yearly)	2008 -2015 (yearly)	Turkey (national)
(정영선 et al., 2021)	Scenario	Carbon emission from building sector	Socio-economic, Urban Form	2012-2020 (yearly)	2050	Korea (national)
(Lee & Kim, 2019)	Scenario	Carbon emission from new apartment buildings	Urban Form	2017	~2030	Korea (national)
(이미진 et al., 2015)	Scenario	Residential cooling and heating energy	Climatic, Socio-economic	2010	2050	Korea (national)

3. Summary of Literature Review

The influencing factors of building energy consumption can be categorized into climatic, socioeconomic, and urban form factors. Based on the three categories, [Table 1] summarizes large-scale building energy consumption prediction studies reviewed in this research. Three major limitations of previous study were found in the process of literature review.

Firstly, previous studies mostly examined future changes of national or metropolitan city scale energy consumption with compromised prediction accuracy and limited suggestions to urban planners and policymakers in designing energy-efficient neighborhoods.

Secondly, in the aspect of variable selection, residential buildings were most frequently investigated in this research area, with seven out of ten researches in the list of reviewed studies considering residential energy consumption as a dependent variable. However, commercial sector was less likely to be examined, as only two studies covered the sector, with Korean paper not being among the two. Furthermore, among the ten reviewed papers on large-scale building energy prediction, only one research by Jung et al. (2021) comprehensively considered independent variables from three categories.

Finally, Methodology-wise, neural network models and scenario analysis were frequently employed in forecasting as separate methodology. However, no study implemented the methods as a combination.

As an attempt to fill in the gap in the literature, this study forecasts building energy consumption in residential and commercial sector of 25 gu in Seoul with consideration of features from three categories using LSTM and scenario analysis.

III. Data

1. Research Range

1) Study Scope

(1) Spatial Scope: Seoul

The spatial scope of this research is Seoul, South Korea. As the capital city of South Korea, Seoul is considered to be one of the major cities in the world, accommodating 51,744,876 population as of the year 2021. Seoul consists of 25 autonomous "gu" districts (자치구), which act as a basic unit of local government. The 25 gu are further divided into 426 administrative "dong" sub-units (행정동).

[Figure 3] Spatial scope: Seoul City, 25 gu

(2) Temporal Scope: 2010~2019, 2030, 2050

The temporal scope of this research is from 2010 to 2050. Ten years of historical data from 2010 to 2019 was used to construct fifty models to predict monthly residential and commercial electricity use in 25 gu, independently. With the constructed LSTM models, forecasts of building energy consumption under four different scenario combinations, which consist of two climate change and two socioeconomic scenarios, were presented for the year 2030. Then, applying three assumptions of urban development to the existing climate change and socioeconomic scenario combinations, total of 12 building energy consumption forecast for the year 2050 were provided.

2) Unit of Analysis

(1) Spatial Unit: Jachi-gu

The spatial unit of the research is 25 gu of Seoul for the following two reasons. First, entrusted by the SMG under the current <Enforcement Rule of Ordinance on Urban Planning>, gu is the smallest unit of municipal government that can determine and implement urban plans (양재섭 et al., 2020). By examining the future building energy consumption at gu level, this study can provide policy guidance to every gu in Seoul for making energy-efficient urban environment. Second, as the major unit of data provided by the SMG is gu, setting the spatial unit as gu can make the most out of the available data.

(2) Temporal Unit: Month

To capture the seasonal changes in energy consumption from the two building sectors, and to make the most out of available data, monthly time series data were collected to forecast the future changes of monthly energy consumption.

2. Choice of Variables

1) Data Availability

As this research investigates the past and future of the building energy consumption, the choice of variables largely relied on the availability of the related data. Therefore, the availability of variables in four sectors, namely energy, climatic, socioeconomic, and urban form were checked rigorously, before setting a variable list used in the study.

Data availability of energy consumption was identified as shown in [Table 2]. The definition of building energy consumption varies, but SMG divides building energy into "residential", "commercial", "public", and "agriculture, forestry and fishery" sectors in the Greenhouse Gas inventories (서울특별시, 2021a). However, the latter two take up only 5% of the greenhouse gas emission from the total building energy consumption, only residential and commercial energy consumption was considered in this research for the simplicity of analysis.

To extract energy consumption from the buildings, sectoral use of energy should be provided. Also, to consider the effect of seasonal climate change to energy consumption in the future, the energy data must be achievable in a monthly basis. Excluding the national or Si-Do scale data and the data shorter than five years, only gas and electricity consumption data from MOLIT, and sectoral electricity consumption data from KEPCO were left in the list. The MOLIT data was too abundant with missing values, therefore the data would be hard to represent energy consumption behavior of each gu. Finally, the KEPCO data was chosen as the source of the dependent variables – residential and commercial electricity consumption.

[Table 2] Availability of energy consumption data in Seoul

Data	Sector Use	Data Site	Spatial Unit	Time Unit	'00	'05	'10	'15	'20	Source
gas&electicity	O	Korea	parcel	M			11		21	MOLIT
electricity	**O**	**Seoul**	**gu**	M	**04**				**21**	**KEPCO**[1]
electricity	O	Seoul	dong	M				16	21	SMG
electricity	O	Korea	gu	M	02				21	SMG
gas	O	Seoul	dong	M				16	21	SMG
gas	O	Seoul	dong	Y		07			20	SMG
gas	O	Korea	company	M	01				20	KOGAS
gas	O	Korea	national	Y	86			19		KOGAS
gas	X	Korea	si	M	00				20	KOGAS
gas	X	Korea	national	H			13	18		KOGAS
gas	O	Seoul	gu	Y	04				20	SMG
GHG	O	Seoul	si(1)	Y		05		19		SMG
GHG	O	Seoul	si(1)	Y			11	19		SMG
total energy	O	Seoul	dong	M				16	21	SMG
total energy	O	Korea	gu	Y				18	20	Green Together
total energy	O	Korea	si	Y				18	20	KOSIS

Notation: Y- yearly, M- monthly, H- hourly frequency

Next, data availability of climatic, socioeconomic and urban form in Seoul was check as shown in [Table 3] and [Table 4].

[Table 3] Availability of climatic, socioeconomic and urban form data in Seoul

No	Division	Data	Data Site	Spatial unit	Time unit	'00	'05	'10	'15	'20	source
1	Climatic	Surface Temperature	Korea	dong	H			10		22	KMA
2	Socio economic	GRDP	Seoul	gu	Y			10	19		SMG
3		GRDP	Seoul	si(1)	Y	85			19		SMG
4		De facto population	Seoul	dong	D				17	22	SMG
5		population	Korea	gu	M			11		22	KOSIS

[1] 서울 열린데이터 광장(한국전력공사, 서울시 전력 사용량(용도별) 통계), 2022.10.21, (https://data.seoul.go.kr/dataList/378/S/2/datasetView.do) – 주거용계, 상업용계 전력 사용량

7		population	Korea	gu	M		21	KOSIS
8		elderly ratio	Korea	gu	M	08	21	KOSIS
9		One-person household	Seoul	gu	Y	00	21	SMG
11		Household number	Seoul	Gu	Y	00	21	SMG
10	Urban Form	building age	Korea	parcel	Y	15	22	KOSIS
11		land use	Korea	gu	Y	90	21	SMG
12		FAR regulation	Korea	Si	Y	12	21	KOSIS
13		CR regulation	Korea	Si	Y	12	21	KOSIS

Notation: Y- yearly, M- monthly, D-daily, H- hourly frequency

[Table 4] Future data availability

Data	Site	Unit	time unit	‘20	‘25	‘30	‘35	‘40	‘45	‘50	Source
Temperature	Korea	Dong Or 1km2	Day							2100	IPCC / KMA
population	Korea	Nation (1)	year							2070	KOSIS
population by age	Korea	Nation (1)	year							2070	KOSIS
population	Korea	Si	year							2050	KOSIS
population by age	Korea	Si	year							2050	KOSIS
GDP growth rate	Korea	Nation (1)	year							2050	KOSIS
GRDP growth rate	Seoul	Si (1)	year					2040			SMG
population	Seoul	Gu	year					2037			SMG
population by age	Seoul	Gu	year					2037			SMG
population by age	Seoul	Gu	year					2037			SMG

2) Choice of Independent Variables

To forecast future energy consumption in a comprehensive manner, it is important to accommodate today’s trends. SMG defines upcoming changes of Seoul in five divisions. The rise of elderly population and 1 or 2 person household, economic slowdown and polarization, increase of natural disaster due to climate change, and lack of development site and mass obsolescence of building complexes (서울특별시, 2014). Upon investigating the data availability of possible features, a set of independent variables were chosen following the criteria presented below.

<Criteria of variable choice>

1. Historical Data Availability

1-1. Data should be obtainable at gu-level

1-2. Data from 2010 to 2019 should be available

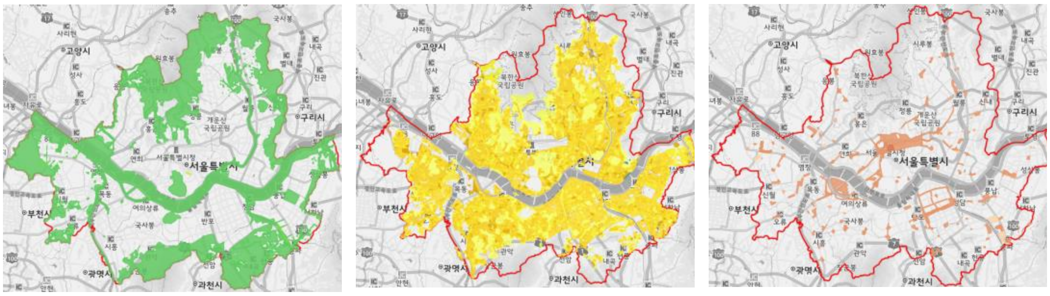
2. Future Data Availability of Climatic, Socioeconomic Features

2-1. Projection data by 2050 should be available

2-2. The projection data should be in gu-level
Or, gu-level disaggregation method should be provided by the official sources

A set of dependent variables, consisting of residential and commercial sector of building energy consumption was prepared. Such sectoral breakdown is based on a literature stating that the sectoral building energy consumption pattern analysis is more accurate than the aggregated one (Moral-Carcedo & Perez-Garcia, 2015).

To represent the climatic condition, monthly average surface temperature was used. For socioeconomic factor, Gross Regional Domestic Product, total registered population, and elderly ratio is going to be collected. As for urban development variables, the selected features should be able to reflect the urban development and land use change of Seoul. Building age was the most representative feature, therefore it was included as a form of derived variables. For this, ages of buildings in every Jachigu were computed for every year of analysis. Therefore, the percentage of newly built buildings were calculated as percentages of buildings under 10 years among the total count of buildings. Seoul doesn't have much space to change in terms of land use, however since the current Seoul government has plans to make Seoul a "Green City", Green Space Ratio was included in the variable list.



[Figure 4] Land use distribution map in Seoul: Green area, residential, commercial purpose (Seoul Spatial Information Map (서울시공간정보지도))

3. Historical Data Collection

Examining the data availability as shown in [Table 2,3,4], the full set of data was collectable from the year 2010. Since the study do not consider the COVID-19 effects on building energy consumption, the data from 2020 was not applicable to the model. Therefore, historical data from 2010 to 2019 was used to construct the prediction model. The variable list presented in [Table 5] shows the unit and counts of the raw data collected from 2010 to 2019. There are two dependent variables, but the models are not aim to produce multi-outputs, and models were constructed independently to forecast monthly electricity consumption of the two sectors. Yearly frequency data were adjusted to monthly frequency using the linear interpolation method, based on a literature which examined the prediction accuracy of neural networks with various frequency data, and concluded that input data interpolation improves the prediction power of such models (Raubitzek & Neubauer, 2021). Land use variables were included to provide the models dependent variable specific feature. Therefore, when constructing residential electricity consumption prediction models, commercial land use variable was excluded from the list, and vice versa. For the descriptive statistics of the historical data, see [Appendix B]. For plots of every variables in every gu, see [Appendix C].

[Table 5] Variable List

Division	Category	Variable Name	Contents	Unit	t unit(t)	Obs.	source
Dependent Variable	Building energy consumption	Residential electricity use	Electricity consumption in residential use buildings	Mwh	Monthly (2010.1~ 2019.12)	3,000	SMG
		Commercial electricity use	Electricity consumption in commercial use buildings	Mwh			SMG
Independent Variable	Climatic	temperature HDD	Monthly average surface temperature	°C			KMA
	Socio economic	GRDP	Gross Regional Domestic Product (2015 base)	1,000₩	Yearly** (2010~2019)	250	KOSIS
		Total population	total registered population	Person	Monthly (2010.1~ 2019.12)	3,000	KOSIS
		Elderly population ratio	Ratio of population older than 65 years old	%			KOSIS
		Youth population ratio	Ratio of population younger than 15 years old	%			KOSIS
	Urban Development	New building ratio	Ratio of buildings under 10 years	%	Yearly ** (2010~2019)	250	MOLIT
		Total Floor Area	Sum of all buildings' floor area in a gu	**m²**			SMG
		Green Area Ratio	Percentage of green area in a gu	%			MOLIT
		Residential Land Use*	Area of residential land use	**m²**			MOLIT
		Commercial Land Use*	Area of commercial land use	**m²**			MOLIT

*land use variables were included corresponding to the dependent variable of the model
** yearly frequency data were adjusted to monthly frequency using linear interpolation

4. Future Data Generation

In order to address the uncertainties of the future, the total of 4 and 12 sets of scenario combinations were employed in the process of forecasting building energy consumption of the year 2030 and 2050. The reason for setting different numbers of scenario combinations is that the purpose of forecasting building energy consumption in the year 2030 differs that of the year 2050.

The aim of forecasting building energy consumption in the year 2030 is to provide the interim evaluation of the 2050 carbon neutrality goal, and to offer an assessment of how much of the current masterplan <2030 Seoul Plan> is in line with the current climate change mitigation strategy <2050 Climate Action Plan>. However, the purpose of 2050 projection is to examine various combinations of urban form alterations under different climatic and socioeconomic conditions to examine the ways of which Seoul can meet the 2050 carbon neutrality goal. Corresponding to each scenario, future data availability was checked and generated following the two-step procedure. First, if the future prediction data is readily available from credible sources based on reasonable historical data and appropriate methods, they were used in the study. Second, if there are future predictions but with outdated historical data, the future data was calculated using the same methods but with updated historical data.

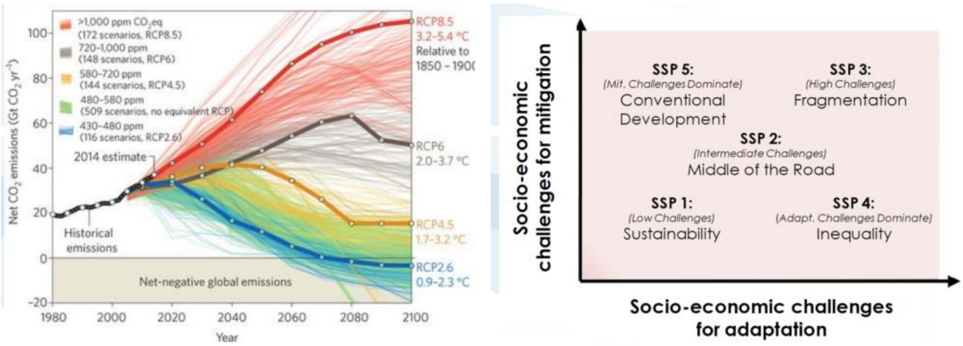
[Table 6] Assumptions adopted for scenario analysis

Category	Scenario Name	Assumptions on future conditions	Time
Climate Change	SSP1-RCP2.6 (SSP126)	Best case scenario: Sustainable society + Very low GHG emissions	2020 ~ 2050
	SSP5-RCP8.5 (SSP585)	Business as Usual: Unsustainable society + Very high GHG emissions	
Socioeconomic Shifts	KOSIS Low	Low birth rate, Low life expectancy, Low net migration	2020 ~ 2050
	KOSIS High	High birth rate, High life expectancy, High net migration	
Urban Development	2030 Seoul Plan (baseline 2030)	Urban development following plans stated in <2030 Seoul Plan> and scheduled urban redevelopment and regeneration projects by 2030	2020 ~ 2030
	Assumption #0	No significant change from 2030	2031 ~ 2050
	Assumption #1	Green city initiative Scenario	
	Assumption #2	High Density Redevelopment Scenario	

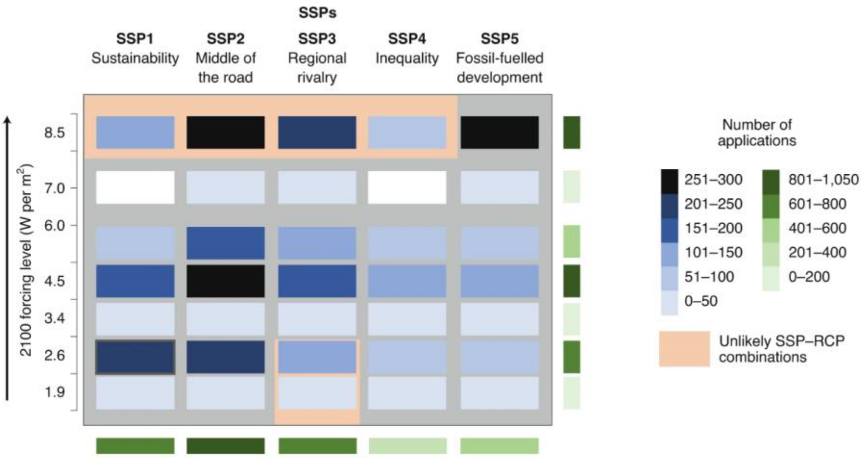
1) Climate Change Scenarios

Climate Scenarios are sets of different possible futures that characterize the uncertainties of complex interactions between human and environmental systems (O'Neill et al., 2021). They have been a key component of global climate change research as they enable the researchers to collaborate under the same set of assumptions on upcoming changes. Among series of climate scenarios, the SSP (Shared Socioeconomic Pathways) – RCP (Representative Concentration Pathway) scenario frameworks were used as future climate assumptions.

The RCPs consist of four pathways that lead to certain radiative forcing by the end of this century. Namely, A very high baseline emission (BAU) scenario that leads to radiative forcing levels of 8.5, two medium stabilization scenarios that end up 6 and 4.5 of radiative forcing, and a low forcing level scenario that lead to 2.6 radiative forcing. IPCC officially adopted RCPs in the 5th Assessment Report (IPCC, 2014) as a basis for the development of new climate change projections. In the same report, the design of the socioeconomic dimension of the scenario framework was established since the RCPs do not form a comprehensive set for elements other than GHG concentrations and associated radiative forcing. The SSP basic Scenarios provide five distinctly different future developments of socio-economic factors with no climate change impacts occurring, nor climate policy responses implemented (O'Neill et al., 2021)(see [figure 5] for elements). As both SSPs and RCPs are incomplete by design (O'Neill et al., 2021), by combining the societal features depicted in the SSPs with RCP climate projection, a rigorous assessment of how the future climate system changes would affect us will become feasible.

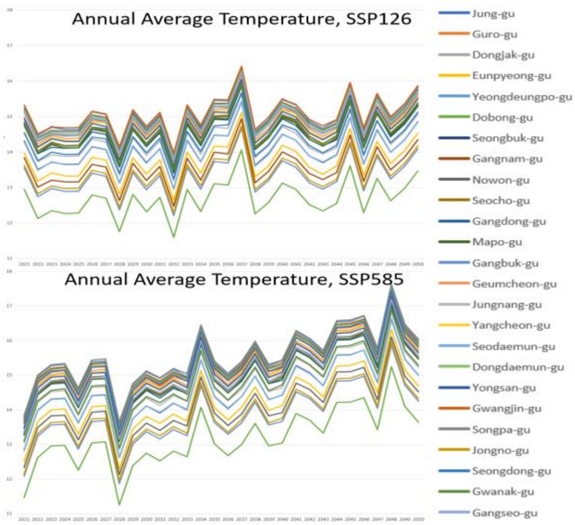


[Figure 5] Elements of RCP (right) and SSP (left) scenarios (Fuss et al., 2014)



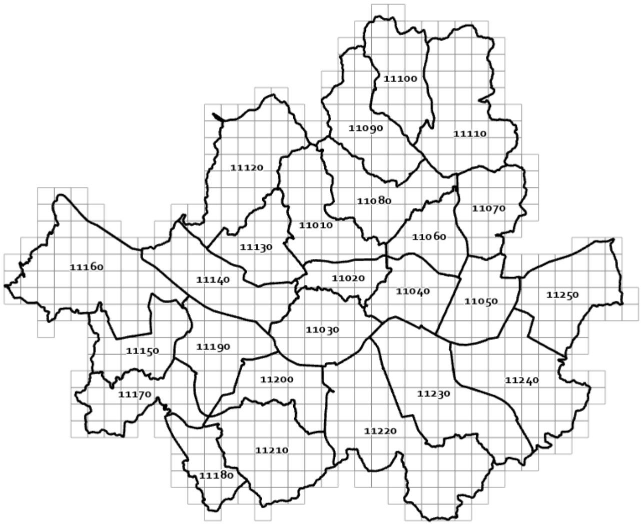
[Figure 6] SSP-RCP scenario combinations (O'Neill et al., 2021)

The Korean Meteorological Administration offers future climate projection data under SSP5-8.5 and SSP1-2.6 scenarios in 1km2 resolution and daily frequency[2]. With Daily minimum, maximum, average surface temperature projection data coming in NetCDF file format, monthly Heating Degree Days and Cooling Degree Days of every gu in Seoul were calculated. The NetCDF file is in 3-Dimensional data structure. Each dimension contains coordinates of designated place, time element and value of the data. In order to extract weather data from the NetCDF files, first the coordinates of every 1km X 1km grid centroid in Seoul were gained using ArcGIS pro as shown in [Figure 8]. Then, the extracted coordinates, together with daily time stemps in the period between January 2020 to December 2050 were used as inputs to the NetCDF files to get average daily surface temperature. Finally, every grid's daily average surface temperature in a gu was aggregated into monthly frequency to represent the gu's monthly average temperature.



[Figure 7] Change of annual average surface temperature under two climate change scenarios

2 기상청 기후정보포털 (기후변화 시나리오>다운로드>데이터), 2022.10.22 http://www.climate.go.kr/home/CCS/contents_2021/35_download1.php



Code	11010	11020	11030	11040	11050
Gu name	Jongno-gu	Jung-gu	Yongsan-gu	Seongdong-gu	Gwangjin-gu
Grid count	10	6	13	11	13
Code	11060	11070	11080	11090	11100
Gu name	Dongdaemun-gu	Jungnang-gu	Seongbuk-gu	Gangbuk-gu	Dobong-gu
Grid count	13	24	28	27	27
Code	11110	11120	11130	11140	11150
Gu name	Nowon-gu	Eunpyeong-gu	Seodaemun-gu	Mapo-gu	Yangcheon-gu
Grid count	53	39	22	29	8
Code	11160	11170	11180	11190	11200
Gu name	Gangseo-gu	Guro-gu	Geumcheon-gu	Yeongdeungpo-gu	Dongjak-gu
Grid count	64	26	16	28	16
Code	11210	11220	11230	11240	11250
Gu name	Gwanak-gu	Seocho-gu	Gangnam-gu	Songpa-gu	Gangdong-gu
Grid count	43	54	47	46	41

[Figure 8] Future climate data processing – 1km2 grid counts of 25 gu

2) Socioeconomic Shifts

Statics Korea (KOSTAT) started announcing Korea's Si-do level population projection results in 5-year basis from 1998. The most recent one is <Population Projection (Si-do): 2020~2050>, which was made public in May 2022 (SMG, 2022). The report provides population projections of 17 Si-do under 7 different scenarios from 2020 to 2050.[3] Gu-level population projection in Seoul was first started from 2016, using Si-gun-gu level population projection disaggregation method invented by the KOSTAT (서울시, 2020). The most recent gu-level projection report was made public in June 2020, containing population projection results of 25 gu in Seoul from 2017 to 2037, based on 2017 data.[4] As the forecasting time period of this research is from 2020 to 2050, Seoul's gu-level population projection data needed to be extended until 2050, by rigorously following the gu-level disaggregation methods presented in the report. Low and High KOSIS scenario in Si-do level projection report was employed to account for the future uncertainties. KOSIS High scenario represents population under high birth rate, high life expectancy, and high net migration assumption, whereas Low scenario represents that of low birth rate, low life expectancy, and low net migration.

SMG uses Cohort Component method to predict the future changes of population fluctuation factors - birth, death, and migration – and applies demographic balancing

[3] KOSIS (통계청, 장래인구추계(시도편): 2020~2050 년), 2022.10.22 https://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=DT_1BPB001&conn_path=I2

[4] 서울 열린데이터 광장 (서울시 자치구별 연령별 인구 (추계인구) 통계), 2022.10.22 https://data.seoul.go.kr/dataList/10837/S/2/datasetView.do#

equation (DBE) to calculate a year-forward population as shown in [Figure 9]. Instead of 2017, population data in 2020, provided by the Ministry of the Interior and Safety (MOIS)[5] was used as a baseline data to project gu-level population from 2020 to 2050. The baseline population was adjusted referring to 2020 Seoul total population projection in <Population Projection (Si-do): 2020~2050>. From the same report, Seoul's fertility rates[6] and mortality rates[7] from 2020 to 2050 under High and Low scenario were taken and used to project population of every gu. To predict net migration, Original-Destination Matrix by age and gender was first constructed with the past 5 years of migration micro data[8], and applied to the future cohort population. The final values were adjusted referring to Si-do level net migration under the two scenarios.[9] 5-year average of sex ratio at birth was calculated for every gu, and used as fixed value. The summary of reference and baseline data used in the population projection process is in [Table 7].

From the Cohort component analysis of every gu, future values of three demographic variables – the total population, ratio of elderly population over 65 years old, and ratio of youth population under 15 years old were calculated,

---

[5] 행정안전부 (주민등록 인구 및 세대현황, 연령별 인구현황〉등록구분: 거주자), 2022.10.22 https://jumin.mois.go.kr/ageStatMonth.do

[6] KOSIS (통계청, 장래 연령별 출산율/시도>고위, 저위 시나리오), 2022.10.22 https://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=DT_1BPA101

[7] KOSIS (통계청, 장래 생명표/시도>고위, 저위 시나리오), 2022.10.22 https://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=DT_1BPA401

[8] MDIS (통계청, 국내인구이동통계), 2022.10.22 https://mdis.kostat.go.kr/dwnlSvc/ofrSurvSearch.do?curMenuNo=UI_POR_P9240

[9] KOSIS (통계청, 장래 성 및 연령별 순이동률/시도> 고위, 저위 시나리오), 2022.10.22 https://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=DT_1BPA401

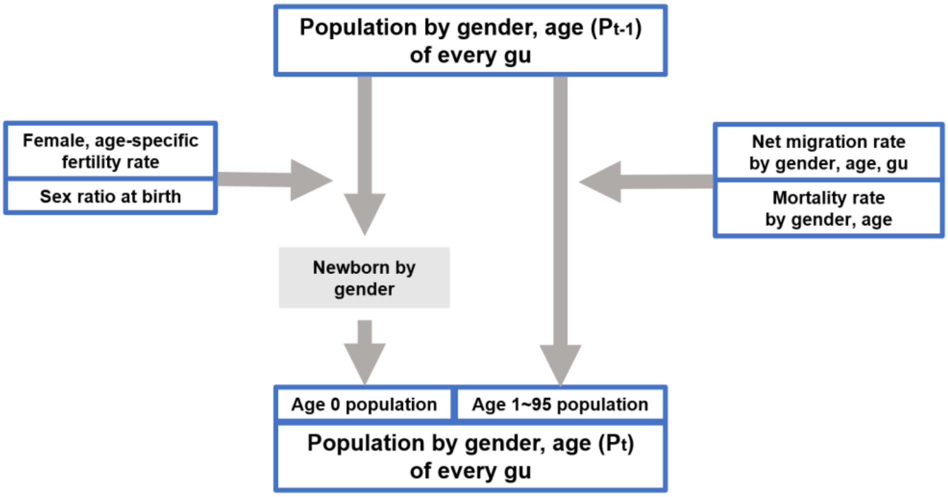
corresponding to the two socioeconomic scenarios. The calculated results were plotted and presented in [Figure10, 11, 12].

The most distinctive socioeconomic shift that is observable from the generated future data, is aging society. By 2025, the average percentage of older adults in Seoul under both Low and High scenarios passed 20%, entering a “Super Aged Society” by definition.At the end of the year 2050, the average older adult ratio of Seoul went up to 39.25% under the Low scenario and 36.51% under the High scenario. KOSIS High scenario resulted in higher total population, lower elderly population ratio, and higher youth population ratio than the Low scenario.

Demographic Balancing Equation:

$$P_t = P_{t-1} + B_{(t-1,t)} - D_{(t-1,t)} + M_{(t-1,t)}$$

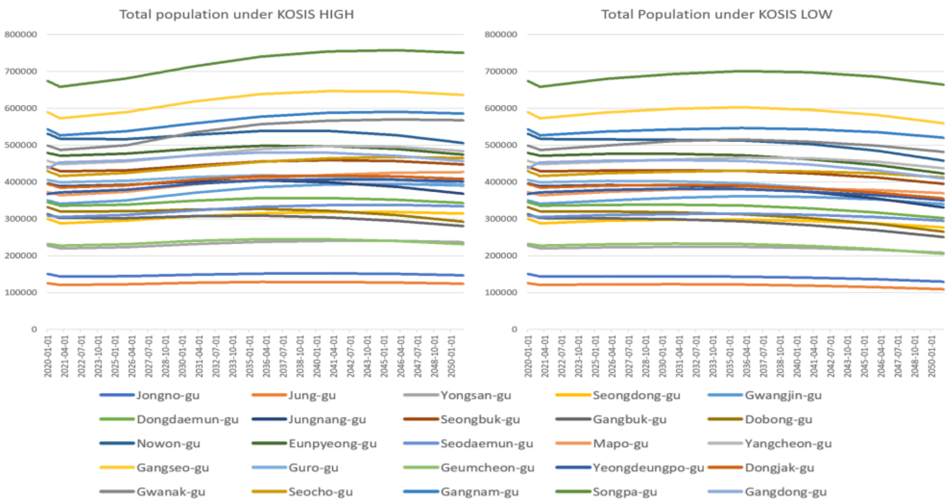
P_t: population in year t, $B_{(t-1,t)}$: birth, $D_{(t-1,t)}$: death, $M_{(t-1,t)}$: net movement



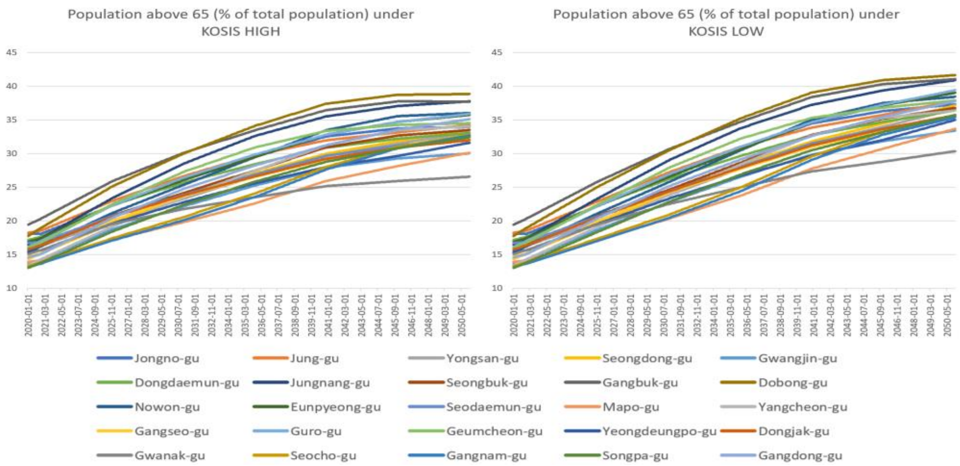
[Figure 9] Gu-level population projection process using Demographic Balancing Equation and Cohort Component Method (서울시, 2020)

[Table 7] List of data used to calculate gu-level population projection by 2050

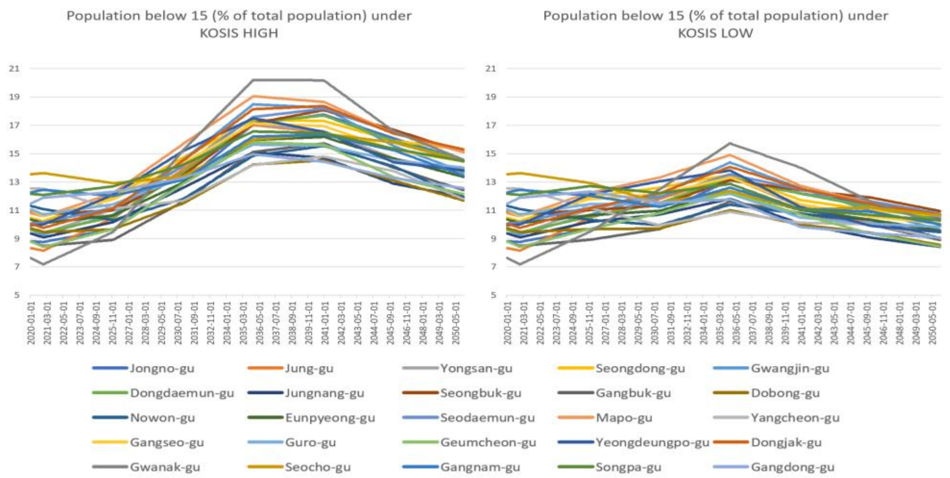
Purpose	Data	year	level	Source
Reference	Sex ratio at birth	2016~2020	Gu	KOSIS
	Net Migration, Net migration rates	2016~2020	Gu	KOSIS
Baseline Data	Population by gender, age	2020	Gu	MOIS
Scenario generation (High, Low)	Fertility rates	2020~2050 (5years gap)	Si	KOSIS
	Mortality rates	2020~2050 (5years gap)	Si	KOSIS
	Net Migration rates	2020~2050 (5years gap)	Si	KOSIS



[Figure 10] Future projection of total population (person)



[Figure 11] Future projection of population above 65 years old ratio (%)



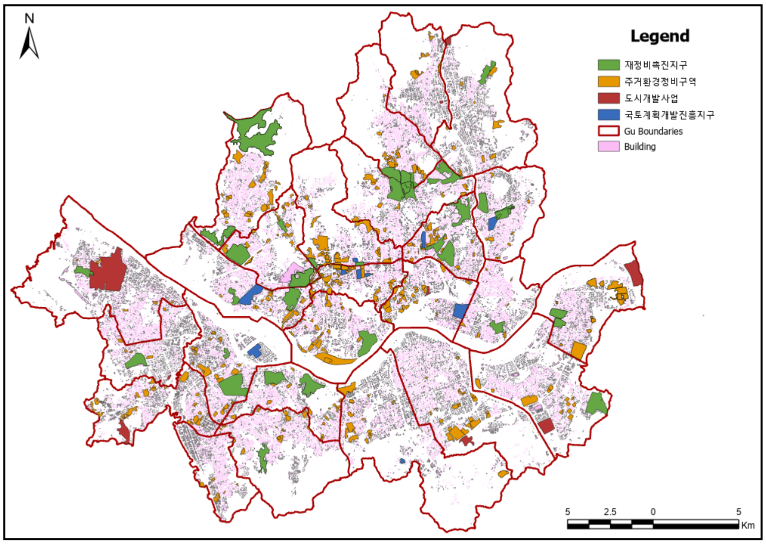
[Figure 12] Future projection of population below 15 years old ratio (%)

3) Urban Development Scenarios

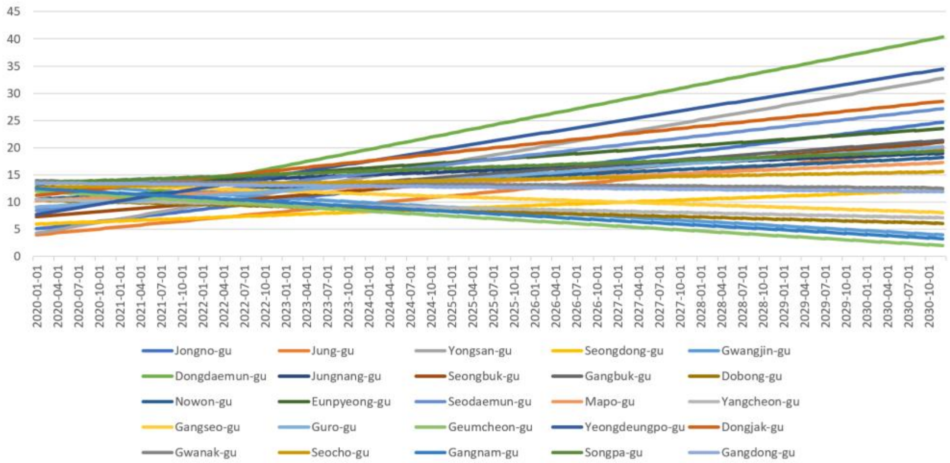
<2030 Seoul Plan> is the current highest-level statutory plan for the urban development in Seoul. SMG also provides the detailed information on urban regenerations and redevelopment projects, as shown in [Figure 13]. By investigating the two pieces of information, the future urban form and land use change data for the year 2030 were collected. To project the newly built building ratio in each gu, ArcGIS was used. First, two kinds of shape files were collected: one containing the information on all the buildings in 2019 from NSDI[10], and the other geographical information on the areas, of which redevelopment is planned to be implemented[11]. Assuming the planned redevelopments are completed by the end of the year 2030, and the number of buildings will stay the same, young building ratio under 10 years were calculated. As for the total floor area by 2030, the <2030 Seoul Plan> states that the total floor area of Seoul in 2030 is expected to increase by 53,563ha.

[10] NSDI (국가공간정보포털 오픈 API > 국가공간 개방데이터 > 파일데이터 > GIS 건물정보 > 서울특별시), 2022.11.01
http://openapi.nsdi.go.kr/nsdi/eios/ServiceDetail.do?provOrg=NIDO&gubun=F&svcId=F018&svcSe=F

[11] SMG (서울공간정보맵> 기초현황 > 도시관리계획) 2022.11.01
https://space.seoul.go.kr/spmsGisMain.do?MenuMain=MENU0001&MenuSub=SUB00001&q=l:%EB%85%B9%EC%A7%80%EC%A7%80%EC%97%AD&loginId=#



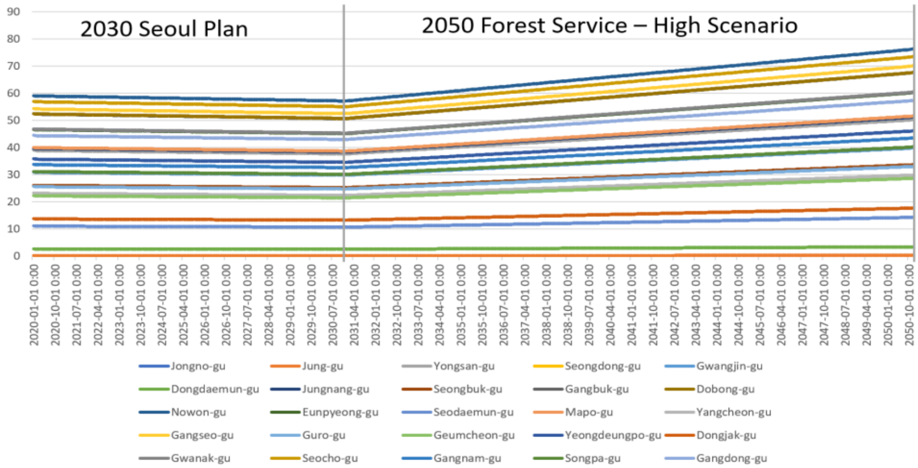
[Figure 13] Areas scheduled for urban redevelopment and regeneration plans in Seoul



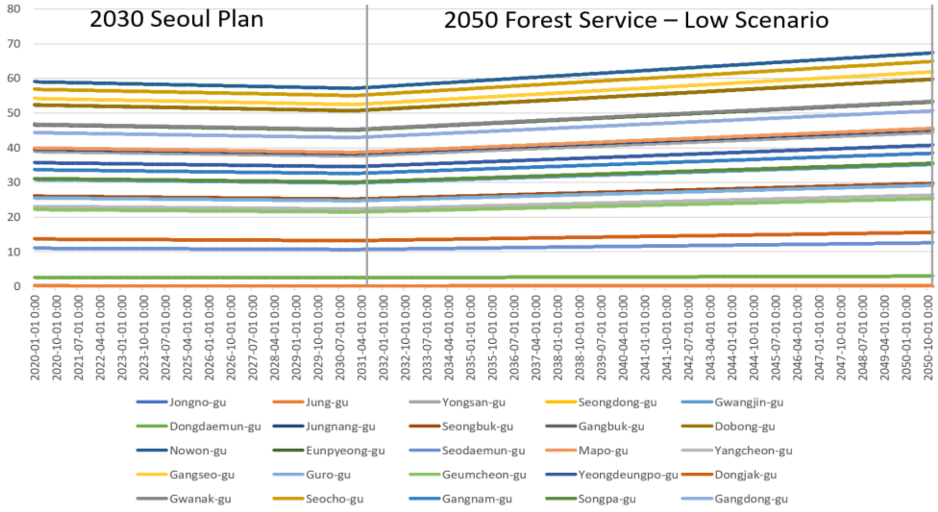
[Figure 14] Change of newly built buildings (% of total building count) under <2030 Seoul Plan>

As for development scenarios of the year 2050, the future data collection is solely dependent on the question, "How should, or would the future Seoul look like?". Upon deliberating on the question, three urban development assumptions were set for 2050. Currently, there's not much room for Seoul in terms of land use change – simply because there are no lands available to be converted. However, there are possibilities of growth in green area ratio as one of the key components of current

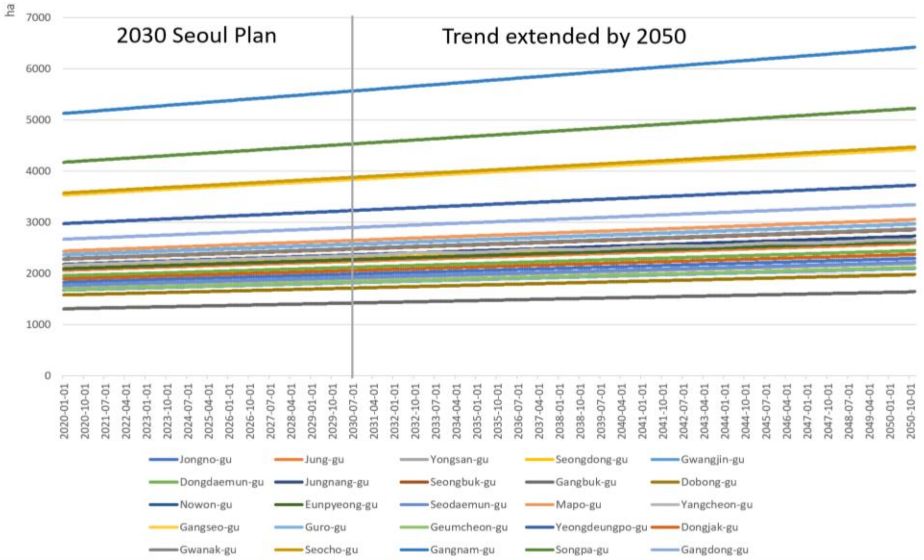
SMG's goal is to make Seoul a "Green City". As part of the Green City initiative, plans to make boulevards into underground roads and convert the sites into parks were proposed (as a matter of fact, the plans were initially stated in <2040 Seoul Plan> that was made public in the early 2022, but the masterplan is currently blanked out). Furthermore, the Korean Forestry Service has come up with a plan to expand the scale of urban forest by 20m2 per capita. Therefore, the first assumption for urban development scenario is the "Green city initiative Scenario", which alters the green area in Seoul of a scale of 20m2 per person. Second assumption in "High Density Redevelopment Scenario", where the growth rate of total floor area by 2030 is extended by 2050 using linear extrapolation. Additionally, assumption 0 was set as a baseline, to represent the future when the urban form condition which resulted from <2030 Seoul Plan> persisted by the year 2050.



[Figure 15] Future of Green Area Ratio, under <2030 Seoul Plan> and 2050 Forest Service Scenario under KOSIS High scenario



[Figure 16] Future of Green Area Ratio, under 2030 Seoul Plan and 2050 Forest Service Scenario under KOSIS LOW scenario



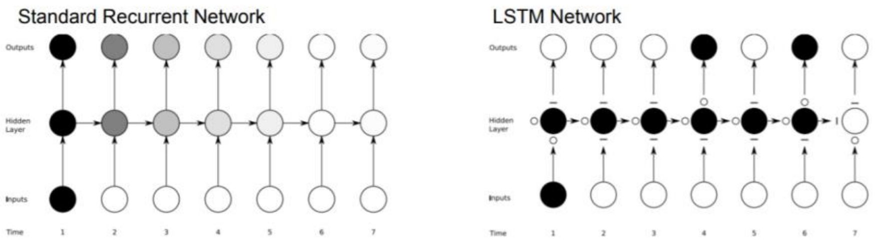
[Figure 17] Future projection of total floor area under <2030 Seoul Plan>, growing trend extended by 2050 using linear extrapolation method

IV. Methodology

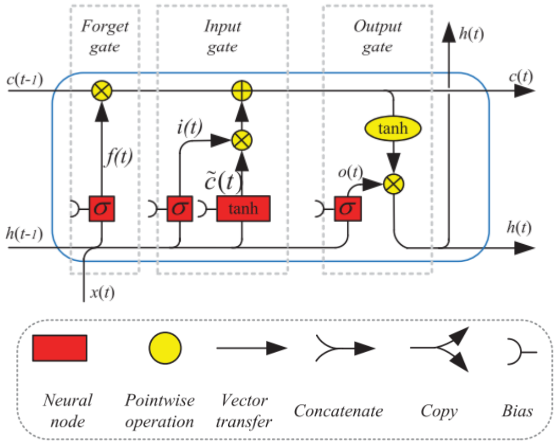
1. Long Short-term Memory Neural Networks

Deep neural networks consist of multiple non-linear hidden units which makes them extremely powerful in learning complicated relationship between model inputs and outputs (Srivastava et al., 2014). Through such, they have brought dramatic advancement of state of art in vision, speech, and other fields (Ioffe & Szegedy, 2015). Recurrent neural networks (RNN) were first developed to extend the usage of Deep neural networks to sequential data. Due to their recurrent structures, RNNs are capable of making use of previous context and can adapt to stretched or compressed input patterns (Graves et al., 2007). However, Bengio, Simard, and Frasconi have argued that the RNNs, which can be characterized as a gradient based learning algorithms, face difficulty when performing tasks where the temporal contingencies present in the input or output sequential data span long intervals (Bengio et al., 1994). In the literature, the difficulty is defined as "vanishing gradient" problem. [Figure 18].

Long Short-Term Memory neural networks (LSTM) were first introduced by Gers, Schmidhuber, and Cummins (2000) as a way to solve the vanishing gradient problem by implementing forget gate to the networks. In recent experience, LSTMs are widely examined in a variety of sequence processing tasks, such as speech and handwriting recognition (Graves, 2013). It is also widely used in processing and predicting time series. In building optimization and urban planning field, LSTMs are widely used in energy consumption and demand prediction studies (Kim & Cho, 2019; Somu et al., 2021; Wang et al., 2020). Another research subject that is investigated frequently with LSTMs are air quality prediction study. Seung et al. (2020) constructed a prediction model and forecasted the air quality of 35 monitoring stations in Beijing (Seng et al., 2021). In Korean context, Kim & Gim (2022) constructed independent LSTM models corresponding to 22 air pollution monitoring stations that were investigated in the study, and analyzed the relationship between air quality and urban form factors.



[Figure 18] Gradient vanishing in Standard RNN, LSTM introduced to solve the problem (Graves, 2013)



$$
\begin{aligned}
f_t &= \sigma(W_{fh}h_{t-1} + W_{fx}x_t + b_f),\\
i_t &= \sigma(W_{ih}h_{t-1} + W_{ix}x_t + b_i),\\
\tilde{c}_t &= \tanh(W_{\tilde{c}h}h_{t-1} + W_{\tilde{c}x}x_t + b_{\tilde{c}}),\\
c_t &= f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t,\\
o_t &= \sigma(W_{oh}h_{t-1} + W_{ox}x_t + b_o),\\
h_t &= o_t \cdot \tanh(c_t).
\end{aligned}
$$

[Figure 19] Architecture of LSTM cell and mathematical expression (Yu et al., 2019)

A typical LSTM cell consists of input gate, output gate and forget gate as shown in [Figure 19]. In the mathematical expression, $\boldsymbol{x_t}$, $\boldsymbol{h_t}$, and $\boldsymbol{y_t}$ denote the input, the recurrent information, and the output of the cell at time *t*, respectively; *W*-s are weights; *b* is bias; $\boldsymbol{c_t}$ denotes the cell state of LSTM at time t. $\boldsymbol{f_t}$ denotes the forget gate, where in case of the value is 0, it decides to get rid of the information, meanwhile in case of 1, it keeps the information. Input gate decides which information should be stored when updating the cell state, and output gate decides which information can be the output based on the cell state.

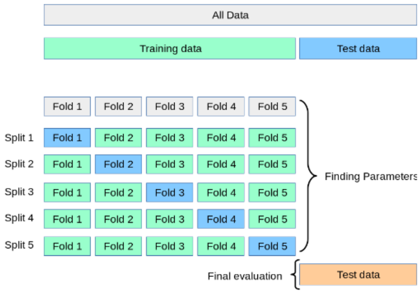
In implementing the LSTM, this study mainly used Keras with combination of TensorFlow. Keras and TensorFlow are open-sourced neural-network library written in Python language. LSTM models corresponding to 25 gu and two target variables were constructed independently, as was done in Kim & Gim (Kim & Gim, 2022).

1) Data Preparation

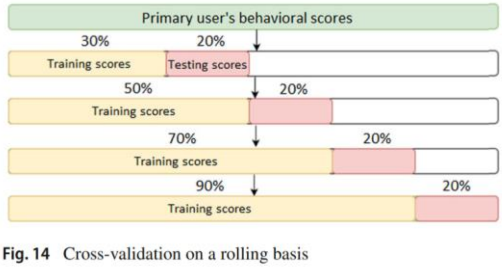
As opposed to the traditional time series models such as ARIMA, Artificial Neural Networks including LSTM do not require the input time series data to be stationary process. However, it is known that with stationary time series data the prediction performance of the prediction model significantly increases. Therefore, differencing and log transformation was considered for the dependent variables. Order 1 lag variable was included, and all variables were standardized before they were fed to the model. Look back size of 12 sliding windows were generated to forecast one step forward value of the target variable.

2) Hyperparameter tuning

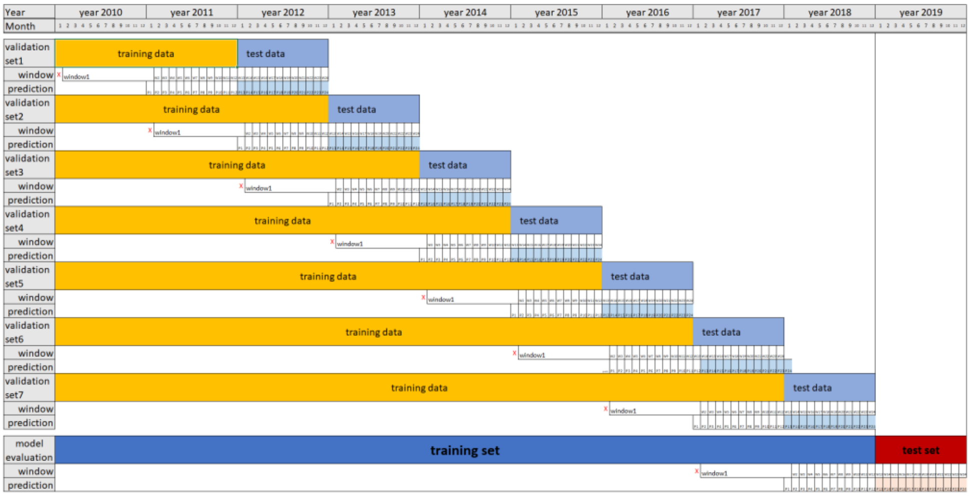
Using the training dataset from 2010 to 2018, hyperparameters of LSTM were tuned. K-fold cross validation method, as presented in [Figure 19] which randomly samples validation set from training set is commonly used to tune the hyperparameters of machine learning models. However, as the data used in this research is characterized as a sequential data, K-fold cross validation is not applicable.



[Figure 19] k-fold cross validation (scikit-learn1.1.2 document)



[Figure 20] Cross-validation on a rolling basis (Walk-Forward Validation) (Amraoui & Zouari, 2022)



[Figure 21] Hyperparameter tuning process through Walk-Forward Validation

Instead, cross-validation in a rolling basis, also known as walk-forward method, like presented in [Figure 20] were applied for validating the model. The training set was divided into seven validation sets consisting of two years of training data and one year of test data, as shown in [Figure 21]. In total, 12 sets of hyperparameters were tested. [Table 8] shows the environment settings options of the LSTM models. Hyperparameters of 50 models were tuned using cross validation in rolling basis, and grid search method was applied to choose the best hyperparameter settings. Additionally, early stopping was applied in deciding the number of training epochs to avoid overfitting. Maximum epoch was set at 200. When the validation loss is larger than the mean of the validation losses of the last 50 epochs, the training process was stopped. See [Appendix D] for the final models' loss curves.

[Table 8] LSTM hyperparameter grid search settings

Class	Setting
Activation Function	ReLU
Loss function	[Mean Absolute Errors, Mean Squared Errors]
Optimizer	Adam
Batch Size	32
Epoch	Maximum 200 with early stopping applied
Number of hidden layers	1
Hidden units	[4, 6, 8]
Learning Rate	[0.01, 0.001]

3) Handling Randomness

Due to the small sample size (n=120), the models were highly prone to randomness, which can eventually affect the credibility of the long-term future forecast. In order to control the randomness, the hyperparameter tuning process was done 20 times for each gu under different random states. The hyperparameter setting with the lowest mean RMSE value of the 20 times validation was chosen as the final hyperparameters. Under the setting, the entire training dataset was fed to 20 models of different random states. The model that showed the closest value with the validation mean RMSE value was taken as the final prediction model.

4) Prediction Accuracy Evaluation

In ASHRAE (American Society of Heating, Refrigerating and Air-Conditioning Engineers) Guideline 14, ASHRAE provides guidance to measure the energy and demand savings due to building energy management projects. In the document, three indices are presented to measure how well a mathematical model describes the variability in measured data. One of them is the Coefficient of Variation of the root mean square error (CVRMSE) (AHSHRAE, 2002). The mathematical expression of CV(RMSE) is as follows:

$$CVRMSE = 100 \times [\sum(y_i - \hat{y}_i)^2 / (n-p)]^{1/2} / \bar{y}$$

Where y_i, $\hat{y}_i$, $\bar{y}$ denote observed data, predicted data, and average of all the observed data, respectively. CV(RMSE) can be useful in determining whether the differences between the two datasets; observed and predicted dataset, are within an acceptable tolerance. It is suggested that when using monthly data, the range of the acceptable tolerance should be within 15% (AHSHRAE, 2002). Following the guideline, the constructed prediction models were tested by comparing the predicted values of 2019 with the actual data using CV(RMSE).

2. Autoregressive Moving Average (ARIMA)

To evaluate the prediction performance of the LSTM model with comparison to conventional statistical method, Seasonal Autoregressive Integrated Moving Average with exogenous variables (hereby ARIMA) models were employed as an alternative prediction model. As a time-series univariate regression model, ARIMA model can predict future values of a dependent variable while accounting for serial autocorrelation and seasonality in sequential data. A typical ARIMA consists of two parts: an autoregressive (AR) process and a moving average (MA) process, which are mathematically expressed as follows.

AR(p): $y_t = \phi_0 + \phi_1 \times y_{t-1} + \phi_2 \times y_{t-2} + \ldots + \phi_p \times y_{t-p} + e_t$ …………………… (1)

MA(q): $y_t = \mu + e_t + \theta_1 \times e_{t-1} + \theta_2 \times e_{t-2} \ldots + \theta_q \times e_{t-q}$ …………………………….. (2)

Where p denotes the most recent value of time that the y value at time t is dependent on, equation (1) is referred to as the p order AR process. Where q denotes the most recent value of error terms that the y value at time t is affected by, equation (2) is referred to as the q order of MA process. In MA process, each error terms are independent of the others. In addition, identifying and removing seasonality is a part of modelling linear time series models. A common way of doing so is differencing, converting a time series of values into a time series of changes over time. A d order differencing refers to the time series at time t being differenced to the time series at time t-d (Nielsen, 2020).

Instead of manually searching for the parameters of the 25 models, auto_arima module in pmdarmia library written in Python language was used in this study. The auto_arima module can automatically set the best possible parameters of an ARIMA model with an optimization procedure. With the same set of data that was used to construct the LSTM models, 25 independent ARIMA models corresponding to every gu in Seoul were made to predict residential electricity consumption. The choice of variables followed that of LSTM, except for the temperature variable. As temperature and energy consumption typically present a non-linear relationship, a quadratic temperature variable was additionally implemented in the ARIMA models. Residuals of automatically generated ARIMA models were diagnosed with the Augmented Dickey-Fuller test and Ljung-Box test. Those models containing unit roots and autocorrelations in the residuals were adjusted manually.

3. Scenario Analysis

[Table 9] Variable alterations depending on Scenario

<table>
<tr><th rowspan="2">Category</th><th rowspan="2">Scenario</th><th>2030</th><th>2050</th></tr>
<tr><th>variable alteration1</th><th>variable alteration2</th></tr>
<tr><td rowspan="2">Climate Change</td><td>SSP126
Best case climate change</td><td colspan="2">Temperature_SSP126</td></tr>
<tr><td>SSP585
Worst case climate change</td><td colspan="2">Temperature_SSP585</td></tr>
<tr><td rowspan="6">Socioeconomic Shifts</td><td rowspan="3">KOSIS High</td><td colspan="2">total popualtion_H</td></tr>
<tr><td colspan="2">Elderly population ratio_H</td></tr>
<tr><td colspan="2">youth population ratio_H</td></tr>
<tr><td rowspan="3">KOSIS Low</td><td colspan="2">total popualtion_L</td></tr>
<tr><td colspan="2">Elderly population ratio_L</td></tr>
<tr><td colspan="2">Youth population ratio_L</td></tr>
<tr><td rowspan="16">Urban Development</td><td rowspan="4">2030 Seoul Plan</td><td>New Building Ratio_0</td><td rowspan="4"></td></tr>
<tr><td>Green Area Raio_0</td></tr>
<tr><td>Totla Floor Area_0</td></tr>
<tr><td>Land Use_0</td></tr>
<tr><td rowspan="4">Assumption #0
No significant change from 2030 Seoul Plan</td><td rowspan="4"></td><td>New Building Ratio_0</td></tr>
<tr><td>Green Area Raio_0</td></tr>
<tr><td>Totla Floor Area_0</td></tr>
<tr><td>Land Use_0</td></tr>
<tr><td rowspan="4">Assumption #1
Green city initiative</td><td rowspan="4"></td><td>New Building Ratio_0</td></tr>
<tr><td>Green Area Raio_1</td></tr>
<tr><td>Totla Floor Area_0</td></tr>
<tr><td>Land Use_0</td></tr>
<tr><td rowspan="4">Assumption #2
High density development</td><td rowspan="4"></td><td>New Building Ratio_0</td></tr>
<tr><td>Green Area Raio_0</td></tr>
<tr><td>Totla Floor Area_2</td></tr>
<tr><td>Land Use_0</td></tr>
</table>

1) Scenarios by the year 2030

Total of four sets of scenario combinations, which consist of two climate change scenarios, and two socioeconomic scenarios, and one urban form and land use data based on <2030 Seoul Plan> were prepared in the future data collection process. Corresponding to each scenario combination, the four datasets on the year 2030 was put into the constructed LSTM model, to project 2030 building energy consumption of all two sectors.

2) Scenarios by the year 2050

Two sets of future climate data, two sets of socioeconomic data, and three sets of urban form and land use data based on three different urban development assumptions are prepared in the future data generation process. A total of twelve future dataset on the year 2050 is going to be put into the LSTM model, to project 2050 building energy consumption of all three sectors.

V. Results and Discussions

1. LSTM construction results

LSTM models to predict monthly residential and commercial building electricity consumption in 25 gu were constructed individually, using nine independent variables from climatic and socioeconomic categories from 2010 to 2018. Yearly frequency data were adjusted to monthly frequency using the linear interpolation method, based on Raubitzek and Neubauer's work that proved input data interpolation improves the prediction power of neural network models (Raubitzek & Neubauer, 2021). Differencing and log transformation were not adopted in any of the models, as the dependent variables did not show significant trend, nor they were characterized as exponentially distributed time series.

The accuracy of the final LSTM models was tested by comparing the observed values of the dependent variable in 2019 with the predicted values from the LSTM models using CV(RMSE). [Tables 10] and [Table 11] show the hyperparameter choices of the final models, the average of 20 validations' CV(RMSE), and the CV(RMSE) of the test set. [Figures 22] and [Figure 23] are plots of the test set prediction results and the actual values of the target variables. The average test CV(RMSE) of the LSTM models was 6.04% for residential energy prediction and 6.40% for commercial energy prediction. With the exception of the Seongdong-gu and Gangseo-gu commercial electricity prediction models, the CV(RMSE) values of 48 models are within the acceptable range specified by ASHRAE Guideline 14 (AHSHRAE, 2002).

[Table 10] Residential electricity prediction models – Validation and test results under the best hyperparameter settings

Model	Residential Electricity Prediction Models				
Gu	hidden layer units	loss function	learning rates	Validation mean CV(RMSE)	test set CV(RMSE)
Jongno-gu	6	mae	0.01	1.44%	3.96%
Jung-gu	8	mae	0.01	1.71%	3.60%
Yongsan-gu	6	mae	0.01	2.18%	7.10%
Seongdong-gu	4	mae	0.01	2.73%	6.96%
Gwangjin-gu	8	mae	0.01	2.49%	3.79%
Dongdaemun-gu	8	mae	0.01	2.64%	6.96%
Jungnang-gu	6	mae	0.001	4.83%	6.38%
Seongbuk-gu	6	mae	0.001	4.04%	7.67%
Gangbuk-gu	6	mae	0.01	2.28%	5.67%
Dobong-gu	8	mae	0.01	1.76%	8.44%
Nowon-gu	8	mae	0.01	1.45%	6.20%
Eunpyeong-gu	8	mae	0.01	1.75%	9.52%
Seodaemun-gu	8	mae	0.01	1.41%	4.48%
Mapo-gu	6	mae	0.01	1.90%	5.95%
Yangcheon-gu	8	mae	0.01	2.97%	3.74%
Gangseo-gu	8	mae	0.01	2.22%	4.71%
Guro-gu	8	mae	0.01	1.75%	3.51%
Geumcheon-gu	8	mae	0.01	2.01%	6.40%
Yeongdeungpo-gu	8	mae	0.01	2.10%	8.47%
Dongjak-gu	4	mae	0.01	2.22%	4.98%
Gwanak-gu	4	mae	0.01	2.51%	5.01%
Seocho-gu	8	mse	0.01	2.62%	4.90%
Gangnam-gu	4	mae	0.01	2.58%	6.66%
Songpa-gu	8	mse	0.01	1.79%	5.92%
Gangdong-gu	4	mae	0.01	3.00%	9.98%
Evaluation Score Mean				**2.34%**	**6.04%**

[Table 11] Commercial electricity prediction models - Validation and test results under the best hyperparameter settings

Model	Commercial Electricity Prediction Models				
Gu	hidden layer units	loss function	learning rates	Validation mean CV(RMSE)	test set CV(RMSE)
Jongno-gu	6	mae	0.01	4.36%	4.42%
Jung-gu	6	mae	0.01	2.51%	3.49%
Yongsan-gu	4	mae	0.001	5.72%	6.09%
Seongdong-gu	4	mae	0.01	3.40%	25.12%
Gwangjin-gu	6	mae	0.01	2.56%	3.24%
Dongdaemun-gu	8	mae	0.01	1.70%	4.87%
Jungnang-gu	8	mae	0.001	2.13%	4.22%
Seongbuk-gu	6	mae	0.01	1.31%	4.31%
Gangbuk-gu	6	mae	0.01	2.31%	2.93%
Dobong-gu	4	mae	0.01	3.43%	3.74%
Nowon-gu	6	mae	0.001	6.44%	7.01%
Eunpyeong-gu	4	mae	0.01	1.73%	5.80%

Seodaemun-gu	4	mae	0.001	1.53%	3.59%
Mapo-gu	6	mse	0.001	2.81%	9.74%
Yangcheon-gu	4	mae	0.01	2.39%	4.56%
Gangseo-gu	6	mae	0.001	7.41%	19.49%
Guro-gu	6	mae	0.01	1.19%	5.86%
Geumcheon-gu	8	mae	0.01	1.43%	3.53%
Yeongdeungpo-gu	8	mse	0.001	2.60%	4.19%
Dongjak-gu	8	mae	0.001	3.45%	4.11%
Gwanak-gu	6	mse	0.001	2.36%	6.74%
Seocho-gu	4	mae	0.001	1.42%	5.02%
Gangnam-gu	6	mae	0.001	1.85%	8.29%
Songpa-gu	4	mae	0.001	3.76%	6.80%
Gangdong-gu	4	mae	0.01	1.68%	2.78%
Evaluation Score Mean				**2.86%**	**6.40%**

2. Prediction Performance Comparison with ARIMA

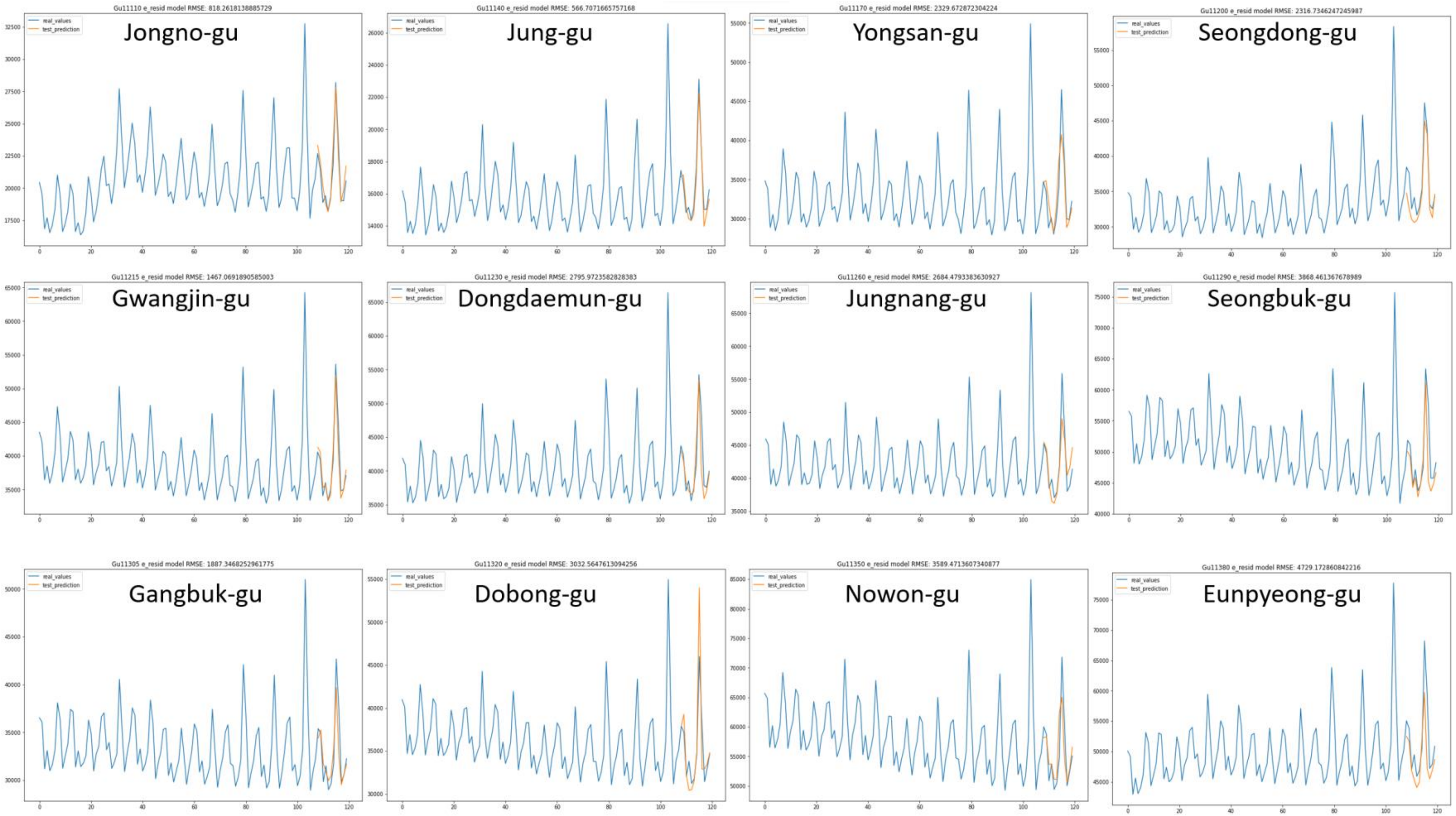
25 ARIMA models for residential electricity prediction were constructed using the auto_arima function in the pmdarima library for each gu. The detailed settings and evaluation scores of these models can be found in [Appendix A]. To compare the prediction power of the two sets of models, root mean squared error (RMSE) metric was used. The mathematical expression of RMSE is as follows.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

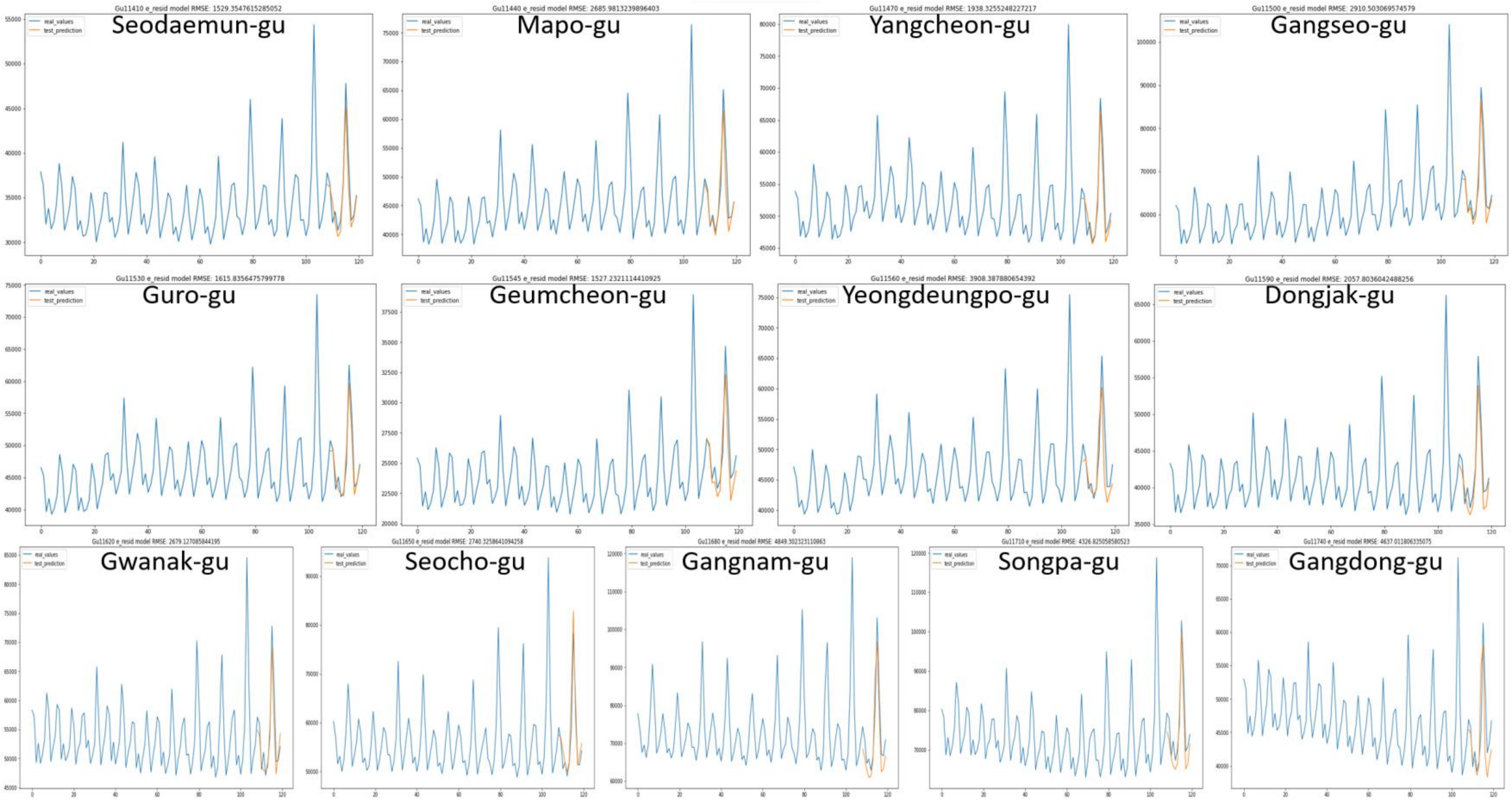
Where $\boldsymbol{y_i}$, $\boldsymbol{\hat{y}_i}$, n denote observed data, predicted data, and the number of the observed data, respectively. As presented in [Table 12], the mean value of the RMSE of the 25 constructed models was 3024.631, which shows that the LSTM models, with a mean RMSE value of 2699.66, perform better in predicting residential electricity consumption than the ARIMA models.

[Table 12] LSTM and ARIMA models residential building energy prediction performance comparison using RMSE

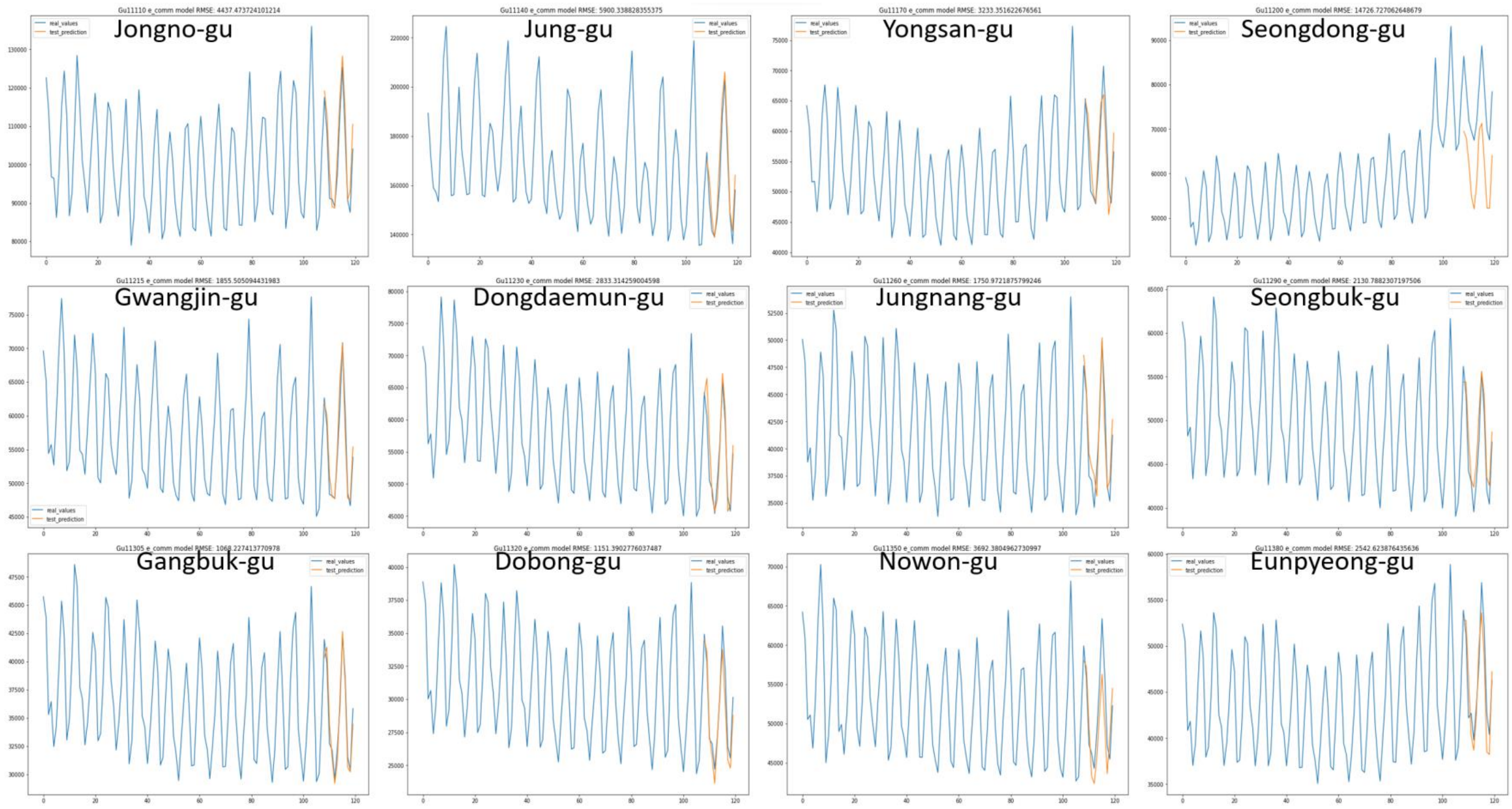
Gu	Test set LSTM RMSE	Test set ARIMA RMSE
Jongno-gu	818.2618	1504.924
Jung-gu	566.7071	1313.357
Yongsan-gu	2329.673	3399.487
Seongdong-gu	2316.735	3789.856
Gwangjin-gu	1467.069	3755.445
Dongdaemun-gu	2795.972	3801.456
Jungnang-gu	2684.479	3585.697
Seongbuk-gu	3868.461	2916.182
Gangbuk-gu	1887.347	1741.083
Dobong-gu	3032.257	1203.442
Nowon-gu	3589.471	2582.806
Eunpyeong-gu	4729.173	4583.533
Seodaemun-gu	1529.355	2711.059
Mapo-gu	2685.981	2766.409
Yangcheon-gu	1938.326	2695.603
Gangseo-gu	2910.503	5082.602
Guro-gu	1615.836	4008.048
Geumcheon-gu	1527.232	2374.784
Yeongdeungpo-gu	3908.388	1997.967
Dongjak-gu	2057.804	3924.95
Gwanak-gu	2679.127	2724.213
Seocho-gu	2740.326	5065.879
Gangnam-gu	4849.302	2683.375
Songpa-gu	4326.825	3397.151
Gangdong-gu	4637.012	2006.463
Mean	**2699.665**	**3024.631**

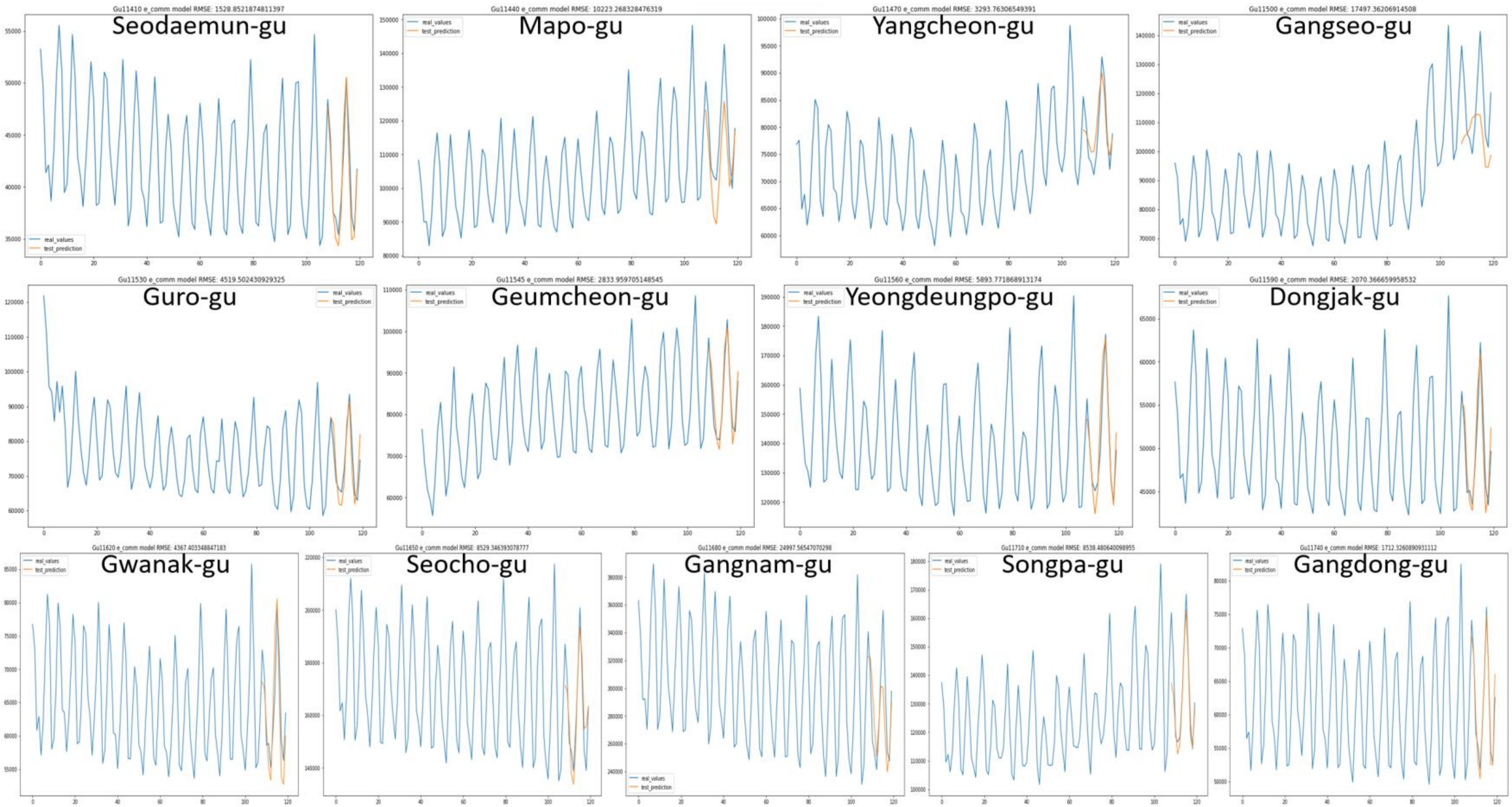


Gu11110 e_resid model RMSE: 818.2618138885729
Jongno-gu
Gu11140 e_resid model RMSE: 566.7071665757168
Jung-gu
Gu11170 e_resid model RMSE: 2329.672872304224
Yongsan-gu
Gu11200 e_resid model RMSE: 2316.7346247245987
Seongdong-gu
Gu11215 e_resid model RMSE: 1467.0691890585003
Gwangjin-gu
Gu11230 e_resid model RMSE: 2795.9723582828383
Dongdaemun-gu
Gu11260 e_resid model RMSE: 2684.4793383630927
Jungnang-gu
Gu11290 e_resid model RMSE: 3868.461367678989
Seongbuk-gu
Gu11305 e_resid model RMSE: 1887.3468252961775
Gangbuk-gu
Gu11320 e_resid model RMSE: 3032.5647613094256
Dobong-gu
Gu11350 e_resid model RMSE: 3589.4713607340877
Nowon-gu
Gu11380 e_resid model RMSE: 4729.172860842216
Eunpyeong-gu
real_values
test_prediction



[Figure 22] Test set result of residential electricity use (Mwh)

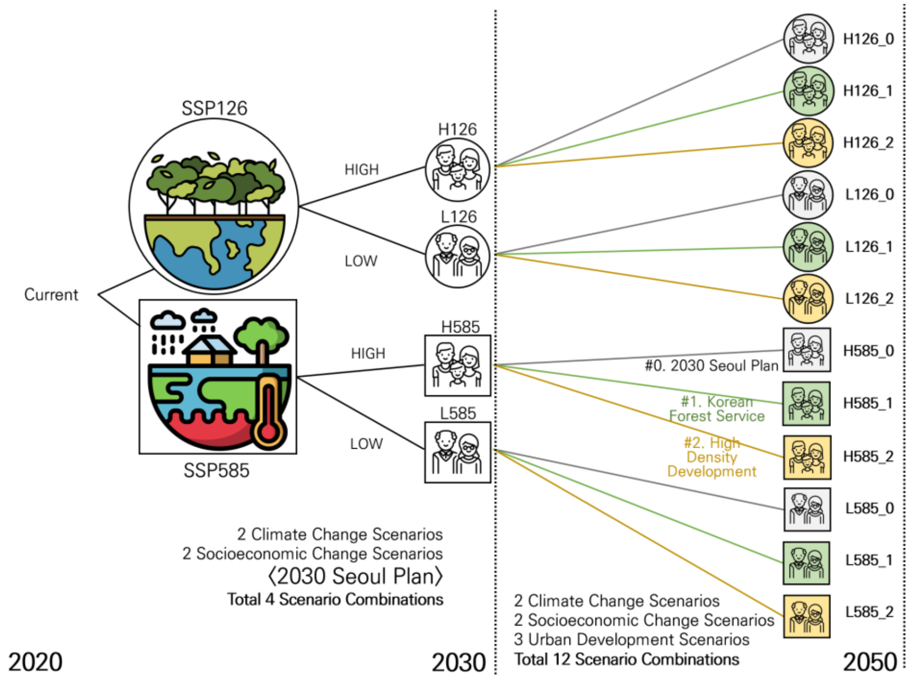

Gu11110 e_comm model RMSE: 4437.473724101214
Jongno-gu
Gu11140 e_comm model RMSE: 5900.338828355375
Jung-gu
Gu11170 e_comm model RMSE: 3233.351622676561
Yongsan-gu
Gu11200 e_comm model RMSE: 14726.727062648679
Seongdong-gu
Gu11215 e_comm model RMSE: 1855.505094431983
Gwangjin-gu
Gu11230 e_comm model RMSE: 2833.314259004598
Dongdaemun-gu
Gu11260 e_comm model RMSE: 1750.9721875799246
Jungnang-gu
Gu11290 e_comm model RMSE: 2130.7882307197506
Seongbuk-gu
Gu11305 e_comm model RMSE: 1068.227413770978
Gangbuk-gu
Gu11320 e_comm model RMSE: 1151.3902776037487
Dobong-gu
Gu11350 e_comm model RMSE: 3692.3804962730997
Nowon-gu
Gu11380 e_comm model RMSE: 2542.623876435636
Eunpyeong-gu
real_values
test_prediction



[Figure 23] Test set result of commercial electricity use (Mwh)

3. Building Energy Consumption Forecasting Results

Using the constructed LSTM models, residential and commercial electricity consumption in 25 gu-s were forecasted, under four scenarios in 2030 and twelve scenarios in 2050. Future values of one climate, four socioeconomic, and four urban form variables were used as inputs to the constructed LSTM models. A step-forward prediction was conducted by the end of 2050 to predict the future values of monthly energy consumption in the two building sectors under twelve scenario combinations. The gu-level forecasting results were aggregated into Seoul level and analyzed. For the gu-level forecasting results, see [Appendix C].



[Figure 24] Scenario combinations used in the forecasting process

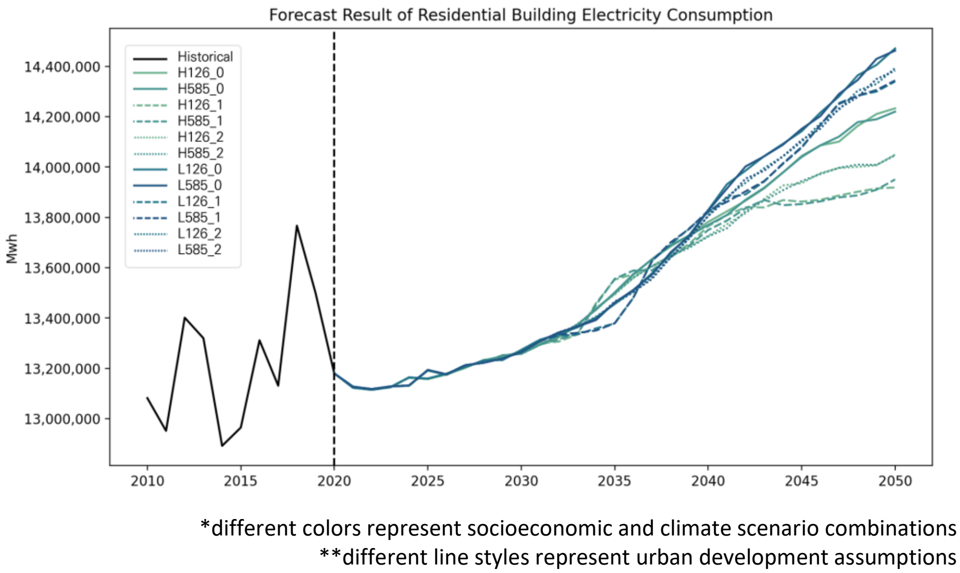
For clarity, scenario combinations will be referred to by abbreviations indicated in [Table 13] from this point on. The first letter indicates whether the combination adopts the High or Low socioeconomic scenario, while the numerical three digits represent which climate change scenario is used, either SSP126 or SSP585. The last digit behind the underbar("_") is based on urban development assumptions, with 0 representing the baseline, 1 representing a green city initiative, and 2 representing a high-density development assumption.

[Table 13] Scenario Combination Abbreviations

Scenario Combination	Scenarios		
Abbreviation	Socioeconomic	Climate Change	Urban Development
H126_0	High	SSP126 (best case)	#0 Baseline
H126_1			#1 Green city
H126_2			#2 High Density Development
H585_0		SSP585 (worst case)	#0 Baseline
H585_1			#1 Green city
H585_2			#2 High Density Development
L126_0	Low	SSP126 (best case)	#0 Baseline
L126_1			#1 Green city
L126_2			#2 High Density Development
L585_0		SSP585 (worst case)	#0 Baseline
L585_1			#1 Green city
L585_2			#2 High Density Development

1) Residential Electricity Consumption Forecasting Results

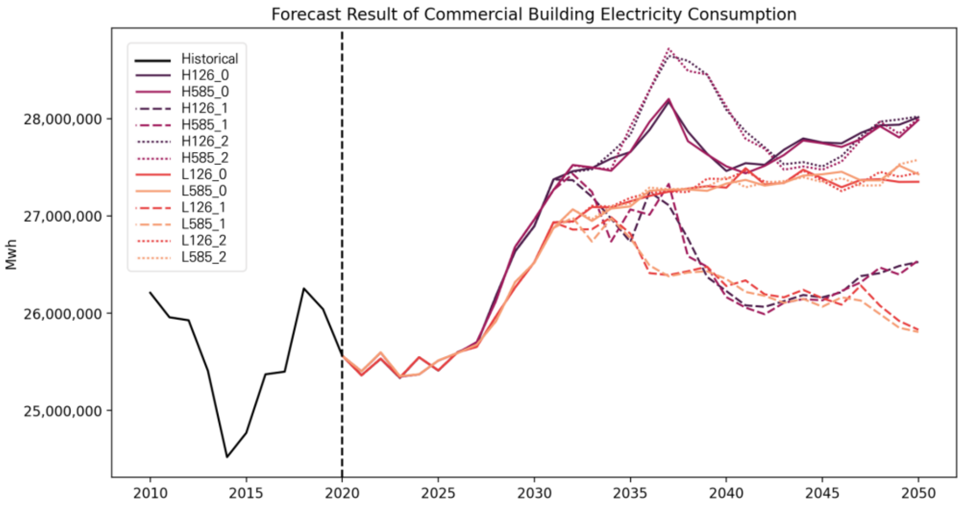
[Figure 25] is the forecasting results of electricity consumption from the residential building under 12 scenario combinations, by the year 2050. The projected electricity consumption in the residential building sector is expected to reach up to 14,462,569 MWh in the L585-0 scenario combination and decrease to 14,049,562 MWh in the H126-1 scenario combination by 2050, resulting in a difference of 3.12%. [Figure 25] shows a clear separation of the high and low socioeconomic scenario combinations into two groups. Within the two groups, the projection results by 2050 further divided into three groups following the urban development assumptions. The results have three key implications. One, socioeconomic conditions have the most significant impact on residential building energy consumption among the three factors studied: climate, socioeconomic, and urban form. Two, smaller populations with a higher ratio of seniors consume more energy than larger populations with a lower ratio of seniors, regardless of climate or urban development conditions. Three, Increasing the size of the urban forest was the most effective method for reducing residential building energy consumption, followed by high-density development with increased total floor area.



[Figure 25] Forecasting Results of future residential electricity consumption

2) Commercial Electricity Consumption Forecasting Results

[Figure 26] shows the results of forecasted electricity consumption in the commercial sector by 2050. It is expected that electricity consumption will reach 28,024,238 MWh in the H126_2 scenario combination and decrease to 25,808,064 MWh in the L585-1 scenario combination, resulting in a reduction of 16.2%. The results show significant differences from the residential energy forecast, revealing three critical implications. Firstly, the fact that all four scenario combinations containing the green city initiative assumption #1 are clustered in the lower part of the plot indicates that urban development is the most significant factor for commercial energy consumption. Secondly, scaling up of urban forests can significantly lower the commercial use energy consumption - under low socioeconomic scenario settings, the average energy consumption from the commercial building sector is reduced by 12.2%, and under high socioeconomic scenario settings, it is reduced by 10.9%. And Finally, scenario combinations containing the High socioeconomic scenario are always expected to consume more commercial electricity than the low- socioeconomic scenario combinations. This reveals the important implication that, unlike residential energy consumption, total population and young population size are positively related to commercial building energy consumption.

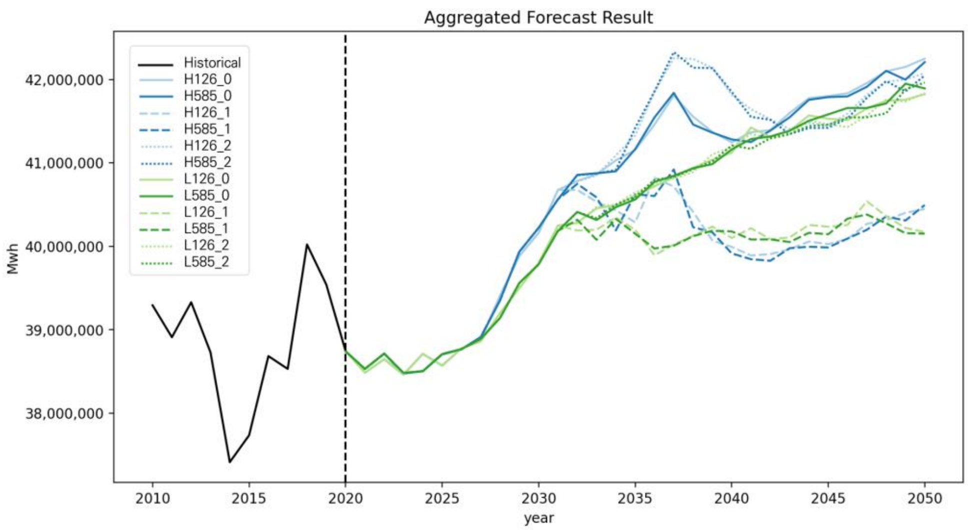


*different colors represent socioeconomic and climate scenario combinations
**different line styles represent urban development assumptions

[Figure 26] Forecasting Results of future commercial electricity consumption

3) Aggregated Total Building Electricity Consumption

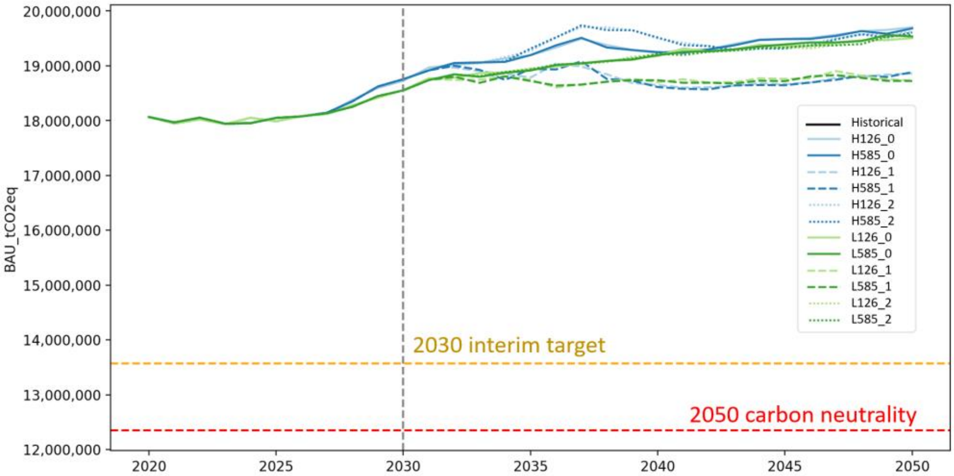
As depicted in [Figure 27], which displays the aggregated results of total electricity consumption from both the residential and commercial building sectors, it is evident that the pattern closely resembles that of the commercial electricity consumption forecast. This is due to the fact that the commercial sector accounts for nearly twice the amount of electricity consumed compared to the residential sector. The total electricity consumption from both sectors ranges from 40,151,927 MWh under the L585_1 scenario combination to 42,249,125 Mwh under the H126_0 scenario combination. It is worth mentioning that [Figure 27] displays roughly four sets of lines, each comprising of two climate change scenarios. This suggests that among the three factors studied, the impact of climate change is the least significant.



*different colors represent socioeconomic and climate scenario combinations
**different line styles represent urban development assumptions

[Figure 27] Forecasting result of future electricity consumption from the two building sectors

4. Evaluation of the 2050 Carbon Neutrality Goal



[Figure 28] Total carbon emission from the two building sectors, BAU emission factors applied

The Seoul Metropolitan Government (SMG) has set a goal to decrease carbon emissions from the building sector by 40% in 2030 and 50% in 2050, as outlined in the <2050 Climate Action Plan> submitted to the C40 in 2020 (서울특별시, 2021b). The plan aims to achieve a reduction of 29,687tCO2eq in the building sector by 2030 and 26,969tCO2eq by 2050, compared to 2005 levels when 14,736 tCO2eq and 14,951 tCO2eq were emitted from residential and commercial buildings, respectively. In 2005, electricity consumption accounted for 45.7% of the building sector's total GHG emissions, a figure that remained unchanged in 2019. If this trend continues until 2050, the building sector's GHG emissions from electricity consumption would need to reach at least 13,573.57 tCO2eq in order to meet the interim target of carbon neutrality by 2030. In the same sense, GHG emission from the building sector's electricity consumption would have to reach roughly 12,349.29 tCO2eq to meet the final goal.

The current GHG emission factor for electricity in Seoul is 5.422 tCO2eq/TOE. By applying this factor to forecasted data, GHG emissions from the building sector is as depicted in [Figure 28]. Based on business-as-usual (BAU) electricity emission factors, none of the twelve scenarios analyzed come close to reaching the 2030 interim target, let alone achieving the 2050 goal of carbon neutrality. [Table 14] highlights the level of supplementary GHG emission reduction required to attain the interim target for 2030 and 2050 carbon neutrality.

[Table 14] Additional GHG emission reduction target breakdown

year	Scenario	Mwh	BAU CO2eq	to 2030 target (CO2eq)	to 2050 target (CO2eq)	Effect of urban development
2030	H126	40,162,407	18,715,682	6,142,112		
	H585	40,222,479	18,743,675	6,170,105		
	L126	39,798,399	18,546,054	5,972,484		
	L585	39,783,751	18,539,228	5,965,658		
2050	H126_0	42,249,125	19,688,092		7,338,802	baseline
	H126_1	40,446,899	18,848,255		6,498,965	-11.44%
	H126_2	42,073,800	19,606,391		7,257,101	-1.11%
	H585_0	42,207,890	19,668,877		7,319,587	baseline
	H585_1	40,495,392	18,870,853		6,521,563	-10.90%
	H585_2	42,048,536	19,594,618		7,245,328	-1.01%
	L126_0	41,823,551	19,489,775		7,140,485	baseline
	L126_1	40,170,829	18,719,606		6,370,316	-10.79%
	L126_2	41,838,512	19,496,747		7,147,457	0.10%
	L585_0	41,892,658	19,521,979		7,172,689	baseline
	L585_1	40,151,927	18,710,798		6,361,508	-11.31%
	L585_2	41,962,520	19,554,534		7,205,244	0.45%

The last column in [Table 14] indicates how much of the GHG emission was reduced due to implementing the urban planning measures – assumption #1 being green city initiative and assumption #2 being high-density development. It is worth noting that under all four socioeconomic and scenario combinations (H126, H585, L126, L585), assumption #1 of scaling up the urban forest resulted in more than a 10% reduction in GHG emission. The effect of assumption #2 was rather insignificant compared to that of assumption #1. However, high-density development tended to reduce GHG emissions under High socioeconomic scenarios. In contrast, it was prone to increase GHG emissions under Low socioeconomic scenarios. How small or large they emit, none of the twelve scenarios were expected to achieve the 2050 carbon neutrality goal.

One of the most realistic ways to reduce GHG emissions from electricity consumption is lowering the GHG emission factor of electricity through the energy transition. The purpose of this research is not GHG emission accounting, hence the estimated future GHG factors were taken from previous literature. Lee et al. (2018) conducted a study on a national GHG reduction strategy considering energy transition and came up with GHG emission factors by 2050 on five years basis, as presented in [Figure 29] (이상엽 et al., 2018). This study took the product of the research directly and used it to calculate the future GHG emission from the building sector when the energy transition has successfully been implemented.

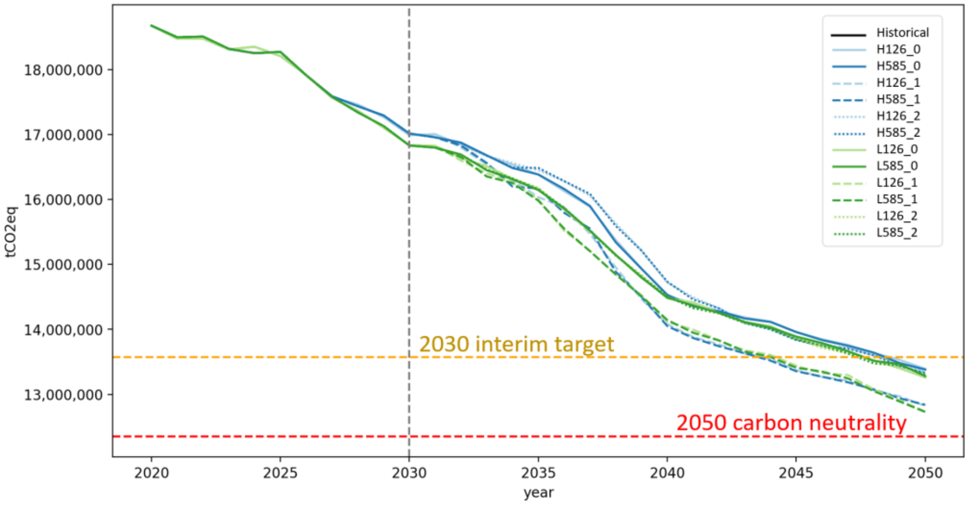
〈표 2-9〉 최종수요 부문 전력배출계수

구분	2015	2020	2025	2030	2035	2040	2045	2050
전환 부문 배출량 (백만 톤CO_2)	243	256.5	276.9	267.4	266.2	244.8	238.7	230.7
전력수요 (백만 TOE)	41.6	45.6	50.4	54.3	57.5	59.8	61.4	62.6
전력배출계수 (톤CO_2/TOE)	5.84	5.63	5.49	4.92	4.63	4.09	3.89	3.69

주: 전환 부문 배출량에는 지역난방도 포함함.
자료: 저자 작성.

[Figure 29] GHG emission factor considering energy transition by 2050 (이상엽 et al., 2018)

[Figure 30] shows total carbon emission from the building sector in case of a successful energy transition. As any of the line plots is not reaching the "2050 carbon neutrality" level, it suggests that even with the implementation of energy transition measures, the objective of achieving 2050 carbon neutrality cannot be fulfilled. [Table 15] shows how much extra GHG reduction should occur to achieve the 2030 and 2050 goals.



[Figure 30] Total carbon emission from the two building sectors, in case of successful energy transition

However, it must be noted that the effort for energy transition is not fruitless, as it dramatically reduces the gap between the goal and the estimated GHG emissions. Moreover, compared with the baseline urban development assumption #0, GHG emissions from building energy consumption under green city initiative assumption #1 have decreased down to at least 52.67% and up to 59.29%, depending on the socioeconomic and climate scenarios. This indicates that the energy transition amplifies the effect of assumption #1 in cutting down building energy consumption.

[Table 15] Additional GHG emission reduction target breakdown of 2030 and 2050, in case of energy transition

year	Scenario	Mwh	CO2eq	to 2030 target (CO2eq)	to 2050 target (CO2eq)	Effect of urban development
2030	H126	40162406.9	16988698.1	3,415,128		
	H585	40222479.3	17014108.74	3,440,539		
	L126	39798399.1	16834722.84	3,261,153		
	L585	39783751	16828526.67	3,254,957		
2050	H126_0	42249125.3	13392972.72		1,043,683	baseline
	H126_1	40446899	12821666.99		472,377	**-54.74%**
	H126_2	42073800.4	13337394.72		988,105	-5.33%
	H585_0	42207889.9	13379901.08		1,030,611	baseline
	H585_1	40495392.2	12837039.31		487,749	**-52.67%**
	H585_2	42048535.9	13329385.87		980,096	-4.90%
	L126_0	41823551.1	13258065.71		908,776	baseline
	L126_1	40170829.4	12734152.92		384,863	**-57.65%**
	L126_2	41838511.9	13262808.28		913,518	0.52%
	L585_0	41892657.9	13279972.55		930,683	baseline
	L585_1	40151927.4	12728161		378,871	**-59.29%**
	L585_2	41962519.8	13302118.78		952,829	2.38%

VI. Conclusion and Limitations

This study forecasted electricity consumption in the residential and commercial building sectors of 25 gu-s in Seoul using LSTM, as an attempt to evaluate the current masterplan of Seoul and examine if it aligns with the 2050 carbon neutrality goal in the building sector. A total number of fifty LSTM models were constructed corresponding to every gu and every building sector, using data from 25 gu in Seoul over the past ten years. Through scenario analysis, this research explored the impact of climate change, and socioeconomic shifts, and urban development on building energy. The conclusion of the research can be summarized as follows.

(1) This study explored how well LSTM performs in building energy consumption prediction task. The results of the modelling process indicate that the LSTM models accurately depicted the residential and commercial building energy consumption patterns in each gu of Seoul, as evidenced by the acceptable CV(RMSE) values (less than 15%). Additionally, the LSTM models constructed in this research demonstrated improved performance in predicting future energy consumption in the building sector compared to the traditional statistical method, ARIMA.

(2) The forecast of electricity consumption in residential buildings by 2050 ranges from 14,049,562 MWh to 14,462,569 MWh with a difference of 3.12%. Socioeconomic conditions have the greatest impact on residential building energy consumption, followed by urban form and climate. Energy was consumed more under the Low socioeconomic scenario which represents smaller populations with a higher senior ratio than the High socioeconomic scenarios.

(3) The forecast of electricity consumption in the commercial sector by 2050 ranges from 25,808,064 MWh to 28,024,238 MWh with a difference of 16.2%. The results show that urban development is the most significant factor for commercial energy consumption, followed by socioeconomic conditions. Scaling up urban forests can significantly lower commercial energy consumption by 10.9-12.2%. Unlike residential sector, High socioeconomic scenario combinations are expected to consume more commercial electricity than low-socioeconomic scenario combinations, indicating that population size and young population size positively impact commercial building energy consumption.

(4) The aggregated results of total building electricity closely resemble the commercial electricity consumption forecast. Total electricity consumption ranges from 40,151,927 MWh to 42,249,125 MWh, with the least significant impact being from climate change.

(5) When applying the estimated GHG emission factor to the electricity forecast results, none of the 12 scenarios come close to reaching the 2030 interim target, let alone achieving the 2050 goal of carbon neutrality. In this case, scaling up the urban forest (assumption #1) resulted in more than a 10% reduction in GHG emission in all four socioeconomic and climate scenario combinations, while high-density development (assumption #2) had a relatively insignificant effect. The study also showed that even with the implementation of energy transition measures, the objective of achieving 2050 carbon neutrality cannot be fulfilled. However, the study found that the effect of assumption #1 in reducing energy consumption is strengthened and becomes more effective when combined with the energy transition.

The key contributions of this study are threefold: first, as a rare attempt to comprehensively understand the sectoral energy consumption of residential and commercial buildings in 25 gu-s of future Seoul, it provided the effects of climate change, socioeconomic shifts, and urban development to building energy consumption. Second, by investigating the cutting-edge machine learning technique application to empirical work, this study has explored how well the LSTM model performs in building energy consumption prediction tasks. Finally, with the result of the forecasting, this study has provided an evaluation for SMG's 2050 carbon neutrality goal by examining the monthly electricity demand of the year 2030 in residential and commercial buildings of 25 Gu-s in Seoul, under urban development plans stated in <2030 Seoul Plan> and additional urban form alterations.

The limitations of this study are as follows: Firstly, the assumption that there is no spatial correlation between gu-s in energy consumption behaviors is somewhat unrealistic. An initial attempt was made to create a single integrated model using an encoder-decoder method to handle 3-dimensional panel data, but the prediction accuracy dropped significantly. As a result, the researcher adopted an alternative approach by constructing multiple models corresponding to each dependent variable and gu. Future studies can further explore the use of the encoder-decoder method. Secondly, the choice of variables relied heavily on the availability of data, which resulted in some chosen independent variables not having a direct relationship with the dependent variable, particularly in the prediction models for commercial building's electricity consumption. The study employed registered population data as a proxy, even though the energy consumption behavior in commercial areas is strongly related to the de-facto population. Finally, the study did not consider the potential impact of disruptive technologies such as net-zero building construction or self-sufficient energy systems in buildings. However, the purpose of prediction research is not just to accurately predict the future, but also to explore various assumptions about future conditions and provide insights for policymakers to deal with the predictable range of the future. Through such, the result of this research would be able to serve as a reference for the future studies to come.

Appendix

[Appendix A] 25 ARIMA models to predict residential electricity consumption in 25 gu, constructed for purpose - Model settings and evaluation results

Jachigu name	SARIMAX(p,d,q)(P,D,Q)(12)	RMSE	NRMSE	MAPE
Jongno-gu	SARIMAX(0,0,0)(1,0,1)(12)	1504.924	0.15	14.39
Jung-gu	SARIMAX(0,0,0)(2,0,1)(12)	1313.357	0.15	11.92
Yongsan-gu	SARIMAX(0,0,0)(1,0,1)(12)	3399.487	0.183	14.11
Seongdong-gu	SARIMAX(0,0,0)(1,0,0)(12)	3789.856	0.238	12.30
Gwangjin-gu	SARIMAX(0,0,0)(1,0,1)(12)	3755.445	0.185	11.81
Dongdaemun-gu	SARIMAX(0,0,0)(1,0,1)(12)	3801.456	0.203	11.19
Jungnang-gu	SARIMAX(0,0,0)(1,0,1)(12)	3585.697	0.190	10.58
Seongbuk-gu	SARIMAX(1,0,2)(1,0,0)(12)	2916.182	0.148	13.25
Gangbuk-gu	SARIMAX(3,0,2)(1,0,0)(12)	1741.083	0.127	13.67
Dobong-gu	SARIMAX(1,0,1)(2,0,1)(12)	1203.442	0.081	11.78
Nowon-gu	SARIMAX(0,0,2)(1,0,0)(12)	2582.806	0.115	11.88
Eunpyeong-gu	SARIMAX(0,0,0)(1,0,0)(12)	4583.533	0.205	9.72
Seodaemun-gu	SARIMAX(0,0,0)(1,0,1)(12)	2711.059	0.164	10.41
Mapo-gu	SARIMAX(0,0,3)(1,0,0)(12)	2766.409	0.111	14.53
Yangcheon-gu	SARIMAX(1,0,2)(1,0,0)(12)	2695.603	0.120	13.23
Gangseo-gu	SARIMAX(0,0,0)(0,0,1)(12)	5082.602	0.166	11.32
Guro-gu	SARIMAX(0,0,0)(1,0,0)(12)	4008.048	0.195	9.93
Geumcheon-gu	SARIMAX(0,0,0)(1,0,1)(12)	2374.784	0.202	9.34
Yeongdeungpo-gu	SARIMAX(0,0,0)(1,0,0)(12)	1997.967	0.085	13.49
Dongjak-gu	SARIMAX(0,0,0)(1,0,1)(12)	3924.95	0.190	11.06
Gwanak-gu	SARIMAX(1,0,2)(1,0,0)(12)	2724.213	0.106	14.12
Seocho-gu	SARIMAX(2,0,5)(1,0,0)(12)	5065.879	0.172	16.23
Gangnam-gu	SARIMAX(0,0,1)(1,0,0)(12)	2683.375	0.066	13.74
Songpa-gu	SARIMAX(0,0,0)(1,0,0)(12)	3397.151	0.095	13.31
Gangdong-gu	SARIMAX(3,0,2)(1,0,0)(12)	2006.463	0.090	13.45
Mean		3024.631	0.149	12.43

[Appendix B] Descriptive Statistics of Model Input, Historical Data (2010-2019, n=120)

Gu Name	Variable	mean	std	min	max
Jongno-gu	Residential Electricity	20643.82	2645.94	16369	32747
	Commercial Electricity	100367.8	12991.88	78999	136031
	Temperature	11.86	10.22	-7.84	27.16
	GRDP	29117252	1834740	25907762	32427863
	Total Population	159551.4	6412.85	151290	171215
	Elderly Ratio	15.32	1.6	12.2	18.1
	Youth Ratio	10.31	1.06	8.83	12.62
	Total Floor Area	15210351	1338723	13690905	18326241
	Young Building Ratio	6.08	1.79	4.49	10.32
	Green Area Ratio	46.78	0.04	46.74	46.82
	Residential Area	9362781	414374.1	8964805	9830838
	Commercial Area	3375791	388445.6	2937285	3749385
Jung-gu	Residential Electricity	15756.7	1977.66	13438	26561
	Commercial Electricity	168860.1	21687.95	135548	224628
	temperature	13.06	10.28	-6.72	28.66
	GRDP	49673783	2151722	46998911	52869673
	Total Population	128831.5	3413.59	123926	135841
	Elderly Ratio	15.25	1.67	12.2	18.2
	Youth Ratio	9.97	1.08	8.36	12.14
	Total Floor Area	19533021	707842.2	17658147	20622728
	Young Building Ratio	4.74	1.72	3.35	8.76
	Green Area Ratio	0.16	0.12	0	0.25
	Residential Area	6205717	149588.1	6037439	6349623
	Commercial Area	3752303	140957.6	3616462	3911718
Yongsan-gu	Residential Electricity	32798.48	4274.1	27919	54911
	Commercial Electricity	53089.92	7545.03	41147	77290
	temperature	13.18	10.29	-6.49	28.76
	GRDP	10708789	697259.7	10010946	11992461
	Total Population	236524.2	6372.65	228507	247206

	Elderly Ratio	14.47	1.45	11.7	16.8
	Youth Ratio	11.24	1.09	9.38	13.3
	Total Floor Area	16265044	809666.6	14505887	17517086
	Young Building Ratio	6.76	2.42	3.86	11.34
	Green Area Ratio	39.85	0.96	38.95	40.93
	Residential Area	11741752	335838.8	11378857	12130669
	Commercial Area	1378349	115774.1	1237935	1490319
Seongdong-gu	Residential Electricity	33284.58	4327.27	28444	58320
	Commercial Electricity	58633.32	10687.78	43837	93148
	temperature	13.34	10.16	-6.29	28.72
	GRDP	10022388	896484.5	8213234	11419293
	Total Population	302271.8	4084.1	295866	310487
	Elderly Ratio	12.22	1.3	9.8	14.6
	Youth Ratio	12.04	1.05	10.49	14.34
	Total Floor Area	18037357	3302140	14959427	33658656
	Young Building Ratio	6.36	1.65	4.67	10.02

	Green Area Ratio	26.19	0.44	25.78	26.69
	Residential Area	9344521	533713.3	8841365	9947641
	Commercial Area	369762	91482.81	283741	473145
Gwangjin-gu	Residential Electricity	38704.11	4715.8	32968	64259
	Commercial Electricity	57240.79	7986.57	45096	77620
	temperature	13.34	10.19	-6.15	28.59
	GRDP	5915710	124853.4	5696485	6187957
	Total Population	364402.5	7424.73	351350	376205
	Elderly Ratio	10.67	1.56	8.1	13.6
	Youth Ratio	11.61	1.21	9.67	14.13
	Total Floor Area	16899799	688926.8	15767049	17954439
	Young Building Ratio	12.38	2.3	8.07	16.56
	Green Area Ratio	31.46	0.6	30.89	32.14
	Residential Area	11477337	110295.4	11373497	11607090
	Commercial Area	197231	2856.63	193152	203281

Dongdaemun-gu	Residential Electricity	40179.03	4544.2	35212	66430
	Commercial Electricity	58150.98	8227.34	44931	79135
	temperature	13.34	10.19	-6.15	28.59
	GRDP	6799703	174486.7	6433936	7078663
	Total Population	359070.4	6819.01	346152	367454
	Elderly Ratio	14	1.76	11	17.1
	Youth Ratio	11.25	1.06	9.63	13.35
	Total Floor Area	18401969	917934.7	16520680	19713848
	Young Building Ratio	6.55	1.22	4.31	9.01
	Green Area Ratio	1.85	0.89	0.84	2.69
	Residential Area	13089645	49543.07	13034193	13145393
	Commercial Area	902423.1	65825.19	828159	973364
Jungnang-gu	Residential Electricity	42095.15	4488.79	37039	68134
	Commercial Electricity	41456.28	5216.12	33780	53974
	temperature	12.77	10.29	-6.99	28.26
	GRDP	4106909	155218	3856334	4447811
	Total Population	415458	8146.76	397015	428766
	Elderly Ratio	12.49	2.03	9.2	16.4
	Youth Ratio	11.33	1.22	9.38	13.87
	Total Floor Area	20684721	600166	19642170	21782589
	Young Building Ratio	11.54	1.98	8.75	15.11
	Green Area Ratio	40.21	1	39.39	41.99
	Residential Area	10737800	177138.2	10491158	10973326
	Commercial Area	302720.6	48422.57	257189	357442
Seongbuk-gu	Residential Electricity	50418.1	5266.9	41695	75716
	Commercial Electricity	49391.09	6343.71	39029	64120
	temperature	12.52	10.23	-7.24	27.90
	GRDP	5552190	142565	5275765	5761704
	Total Population	465011.8	17621.85	435270	489703
	Elderly Ratio	13.19	1.67	10.4	16
	Youth Ratio	12.8	1.09	10.97	14.77

	Total Floor Area	21525162	579130.5	19961118	22806896
	Young Building Ratio	7.54	1.89	5.59	11.38
	Green Area Ratio	26.39	0.31	25.97	26.74
	Residential Area	17407613	343811.7	17084539	17829600
	Commercial Area	672287.5	243397.1	397229	901153
Gangbuk-gu	Residential Electricity	33265.17	3342.07	28938	50984
	Commercial Electricity	36426.19	4814.31	29281	48607
	temperature	11.76	10.24	-8.04	27.08
	GRDP	3072420	259302.3	2759140	3897307
	Total Population	333593.6	9835.55	313954	346943
	Elderly Ratio	15.11	2.27	11.4	19.3
	Youth Ratio	11.11	1.34	8.83	13.5
	Total Floor Area	12530146	440853.5	11543582	13150749
	Young Building Ratio	9.26	1.65	6.88	12.73
	Green Area Ratio	55.92	3.77	52.38	60.18

	Residential Area	9938757	925556.2	9067850	10985275
	Commercial Area	298307	24734.55	270342	322150
Dobong-gu	Residential Electricity	35912.67	3619.14	30902	54949
	Commercial Electricity	30825.83	4025.19	24361	40202
	temperature	11.22	10.24	-8.70	26.52
	GRDP	3039029	113141.9	2892873	3208282
	Total Population	354159	10343.97	333362	369428
	Elderly Ratio	13.29	2.23	9.9	17.6
	Youth Ratio	12.1	1.42	9.78	14.82
	Total Floor Area	17087185	5733291	15056489	46224370
	Young Building Ratio	10.94	2.45	7.46	16.21
	Green Area Ratio	47.43	5.31	41.43	52.43
	Residential Area	9331319	1100765	8084190	10366463
	Commercial Area	297054.4	31994.87	258659	327000
Nowon-gu	Residential Electricity	57886.36	5655.18	49249	84952

	Commercial Electricity	52687.57	6793.35	42690	70274
	temperature	12.05	10.30	-7.86	27.56
	GRDP	5801313	231998.6	5504884	6236040
	Total Population	579656.4	23593.47	532905	612815
	Elderly Ratio	11.58	1.78	9	15.2
	Youth Ratio	13.79	1.54	11.33	16.74
	Total Floor Area	23303761	619698.7	22653202	26299359
	Young Building Ratio	9.97	1.9	6.55	14.03
	Green Area Ratio	60.7	1.74	59.07	62.69
	Residential Area	13264335	634169.1	12660506	13980338
	Commercial Area	578041.7	9880.39	568760	590480
Eunpyeong-gu	Residential Electricity	49699.19	5170.26	42941	77765
	Commercial Electricity	43813.86	5694.03	35085	58862
	temperature	12.00	10.33	-7.41	27.49
	GRDP	4079331	320786.3	3678726	4601453
	Total Population	492182.5	9348.68	466950	504701

	Elderly Ratio	13.44	1.83	10.5	16.8
	Youth Ratio	12.62	1.31	10.38	14.81
	Total Floor Area	19210721	895515.4	17812389	20931468
	Young Building Ratio	13.77	2.81	10.72	19.65
	Green Area Ratio	47.65	1.05	46.66	48.84
	Residential Area	15069609	262534.8	14817328	15376440
	Commercial Area	447145.2	64521.64	384474	523842
Seodaemun-gu	Residential Electricity	34160.47	3688.45	29777	54390
	Commercial Electricity	42596.59	5452.08	34342	55548
	temperature	12.49	10.27	-7.11	28.00
	GRDP	7549932	409041.7	6389459	8107945
	Total Population	314615.8	4818.5	306681	327561
	Elderly Ratio	14.23	1.48	11.4	16.7
	Youth Ratio	11.6	1.04	10.08	13.89
	Total Floor Area	16071768	923556.1	14298360	17714232
	Young Building Ratio	8.01	1.77	5.86	11.8

	Green Area Ratio	10.95	0.16	10.77	11.1
	Residential Area	15471807	28701.04	15439372	15498794
	Commercial Area	241027.8	37624.05	205650	283546
Mapo-gu	Residential Electricity	45165.13	5820.84	38283	76414
	Commercial Electricity	104927.2	13175.37	82924	148281
	temperature	12.99	10.26	-6.57	28.58
	GRDP	17313478	1610882	13152867	18987571
	Total Population	383025.2	5905.34	373200	393334
	Elderly Ratio	12.09	1.09	10	13.9
	Youth Ratio	12.54	1.01	10.82	14.46
	Total Floor Area	22193462	1650709	19001124	24379410
	Young Building Ratio	12.36	3.11	9.67	18.63
	Green Area Ratio	43.11	3.3	40.01	46.84
	Residential Area	12699573	615280.2	12089969	13399356
	Commercial Area	734091.8	179499	564778	940188
Yangcheon-gu	Residential Electricity	51838.46	5345.43	45592	79932
	Commercial Electricity	72254.86	8153.54	58123	98773
	temperature	13.16	10.26	-6.57	28.58
	GRDP	6430639	148351.4	6260452	6729834
	Total Population	484959.9	13196.8	458165	501478
	Elderly Ratio	10.01	1.7	7.4	13.3
	Youth Ratio	14.25	1.19	12.56	16.75
	Total Floor Area	20655567	481663.5	19313778	21621356
	Young Building Ratio	11.56	2.96	8.12	17.84
	Green Area Ratio	23.63	0.89	22.87	25.33
	Residential Area	12498393	137229.5	12303891	12731777
	Commercial Area	701338.6	84579.35	609277	796830
Gangseo-gu	Residential Electricity	61764.08	7680.27	53116	104016
	Commercial Electricity	89791.47	17090.02	67429	143503
	temperature	13.05	10.27	-6.43	28.79

	GRDP	11906451	3272239	8259388	16743106
	Total Population	583055.2	12738.03	567173	601850
	Elderly Ratio	11	1.66	8.3	14.2
	Youth Ratio	13	1.09	11.08	15.27
	Total Floor Area	57317683	36740542	24805741	1.19E+08
	Young Building Ratio	15.4	3.92	10.69	24.3
	Green Area Ratio	55.25	1.05	54.27	56.45
	Residential Area	14187152	476817.4	13654836	14719962
	Commercial Area	1366884	65276.97	1321659	1492974
Guro-gu	Residential Electricity	46029.76	5075.69	39265	73488
	Commercial Electricity	77155.27	11412.53	58574	121837
	Temperature	13.02	10.25	-6.57	28.71
	GRDP	12372553	481412.6	11881642	13302390
	Total Population	420006.4	7919.78	403668	428914
	Elderly Ratio	12.01	2.15	8.7	16
	Youth Ratio	13.05	1.1	11.11	14.96

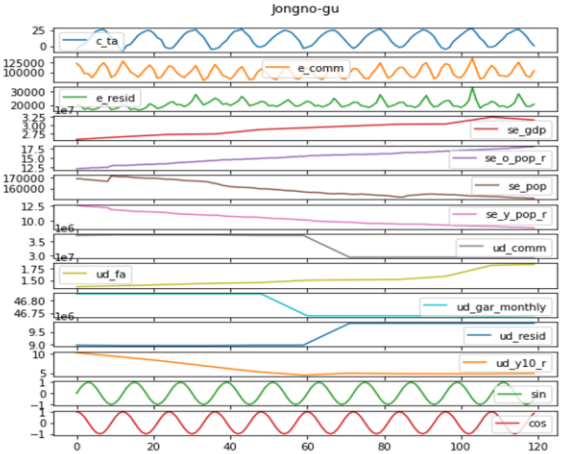
	Total Floor Area	21691748	1035856	19304535	23701803
	Young Building Ratio	10.37	2.75	7.38	15.97
	Green Area Ratio	27.06	1.64	25.61	29.47
	Residential Area	8624634	1386120	7211810	10188383
	Commercial Area	511792	12763.22	473561	523690
Geumcheon-gu	Residential Electricity	23867.22	2715.69	20763	38931
	Commercial Electricity	80201.53	10368.94	55625	108565
	temperature	13.20	10.24	-6.23	28.98
	GRDP	15365184	776166.3	13429693	16745777
	Total Population	238991.5	4135.26	232644	246417
	Elderly Ratio	12.36	2.01	9.1	16
	Youth Ratio	11.01	1.35	8.85	13.95
	Total Floor Area	15054669	1051603	13426024	16902274
	Young Building Ratio	10.82	2.18	7.72	15.17
	Green Area Ratio	21.73	0.56	21.09	22.25

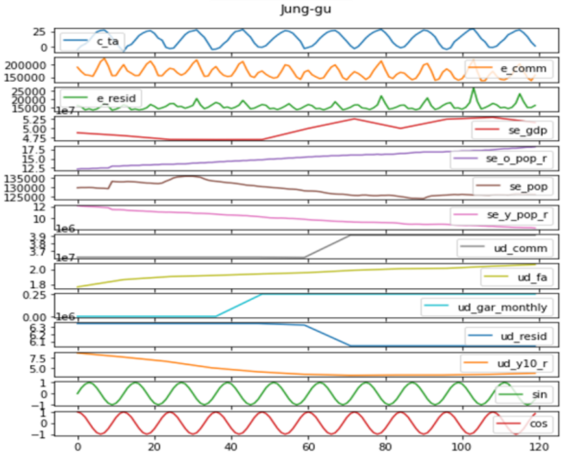
	Residential Area	5941311	90840.92	5845488	6097205
	Commercial Area	164204.5	12903.93	149622	176338
Yeongdeungpo-gu	Residential Electricity	46162.99	5454.03	39352	75448
	Commercial Electricity	140573.9	17584.83	115300	190389
	temperature	13.51	10.25	-6.06	29.06
	GRDP	30325041	1882208	27458784	34201860
	Total Population	383904.9	13213.1	367678	407798
	Elderly Ratio	12.74	1.68	9.8	15.5
	Youth Ratio	11.8	1.19	9.96	14.26
	Total Floor Area	26573669	1357533	23876584	29742853
	Young Building Ratio	7.3	1.61	5.21	10.61
	Green Area Ratio	32.03	3.96	27.56	35.76
	Residential Area	7043930	851920	6243685	8013840
	Commercial Area	2523865	80644.66	2447002	2645273
Dongjak-gu	Residential Electricity	41325.21	4484.86	36306	66210
	Commercial Electricity	50397.47	6114.65	42206	67624
	temperature	13.48	10.26	-6.10	28.98
	GRDP	6019867	230752.5	5521181	6333388
	Total Population	402296.7	4865.76	394249	411369
	Elderly Ratio	12.75	1.62	10	15.7
	Youth Ratio	11.81	1	10.07	13.78
	Total Floor Area	18051481	716187.6	16095569	18952205
	Young Building Ratio	11.45	2.38	8.67	16.26
	Green Area Ratio	9.45	4.57	4.28	13.74
	Residential Area	14654344	763357.6	13790984	15386262
	Commercial Area	307737.1	33758	263523	344623
Gwanak-gu	Residential Electricity	53464.08	5712.59	46775	84549
	Commercial Electricity	64837.5	7775.76	53608	85785
	temperature	12.77	10.18	-6.69	28.25
	GRDP	5568724	61673.58	5365298	5679347
	Total Population	515499.2	10049.76	500094	532858

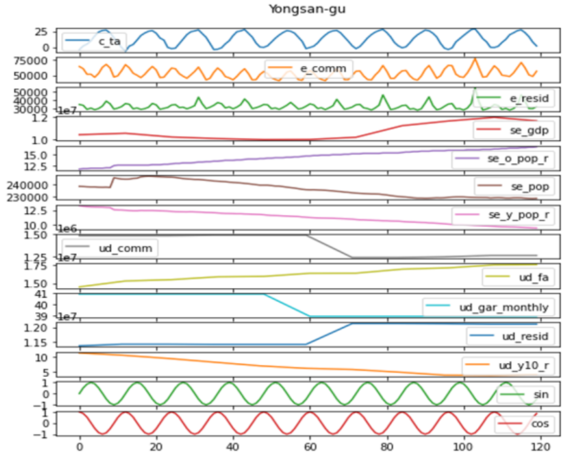
	Elderly Ratio	11.99	1.78	8.9	15
	Youth Ratio	10.03	1.34	7.67	12.51
	Total Floor Area	20780823	787488.2	18580082	22929469
	Young Building Ratio	13.77	2.68	10.12	19.36
	Green Area Ratio	52.69	6.23	46.81	59.74
	Residential Area	13269526	1821994	11556104	15335188
	Commercial Area	368351.1	19526.55	350000	392024
Seocho-gu	Residential Electricity	55914.55	6858.47	48834	93804
	Commercial Electricity	169774.3	20819.75	135086	217557
	temperature	12.96	10.24	-6.63	28.38
	GRDP	30584082	2125739	26606520	33432374
	Total Population	439224.1	6536.64	426355	450504
	Elderly Ratio	10.56	1.49	8	13.2
	Youth Ratio	14.49	0.42	13.54	15.07
	Total Floor Area	33687905	1561469	31059732	35708514
	Young Building Ratio	12.21	2.86	6.54	17.69
	Green Area Ratio	57.41	0.59	56.91	58.36
	Residential Area	18620970	291134.1	17939082	18890070
	Commercial Area	1330584	10170.55	1317259	1340154
Gangnam-gu	Residential Electricity	72792.3	9107.38	62844	118932
	Commercial Electricity	301708.7	40148.34	230705	389497
	temperature	13.45	10.20	-6.12	28.82
	GRDP	59993260	5375238	50124725	67789806
	Total Population	563358.4	10396.39	541854	579722
	Elderly Ratio	10.02	1.64	7.3	13
	Youth Ratio	12.77	0.45	12.19	13.78
	Total Floor Area	48254324	2060439	44664315	51243628
	Young Building Ratio	14.34	4.92	8.53	24.85
	Green Area Ratio	36.25	2.2	33.73	40.08
	Residential Area	22891222	1175774	20959660	24298708
	Commercial Area	2052418	271274.2	1676116	2320955

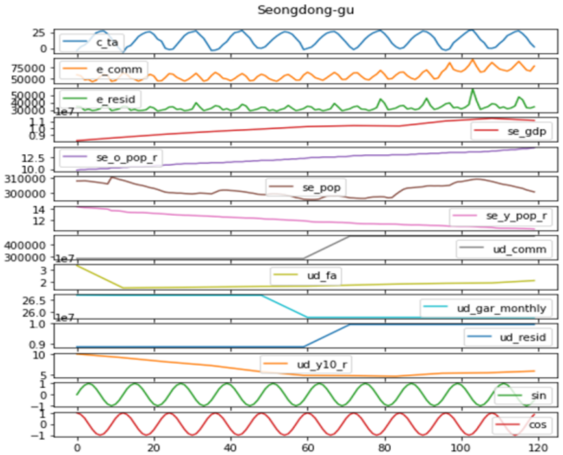
Songpa-gu	Residential Electricity	73075.42	8218.93	63101	118807
	Commercial Electricity	125561	15972.23	101680	179037
	temperature	13.52	10.19	-6.02	28.82
	GRDP	23710702	2993148	19306616	28427927
	Total Population	670939.6	9176.55	655309	686982
	Elderly Ratio	9.86	1.61	7.3	12.9
	Youth Ratio	13.66	0.95	12.18	15.48
	Total Floor Area	37132748	2805437	31806035	41727437
	Young Building Ratio	16.29	4.97	11.15	25.68
	Green Area Ratio	30.75	0.48	29.93	31.18
	Residential Area	21268694	226242	21015588	21606657
	Commercial Area	2213464	62157.78	2128822	2284846
Gangdong-gu	Residential Electricity	46468.88	5088.01	38631	71180
	Commercial Electricity	61519.95	8072.6	49576	82505
	temperature	12.98	10.26	-6.81	28.51
	GRDP	7852727	444269.6	6900908	8720189
	Total Population	466171.4	24586.88	424235	496776
	Elderly Ratio	10.74	2.08	7.6	14.5
	Youth Ratio	12.82	1.02	11.3	14.78
	Total Floor Area	23761200	1391122	18465038	26693250
	Young Building Ratio	13.62	2.84	9.79	18.99
	Green Area Ratio	43.57	1.43	40.37	44.43
	Residential Area	13239766	369517.6	12965432	14051893
	Commercial Area	628285.3	43374.23	579673	680697

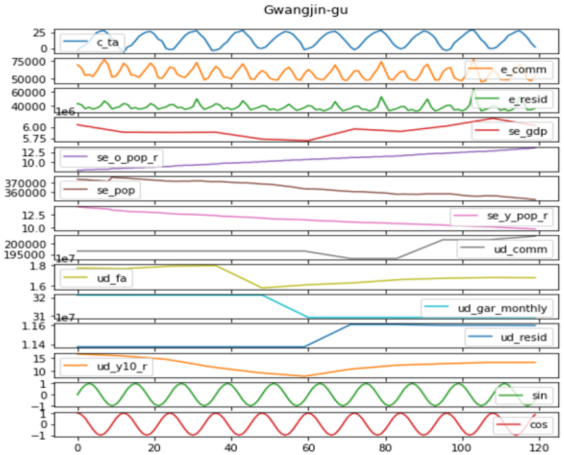
[Appendix B] Plot charts of 13 variables in 25 gu

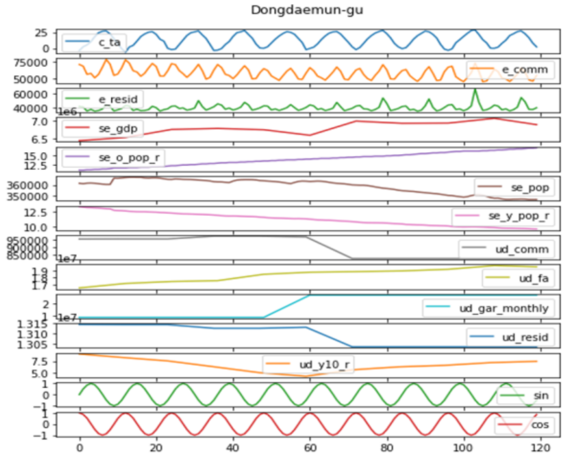


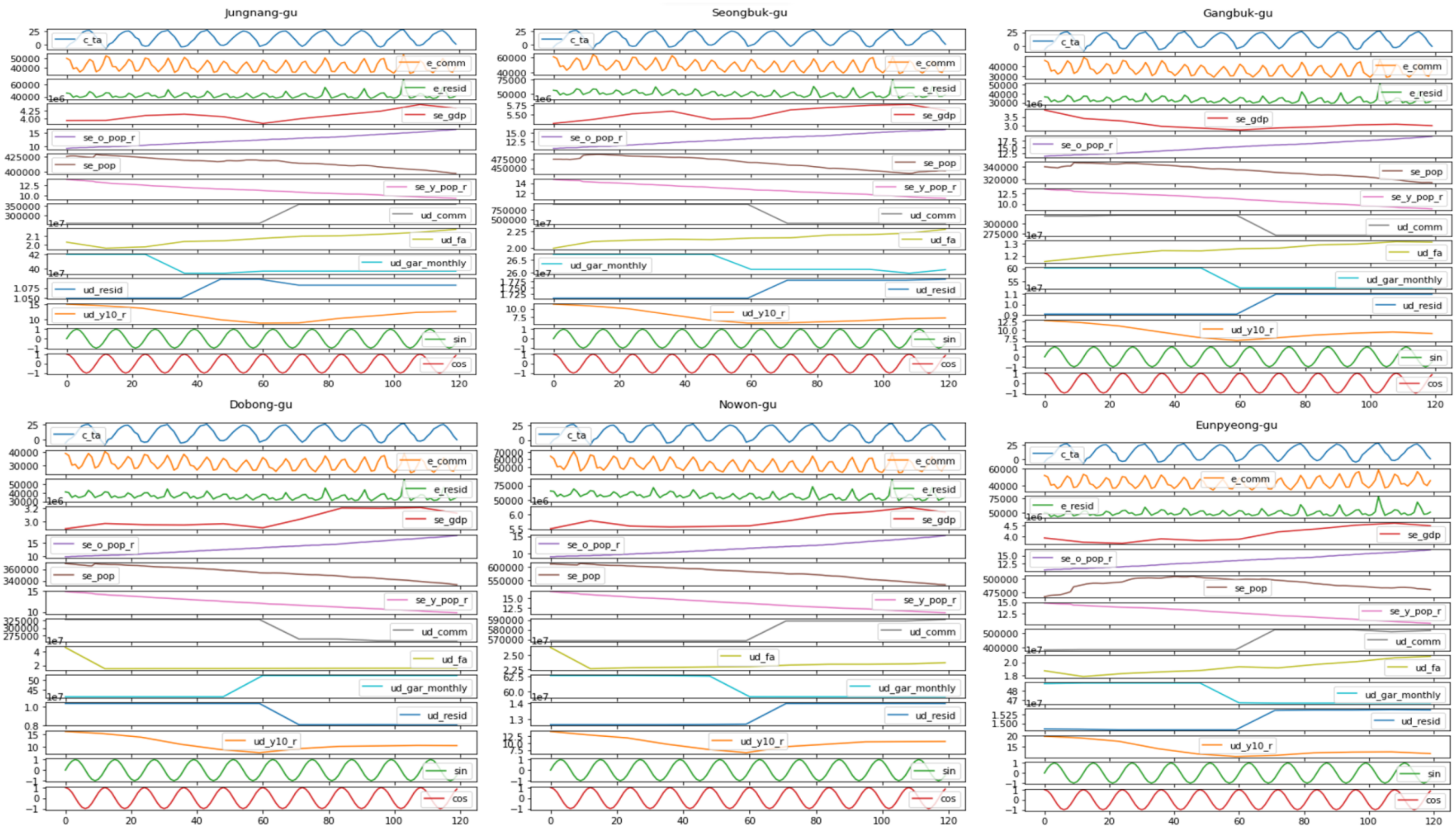


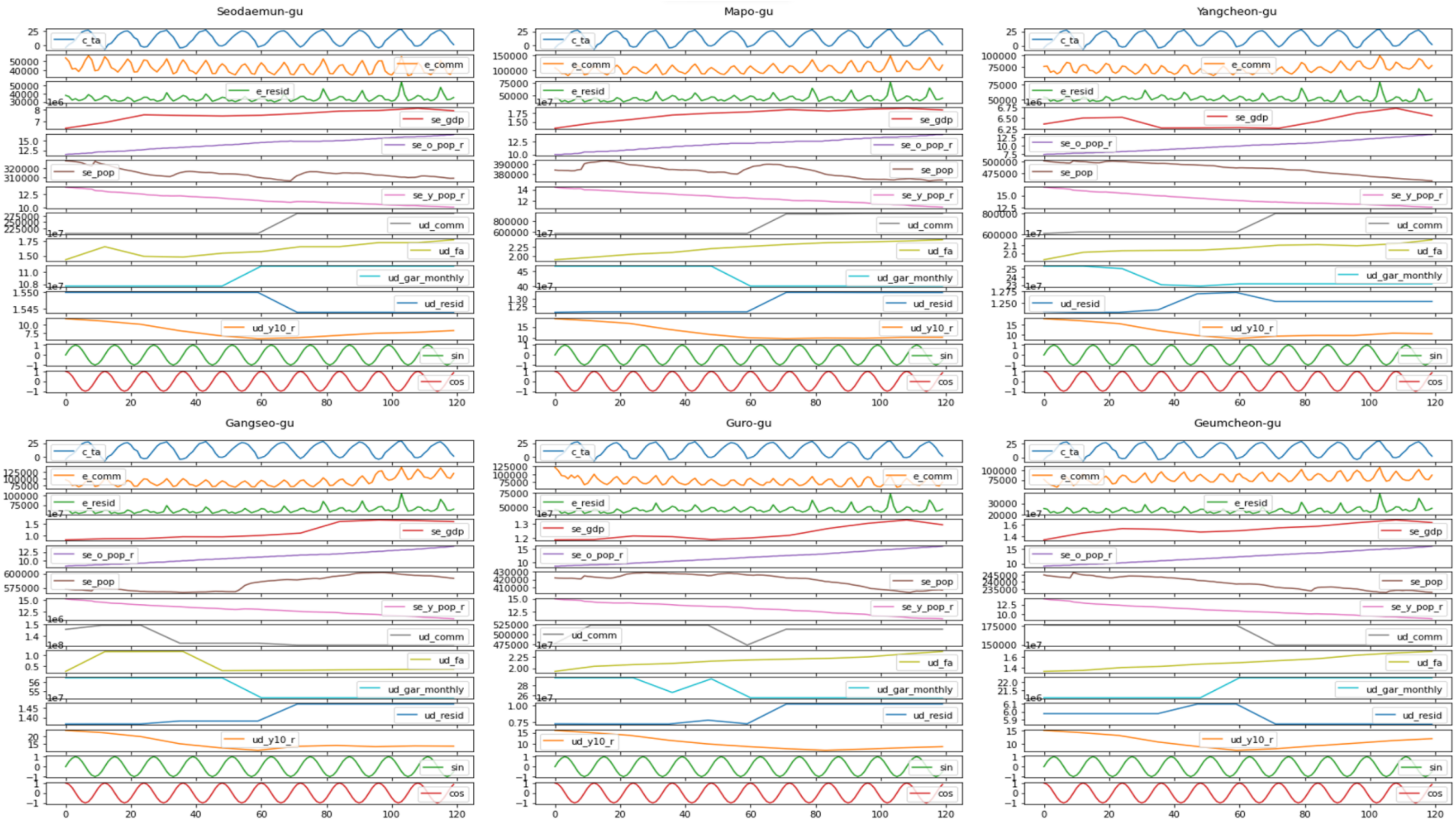









Jungnang-gu
Seongbuk-gu
Gangbuk-gu
Dobong-gu
Nowon-gu
Eunpyeong-gu
c_ta
e_comm
e_resid
se_gdp
se_o_pop_r
se_pop
se_y_pop_r
ud_comm
ud_fa
ud_gar_monthly
ud_resid
ud_y10_r
sin
cos


Seodaemun-gu
Mapo-gu
Yangcheon-gu
Gangseo-gu
Guro-gu
Geumcheon-gu
c_ta
e_comm
e_resid
se_gdp
se_o_pop_r
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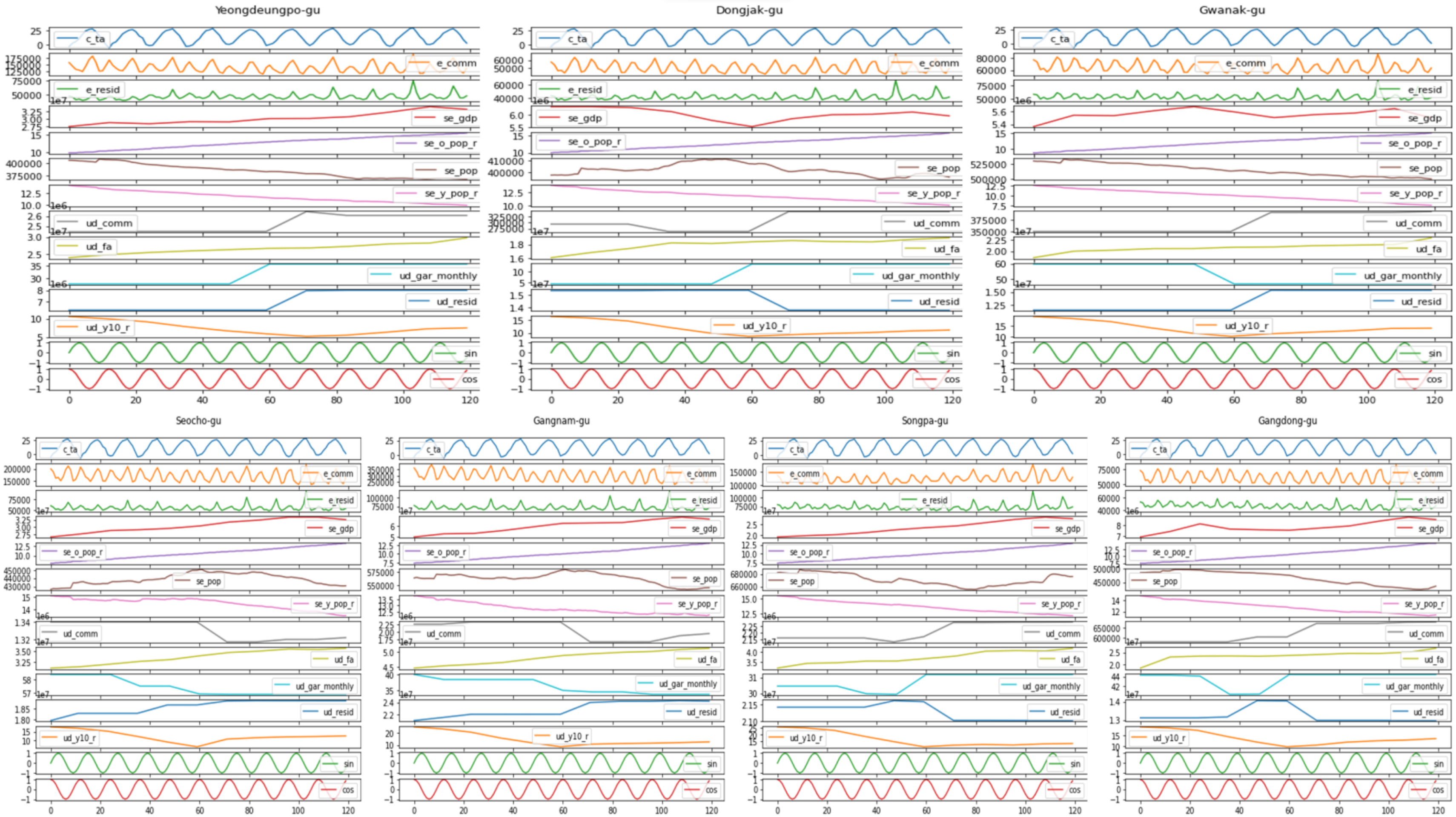
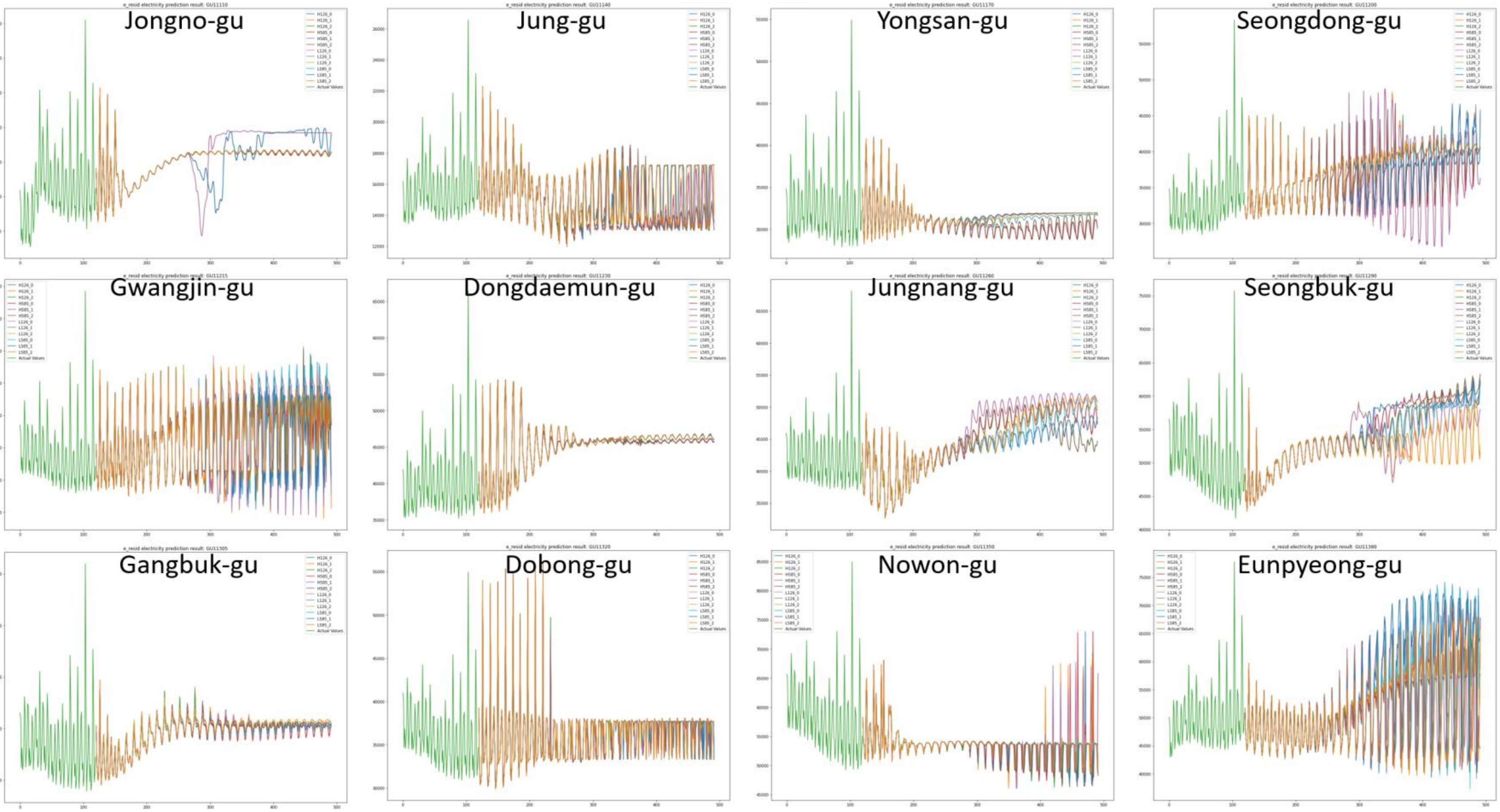
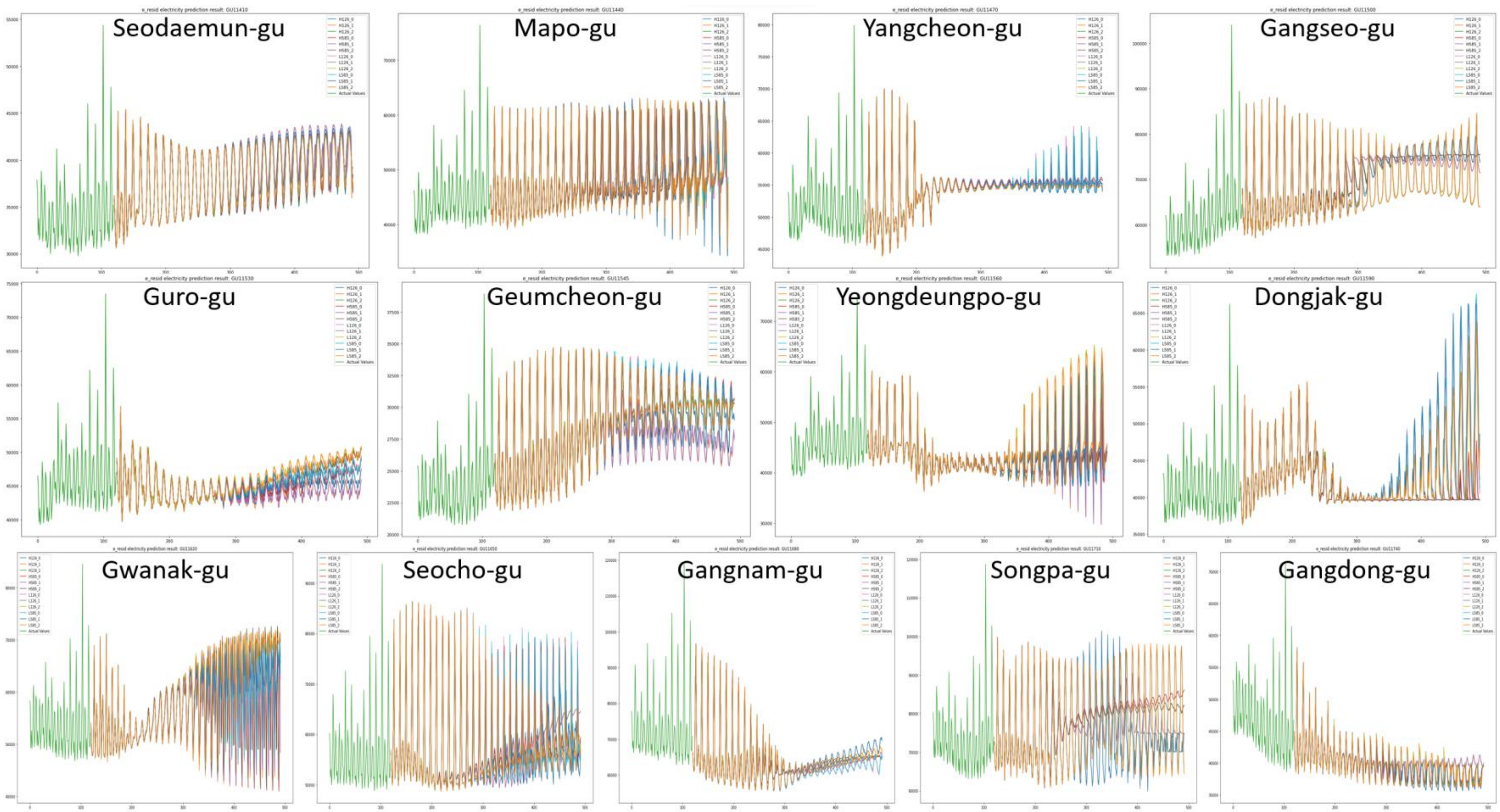
ud_resid
ud_y10_r
sin
cos

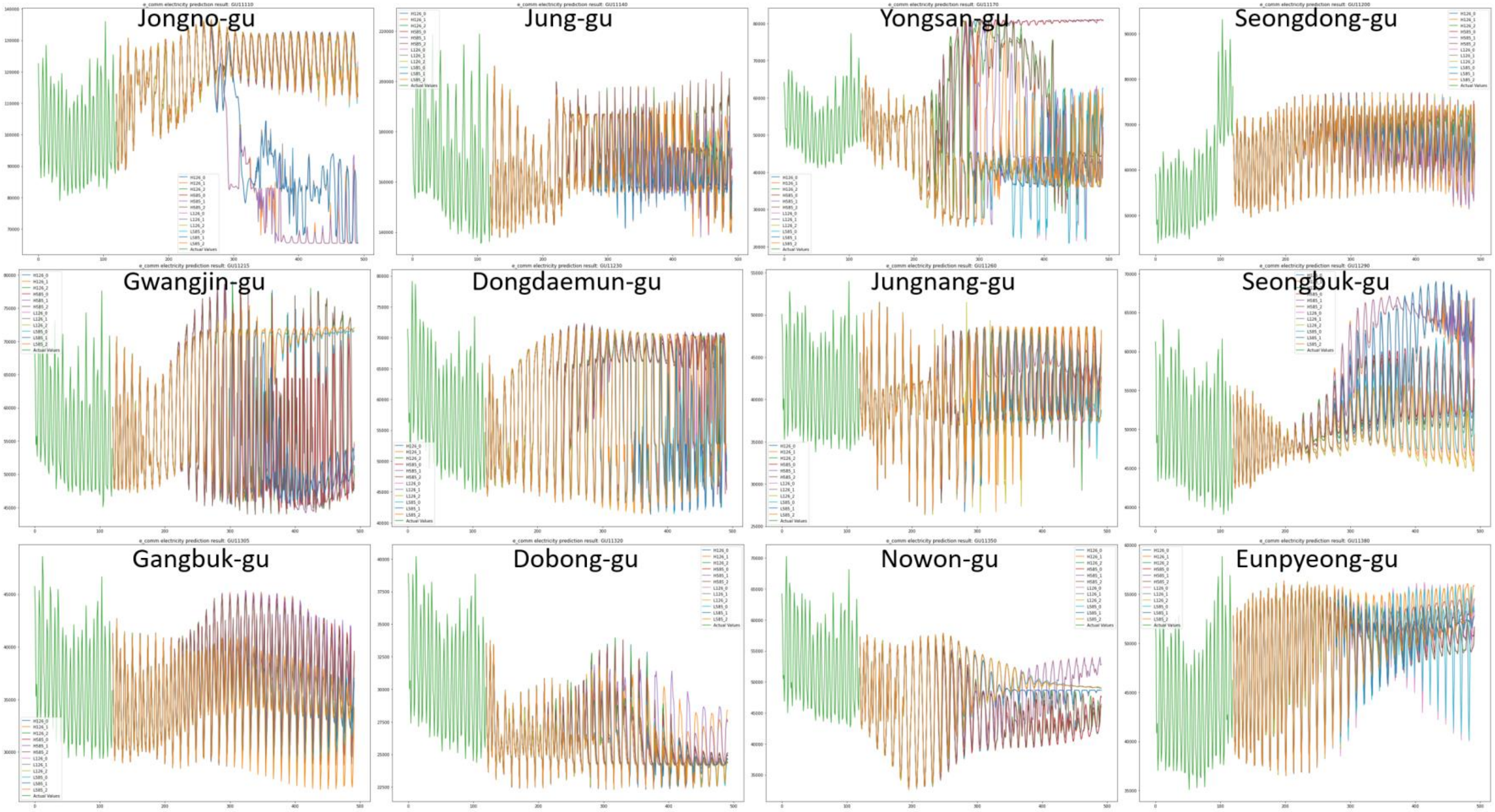

Yeongdeungpo-gu
Dongjak-gu
Gwanak-gu
Seocho-gu
Gangnam-gu
Songpa-gu
Gangdong-gu
c_ta
e_comm
e_resid
se_gdp
se_o_pop_r
se_pop
se_y_pop_r
ud_comm
ud_fa
ud_gar_monthly
ud_resid
ud_y10_r
sin
cos

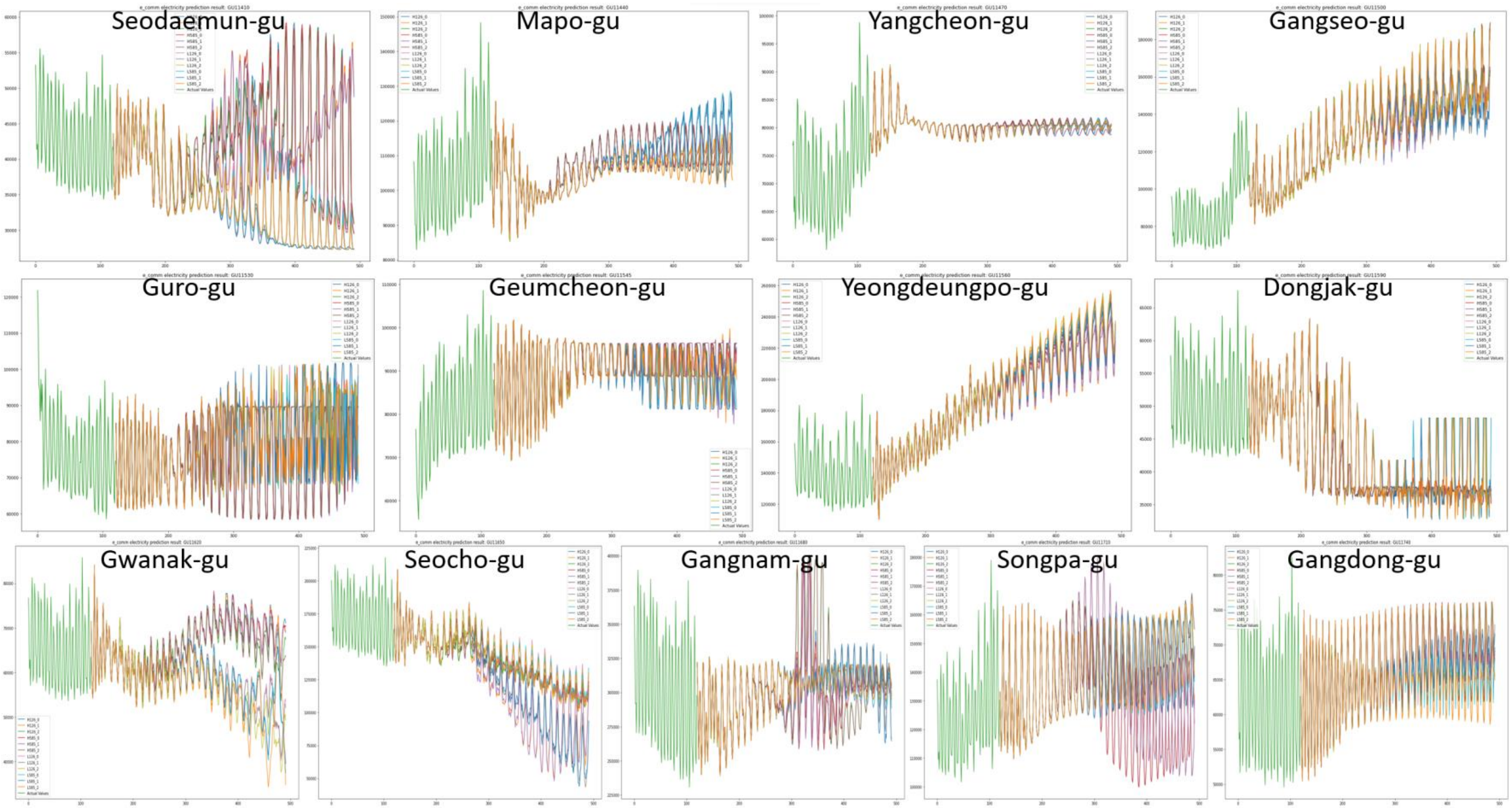
[Appendix C-1] Forecasting result of residential electricity consumption of 25 gu under twelve scenario combinations, by the year 2050




Seodaemun-gu
Mapo-gu
Yangcheon-gu
Gangseo-gu
Guro-gu
Geumcheon-gu
Yeongdeungpo-gu
Dongjak-gu
Gwanak-gu
Seocho-gu
Gangnam-gu
Songpa-gu
Gangdong-gu

[Appendix C-2] Forecasting result of commercial electricity consumption of 25 gu under twelve scenario combinations, by the year 2050

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Mapo-gu
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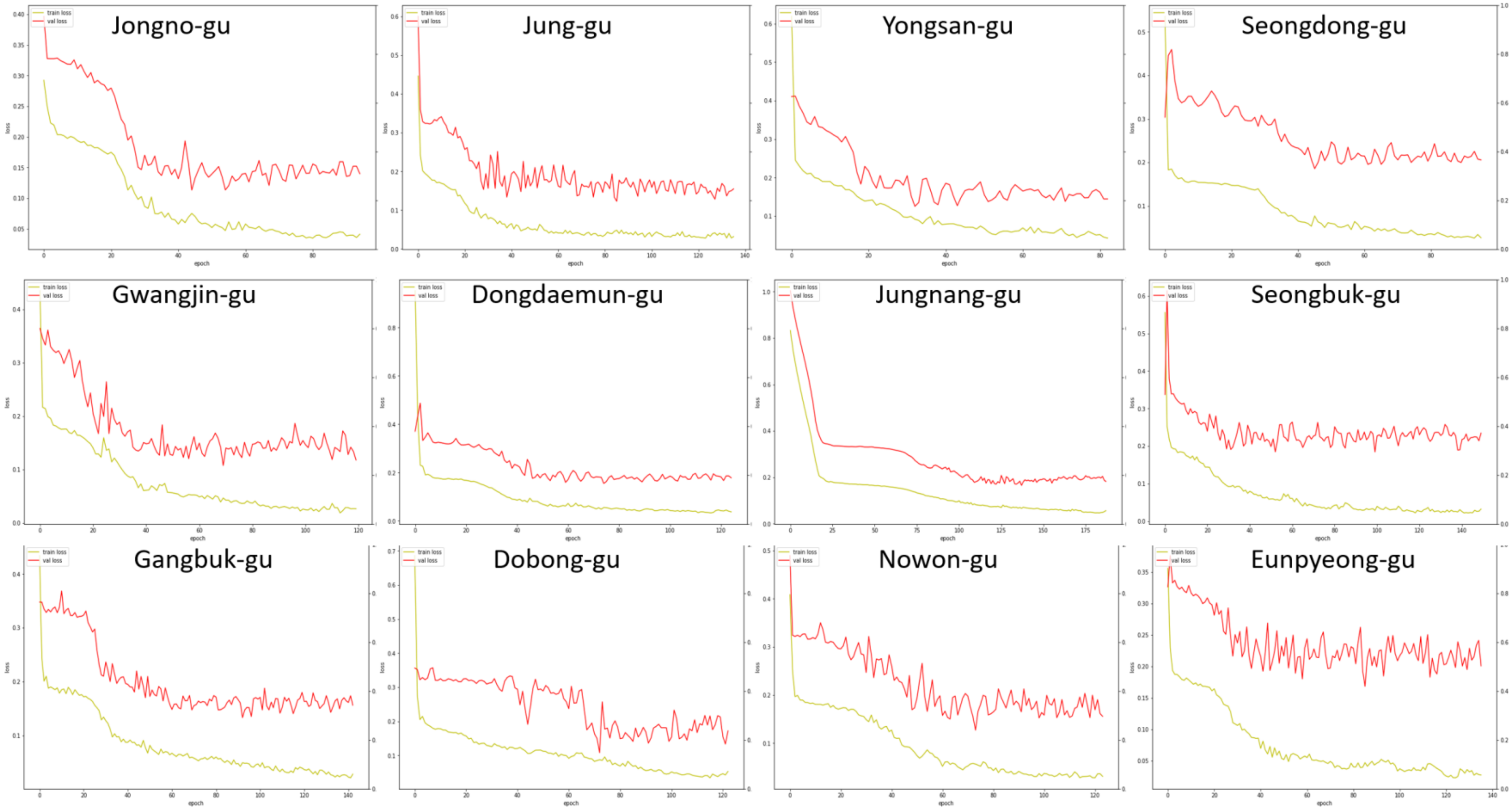
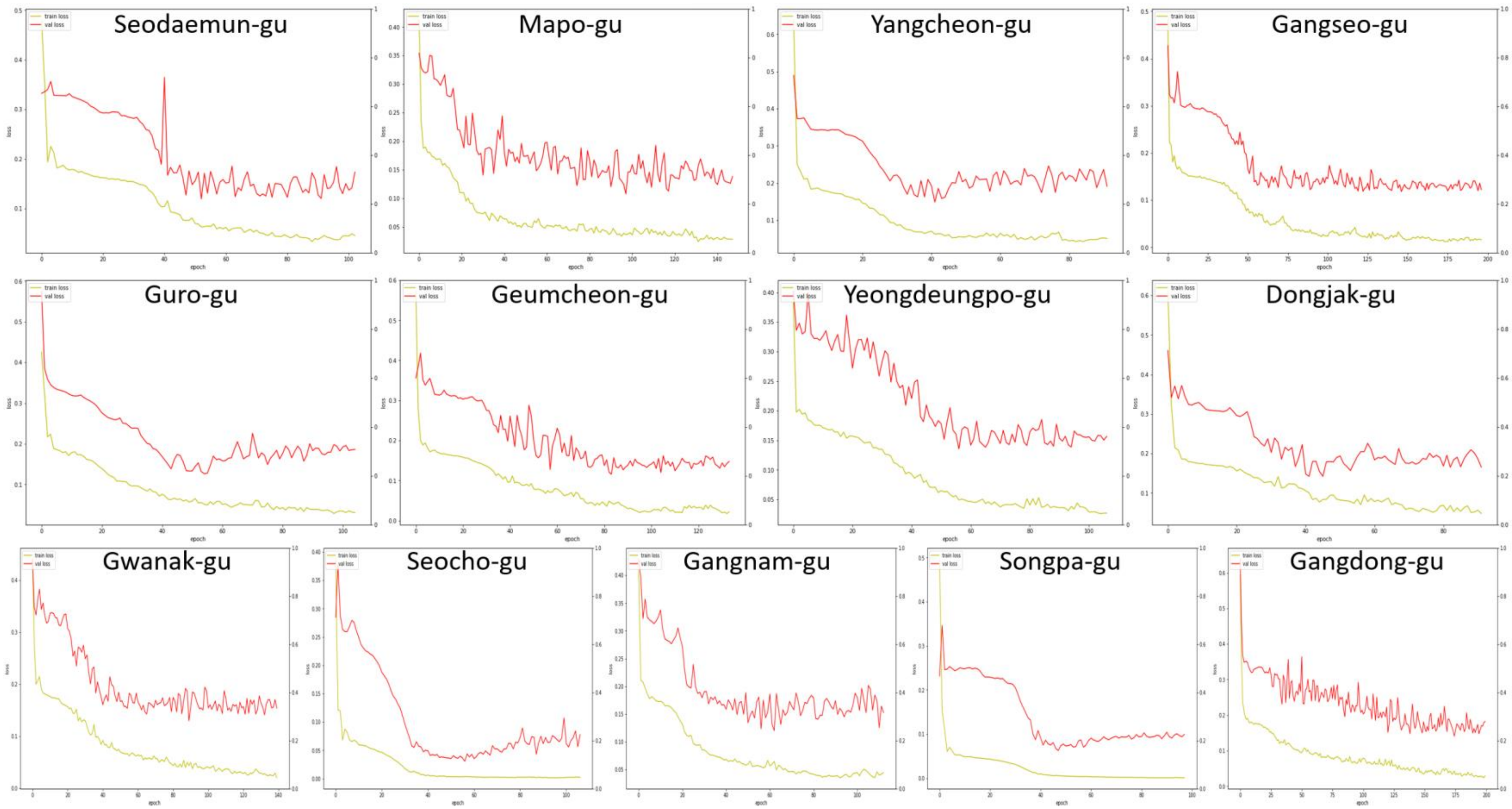
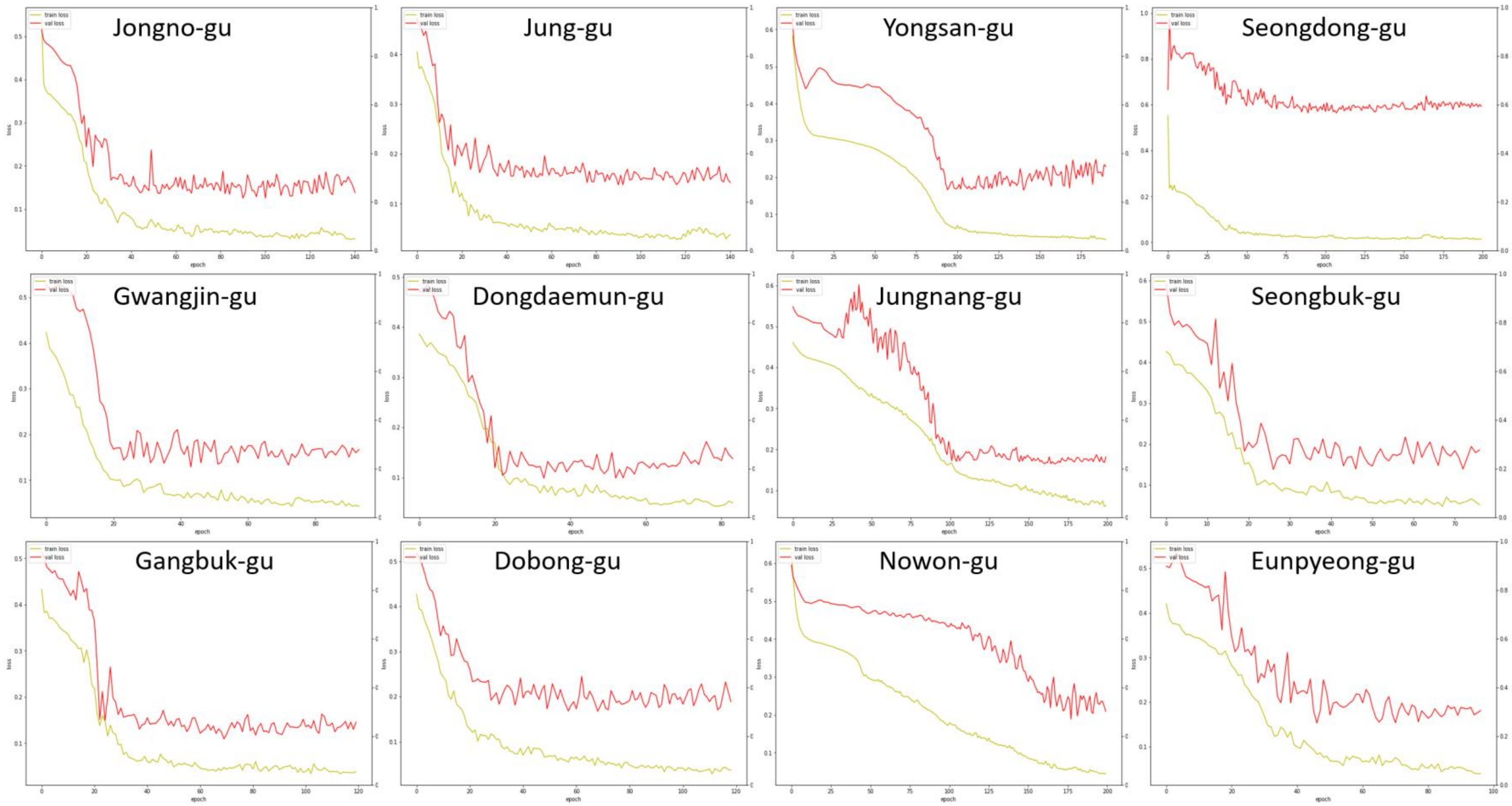
Gangseo-gu
Guro-gu
Geumcheon-gu
Yeongdeungpo-gu
Dongjak-gu
Gwanak-gu
Seocho-gu
Gangnam-gu
Songpa-gu
Gangdong-gu

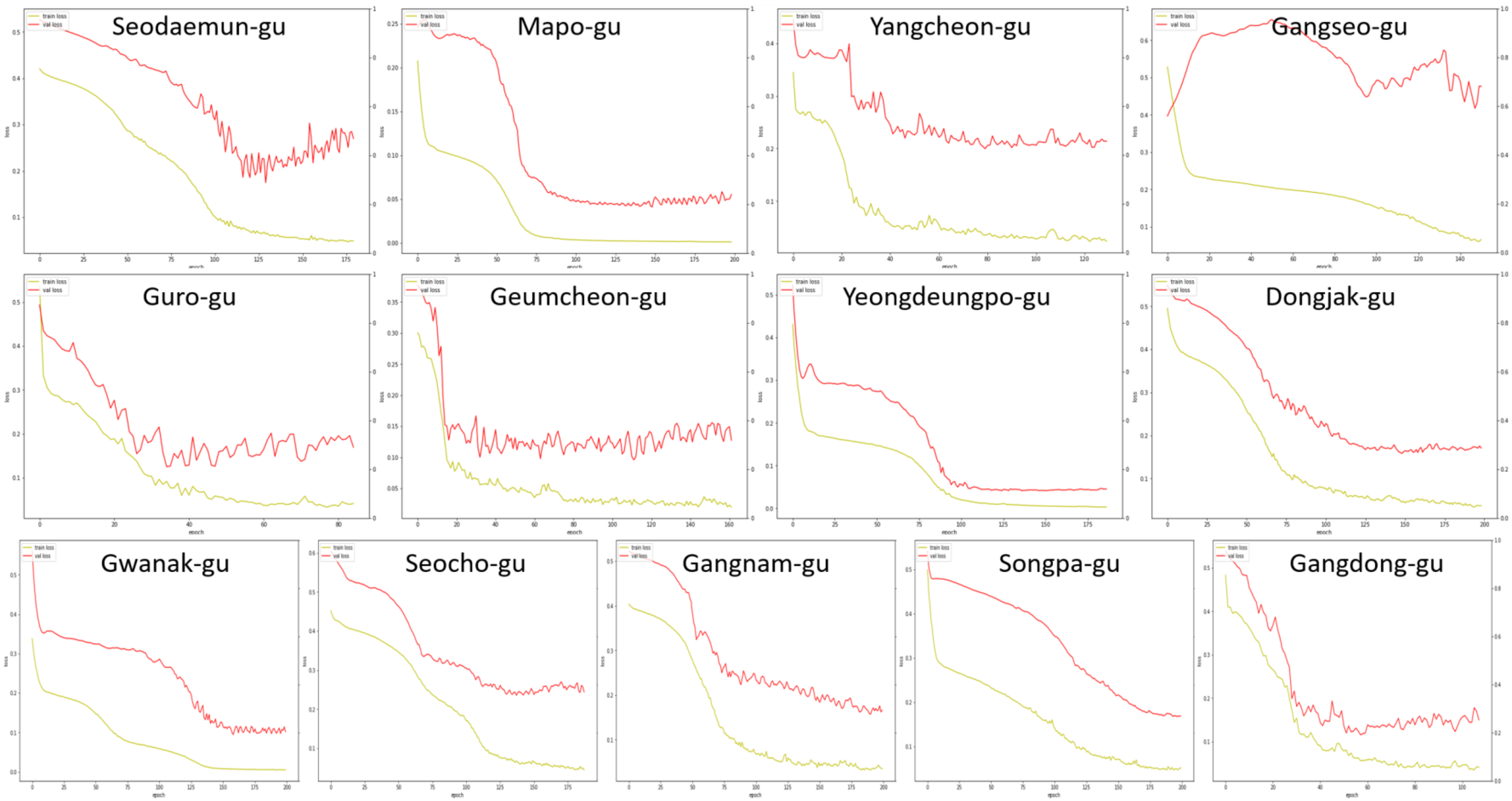
[Appendix D-1] Loss curves - Residential electricity prediction LSTM models (Red line: Validation loss, Green line: Train loss)




Seodaemun-gu
Mapo-gu
Yangcheon-gu
Gangseo-gu
Guro-gu
Geumcheon-gu
Yeongdeungpo-gu
Dongjak-gu
Gwanak-gu
Seocho-gu
Gangnam-gu
Songpa-gu
Gangdong-gu
train loss
val loss

[Appendix D-2] Loss curves - Commercial electricity prediction LSTM models (Red line: Validation loss, Green line: Train loss)




Seodaemun-gu
Mapo-gu
Yangcheon-gu
Gangseo-gu
Guro-gu
Geumcheon-gu
Yeongdeungpo-gu
Dongjak-gu
Gwanak-gu
Seocho-gu
Gangnam-gu
Songpa-gu
Gangdong-gu

국문초록

기후 위기에 대한 적극적 대응의 필요성이 국제적 합의로 확산되는 가운데, 서울시는 2050 탄소 중립을 선언하고 2021년 C40에 기후 행동계획을 제출했다. 2020년 기준 서울시 총 온실가스 배출량의 74.8%가 건물 부문에서 발생한 만큼, 본 목표를 달성하기 위해서는 에너지 효율적인 도시환경 설계를 통해 건물 에너지 소비를 절감하는 것이 필수적이다. 그럼에도 불구하고, 현 서울시 최고 수준 법정계획인 <2030 서울플랜>이 서울시가 제시한 2050 탄소중립 목표에 부합하는지에 관한 연구는 부재한 실정이다. 이러한 배경하에 본 연구는 2050 탄소 중립 목표에 대한 평가를 목적으로 2030년 및 2050년 서울의 건물 에너지 소비량을 예측하였다. 이를 위해 2010년부터 2019년까지의 과거 데이터를 사용하여 LSTM (Long Short-Term Memory) 딥러닝 예측 모형을 구축하였으며, 미래 환경의 불확실성을 고려하고자 시나리오 분석 방법을 활용하였다. 2030년 건물 에너지 소비량 예측에 있어서는 <2030 서울플랜>을 참고한 기본 도시개발 시나리오 1개, 기후변화 시나리오 2개, 사회경제 시나리오 2개로 구성된 시나리오 조합 총 4개를 적용하였다. 2050년 미래 에너지 소비량을 예측에 있어서는 기본 도시개발 시나리오를 3개의 도시개발 가정으로 대체하여, 총 12개의 시나리오 조합을 사용하였다. LSTM 모형 구축 결과, 연구에서 사용한 모형의 CV(RMSE) 값은 오차범위 이내로, 현재 건물 부문의 에너지 소비행태를 적절히 반영하고 있었다. 또한 구축된 LSTM 모형의 에너지 소비 예측 정확도는 전통적인 통계 방법인 ARIMA의 예측 정확도를 상회하였다. 에너지 소비 예측 결과에 따르면, 2050년까지 주거용 건물 부문의 전력 소비량은 14,049,562MWh에서 14,462,569MWh까지 증가할 것으로 보인다. 주거용 건물 에너지 소비에 영향을 미치는 가장 중요한 요인은 사회경제적 환경이며, 다음으로 도시 형태와 기후인 것으로 분석되었다. 상업용 건물의 전력 소비량은 25,808,064MWh에서 28,024,238MWh 사이로 예측되었다. 상업

부문의 에너지 소비에 영향을 미치는 가장 중요한 요소는 도시 개발 요소였으며, 다음으로 사회 경제적 환경이었다. 도시 숲 확대는 상업용 건물 에너지 소비를 10.9 ~ 12.2% 절감하는 효과가 있는 것으로 나타났다. 2050 탄소중립 목표를 평가한 결과, 성공적으로 에너지 전환을 이루었다는 가정하에조차 2050 탄소중립 목표를 달성할 수 있는 시나리오는 없는 것으로 나타났다. 그럼에도 불구하고, 본 연구는 에너지 전환을 통해 극적인 탄소 배출량 감축을 이룰 수 있으며, 또한 도시 숲 확대 대책과 에너지 전환을 결합 시 건물 에너지 소비 감축 효과가 강화된다는 점을 입증하였다.

키워드: 건물 에너지 예측, 딥러닝, LSTM, 2050 탄소중립, 시나리오 분석방법

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Bibliography

AHSHRAE. (2002). *ASHRAE Guideline 14 - Measurement of Energy and Demand Savings*. R. a. A.-C. E. American Society of Heating.

Amasyali, K., & El-Gohary, N. M. (2018). A review of data-driven building energy consumption prediction studies. *Renewable & sustainable energy reviews*, *81*, 1192-1205. https://doi.org/10.1016/j.rser.2017.04.095

Amraoui, N., & Zouari, B. (2022). Anomalous behavior detection-based approach for authenticating smart home system users. *Int J Inf Secur*, *21*(3), 611-636. https://doi.org/10.1007/s10207-021-00571-6

Ang, B. W., Wang, H., & Ma, X. J. (2017). Climatic influence on electricity consumption: The case of Singapore and Hong Kong. *Energy*, *127*, 534-543. https://doi.org/10.1016/j.energy.2017.04.005

Bengio, Y., Simard, P., & Frasconi, P. (1994). Learning Long-Term Dependencies with Gradient Descent Is Difficult. *Ieee Transactions on Neural Networks*, *5*(2), 157-166. https://doi.org/Doi 10.1109/72.279181

Bilgili, M., Sahin, B., Yasar, A., & Simsek, E. (2012). Electric energy demands of Turkey in residential and industrial sectors. *Renewable & sustainable energy reviews*, *16*(1), 404-414. https://doi.org/10.1016/j.rser.2011.08.005

Brounen, D., Kok, N., & Quigley, J. M. (2012). Residential energy use and conservation: Economics and demographics. *European Economic Review*, *56*(5), 931-945. https://doi.org/10.1016/j.euroecorev.2012.02.007

Chen, Y. J., Matsuoka, R. H., & Liang, T. M. (2018). Urban form, building characteristics, and residential electricity consumption: A case study in Tainan City. *Environment and Planning B-Urban Analytics and City Science*, *45*(5), 933-952. https://doi.org/10.1177/2399808317690150

Ciancio, V., Salata, F., Falasca, S., Curci, G., Golasi, I., & Wilde, P. D. (2020). Energy demands of buildings in the framework of climate change: An investigation across Europe. *Sustainable Cities and Society*, *60*. https://doi.org/ARTN 102213

10.1016/j.scs.2020.102213

D'Agostino, D., Parker, D., Epifani, I., Crawley, D., & Lawrie, L. (2022). How will future climate impact the design and performance of nearly zero energy buildings (NZEBs)? *Energy*, *240*. https://doi.org/10.1016/j.energy.2021.122479

Fan, J. L., Hu, J. W., & Zhang, X. (2019). Impacts of climate change on electricity demand in China: An empirical estimation based on panel data. *Energy*, *170*, 880-888. https://doi.org/10.1016/j.energy.2018.12.044

Fuss, S., Canadell, J. G., Peters, G. P., Tavoni, M., Andrew, R. M., Ciais, P., Jackson, R. B., Jones, C. D., Kraxner, F., Nakicenovic, N., Le Quere, C., Raupach, M. R., Sharifi, A., Smith, P., & Yamagata, Y. (2014). COMMENTARY: Betting on negative emissions. *Nature Climate Change*, *4*(10), 850-853. https://doi.org/DOI 10.1038/nclimate2392

Graves, A. (2013). Generating sequences with recurrent neural networks. *arXiv preprint arXiv:1308.0850*.

Graves, A., Fernandez, S., & Schmidhuber, J. (2007). Multi-dimensional recurrent neural networks. *Artificial Neural Networks - Icann 2007, Pt 1, Proceedings*, *4668*, 549-+. <Go to ISI>://WOS:000250338200056

Gunay, M. E. (2016). Forecasting annual gross electricity demand by artificial neural networks using predicted values of socio-economic indicators and climatic conditions: Case of Turkey. *Energy Policy*, *90*, 92-101. https://doi.org/10.1016/j.enpol.2015.12.019

Ioffe, S., & Szegedy, C. (2015). Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift. *International Conference on Machine Learning, Vol 37*, *37*, 448-456. <Go to ISI>://WOS:000684115800048

IPCC. (2014). *AR5 Synthesis Report: Climate Change 2014*.

IPCC. (2018). *Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change*. Ipcc.

Kim, M.-H., & Gim, T.-H. T. (2022). Deep learning-based investigation of the impact of urban form on the particulate matter concentration on a neighborhood scale. *Environment and Planning B: Urban Analytics and City Science*. https://doi.org/10.1177/23998083221111162

Kim, T. Y., & Cho, S. B. (2019). Predicting residential energy consumption using CNN-LSTM neural networks. *Energy*, *182*, 72-81. https://doi.org/10.1016/j.energy.2019.05.230

Lee, S.-M., & Kim, E.-J. (2019). Analysis of GHG Reduction in Apartment Buildings by 2030 according to Various Prediction Scenarios. *Journal of KIAEBS*, *13*(6), 515-526. https://doi.org/10.22696/jkiaebs.20190044

Liu, S., Zeng, A., Lau, K., Ren, C., Chan, P. W., & Ng, E. (2021). Predicting long-term monthly electricity demand under future climatic and socioeconomic changes using data-driven methods: A case study of Hong Kong. *Sustainable Cities and Society*, *70*. https://doi.org/ARTN 102936

10.1016/j.scs.2021.102936

Moral-Carcedo, J., & Perez-Garcia, J. (2015). Temperature effects on firms' electricity demand: An analysis of sectorial differences in Spain. *Applied energy*, *142*, 407-425. https://doi.org/10.1016/j.apenergy.2014.12.064

Nakata, T., Rodionov, M., Silva, D., & Jupesta, J. (2010). Shift to a low carbon society through energy systems design. *Science in China Series E: Technological Sciences*, *53*(1), 134-143. https://doi.org/10.1007/s11431-009-0420-x

Nielsen, A. (2020). *Practical time series analysis : prediction with statistics and machine learning*. Sebastopol, CA : O'Reilly Media, Inc. http://snu-primo.hosted.exlibrisgroup.com/82SNU:82SNU_INST21808046310002591

http://snu-primo.hosted.exlibrisgroup.com/82SNU:82SNU_INST51815818610002591

O'Neill, B. C., Carter, T. R., Ebi, K., Harrison, P. A., Kemp-Benedict, E., Kok, K., Kriegler, E., Preston, B. L., Riahi, K., Sillmann, J., van Ruijven, B. J., van Vuuren, D., Carlisle, D., Conde, C., Fuglestvedt, J., Green, C., Hasegawa, T., Leininger, J., Monteith, S., & Pichs-Madruga, R. (2021). Achievements and needs for the climate change scenario framework (vol 18, pg 1074, 2020). *Nature Climate Change*, *11*(3), 274-274. https://doi.org/10.1038/s41558-020-00981-9

Park, J., & Yun, S.-J. (2022). Social determinants of residential electricity consumption in Korea: Findings from a spatial panel model. *Energy (Oxford)*, *239*, 122272. https://doi.org/10.1016/j.energy.2021.122272

Raubitzek, S., & Neubauer, T. (2021). A fractal interpolation approach to improve neural network predictions for difficult time series data. *Expert Systems with Applications*, *169*. https://doi.org/ARTN 114474

10.1016/j.eswa.2020.114474

Seng, D. W., Zhang, Q. Y., Zhang, X. F., Chen, G. S., & Chen, X. Y. (2021). Spatiotemporal prediction of air quality based on LSTM neural network. *Alexandria Engineering Journal*, *60*(2), 2021-2032. https://doi.org/10.1016/j.aej.2020.12.009

Shahbaz, M., Sarwar, S., Chen, W., & Malik, M. N. (2017). Dynamics of electricity consumption, oil price and economic growth: Global perspective. *Energy Policy*, *108*, 256-270. https://doi.org/10.1016/j.enpol.2017.06.006

SMG. (2020). *제 5 차 서울특별시 지역에너지계획*.

SMG. (2022). 장래 인구추계(시도편): 2020~2050 년.

Somu, N., Raman M R, G., & Ramamritham, K. (2021). A deep learning framework for building energy consumption forecast. *Renewable and Sustainable Energy Reviews*, *137*. https://doi.org/10.1016/j.rser.2020.110591

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A Simple Way to Prevent Neural Networks from Overfitting. *Journal of machine learning research*, *15*, 1929-1958. <Go to ISI>://WOS:000344638300002

Wang, J. Q., Du, Y., & Wang, J. (2020). LSTM based long-term energy consumption prediction with periodicity. *Energy*, *197*. https://doi.org/ARTN 117197

10.1016/j.energy.2020.117197

Zheng, S. G., Huang, G. H., Zhou, X., & Zhu, X. H. (2020). Climate-change impacts on electricity demands at a metropolitan scale: A case study of Guangzhou, China. *Applied energy*, *261*. https://doi.org/ARTN 114295

10.1016/j.apenergy.2019.114295

Zuo, Z. L., Guo, H. X., & Cheng, J. H. (2020). An LSTM-STRIPAT model analysis of China's 2030 CO2 emissions peak. *Carbon Management*, *11*(6), 577-592. https://doi.org/10.1080/17583004.2020.1840869

서울시. (2020). *서울특별시 자치구별 장래가구특별추계 (2017-2047)*.

서울특별시. (2014). *2030 서울도시기본계획*.

서울특별시. (2021a). *2019 서울시 온실가스 인벤토리 보고서*.

서울특별시. (2021b). *2050 서울시 기후행동계획*.

양재섭, 신민철, & 반영권. (2020). *분권화시대 자치구 도시계획 운영실태와 역할 강화 방향*. https://www.si.re.kr/node/63286

이미진, Mi Jin, L., 이동근, Dong Kun, L., 박찬, Chan, P., 박진한, Jin Han, P., 정태용, Tae Yong, J., 김상균, Sang Kyun, K., 홍성철, & Sung Chul, H. (2015). 기후변화와 사회,경제적 요소를 고려한 가정 부문 냉난방 에너지 사용량 변화 예측. *환경영향평가*, *24*(5), 487-498. https://doi.org/10.14249/eia.2015.24.5.487

이상엽, 김대수, & 정예민. (2018). *에너지전환을 고려한 중장기(2050) 국가 온실가스 감축전략* (기후환경정책연구, Issue.

정영선, 조수현, 문선혜, & 지창윤. (2021). 2050 탄소중립 달성을 위한 건물부문 온실가스 감축 시나리오 연구. *대한건축학회논문집*, *37*(10), 189-197.

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