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Environmental Performances of Electric Vehicles on Regional Effective Factors using System Dynamics

시스템 다이내믹스를 이용한 지역별 영향인자 변화에 따른 전기차의 환경개선효과 분석

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Abstract

Greenhouse gases (GHGs) are considered key factors driving climate change, and electric vehicles (EVs) are proposed as a potential solutions. EVs represent eco-friendly modes of transportation that do not emit carbon dioxide and other GHGs into the atmosphere. In addition, the energy sources associated with EVs would reduce GHG emissions, which have steadily increased over the last several decades. The energy sector accounts for 93% of the total national GHG emissions among five sectors, including industrial processing, agriculture, land-use change and forestry, waste, and energy. Although all of these sectors contribute to GHG emissions. the energy sector is the major source of GHG emissions. Among the numerous sub-sectors under the energy sector, GHG emissions of the road transport sub-sector accounted for 95.9% of the total emissions in the transport sector, with 94,270 Gt CO_2e in 2017. The Korean government proposed the adoption of eco-friendly vehicles to achieve the GHG reduction goals in line with the Paris Climate Agreement, which goes into effect in 2021. In addition, the government have proposed promoting eco-friendly vehicles as a strategy of achieving a 37% reduction of the 851 million ton CO_2e GHG emissions forecast by 2030.

The Korean government has proposed various policies to increase the

adoption of EVs, as eco-friendly cars, with the aim of reducing GHG emissions. The government has set a goal of 3 million EVs by 2030, and has provided various incentives such as tax exemptions, purchase subsidies, highway tolls, and discounts on parking fees in public parking facilities to promote the purchases of eco-friendly cars in Korea. Despite these favorable government policies, the rate of EV adoption in Korea has fallen short of expectations. Compared to the goal of 3 million EVs by 2030, the number of EVs registered in Korea in 2019 was only approximately 8.8t thousand which was far below the high goal set by the government. In 2019, only 0.5% of all passenger vehicles in Korea were EVs.

According to a survey to evaluate the perceptions of actual buyers of EVs in Korea and the willingness of prospective buyers to purchase EVs, in general, current owners reported that they would not repurchase EV. Prospective buyers reported that they would not purchase EVs for reasons such as reduced subsidies, long charging times, and the short driving range of EVs. In terms of charging, which is a key factor for EV owners, KEPCO's detailed plan for the electricity supply include significantly increasing charging fees for EVs starting in the second half of 2020. Consequently, the charging costs that purchasers of EVs need to pay will increase further and will negatively affect intention to purchase. However, following implementation of the government’s policy of propagation of EVs and according to various studies, the EV adoption is still expected to increase, and improvements in power generation could lead to an increase in EV purchases.

Although no pollutants are emitted while driving EVs, policies that promote an increase in EVs do not take into account the life cycles of EVs from pre-manufacturing to the disposal, and thus, they do not adequately predict the potential environmental impacts. In the life cycle of EVs, the production of the electricity required for the operation of EVs generates the highest amount of GHG emissions during the use stage. Thus, production of EVs still has a major impact on the environment. Since such environmental impacts depend on the energy mix, environmental impact assessments should consider the national energy mix. New environmental impact assessment activities are needed and such activities should consider changes in the energy mix and changes in the propagation of EVs. These activities would impact the outcomes in two categories, global warming potential and particulate matter potential, which are both linked to automobile use and energy production.

As interest in EVs has increased, numerous studies on the propagation of EVs have been conducted. As a result, various factors that influence the spread of EVs have been identified. In the majority of the studies that have examined the factors influencing the spread of EVs, panel analysis has been conducted using annual data at the national level. Subsidies, which is a major factor influencing EV uptake in Korea, are divided into the national subsidy and regional subsidies. Therefore, regional characteristics should be taken into account and analyzed at the regional level since different regions (e.g., Jeju Island) have unique operational environments for EVs. In addition, few studies have examined the balance of subsidies or the change in the number of supportable EV residuals based on monthly data rather than annual data. Several studies have also focused on the propagation of EVs using system dynamics, but, most studies have been qualitative research rather than quantitative research. In addition, numerous studies have evaluated environmental effects by applying changes in the energy mix. However, few studies have considered both the propagation of EVs and their environmental impacts.

Therefore, the present study evaluates the impact of subsidy policies on the propagation of EVs by region and environmental improvement effects. First, we investigated the factors influencing the propagation of EVs using monthly panel data by region. Changes in EV uptake were then analyzed by region based on identified factors. Lastly, to analyze the environmental implications of EV propagation, the environmental improvement impacts of EV propagation were analyzed considering the national grid power supply plan based on a life cycle assessment (LCA). Our analysis of EV propagation based on monthly time series data by region aimed to quantitatively analyze the factors influencing the spread of EVs in Korea.

This study confirmed the stationarity of the factors considering the influence of seasonality in the monthly time series data based on regional characteristics. In addition, an EV propagation model was designed based on panel fixed effect and panel random effect models, using the Hausman test. Analysis of the factors influencing EV propagation in 16 cities and provinces in Korea using panel fixed effect and panel random effect models, revealed that the EV propagation models had explanatory powers of 48% and 50%, respectively. The factors classified in the five categories had different effects depending on the model, and the panel fixed effect using the Hausman test was more appropriate for describing the model. However, more variables in the panel random effect model were analyzed as significant factors than in the fixed effect model. The number of newly registered diesel vehicles and the total number of newly registered passenger vehicles in the vehicle category had negative and positive effects on EV propagation, respectively, in both the panel fixed effect model and the panel random effect model. However, in the random effect model, the prices of diesel and gasoline vehicles also influenced EV propagation. In the panel fixed effect model, only the national subsidy and regional subsidies showed positive effects on the propagation of EVs. The random effect model also showed that a tax exemption, which had a positive effect on the spread of EVs, was also a factor influencing EV propagation. The population density in the census category, the number of vehicles per capita, and the PM10 concentration, representing environmental factors, were analyzed as influential factors in both models. In addition, the monthly average and minimum temperatures in the climate category, which could reveal whether weather conditions in each region influence EV spread, were found to be influential in the panel fixed effect model. However, in the panel random effect model, all factors in the climate category were not influential.

The system dynamics model of EV propagation was based on factors influencing the spread of EVs. The present study used the Stella Architect software platform to analyze dynamic changes in the spread of EVs by region. system dynamics is a technique that identifies dynamic change mechanisms of targets, and shows systemic trends with a non-linear feedback system and simulates and analyzes them based on various factors. In the present study, we used system dynamics to estimate the number of EVs propagated by region. A bull's eye diagram, causal loop diagram, and stock-flow diagram were constructed, and factors such as subsidies, charging facilities, fuel prices, electricity prices, and the number of vehicles by fuel applied. The system dynamics modeling was conducted based on correlations between variables. The system dynamics model of EV propagation by region was applied using the number of new EVs registered as the dependent variable to reveal differences based on regional characteristics. The subsidy variables were divided into national and regional variables, and the number of newly registered EVs was set as the dependent variable and multiple regression analysis was conducted.

In addition, four policy scenarios – Subsidy Cliff, Phase-out, Phase-in 50%, and Phase-in 350% – were adopted to verify whether the 2030 EV goal set by the government could be achieved. According to the analysis, 1.37 million EVs would be adopted in 2030 under the Subsidy Cliff scenario, 1.40 million under the Phase-out scenario, 1.87 million under the Phase-in 50% scenario, and 3.01 million under the Phase-in 350% scenario. The results from these scenarios show that three scenarios, excluding the Phase-in 350% scenario, in which subsidies would increase to 350% by 2030, would require an additional 1.63 million, 1.60 million, and 1.13 million EVs, respectively, to achieve the national EV propagation goal. Under the four scenarios, the regions where the largest number of EVs would be adopted by 2030 were Jeju, Seoul, Gyeonggi, and Daegu. However, the result of the analysis of the spread of EVs compared to the number of residents were contrary to the results of the analysis of the number of EVs based on region. Jeju, Ulsan, Gangwon, and Jeonnam would have the largest number of EVs per capita by 2030. Except for Jeju, the three other regions did not have many EVs compared to the total number of EVs, but the regions would have many EVs compared to the relatively low populations (i.e., EV per capita). Ulsan was projected to have the lowest number of EVs in Korea. However, considering the population, Ulsan would have the largest number of EVs per capita, except for Jeju, which is considered an effect similar to that observed in Ulsan, where an automobile factory is located. The results illustrate the potential propagation of EVs in regions where EVs are produced or where factories are located.

The life cycle assessment (LCA) used to analyze the environmental impacts of EV propagation was based on the national power supply plan. LCA is an analysis method that quantifies the environmental impact of products or services. Prior to analyzing the propagation of EVs, the LCA of electricity production of EVs was evaluated at the goal and scope stages, and 1kWh of electricity production was set as a functional unit for the LCA. In addition, the inventory of pollutants generated during electricity production was analyzed.

With regard to the environmental impact of the number of EVs propagated, the annual mileage provided by the KOSIS was applied based on an 11-year vehicle lifespan of EVs. In addition, the 8th Power Supply and Demand Plan and the additional energy transition option of coal-fired power generation to renewable energy were applied for comparative analyses. The 8th Plan was calculated based on the rated capacity presented as an environmental option, and the application of the energy transition to renewable energy. The GHG emissions of

EVs were 81.7g CO_2e/VKT under the 8th Plan option, and 37.2g CO_2e/VKT for the energy transition option to renewable energy. The energy transition option, showed the lowest GHG emissions, with emissions that were 3.1 times lower than emission of the actual energy mix in 2016, and 4.57-fold and 4.25-fold lower compared to gasoline and diesel-powered vehicles, respectively. In addition, considering the recent rise in particulate matter-related issues, the environmental impact of particulate matter emissions from vehicles was analyzed. EVs. EVs emitted 20.7 mg PMe/VKT per 1km of driving. When the energy transition plan option was applied, PM emissions were less than those emitted by internal combustion engine vehicles.

In the present study, monthly regional panel data were used to analyze factors influencing the propagation of EVs. However, panel analysis was conducted using monthly data rather than annual data. However, there were data acquisition limits that varied across regions. In particular, major factors such as the charging facilities and charging price, which affect the spread of EVs, were not included. Future studies and models should include monthly data on charging facilities for each region. In addition, in the present study, the PM10 variable was applied in the analyses, but if the monthly particulates on bad days were applied as mentioned in a previous study, more accurate results could be obtained for the environmental aspect.

The second part of the three analyses conducted in the study using

system dynamics was analyzed under four scenarios. The scenario that increases the current budget by 35% per year to achieve a 350% increase by 2030 could help meet the national EV propagation goal. However, given that Korea has implemented a policy of suspending EV subsidies as of 2023, it will be challenging to maintain the current budget for 35% subsidies per year for 10 years. Therefore, it is necessary to collect fees such as an environmental pollution tax from internal combustion engine vehicles to return the subsidies or give rebates for eco-friendly car such as EVs. In the future, more reliable research will promote the spread of EVs. The effects of feebate programs could also be considered.

Keywords : Electric vehicle, panel analysis, regional factors, System Dynamics, EV propagation, LCA, environmental performance

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List of Abbreviations

EV	:	Electric Vehicle
ICEV	:	Internal Combustion Engine Vehicle
GHG	:	Greenhouse Gas
PM	:	Particulate Matter
LCA	:	Life Cycle Assessment
LCI	:	Life Cycle Inventory
8th Plan		8th National Plan for Electricity Supply and Demand
SU	:	Seoul
BS	:	Busan
DG	:	Daegu
IC	:	Incheon
GJ	:	Gwangju
DJ	:	Daejeon
US	:	Ulsan
GG	:	Gyeonggi
GW	:	Gangwon
CB	:	Chungbuk
CN	:	Chungnam
JB	:	Jeonbuk
JN	:	Jeonnam
GB	:	Gyeongbuk
GN	:	Gyeongnam
JJ	:	Jeju

Chapter I. Introduction

1. Background

Among the various categories of environmental impacts, greenhouse gases (GHG) are recognized a major factor contributing to climate change (Solomon et al, 2007; Scipioni et al, 2010). Considering the rapid increase in greenhouse gas emissions in domestic greenhouse gas emissions sectors, electric vehicles (EVs), environmentally-friendly vehicles that do not generate carbon in transportation, are proposed as a solution (Yeo and Park, 2015; Chu et al, 2017). The energy sector accounts for 93 percent of total domestic greenhouse gas emissions in five sectors: industrial process, agriculture, land use and forestry, waste, and energy. Energy is cited as a major source of greenhouse gas emissions. In particular, greenhouse gas emissions in road transportation accounted for 94,270 Gg tonCO_2e in 2017 and 95.9% of the total GHG emissions from transportation, which is 203% higher than 30,901 Gg ton CO_2e in 1990 (GGIR, 2020). South Korea, the world's 11th largest contributor to greenhouse gas emissions, announced its "First Basic Plan for Climate Change" in 2016 to achieve a 37% reduction from the 851 million ton CO_2e of greenhouse gas emission forecast by 2030 under the Paris Climate Agreement, which will take effect in

2021. The Basic Plan incorporates strategies to achieve the national greenhouse gas reduction objective related to the seven major sectors, including conversion, industry, buildings, transportation, public, waste, and agricultural and livestock emission forecasting (Interagency Committees, 2016). The transportation sector set a reduction goal of 24.6% of the Business as Usual (BAU) plan and proposed the propagation of eco-friendly vehicles as a core policy (Interagency Committees, 2016).

The Korean government also proposed various policies to expand the propagation of eco-friendly EVs to reduce greenhouse gas emissions. In addition to the measures to boost EVs in 2009, Korea announced a comprehensive roadmap for eco-friendly vehicles in 2010, which laid the groundwork for the roll-out of EVs (KOTI, 2013). In 2012, the Ministry of Environment selected eight local governments to spearhead the EV project and expanded it to 10 local governments in 2013 to start supplying EVs for the private sector (KOTI, 2013). As the spread of EVs grew, the supply of EVs in Korea increased by 60.1 times from 1,447 in 2013 to 87,926 in 2019 (MOLIT, 2014; MOLIT 2020). In 2022, countermeasures of comprehensive particulate matter management implemented in 2017 set a propagation goal of EVs at 350 thousand by 2030. The government also offered benefits such as tax exemptions and purchasing subsidies, tolls, and discounts on parking fees for public parking facilities to promote the use of eco-friendly vehicles in Korea. In March 2019, the government proposed a system to increase low-pollution vehicles in some areas, but after passing a revision in the Clean Air Conservation Act, it will be implemented nationwide starting in 2020.

Despite the government's adoption of various policies, the speed of EV penetration in Korea has fallen short of expectations. To reduce greenhouse gas emissions to 536 million ton CO_2e by 2030 through the Second Basic Plan for Climate Change, the government set a goal of three million EVs for the propagation of EVs in the transportation sector by 2030 (ME, 2019). However, as of 2019, the number of registered EVs in South Korea was only about 8.8 million, far below the government’s propagation goal (MOLIT, 2019b). This number is only about 0.5% of all passenger vehicles in South Korea (MOLIT, 2020) and 1.57% of the total number of EVs in the world (IEA, 2018). According to a survey on the intention to buy EVs and the actual purchasers of EVs, satisfaction with EVs as eco-friendly vehicles is above average. However, 24.9% of actual purchasers indicated that they would not buy another EV considering the proposed reduction in subsidies, long charging times, and short distances they can drive on a charge (ME, 2017). Prospective buyers also indicated that they had no intention of purchasing an EV due to the high price of EVs and difficulty charging them. Notably, it is reported that the reduction in government subsidies for the promotion of the purchase of EVs is the most significant obstacle contributing to the slow spread of EVs (Huh et al, 2018). According to the Korea Electric Power Corporation's proposed revision of the detailed regulation for electricity supply, the charging price for EVs has risen by about 40% from 178 KRW/kW to 240 KRW/kW since the second half of 2020 (KEPCO, 2020). Consequently, the charging cost for an EV will increase further and affect the intention to purchase (Bae, 2020).

In line with the growing interest in EVs, numerous studies have analyzed the potential propagation of EVs and several factors affecting the spread of EVs have been suggested. Charging facilities, population density, fuel prices, temperature, the price of electricity, and the number of vehicles owned per person have been identified as the main factors limiting the propagation of EVs. Li et al. (2017) analyzed the impact of renewable energy and socioeconomic influences on the spread of EVs in 14 countries, including the United States, China, Norway. However, subsidies for EV consumers in these countries are not an influencing factor. Thus, the studies are limited in analyzing the impact of subsidies. Kerkhof and Boonen (2013) compared the Dutch propagation of EVs by dividing EVs and other eco-friendly cars to analyze each factor and propose policy influencing factors and suggested an effective assessment of the propagation based on their findings. Using data at the national level, Sierzchula et al. (2014) also analyzed the relationship between financial grants and socioeconomic and socio-demographics factors to demonstrate the influence of factors in each field through the relationship analysis of each factor and the EV market share.

Regional characteristics should also be considered since subsidies are divided further into national subsidies and regional subsidies. In Korea, in addition to national subsidies, subsidies are paid differently by region. Subsidies for purchasing EVs are also categorized as national subsidies and regional subsidies that are supported by local governments. Consequently, special regions such as Jeju Island ("Jeju" hereafter) and “the Jeju Special Self-Governing Province Ordinance on Promotion of EV Propagation and Promotion of Use of EVs" have implemented regional subsidies independently. After declaring the 2.0 era of EVs, Jeju implemented several policies on EVs and provided more subsidies to local governments compared to other regions to promote a “Carbon Free Island” (Huh et al., 2018). With this policy, EVs registered in Jeju as of 2018 accounted for about 28.1% of all EVs in Korea, and 3.42% of all registered vehicles in the province are now EVs, which is far higher compared to other regions. This example illustrates why it is imperative to analyze the spread of EVs by taking into account regional characteristics.

With the implementation of government policies and various studies aimed at promoting EVs, the demand for EVs is expected to increase. However, all environmental factors must be taken into consideration when analyzing the impacts. For example, changes in electric power generation, which is the fuel for EVs, will become more important. The positive environmental characteristics of EVs are highlighted considering that no pollutants are emitted while driving (Sioshansi and Denholm, 2009; Au et al., 2014). However, the adoption of EVs is often promoted without including the full environmental impact throughout the life cycle of EVs from pre-manufacturing to disposal stages. According to the Soul EV's environmental performance label, the power generation phase for EVs during their life cycle produces the largest amount of carbon in the use phase, which means that EVs still have a major environmental impact (EPD, 2020). Since the environmental impact of the EVs is dependent on the composition of the power mix, a comprehensive environmental impact assessment should be conducted considering the national power mix.

As of 2017, the composition of Korea's power mix constituted 45% coal-fired power, 30% nuclear power, 17% LNG, 6% renewable energy, and 2% from other sources. Since most of the electricity is generated through coal-fired and nuclear power generation, a comprehensive environmental impact assessment should be conducted. Korea’s 8th Basic Plan for Electricity Supply and Demand, the national power supply plan for 2017 to 2031, manages the power mix for the conversion of coal-fired power and nuclear power generation into renewable energy. According to Korea's 2016 actual power mix, emissions by fuel were 115g/km for EVs, 170g/km for gasoline cars, and 158g/km for diesel cars, with EVs producing the least amount of carbon dioxide (Kim et al, 2019). However, the two most important categories related to automobile propagation and energy production show conflicting results in greenhouse gas and particulate matter. Thus, with changes in a spread of EVs, an environmental impact assessment needs to take into consideration any changes in the power mix composition.

2. Objectives

The purpose of this study was to analyze changes in the penetration of EVs based on subsidy policies, and to evaluate environmental improvements based on the number of EVs in use. The methods used are as follows:

(1) Panel Analysis with regional panel data was used to identify the factors affecting EV propagation in Korea.

(2) Stella Architect, a system dynamics modeling program, was used to evaluate regional EV propagation based on three subsidy policies.

(3) Life cycle assessment (LCA) of EV propagation was employed to analyze the environmental implications of EV propagation considering the 8^{th} National Plan for Electricity Supply and Demand.

Based on the results of the statistical evaluation, system dynamics evaluations, and LCA are presented to project the spread of EV and environmental implications of EVs depending on their use.

Ⅱ. Literature Review

1. Determinant of EV Propagation

Numerous studies have identified factors that affect the growth in EVs as interest in this type of transportation is growing. The factors have been broadly classified as internal and external factors. Internal factors include the EV purchase price (Graham-Rowe et al., 2012; Carley et al., 2013), the relatively short driving range (Egbue and Long, 2012; Carley et al., 2013), and longer charging time (Graham-Row et al., 2012; Hackbarth and Madlener, 2013). External factors include the fuel price (Tseng et al., 2013); Sierzchula et al. , 2014; Wu et al., 2015; Li et al., 2017), consumers’ propensity to buy EVs, the charging network or infrastructure (Kerkhof and Boonen, 2013; Ito et al., 2013; Sierzchula et al., 2014; Madina et al., 2016; Li et al., 2017), public visibility, and policy mechanisms. Special attention has been given to policy mechanisms that have significant impacts on the propagation and activation of EVs, including financial incentives, non-financial incentives, and support for the charging infrastructure. Table 1 summarizes the factors affecting the increase in EVs in previous studies.

Among the internal factors, the price of EVs has been shown to have a significant impact on consumers' decision to purchase an EV. According to a 2011 survey of consumers in 21 major cities in the United States, the price of EVs was a major barrier to purchasing EVs (Carley et al., 2013). In another survey conducted in the United States and the United Kingdom on drivers of internal combustion engine vehicles (ICEV), the high price of EVs was identified as the main reason for participants' reluctance to purchase EVs (Graham-Rowe et al., 2012). Tran et al. (2013) also found that the price of EVs is a major barrier to purchasing, and a reduced price would likely lead to an increase in buyers' willingness to purchase an EV. Carley et al. (2013) and Egbue and Long (2012) analyzed that the driving range as well as the price detered buyers. Hackbarth and Mardlener, (2013) also showed that the willingness to purchase an EV would grow if the driving range increased and the charging time decreased.

Among the external factors, fuel prices have been identified in various studies as a significant factor when comparing ownership costs of ICEVs and EVs. Unlike Tseng et al. (2013) and Wu et al. (2015) who argued that the high ownership cost of ICEV compared to EVs affected EV purchases, Sierzcula et al. (2014) and Li et al. (2017) found that fuel prices and EV charging issues had less impact on the propagation of the EV market share. Although the price of EVs has been identified as a major factor in purchasing EVs, subsidies or incentives to buy EVs have not been shown to be significant factors, even though they would reduce the price burden (Kerkhof and Boonen, 2013; Sierzchula et al., 2014; Mersky et al., 2016; Langbroek et al., 2016). The purchasers' level of education was considered an influencing factor as well, but the results of a survey and research were inconclusive (Carely et al., 2013; Hackbarth and Madlener, 2013; Sierzchula et al., 2014; Li et al., 2017). Furthermore, the presence or absence of an island in the region was analyzed as having a possible impact on limited traveling distances and thus islanders' propensity to purchase EVs (Kerkhof and Boonen, 2013).

Sierzchula et al. (2014) also considered diverse factors as key drivers of EV propagation. They identified several factors that did not affect the demand for EVs in the first year after EVs were introduced, including the number of EV models that were purchased, the urban population density, the number of vehicles owned per capita, and the index of environmental regulations.

Although several determinants for EV propagation have been identified, few studies have used both regional and monthly data. Therefore, this study used both regional and monthly panel data from 17 regions in Korea. In addition, many studies have examined the relationship between EVs and climate factors, but few EV propagation studies have considered climate and environmental factors as key drivers. Therefore, climate and environmental factors of 17 regions in Korea were used in this study. The climate factors included in the current study were monthly average temperature, monthly maximum temperature, monthly minimum temperature, and precipitation. The concentration of particulate matter (PM) as an environmental factor was also included to determine if it impacts EV propagation.

Table 1. Factors on EV Propagation in Previous Studies

Type of Factors	Factors	Studies
Internal factors	EV price	Graham-Rowe et al.(2012); Carley et al.(2013); Tran et al.(2013)
	Driving range	
	Charging Time	Graham-Row et al.(2012); Hackbarth and Madlener(2013)
External factors	Incentives	Kerkhof and Boonen(2013); Sierzchula et al. (2014); Langbroek et al.(2016); Mersky et al.(2016)
	Charging infrastructure	Kerkhof and Boonen(2013); Ito et al.(2013); Sierzchula et al.(2014); Madina et al.(2016); Li et al.(2017)
	Index of environmental regulations	Hidrue et al.(2011); Graham-Rowe et al.(2012); Sierzchula et al. (2014)
	Fuel prices	Tseng et al.(2013); Sierzchula et al. (2014); Wu et al.(2015); Li et al.(2017)
	Income	Hidrue et al.(2011); Kerkhof and Boonen(2013); Sierzchula et al. (2014);
	Island	Kerkhof and Boonen(2013)
	Education level	Carely et al.(2013); Hackbarth and Madlener(2013); Sierzchula et al.(2014); Li et al.(2017)
	Vehicles per capita	Sierzchula et al. (2014)
	Headquarters of EV producers	

	Electricity prices	
	Number of EV models	
	Year EV was introduced	
	Urbanization	Sierzchula et al.(2014); Li et al.(2017);
	Population density	Kerkhof and Boonen(2013); Li et al.(2017)

2. System Dynamics Modeling

A system dynamics approach is a simulation method to help understand, visualize, and analyze complex systems (Zhao et al., 2011; Feng et al., 2013). Numerous studies have used the system dynamics approach since Forrester introduced it in the 1960s due to its advantage of analyzing the cause and effect relationship among the factors in a system. Using the system dynamics approach has also helped policymakers simulate sustainable development strategies for propagation of EVs and alleviation of air pollutants.

For example, Sheperd et al. (2012) analyzed changes in the market share of EVs depending on the impact of factors affecting the uptake of plug-in hybrids (PHEVs) and battery electric vehicles (BEV). The results showed that subsidy factors along with other factors played an important role in tipping the market into a successful trajectory in the U.K. For example, the average vehicle life and emissions rate could have a greater impact over time. In China, Feng et al. (2013) evaluated the urban energy consumption in Beijing based on the spread of EVs using the Stella Architect software platform for system dynamics. Their study also analyzed CO2 emissions from six sectors including agriculture, industry, service, residential, transport, and transformation.

With respect to various impacts of EVs, Onat et al. (2016) analyzed the environmental, social, and economic impacts of EVs using an integrated system dynamics approach and life cycle sustainability assessment. Several studies have also related national level propagation or propagation in a city to EVs and the environmental implications of EVs. However, to the best of my knowledge, little attention has been paid to research at the regional level for propagation of EVs using effective factors from the perspective of system dynamics.

3. Environmental Impacts of EV Propagation

In many countries, EVs have been widely promoted as a good way to reduce the environmental impact. Thus, several studies have evaluated the environmental implications in categories such as global warming potential, particulate matter, and ozone depletion. Hawkins et al. (2013) compared environmental impacts of EVs and ICEVs through the whole life cycle using life cycle assessment (LCA), and concluded that it was counterproductive to promote EVs if the country or region produced electricity from coal, oil, or lignite combustion. With respect to energy sources, Choma and Ugaya (2017) considered the environmental implications of the use phase of EVs and ICEVs in Brazil using LCA. Ma et al. (2012) examined the reduction of GHG emissions from EVs by analyzing the environmental impacts of EVs based on an analysis of actual operation conditions in the U.K. and California, considering the share of electricity generation plants. They concluded that EVs had a reduced effect on GHG emissions compared to ICEVs when all phases of the life cycle were considered.

Other LCA studies considering the electricity power mix of Korea include Kim et al. (2019) who evaluated the environmental implications of EV batteries (BEV) by comparing the potential implications of BEV with those of ICEV in several categories. They also evaluated the national power portfolio for the environmental impacts of BEV based on the national power roadmap of South Korea.

Although several studies have evaluated the environmental impact of EVs compared with ICEV, few studies have applied both EV projections and the national power mix in assessing the environmental impact of EVs. Therefore, this study applied the total number of EVs projected from a system dynamics analysis and the national power mix from the 8^{th} National Plan of Electricity Supply and Demand (8th Plan) to evaluate the potential environmental impact of EVs in 2030.

III. Data and Methods

1. Panel Analysis for Deriving Affecting Factors of EV Propagation

1.1. Scope of Study

EVs were first introduced in 2011 in Korea and were disseminated as a pilot distribution to government agencies from 2011 to 2012. In 2013, the policy for public propagation was ready to implement, and distribution of EVs began. Therefore, the analysis period for this study is set from 2013 to 2018, but the data used in the study is monthly data over six years (Table 2). The monthly data in this study is from 17 metropolitan cities and provinces including Sejong Special Self-Governing city.

Table 2. Scope of Study for Panel Analysis

Study Period	2013 - 2018
Study Area	17 Regions in Korea
Type of Data Used	Monthly Data

1.2. EV Trends in Korea

An EV is known as an eco-friendly vehicle or green car (Kampman et al., 2010). It can be classified into three main types depending on the amount of electricity needed as the power source: battery electric vehicles (BEV), plug-in hybrid electric vehicles (PHEV), and hybrid electric vehicles (HEV) (Figure 1). In this study, electric vehicle (EV) refers to a battery electric vehicle. BEVs are fully electric-charged EVs with no engine. They are also known as zero emission vehicles since there are no greenhouse gas emissions while driving. PHEVs have batteries that can be recharged through both regenerative braking and plugging into an external power source. HEVs are powered by both gasoline and electricity, but charging is only possible via their braking system.

Only 1,447 EVs were purchased in 2013, the first year of distribution, which accounted for only 0.01% of the total number of passenger vehicles (Figure 2). However, with added propagation policies for EVs and technological improvements, by 2019, the cumulative number of EVs was 87,000, which was 0.46% of all passenger vehicles.

The propagation status of EVs in 2013 and 2018 is shown in Figure 3, with Jeju and Seoul representing the provinces that supplied the most BEVs in both years. In Jeju, the local government has attempted to establish a specialized EV zone for the broader distribution of BEVs. The local government has also implemented the “Carbon-free Island 2030 Plan” to promote EVs.

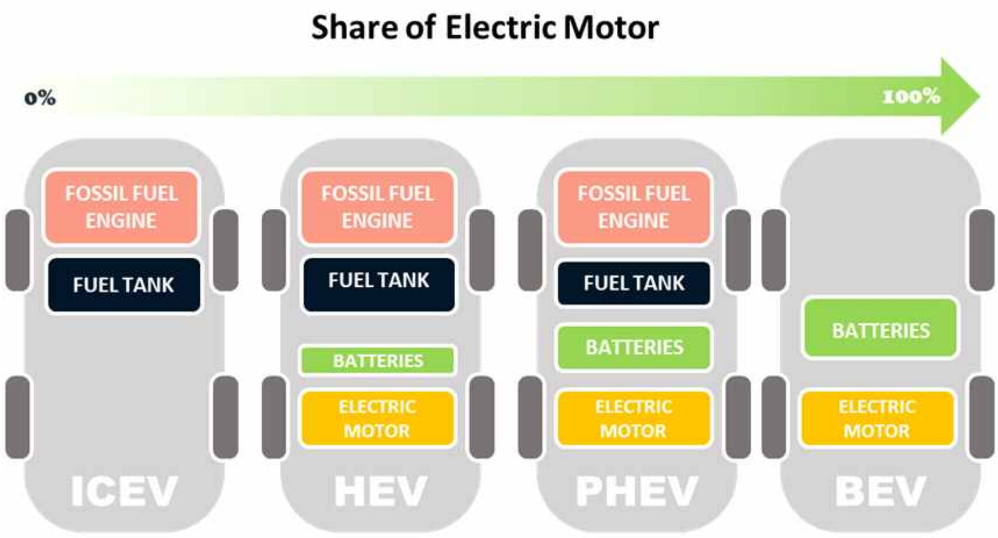


Figure 1. Main Types of EVs

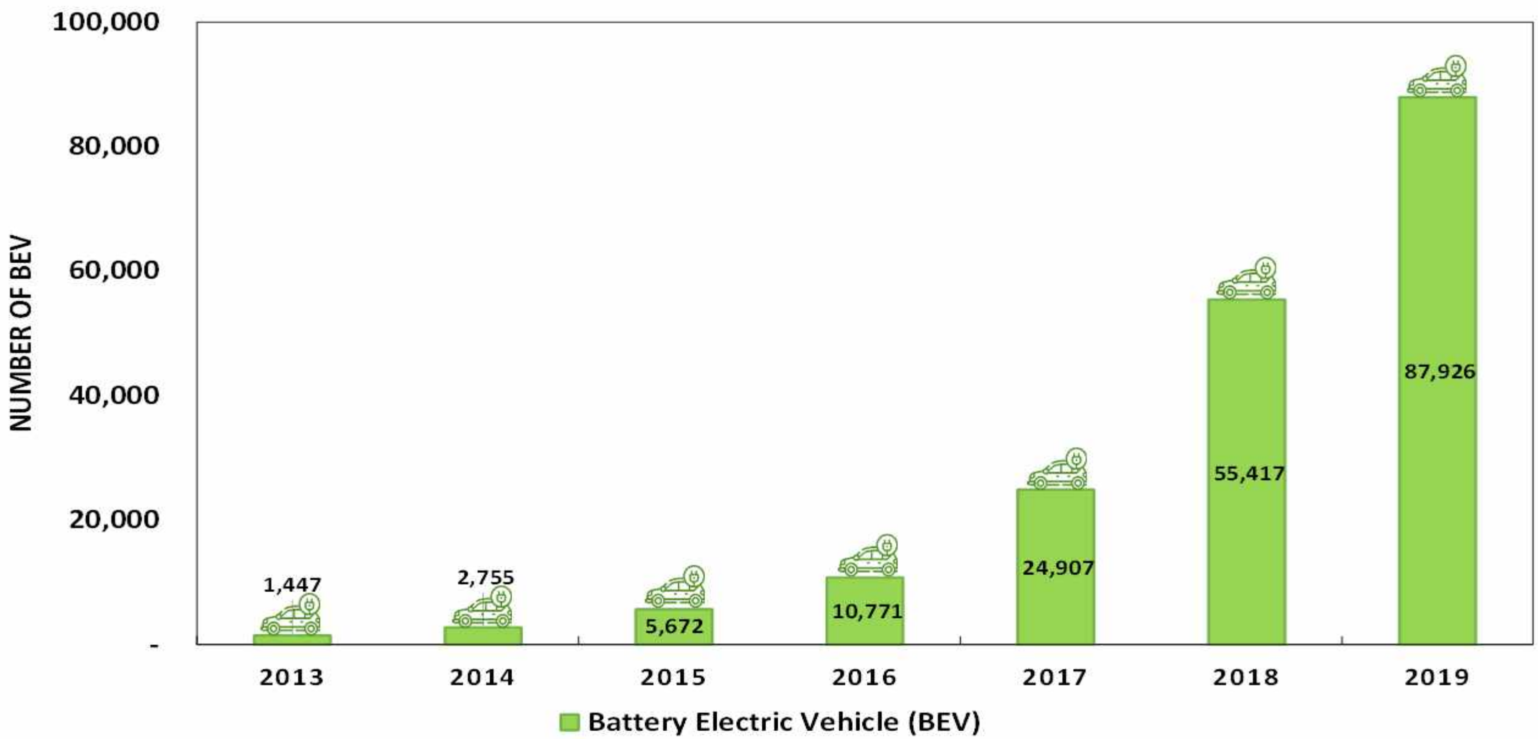
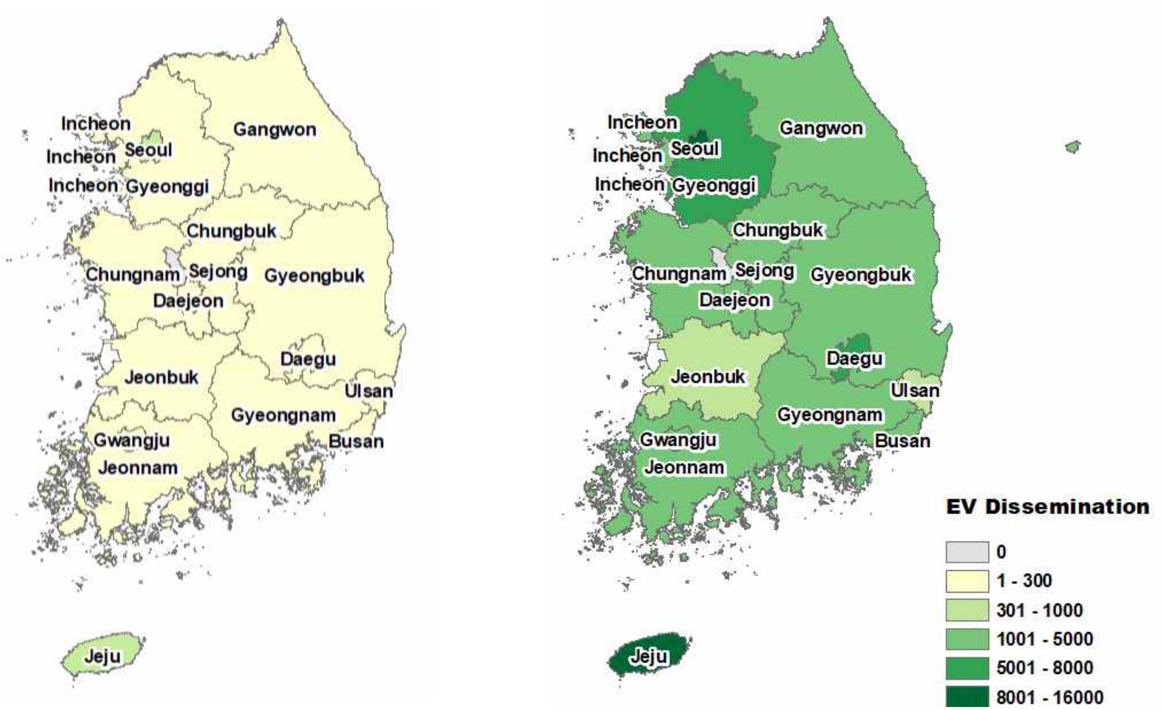


Figure 2. EV Trends in Korea



(a) 2013 (b) 2018

Figure 3. EV Propagation in Korea

1.3. Categories of Affecting Factors

To analyze the factors affecting the propagation of EVs in Korea, data from 17 metropolitan cities and provinces were collected and used, including from Sejong Special Self-Governing City. In addtion, the factors based on monthly data were selected for analysis. The variables and sources used for the panel analysis are shown in Table 3. Because they are time-linked cross-sectional data, there may be heteroscedasticity issues in the cross-sectional data as well as an auto-correlation problem of the time series data (Kim, 2004). To resolve these problems, we used balanced panel data that integrates the time series and the cross-sectional data. By applying panel data, the variability can be accurately analyzed with fewer problems from multicollinearity (Kang, 2009).

In considering the regional characteristics, this study set the number of newly registered EVs as the dependent variable to examine the factors affecting the propagation and activation of EVs in Korea. This study used the number of newly registered EVs at that time, but did not apply the data on scrapped EVs to determine the degree of newly disseminated EVs in Korea. All the panel data used in this study are monthly data.

In general, the panel analysis is mainly analyzed using annual data. However, previous studies for the spread or activation of propagation have used the monthly format of data for panel analysis. For example, panel analysis was conducted using monthly data in Li and Shiu (2012) and Hausman et al. (1993). Li and Shiu (2012) conducted panel analysis of internet dissemination in China using monthly panel data, and Hausman et al. (1993) used monthly format of data to examine telephone penetration in the United States.

Table 3. Variables and Sources

Types	Categories	Variables	Description	Source
		i	Region in Korea	-
		t	Month	
Dependent Variable		EV	Number of newly registered EVs	MOLIT(2019a)
Independent Variables	Vehicle	DIESEL CAR	Number of newly registered diesel cars	
		GASOLINE CAR	Number of newly registered gasoline cars	
		TOTAL CAR	Total number of car registered	
		PRICE OF DIESEL	Monthly average diesel price	Opinet(2019) EIA(2020)
		PRICE OF GASOLINE	Monthly average gasoline price	
	Policy	NATIONAL SUBSIDY	National subsidy balance	ME(2019)
		REGIONAL SUBSIDY	Regional subsidy reserved	
		TAX EXEMPTION	Tax exemption amount per EV	
	Demographic	POPULATION DENSITY	Number of people per square km of land area	KOSIS(2019); MOLIT(2019a)
		CAR PER CAPITA	Number of car owned per capita	
	Climate	AVERAGE TEMP.	Monthly average temperature	KMA Monthly Weather Report KMA(2019)
		MINIMUM TEMP.	Monthly minimum temperature	
		MAXIMUM	Monthly maximum temperature	

		TEMP.		
		PRECIPITATION	Monthly average precipitation	
	Environment	PM10 CONCENTRATION	Monthly average concentration of particulate matters	AirKorea Monthly Report of Air Quality AirKorea(2019)

1.3.1. Vehicle Sector

(1) Number of Vehicles

Factors related to vehicles include the number of newly registered diesel vehicles, the number of newly registered gasoline vehicles, and the total number of newly registered vehicles. In this study, the variables were not cumulative, but monthly data were used for the number of EVs, diesel vehicles, gasoline vehicles, and total number of vehicles. Moreover, the variables for each month were set to analyze changes in the number of vehicles by fuel or the number of newly registered EVs compared to the total number of vehicles. The number of newly registered diesel vehicles, gasoline vehicles, and total number of newly registered vehicles was set to reflect the competitiveness of EVs and internal combustion engine vehicles using data provided by Statistics of the Ministry of Land, Infrastructure and Transport. Data on gasoline and diesel prices were provided by Opinet.

(2) Fuel Price

According to a survey of actual buyers of EVs by the Ministry of Environment, the low maintenance cost of EVs is an important factor for purchasing. In particular, the reduced fuel cost compared to that of internal combustion engine vehicles contributed to their decision (ME, 2017). Therefore, fuel prices need to be considered for analysis as a factor that affects the EV purchase decision. The cost of gasoline and diesel fuel has fluctuated considerably since 2013 (Figure 4). In early 2013, the price of both gasoline and diesel fuel reached a peak, but the prices bottomed out at the end of 2015. By 2018, prices had risen again and the spread of EVs was high. However, unlike electricity prices, fuel prices need to be considered in light of the high volatility.

The fuel price data used in this study were the monthly data of gasoline and diesel prices. The monthly average gasoline and diesel price data for each region was set from January 2013 to December 2018. The fuel price data were provided by Opinet of Korea National Oil Corporation. The applied fuel prices are the average sales prices of gasoline and diesel. The gasoline price refers to the price of regular unleaded gas and the diesel price refers to the price of diesel fuel for vehicles.

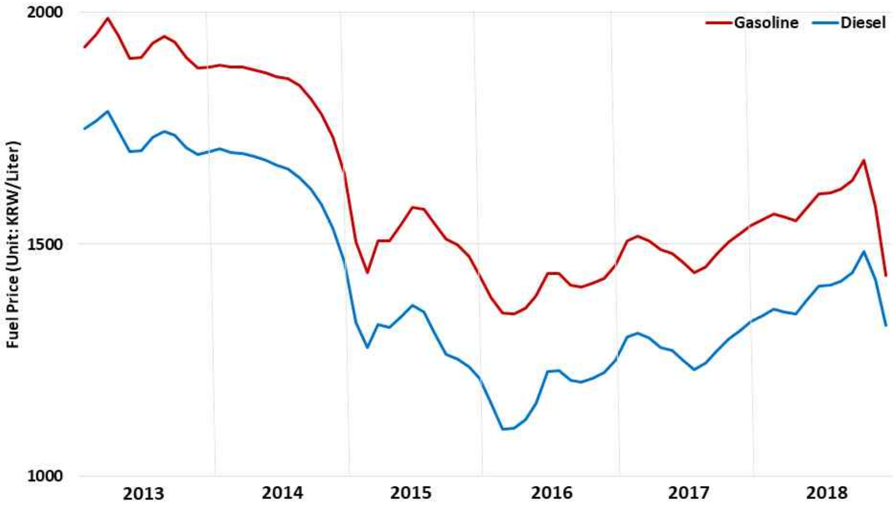


Figure 4. Monthly Changes in Gasoline and Diesel Prices from 2013 to 2018

1.3.2. Policy Sector

External factors related to the policy sector have included a national subsidy, regional subsidy, and the charging infrastructure. However, the charging infrastructure factor was excluded in the current study due to the limited ability to obtain monthly data on domestic charging facilities.

(1) Subsidies

The national subsidy and regional subsidies were chosen as policy factors. When public propagation for EVs started, the national subsidy was 15 million KRW, but it was gradually reduced over time. The earmarked national subsidy for 2018 was 12 million KRW. Unlike previous national subsidy policies, the policy for the national subsidy changed in 2018. The government began to make different payments depending on the type and model of the EV. Therefore, the national subsidy amount for 2018 was applied based on the Hyundai Kona. The data for the national subsidy was provided by the Ministry of Environment.

The balance rather than the total amount was applied to the value of the national subsidy. To calculate the balance, this study used the monthly data on newly registered EVs of each region and the national subsidy for an EV. The equation for calculating national subsidy is as follows in Equation 1.

$$NatlSubsidy_{i,t} = AnnualBudget_t - (NofEV_{i,t} \times {}_{sidy_{i,t}}) \quad (1)$$

where $Natl.Subsidy_{it}$ denotes the national subsidy balance of region i at time t, $AnnualBudget_{it}$ denotes the budget of national subsidy at time t, $NofEV_{it}$ denotes newly registered EVs in region i at time t, and $Subsidy_{it}$ denotes the national subsidy per EV in region i at time t.

Applying the amount of the regional subsidy for each region was limited since each region has different regional subsidy amounts for individual models of EVs. Only data on the total amount of regional subsidies are available from the Ministry of Environment. Thus, this study used the monthly remaining number of EVs that could be afforded for each regional subsidy instead of the amount of the total regional subsidy. The equation for calculating the regional subsidy is as follows in Equation 2.

$$RegSubsidy_{i,t} = AnnualBudget_{i,t} - NofEV_{i,t} \quad (2)$$

where $Reg.Subsidy_{it}$ denotes the remaining number that can be offered as a regional subsidy in region i at time t, $AnnualBudget_{it}$ denotes the total capacity that the regional subsidy can support at time t, and $NofEV_{it}$ denotes newly registered EVs in region i at time t.

Since national and regional subsidies are based on the annual budget, it was difficult to identify the relationship between the monthly change of subsidies and EV propagation. To reflect regional characteristics of the national and the regional subsidies, the subsidies were calculated as the balance and the remaining subsidies that citizens could receive, along with applying monthly data.

(2) Tax Exemption

The Korean government has provided various financial supports for EV buyers to promote EVs in Korea. In addition to the national and regional subsidies, they also allow a tax exemption. The data for a tax exemption was calculated as the sum of the individual consumption tax, education tax, acquisition tax, and public bond discount. When EVs for the public began to spread in 2013, the tax exemption was up to 2.6 million KRW. The amount of the tax exemption increased with government's policy to boost the supply of EVs. In 2018, the government allowed EV purchasers to receive up to 5.9 million KRW via a tax exemption.

1.3.3. Demographic Sector

(1) Car per capita

Factors in the demographic sector include the number of cars owned per capita and population density. The number of passenger cars registered in Korea reached 19.18 million at the end of December 2019, representing about 2.5 people per car (MOLIT, 2019; KOSIS, 2020). The automobile market is expected to continue to develop due to factors such as policy support for eco-friendly vehicles and the introduction of new vehicle models leading to a probable increase in the number of cars in Korea (Park et al, 2012). Given these trends, a variable related to the number of vehicles would be useful to analyze the propagation of EVs.

The number of cars owned per capita is the number the total number of cars in an area divided by the population. Population density was calculated using the population reported in the national census. Cars per capita was 0.41 in 2013, the year EVs were first publically propagated, and 0.50 in 2018 (Figure 5), a 22% increase.

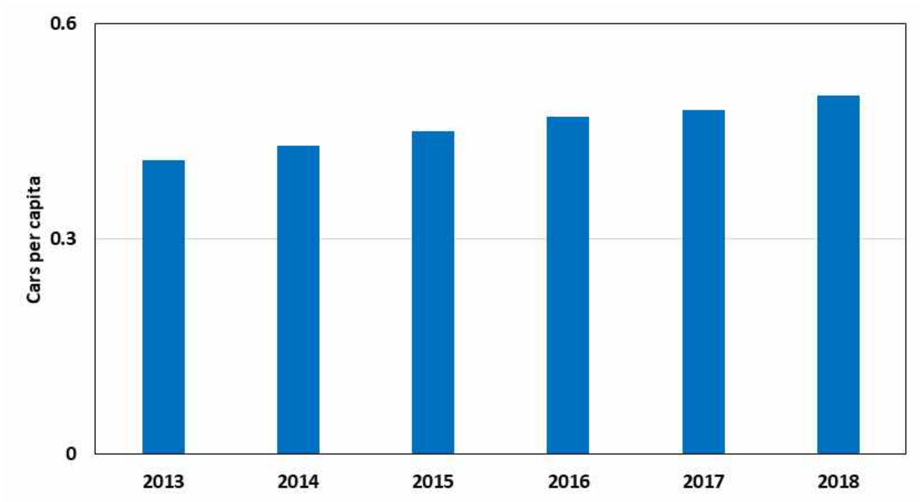


Figure 5. Vehicles per capita in Korea from 2013 to 2018

(2) Population Density

Population density refers to the population per area of a region. In previous studies, population and regional areas may have been considered separately, but it is generally assumed that the effect of the two variables and population density are similar (Boisjoly et al., 2018). Thus, population density is representative of the population of the region, and thus data from a population survey is commonly used. However, it is difficult to apply this approach to this study since the population survey is only conducted every five years.

Therefore, population density was calculated using the monthly population and the area of each region, obtained from the Korea Statistical Information Service.

1.3.4. Climate Sector

Both temperature and precipitation variables included in the climate sector were provided by the Korean Meteorological Administration. The study also used the average temperature, maximum temperature, minimum temperature, and precipitation variables as monthly data.

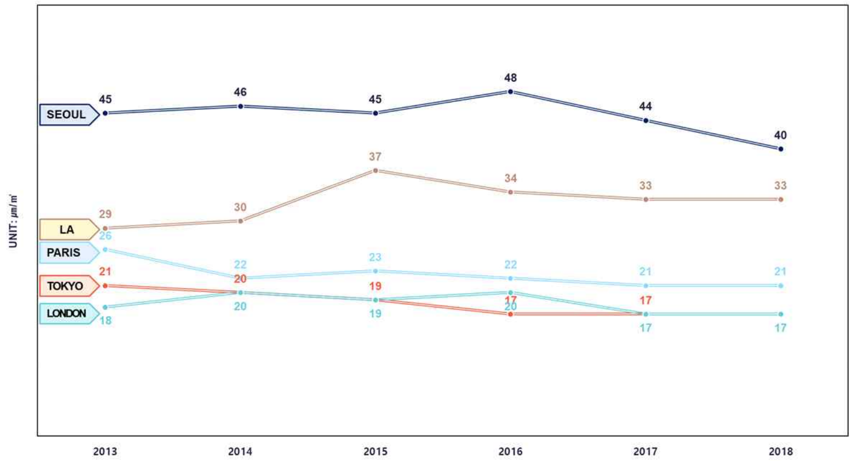
EVs change in range and energy efficiency according to temperature and humidity (Yuksel and Michalek, 2015). Thus, in this study, climate factors were included as factors that influence the spread of EVs by reflecting these characteristics of EVs. The monthly average temperature is based on the total daily temperature based on weather observation data. The maximum and minimum temperatures were applied to the highest and lowest temperatures each month. Precipitation was recorded from the weather observation data as the monthly total of daily precipitation, which is the total amount of precipitation per month.

1.3.5. Environmental Sector

(1) PM10

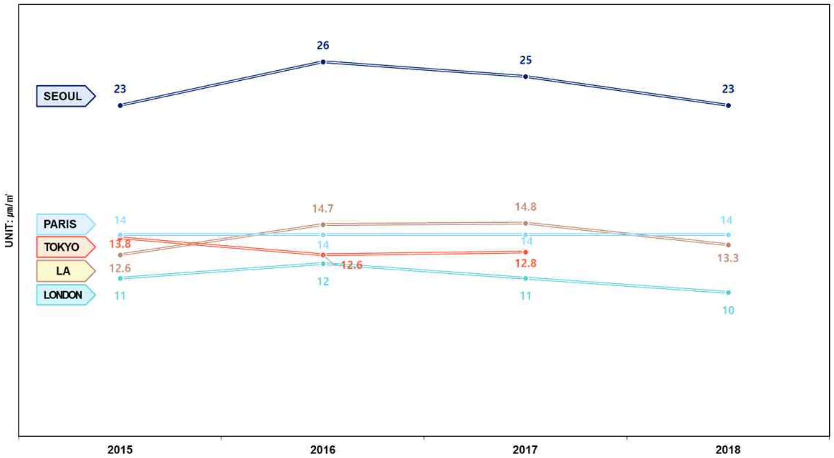
The Air Quality Index (AQI) is used to report air quality. It includes measures of particulate matter ($PM_{2.5}$ and PM_{10}), ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2) and carbon monoxide (CO) emissions (AirNow, 2020). Particulate matter, small particles of less than 10㎛, are divided into two types, PM_{10} and $PM_{2.5}$, based on their diameter. They are mainly emitted from combustion of fossil fuels through industrial activities.

The concentration of particulate matter in Korea is higher than in other countries, and the influence of the particulate matter is important. The annual average concentration of PM_{10} in Korea in 2018 was 40.7㎛/㎥, which was 2.4 times higher than that of other countries during the same period (Figure 6). In addition, $PM_{2.5}$ was more than two times higher in Seoul than in London, and the pollutant level was serious compared to other major cities (Figure 7).



Source: AirKorea, 2020; EPA, 2020; UK AIR, 2020; AirParif, 2020; Bureau of Environment Tokyo, 2020

Figure 6. PM_{10} Concentration in the Major Cities



Source: AirKorea, 2020; EPA, 2020; UK AIR, 2020; AirParif, 2020; Bureau of Environment Tokyo, 2020

Figure 7. $PM_{2.5}$ Concentration in the Major Cities

The trends of particulate matter are a representative index of pollution. Particulate matter has an impact on human health (Pikridas et al., 2018; Seifi et al., 2019) so it is appropriate to analyze $PM_{2.5}$. The concentrations of $PM_{2.5}$ have been gathered in Korea only since 2015. Thus, this study analyzed the data in cities and provinces in Korea from 2013 to 2018 using the concentration of PM_{10}. The national annual average concentration of PM_{10} in Korea was 41$\mu g/m^3$ per day. Furthermore, eight regions (Busan, Gwangju, Daejeon, Gyeonggi, Chungbuk, Jeonbuk, Gyeongbuk and Gyeongnam) out of 16 were had higher or equal concentrations to the national average concentration of PM_{10}. The PM10 concentration of each region in 2018 is shown in Figure 8. Jeonnam and Jeju had the lowest PM_{10} concentration (35$\mu g/m^3$), but even in the regions with the lowest concentration of PM_{10} in Korea, PM_{10} was higher than in other major international areas indicating that the level of air pollution nationwide is critical.

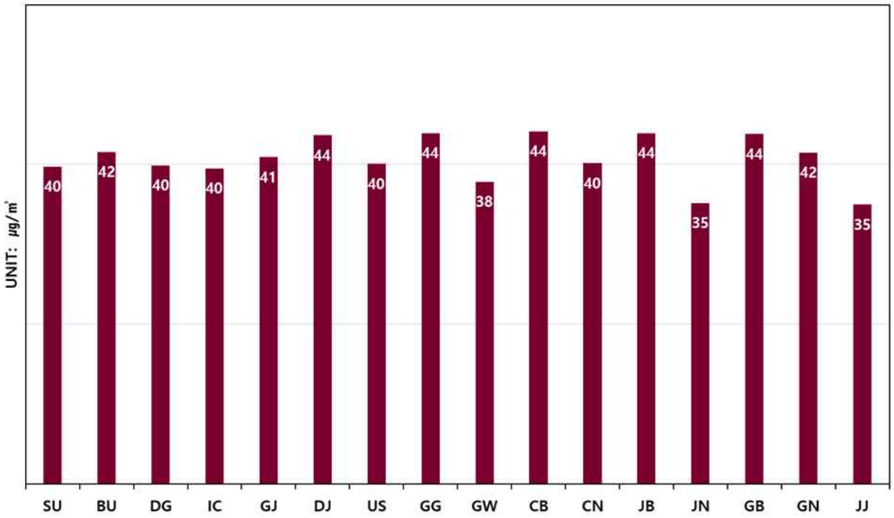


Figure 8. Concentration of PM_{10} in 2018 by Region

1.4. Stationarity Test

Stationarity means that the statistical properties of a process generating a time series do not change over time (Figure 9). More specifically, it does not mean that the series does not change over time but that the series does not change itself (i.e., the variable or factors) over time. It is important to test stationarity of variables to ensure that they do not change. The process of testing stationarity of factors is a prerequisite for panel analysis.

Factors that have been reported to affect the propagation of EVs were tested for their stationarity to ensure statistical significance prior to panel analysis. If the variable is non-stationarity, several situations could occur such as the following. Even though there is no correlation between variables, it is possible that the coefficient of determination (R2) is high due to spurious regression, and the statistic of Durbin-Watson(DW) may be low. The stationarity of the variables applied to the analysis must be confirmed to apply the panel data (Kwon, 2017), since the result may be distorted depending on the stationarity status of these time series data.

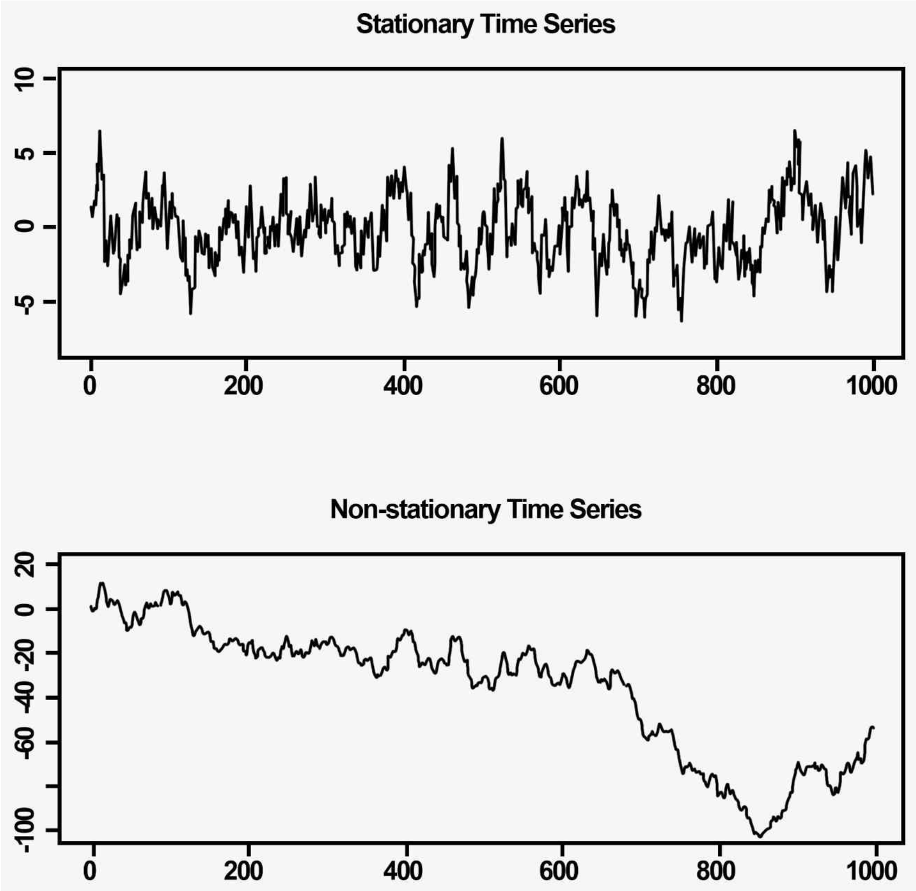


Figure 9. Time Series Generated by a Stationarity (Above) and Non-stationarity (Below) Process (Source: Halder and Ozdemir, 2018)

The Augmented Dickey Fuller (ADF) test was used to check the stationarity of each variable of the panel data. The ADF test is a method for testing the presence or absence of unit roots by adding lags to the Dickey Fuller test. The null hypothesis is “the unit root exist in the panel data,” and the alternative hypothesis is “each time series has stationarity at a regular interval” (Nam and Lee, 2013). This means that when the variable rejects the null hypothesis through the ADF test and adopts the alternative hypothesis, the variable takes on stationarity and shows statistics of χ^2.

1.5. Panel Analysis Model

For the analysis of this study, R 3.3.1, R studio and panel linear model (plm) packages were used. In other words, a panel regression analysis was performed with the advantage of controlling the unique elements and individual effects of each region.

1.5.1. Pooled Ordinary Least Square

This study examined the trends and characteristics of each variable by year, after examining which variables and interactions should be included in this analysis. The analysis was performed using a pooled ordinary least square estimation to determine whether an independent variable can explain individual characteristics. A pooled ordinary least square is a method for analyzing cross-sectional data accumulated over t years using an ordinary least square when the data of each year are randomly sampled within a population (Wooldridge, 2002). A pooled ordinary least square is the same as applying an ordinary least square estimation to an analysis of all observations as different individual regions (Wooldridge, 2002). A consistent estimator can be obtained when panel data are used like an IID sample, which are all pooled (Woo and Kim, 2020). When the pooled ordinary least square model is applied to a model with fixed effects, the commonality due to the unique attributes of the individual could potentially be mistaken for causality. The variables within the pooling data are not controllable, and thus there may be bias within the estimates (Kang, 2009). On the other hand, the panel data analysis controls the unobserved heterogeneity as much as possible to estimate the effects of the variables (Eom, 2008).

1.5.2. Fixed Effect Model

The effective ways to analyze the panel data can be subdivided into a fixed effect model and a random effect model depending on the form of the specific constant term μ_i. These two models greatly differ in whether an observed individual-specific effect includes a correlation with independent variables (Greene, 2012). A fixed effect model assumes an unobservable characteristic as a fixed constant (Choi, 2007). The estimation method of this model is to convert each variable into a within model variable and subtract it to eliminate μ_i. Therefore, the endogeneity issue can be solved even if a correlation exists between the error term and the variable.

The panel linear regression model used in this study is shown by the following equation:

$$\begin{aligned} y = {} & \beta_1 Dieselcar_{i,t} + \beta_2 Gasolinecar_{i,t} + \beta_3 Totalcar_{i,t} + \\ & \beta_4 NatlSubsidy_{i,t} + \beta_5 RegSubsidy_{i,t} + \\ & \beta_6 PopulationDensity_{i,t} + \beta_7 CarperCapita_{i,t} + \\ & \beta_8 AvgTemp_{i,t} + \beta_9 MinTemp_{i,t} + \mu_i + \epsilon_{i,t} \end{aligned}$$

where i denotes region, t denotes time in months, and y is the dependent variable, which is the newly registered EV. x_{it} is dependent variable that affects the propagation of EV. μ_i is individual-specific constant, which represent a fixed effect by region. Also, β is the estimation coefficient, and ϵ_{it} is an error term.

To estimate factors affecting the spread of EVs, this study used the panel fixed effect model and the panel random effect model. The open source program R ver. 3.3.1 and R studio were used for panel analysis. The final step of the panel analysis was the Hausman test, which was conducted to determine which model was appropriate for the propagation of EVs. If an individual effect is a fixed effect, the within estimator is the most efficient estimator, and it is necessary to test how much difference there is compared to the estimator of the random effect. If the value of the Hausman test is large, the fixed effect is more appropriate than the random effect model.

1.5.3. Random Effect Model

In analyzing panel data, the suitability of panel models and assumptions of the panel data should be complied using various statistical test. First, the panel data tested the independence of the time series and the homoscedasiticity assumption that the error term should be complied. Wald test for heteroscedasticity was performed next. The null hypothesis that all objects have homoscedasiticity was accepted. Therefore, it can be concluded that these panel data have equal variance among individuals. The key consideration when choosing a fixed effect model or random effect model approach is whether there is a correlation between the unobserved individual-specific effect and independent variables. In this study, the fixed effect model is the preferred model. However, both the fixed effect model and the random effect model were analyzed to fully explore the panel data and to review the suitability of the panel models.

2. System Dynamics on Electric Vehicle Propagation

2.1. Scope of study

The time range for this study is 18 years from 2013 to 2030 (Table 4). The period starts in the year when public propagation of EV began, which was set by the national plan for propagation of EVs. The study areas included 16 cities and provinces in Korea. Sejong Special Self-Governing city was excluded due to limited availability of the data. The Sejong city started to establish its own data in 2016. Annual data were used to identify changes in the spread of EVs using a system dynamics approach. The analysis was conducted including major factors of the propagation of EVs, such as charging facilities, which have been excluded from previous panel analyses.

Table 4. Scope of study for System Dynamics Analysis

Study Period	2013 - 2030
Study Area	16 Regions in Korea
Type of Data Used	Annual Data

2.2. Data for System Dynamics Analysis

2.2.1. Propagation and Activation Policy on Electric Vehicles

The promotion of EVs has been a response to climate change, and in particular, an attempt to reduce air pollutants such as particulate matter and greenhouse gases. The government's policies are meant to prepare for the reorganization of the automobile market from vehicles with internal combustion engines to environmental-friendly vehicles. To expand the propagation of environmental-friendly vehicles, Korea has established and implemented the "Basic Plan for the Development and Propagation of Environmental Friendly Vehicles" every five years. The Third Plan, which was announced in 2015, included special countermeasures to address particulate matter, and the propagation plan was upgraded from the previous plan. The Korean government formulated new policies after several rounds of planning to encourage domestic penetration and increase EV propagation goals. According to the National Plan for Disseminating Environmental Friendly Vehicles and Charging Infrastructure, the target for the number of EVs to be disseminated was set at three million by 2030. Furthermore, a revision of the Atmospheric Environment Conservation Act was approved in 2019, and the system for the propagation of low-emission vehicles, which had been implemented only in some parts of the country, was scheduled to be implemented nationwide starting in 2020. The propagation plan for these policies for promoting EVs in Korea is listed in Table 5.

Besides the government's revision of laws and implementation of plans to promote the spread of EVs, the government has provided practical support for EV buyers in accordance with the regulations related to enforcement decrees, such as the Subsidy Management Act (ME, 2017). The benefits for buyers of EVs can largely be divided into financial and non-financial support. There is no non-financial support in Korea, but the financial support includes subsidies for purchasing EVs, tax exemptions, and reduced tolls and parking fees. The subsidies for purchasing EVs include both a national subsidy from the government and regional subsidies from local governments.

For the national subsidy, 15 million KRW was provided for each EV in 2013. However, the amount of the subsidy has gradually declined to 9 million KRW in 2020 and 8 million KRW in 2021, respectively (ME, 2013; ME, 2020; Choi, 2019). The government will not provide a purchase subsidy starting in 2023. The amounts provided as regional subsidies vary depending on the norms set by the local governments. Only Jeju and

Changwon provided purchasing subsidies in 2013. However, most local governments across the country are now leading the way in the propagation of EVs by providing regional subsidies.

Table 5. Propagation and Activation Policy on EVs

Policy	Year	Propagation Plan
Strategies for the Development of Green Car Industry	2010	1.04 million in 2020
Third Basic Plan for Environmental-friendly Vehicle Development and propagation (2016-2020)	2015	200 thousand in 2020
The First Framework on Climate Change	2016	1 million in 2030
Implementation Plan for Electric Vehicle and Hydrogen Vehicle Development Strategies	2017	250 thousand in 2020
Countermeasures for Management of Particulate Matters	2017	580 thousand in 2025
Policy for propagation of Electric Vehicle and Hydrogen Vehicle	2018	430 thousand in 2022
The Second Framework on Climate Change National Plan for Disseminating Environmental Friendly Vehicle and Charging Infrastructure	2019	3 million in 2030

2.2.2. Model Parameters for System Dynamics Analysis

Variables used as parameters for the system dynamics model were estimated using data from 2013 to 2018. The regression equation was estimated using multiple regression analysis with all variables except subsidy variables as the independent variables and new EVs as the dependent variable. Subsidy variables including the national subsidy, and regional subsidies, were split further to incorporate regional characteristics. The number of newly registered EVs was also set as a dependent variable to perform multiple regression analysis. Actual data for all variables, except the national subsidy and regional subsidies, for which data for 2020 were provided, were applied to calculate the estimates for 2030 using data from 2019.

(1) Subsidy Variables

In the system dynamics model for the propagation of regional EVs, subsidies were divided into national and regional subsidies. This amount included the total budget set aside for subsidies for all EVs, rather than subsidies per vehicle. National subsidies from 2013 to 2020 were based on data provided by the Ministry of Environment. For regional subsidies, the budget specified in the revenue budget business statement was allocated to the general accounts of each local government's annual budget.

(2) Vehicle Variables

The vehicle variables used in the system dynamics model were passenger vehicles, and ICEV inflow, EV inflow, and scraped EV. First, the passenger vehicle variable was applied according to a study by the Korea Energy Economics Institute, which indicated that the total number of vehicles increased by 1.8% annually for all vehicles. The total number of vehicles in the present study refers to the total number of passenger gasoline, diesel, and electric vehicles, not all vehicles, with an annual increase of 1.8%. The total number of gasoline, diesel, and electric vehicles accounted for approximately 90% of all vehicles. Therefore, the same annual increase rate was applied to estimate the total number of passenger gasoline, diesel, and electric vehicles in 2030 (MOLIT, 2019).

The ICEV inflow and ICEV are subject to change as the EV inflow changes, and the value for ICEV inflow and ICEV excludes the number of EV inflow. Scrapped EVs, categorized as EV inflow, were converted using a vehicle lifespan of 150,000 kilometers and annual mileage (Hawkins et al., 2013). Based on the 11-year life span of EVs, the scrapping rate of EVs was set at 9.7% (Lee and Ha, 2015). Consequently, 9.7% of newly registered vehicles in 2013 will be scrapped by 2024, and all current EVs will be scrapped by 2025, based on the scrapping rate after excluding the number of cars scrapped in 2024.

(3) Fuel Price Variable

The fuel price data used in this study were the annual data of gasoline and diesel prices. The 2013 to 2018 data for average gasoline and diesel price data for each region were obtained from the Opinet of Korea National Oil Corporation. The applied fuel prices were the average retail prices of gasoline and diesel. The gasoline price refers to the price of regular unleaded gas and the diesel price refers to the price of diesel fuel for vehicles. The estimated fuel prices of gasoline and diesel from 2020 to 2030 were acquired from the Energy Information Administration. The estimated prices were used as crude oil prices.

(4) Charging Infrastructure Variable

The short driving range and insufficient number of charging stations compared to the infrastructure for internal combustion vehicles has been cited as the primary reasons consumers are reluctant to purchase EVs (ME, 2017). The short driving range is a problem that can be resolved through technological development. However, as the government encourages increased propagation of EVs and increased production, an insufficient number of charging facilities will limit the ability to charge EVs. The lack of adequate charging facilities for EVs is a huge concern for consumers, and the number of charging facilities has been a significant factor in the propagation of EVs. In the system dynamics model of this study, charging facilities designated as level 3 DC, which are fast chargers, were used in this study. Information on these chargers is presented in the current status of the propagation report of EVs and construction of the charging infrastructure provided by the Ministry of Environment. Data from 2013 to 2018 were used to estimate the regression equation for modeling.

(5) Electricity Price Variable

The electricity price is a factor that significantly affects the low maintenance costs of EVs. A decrease in the cost of electric charging for EVs could lead to an increase in the use of EVs, which is applied as a parameter for system dynamics modeling.

The electricity prices from 2013 to 2018 were obtained from the Korea Electric Power Corporation. The government's special discounts for electricity to charge EVs, which is essential for the operation of EVs, is a factor that significantly affects maintenance costs especially when maintained at a lower price compared to gasoline and diesel. Although charging rates vary depending on the season and time, the rates generally ranged from 170 to 180 KRW per kWh. However, the preferential benefit with discounts on charging rates for EVs ends in June 2020 and will be gradually raised starting in July. If the charging rate increases, it is anticipated that the charging rate per kWh will increase by at least 40 percent compared to the previous increase.

Table 6. Model Parameters and Sources

Categories	Variables	Description	Source
Vehicle	ICEV	Total number of internal combustion vehicles	MOLIT(2019a)
	Passenger Vehicle	Total umber of passenger vehicles of gasoline powered, diesel powered and electricity powered.	
	Scrapping EV	Number of vehicles scrapped	Lee and Ha(2015) MOLIE(2019a)
Fuel Price	Electricity Price	Annual average of electricity price	KEPCO (2019)
	Diesel	Annual average diesel price	Opinet(2019)
	Gasoline Price	Annual average gasoline price	
Charging Facility	Charging Infrastructure	Number of charging infrastructure	ME(2019)
Subsidy	National Subsidy	National subsidies for each year	ME(2013); ME(2013) ME(2013); ME(2013) ME(2013); ME(2013)
	Regional Subsidy	Regional subsidies of 16 regions	Website of each provinces and cities

2.3. System Dynamics

2.3.1. Introduction to System Dynamics

System Dynamics is a systematic analysis method introduced by Forrester and other industrial engineers in 1961. This simulation method is used for analyzing and solving complex problems faced by society through focusing on policy analysis and design (Forrester, 1961). System Dynamics is a dynamic way to define a system with the components which are either directly or indirectly related to an expected problem, and to then discover the causality and feedback loops between the different variables. Then, it analyzes the various system characteristics and behaviors through running simulations against a set timeline. Thus, system dynamics can predict how dynamic the target variable will be over a set period of time (Meadows, 1980).

In this study, Stella Architect, a system modeling simulation software, was used in order to analyze the spread of electric vehicles. Stella is a system dynamics simulation program developed by isee systems that makes the data easy to modify and regenerate (Kim et al., 2012). It enables the visual development of models through programs to help analyze and predict complex changes in specific criteria, meaning that it is a useful tool for informing scientific decision-making (Lee et al, 2007; Kim et al., 2012).

2.3.2. Characteristics of System Dynamics

System dynamics is a systematic analysis method introduced by Forrester and other industrial engineers in 1961. This simulation method is used to analyze and solve complex societal problems by focusing on policy analysis and design (Forrester, 1961). System dynamics is a dynamic method to define a system with components that are either directly or indirectly related to an expected problem, and to then discover the causality and feedback loops between the different variables. It is then used to analyze various system characteristics and behaviors by running simulations against a set timeline. Thus, system dynamics can predict how dynamic the target variable will be over a set period of time (Meadows, 1980).

In this study, Stella Architect (Stella, hereafter), system modeling simulation software, was used to analyze the spread of EVs. Stella is a system dynamics simulation program developed by ISEE systems. It makes the data easy to modify and regenerate (Kim et al., 2012) and enables the visual development of models through programs to help analyze and predict complex changes in specific criteria. Thus, it is a useful tool to inform scientific decision-making (Lee et al, 2007; Kim et al., 2012).

2.3.2. Characteristics of System Dynamics

The characteristics of system dynamics are as follows. First, system dynamics focuses on changes in system configuration over time, by observing a system's processes of change, evolution, and decline (Kim et al., 2001). Numerous studies have used system dynamics to understand the complexities of systems by revealing relationships between various stakeholders and identifying solutions (Sterman, 2000; Cho and Gillepie, 2006).

System dynamics considers the underlying causes of behavior changes in the feedback structure. Therefore, it is important to clearly understand the structure (Forrester, 1969; Kim et al., 2001; Meadows, 2008). Feedback is a cyclical structure in which the causal relationship of a variable is not a one-way process. Identifying the linear effect relations of the independent variables affecting the system has limitations in analyzing the changes in the behavior of the system. Moreover, suggestions for making new policies can be more efficiently presented by discovering the feedback structure.

Comparing the characteristics of system dynamics with statistical methodologies makes the difference more apparent (Figure 10). A statistical method is a typical example of laundry-list thinking (or event-oriented thinking). A thinking system of statistical methods arranges the factors related to a problem and then defines the relative importance of the factors (Richmond, 1993). Laundry-list thinking assumes that causal relation between the dependent and independent variables flows in a single direction. Since each independent variable assumes that it is independent of the other, only the direction of the influence of the independent variable on the dependent variable is more important than the influence mechanism operating between the variables (Meadows, 1991). For these reasons, statistical methods are difficult to apply to an issue with interconnected or interdependent realities (Kim et al., 2001). Therefore, the problems should be viewed using system dynamics, which can be dynamically analyzed through systems thinking.

A statistical method is inferred based on existing empirical data, whereas system dynamics is deduced through the causal relations between variables. System dynamics is used to analyze dynamic behavior, but the statistical method analyzes static behavior. The focus of the statistical method is the correlation between two variables, but for system dynamics, it is a circular relation between variables. System dynamics can forecast a long-term policy, but the statistical method in policy forecasting is short-term. The difference between system dynamics and the statistical method is shown in Table 7.

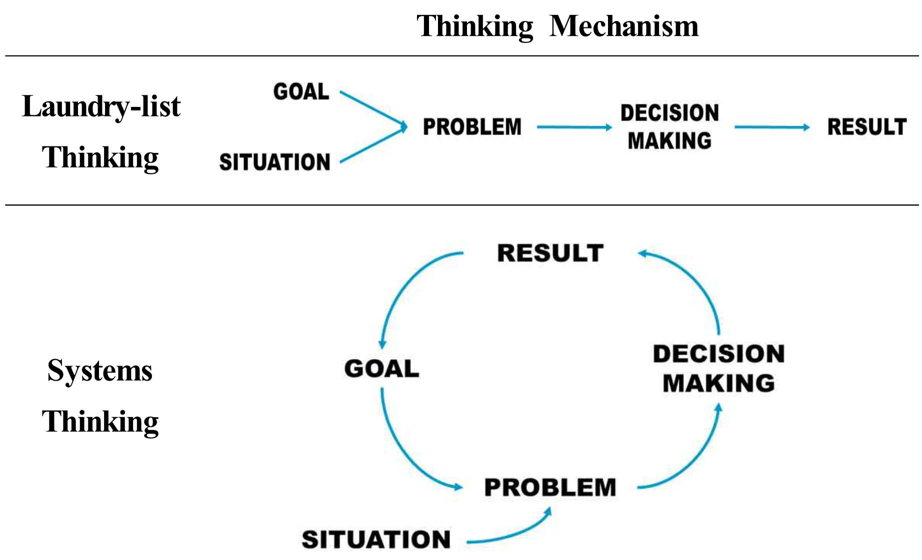


Figure 10. Thinking Mechanism of Laundry-list and Systems Thinking

To analyze the system's behavior, system dynamics considers not only the concept of time but also the boundaries of the constraints system such as the time delay between causality and resource capacity (Kim, 1999; Sterman, 2000; Kim, 2004; Cho and Gillespie, 2006). A time delay can cause a problem in the system by misleading the observer in terms of what happens when something does not actually happen. In addition, constraints are the reason the system cannot continue to move in the desired direction, and the existence of other systems divided by their boundaries is the leading cause for generating unintended consequences.

Table 7. Comparison of System Dynamics and Statistical Perspective

	System Dynamics	Statistical Perspective
Interference method	Causal relationship between variables	Existing empirical data
Analysis object	Dynamic behavior	Static behavior
Perspective of Analysis	Circular relationship among variables	Correlation between two variables
Goal of analysis	Structural accuracy	Numerical accuracy
Policy prediction	Long-term prediction	Short-term prediction
Policy application	Easy to apply policy	Difficult to apply Policy

2.3.3. Steps of Modeling System Dynamics

The modeling process uses the system dynamics approach which begins with the identification of the type of problem to be solved and determines the boundaries of the system. The model conceptualization step is to examine the correlations between the various causes of the identified problem and to determine the level of aggregation of the modeling variables to create a causal loop diagram. A model is constructed based on the conceptualized causal loop diagram and the behavior of the model is analyzed using a simulation of the model. The validity of the model is evaluated around the actions of the major variables shown in the prepared model (Barlas, 2002). Once the validity of the model is established, it is possible to simulate the virtual behavior of the system through appropriate scenarios to identify the dynamic changes in the variables depending on the conditions of the system. The flowchart of the modeling process using system dynamics is shown in Figure 11.

Figure 11. Flowchart of System Dynamics

2.4. Policy Scenarios for EV Propagation

The national subsidy and the regional subsidies as a policy factor, have a huge impact on the growing interest in EVs and must be considered when analyzing EV propagation. According to a research report from the Ministry of Environment, 76% of actual and potential buyers of EVs responded that they would give priority to an EV subsidy policy (ME, 2017). Since policies on national and regional subsidies can be adjusted, this study attempted to review the changes in the propagation of EVs as a result of adjustments in the subsidy policy. In Korea, national and regional subsidies are provided separately, so it is necessary to consider subsidies for each region. This study analyzed changes in the spread of EVs by applying four policies based on the local governments' budget related to EV purchasing subsidies. The four policy scenarios are as follows:

(1) Subsidy Cliff scenario

(2) Phase-out Subsidy scenario

(3) Phase-in 50% Subsidy scenario

(4) Phase-in 350% Subsidy scenario

The Subsidy Cliff scenario currently enforced in Korea refers to the steep drop off of EV purchasing subsidies. According to this policy, there will be no subsidy for EVs after 2023. The subsidy for 2020 will be maintained only until 2022.

The Phase-out Subsidy scenario is one in which subsidies for EVs are gradually reduced until 2030. The actual budgets of national and regional subsidies were applied until 2020. The subsidies from 2021 to 2030 will be further reduced by 10% year-to-year. In other words, the budget of EV subsidies in 2021 will be reduced by 10% year-to-year, and the subsidy budget for 2025 will be cut by 50% year-to-year. By 2030, there will be no subsidy for EVs.

The Phase-in Subsidy scenario considers a gradual increase in subsidies by 2030, unlike the Subsidy Cliff scenario and the Phase-out scenario, which is similar to the German EV policy. The Phase-in Subsidy scenario consists of a 50% increase and a 350% increase by 2030. Based on the actual subsidy in 2020, the subsidy budget is set to increase by 5% every year until it is 50% by 2030. For the Phase-in 350% Subsidy scenario, the subsidy is set to increase by 35% every year until it is 350% by 2030.

3. Life Cycle Assessment of EV Propagation

3.1. National Plan for Electricity Supply and Demand in Korea

The National Basic Plan for Electric Supply and Demand (BPE) is set for the next 15 years. The plan is established pursuant to Article 25 of the Electricity Utility Act and Article 15 of the Electricity Utility Decree biennially for the mid- to long-term forecast of electric power demand and the corresponding installation of facilities for electricity generation. Since the first BPE was established in 2002, eight basic plans for long-term electricity supply and demand have been released. These plans reflect stable power supply and economic efficiency.

The latest plan, the 8th Basic Plan for Long-term Electricity Supply and Demand (8th Plan) covers 2017-2031. Under the national policy, the environment and public safety are considered based on the amended Electricity Utility Act. Moreover, consideration of the effects on the environment and public safety as well as the economy in operating the electricity market and system are mandated.

To reduce environmental impacts such as particulate matter and greenhouse gas emissions from power plants, the 8th BPE suggests and emphasizes the Energy Transition Roadmap. This Roadmap includes phasing out the use of nuclear energy and increasing the share of renewable energy to 20% of generation output by 2030 under the basic energy policy of the Korean government (MOTIE, 2017). With emerging social issues related to high density of fine dust, the national movement to phase out coal power plants has gathered momentum. In addition, the government has suggested a comprehensive anti-fine dust measure that includes reducing emissions by 30% (MOTIE, 2017). The government also aims to increase the share of LNG and renewable energy in the generation mix to 39% while lowering that of coal by 2030 (MOTIE, 2017).

3.2. Life Cycle Assessment

3.2.1. Life Cycle Assessment Introduction

Life cycle assessment (LCA) quantifies all inputs and outputs, measures their potential environmental impact, and compares the environmental impact over the entire lifetime of specific products and or services. According to the International Organization for Standardization (ISO) 14040, the definition of LCA is as follows.

> Life cycle assessment is a technique for assessing the environmental aspects and potential impacts associated with a product, by
>
> - compiling an inventory of relevant inputs and outputs of a product system,
> - evaluating the potential environmental impacts associated with those inputs and outputs,
> - interpreting the results of the inventory analysis and impact assessment phases in relation to the objectives of the study.
>
> LCA addresses the environmental aspects and potential environmental impacts (e.g. use of resources and the environmental consequences of releases) throughout a

product's life cycle from raw material acquisition through production, use, end-of-life treatment, recycling, and final disposal (i.e. cradle-to-grave).

According to the ISO 14040, LCA includes four stages (Figure 12): goal and scope definition, inventory analysis, impact assessment, and interpretation.

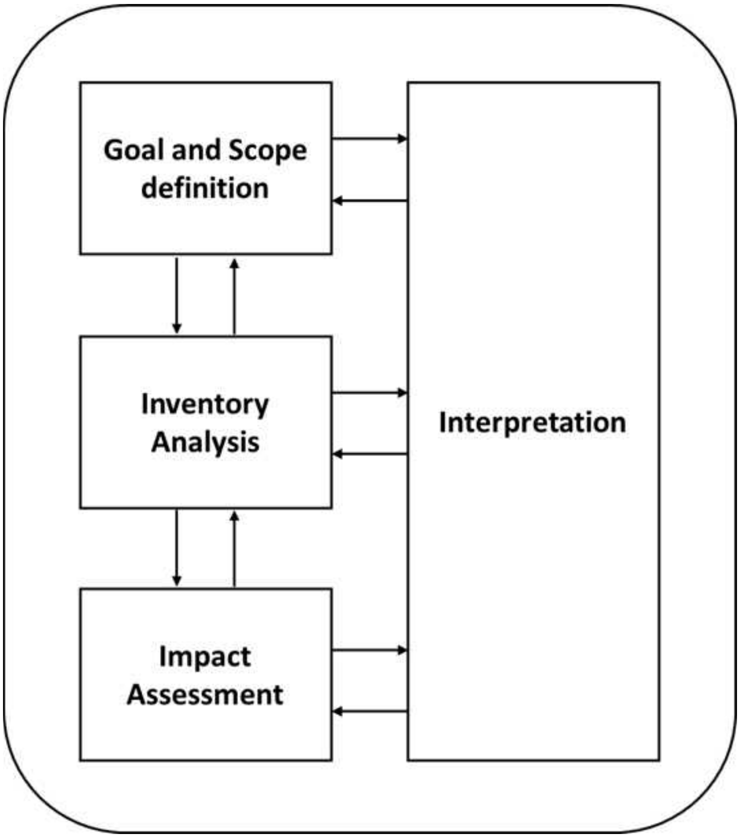


Figure 12. Stages of Life Cycle Assessment

3.2.2. Goal and Scope Definition

LCA starts with setting the goal and scope of the study. At this stage, the background of the study should be presented. Specifically, a functional unit, the scope of analysis, and the allocation method are determined. The functional unit is quantified and expressed specifically to determine what to analyze. In particular, setting up the functional unit is important when comparing different products or services that can be replaced. It also defines the amount and level of functions to be evaluated and then calculates the products or services needed. The functional unit of this study is one kilometer. Setting up the system boundary is the process of determining what the process should include in the boundary. This study was set well-to-wheel, or the use phase, as the system boundary from various stages for generating 1kWh of electricity (Figure 13). Fuel economy (km per kWh) and the average annual mileage of EVs were applied to calculate the environmental impact of each EV. The fuel economy of an EV used to calculate the amount of emissions when the EV travels 1km was calculated and applied based on the average fuel economy from 2013 to 2018 for the EV model released each year. The annual mileage was applied using the Korea Transportation Safety Authority's annual average daily mileage statistics. When evaluating the LCA, the power mix was applied with the rate capacity of the 8th National Plan for Electricity Supply and Demand.

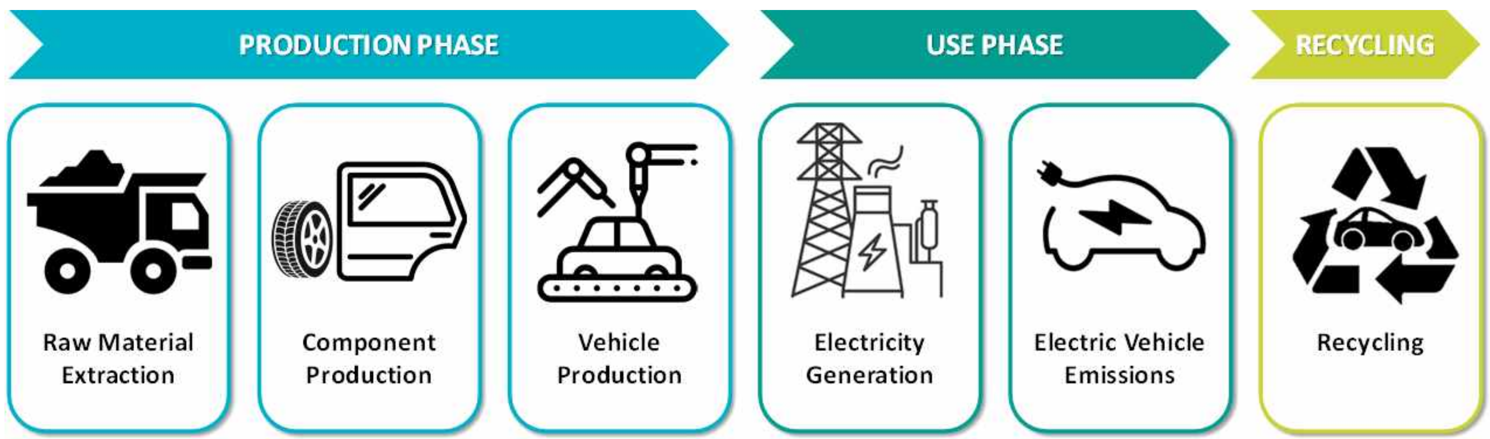


Figure 13. Life Cycle of EV from Production to Recycling

3.2.3. Life Cycle Inventory Analysis

Life cycle inventory analysis (LCIA) is the stage in which the inventory is made in the manufacturing phase of the material. The inventory analysis includes collecting and compiling data in the Life Cycle Inventory (LCI). This process is iterative because the data collection and calculation procedures can identify new data requirements or limits. The value of the inputs and the outputs should be applied in accordance with the functional unit determined in the goal and scope definition stage. This study used electricity data from the national LCI Database provided by the Institute of Environmental Industry and Technology.

3.2.4. Life Cycle Impact Analysis

The third stage of the LCIA is to evaluate the possible impact to the environment based on the results of the LCI analysis. The LCIA should include a characterization process in which the impact category is selected and the classified outputs are converted into one unit. Normalization and weighting can then be selected. Normalization establishes the relative importance of the index results of the impact category. Weighting determines the importance of the impact category considering the social importance. It is possible to derive an environmental index for the product or service by adding values obtained by multiplying the normalization results from each impact category based on the weighting factor of the categories. In other words, the results of the environmental impact are compared with the environmental impact of the part the researcher is interested in at the normalization step. Weighting values are also given to different environmental impact indexes at the weighting stage, and the weighted values are added together to derive one numerical value. This study used TOTAL (a tool for type III labelling and LCA) software developed by the Korea Institute of Environmental Industry. Among the life cycle impact categories, this study selected and compared global warming potential (GWP) and particulate matter potential (PM), which have the most impact on the production of electricity. Commonly used LCI categories are presented in Table 8.

Table 8. Life Cycle Impact Categories

Category		Unit
ADP	Abiotic Depletion Potential	1/yr
AP	Acidification Potential	kg SO2-eq
EP	Eutrophication Potential	kg PO43- -eq
FAETP	Freshwater Aquatic Ecotoxiticy Potential	kg 1,4 DCB-eq.
GWP	Global Warming Potential	kg CO2-eq.
HTP	Human Toxicity Potential	kg 1,4 DCB-eq.
MAETP	Marine Aquatic Ecotoxicity Potential	kg 1,4 DCB-eq.
ODP	Ozone Depletion Potential	kg CFC11-eq.
POCP	Photochemical Oxidants Creation Potential	kg ethylene-eq.
TETP	Terrestrial Ecotoxicity Potential	kg 1,4 DCB-eq.
PM	Particulate Matters Potential	kg PM2.5-eq.

3.3. Policy Scenarios and Environmental Options for EV Propagation

The change in the environmental impact of EV propagation was analyzed based on a combination of the subsidy policy scenarios and environmental options. The policy scenarios and environmental options comprised four scenarios and two options, respectively. This study analyzed whether the propagation of EVs through a total of eight combinations would improve or worsen the environmental impact (Figure 14).

Environmental options include the 8th Plan and Energy Transition. The 8th Plan option includes measures recommended by the 8th Basic Plan established in 2017 for electricity supply and demand, as well as the government's policy direction to reduce coal-fired power generation further and switch to renewable energy sources (Figure 15). The options for a transition to new renewable energy sources were established based on the 8th Plan, which focuses on reducing the portion of nuclear power generation and coal-fired power generation and aims to establish new sources of renewable energy.

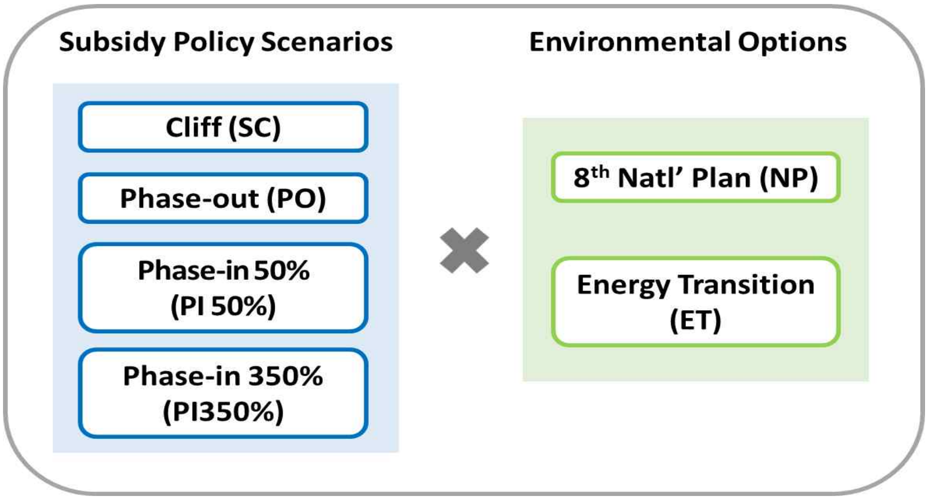


Figure 14. Collaboration of Policy Scenarios and Environmental Options for Environmental Implications of EV Propagation

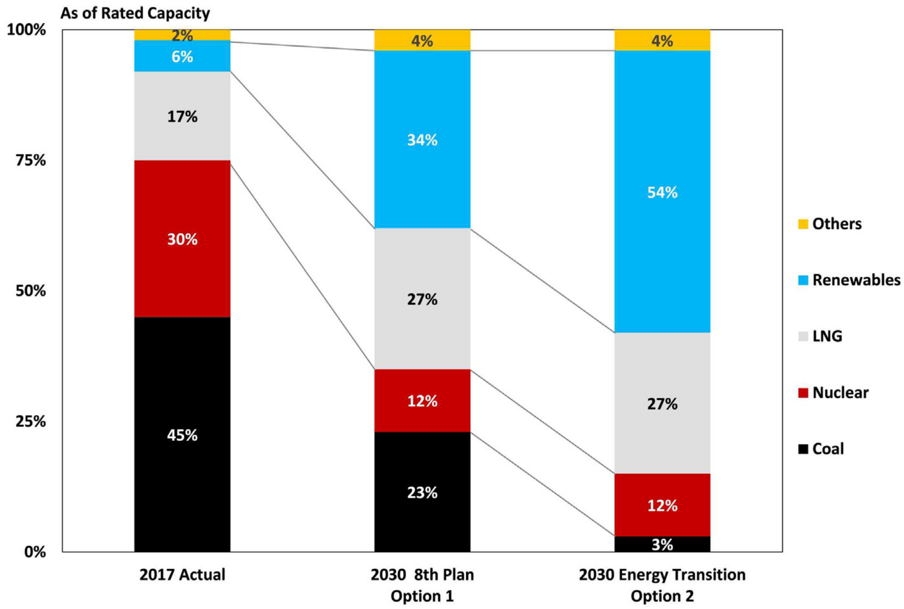


Figure 15. Share in Total Power Generation Mix of 2017 Actual, 8th Plan and Energy Transition Options

IV. Results and Discussions

1. Key Drivers of Electric Vehicle propagation

1.1. Descriptive Statistics of Factors

Table 9 shows the regional average and variance of newly registered EVs in 17 regions in the six-year period from 2013 to 2018. The region with the highest average number of newly registered EVs was Jeju Island. Jeju, the leading city for EVs, started the nation's first public supply project for EVs. There was a big difference between Jeju and Seoul, which had the second highest average. The lowest number of newly registered EVs in Korea was Sejong Special Self-Governing City where the number of newly registered EVs was only 25 from 2013 to 2016. However, the propagation of EVs was promoted through regional subsidies that have been provided since 2017.

The results of the descriptive statistics for each of the independent variables are shown in Table 10. Among the vehicle factors, the maximum newly registered diesel and gasoline vehicles was 14.84 thousand and 11.10 thousand, respectively, indicating that the maximum number of new diesel vehicles was

1.34 times more than that of new gasoline vehicles. According to MOLIT (2020), the number of newly registered passenger vehicles increased 2.6 times year-on-year. This increase was due to the release of several new models, active marketing by imported car manufacturers, and stable oil prices in 2015. The difference between the beginning of the year and the end of the year was substantial. The difference between the minimum and maximum value was also considered by applying the balance and remaining support.

The variables related to temperature including the monthly average temperature, the monthly minimum temperature, and the monthly maximum temperature differed from the annual temperature data. The monthly maximum temperature varied depending on the temperature difference in each season. The amount of precipitation also showed a substantial difference between the minimum and maximum values of the factor due to variation in precipitation during dry spells without rain and rainy seasons in June and July when heavy rain falls.

Table 9. Conditional Mean and Variance of Newly Registered EV

Region	Mean	Variance
Seoul	129.96	40,025.48
Busan	20.64	1,058.60
Daegu	91.60	28,742.30
Incheon	17.83	811.83
Gwangju	20.03	1,077.91
Daejeon	18.33	1,526.34
Ulsan	11.64	472.12
Sejong	5.42	291.15
Gyeonggi	86.71	19,754.86
Gangwon	18.83	1,106.14
Chungbuk	16.49	2,922.14
Chungnam	15.11	805.85
Jeonbuk	13.74	669.75
Jeonnam	26.17	1,210.73
Gyeongbuk	27.00	1,842.65
Gyeongnam	27.88	1,697.07
Jeju	212.07	62,780.43
Observations	72	

Table 10. Descriptive Statistics of Variables

Categories	Variables	Unit	Minimum	Maximum	Average
-	EV	cars	0	1,091	44.72
Vehicle	DIESEL CAR	thousand cars	0	14.84	2.05
	GASOLINE CAR	thousand cars	0	11.10	1.19
	TOTAL CAR	thousand cars	0	24.84	3.36
	DIESEL PRICE	won/L	1,079.62	1,869.29	1,423.11
	GASOLINE PRICE	won/L	1,327.02	2,067.42	1,624.66
Policy	NATL' SUBSIDY	Billion won	0	748.76	29.26
	REG. SUBSIDY	cars	0	6723.00	264.83
	TAX EXEMPTION	million won/ea	2.60	3.90	2.82
Demographic	POPULATION DENSITY	population/ha	0.91	168.54	21.72
	CAR PER CAPITA	cars/person	0.24	0.68	0.35
Climate	AVERAGE TEMP.	℃	-4.7	29.00	13.50
	MINIMUM TEMP.	℃	-20.50	23.20	2.91
	MAXIMUM TEMP.	℃	7.2	39.60	25.16
	PRECIPITATION	mm	0	676.20	98.90
Environment	PM10 CONCENTRATION	$\mu g/m^3$	19	88	44.36

1.2. Identification of Stationarity of Factors

The Augmented Dickey Fuller (ADF) test (Table 11) showed that all 15 variables had stationarity for the five categories (i.e., vehicle related, policy, demographical, climate, environment) applied to the analysis. The null hypothesis that a unit root exists in the panel data at a significant level of 0.01 was rejected, and the alternative hypothesis that the variable has stationarity was confirmed.

Table 11. Stationarity for variables using Augmented Dickey Fuller Test

Categories	Variables	ADF Statistic
	NEW EV	-232.79 ***
Vehicle	DIESEL CAR	-365.82 ***
	GASOLINE CAR	-351.78 ***
	TOTAL CAR	-367.92 ***
	PRICE OF DIESEL	-29.73 ***
	PRICE OF GASOLINE	-32.06 ***
Policy	NATIONAL SUBSIDY	-256.94 ***
	REGIONAL SUBSIDY	-231.07 ***
	TAX EXEMPTION	-17.532 ***
Demographic	POPULATION DENSITY	-272.30 ***
	CAR PER CAPITA	-304.14 ***
Climate	AVERAGE TEMP.	-46.12 ***
	MINIMUM TEMP.	-58.90 ***
	MAXIMUM TEMP.	-59.23 ***
	PRECIPITATION	-149.10 ***
Environment	PM10 CONCENTRATION	-120.00 ***

***p<0.01

1.3. Result of Goodness of Fit Test

To analyze the panel data factors more effectively, an analysis was conducted through the Hausman test to determine the suitability of the panel fixed effect model and the panel random effect model to the panel data. The random effect model leads to more efficient estimates, but these estimates may be biased if stronger assumptions associated with the random effect model does not hold. Thus, there is a trade-off between the bias and efficiency of the fixed effect model and random effect model (Dougherty, 2007). The Hausman test revealed that χ^2 rejected the null hypothesis of "no correlation between individual effects and variables" at a 1% significance level with 1611.30 and $p<2.2e-16$ (Lee and Kim, 2013). Therefore, the panel fixed effect model was identified as the most appropriate model for analyzing the factors affecting the propagation of the EVs. Both the fixed effect model and random effect model were reported to fully explore the regional panel data.

1.4. Panel Fixed Effect of EV Propagation

The Breush-Pahan Lagrange Multiplier Test (LM test) was performed to verify the validity of the results of the panel analysis by applying the six-year panel data in the analyzed model between the number of newly registered EVs and the factors considering regional characteristics. The F-statistics results showed that the differences were statistically significant at the 0.05 level, indicating that panel analysis was superior to integrated analysis of the cross-section data using the LM test. In addition, the results of the F-test for verification of POLS and fixed effects revealed that the significance level of the F-test was within 5% and the fixed effect model considering that the object characteristics of the panel was appropriate in the model.

The present model is a statistically significant model with approximately 48% explanatory power (Table 12). Among the 15 variables that were used to conduct the stationarity test, we selected that following variables that influenced the increase of EV purchases: number of newly registered diesel vehicles, number of gasoline vehicles, total number of newly registered vehicles, national subsidies, regional subsidies, population density, number of vehicles owned per capita, monthly average temperature, monthly minimum temperature, and PM10 concentration.

The present model used newly registered EVs as the dependent variable. Among the statistically significant factors, the following positively influenced the propagation of EVs: total number of newly registered vehicles, regional subsidies, number of vehicles owned per capita, and monthly minimum temperature. In contrast, the number of newly registered diesel vehicles, the number of gasoline vehicles, national subsidies, population density, monthly average temperature, and PM10 concentration negatively influenced the increase of EVs. Factors influencing this increase can be classified into policy-controllable or adjustable factors, such as subsidies, and uncontrollable factors such as temperature and population density across regions. Among them, the national subsidy balance and the number of regional subsidies reserved had contrasting effects on the spread of EVs. In addition, an increase in the number of EVs decreased the balance of the national subsidy, and a 10 billion KRW increase in the national subsidy would result in a 0.61 decrease in the number of newly registered EVs. By contrast, the number of EVs remaining that could be subsidized by local governments was correlated with the number of newly registered EVs. Furthermore, when the number of remaining EVs that could be subsidized increased, the reserved regional subsidies increased by 0.05. The trends were assessed to be caused by differences between national and regional methods of subsidizing. For government-funded subsidies, the Ministry of Environment provides subsidies based on the type of EV subject to spread under the Subsidy Management Act. However, regional subsidies are judged to have had conflicting effects as local governments maintained the fairness of subsidies by paying the same amount to electric passenger vehicles in accordance with Article 10 of the "Environment-Friendly Automobile Act."

In terms of the environmental effects, the number of newly registered EVs negatively influenced PM10 concentration. Unlike internal combustion engine vehicles, EVs are zero emissions vehicles (ZEV) since they emit no particulate matter directly associated with health. Increased consumer awareness of this factor has led to more eco-friendly consumption (Kang, 2015; Kim, 2009).

The monthly average and minimum temperatures are climate factors that affect the adoption of EVs; however, these variables cannot be adjusted. The number of newly registered EVs is projected to decrease by 4.27 when the monthly average temperature increases by 1 degree Celsius. In addition, a rise in the monthly minimum temperature by 1 degree Celsius would result in an increase in the number of newly registered EVs by 2.60 units given that EV batteries are vulnerable to low temperatures and thus have a shorter driving range in low temperatures (Yuksel and Michalek, 2015; Taggart, 2017).

The number of registered diesel vehicles and total registered vehicles exhibited negative and positive relationships, respectively, with the number of newly registered EVs. When the number of newly registered diesel vehicles decreased by 1,000, the number of newly registered EVs increased by 46.59. Newly registered gasoline vehicles also exhibited a negative relationship with EVs, showing that when 1,000 new gasoline vehicles were registered, EVs increased by 46.80. However, when the total number of passenger vehicles increased by 1,000, the number of EVs increased by 46.54. This increase in the number of newly registered EVs is directly correlated with the increase in the total number of passenger vehicles. In addition, the increase in the number of newly registered EVs following a rise in the price of diesel fuel is thought to be due to the tendency of many automobile consumers to prefer highly efficient cars such as EVs to reduce the burden of fuel costs (Choi et al., 2012).

Table 13 shows the results of applying the panel fixed-effects by region, including the constants of each city and province reflecting the characteristics of the region. Most metropolitan cities, including Seoul, had a positive constant. However, Ulsan and Sejong Special Self-Governing City had negative constants.

According to Sierzchula et al. (2014), the adoption of EVs is relatively high in regions where EV manufacturing headquarters and factories are located; however, the adoption of EVs in Ulsan was not enhanced despite the presence of EV manufacturing a plant and EV parts factory in the city. Most of the constants in metropolitan cities were positive values. Conversely, all nine provinces had negative constants.

Table 12. Factors Affecting Propagation of EVs

Categories	Variables	Fixed Effect	
		Estimated	t-value
	Intercept	-	-
Vehicle related	DIESEL CAR	-46.59	-8.01 ***
	GASOLINE CAR	-46.80	-5.83 ***
	TOTAL CAR	46.54	8.31 ***
	PRICE OF DIESEL	0.14	1.25
	PRICE OF GASOLINE	-0.04	-0.32
Policy	NATIONAL SUBSIDY	-0.61	-6.61 ***
	REGIONAL SUBSIDY	0.05	5.52 ***
	TAX EXEMPTION	0.04	0.57
Demographic	POPULATION DENSITY	-34.71	-9.44 ***
	CAR PER CAPITA	1924.90	16.92 ***
Climate	AVERAGE TEMP.	-4.27	-2.03 *
	MINIMUM TEMP.	2.60	2.06 *
	MAXIMUM TEMP.	1.67	1.33
	PRECIPITATION	-0.04	-1.37
Environment	PM_{10} CONCENTRATION	-0.54	-2.34 *

N	1,224
R^2	0.50
Adj. R^2	0.48
Hausman Test(χ^2)	1611.3

1) *p<0.1, **p<0.05, ***p<0.01
2) R^2 within is the coefficient of determination after eliminating effectiveness between groups, which is a concept in within group.

Table 13. Estimated Intercepts of Region Fixed Effects Model

Region	Intercept
Seoul	5989.80
Busan	1101.78
Daegu	342.31
Incheon	181.60
Gwangju	365.50
Daejeon	307.89
Ulsan	-425.81
Sejong	-677.95
Gyeonggi	-252.02
Gangwon	-744.98
Chungbuk	-724.23
Chungnam	-715.37
Jeonbuk	-689.15
Jeonnam	-715.76
Gyeongbuk	-750.10
Gyeongnam	-700.23
Jeju	-828.85

1.5. Panel Random Effect of EV propagation

This model, estimated using panel random effects, has been identified as a model with 50% explanatory power. The results showed the estimated number of newly registered diesel vehicles, the total cars, diesel prices, gasoline prices, national subsidies, regional subsidies, tax exemption, population density, cars per capita, and concentration of PM10.

The number of newly registered diesel and gasoline vehicles had a positive effect on the number of newly registered EVs. The total number of passenger vehicles showed to have a positive effect on the number of newly registered EVs. In other words, as the number of newly registered EVs increased, the number of new diesel vehicles decreased, but the total number of newly registered vehicles also increased. The number of diesel vehicles and the total number of vehicles were significant factors in both the fixed effect model and the random effect model. A decrease of 1,000 newly registered diesel and gasoline vehicles resulted in an increase of 43.75 and 56.37, respectively.

In the random effect model, all three factors (i.e., policy factor national subsidies, regional subsidies and tax exemptions), which are adjustable variables, were statistically significant, unlike the fixed effect model. For national subsidies, the propagation of EVs was negatively affected, but regional subsidies and tax exemption had positive effects. The number of new EVs increased as the balance of the national subsidy budget decreased, while the number of newly registered EVs increased by nine as the number of remaining units of regional subsidies increased by 100. In other words, if the tax exemption per EV increases by 100 million KRW, the number of newly registered EVs will increase by 30. In addition, tax exemptions will have a greater impact on the spread of EVs than subsidies from local governments.

The population density and number of vehicles per capita that constitute the factors of the demographic category were statistically significant factors in the random effect model. Unlike a previous study (Sierzchula et al, 2014) where the number of vehicles per capita did not affect the propagation of EVs, our results indicated that both the fixed effect model and the random effect model in this study affected the distribution of EVs. When the number of vehicles per capita increased by one, the number of newly registered EVs increased by about 864 units, and among the factors considered, this variable had the greatest impact on the propagation of EVs. The factors of climate categories were also found to affect the propagation of EVs such as monthly average temperature and the monthly minimum temperature in the panel fixed effect model. However, the panel random effect model verified that all climate factors had an impact on the spread of EVs.

For environmental factors, the concentration of PM10, was found to be statistically significant at the 1% significance level and had a negative impact on the number of new EVs used. This finding shows that environmental factors are related to the activation of the propagation of EVs and the number of newly registered EVs increased when the concentration of PM10 was lower. Considering the fact that particulate matter is increasing in Korea, if the concentration of PM10 is reduced due to an increase in the propagation of EVs, it can further stimulate consumers' desire for eco-friendly consumption by buying EVs.

Table 14. Factors Affecting Propagation of EVs

Categories	Variables	Random Effect	
		Estimated	z-value
	Intercept	-310.40	-5.45 ***
Vehicle related	DIESEL CAR	-43.75	-7.79 ***
	GASOLINE CAR	-56.37	-6.98 ***
	TOTAL CAR	51.90	8.89 ***
	PRICE OF DIESEL	0.54	3.42 **
	PRICE OF GASOLINE	-0.34	-2.79 **
Policy	NATIONAL SUBSIDY	-0.71	-7.33 ***
	REGIONAL SUBSIDY	0.09	8.75 ***
	TAX EXEMPTION	0.30	4.94 ***
Demographic	POPULATION DENSITY	1.15	13.77 ***
	CAR PER CAPITA	863.75	14.86 ***
Climate	AVERAGE TEMP.	-3.71	-1.63 ***
	MINIMUM TEMP.	1.41	1.05
	MAXIMUM TEMP.	2.58	1.95
	PRECIPITATION	-0.02	-0.65
Environment	PM_{10} CONCENTRATION	-0.97	-3.98 ***

N	1,224
R^2	0.51
Adj. R^2	0.50
Hausman Test(χ^2)	1611.3

1) $*p<0.1$, $**p<0.05$, $***p<0.01$

2) R^2 within is the coefficient of determination after eliminating effectiveness between groups, which is a concept in within group.

2. System Dynamics Modeling for EV Propagation

2.1. A Bull's Eye Diagram of EV Propagation Model

A bull's eye diagram is an efficient and effective way to describe the system dynamics model. It is important to create key drivers in the center of the bull's eye diagram. A bull's eye diagram includes both an endogenous and exogenous variable. Figure 16 shows the bull's eye diagram of the EV propagation model. An endogenous variable proceeds from or is derived from within and an exogenous variable originates from outside the system or is derived externally (Ford, 2010). The endogenous variables were passenger vehicles, ICEV, ICEV (Diesel+Gasoline) inflow and EV inflow. The exogenous variables included the national subsidy, regional subsidies, gasoline prices, diesel prices, electricity prices, scrapped EVs, and the charging infrastructure.

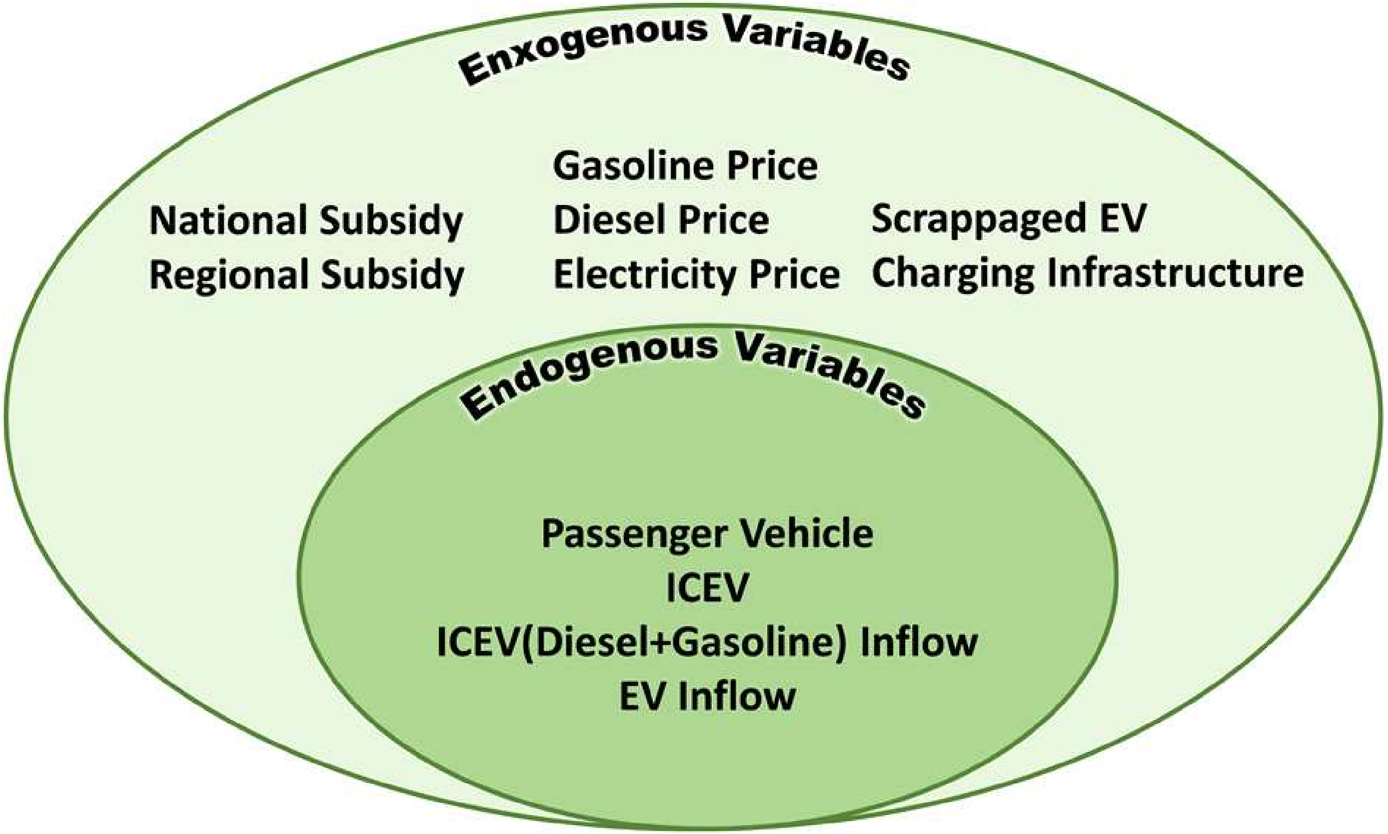


Figure 16. Bull's Eye Diagram of EV Propagation Model

2.2. Causal Loop Diagram of EV propagation

The system dynamics approach reflects a problem using a causal loop diagram along with a feedback loop (Qi et al., 2009). A causal loop diagram is a combination of a variety of cause-and-effect diagrams that provide a quick schematic view of the entire system. By using a causal loop diagram, the researcher can determine how many causal relationships are combined to constitute a single system (Kim et al, 2001; Kim, 2004). It also makes it possible to grasp the process through which complex system behavior is generated.

In general, a causal loop diagram includes three components (Hall et al, 1994). The direction of relations between variables is indicated by using arrows, and (+) and (-) or (s) or (o). The starting point (arrow tail) of the arrow refers to an affecting variable, and the end point (arrow head) indicates a variable that is affected. The (+) symbol on the arrow indicates that the two variables are in the same direction, and a (-) symbol indicates that the changing directions of the two variables are different. Finally, when multiple causal relationships form one single closed reflux, it is called a feedback loop (Weick, 1979).

Figure 17 is the causal loop diagram of the EV propagation system used in this study. The EV propagation diagram includes four factors: the national subsidy, regional subsidies, the charging infrastructure, and crude oil prices. The factors used in the diagram are controllable policy variables.

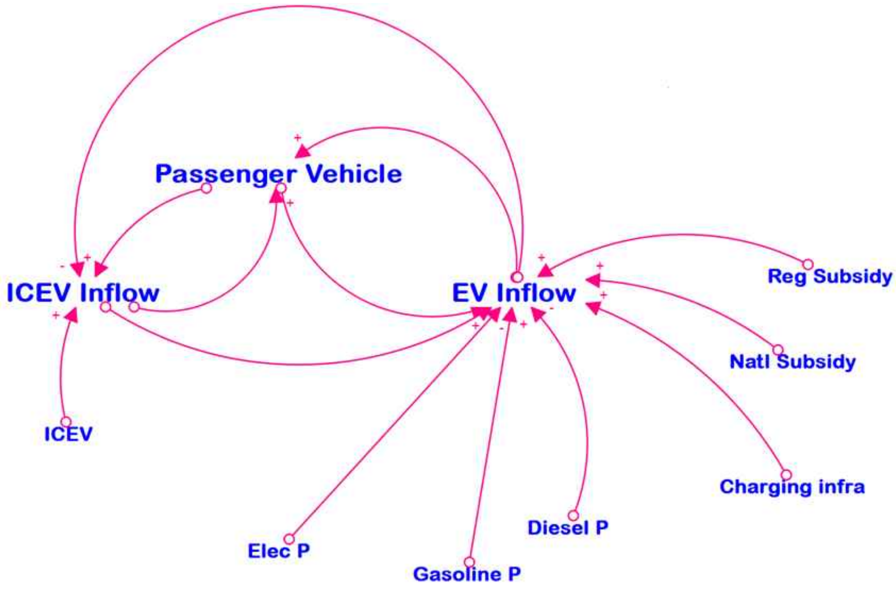


Figure 17. Causal Loop Diagram of EV Propagation

2.3. Stock and Flow Diagram of EV propagation

A stock-flow diagram is a model with a stock variable, flow variable, and auxiliary variable. These variables allow the system structure for dynamic analysis to be simulated in a program (Jung, 2012). It is designed to divide the variables used in the causal loop diagram into the stock variable, flow variable, and auxiliary variable to perform simulations to solve problems. The stock variable accumulates in the system, indicating the state of the system at a certain point in time, and the flow variable is a variable that flows through the system and reflects the activity of the system (Valchos et al, 2007).

In the regional propagation of the EV model, a passenger vehicle is a stock variable, and the ICEV flow and EV flow are flow variables. In addition, there is an auxiliary variable that helps calculate the stock and flow values as an indicator of an activity or condition. Auxiliary variables used in this model were a scrapped EVs, electricity prices, gasoline prices, diesel prices, ICEVs, charging infrastructure, national subsidy, and regional subsidies. To verify the results, this study used a model with a prototype of stock-flow diagram for EV propagation. The prototype of the stock-flow diagram for EV propagation is shown in Figure 18.

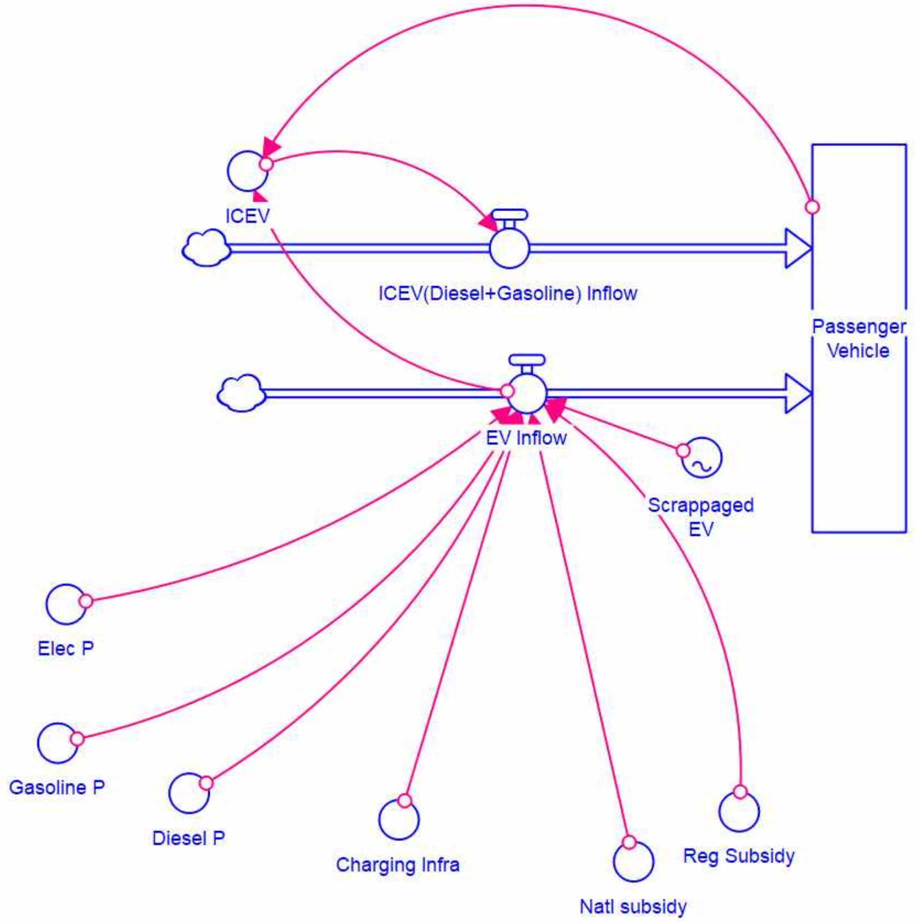


Figure 18. Prototype of Stock-flow Diagram for EV Propagation

To implement the regional propagation of EV model through system dynamics using Stella Architect, the correlation between each variable and the model variables must be modeled using reasonable formulas and values. Modeling logic for the model variables used in the regional propagation of EV model built for this study are shown in Table 15.

A passenger vehicle, which was a stock variable of the regional propagation of EV model, consisted of the sum of EV inflow and ICEV (diesel+gasoline) inflow. There were two flow variables in this model. The ICEV (diesel+gasoline) inflow variable includee values from ICEV, which was an auxiliary variable. The other variable, EV inflow, included electricity prices, gasoline prices, the charging infrastructure, diesel prices, national subsidy, regional subsidies, scrapped EV and the y-intercept of each region.

The modeling logic for all auxiliary variables except the national subsidy and regional subsidies was built using regression analysis using data for each variable from 2013 to 2018. The data on the charging infrastructure of each region included the number of level-3 DC fast chargers by region in 2019. These data were provided by the Ministry of Environment. Electricity prices were constructed with a regression coefficient analyzed and data applied from the lookup function of the system dynamics platform program. The data on electricity prices of each year were obtained from Korea Electric Power Corporation. The gasoline price variable and diesel price variable were also built with the regression coefficient analyzed the data applied based on the lookup function of Stella Architect. The price data for regression analysis was obtained from Opinet by Korea National Oil Corporation and the data for the lookup function was acquired from the Energy Information Administration (EIA). For the ICEV variable, the EV inflow was excluded from the number of newly registered passenger vehicles. The passenger vehicle variable was applied according to a study from the Korea Energy Economics Institute, which indicated that the total number of vehicles increased by 1.8% annually for all vehicles. The total number of vehicles in the present study refers to the total number of gasoline, diesel, and electric vehicles, not all vehicles with an annual increase of 1.8%. The total number of gasoline, diesel, and electric vehicles accounted for approximately 90% of all vehicles. Therefore, the same annual increase rate was applied to estimate the total number of gasoline, diesel, and electric vehicles in 2030 (MOLIT, 2019). The number of scrapped EVs was set as 9.7% of EVs from 2013 to 2018 (Lee and Ha, 2015). The 9.7% scrapping rate of EVs was based on a scrapping rate of 11-year old vehicles due to the lifespan of EV batteries.

Table 15. Model Variables and Modeling Logic of EV Propagation Model

Variables		Modeling Logic		Unit
Stock variable	Passenger Vehicle	EV_Inflow + ICEV(Diesel+Gasoline)_Inflow		cars
Flow variables	ICEV (Diesel+Gasoline) Inflow	ICEV		cars
	EV Inflow	Elec_P+Gasoline_P+Charging_Infra+Diesel_P+Natl_subsidy+ Reg_Subsidy-scrapped_EV+y-intercept		cars
		y-intercept_SU= 9198.318 y-intercept_BS= 9305.563 y-intercept_DG= 9284.848 y-intercept_IC= 9317.98 y-intercept_GJ= 9351.477 y-intercept_DJ= 9309.27 y-intercept_US= 9297.422 y-intercept_GG= 9263.567	y-intercept_GW= 9313.2 y-intercept_CB= 9320.546 y-intercept_CN= 9317.34 y-intercept_JB= 9315.064 y-intercept_JN= 9300.2 y-intercept_GB= 9252.529 y-intercept_GN= 9210.178 y-intercept_JJ= 9006.045	
Auxiliary	National Subsidy	Scenarios		Billion

variables			KRW
	Regional Subsidy	Scenarios	Billion KRW
	Charging Infrastructure	8.398*Charging_infra_REGION Charging Infra_SU= 97 / Charging Infra_GW= 66 Charging Infra_BS= 27 / Charging Infra_CB= 62 Charging Infra_DG= 16 / Charging Infra_CN= 68 Charging Infra_IC= 24 / Charging Infra_JB= 62 Charging Infra_GJ= 9 / Charging Infra_JN= 72 Charging Infra_DJ= 14 / Charging Infra_GB= 97 Charging Infra_US= 9 / Charging Infra_GN= 72 Charging Infra_GG= 132 / Charging Infra_JJ= 99	ea
	Electricity Price	-7.24*Graph(Time) (2019, 173.8), (2020, 173.8), (2021, 346.0), (2022, 692.0), (2023, 692.0), (2024, 692.0), (2025, 692.0), (2026, 692.0), (2027, 692.0), (2028, 692.0), (2029, 692.0), (2030, 692.0)	KRW
	Gasoline Price	9.685*Graph(Time) (2019, 1043.927), (2020, 1082.624), (2021, 1118.295), (2022, 1157.401), (2023, 1197.244), (2024, 1236.35), (2025, 1277.911), (2026, 1321.68), (2027, 1369.213), (2028, 1420.346), (2029, 1474.424), (2030, 1524.984)	KRW

	Diesel Price	-9.043*Graph(Time) (2019, 1043.927), (2020, 1082.624), (2021, 1118.295), (2022, 1157.401), (2023, 1197.244), (2024, 1236.35), (2025, 1277.911), (2026, 1321.68), (2027, 1369.213), (2028, 1420.346), (2029, 1474.424), (2030, 1524.984)	KRW
	ICEV	(Passenger Vehicle*(1.018)-Passenger Vehicle)-EV_Inflow	cars
	Scrapped EV	Applied scrappage rate of 9.7% to EVs from 2013 to 2019	cars

2.4. Propagation Results of EV considering Policies

2.4.1. Subsidy Cliff Scenario

Based on the Subsidy Cliff scenario, the outlook for the spread of EVs by region between 2019 and 2030 was analyzed to be a gradual trend until 2023 when subsidies will be suspended (Figure 19; Table 16). The total number of EVs in Korea in 2030 was estimated to be 1.36 million in 2030, far below the goal of 3 million EVs proposed by the government in 2030. In Figure 19, there were turning points on the EV propagation graphs of 16 regions. These points correspond to the suspension of subsidies for purchasing EVs in 2023.

The projection for the spread of EVs by region in 2030 showed that the largest number of EVs varied widely, with 126 thousand EVs in Jeju Island, which aims to become a “Carbon Free Island.” This was followed by Gyeonggi, Seoul and Daegu. In Gyeonggi and Seoul, 114 thousand and 109 thousand EVs, respectively, were projected by 2030, when the Subsidy Cliff scenario was applied. In addition, Daegu, Gyeongbuk, and Jeonnam showed large numbers of projected EVs: 95 thousand for Daegu, 85 thousand for Gyeongbuk, and 82 thousand for Jeonnam. In contrast, Ulsan was expected to have the smallest number of EVs among the 16 regions in Korea. It was projected that Ulsan will have 70 thousand EVs.

Table 16. Projection of Subsidy Cliff Scenario in 2030

Region	EV Projection in 2030
Jeju	126 K
Gyeonggi	114 K
Seoul	109 K
Daegu	95 K
Gyeongbuk	85 K
Jeonnam	82 K
Chungnam	81 K
Gyeongnam	78 K
Incheon	76 K
Gangwon	76 K
Jeonbuk	76 K
Busan	75 K
Daejeon	74 K
Gwangju	71 K
Ulsan	70 K

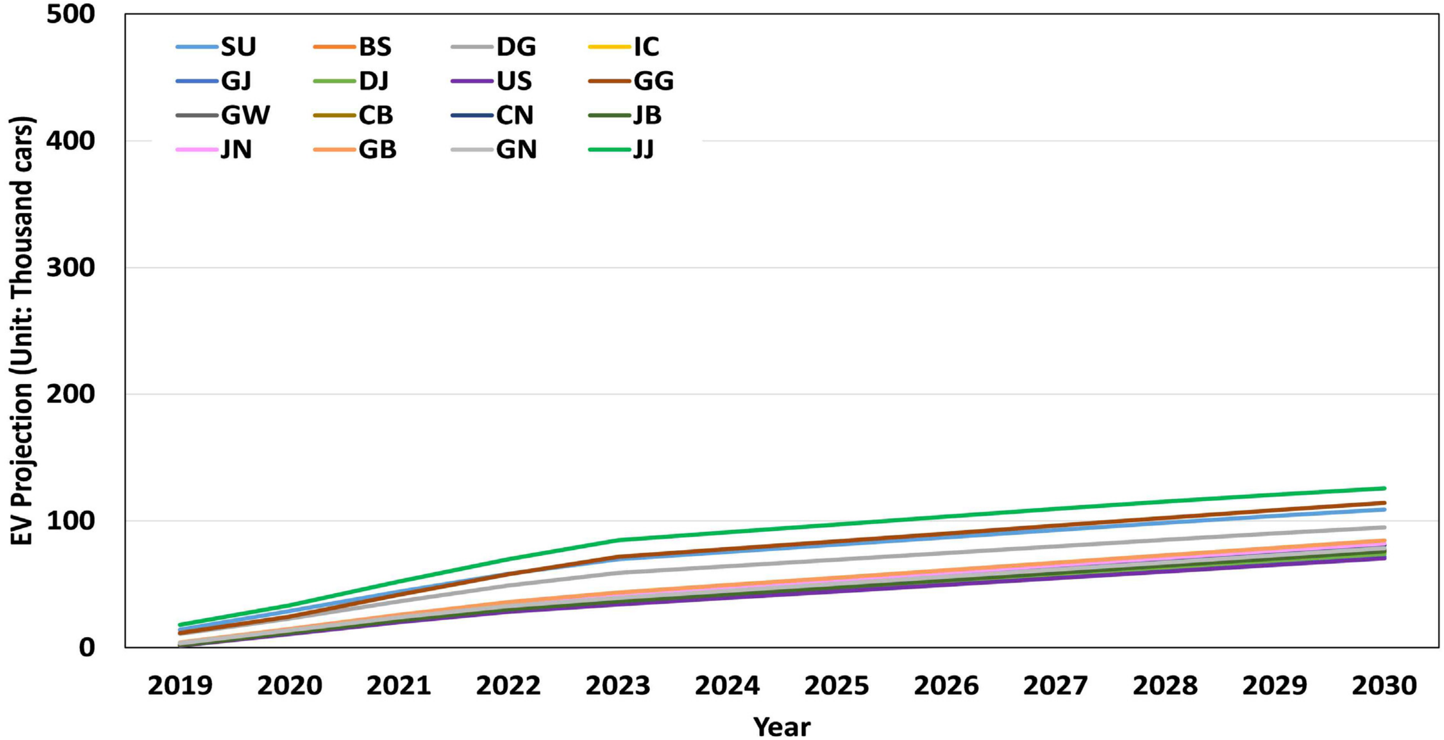


Figure 19. EV Projection of Subsidy Cliff Scenario from 2019 to 2030

2.4.2. Phase-out Subsidy Scenario

The Phase-out subsidy scenario is a scenario in which subsidies are gradually reduced and there is no subsidy in 2030. The actual budget was applied until 2020, and the amount of the budget was further reduced by 10% year-on-year starting in 2021. Unlike the Subsidy Cliff scenario where subsidies were suddenly suspended, the number of EVs in the Phase-out scenario was expected to increase moderately by 2030, and 1.37 million EVs were expected to spread through South Korea. Figure 20 presents points on the EV propagation graphs of 16 regions in 2022. These points were based on the number of scrapped EVs. Based on an 11-year life span of EVs, the scrapping rate of EVs was set as 9.7% according to Lee and Ha (2015). The scenario was also analyzed to be below the national propagation goal of 3 million EVs.

As for EVs propagated by region, Jeju Island was projected to have the largest number of EVs with 134 thousand EVs in 2030. As in the case of the Subsidy Cliff scenario, the projected numbers of EVs in the top five regions in 2030 were as follows: Jeju (130 thousand), Gyeonggi Province (120 thousand), Seoul (113 thousand), Daegu (98 thousand), and Gyeongbuk (86 thousand) as shown in Table 17 and Figure 20. At the opposite end of the projections, Ulsan was expected to have the smallest number of EVs among the 16 regions with only 71 thousand.

Table 17. EV Projection of Phase-out Scenario in 2030

Region	EV Projection in 2030
Jeju	130 K
Gyeonggi	120 K
Seoul	113 K
Daegu	98 K
Gyeongbuk	86 K
Jeonnam	84 K
Chungnam	82 K
Chungbuk	78 K
Incheon	77 K
Gangwon	77 K
Jeonbuk	76 K
Daejeon	75 K
Busan	75 K
Gwangju	72 K
Ulsan	71 K

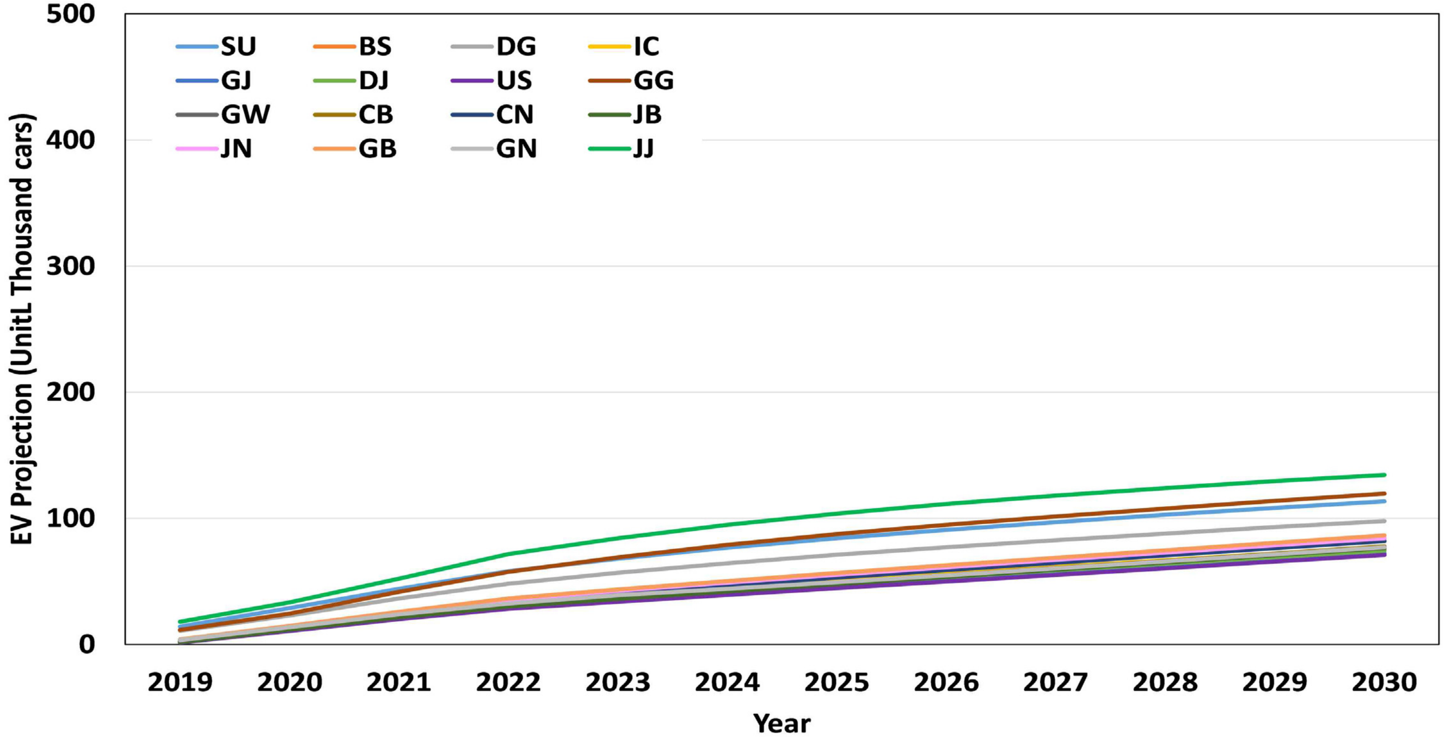


Figure 20. EV Projection of Phase-out Scenario from 2019 to 2030

2.4.3. Phase-in Subsidy Scenario

In the Phase-in scenario, subsidies gradually increase until 2030. This scenario was constructed to report the change in the spread of EVs over 10 years from 2021 to 2030 when subsidies are provided at a increased rate annually. This scenario is similar to the policy implemented by the German government to dramatically promote the supply of EVs through the expansion of subsidies for EVs. Therefore, based on the German policy, a Phase-in 50% scenario was constructed in which EV subsidies would increase by an additional 5% each year with the aim of increasing the recent actual subsidy budget by 50% in 2030. In addition, a Phase-in 350% scenario was established to report dynamic changes in the number of EVs propagated with an increase at a much higher rate.

When the Phase-in 50% scenario and Phase-in 350% scenario were applied using system dynamics, the expected number of EVs propagated was 1.87 million and 3.01 million, respectively. The propagation projection of EVs in Korea in 2030 was 249 thousand EVs expected in Jeju, which was the largest number of EVs, when the Phase-in 50% scenario was applied. In addition to Jeju, four regions showed a large number of EVs propagated: Gyeonggi (206 thousand), Seoul (181 thousand), Daegu (149 thousand) and Gyeongbuk (110 thousand) Ulsan and Gwangju showed the lowest propagation of EVs, with 78 thousand expected for each region. The propagation projection of EVs under the Phase-in 50% scenario in 2030 is shown in Table 18.

For the Phase-in 350% scenario, the same five regions as the Phase-in 50% scenario showed the largest number of EVs as follows: Jeju (482 thousand), Gyeonggi (418 thousand), Seoul (360 thousand), Daegu (159 thousand), and Gyeongbuk (155 thousand). Ulsan still showed the lowest propagation of EVs at 85 thousand under the Phase-in 350% scenario.

Table 18. EV Projection of Phase-in 50% Scenario in 2030

Region	EV Projection in 2030
Jeju	249 K
Gyeonggi	206 K
Seoul	181 K
Daegu	149 K
Gyeongbuk	110 K
Jeonnam	109 K
Chungnam	101 K
Incheon	96 K
Busan	89 K
Chungbuk	87 K
Gyeongnam	86 K
Gangwon	85 K
Daejeon	85 K
Jeonbuk	83 K
Gwangju	78 K
Ulsan	78 K

Table 19. EV Projection of Phase-in 350% Scenario in 2030

Region	EV Projection in 2030
Jeju	482 K
Gyeonggi	418 K
Seoul	360 K
Daegu	159 K
Gyeongbuk	155 K
Jeonnam	154 K
Chungnam	150 K
Incheon	143 K
Busan	122 K
Gyeongnam	114 K
Daejeon	113 K
Chungbuk	110 K
Gangwon	106 K
Jeonbuk	102 K
Gwangju	96 K
Ulsan	85 K

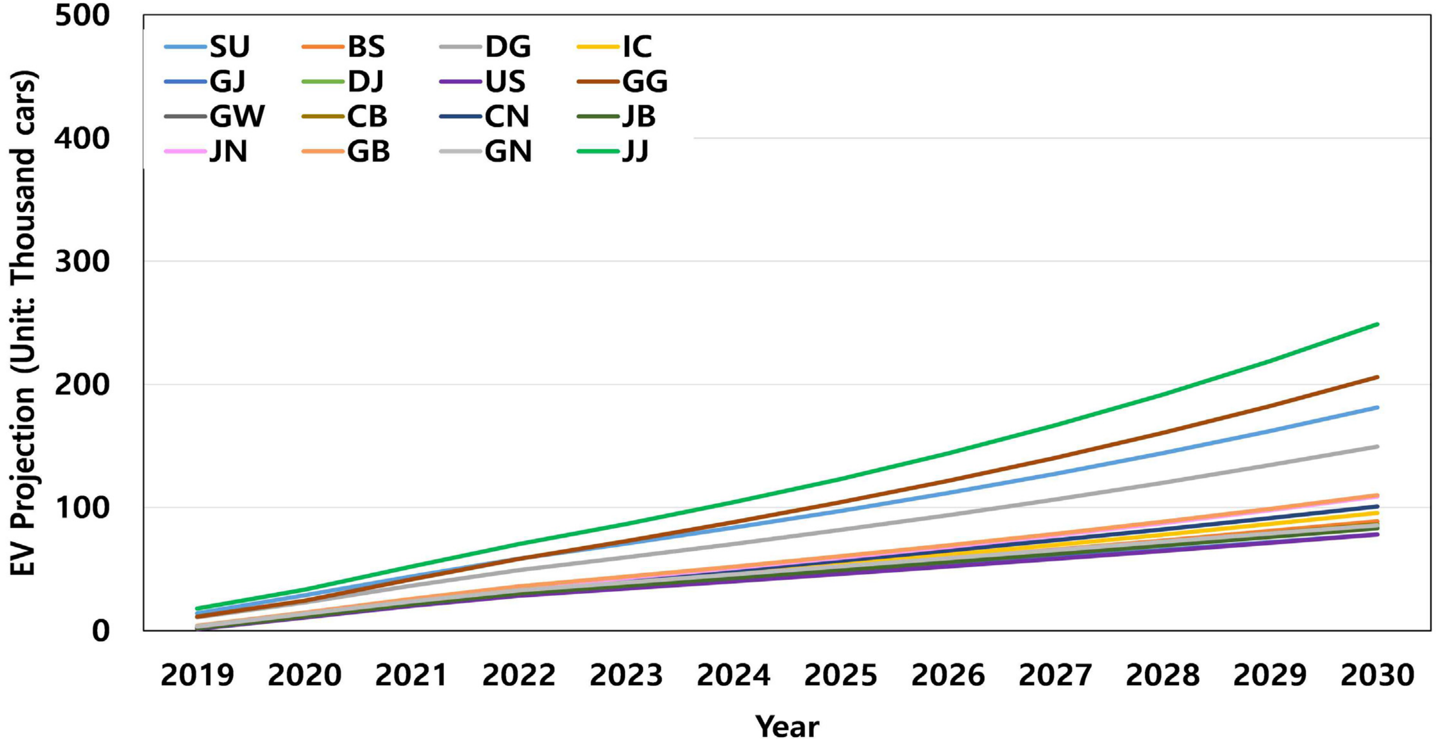


Figure 21. EV Projection of Phase-in 50% Scenario from 2019 to 2030

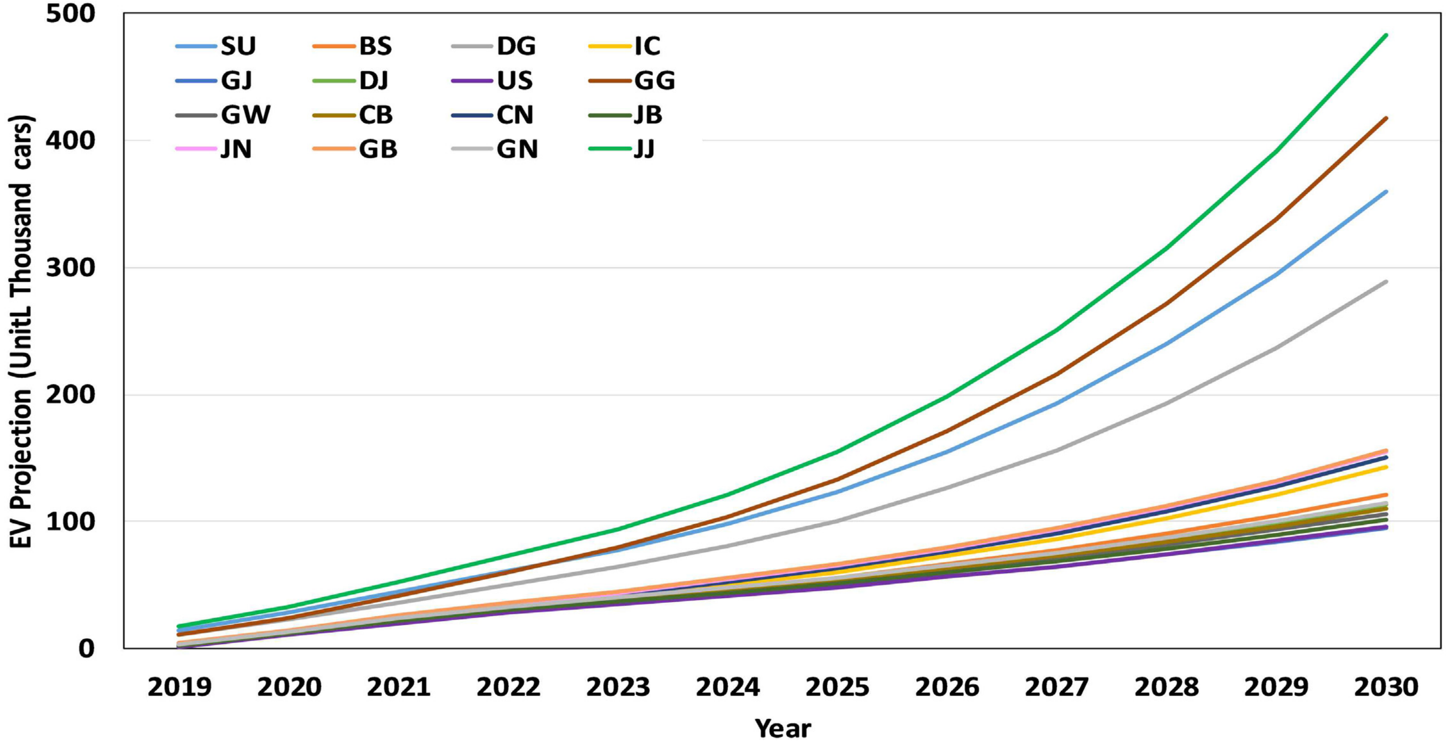


Figure 22. EV Projection of Phase-in 350% Scenario from 2019 to 2030

2.4.4. Regional EV Projection per thousand in 2030

In the four previous scenarios, the number of EVs in Korea was expected to increase over time depending on the affecting factors and subsidies. However, it is also necessary to examine regional propagation of EVs compared to the number of residents in each region. The results of the analysis of the propagation of EVs compared to the number of residents in the region showed opposite results to the analysis of the total number of EVs propagated in each region (Table 20; Figure 23).

Jeju, Ulsan, Gangwon, and Jeonnam regions were projected to have the largest number of EVs per thousand residents in 2030, under the Subsidy Cliff scenarios where subsidies were not supported. Jeju, which had the largest number of EVs per thousand residents, had a projected 167 EVs per thousand residents in 2030. Except for Jeju, where EVs are specialized, the total number of EVs of the other three regions were not heavily propagated, but compared to their small populations, many EVs were found to have been well propagated. In Ulsan, the smallest number of EVs among the 16 cities and provinces was analyzed to be well propagated. Despite the small population, Ulsan was expected to have the largest number of EVs per thousand residents, with 64 EVs per thousand. Ulsan is only half the size of Jeju, but the number of projected EVs was 1.28 times higher in Ulsan and 1.33 times higher in Jeju than Gangwon (50 EVs per thousand) and Jeonnam (48 EVs per thousand) where EVs per thousand were propagated. There seems to be the same effect in Jeju and Ulsan. That is, where EVs are produced or where factories are located, there is a high number of EVs per capita in the area (Sierzchula et al., 2014).

Over time, many EVs were propagated compared to 2019, and EVs spread with a slight difference by region, but the order of the numbers per region where many EVs were propagated was almost the same for each scenario. In the case of a Phase-out scenario in which subsidies for EVs would be gradually reduced, the results large compared to the small population, similar to the Subsidy Cliff scenario. As in previous scenarios, Jeju and Ulsan were projected to have the largest number of a EVs per thousand (i.e., per capita) in 2030. The number of EVs per thousand were as follows: Jeju (179), Ulsan (65), Daejeon (52), Gwangju (51), and Gangwon (51). According to the analysis, the smallest number of EVs per thousand residents was projected to be in Gyeonggi (8) and Seoul (12). Although Seoul and Gyeonggi had the largest projected overall regional propagation of EVs, they also have the largest population in Korea. Despite the large projected supply of EVs, they are projected to have the smallest number of EVs per thousand.

For the Phase-in 50% and 350% scenarios, Jeju was projected to have the highest number of EVs per thousand with 332 (50% scenario) and 643 (350% scenario) EVs. The descending order of the number of EVs per thousand was Jeju, Ulsan, Daegu, Jeonnam, and Daejeon. The fewest EVs were propagated in Seoul and Gyeonggi. Compared to the Subsidy Cliff scenario, Jeju and Ulsan, where the largest number of EVs per thousand were expected to be propagated, EVs under the Phase-in 50% and Phase-in 350% scenarios propagated 1.99 times, 1.11 times, 3.85 times more, than with the Subsidy Cliff scenario. The number of EVs per thousand residents projected in Seoul and Gyeonggi was analyzed to be 20 and 14 per thousand residents, respectively, in the Phase-in 50% scenario. Under the Phase-in 350% scenario, where the final number would meet the government's EV propagation goal, Seoul and Gyeonggi were expected to propagate 39 and 29 EVs per thousand residents, respectively.

Table 20. Regional EV Projection per Thousand in 2030

	Subsidy Cliff	Phase-out Subsidy	Phase-in 50% Subsidy	Phase-in 350% Subsidy
Seoul	12	12	20	39
Busan	24	24	29	39
Daegu	42	43	65	126
Incheon	25	26	32	47
Gwangju	51	51	55	67
Daejeon	51	52	59	79
Ulsan	64	65	71	88
Gyeonggi	8	8	14	29
Gangwon	50	51	56	70
Chungbuk	46	46	52	66
Chungnam	35	35	44	65
Jeonbuk	44	44	48	59
Jeonnam	48	49	63	90
Gyeongbuk	33	33	42	60
Gyeongnam	24	23	26	34
Jeju	167	179	332	643

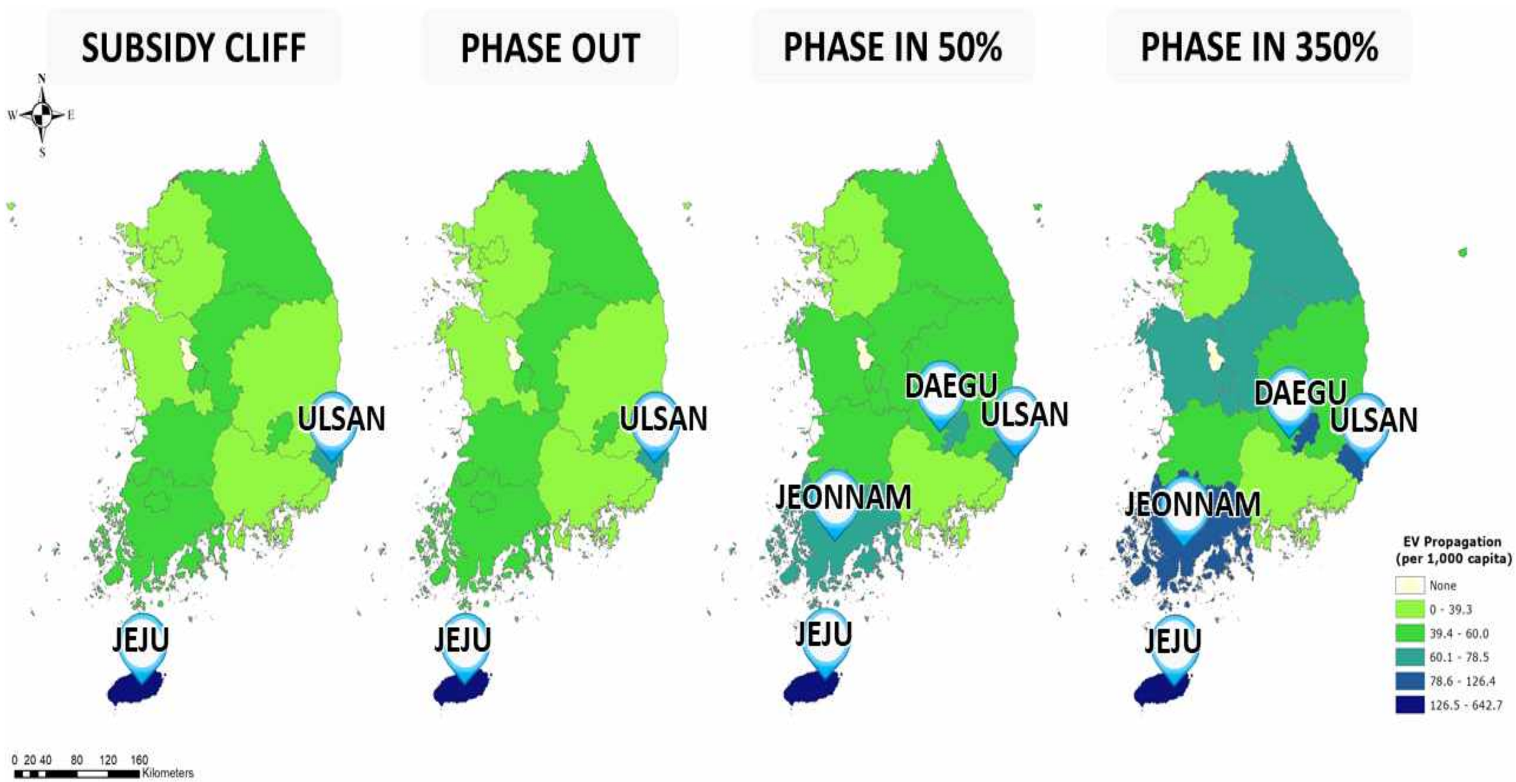


Figure 23. Regional EV Propagation per Thousand in 2030

2.4.5. Policy Implications of EV Projection considering Policy Scenarios

The four scenarios (i.e., Subsidy Cliff, Phase-out, and Phase-in 50%, and Phase-in 350%) did not show much difference until 2022, but the change in subsidies began to take effect in 2023. From 2019 to 2030, the Subsidy Cliff and Phase-out scenarios showed a similar increase in EVs. However, the difference between the two Phase-in scenarios began to widen significantly by increasing the annual subsidies by 5% and 35%.

Except for the Phase-in 350% scenario, the other three scenarios showed that 1.63 million, 1.60 million, and 1.13 million EVs, respectively, would partially meet the national EV propagation goal. However, it would be difficult to achieve the Phase-in 350% scenario to meet the country's target propagation number, because it would require increasing the budget by 35% each year. Even if all three scenarios were applied except for the 350% increase scenario, it would be difficult to reach the propagation goal of EVs even though it would be approximately 34 times higher than the number of EVs in 2019. Therefore, further propagation would require application of policy scenarios with different characteristics including both non-financial incentives and financial incentives.

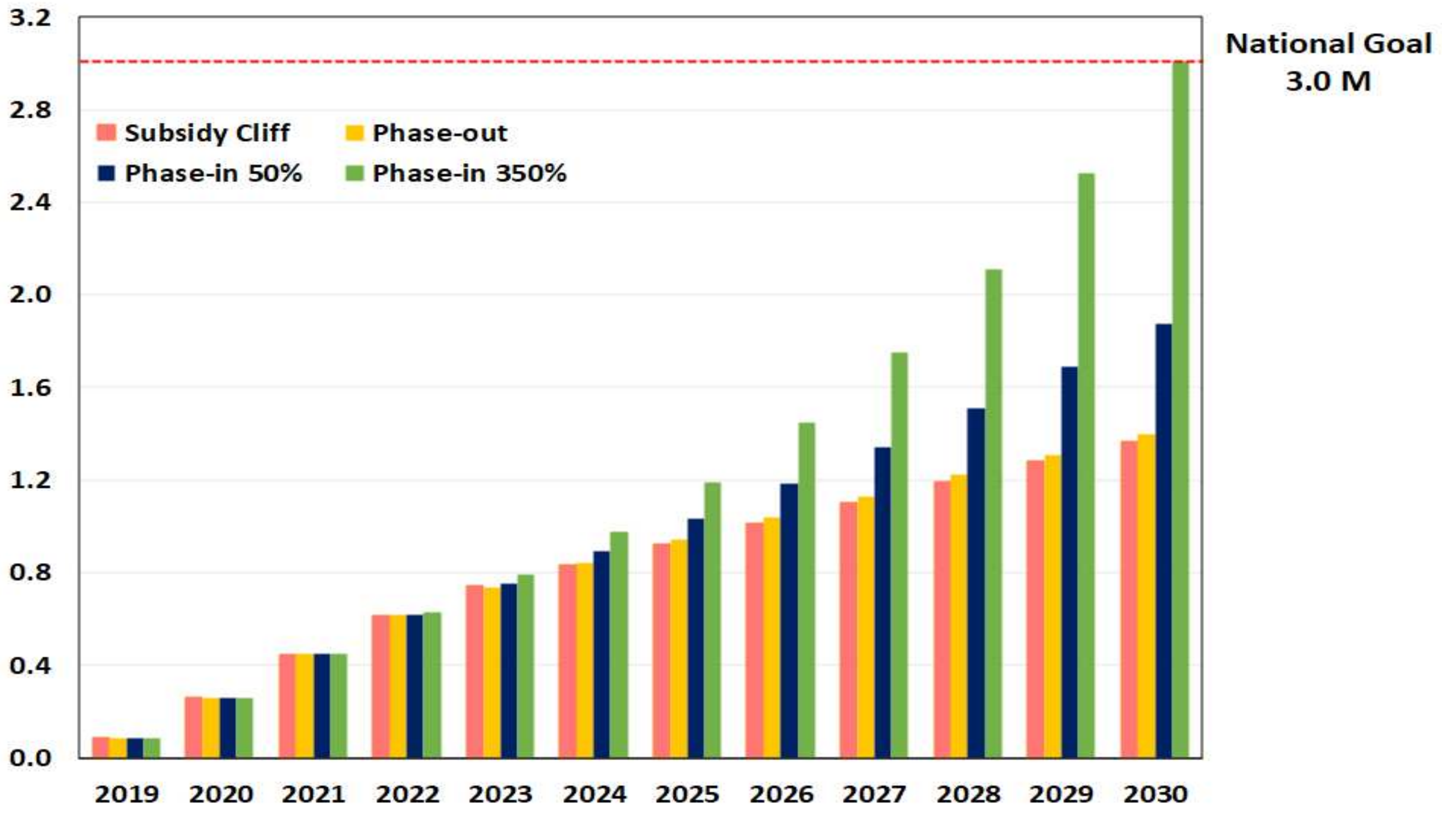


Figure 24. EV Projection based on Four Policy Scenarios - Subsidy Cliff, Phase-out, Phase-in 50%, and Phase-in 350%

3. Environmental Performances of EV Propagation

3.1. Environmental Performances of EVs Compared to ICEVs

Impact categories are commonly used to evaluate LCA. Impact categories could be different depending on the LCIA methodologies such as ILCD, TRACI, ReCiPe, and CML (Greendelta, 2016). There are several impact categories including abiotic depletion potential (ADP), acidification potential (AP), eutrophication potential (EP), global warming potential (GWP), particulate matters potential (PM), freshwater aquatic ecotoxicity potential (FAETP), human toxicity potential (HTP), and ozone depletion potential (ODP). The impact categories used in this LCA to analyze the environmental performance of EVs focused on the two most important categories related to the propagation of automobiles and energy production: global warming potential (GWP) and particulate matter potential (PM).

To compare the environmental performance of EVs with those of internal combustion engine vehicles, the emissions of the global warming potential and particulate matter categories were analyzed using the emissions per vehicle kilometers traveled

(VKT) of diesel-powered vehicles and gasoline-powered vehicles, based on Kim et al. (2019) calculations. In their study, GHG emissions from the actual power mix in 2016 were analyzed as 170g CO_2e/VKT for gasoline vehicles, 158g CO_2e/VKT for diesel vehicles, and 115g CO_2e/VKT for EVs, indicating that EVs emitted the least amount of greenhouse gases. However, although they analyzed that EVs emitted the least GHG emissions, EVs generated the largest particulate matter with 54mg PMe/VKT compared to 24.3mg PMe/VKT for diesel vehicles and 12.4mg PMe/VKT for gasoline vehicles.

The environmental options in the 8th National Plan and energy transition option reported different emissions of greenhouse gases and particulate matter. In the 8th Plan option, the GHG emissions of EVs generated 81.7g CO_2e/VKT, and in the energy transition option, EVs generated 37.2g CO_2e/VKT (Figure 25). Among the five options (i.e., actual power mix, national plan, energy transition, gasoline powered vehicle, and diesel powered vehicle), the energy transition option with the lowest GHG emissions was 3.1 times lower than emissions of 115g CO_2e/VKT from the actual power mix in 2016. In the case of internal combustion engine vehicles, EVs reportedly emitted 4.57 times and 4.25 times less greenhouse gases than gasoline and diesel vehicles, respectively, when the energy transition option was applied.

Given the recent rise of particulate matter-related issues, this study analyzed the environmental impact of particulate matter emissions from vehicles. According to the 8th Plan, 20.7 mg PMe of particulate matter was emitted when driving an EV for 1km. When another environmental option was applied—the energy transition option—the EV emitted 9.4 mg PMe/VKT. When applying the 8th Plan, EVs showed the largest amount of particulate matter emissions among the energy transition options and internal combustion engine vehicles. With the energy transition option, which showed less particulate matter emissions than the 8th Plan, EVs emitted 1.32 times less particulate matter than gasoline vehicles.

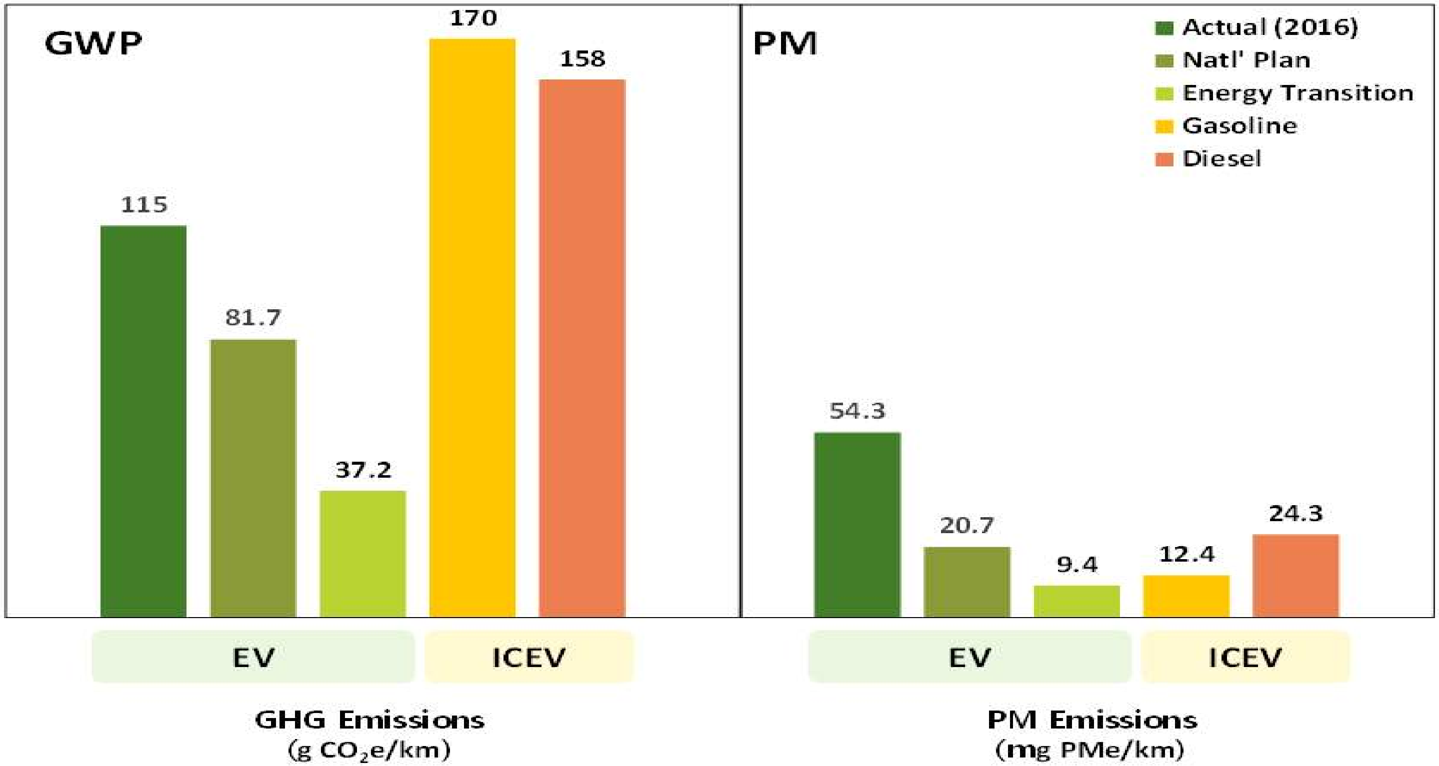


Figure 25. CO_2 and PM Emissions from EV and ICEV per km

3.2. Environmental Implications of Combination of Policy Scenarios and Environmental Options for EV Propagations

3.2.1. Emissions Considering Environmental Options and Policy Scenarios

The environmental impact of EVs depends on how they generate electricity because there are no pollutants emitted while driving. As of 2019, Korea has produced electricity according to the national power mix of the 8th Electricity Supply and Demand Plan. Therefore, the environmental impact of EVs at the use phase was analyzed based on the environmental options with the 8th Plan and the energy transition option. Based on this, the environmental impact of EVs was analyzed by applying the environmental options and policy scenarios together. Figure 26 shows the results from the analysis of total GHG and particulate emissions generated from EVs in the use phase by using the propagation projection of EV and emissions per 1VKT.

In 2030, when the 8th Plan and energy transition option were applied, the reduction of GHG emissions were approximately 54% compared to when only the 8th Plan was applied. Based on the policy scenario, in combination with the 8th Plan, the subsidy clip scenario produced 1,471kt CO_2e, the Phase-out scenario produced 1,502kt CO_2e, the Phase-in 50% scenario produced 2,013kt CO_2e, and the Phase-in 350% scenario produced 3,237kt CO_2e of greenhouse gases. The Phase-in 350% scenario, which achieves the national propagation goal of EVs, was analyzed to emit about 2.2 times more GHG emissions than the Subsidy Cliff scenario, which propagated the least EVs, but this scenario was determined to increase emissions as more EVs were deployed. The energy transition option, which was analyzed to emit 37.2g CO_2e of GHG emissions per 1km of driving, produced less greenhouse gases than the 8th Plan option as EVs were propagated by the policy scenario.

According to the particulate emissions from the propagation of EVs using the policy scenario, the 8th Plan option, which emitted 20.7mg PMe/VKT, showed more particulate emissions than the energy transition option, which generated 9.4 mg PMe/VKT. The total particulate emissions generated from the Subsidy Cliff scenario were 373ton PMe for the 8th Plan option and 170ton PMe for the energy transition option, respectively. For the Phase-out scenario, the 8th Plan emitted total emissions of 381ton PMe, which is 2.2 time more than particulate emissions from the energy transition (173ton PMe). For the Phase-in scenarios, of course, a combination of the Phase-in 350% scenario and the 8th Plan showed the largest amount of particulate emissions at 821ton PMe. With these results of GHG and PM emissions from EVs, as the number of EVs propagated increases, GHG and PM emissions increase. Therefore, the propagation of EVs may seem to have an adverse effect on the environment. However, if this is applied to the total number of passenger vehicles, there could be other consequences.

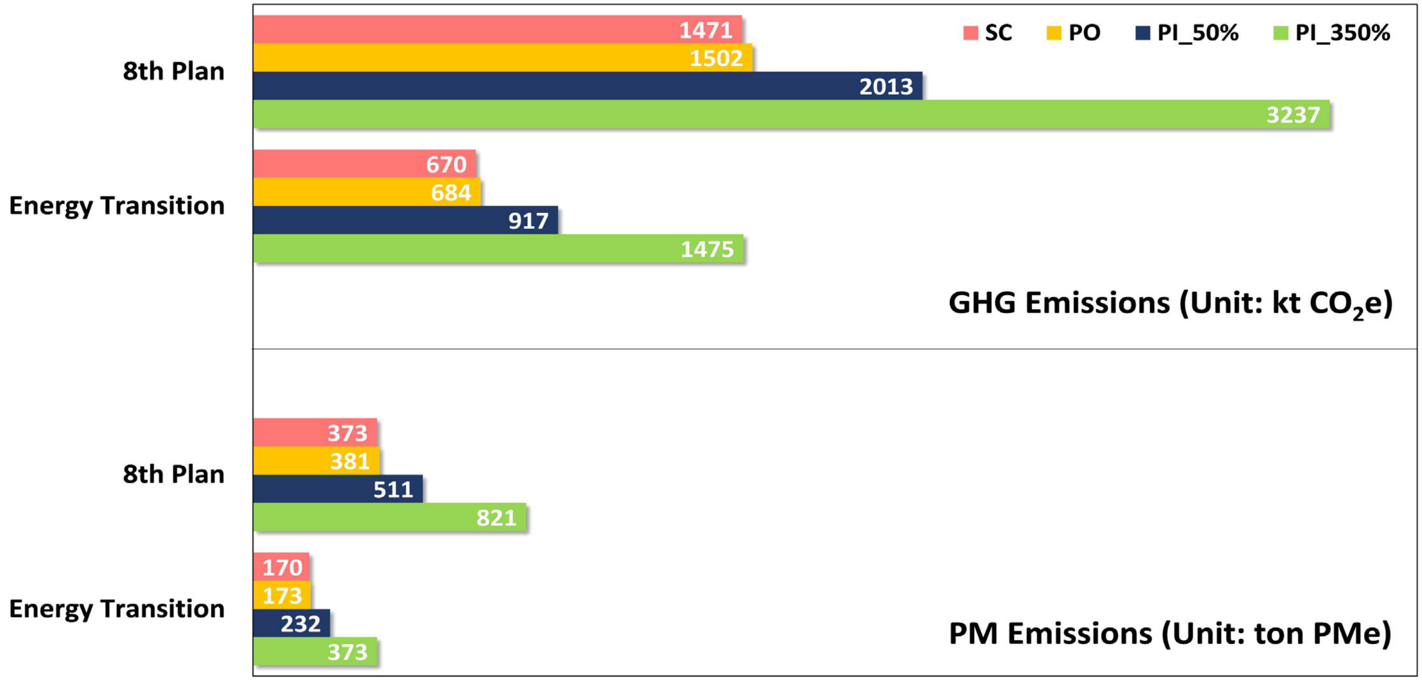


Figure 26. GHG and PM Emissions of EVs in 2030 based on the Policy Scenarios and Environmental Options

3.2.2. Total Emissions from ICEV and EV Considering Energy Transition Option and Policy Scenarios

The results of applying the 8th Plan option and energy transition option were analyzed in light of a policy to verify greenhouse gas and particulate matter emissions from the use phase of EVs. This study analyzed that the more EVs there are, the greater the environmental impact. However, it is necessary to consider the impact of the propagation of EVs on the environment by also considering the emissions of all passenger vehicles in Korea. The total GHG emissions of gasoline, diesel, and electric vehicles were 40,060kt CO_2e, reflecting the actual passenger vehicles in 2019. In addition, the GHG emissions from EVs was 115kt CO_2e, which is equivalent to 0.3% of the total GHG emissions. Furthermore, greenhouse gases emitted from gasoline and diesel vehicles accounted for 66.2% and 33.5% of total greenhouse gas emissions, respectively.

Next, the study applied the 2030 EV outlook for each policy scenario and compared the greenhouse gas and particulate emissions from the 8th Plan and energy transition options with the emissions of internal combustion engines. The greenhouse gas emissions of gasoline, diesel and EVs are shown in Figure 27. Both the 8th Plan and the energy transition option showed different GHG emissions from internal combustion engine vehicles (ICEV) based on each policy scenario, but the same policy showed the same emissions regardless of environmental options. This is the same phenomenon as the number of EVs being converted from ICEVs to EVs, which are expected based on each policy scenario. The 8th Plan and energy transition options for 2030 showed that the total GHG emissions decreased as the Subsidy Cliff scenario propagated the least EVs, and the Phase-in 350% scenario propagated the most EVs. Four scenarios (i.e., the total emissions of Subsidy Cliff, Phase-out, Phase-in 50%, Phase-in 350%) were calculated as 47,424kt CO_2e, 47,394kt CO_2e, 47,077kt CO_2e, 46,735kt CO_2e, respectively. As more EVs are propagated, and the more transition from internal combustion engine vehicles to EVs, the least GHG emissions are likely to be emitted in the application of the Phase-in 350% scenario with the most EVs propagated. The energy transition option, which showed a reduction of about 55% in GHG emissions compared to the 8th Plan, also showed a decrease in overall greenhouse gas emissions as EVs spread. In particular, the Phase-in 350% scenario, which propagated the largest number of EVs, produced 44,973kt CO_2e, with a reduction of about 5.2% compared to the combination of the 8th Plan and the Subsidy Cliff scenario.

Particulate matter emissions were calculated to verify the environmental impacts of the automobile sector. The amount of particulate matter generated from EVs increased as EVs became more widespread. However, from the perspective of PM emissions from all types of vehicles, the total PM emissions were reduced because internal combustion engine vehicles, especially diesel cars, were converted to EVs. Among the eight combinations, the lowest total PM emissions were from the combination of the energy transition and Phase-in 350% scenarios, generating a total of 24,698 tons of PMe in the analysis. In addition, a combination of the 8th Plan, which emitted the most PM emissions, and the Subsidy Cliff scenario were found to generate 26,070 tons of particulate matter. The combination of the energy transition option and Phase-in 350% scenario, which emitted the least amount of particulate matter, were analyzed to reduce particulate matters by 5.6% compared to the combination that showed the most PM emissions. These results showed that a combination of the energy transition options and Phase-in 350% scenario produced the least amount of greenhouse gases, with the greatest synergy between EV propagation and the power mix. The more EV propagation, the less GHG and PM emissions generated from internal combustion engine vehicles to EVs.

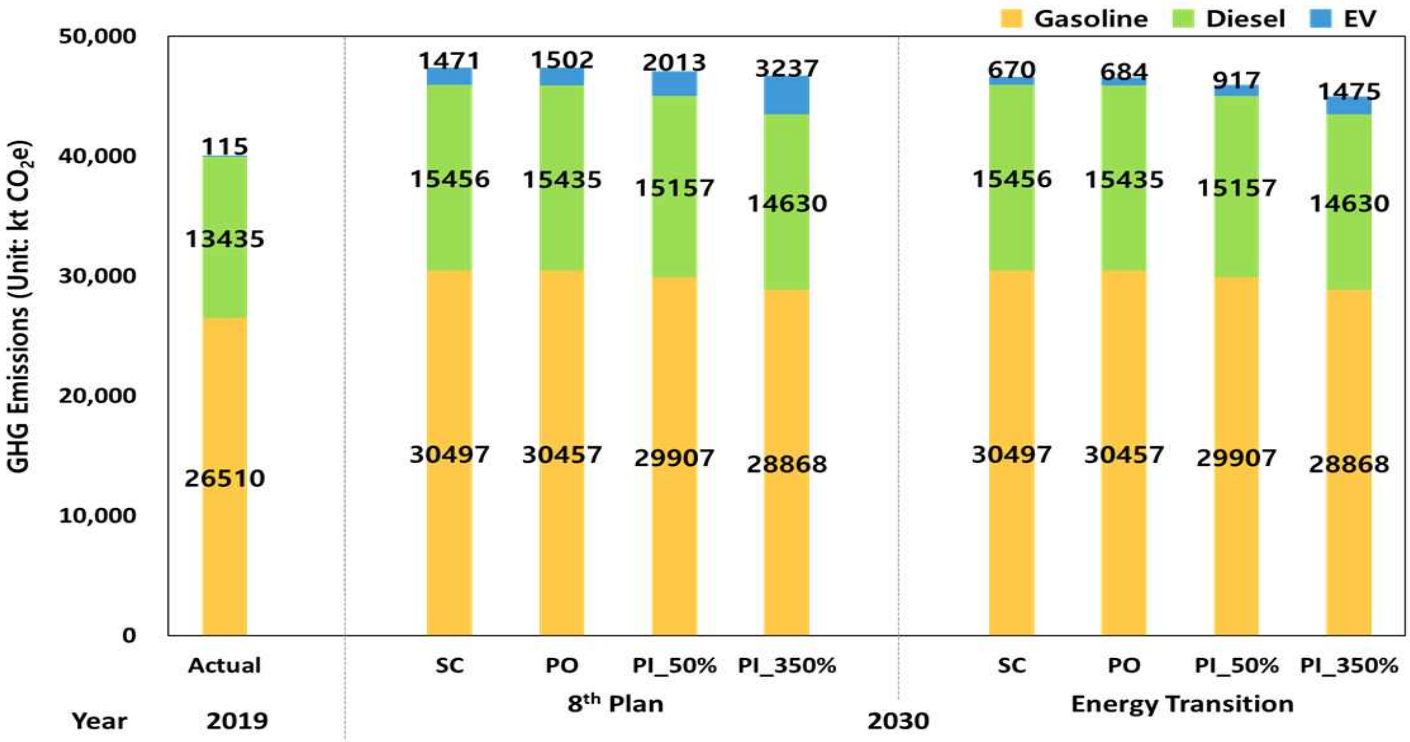


Figure 27. GHG Emissions of Gasoline, Diesel, and EVs in 2019 and 2030 based on the Combination of Policy Scenarios and Environmental Options

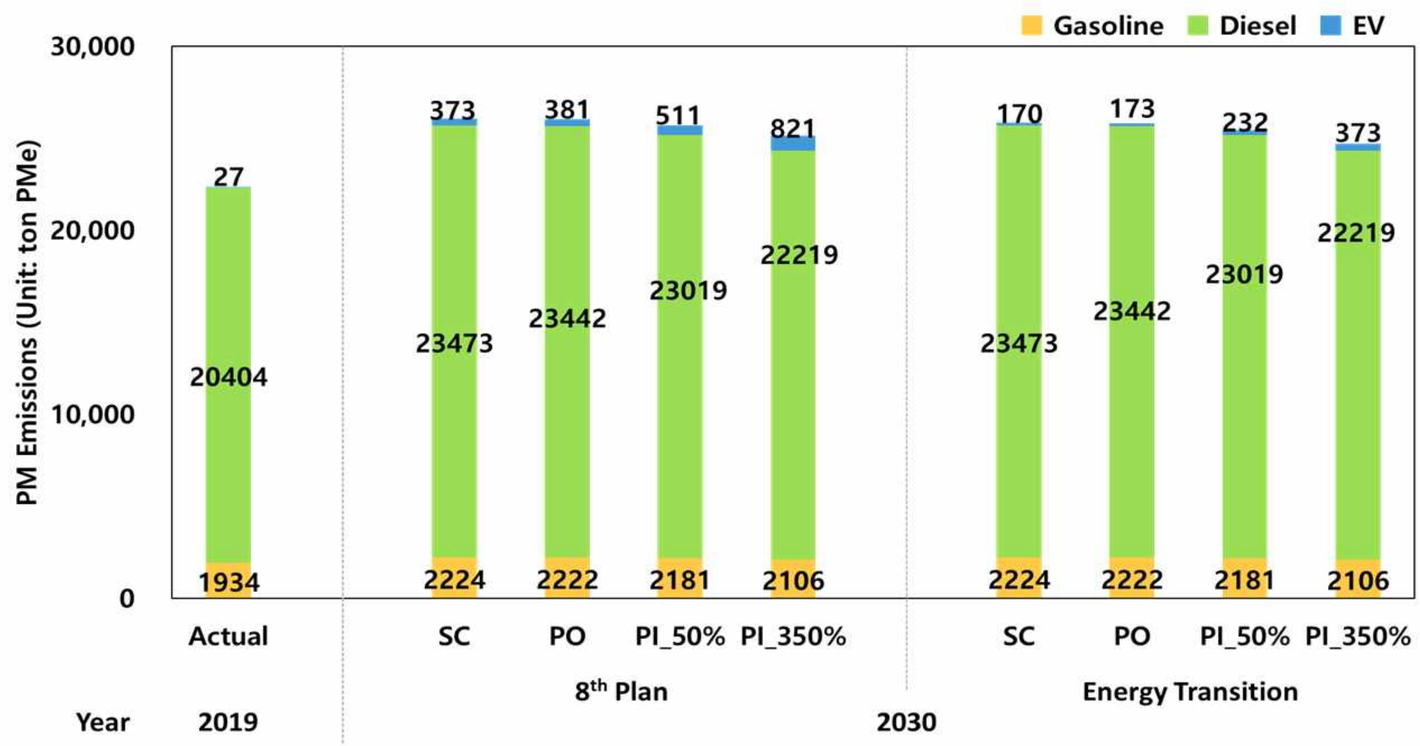


Figure 28. PM Emissions of Gasoline, Diesel, and EVs in 2019 and 2030 based on the Combination of Policy Scenarios and Environmental Options

V. Conclusion

In light of the greenhouse gas emissions (GHGs) from the transportation sector, the propagation of EVs has been widely considered as an effective way to reduce emissions from the transportation sector. The Korean government has actively promoted EVs as a substitute for internal combustion engine vehicles (ICEVs) to mitigate environmental impacts. The government's national and regional policies have been formulated to achieve the penetration goal of three million EVs in South Korea by 2030.

This study conducted three analyses to evaluate policy and environmental aspects of regional EV propagation. Initially, this study used a panel analysis to evaluate the affecting factors of EV propagation in five categories (i.e., policy, vehicle, demographic, climate, and environment) and to determine the key drivers of the spread of EVs using regional panel data of 17 regions in Korea. The second analysis method to calculate the dynamic change of regional EV propagation was a system dynamics approach. Lastly, the environmental performances of EV propagation was evaluated using a life cycle assessment.

The results of the first analysis using panel analysis was that the number of newly registered diesel cars and gasoline cars showed a negative effect on EV penetration, whereas the total number of newly registered cars showed a positive effect. In the policy category, both national and regional subsidies affected penetration in opposite directions. The national subsidy negatively affected the increase of EVs; however, regional subsidies positively affected penetration. Population density and cars owned per capita also had negative and positive implications, respectively, for EV penetration. Factors in the climate and environment categories showed a weak impact on EV propagation.

Based on the results of the changes in policy affecting factors using system dynamics, this study analyzed that in 2030, the numbers would be substantially different depending on the scenario: 1.37 million EVs under the Subsidy Cliff scenario, 1.40 million under the case of Phase-out scenario, 1.87 million under the Phase-in 50% scenario, and 3.01 million under the Phase-in 350% scenario. Except for the Phase-in 350% scenario, the rest of the scenarios did not meet the government’s 2030 goal for the spread of EVs. According to the calculated number of EV by scenario, the largest number of EVs in 2030 is expected in Jeju, Gyeonggi, Seoul and Daegu. However, the results of the spread of EVs per capita showed conflicting results from the total number of EVs propagated in each region. The regions with the largest number of EVs per capita in 2030 are projected to be Jeju, Ulsan, Gangwon, and Jeonnam. Except for Jeju, the other three regions did not have many EVs in terms of the total number of EVs. Ulsan showed the smallest number of EVs, but in comparison to the population Ulsan had the largest number of EVs per capita except for Jeju, which is a special case. Ulsan, where the automobile manufacturing plants are located, is believed to have a production site effect as demonstrated in previous studies showing highly propagated EVs in regions where EVs are produced or where manufacturing plants are located.

Analysis of the 8th National Plan, which was calculated based on the rated capacity and the application of the transition to renewables, provided several environmental options. GHGs of EVs were shown to emit 81.7g CO_2e/VKT under the 8th National Plan option, and 37.2g CO_2e/VKT under the energy transition option from coal to renewables. The energy transition option, which showed the lowest GHG emissions, was 3.1 times lower than the actual power mix in 2016, and 4.57 and 4.25 times lower than gasoline and diesel, respectively. EVs, which had the largest amount of particulate matter emissions among gasoline, diesel, and electric vehicles, was calculated based on the 8th National Plan to emit 20.7mg PMe/VKT when driving 1km. In addition, EVs generated 9.4mg PMe/VKT based on the energy transition option. The number of EVs was 1.32 times less than gasoline vehicles, which generated 12.4mg PMe/VKT when the energy transition option was applied

In this study, monthly regional panel data were used to analyze factors affecting the propagation of EVs. However, the panel analysis using monthly data rather than panel analysis using annual data was limited in obtaining data by region since major factors were not included such as charging facilities and electricity prices that affect the propagation of EVs. It is expected that monthly regional data on charging facilities will be considered in the future. In this study, the PM_{10} variable was applied to concentration using the panel analysis. In the future, if the monthly PM on bad days is applied as mentioned in a previous study, it is estimated that more accurate results will be obtained.

Among the three analyses performed in this study, the analysis using system dynamics was most suitable for the various scenarios, which increased the current budget by 35% per year to meet a 350% increase by 2030. For Korea, which has implemented a policy of suspending subsidies for EVs as of 2023, it would be difficult to maintain the current budget for subsidies for EVs at 35% per year for 10 years, so Korea would need to collect additional fees such as an environmental pollution tax from internal combustion engine vehicles to make up for the subsidies for eco-friendly EVs. Future research can connect the supply of EVs with the Feebate System.

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Abstract in Korean

시스템 다이내믹스를 이용한 지역별 영향인자 변화에 따른 전기차의 환경개선효과 분석

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기후변화와 관련하여 온실가스는 주요한 영향을 미치는 요인으로 인식되며, 꾸준히 증가하는 온실가스를 감축하고자 에너지 부문 중 수송부문에서도 탄소를 배출하지 않는 친환경 자동차로서 전기차는 해결책으로 제시되고 있다. 에너지 부문은 다섯 개 부문인 산업공정, 농업, 토지이용 변화 및 임업, 폐기물, 에너지 부문 중 국내 총 온실가스 배출량의 93%를 차지하여 온실가스 배출에 있어 크게 기여하고 있으며, 이로 인해 에너지 부문은 주요 온실가스 배출원으로 지목되었다. 그중 도로수송부문의 온실가스 배출량은 2017년 94,270 Gg

ton CO_2e로 전체 수송부문의 95.9%를 차지하며, 2021년부터 효력이 발생하는 파리기후협약에 따라 온실가스 감축 목표를 달성하고자 2030년 온실가스 배출전망량 851백만 ton CO_2e 대비 37% 감축 달성을 위한 방안으로 친환경 자동차 보급을 제시하였다.

우리나라 정부는 온실가스 감축을 목표로 친환경 자동차 중 전기차 보급확대를 위해 다양한 정책을 제시하였다. 정부는 2030년 전기차 보급목표 대수를 3백만 대로 설정하며, 국내 친환경 자동차 보급확대를 위해 세제감면과 구매보조금 지급, 고속도로통행료, 공영주차장 주차비 할인 등의 다양한 혜택을 제공하고 있다.

하지만 이러한 정부의 다양한 정책적 노력에도 불구하고 국내 전기차 보급 속도는 기대에 못 미치고 있다. 정부는 2030년까지 배출되는 온실가스를 감축하기 위해 수송부문의 경우 2030 전기차 보급목표를 300만 대로 설정하였지만, 우리나라의 2019년 전기차 등록 대수는 약 8.8만 대에 불과하며 정부가 설정한 높은 목표 대수에 한참 못 미치는 수준이다. 이는 국내 전체 승용차의 0.5% 수준이다. 우리나라 전기차 실구매자의 재구매 의사와 예비구매자의 전기차 구매 의사와 관련하여 진행된 설문조사에 따르면, 보조금 축소와 긴 충전시간, 짧은 항속거리 등과 같은 이유로 전기차 재구매 혹은 구매를 하지 않겠다는 의견을 제시하였다. 주행을 위해 꼭 필요한 요소인 충전과 관련한 사항은 민감한 사항이지만 한국전력의 전기공급 시행세칙 변경안에 따르면, 2020년 하반기부터 전기차 충전료가 대폭 인상추진 중이다. 이로 인해 전기차 실구매자가 부담해야 하는 충전비용은 더욱 늘어나며 구매의향에 영향을 미칠 것으로 조사되었다.

전기차 보급을 위한 정부의 정책 시행과 다양한 연구가 진행되는 흐름 속에서 전기차의 보급이 증가할 것으로 전망됨에 따라 전기차의 연료인 발전의 변화도 중요성이 높아지고 있다. 전기차는 주행 중에 배출되는 오염물질이 없다

는 점에서 환경성이 부각되며 장려되고 있지만, 전기차의 제조 전 단계부터 폐기단계까지의 생애주기를 고려한 환경영향은 포함되지 않은 채 전기자동차는 장려되고 있다. 전기차의 생애주기 중 전기차 운행을 위한 전력 생산단계는 생애주기 중 사용단계에서 가장 많은 탄소량이 배출되며 이로 인해 전력생산은 전기차의 환경영향에 주요한 영향을 미친다. 전원믹스 구성에 따라 환경영향이 달라지기 때문에 국가 전원믹스를 고려한 환경영향평가가 이루어져야 한다. 자동차 보급과 에너지 생산과 관련된 중요한 두 카테고리인 온실가스와 미세먼지에서 상반된 결과를 보이기에 전원믹스구성의 변화와 전기차 보급 변화에 따른 환경영향평가가 필요하다.

전기차를 향한 관심의 증가하며 전기차 보급 관련 다양한 연구들이 수행되며, 전기차 보급에 영향을 미치는 다양한 인자들을 제시하였다. 그중 충전시설, 인구밀도, 유가, 온도, 전력가격, 보조금, 1인당 보유차량 대수 등이 전기차 보급의 주요 인자로 알려져 있다. 전기차 보급의 영향인자를 연구한 대다수의 연구에서 국가 단위의 연간자료를 사용하여 패널 분석을 진행하였다. 하지만, 우리나라는 주요 영향인자 중 보조금이 국고 보조금과 지자체 보조금으로 나뉘어 지급되고 있기에 지역적 특성이 고려되어야 하며, 제주도와 같은 전기차에 특수성을 띄고 있는 지역이 있기에 지자체 레벨에서 분석이 되어야 한다. 이와 더불어, 연간자료가 아닌 월간 자료 사용에 따라 보조금의 잔액 혹은 잔여 대수 변화를 적용한 연구는 찾아보기 어렵다. 시스템 다이내믹스를 이용한 전기차 보급 관련 다양한 연구들이 있었지만, 정량적인 연구보다는 정성적인 연구에 초점을 둔 연구들이 대부분이었다. 또한, 전기차 전원믹스 구성 변화를 적용하여 환경영향을 평가한 연구들은 많았지만, 전기차 보급량과 환경영향을 모두 고려한 연구는 찾아보기 어렵다.

따라서 본 연구에서는 지역별 전기차 보급에 대한 보조금 정책의 영향과 환경개선효과에 대해서 평가하였다. 먼저, 지역별 월간 패널자료를 이용하

여 전기차의 보급 활성화에 영향을 미치는 인자를 분석하였으며, 분석된 인자들을 바탕으로 시스템 다이내믹스를 이용한 보조금 정책에 따른 지역별 전기차 보급량 변화를 분석하였다. 마지막으로 전기차 보급에 따른 환경성 분석을 위해 전과정평가를 이용하여 국가전력수급계획에 따른 전기차 보급의 환경개선효과를 보고자 하였다.

본 연구의 첫 번째 전기차 보급 분석을 통해 지역별 월별 시계열 자료를 바탕으로 우리나라의 전기차 보급에 영향을 미치는 요인을 정량적인 분석을 하고자 하였다. 먼저 지역적 특성을 고려한 월 단위의 시계열 자료에서 나타나는 계절성 등에 대한 영향을 고려하기 위해 인자의 정상성을 확인하였다. 또한, 하우즈만 검정을 통해 패널고정효과모형과 패널확률효과모형에 대한 전기차 보급 모형을 설계하였다.

패널고정효과모형과 패널확률효과모형으로 국내 17개 시·도를 대상으로 전기차 보급 영향인자를 분석한 결과, 각각 48%와 50%의 설명력을 갖는 전기차 보급 모형을 확인하였다. 5개의 카테고리인 차량관련과 정책, 인구조사, 기후, 환경에 분류된 인자들은 모형에 따라 각기 다른 영향을 보이는 것으로 나타났으며, 하우즈만 검정을 통해 패널고정효과가 모형을 설명하기에 더욱 적절한 것으로 분석되었으나, 고정효과 모형보다 패널확률효과모형에서 더 많은 변수가 통계적으로 유의한 영향인자로 분석되었다.

차량 관련 카테고리의 신규등록 디젤차량 대수와 전체 신규등록 차량 대수는 패널고정효과모형과 패널확률효과모형 모두에서 각각 부(−)의 영향과 정(+)의 영향을 미치는 것으로 분석되었다. 하지만 확률효과모형의 경우, 디젤의 가격과 가솔린의 가격 또한 영향인자로 분석되었다. 패널고정효과모형에서는 국고 보조금과 지자체 보조금만이 영향인자로 각각 부(−)의 영향과 정(+)의 영향을 미치는 것으로 확인되었으나 확률효과모형은 전기차 보급에 긍정적 영향을 미치는 세금감면도 영향인자로 나타났다. 인구조사

카테고리의 인구밀도와 1인당 차량보유대수, 환경적 요인을 대변하는 미세먼지지수는 두 모형 모두에서 영향인자로 분석되었다. 각 지역의 기상조건이 전기차 보급 활성에 영향을 미치는지를 볼 수 있는 기상카테고리의 인자 중 월평균 온도와 월최저온도가 패널고정효과모형에서 영향력이 있는 것으로 나타났다. 하지만 패널확률효과모형에서는 기상카테고리의 모든 인자가 영향인자가 아닌 것으로 분석되었다.

앞서 분석된 전기차 보급에 영향을 미치는 인자들을 바탕으로 시스템 다이내믹스를 이용하여 지역별 전기차 보급의 동태적 변화를 보기 위해 Stella 플랫폼을 이용하였다. 시스템 다이내믹스는 시스템적 거동을 보이는 대상의 역동적인 변화메커니즘을 비선형적인 피드백 시스템으로 파악하고, 이를 다양한 요인을 고려하여 시뮬레이션하여 분석하는 기법이다. 본 연구에서는 시스템 다이내믹스를 이용한 지역별 전기차 보급대수 추정을 위해 Bull's eye diagram과 causal loop diagram, stock-flow diagram을 구축하고 보조금, 충전시설, 유가, 전력가격, 연료별 차량 대수 변수로 적용하였다. 이러한 시스템 다이내믹스 모델링을 통해 변수 간의 상관관계를 수식화하였다.

지역별 전기차 보급의 시스템 다이내믹스 모델은 지역별 특성에 따른 차이를 보고자 보조금 변수를 제외한 모든 변수는 신규 전기차 등록대수를 종속변수로 pooled OLS 회귀분석을 하여 수식을 적용하였으며, 보조금 변수는 지역별로 구분하여 신규 전기차 등록대수를 종속변수로 설정하고 다중회귀분석을 진행하였다. 이와 더불어 네 가지 정책시나리오-Subsidy Cliff, Phase-out, Phase-in 50%, Phase-in 350%-를 구축하여 우리나라 2030년 전기차 보급목표인 3백만 대 달성 가능 여부를 확인하였다.

이러한 분석을 통한 결과에 따르면, 2030년 국내 전기차는 Subsidy Cliff 시나리오일 경우 1.37 백만 대와 Phase-out일 경우 1.40 백만 대,

Phase-in 50%일 경우, 1.87 백만 대, Phase-in 350%일 경우 3.01 백만 대가 보급될 것으로 분석되었다. 해당 시나리오의 결과를 보면, 보조금이 2030년 350%까지 인상되는 Phase-in 350% 시나리오를 제외한 세 가지 시나리오인 Subsidy Cliff와 Phase-out, Phase-in 50%가 국가 전기차 보급목표에 각각 1.63백만 대, 1.60 백만 대, 1.13 백만 대의 전기차가 추가적으로 보급되어야 하는 것으로 나타났다.

구축된 네 가지 시나리오를 지역별 전기차 보급 대수로 보면, 2019년 가장 많은 전기차가 보급된 지역은 제주, 서울 경기 대구 순이었으며, 2030년은 제주 경기 서울 대구 순으로 분석되었다. 시간이 지나며 2019년 대비 많은 전기차가 보급되었음에도 전기차 보급이 활성화된 지역은 순서의 차이는 있었으나 동일하였다. 하지만 전기차 보급을 거주 인구수와 대비하여 분석한 결과, 지역별 전체 전기차 보급 대수를 분석한 결과와 상반된 결과가 산출되었다. 2030년에 가장 많은 1인당 전기차 대수가 나온 지역은 제주, 울산, 강원, 전남 순이었다. 제주를 제외한 세 지역은 전체 보급대수로 보았을 때는 많은 전기차가 보급된 지역이 아니었지만 적은 인구수 대비 많은 전기차가 보급된 것으로 나타났다. 울산의 경우, 전체 전기차 대수를 보면 16개 시도에서 가장 적은 전기차가 보급되는 것으로 분석되었지만 인구대비로 보았을 경우는 특수케이스인 제주를 제외한 제일 많은 1인당 전기차 대수가 보급된 곳으로 분석되었다. 이는 자동차 공장이 있는 울산이 기존연구에서 전기차의 생산지나 공장이 있는 지역의 전기차 보급이 높게 나타난 것과 같은 생산지 효과로 사료된다.

본 연구의 세 번째 전기차 보급 분석인 국가전력수급계획에 따른 전기차 보급의 환경영향을 보기 위해 사용된 전과정평가는 제품이나 서비스의 환경영향를 정량화하는 분석 방법이다. 전기차 보급에 따른 분석을 하기에 앞서 목적 및 범위설정 단계에서 전기차의 연료생산 시의 전과정평가를 실

시하였으며, 전과정평가시 1kWh의 전력 생산 시를 기능단위로 설정하였다. 이와 더불어 전력생산 시에 발생하는 오염물질의 인벤토리를 분석하였으며, 본 연구에서는 전기차의 보급에 따른 환경영향을 분석하기 위해 차량의 수명인 11년과 통계청에서 제공하는 연간 주행거리, 두 번째 분석에서 산출된 정책별 전기차 보급 대수를 적용하여 보급 대수에 따른 환경영향을 분석하였다. 또한, 제8차 전력수급계획 옵션과 석탄화력발전의 신재생에너지로의 추가적 전환 옵션을 적용하여 비교 분석하였다.

환경 옵션으로 제시된 정격용량을 기준으로 산출한 제8차 계획과 신재생에너지로의 전환을 적용하여 전기차의 온실가스와 미세먼지 배출량을 보면, 온실가스는 8차 계획 옵션 시 81.7g CO_2e/VKT가 배출되며, 신재생에너지로의 전환 옵션 시, 37.2g CO_2e/VKT의 온실가스가 배출되는 것으로 나타났다. 온실가스 배출량이 가장 낮게 나온 신재생에너지로의 전환 옵션은 2016년의 실질 전원구성과 3.1배 차이가 나며, 내연기관차인 휘발유차와 경유차와는 각각 4.57배와 4.25배 차이가 나는 것으로 분석되었다. 또한, 최근 미세먼지 관련 이슈가 크게 대두됨에 따라 차량에서 배출되는 미세먼지 배출량의 환경영향을 분석해보았다. 휘발유와 경유, 전기차 중 가장 많은 미세먼지 배출량을 보였던 전기차는 8차수급계획 옵션을 적용 시 1km 주행 시 20.7mg PMe를 에너지 전환 옵션을 적용 시 9.4mg PMe/VKT를 배출하는 것으로 산출되어 12.4mg PMe/VKT의 배출량을 보인 내연기관차(휘발유) 보다 1.32배 적을 것으로 나타났다.

본 연구에서 전기차 보급에 영향을 미치는 인자분석을 위해 월간 지역패널자료를 이용하여 분석을 진행하였다. 하지만, 일반적인 연간자료를 이용한 패널분석이 아닌 월간 자료를 이용한 패널 분석을 하며 지역별 자료 구득에 있어 한계가 존재하였다. 특히, 전기차 보급에 영향을 미치는 충전시설이나 충전전력요금과 같은 주요 영향인자가 포함되지 않았다

는 점에서 향후, 지역별 충전시설의 월간 자료의 구축이 요구된다고 판단된다. 이와 더불어 본 연구에서는 미세먼지 변수를 농도로 적용하여 분석을 진행하였지만 향후, 기존의 연구에서 언급된 바와 같이 월별 미세먼지 나쁨 일수를 적용할 경우, 환경성 부분에서보다 더 정확한 결과 도출이 가능할 것이라 사료된다.

본 연구에서 진행한 세 가지의 분석 중 시스템 다이내믹스를 이용한 두 번째 파트의 분석은 다양한 시나리오 중 현재 예산을 매해 35% 증액하여 2030년 350% 인상에 도달하는 시나리오가 적합한 것으로 분석되었다. 하지만, 2023년을 기점으로 전기차 보조금 지급을 중단하는 정책을 시행하고 있는 우리나라의 입장에서는 현재 전기차 보조금을 위한 예산을 매년 35%씩 10년 동안 지속하는 것에는 어려움이 있기에 내연기관차로부터의 환경오염세와 같은 fee를 징수하여 친환경차인 전기차의 보조금을 rebate하는 피베이트 제도 (Feebate)를 해야 할 필요가 있다고 사료된다. 향후, feebate와 전기차 보급을 연계하여 연구가 가능할 것으로 판단된다.

Keywords : 전기자동차, 패널분석, 정책영향인자, 지역패널자료, 시스템 다이내믹스, 전기차 보급, 전과정평가, 환경개선효과

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