

The Projected Pathways and Environmental Impact of China's Electrified Passenger Vehicles

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Summer Jiakun Zhao

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Author: _____
Engineering Systems Division
May 8, 2015

Certified by: _____
Professor John B. Heywood
Professor of Mechanical Engineering
Sun Jae Professor, Emeritus
Thesis Supervisor

Accepted by: _____
Professor Dava Newman
Professor of Aeronautics and Astronautics and Engineering Systems
Director, Technology and Policy Program

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Abstract

As the world's largest market for car sales, China's rapidly rising number of light-duty vehicles (LDVs) on the road have resulted in serious problems such as increasing CO₂ emissions, energy insecurity, and air pollution. The question I examine here is how electrified vehicles (EVs) can help reduce China's energy demand and greenhouse gas (GHG) emissions in the future, and EV includes hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV), and battery electric vehicle (BEV). First, by building and using an Electricity Supply and Emissions Model (ESEM), I forecast the life-cycle GHG emissions intensity factors of the electric grid between now and 2050, proposing three scenarios that represent different levels of adoption of renewable generation by utilities. Then, by developing three EV penetration scenarios with other assumptions such as vehicles distance traveled and powertrain mix for a China FLEET model, I project the stock, energy demand, and life-cycle GHG emissions of the LDV fleet for each scenario until 2050. By comparing the results of these different scenarios, I demonstrate to what extent electrification can reduce the LDV fleet's energy demand and emissions impact.

Results from this study show that there is a significant potential for electrification to reduce the automotive energy demand, oil dependence, and life-cycle GHG emissions of the LDV fleet, because EVs and especially BEVs are much more efficient than traditional gasoline vehicles. Compared to growing the renewable energy contribution to the electricity supply system, expanding EVs in the fleet can occur on a faster time scale, provided that they become more attractive relative to conventional gasoline vehicles; the greater potential for aggressive EV penetration to reach a significant percentage suggests that strong efforts of promoting EVs are likely needed to take advantage of their reduction opportunities. However, cleaning up the grid is important not only because it helps lower the emissions of aggressive EV expansion, but also because power generation accounts for the majority of China's total energy consumption and emissions. Results also show that, in order to help China reverse the rising trajectory of CO₂ emissions by 2030, the aggressive EV scenario and the more-renewables electricity scenario will likely be needed, which could enable the LDV fleet to peak its emissions as early as 2033.

Thesis Supervisor: John B. Heywood
Title: Professor of Mechanical Engineering
Sun Jae Professor, Emeritus

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Abbreviation

BEV	Battery Electric Vehicle
CNG	Compressed Natural Gas
EI	Emissions Intensity
EPPA	Emissions Prediction and Policy Analysis (model)
ESEM	Electricity Supply and Emissions Model
EV	Electrified Vehicle (including HEV, PHEV, and BEV)
FC	Fuel Consumption
GHG	Greenhouse Gas
HEV	Hybrid Electric Vehicle
ICE NA-SI	Naturally Aspirated Spark-Ignition Internal Combustion Engine
LDV	Light Duty Vehicle
Mmt	Million metric tons
Mtoe	Million tons of oil equivalent
NDRC	National Development and Research Council
NEA	National Energy Administration
NEV	New Energy Vehicle (including PHEV, BEV, and fuel-cell vehicle)
PDT	Person Distance Traveled
PEV	Plug-in Electric Vehicle (including PHEV and BEV)
PHEV	Plug-in Hybrid Electric Vehicle
RE	Renewable Energy
TCAEM	Tsinghua China Automotive Energy Model
Turbo-SI	Turbo-charged Spark-Ignition Engine
VDT	Vehicle Distance Traveled

Chapter 1 Introduction

1.1 Proposed Solutions

As China becomes the largest economy in the world, it has also become the largest market for car sales. However, the tremendous growth of China's vehicle fleet has led to serious air pollution, CO₂ emissions, traffic congestion, and energy insecurity. In fact, China's transportation sector ranks second in emitting CO₂ pollution, just after the United States (The World Bank 2012). To address these problems, China has taken actions such as raising the fuel standards, limiting vehicles on the road, improving the energy efficiency of vehicles, and adopting new energy vehicles.

My research focuses on electrified vehicles (EVs) as a way to help reduce fuel consumption and greenhouse gas emissions. EV in this study includes hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV) and battery electric vehicle (BEV), and this study puts a main focus on PHEV and BEV. These vehicles use electricity and are more efficient than regular gasoline vehicles; so they have high potential for reducing energy demand, solving energy insecurity and related environmental problems. However, it is not clear exactly how effective EV could be in reducing energy demand when it is blended into the fleet, and there are debates regarding how effective EV is in reducing the overall emissions of the fleet, especially as it gets electricity from generating sources dominated by coal in China.

Therefore, the questions this study explores are: (1) To what extent would EV make a difference in reducing the energy demand and emissions of the fleet? (2) How clean should the electricity supply system be in order for EV to effectively reduce the emissions of the fleet? I focus on China's light-duty vehicle fleet, investigating this fleet within the time frame of now to 2050. In addition, because China aims to reverse the rising trajectory of CO₂ emissions by 2030,¹ this study also uses this as a benchmark to find out what scenarios of EV expansion and renewables adoption would contribute to reaching the CO₂ peaking goal.

¹ In 2014, President Obama and President Xi signed a U.S.-China joint statement together, in which China announced that it will enable the CO₂ emissions to reach the peak by 2030.

In order to address the first question, a China FLEET model is used that adopts a bottom-up approach to forecast the vehicle stock, fuel use, and emissions of the fleet, by tracking vehicle sales, scrappage rates, vehicle distance traveled, fuel consumption, and emission intensity factors of fuel sources. I developed three EV penetration scenarios (sensible, aggressive, and passive) and modified the model to reflect my assumptions.

To address the second question, I built an Electricity Supply and Emissions Model to forecast the electricity generation and the average greenhouse gas (GHG) emissions intensity factors of the grid in China until 2050. To reflect the different levels of aggressiveness in incorporating renewables in the grid, I carried out this model given three different electricity scenarios: planned, more-renewables and less-renewables.

The uniqueness of my study is that it evaluates and forecasts electrification's impact on the energy demand and emissions of the fleet, by varying the level of EV penetration and renewables adoption through different scenarios. It also makes specific assumptions that other studies have not incorporated. The next sections provide a literature review, discuss my contribution in more details, and introduce the structure of the rest of the thesis.

1.2 Literature Review

A variety of studies have forecast the potential for electrified vehicles (EVs) to reduce the environmental impact of the transportation system. Most of the studies use models that forecast the growth of either the transportation sector as a whole or the light-duty vehicle (LDV) fleet, and then they make assumptions about the level of EV penetration in the fleet and forecast the environmental impact based on the EV scenario. For example, Ou et al. designed five scenarios including one with high EV penetration, using a bottom-up model to analyze the energy demand and GHG emissions impact for the entire transportation sector under each scenario until 2050 (Ou, Zhang, and Chang 2010). The China Automotive Energy Research Center at Tsinghua University built a TCAEM model that forecasts the development of the entire automotive sector, and it specifically designs an EV scenario to evaluate how EV penetration changes the energy

usage and emissions of the transportation sector (China Automotive Energy Research Center Tsinghua University 2012). They find that EV penetration can greatly improve the efficiency of the automotive energy system and reduce the country's reliance on foreign oil.

Instead of working at the national level, Wu et al. focus on three distinctively well-developed regions in China to evaluate the impact of EV penetration on reducing CO₂ emissions from the LDV between 2010 and 2030 (Y. Wu et al. 2012). Different scenarios of EV penetration and grid emissions intensity were constructed for these regions. They find that EV penetration could effectively mitigate gasoline demand and emissions, although the emissions reduced from EV are less than from gasoline vehicles because of the heavy coal consumptions in the power sector.

The study conducted by Hao et al. is the closest to my analysis in terms of the scope, except that it does not analyze different scenarios of EV penetration and grid's renewable energy expansion (Hao, Wang, and Ouyang 2011). Hao et al. forecast the fuel consumption and GHG emissions of the LDV fleet between 2010 and 2050 in various designed scenarios, including the *promoting EV scenario*. They calculate how promoting EV could reduce the environmental impact compared to the reference and other scenarios including downsizing the vehicles and limiting vehicle trips. The EV in the study includes HEV, PHEV and BEV, and they are further categorized into private passenger vehicles, business passenger vehicles, and taxis. They find out that in terms of fuel conservation, constraining vehicle registration and improving fuel efficiency are the most effective options, and promoting EV adoption is effective only over the long term. In addition, EV penetration would not save as many emissions as the other two methods do due to the higher GHG emissions intensity factors of the grid.

A small number of studies directly analyze the growth of EV in China in the short term, including a study using the Bass model to forecast the stock of EV from 2011 to 2020, taking into account oil prices, innovation and imitation effects (Ming et al. 2013). Another study uses a dynamic segmentation approach to forecast the market share development of EV in China, capturing patterns distinct from those observed in developed countries through 2050 (Qian and Soopramanien 2014).

Other studies examine the environmental impact of EVs at the vehicle level. For example, Huo et al. measure the CO₂, SO₂, NO_x emissions of EVs in different regions of China, comparing their emissions per kilometer with conventional vehicles, in both 2008 and 2030 (Huo et al. 2010). They find that EVs are promising, but using electricity from today's coal-heavy power grid will offset EVs' potential emissions reduction benefits. Another study uses the GREET-based Tsinghua_LCAM model to analyze and forecast the energy and emissions saving per km for PHEV and BEV on regional-level power grids, comparing them with that of conventional vehicles in the time period of 2012-2020 (G. Zhou, Ou, and Zhang 2013). They find a big difference in energy and emissions savings for EVs powered by different regional grids, and in the future, those savings due to EV development are expected to be more significant.

1.3 Contribution and Organization

The contribution of my analysis is to evaluate the impact of vehicle electrification on total LDV fleet's energy demand and GHG emissions, by varying the aggressiveness of EV penetration in the fleet and renewables adoption in the grid. In this research, an original Electricity Supply and Emissions Model (ESEM) is developed with three electricity scenarios, which are combined with three EV scenarios used as inputs for the China FLEET model. Together, these two models and a combination of scenarios show the relative impact, importance and inter-dependency of expanding EV use and cleaning up the grid. Such analysis has not been performed previously for the LDV fleet on a national scale.

Second, this study makes detailed assumptions about various aspects of the LDV fleet, which has not been captured by previous studies. For example, it divides the powertrain BEV into regular-BEV and micro-BEV to reflect the trend of a strong micro-BEV growth in China's EV industry. It also makes different assumptions for vehicle types categorized into private, non-private, mini-bus and mini-trucks, and it tailors assumptions such as vehicle distance traveled (VDT) and fuel consumption to powertrains like micro-BEV. The China FLEET model allows us to see what assumptions are most critical to achieve energy and emissions reduction, and through identifying the peaking time of emissions in different scenarios, it is able to draw policy implications for the government.

In the rest of the study, Chapter two presents the Electricity Supply and Emissions Model (ESEM), demonstrating the model structure, scenarios, data, assumptions, and results. The main result, the GHG EI factors, is imported to the China FLEET model.

Chapter three gives an overview of the EV market in China, including critical governmental policies promoting EVs, the market size and growth, the emergence of the micro-BEVs, and the challenges such as battery technologies and charging infrastructure.

Chapter four introduces the China FLEET model and compares it with two other models that also forecast fleet energy demand and emissions; this comparison enables a better understanding of the FLEET model and how it differs from others.

Chapter five demonstrates the data and assumptions developed for the China FLEET model, including the split of BEV, sales mix in different scenarios, VDT, fuel consumption, and GHG emissions intensity factors.

Finally, Chapter six provides the important findings and results in terms of vehicle stock, energy demand, and GHG emissions forecast, and Chapter seven concludes with a short discussion of policy implications and limitations of this study.

Chapter 2 Electricity Supply and Emissions Model (ESEM)

2.1 Introduction

As of 2012, China had the world's highest installed generating capacity (EIA 2012), burned the most coal, and was the largest source of CO₂ emissions in the world. Thus, it is critical to make China's electricity supply system green enough in order to reduce the environmental impact of its anticipated large numbers of electrified vehicles. The GREET model shows that power generation is responsible for 99% of total fuel-cycle CO₂ emissions of EVs powered by coal-based electricity, suggesting that power generation is by far the dominant contributor to CO₂ emissions of EVs (Huo et al. 2010). This section presents the Electricity Supply and Emissions Model (ESEM) used in the study, which forecasts the lifecycle greenhouse gas (GHG) emissions intensity (EI) factor of the power supply sector in China between 2015 and 2050.

I start by briefly introducing the model and giving some background information on China's electric power sector. Then, the three scenarios will be presented, along with the model structure, the data and assumptions, and the results.

As a high-level overview, ESEM includes six primary energy sources and their power generation technologies: coal, natural gas, nuclear, hydro, wind and solar.² It assumes three scenarios for how the power sector would develop: the *Planned* scenario that reflects the government's mandates, the *More-Renewables* scenario that assumes aggressive development of non-fossil energy, and the *Less-Renewables* scenario that assumes modest non-fossil energy growth. The major output of the model is the EI factor of the power grid, which will be directly imported into the China FLEET model described in Chapter 4.

There are many different ways of forecasting the electricity generation of the grid. One way is to use economic analysis such as the interaction among elements such as GDP, pricing, global trade,

² I did not include oil and biomass because they currently constitute very small proportions of the entire power generation mix. Furthermore, the share of oil-generated electricity will continue to decrease until it reaches 0 [citation]. Therefore, given that their impacts on the grid and the environment would be low in the future, I do not see it necessary to include oil and biomass in the electricity generating system.

and policies to predict the energy demand, an example of which is the China-in-Global Energy Model (C-GEM) developed by Tsinghua and MIT (Zhang et al. 2014). Other ways include using the load duration curve and screening curve model to forecast the energy mix by ranking generating capacities in the order of decreasing marginal cost. Mathews and Tan projected electricity generation through 2050 based on observed logistic industrial dynamics for adopting renewable energies and the continued development of fossil fuels (Mathews and Tan 2013). ESEM is different from these approaches.

China has six major regional electric power grids: the North China, Northeast China, East China, Northwest China, Central China, and South China power grids. The State Grid Corporation of China governs these grids except the South China power grid. There is a wide difference among the grids in that while the north and northeast grids have 98% and 93.11% thermal power of the total power supply, the central and southern grids only have 62.36% and 67.28% thermal power (G. Zhou, Ou, and Zhang 2013).

China's power grid system operates very differently from that in the United States. In terms of investment, the power sector is largely under the central government's ownership, with increasing amount of investment from the provincial governments. It is up to the central government to approve generation projects larger than 50 MW, and it also has control over wholesale and retail pricing in the electricity market (Kahrl, Williams, and Hu 2013). Because of this, when forecasting the capacity expansion of the power sector, it is important to analyze what the central government's intended plan is; a model based on governmental mandates might give more insight than a model that assumes a free market and optimizes costs.

China also dispatches generators differently. Dispatch involves the grid operator asking generators to increase or decrease output in order to meet the demand. In the U.S. and most of the world, grid operators typically dispatch generators in the order of increasing variable cost of operation (Kahrl, Williams, and Hu 2013). In this way, the more fuel efficient and less costly generators will operate for more hours while the less efficient and more costly ones will operate for fewer hours. However, China does not dispatch generators in this cost efficient way.

Instead of using the “merit order” approach in dispatching generators, China uses the “Generation quota system” (Kahrl, Williams, and Hu 2013). Under this approach, in order to guarantee reasonable returns for the generators, the provincial National Development and Reform Commission (NDRC) set the annual operating hours (or the capacity factor) for the generators, and these have to be approved nationally by NDRC. Therefore, the dispatch priority of generators in China is not based on marginal cost. Nevertheless, several provinces have slowly started to pilot the “Energy Efficient Dispatch” since 2007, which prioritizes wind, solar, hydro and nuclear in the dispatch order, but the implementation has been difficult, and during heating seasons thermal plants are still given priority (Kahrl, Williams, and Hu 2013). Although this pilot approach could improve the efficiency, it still does not optimize dispatch based on the variable cost of the generators.

An implication of China’s quota-based dispatch is that the normal method of using the Load Duration Curve to forecast the capacity factor may not be appropriate for China, since dispatch does not occur on the basis of variable cost. So, in ESEM, I kept the annual operating hours to be almost constant to mirror reality.

This approach also partially explains why there is so much curtailment of wind and solar and the current capacity factors of which are very low. The annual capacity factors for wind and solar have been below 25% and 15%, respectively, in China, while they are normally above 30% and 15% in the U.S. (U.S. Energy Information Administration 2015). One of the reasons is, as explained above, that thermal power plants dominate the power generation and there is no systematic, nationwide policy to prioritize the dispatch of renewables. Other reasons include: (1) systematic technology failures among the wind industry in China; equipment such as blades, generators and converters have broken down, which would reduce the capacity factor (Z. Wang, Qin, and Lewis 2012); (2) difficulties of grid integration due to poor quality control and lack of policy incentives (Z. Wu, Sun, and Du 2014); (3) a lack of transmission grid connections for remote wind and solar resources (C. Li et al. 2015); and (4) a lack of appropriate backup generation capacity that uses resources such as natural gas and hydro (M. Yang, Patiño-Echeverri, and Yang 2012).

In addition to modeling the power system in a way that captures the observed operational characteristics in China, I constructed two other scenarios that assume potential changes in policies and outcomes that favor more or less renewable energy growth. They are briefly presented in the next section.

2.2 Scenarios

The first scenario is called the “Planned” scenario; its goal is to reflect the government’s current intention. It models the government’s planned path: i.e., how it intends the electricity sector to develop. What this scenario describes is likely to happen in that governmental mandate and plans play a major role in shaping the direction of the electricity sector. Under this scenario, the capacity of the grid is forecasted in accordance with the Chinese government’s mandates, action plans, and recommendation documents.

For example, the government and related agencies have published action plans and recommendation documents that guide the development of the installed capacity growth of the power sector, such as the Energy Development Strategy Action Plan (2014-2020) released by the State Council. I also consulted other governmental documents such as the China Renewable Energy Center’s roadmap for developing renewable energy until 2050 and the recommendation documents published by the National Energy Administration.

The second and third scenarios are called “More-Renewable Energy” and “Less-Renewable Energy” scenarios, the abbreviations of which are “More-RE” and “Less-RE”. These two scenarios represent the potential changes in policies leading to the different possible outcomes of the development. Under *More-RE*, the government will issue stricter policies that contain the development of thermal power plants, and larger amount of wind and solar capacity will be built compared to the planned scenario. Under *Less-RE*, the government will focus less on increasing renewables and containing emissions from thermal power plants; as a result, coal and natural gas increase more significantly while wind and solar grow more modestly than the planned scenario. Both scenarios assume that the nuclear and hydro capacity would not vary too much from the

planned scenario, and all three scenarios have the same total electricity generation. More details will be explained in the Data & Assumptions section.

By running these scenarios in ESEM, I generate the emissions intensity factors for each scenario, which will be applied to the China FLEET model. Below is a detailed description of ESEM.

2.3 Model Structure

The model uses three major sets of inputs: (1) the installed capacities for the three scenarios, (2) the annual utilization hours³, and (3) the lifecycle greenhouse gas (GHG) emissions intensity factor for each power generating technology. The annual utilization hours (the second input) are the total hours in a year during which each power generating technology is utilized. It reflects the actual hours the facilities run in a year, so this would be after any curtailment takes place for renewables such as wind and solar. The utilization hours can be expressed as the inverse of the capacity factor. The conversion between them is shown below:

$$Capacity\ Factor = \frac{Annual\ Utilization\ Hours}{365\ (days) \times 24\ (hours)} = \frac{Annual\ Utilization\ Hours}{8760\ (hours)}$$

There are three major outputs for each scenario on a yearly basis between year 2015 and 2050: (1) the generation and energy mix, (2) the CO2 emissions of the entire grid, and (3) the lifecycle GHG emissions intensity (EI) factor of the grid. The EI factor output is the most important one as it will be used as an input to the FLEET model.

Figure 2-1 shows the block diagram of the model. The outputs are not generated simultaneously, as some of the outputs are used as inputs elsewhere in the model.

³ 年利用小时数 in Chinese

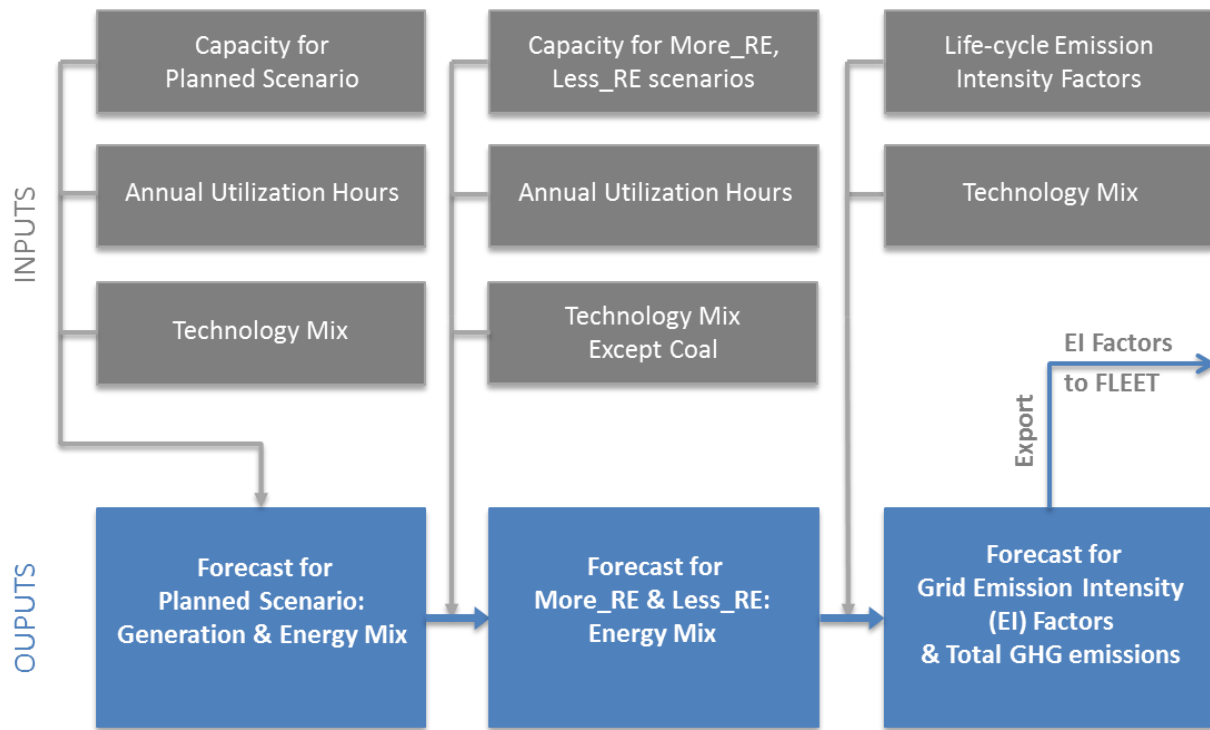


Figure 2-1 Diagram of the Electricity Supply and Emissions Model (ESEM)

As Figure 2-1 shows, the total generation and energy mix of the planned scenario (P) are the first outputs. The total generation is derived by multiplying together the generating capacity and annual utilization hours by technology (T) for a given year (Y).

$$Total\ Generation_{Y,P} = \sum Capacity_{Y,P,T} \times Annual\ Utilization\ Hours_{Y,P,T} \quad (2.1)$$

The energy share (ES) for each technology in a given year is determined by dividing the generation per technology by the total generation in that given year:

$$ES_{Y,T} = \frac{Generation_{Y,T}}{Total\ Generation_Y} \quad (2.2)$$

The total generation output from the first scenario will serve as an input for the other two scenarios More-RE (M) and Less-RE (L). The reason is that the society's demand for electricity

would not change regardless of how aggressive the expansion of power capacity or how aggressive the policies are; so the total generation should be the same across all three scenarios:

$$Total\ Generation_{Y,P} = Total\ Generation_{Y,M,L} \quad (2.3)$$

While the total generation stays the same, the energy mix would be different. The generation (G) for natural gas (NG), nuclear, hydro, wind and solar are determined in the same way by multiplying capacity and annual utilization hours; for example:

$$Solar_{G,Y,M,L} = Capacity_{solar,Y,M,L} \times Annual\ Utilization\ Hours_{solar,Y,M,L} \quad (2.4)$$

But the generation of coal for a given year is determined by subtracting from the total generation the sum of the all the other technologies' generations:

$$Coal_{G,Y,M,L} = Total\ Generation_{Y,M,L} - \sum NG_{G,Y,M,L} + Nuclear_{G,Y,M,L} + Hydro_{G,Y,M,L} + Wind_{G,Y,M,L} + Solar_{G,Y,M,L} \quad (2.5)$$

The energy mix for the More-RE and Less-RE scenarios is calculated in the same way as equation (2.2).

Finally, the third set of outputs, the emissions intensity factors and the total emissions are generated. The annual average emissions intensity factor of the grid for each scenario is derived by weighting the emissions intensity factor (EI) in each year for each technology by its energy share (ES):

$$Average\ Emission\ Intensity\ of\ Grid_{Y,P,M,L} = \sum EI_{Y,P,M,L,T} \times ES_{Y,P,M,L,T} \quad (2.6)$$

The total GHG emissions in a given year for each scenario are determined by multiplying together the EI factor and the corresponding generation for each technology:

$$Total\ GHG\ emissions_{Y,P,M,L} = \sum EI_{Y,P,M,L,T} \times Generation_{Y,P,M,L,T} \quad (2.7)$$

The result of the annual average emissions intensity of the grid for each scenario (2.6) is then exported from ESEM and imported into the China FLEET model.

It is important to note that ESEM forecasts the average generation mix rather than the marginal generation mix. Although in reality the additional demand from electric vehicle comes from the units on the margin that will be dispatched, it requires extensive development of electric power system dispatch models and forecasting the detailed hourly charging scenarios. In China, the hourly load profiles of national and regional grids and the load duration curve are not publicly available. Therefore, ESEM forecasts the average emissions intensity of the grid; the marginal analysis is beyond the scope of this study.

2.4 Data & Assumptions

This section discusses the assumptions made and data collected for ESEM's three major inputs: the emissions intensity (EI) factors for different power generation technologies; the power generating capacity for each generation technology in each scenario; and the annual utilization hours for each generation technologies.

2.4.1 Emissions Intensity (EI)

ESEM focuses on projecting the EI of the grid at the national level, although it would be interesting to capture the regional EI differences. The reason for not working at the regional level is that there is a lack of data on the provinces, including the breakdown of coal and natural gas in thermal energy production as well as the provincial governments' capacity expansion plans. Also, there is increasingly more inter-connection power transfer among the regional grids. Due to the

Strong Smart Grid plan in China, the originally isolated grids will have more inter-regional power transmissions (C. Wang et al. 2014), and so it would be overcomplicated to forecast the expansion in each grid in the future.

To forecast the average lifecycle GHG EI factor for each electricity generation technology at the national level, we need current data on the technologies as well as the projected improvement of technology efficiencies.

To obtain a comprehensive view of the current EI factors of different power generating sources, I reviewed a number of literatures. The complete overviews of the range of GHG EI of the generating technologies in the world have been conducted by IPCC (Schlömer et al. 2014) and the World Nuclear Association (World Nuclear Association 2011). The GHG EI of actual solar and wind power plants in China is measured by studies such as C.Q. Chen et al. (G. Q. Chen, Yang, and Zhao 2011) (G. Q. Chen et al. 2011); other studies summarize the GHG intensity of power technologies based on literature review (Nugent and Sovacool 2014) (Liu et al. 2012). An assessment and comparison of the four clean-coal-power-generation technologies in China, including the ultra super-critical power generation, is provided by Liang et al. (Liang et al. 2013).

Ou et al. have generated a series of papers evaluating the current and future life-cycle GHG EI factors for the electricity supply in China at both national and regional levels, using a Well-to-Meter analysis that adjusted the GREET model to be specific to China (Ou, Zhang, and Chang 2010). The Well-to-Meter approach not only examines the upstream (resource extraction and transportation) and the production and generation, but also the downstream electricity transmission and delivery in China. GHG emissions are calculated as CO₂ equivalents (CO_{2-e}) by the expression based on the global warming potentials of GHG (Ou, Xiaoyu, and Zhang 2011):

$$GHG = CO_2 + 23CH_4 + 296N_2O$$

The GHG EI base-year data in ESEM come from a total of nine studies from the above-mentioned. Ou et al.'s 2011 data are most relevant, comprehensive, and within the boundaries derived from eight other studies; therefore they are the main ones adopted. However, Ou et al.

(2011) assume zero GHG emissions for wind and solar, which ignores manufacturing-related emissions. I therefore use IPCC’s average life-cycle GHG EI for wind and solar (Schlömer et al. 2014). The summary of the base-year GHG IE is shown in Table 2-1.

Table 2-1 Current lifecycle GHG IE for each technology

Technologies	Coal	Natural Gas	Nuclear	Hydro	Wind	Solar
g CO_{2-e}/kWh	1051.2	561.6	23.4	17.82	10.8	46.8

The EI are expected to gradually decrease as the energy technologies improve over time. For coal, the most efficient generation technology is the ultra super-critical (USC) power generation. It is reported that at present China has around 200 units of USC plants, and the lifecycle EI for USC is 801 g CO_{2-e}/kWh (Liang et al. 2013). The 700°C USC power plant is the most efficient possibility, as it could reach a net efficiency of 50% and more (National Energy Administration 2010). However, because of the difficulties in its required materials, technologies, and limit on plant sizes, it is unlikely that the average coal power plants will be as efficient as a 700°C USC by 2050. So I use 801 g CO_{2-e}/kWh as the lowest boundary the average coal power plants in China will reach.

As required by the Chinese government, the efficiencies of coal-fired power plants have gradually been improving, and the rate of coal consumption in the power supply has been decreasing. The historical coal consumption rate is shown in Table 2-2 (Qi 2014); it has been reduced steadily by 1% per year over the past several years.

Table 2-2 Historical annual coal consumption rate

	2007	2008	2009	2010	2011	2012	2013
g coal/KWh	356	345	340	333	329	324	321

I therefore assume that the EI for coal generation will also decrease by 1% per year from the current level of 1051 g CO_{2-e}/kWh, until it reaches 801 g CO_{2-e}/kWh as shown in Table 2-3. It turns out that in ESEM the EI for coal generation will reach this level by year 2038 and then stay flat until 2050.

For the other generation technologies, the lowest boundaries for their EI are set according to the lower bound of the EI range that the IPCC reports for each technology (Schlömer et al. 2014). A logarithmic function is used to derive the decreasing rate of EI for these technologies. The input data and assumptions for EI are summarized in Table 2-3:

Table 2-3 Assumptions of the changes in EI for each technology

(CO _{2-e} /kWh)	Base – 2011	Growth Rate	Lowest Boundary
Coal	1051.2	-1.0%	801.0
Natural Gas	561.6	-0.8%	410.4
Nuclear	23.4	-4.7%	3.6
Hydro	17.8	-4.0%	3.6
Wind	10.8	-2.8%	3.6
Solar	46.8	-6.4%	3.6

The EI assumptions are set to be different across the three scenarios: under the planned and More-RE scenarios, EI is set to change in the way described above; under the Less-RE scenario, however, EI is set to stay constant. The purpose of this is to stress the passive nature of Less-RE; under this scenario, very little progress is made on improving the efficiencies of the power generating technologies.

2.4.2 Electricity Generating Capacity

2.4.2.1 Historical data

Figure 2-2 shows the historical capacity expansion of China's electricity system. Fossil fuels, including coal and natural gas, accounted for 67% of the total installed capacity, and the share of non-fossil capacity in the electricity sector was around 33% in 2014.

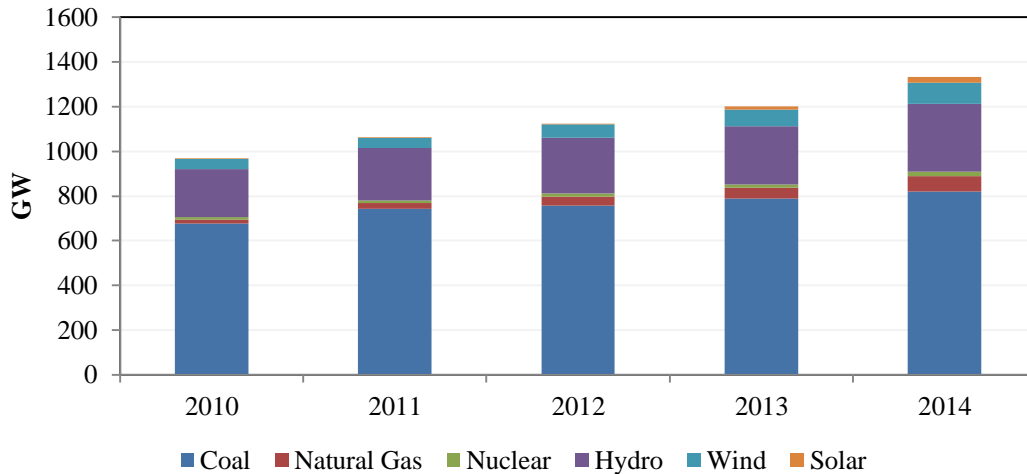


Figure 2-2 Historical installed capacity for each technology (China Electric Power Yearbooks)

Across all the three scenarios that will be introduced later, the assumptions of how hydro and nuclear would develop stay relatively the same. It is expected that a substantial amount of hydro and nuclear will be developed in China since they are currently cost-effective substitutes for coal (Zhang et al. 2014). Literatures suggest that the upper limit for hydro capacity expansion is expected to be between 400 and 500 GW, and a growth rate of 1-2% per year would get it there (National Energy Administration 2013). The Chinese government has also been determined to develop nuclear energy, although public attitudes toward nuclear power may hold expansion back. In my scenarios, because the EI of hydro and nuclear is small and the changes in capacity would not give vastly different results, I keep their capacities relatively the same across scenarios.

2.4.2.2 *Planned scenario:*

The Chinese government has issued plans and suggestions on how the capacity for the different technologies could develop in the future. For example, the Energy Development Strategy Action Plan (2014-2020) issued in 2013 mandated that the electricity generating capacity of nuclear, hydro, wind and solar reach respectively 58 GW, 350 GW, 200 GW, and 100 GW by 2020 (China State Council 2014). NEA also suggested that the total generating capacity would reach around 3300 GW and gave the ranges of the expected capacities of the different technologies in 2050 (National Energy Administration 2013).

With information collected from these sources and studies conducted by the government-affiliated agencies, I develop the assumptions that the share of non-fossils will reach 44% and 54% in 2030 and 2050, respectively, as shown in Table 2-4:

Table 2-4 Assumptions of installed capacity for each technology in planned scenario

(GW)	2015	2020	2030	2050
Coal	850	1000	1300	1450
Natural Gas	72	82	100	125
Nuclear	25	58	180	350
Hydro	320	350	400	500
Wind	110	200	350	700
Solar	38	100	150	225
Total	1415	1790	2480	3350

2.4.2.3 *More-RE scenario*

Under this scenario, I assume wind and solar will develop aggressively, as shown in Table 2-5. The China Renewable Energy Center made forecasts of the development of renewables until 2050 (China Renewable Energy Center 2014). Because the Center is known for making overly aggressive projections, I took the average of the capacity forecasts from its reference and aggressive scenarios to form the capacity inputs for wind and solar. Hydro and nuclear grow slightly more slowly than those in the planned scenario, and natural gas almost stays flat.

Table 2-5 Assumptions of installed capacity for each technology in the more-RE scenario

(GW)	2015	2020	2030	2050
Natural Gas	70	70	70	70
Nuclear	25	58	150	300
Hydro	310	350	400	450
Wind	120	250	800	1500
Solar	50	195	435	1360

2.4.2.4 *Less-RE scenario*

Under this scenario, I assume wind and solar will develop modestly. Their installed capacities are roughly half of the capacities in the planned scenario, as shown in Table 2-6. Hydro and nuclear grow slightly more slowly than in the planned scenario, and natural gas grows significantly.

Table 2-6 Assumptions of installed capacity for each technology in the less-RE scenario

(GW)	2015	2020	2030	2050
Natural Gas	80	115	170	250
Nuclear	25	58	150	300
Hydro	310	350	400	450
Wind	105	120	180	350
Solar	30	45	70	110

2.4.3 Annual Utilization Hours

The annual utilization hours for coal, natural gas, nuclear and hydro are similar to values typical in the U.S. I assume a modest increase in the utilization hours for these technologies due to the potential improvement in their efficiencies.

The annual utilization hours, or the capacity factor, are very low for solar and wind, and the reasons have been illustrated in Section 2.1. In theory, the capacity factor for wind should decrease over time, because the initial plants are always built in the locations with the best wind resources, and future plants will be built at less favorable sites. However, it is unclear whether the initial wind power plants were all built at the best locations in China. In addition, the curtailment for wind and solar is very likely to decrease since the Chinese government has been increasingly prioritizing wind in the dispatch, and more interconnection grids have been built to better integrate the renewable sources. Given the uncertainties of how these effects would offset one another, I assume a modest increase in the annual utilization hours for both wind and solar. The summary of the assumptions is shown in Table 2-7.

Table 2-7 Assumptions of annual utilization hours for each technology

(Hours/Year)	2015	2020	2030	2050
Coal	5100	5100	5000	5000
Natural Gas	2500	2800	2800	2800
Nuclear	7500	7800	7800	7800
Hydro	3300	3400	3400	3400
Wind	1600	1800	2000	2000
Solar	900	1000	1200	1200

2.5 Results from ESEM

This section first presents the results of the electricity generation forecast and the difference among the scenarios. Then it reports the emissions intensity factors that will be imported to the China FLEET model.

2.5.1 Electricity Generation Results

As shown in Figure 2-3, the total electricity generation in the planned scenario will reach 13,700 TWh in 2050, with 56% coming from fossil fuels including coal and natural gas. The share of nuclear, hydro, wind and solar will reach 20%, 12%, 10% and 2%, respectively, by 2050. The total power generation grows rapidly before slowing down after year 2030. This is partially due to a slower growth rate of coal generation after 2030, and is in line with expectations that China's economic growth will slow down. The generation output from hydropower stays relatively flat while nuclear rises to claim the biggest share of the non-fossil generation.

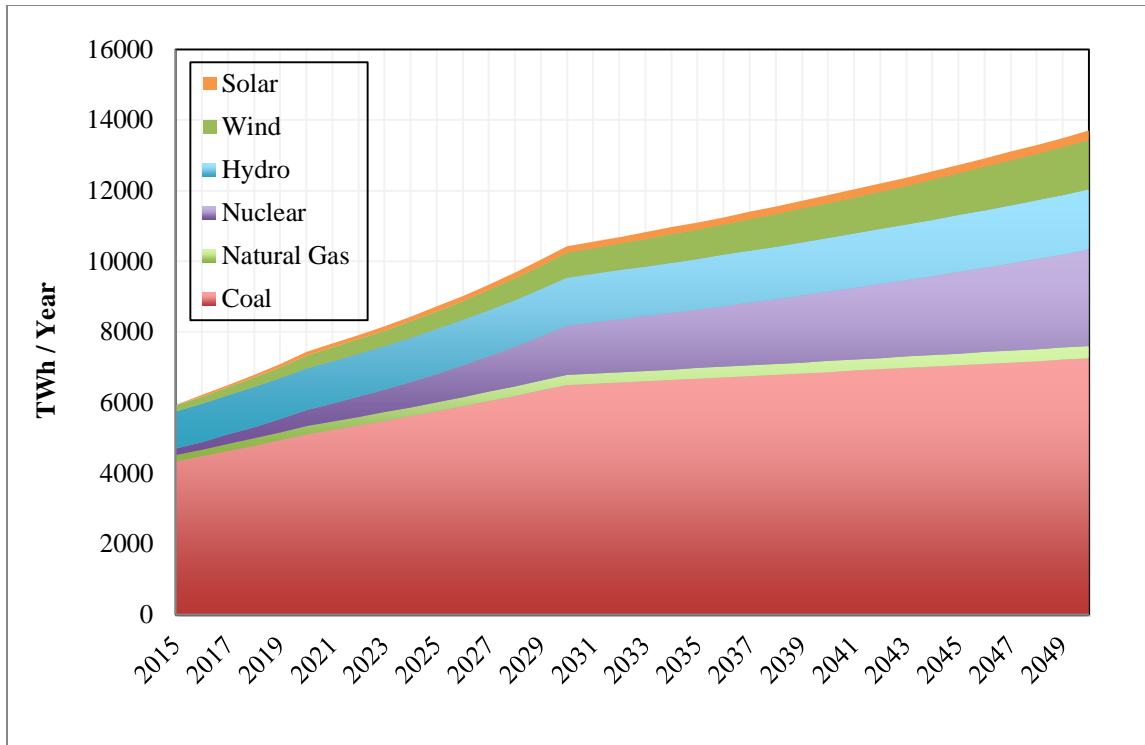


Figure 2-3 Electricity Generation Forecast for the Planned Scenario

A number of studies have forecast the installed capacity and generation of electricity until 2050, including Ernest Orlando Lawrence Berkeley National Laboratory (N. Zhou et al. 2011), the China State Grid Energy Research Institute (Hu 2011), China Development Bank (J. Wu 2013), Tsinghua-MIT China Energy & Climate Project (Zhang et al. 2014), and the China Automotive Energy Outlook 2012 report using the Tsinghua China Automotive Energy Model (TCAEM).

Figure 2-4 presents a comparison between their results and the generation forecast from the ESEM's planned scenario. It shows that the result from ESEM (black line) matches closely with the forecast conducted by the research branch of the China State Grid. It also falls into the range of results from the other studies as well.

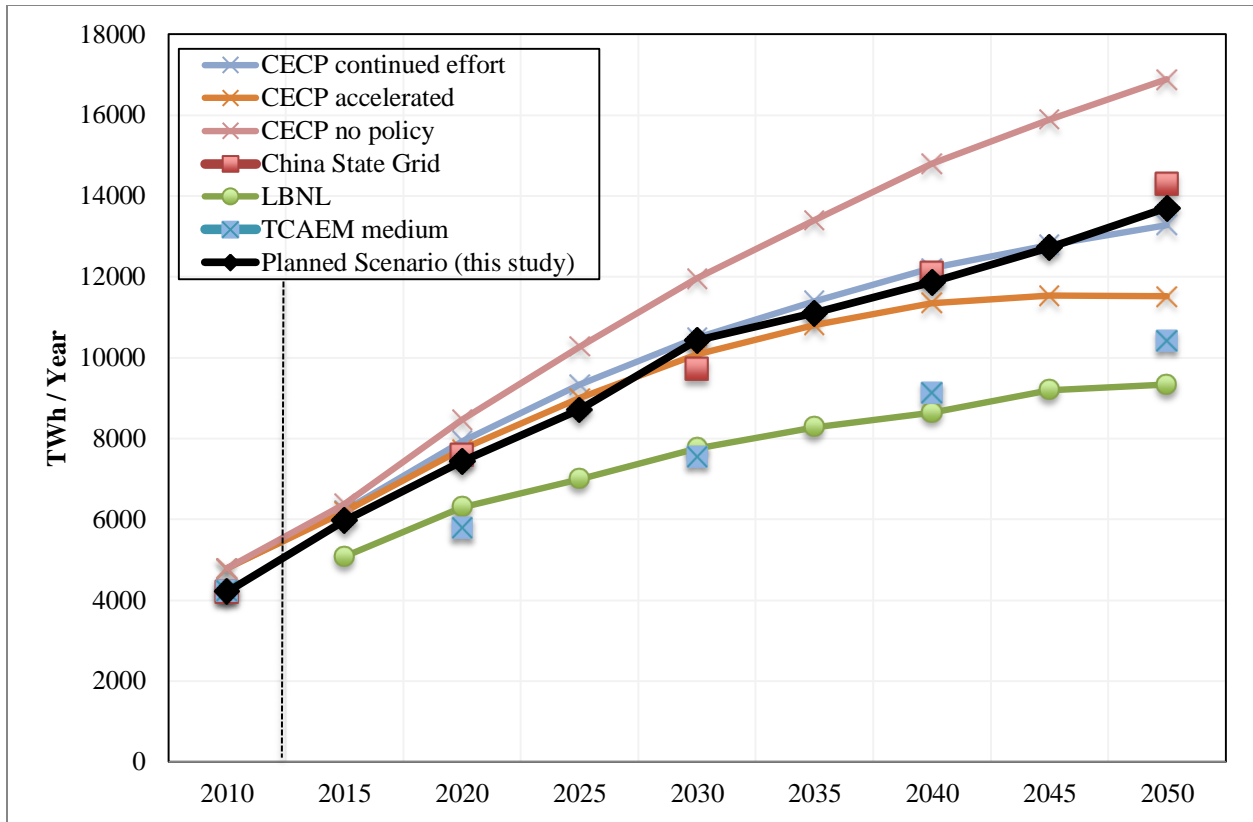


Figure 2-4 Comparison of the total generation forecast from ESEM with other studies

The forecast of the total electricity generation is the same for all three scenarios, but the energy mix varies in different scenarios. As shown in Figure 2-5 (left) for the more-RE scenario, fossil fuels will take up only 38% of the total generation in 2050. The share of wind and solar will rise to 22% and 12%, more than doubling their shares in the planned scenario. Nuclear and hydro's share is similar to that in the planned scenario, reaching 17% and 11% by 2050. It is difficult to eliminate coal in China's context due to its abundant resources; but the trend shows that the share of coal in the total electricity generation will be increasingly smaller.

In contrast, the less-RE scenario (right) will have 66% fossil fuels by 2050, almost doubling the share of fossil energy generation in the more-RE scenario. The coal consumption is shown to grow continually until reaching 61%. While the share of nuclear and hydro stays the same, wind and solar will only rise to 5% and 1% of the total electricity generation in 2050.

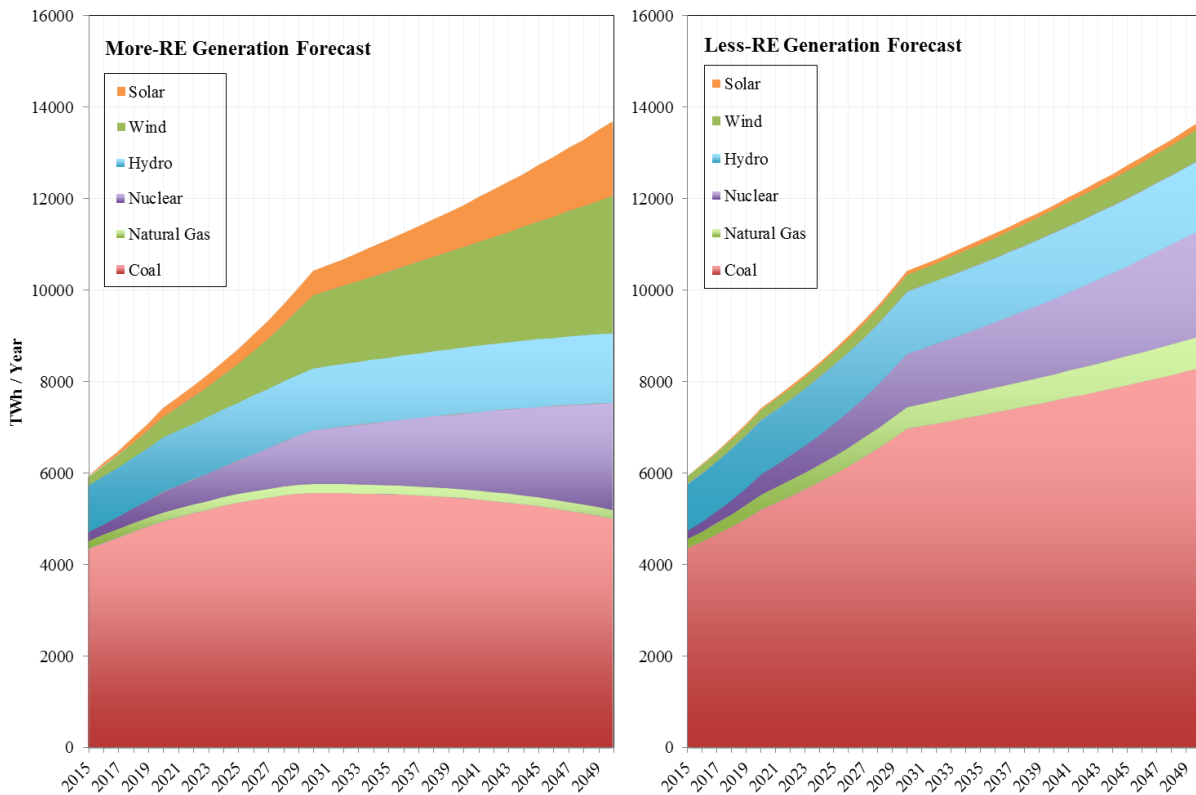


Figure 2-5 Electricity generation forecast in the more-RE (left) and less-RE scenario (right)

In a summary, the comparison of the three scenarios in terms of their shares of non-fossil power generation is shown in Table 2-8. The non-fossil energy sources (including nuclear, hydro, wind and solar) will contribute around 34% of the total electricity generation in less-RE in year 2050, while the non-fossil share in more-RE is almost twice of that, reaching 62% by 2050. The magnitude of the difference between the lower and upper bounds is a factor of two.

Table 2-8 Results comparison: shares of non-fossil electricity generation

	2015	2020	2030	2040	2050
Planned	24.4%	28.3%	35.0%	39.5%	44.5%
More-RE	24.3%	30.8%	44.6%	52.3%	62.1%
Less-RE	23.6%	25.6%	28.5%	29.8%	34.3%

2.5.2 GHG Emissions Intensity (EI) Results

The forecasted GHG EI of the grid in all three scenarios will reduce over time, but the rate of the decrease varies, as shown in Figure 2-6. In 2050, the EI of the grid for less-RE, planned, and more-RE will reach 660, 435, and 300 g CO₂-e/kWh, respectively. This result indicates that when the grid generates more electricity from renewable energy resources, its EI can be lowered by 30% than that for the planned scenario, and more than 50% than the less-RE scenario. Therefore, to clean up the grid, the adoption of renewable energy is critical.

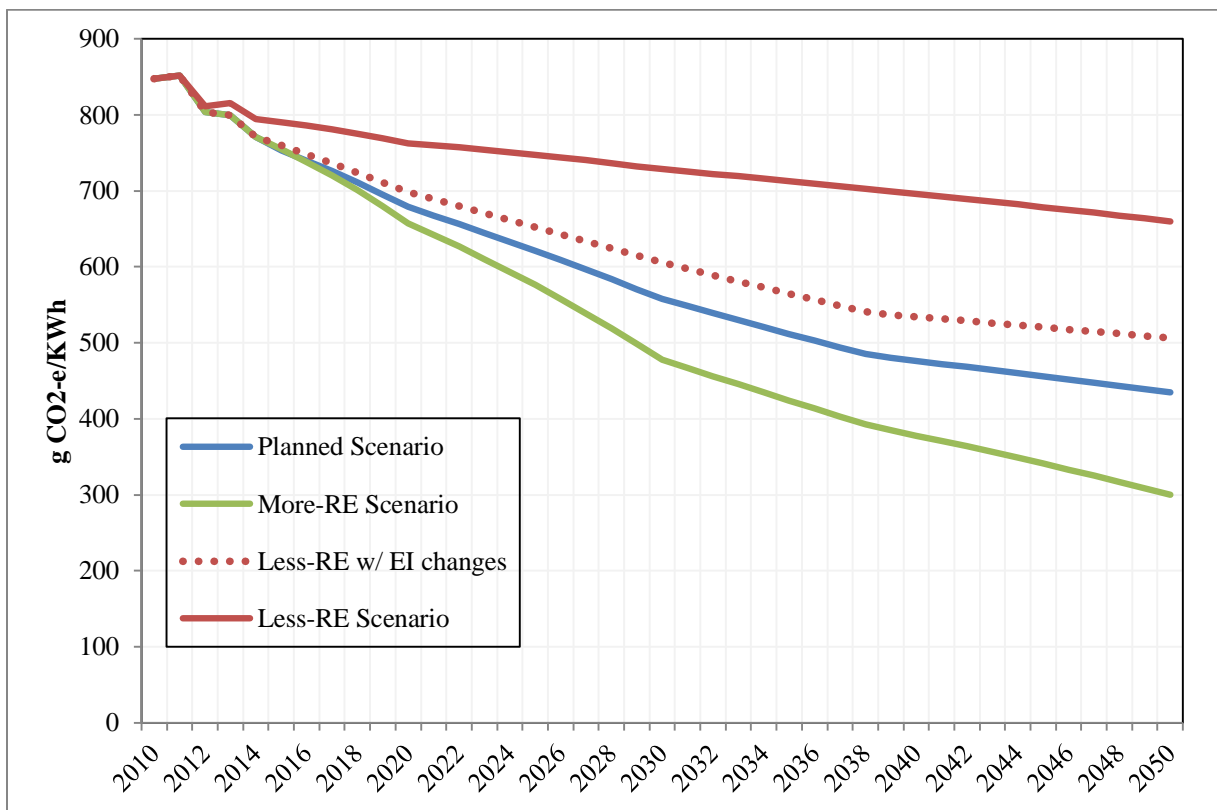


Figure 2-6 Forecast of the lifecycle GHG emissions intensity factors from the three scenarios

Improving the efficiency of the power generation technologies is also important. Note that the difference of EI between the less-RE and planned scenarios will be almost 66% more than the difference between planned and more-RE scenario. The reason is that I assumed there is no efficiency improvement for the power generating technologies in less-RE, so the EI for each technology stays the same. If I assumed technology improvement for this scenario, the result

would have been the dotted line in the graph, showing that the difference between less-RE and planned would actually be smaller than the difference between more-RE and planned. This result reflects the significance of the technological efficiency improvement in order to reduce the GHG EI of the grid. These EI factors will be imported into the China FLEET model to analyze the environmental impact of EVs.

Chapter 3 EV Market in China

This chapter gives some background information on the EV market in China. To understand the assumptions made in the model, it is important to be aware of the policy context and the business environment for EVs. Section 3.1 introduces the pertinent governmental policies; Section 3.2 presents the EV market size, growth, and the market leaders; Section 3.3 discusses the relevant challenges for developing EVs.

3.1 Governmental Policies on EV

To enable a sustainable development of the transportation sector, China has launched a series of policies to raise fuel qualities, set fuel economy standards, encourage energy savings, restrict vehicle driving and purchases, and to promote new energy vehicles. Below I give a brief overview of the relevant policies on EVs.

As early as 2008, China launched a demonstration program called *Ten Cities & Thousand Units* to accelerate the development of energy-saving and new-energy vehicles, including HEVs, PHEVs, and BEVs. The large-scale pilot expanded from ten to twenty-five cities, focusing on deploying EVs for government and public fleet applications (such as taxis, buses, and government cars). By 2010, there were around 12,000 light and heavy-duty EVs in China's vehicle stock (Y. Wu et al. 2012).

In 2012, China enacted the *Energy-efficient and New-energy Vehicle Industry Development Plan* (2012–2020). The *Plan* specified that the new energy vehicles (NEVs) mainly include PHEVs, BEVs, and fuel-cell vehicles, and currently most of the NEVs are PHEVs and BEVs. It clearly prioritized PHEVs and BEVs over HEVs, saying that PHEVs and BEVs will be developed in a coordinated manner and then the focus will be shifted from PHEVs to BEVs. The *Plan* also set subsidies and goals for the NEV stock to reach 0.5 million by 2015 and 5 million by 2020.

In 2013, China released the *Notice of Continuous Development of the Promotion for New Energy Vehicles*, to continue subsidizing NEVs for three years (2013-2015) but reduced subsidies from

the 2013 level by 10% and 20% in 2014 and 2015. It also sets mandates for the minimum NEV sales to be 10,000 and 5,000 for mega cities and other cities, respectively.

In 2014, China issued the *Guidance to Accelerate the Popularization and Application of New Energy Vehicles*. One of its provisions eliminated the purchase tax for NEVs until 2017, and it again established PHEVs and BEVs as the main focus of the development. The *Guidance* also specified the pricings and development of PEV charging infrastructure, provided solutions for reducing local market protectionism, and encouraged innovative business models.

In 2014, the Chinese government also distributed a number of documents, including the *Notice on Further Promoting the New Energy Vehicles*, which modified the subsidies so that the 2014 and 2015 levels are 5% and 10% less than the level in 2013. A summary of the subsidies for PHEV and BEV is shown in Table 3-1 (Ling 2015).

Table 3-1 Subsidies for passenger PEV between 2013 – 2015

Vehicle type	Electric Range I	2015 (¥/year)	2014 (¥/year)	2013 (¥/year)
Passenger BEV	$80 \leq R < 150$	31,500	33,250	35,000
	$150 \leq R < 250$	45,000	47,500	50,000
	$R \geq 250$	54,000	57,000	60,000
Passenger PHEV	$R \geq 50$	31,500	33,250	35,000

The Chinese government has been aggressively using policies to stimulate the growth of PHEV and BEV markets, and it has made some progress, as the next section will show. However, in reality the number of NEVs is still much lower than the intended goal. The NEV sales were 84,900 in 2014, and the stock reached 119,000 by the end of 2014 (J. Yang 2015). It is still quite unlikely for the NEV stock to get to 0.5 million by the end of 2015 as desired by the *Plan*. In addition, in 2014 only five cities had more than 5,000 sales of NEVs. Therefore, the *Plan's* goal might have been too optimistic.

But the government's intention to develop PHEVs and BEVs is strong, at least for now. The government understands that developing EVs has not just environmental but economic and social

benefits. As China's economic growth has gradually slowed down, boosting the domestic EV industry is seen as a potential new driver of economic growth.

3.2 The PEV Industry in China

The policy section has shown that PEV (plug-in electric vehicles), including BEV and PHEV, is a development priority in China. This section provides a brief overview of China's PEV industry. Developing PEVs is not only a strategy for reducing the pollution, but it is also a strategy for increasing the competitiveness of the domestic industry and stimulating the sustainable economic growth. Some assumptions used in the model are derived from this market dynamics. It is therefore important to understand the size and growth of this market, the new trend of micro-BEVs, and the PEV market leaders.

3.2.1 Passenger PEV Market Growth

The PEV market, including PHEVs and BEVs, has grown rapidly in the past few years. The growth rate of BEVs was more than 200%, albeit from a small base, increasing from 14,812 to 45,000 from 2013 to 2014. The sales of PHEVs jumped from 200 in 2013 to 17,000 in 2014 (Tsinghua Automotive Engineering Department, 2015). The sales of HEVs have been steadily growing, but since the government does not consider HEV as a type of NEV eligible for subsidies, its growth is much slower than the PEV's. The historical sales are shown in Figure 3-1.

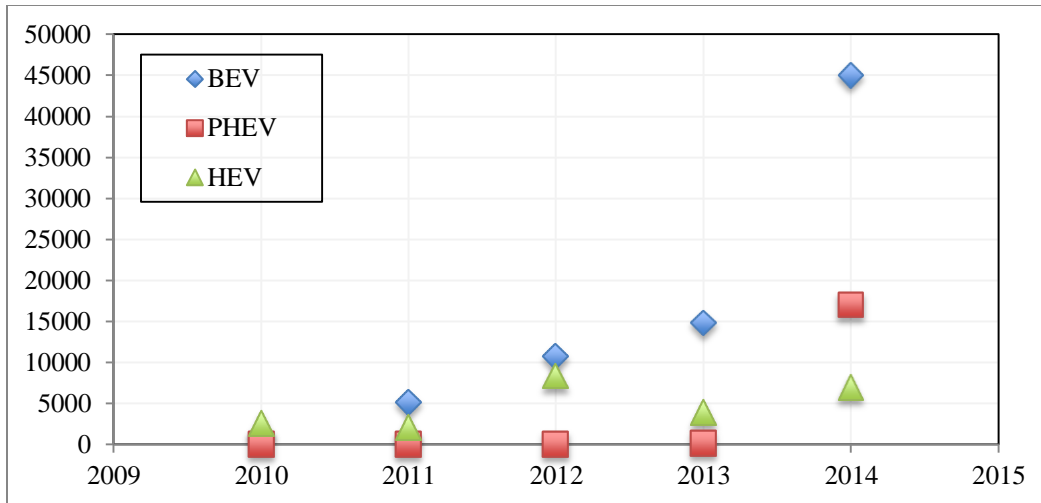


Figure 3-1 Passenger EV historical sales

The major players in the passenger PEV industry are domestic Chinese companies. Among them, BYD had the highest market share and sold most vehicles in 2014, followed by companies such as Chery, Zotye, GAC Toyota and BAIC.⁴ The market leaders are shown in Table 3-2.

Table 3-2 Specs of passenger PEV market leaders⁵

Categories	BYD Qin (PHEV)	BAIC E150EV (BEV)	BYD E5 (BEV)
Size:	4.74m×1.49m×2.66m	3.998×1.72m×1.503m	4.56m×1.822m×1.645m
Mass:	1720 kg	1370 kg	2380 kg
Engine:	1.5 L turbo-charged	N/A	N/A
Battery:	Lithium-ion (LiFePO4)	Lithium-ion	Lithium-ion (LiFePO4)
Electric Range:	70 km	200 km	300 km
Highest speed:	185 km/h	120 km/h	140 km/h
Price:	≥ ¥190,000 (\$30,917)	≥ ¥220,800 (\$35,929)	≥ ¥309,800 (\$50,410)

The leading vehicle brand in the passenger PHEV market is BYD Qin, with 14,747 vehicles sold in 2014, claiming 88% of the market share (BYD 2015). The second place is ROEWE 550 with much lower sales, and together BYD Qin and ROEWE constitute most of the PHEV market. A summary of the features of BYD Qin is shown in Table 3-2.

⁴ The Chinese for BYD, Chery, Zotye, GAC Toyota, BAIC, ROEWE, JAC are 比亚迪, 奇瑞, 众泰, 广汽丰田, 北汽, 荣威, 江淮

⁵ Data gathered from auto.sohu.com and the official websites of car manufacturers; same for Table 3-3.

The leaders in the regular passenger BEV market include BAIC E150EV, BYD E6, JAC iEV4, ROEWE E50, and others. The first place is BAIC E150EV, with sales more than 2,500 vehicles, followed by BYD E6 with sales close to 2,500 in 2014. Their specs are shown in Table 3-2.

3.2.2 The New Trend of Micro-BEVs

The trend of micro-BEVs emerged in China and this market flourished in 2014, with a rapid growth of sales and new birth of many varieties of businesses and products. Micro-BEVs are expected to not just solve the problems such as environmental degradation and energy fuel crisis for the transportation sector; they could also help mitigate the difficulties of parking and traffic congestion as well as satisfy the need of the disadvantaged people, such as the poor and the elderly, due to their inexpensive price and convenience. Their development is also considered as a competitive advantage for the China BEV industry.

The definition of micro-BEVs varies, since the government does not tightly regulate the design of this group of vehicles. A typical micro-BEV has these following features: (1) pure electricity powered; (2) < four passengers; (3) highest speed: 50 km/h – 80 km/h; (4) mileage \geq 80 km with a 50 km/h cruising mode; (5) fuel consumption: 10 – 15 kWh/100km; (6) weigh somewhere around 800kg; (7) normal price range: 30K – 50K RMB (4,842 – 8,069 USD).

Because of its inexpensive price and low cost of driving, the micro-BEV has been very popular in rural areas and the rural-urban fringe zones in China. Consumers range from mid-aged working-class women, civil servants, retired personnel and small retailers, to villagers; they use micro-BEVs to go to work, attend business activities, send children to schools, do shopping, run errands in cities, and use them as taxis to earn extra money (ChinaEV100 2015).

Another group of consumers being targeted are people who are young and can afford expensive cars. Rather than defining micro-BEVs as the “scooter for the elderly,” some car manufacturers, such as Litong and Leiding, strive to make their micro-BEVs fashionable and high-quality, aiming at people born after 1980s and 1990s (EVtimes 2015). The micro-BEVs made for higher-

end customers usually use lithium-ion batteries; popular brands of such micro-BEVs include Zhidou and Chery EQ.

According to ChinaEV100, some low-speed BEVs are also considered as part of the micro-BEV category. These low-speed BEVs typically take fewer than four people, use ~12 kWh lead-acid battery, and have the highest speed at 55 km/h, priced at around 30K RMB (4842 USD), with a range of 100 km and an electricity efficiency within the range of 10 – 15 Wh/100km.

The expansion of low-speed BEVs has been rapid in the countryside for several reasons. First, because the average trips residents make are around 20km in small and mid-sized cities and 30-40km in large cities, the low-speed BEV's mileage ranges satisfy people's basic needs (ChinaEV100 2015). Second, they are safer and more comfortable substitutes for the existing popular transportation tools in rural areas, such as motorcycles and electric two-wheelers. Third, their low cost of purchase, usage, and maintenance makes them affordable for low-income residents. Furthermore, low-speed BEVs are convenient to charge at home, and they fit the narrow and complicated road conditions in rural areas. Lastly, they do not cause pollutions or noises, and due to their low speeds, they are easy and safe to learn.

ChinaEV100 was founded in May 2014 for the purpose of spurring the development of the Chinese EV industry. It gathers researchers, governmental officials, and business people coming from a variety of backgrounds. One of their main research focus areas in 2014 was the low-speed BEV. They believe that this is not only an important breakthrough for the EV industry in China, but it is also a pathway to realize the car-driving dream of the millions of people in China while keeping pollution under control. ChinaEV100 suggests that the challenge right now is that low-speed BEV does not have a proper "name" in the transportation sector, and there is a lack of unified policies and proper regulation enforcements for them, resulting in low-quality BEVs proliferating in the market and some cases of traffic rule violations.

The leading companies that produce micro-BEVs include Kangdi, Zotye, and Chery. Kangdi led with the highest sales of 10,022 different micro-BEVs in 2014; Zotye Zhidou E20 sold 7,341

while Chery QQ3EV sold 7,866 in 2014 (d1EV 2015). A summary of the specs of these vehicles is shown in Table 3-3.

Table 3-3 Specs of passenger micro-BEV market leaders

Categories	Kangdi EV	Zotye Zhidou E20	Chery QQ3EV
Size:	~2.900m×1.545m×1.590m	2.765m×1.54m×1.555m	3.55m×1.495m×1.485m
Mass:	Around 980 kg	670 kg	890 kg
Battery:	Lead-acid	Lithium-ion	Lead-acid
Electric Range:	<120 km	120 km	120 km
Speed:	Around 50 km/h	≤ 80 km/h	50 km/h (optimum speed)
Price:	Around ¥7,000 (\$1,139)	≥ ¥108,800 (\$17,704)	≤ ¥48,000 (\$7,811)

3.3 Challenges of PEV Development

Despite the strong governmental support for PEV development and a fast-growing market, there are non-negligible obstacles that could effectively deter development. PEVs, especially BEVs, are considered inconvenient because of their limited range, long recharging time, and inadequate charging facilities; these factors could greatly reduce their market prospects. Section 3.3.1 and 3.3.2 address the progress as well as challenges in developing the BEV battery technologies and charging infrastructures.

3.3.1 Battery Technologies

The battery technology development plays a key role in solving the inconvenience problem of BEVs, by increasing the battery energy density, lengthening its lifetime, and reducing the recharging time. Lithium-ion battery is the most advanced technology so far in the world, with higher density, longer lifetime and shorter recharging time compared to other technologies such as lead and nickel-metal batteries. Below is a brief overview of the lithium-ion battery industry and related challenges in China.

The lithium-ion battery industry has been growing rapidly. There were more than 100 businesses producing lithium-ion batteries by the end of 2013, with a total battery production capacity

reaching 4 billion Amperes (ChinaEV100 2015). The leading companies in the market include BYD Auto, Zhejiang Wanxiang, Tianjin Lishen, and ATL.

China's technical capability of producing lithium-ion battery cells is approaching the most advanced international level. For example, the energy density has reached 160 Wh/kg and 142 Wh/kg for 25 Ah lithium manganese batteries and 50 Ah lithium ion phosphate batteries, respectively (China Automotive Technology Research Center et al., 2013). China's lithium-ion technology is already mature enough for large-scale commercialization.

However, there are a few weaknesses of the battery industry in China right now: (1) the average quality and lifetime of the battery is still low compared to international standards; (2) difficulties exist in the battery-cell grouping and integration technologies; (3) being good at making small lithium batteries, China may face obstacles producing batteries with large volume and high energy densities (China Automotive Technology Research Center et al., 2013).

In order to mitigate the inconvenience factor of BEVs, China has to overcome these challenges. China should also improve its capability of innovation, R&D and standardization to create even better battery technologies.

3.3.2 Charging Infrastructure

Currently there are three charging modes in China: (1) slow charging that takes 4 – 8 hours; (2) fast charging that is supposed to take 10 – 30 minutes, but most of which takes 1 – 3 hours; (3) battery swapping, which in Hangzhou only takes 3 – 5 minutes (China Automotive Technology Research Center et al., 2013).

A big problem facing China right now is the inadequate charging infrastructure. The government has set ambitious goals to address this issue but many challenges still exist.

In 2012, China released the *12th Five-year Plan for Electric Vehicles Technology Development*, setting the goal to build up to 2,000 charging stations and 400,000 charging piles in more than 20

cities and their suburbs by 2015. The major builders of charging stations include power suppliers such as State Grid and China Southern Power Grid, automobile fuel suppliers such as Sinopec and CNNOOC, and IT companies such as China Potevio (Z. Li and Ouyang 2011).

However, according to the data published by the Ministry of Industry and Information Technology, China has only built 723 charging stations and 28,000 charging piles by the end of 2014, which is less than half of the intended goal for 2015 (EVlook 2015). China's investment in building charging stations will exceed 60 billion RMB (9.8 billion USD) by the end of 2015.

There are multiple explanations for the slow proliferation of charging stations. For private charging, because people normally live in apartments belonging to a residential community, they rely on the community to build charging piles on already limited parking spaces. Regarding who should pay for the establishment of charging facilities, there have been difficulties in negotiating among the community property managers, the utilities, car companies, and car owners themselves. Therefore many charging facilities ended up not being built (ChinaEV100 2015).

For public charging, first the locations of charging piles were not properly planned out. According to ChinaEV100, the utilization of the charging piles was as low as 6.2% in Shanghai city. The property right of land is also not well defined, deterring the establishment of charging stations. Furthermore, the standard of charging interfaces has not been unified; the charging stations and piles use different standards of charging interfaces produced by car companies, so one station sometimes cannot provide charging services for different brands of cars.

To accelerate the development of EVs in China, it is critical to build up the charging infrastructure to an adequate level and to meet the demand. Planning out charging station locations, unifying the charging interface standards, and specifying the financial responsibilities for building charging facilities are some of the solutions to consider.

The background information and challenges discussed in this chapter will be reflected in Chapter 4 where the assumptions and scenarios are introduced.

Chapter 4 The FLEET Model

4.1 Introduction to the FLEET Model

The China FLEET model is created by Ingrid Akerlind working with Professor John Heywood for her master thesis. Akerlind built it based on the US fleet model created by the “On the Road” group at MIT and applied it to suit the Chinese data and context. The FLEET model is a tool to track and forecast the stock, travel, fuel use, and greenhouse emissions of the light duty vehicle (LDV) fleet (Heywood et al. 2008). It uses a bottom-up approach to capture the dynamics of fleet turnover and usage as well as the fleet’s energy and environmental impact.

The China FLEET model includes four passenger vehicle types, including private car, non-private car, mini-truck and mini-bus. These vehicle types constitute the LDVs, which are the non-freight and non-bus vehicles anyone could potentially purchase. The six vehicle powertrains in the original FLEET model contain the naturally aspirated internal combustion engine vehicle (ICE NA-SI), turbo-charged spark ignition engine vehicle (Turbo-SI), diesel vehicle, hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV), and battery electric vehicle (BEV). For this research, the BEV category was subdivided to regular-BEV and micro-BEV, which will be discussed more in the next chapter.

The FLEET model is presented in Figure 4-1, with inputs in grey and four sequential outputs in blue. First, it uses the sales of different vehicle types as well as the ratios of sold to scrapped vehicles to forecast the vehicle stocks. Then the model multiplies together the stock by model year, the age-differentiated vehicle distance traveled, and the fuel consumption for each powertrain to obtain the second output, the energy demand of the vehicle fleet. The energy demand can be further disaggregated by fuel to calculate the fuel demand output, and the fuel mix includes gasoline, methanol, compressed natural gas (CNG), diesel, and electricity. Then GHG emissions output is calculated from multiplying the fuel demand and the corresponding emissions intensity factor for each fuel source.

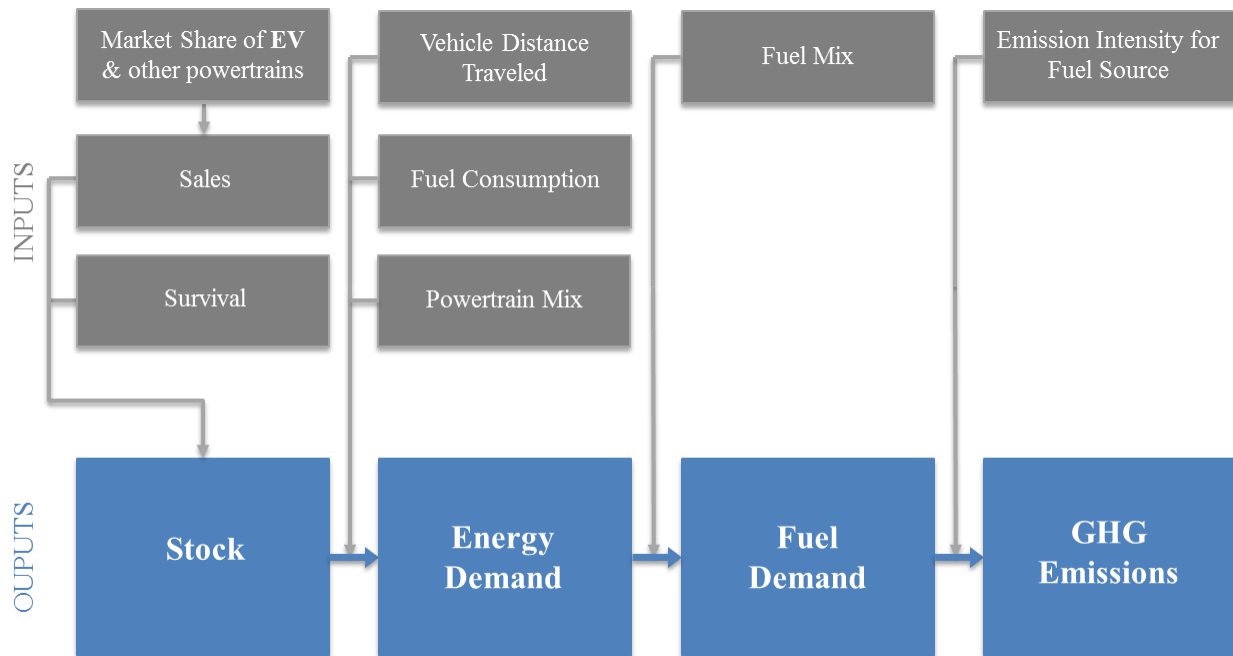


Figure 4-1 The China FLEET model diagram with EV scenarios added (Akerlind 2013)

The outputs of the model can be analyzed by disaggregating the data into vehicle types and powertrains. The main equations of the model are shown below (Akerlind 2013).

The stock of the vehicles can be derived in a given calendar year (CY), model year (MY) and vehicle type (v). The sales number and survival ratio of the vehicles are multiplied together to calculate the stock, as shown in equation 4.1. The sales numbers are forecast based on historical sales and projected growth rate of the sales.

$$Stock_{v,MY,CY} = Sales_{v,MY,CY} \times Survival_{v,MY,MY-CY} \quad (4.1)$$

The survival ratio of the vehicles is determined by the appropriate vehicle scrappage rate. Akerlind calculated vehicle scrappage by using a logistic regression expression, which is the same as the methodology developed by Hao et al. They defined vehicle scrappage rate as the absolute value of the derivative of vehicle survival ratio with respect to the age of the vehicle (Hao et al. 2011). In Equation 4.2, (t) denotes the vehicle age, (B) is the rate at which vehicles

disappear from the vehicle stock, and (T) is the vehicle half-life, meaning the age where half of the vehicles from model year remain in use.

$$\text{Vehicle Survival Ratio} = \exp\left(-\left(\frac{t}{T}\right)^B\right) \quad (4.2)$$

Then to obtain the energy demand per vehicle powertrain (P) for a given calendar year, the stock of vehicles, the annual vehicle distance traveled (VDT) per vehicle, the sales mix of the powertrains, and the fuel consumption are multiplied together, as indicated in Equation 4.3. The annual VDT per vehicle is projected through an exponential decay function. Equation 4.4 shows how fuel demand per fuel source (f) is obtained by multiplying the fraction of powertrain energy demand supplied by a given fuel and the energy demand for a powertrain.

$$\text{Energy Demand}_{P,CY} = \sum_{MY,v} \text{Stock}_{v,MY,CY} \times \text{VDT}_{v,MY,MY-CY} \times \text{Powertrain}_{v,P,MY} \times \text{FC}_{v,P,MY} \quad (4.3)$$

$$\text{Fuel Demand}_{f,CY} = \sum_P \text{Energy Demand}_{P,CY} \times \text{Fuel}_{f,P,CY} \quad (4.4)$$

The total emissions per year are obtained by multiplying together the fuel demand per fuel source and each fuel's emissions intensity in a given year, as shown in 4.5. For example, the emissions intensity factors of the electricity grid obtained from ESEM described in Chapter 2 are imported to the FLEET model in this step and multiplied with the electricity consumption to obtain the total emissions.

$$\text{Emissions}_{CY} = \sum_{f,i} \text{Fuel Demand}_{f,CY} \times \text{Emission Intensity}_{f,CY} \quad (4.5)$$

To make the China FLEET model suitable for generating different EV scenarios, I added another set of input, the sales mix of EVs and other vehicle powertrains under different vehicle types for years 2015, 2017, 2020, 2025, 2030, 2040, and 2050. This input is represented in the upper left grey box in the model diagram in Figure 4-1. I set the market shares of BEVs and PHEVs to be the major inputs, according to which the market shares of other powertrains change. Then based

on the sales growth for different vehicle types, the growth rate and sales for each powertrain can be determined.

The other modifications I made to the China FLEET model include adding the powertrain *micro-BEV* as well as making changes to the vehicle distance traveled, energy consumption, and GHG emissions factors. These modifications are detailed in Chapter 5. The remainder of this chapter examines FLEET in comparison to other models, which all make predictions of the energy demand and GHG emissions of the vehicle fleet in China.

4.2 Comparison of Three Models: FLEET, TCAEM and EPPA

4.2.1 Introduction of Models

Three studies with different models were produced in similar time periods and forecasted the passenger light duty vehicles (LDVs) growth in China until 2050. To find out how different the results vary and how the underlying assumptions drive the outcome of the model, I conducted a comparison analysis on these three studies. The first is Akerlind's 2013 master thesis using the China FLEET model. The second is the China Automotive Energy Outlook 2012 report, using the Tsinghua China Automotive Energy Model (TCAEM), developed by the China Automotive Energy Research Center at Tsinghua University. The third one is Kishimoto's 2012 master thesis, using the fifth version of the Emissions Prediction and Policy Analysis (EPPA) model, developed by the Joint Program on the Science and Policy of Global Change at MIT.

TCAEM is a hybrid of an automotive energy supply model, an automotive traffic demand model, and an integration and optimization model. As Figure 4-2 shows, the model has inputs such as the economic and demographic factors as well as assumptions on technology advancement and public policies. The outputs include energy demand, costs and emissions. Similar to the FLEET model, its automotive traffic demand model also uses vehicle sales, scrappage rates, and vehicle distance traveled (VDT) to forecast vehicle stock and energy demand. In contrast to the FLEET model, TCAEM has tools to optimize the fuel mix, so that total costs and emissions are minimized while efficiency and energy security are maximized. TCAEM examines the entire

transportation sector, but only the passenger vehicle sector is being compared in this comparison study.

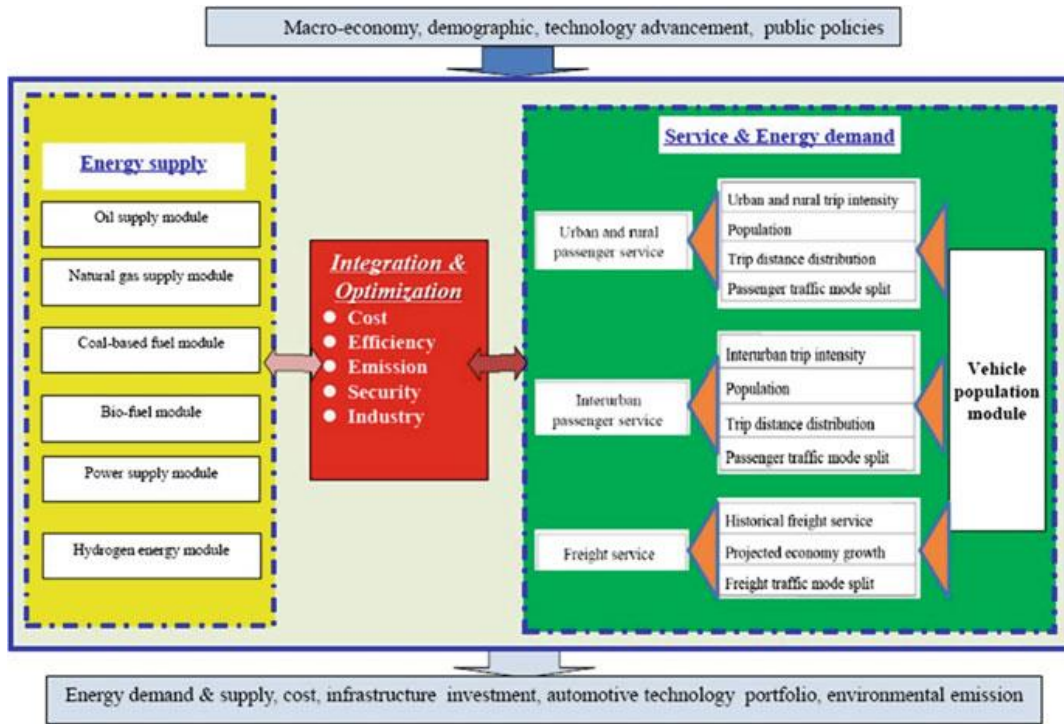


Figure 4-2 TCAEM Model (China Automotive Energy Research Center Tsinghua University 2012)

Quite different from the previous two models, EPPA is a computable general equilibrium (CGE) model of the world economy, covering 16 world regions and 24 sectors such as agriculture, gas, electricity, and the transport sector (Paltsev et al. 2005). It captures the interrelations among these regions and sectors, and it has been applied to study many policy impacts on the economy and emissions.

In the transport sector, rather than using a bottom-up approach to make forecasts by accumulating sales and VDT, EPPA uses a top-down method to forecast stock and energy demand by indexing them to components of household consumption. The model generates the households' spending on the transport sector, which is then converted to the VDT forecast. Then based on the fuel prices and assumed elasticity factors, the model generates the vehicle stock and energy demand forecasts. EPPA divides the transport sector into *purchased* (i.e. bus, trains, air)

and *own-supplied* transport, and only the latter is examined here because it contains the passenger LDVs (Kishimoto, Paltsev, and Karplus 2012).

There are some challenges of conducting this comparison analysis. One is that the models have different levels of detail, which makes it necessary to carefully understand every specific assumption and obtain the exact data of the assumption to compare the models. Another challenge is that the three studies include different vehicle types. As Table 4-1 shows, FLEET and TCAEM do not consider motorcycles and electric two-wheelers while EPPA does. EPPA does not have specific data on taxis because they are incorporated in its whole *purchased* transport sector and cannot be extracted. Therefore, there is some discrepancy of the data in the starting year, which will be reflected in the comparison results presented later.

Table 4-1 Comparison of vehicle data classifications

Categories	FLEET	EPPA	TCAEM
Private Cars	✓	✓	✓
Non-private Cars (Taxis)	✓	✗	✓
Minitrucks (SUVs)	✓	✓	✓
Minibuses (mainbaoche)	✓	✓	✓
Motorcycles/Electric 2-wheelers	✗	✓	✗

4.2.2 Comparison of Results

Below I present the results of the comparison, mainly in terms of the vehicle stock and energy demand forecasts; at the same time I explain the factors and assumptions that contribute to the differences among the results. For simplicity, I use FLEET, TCAEM and EPPA to represent the three studies and models.

The first set of results compared is the forecast of the total passenger vehicle stock. As Figure 4-3 shows, the stock forecasts from FLEET and TCAEM are very similar, reaching 578 and 548 million vehicles by 2050, with only a 5% difference. This similarity is likely due to the similar categories of vehicles examined and the similar bottom-up approaches adopted by both studies. Additionally, their stock projections level off after 2030, because they both assume that the

growth rate of vehicle sales will slow down after 2030, which results in a slower building of vehicle stocks.

There are two areas where EPPA's stock forecast is different from the others. First, the projection maintains a straight line without any leveling off. This is because the stock is indexed to the share of the household consumption on transport, which keeps rising. The fifth version of EPPA Kishimoto used assumes homothetic preferences, meaning as households become wealthier, they will continue spending the same share of income on transportation.⁶ Therefore, since household consumption is projected to grow steadily in the future and the transport consumption also grows proportionally, the stock output turns out to be linear.

Second, EPPA's stock forecast will be almost 100 million vehicles lower than the other two studies' in 2050. This is because the price elasticity feedback plays an important role in EPPA. The model assumes that as fuel price increases in the future, operating vehicles would become more expensive, so people tend to buy fewer vehicles and use alternative purchased modes of transport instead.

⁶ The EPPA 6 version released in 2015 has added non-homothetic preferences, although this formulation is still not applied to household transport (H. Chen et al. 2015).

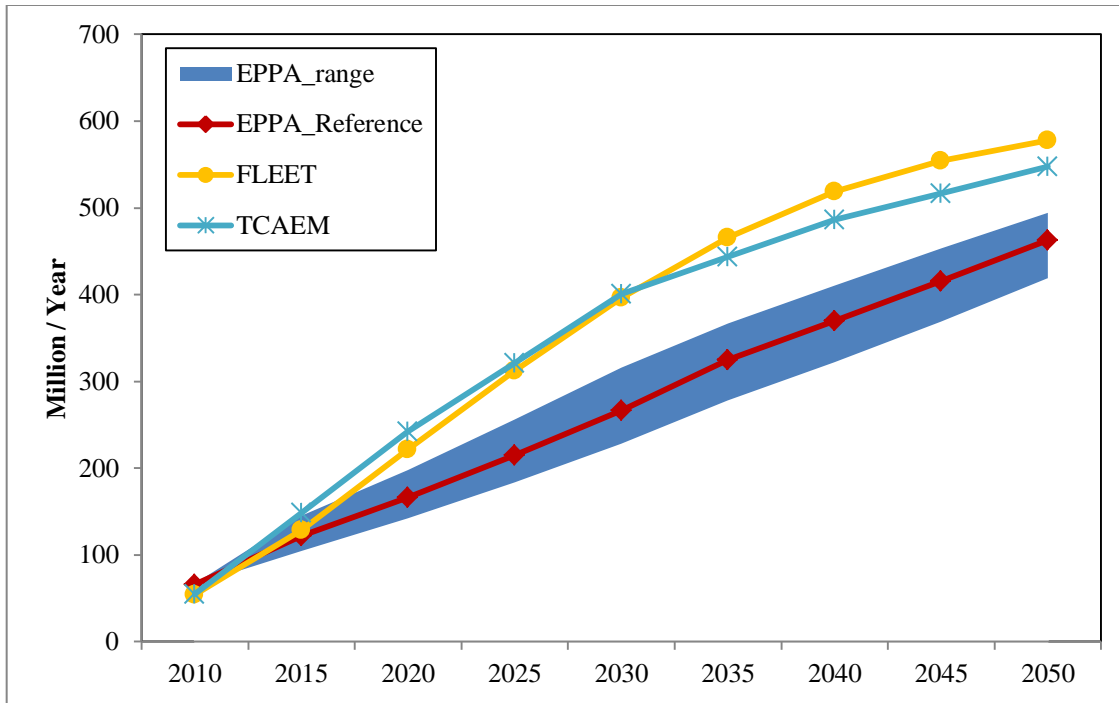


Figure 4-3 Comparison of the passenger vehicle stock forecast

The second set of results compared is the energy demand of passenger LDVs. As Figure 4-4 shows, the energy demand forecasts from the three studies are quite different.⁷

First, there is a 40% difference between FLEET and TCAEM’s energy demand projections in 2050. This discrepancy could be explained by the different assumptions made for VDT and fuel consumptions by the two models, which will be discussed later. Their energy demand forecasts, however, have similar shapes, such as the trend of gradually leveling off; this could be due to the similar shapes in their vehicle stock forecasts.

Second, the forecast from EPPA is drastically different from the other two studies’. An explanation is that Kishimoto did not assume specific technological advancement, vehicle fuel consumption improvement, or stringent fuel economy policies for the model. One thing we did

⁷ The discrepancy in 2010 between EPPA and the other two studies is likely due to Kishimoto’s inclusion of fuel consumption from motorcycles and electric two-wheelers, as explained earlier.

was applying the fuel economy assumption from Akerlind’s study to the EPPA model and examining how that would change the EPPA results.

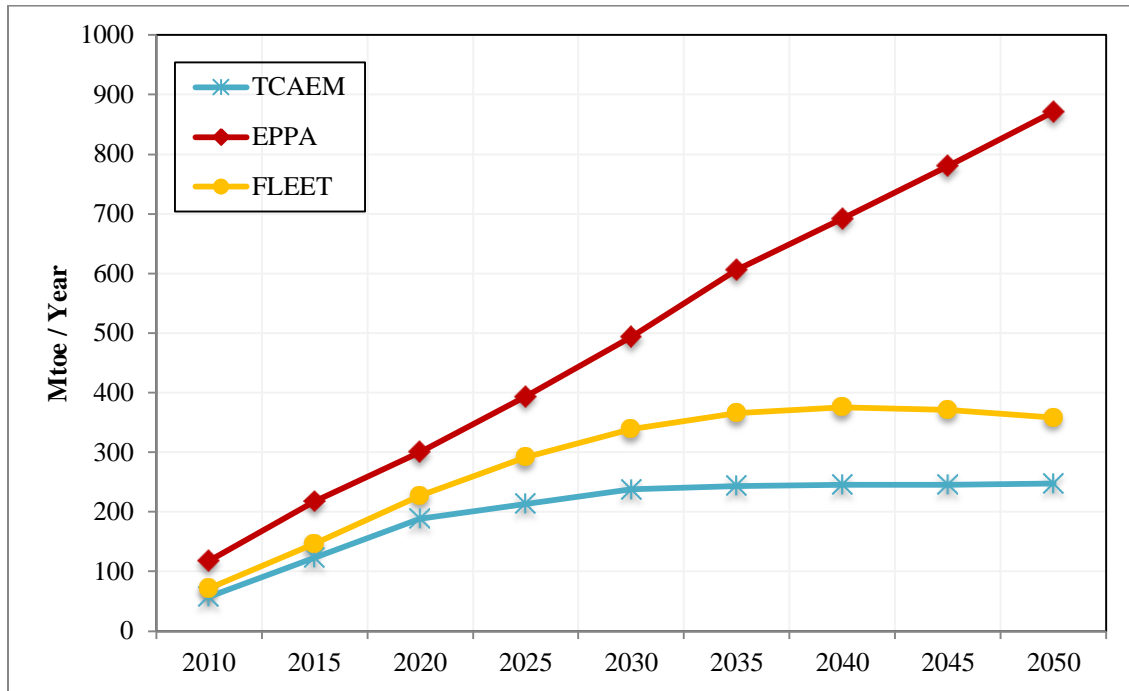


Figure 4-4 Comparison of the energy demand forecast

4.2.3 Comparison of Key Assumptions

In order to understand the reasons behind the differences of the energy demand forecasts, some key drivers were investigated. There are four main factors that drive the fuel consumption: (1) vehicles distance traveled (VDT); (2) fuel consumption (FC) improvement; (3) electrification level; (4) vehicle stock. For example, reducing FC, VDT, and vehicle stock while increasing the electrification level could collectively reduce the energy demand of the vehicle fleet.

In this comparison analysis, factor (3) is not examined because all three studies assume low electrification. Factor (4) is not examined because vehicle stock is not an input for forecasting energy demand in EPPA and the vehicle stock output is similar between FLEET and TCAEM. Therefore, only VDT and FC improvement assumptions are compared among the three studies.

The assumptions of VDT/vehicle/year from the three studies are shown in Figure 4-5. The FLEET and TCAEM models have different categorizations of vehicles; in FLEET, VDT assumptions are made for vehicle types such as private car, mini-trucks, etc., while TCAEM classifies vehicles into different sizes such as micro, small, etc. The solid lines represent the FLEET assumptions, which are shown to be relatively higher than the dotted lines representing TCAEM assumptions. The red line with squares represents the VDT/vehicle/year in EPPA, which is within the range but higher than the average of other two studies' assumptions.

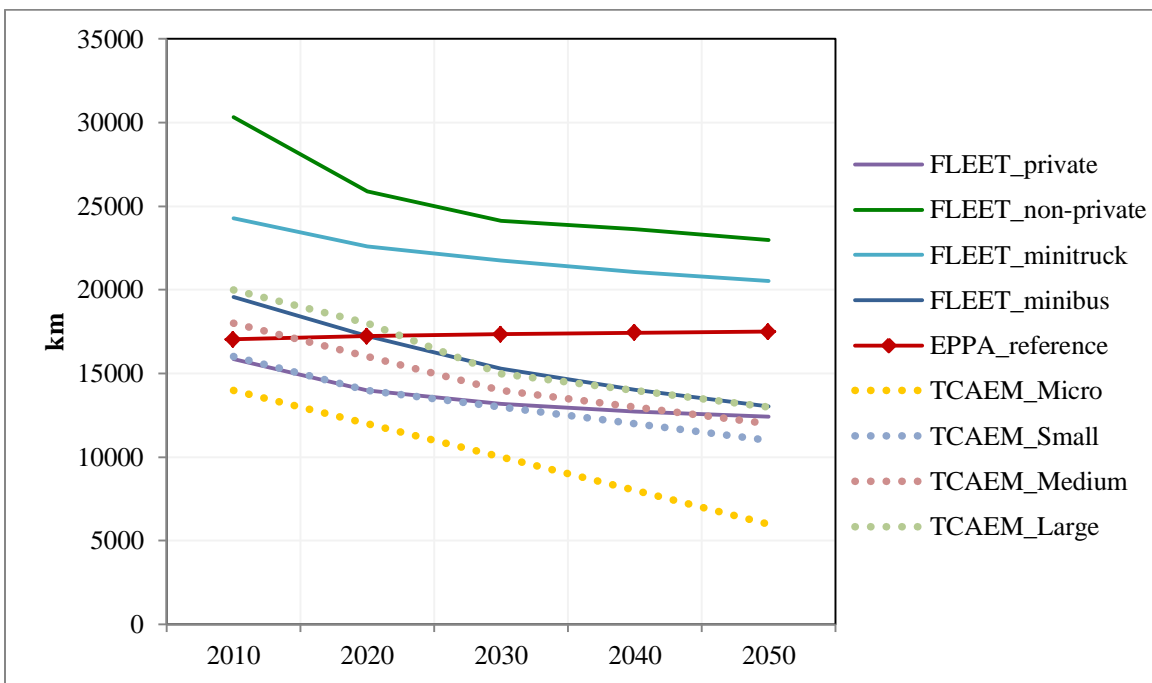


Figure 4-5 VDT/vehicle/year comparison among three studies

To compare the VDT in more detail, the average VDT per vehicle per year is calculated, as shown in Figure 4-6. In FLEET, the ratio of the stock for private, non-private, mini-truck, and mini-bus changes over time and will reach around 71:4:3:22 (vehicle type) in 2050. I applied this annual ratios and obtained the average VDT over time. The average VDT will reach 13200 km/vehicle/year for FLEET in 2050.

In the TCAEM forecast, Tsinghua assumes the ratio of 30:50:10:10 (vehicle size) for mini, small, mid and large cars; the average VDT is obtained after applying this ratio. TCAEM's average VDT is the lowest among the three studies, reaching 9800 km/vehicle/year in 2050.

TCAEM's average VDT assumption will be around 25% lower than FLEET's in 2050, and this difference could account for more than half of their energy demand forecast discrepancy. Both FLEET and TCAEM have a decreasing trend of VDT mainly because they both assume that more traffic congestions on the road will lead to fewer average miles driven.

However, EPPA's VDT remains flat and even increases slightly. This is because VDT is not an input but an output linked to the household consumption for the EPPA model. In EPPA, the total PDT (Person Distance Traveled) indexed to the total household consumptions on transport continues to increase in the future. Then the per-capita PDT is derived from dividing total PDT by the population. I converted PDT to VDT by using an average occupancy rate of 2 and the equation of $VDT = (PDT/Occupancy)/Stock$. Since household consumption rises more quickly than the population growth, there is a slight increase in per capita PDT and therefore a slight increase in VDT/vehicle/year.

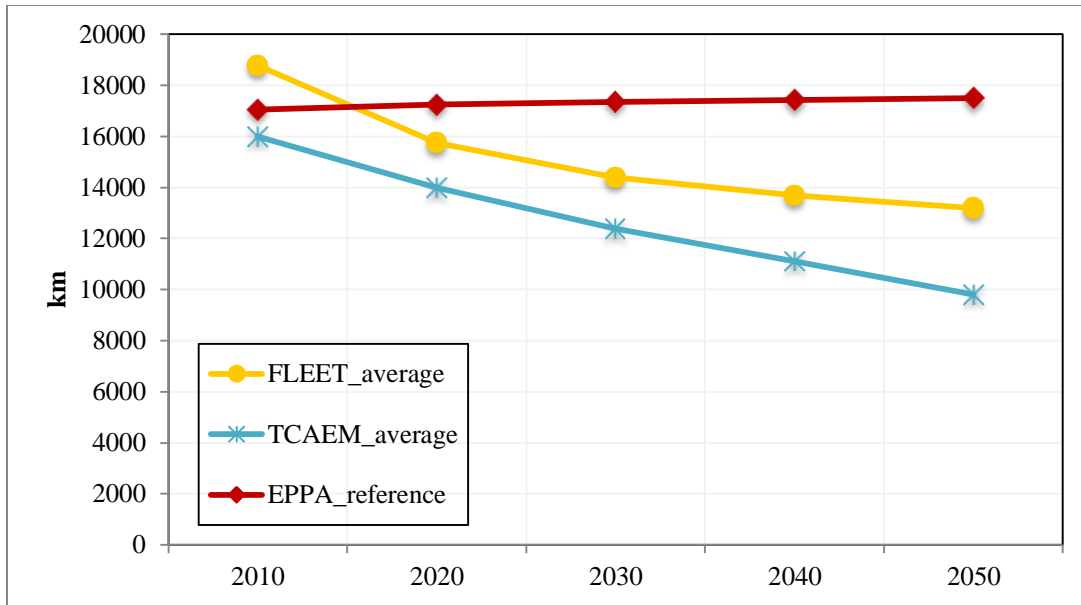


Figure 4-6 (Weighted) Average VDT/vehicle/year comparison among three studies

The second assumption compared is the FC improvement. There are different ways of comparing FC; one can look at the FC for the average new vehicle fleet or for the total vehicle fleet. The former is examined here because only these data are available for EPPA and TCAEM. Figure 4-7 shows the comparison of the average *new* vehicle fleet FC among three studies.

In TCAEM, the FC assumptions are still made for different vehicle sizes. The fixed ratio of 30:50:10:10 for mini, small, mid and large size vehicles was then applied to obtain the average new vehicle FC. As shown in the figure, the average FC will decrease to 5 liters/100km by 2050.

Interestingly, FLEET's forecast almost intersects with TCAEM's by 2050. FLEET's on-road FC assumption is the real rather than labeled FC of the average new vehicle fleet, and it will decrease to 5.24 liters/100km by 2050. Although it is very close to the TCAEM assumption, it is important to note that the two models' FC assumptions were quite different before 2050, which would make the FC for the average *total* fleet higher for FLEET than for TCAEM. This could also partially explain the discrepancy of the energy demand forecast between the two models.

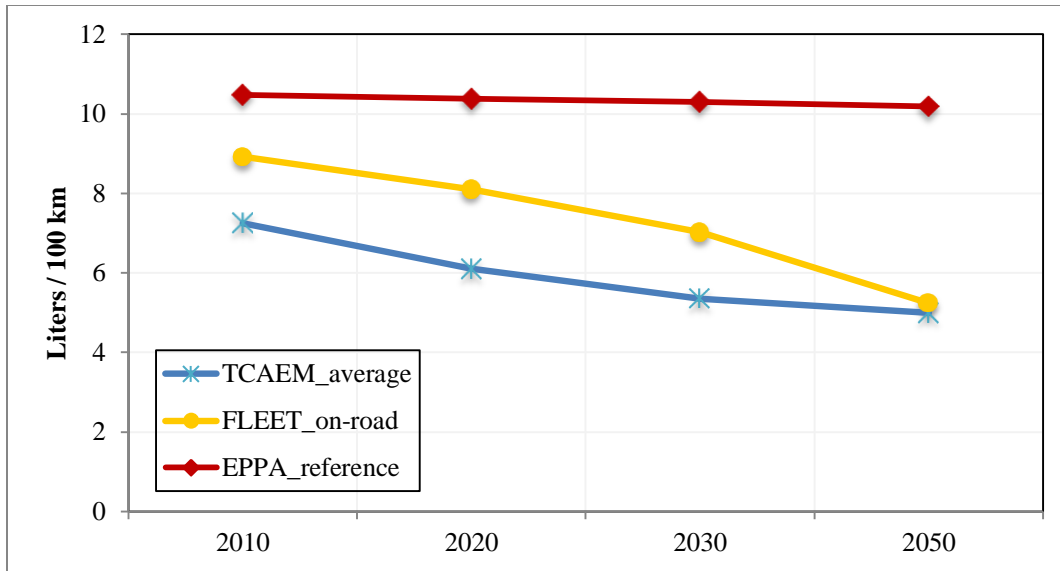


Figure 4-7 Fuel consumption of the average new vehicle fleet comparison among three studies

It is obvious that the EPPA study did not assume any FC improvement over time, which is why the line is almost flat and much higher than the other two in Figure 4-7. But if EPPA changes its FC assumptions, would it change its energy demand forecast dramatically?

An experiment can be run to find out the answer. We converted the FC improvements from the FLEET model into the right format and inserted them into the EPPA model, which derived Figure 4-8.

In Figure 4-8, the dotted line represents the original forecast of the energy demand from EPPA, and the red solid line is the new energy demand forecast after the FC assumptions from FLEET are applied to EPPA. The result shows that EPPA's energy demand projection bends down after 2030 and even becomes lower than the FLEET's projection. This indicates that FC improvement is a crucial driver for forecasting energy demand.

There are two reasons why EPPA's new projection bends down even further than FLEET's. One is the price elasticity. First, as the FC improvement requirement becomes more stringent, the relative cost of owning and driving a vehicle increases; then the price-sensitive consumers will

seek other transportation modes. This is one of EPPA's unique features; it emphasizes the relationship among economic changes, consumer behaviors and transportation demand.

The second is a lack of alternatives in EPPA. EPPA only has the options of ICE, PHEV, BEV, and CNG powertrains, and Kishimoto only used ICE and PHEV in the study. So when the price is high and there are no substitutes for traditional powertrains, the vehicle ownership will drop. So far, other alternative vehicle powertrains have been parameterized for the U.S. by Karplus, but the parameterization has not been done for China, except PHEV (Karplus et al. 2013).

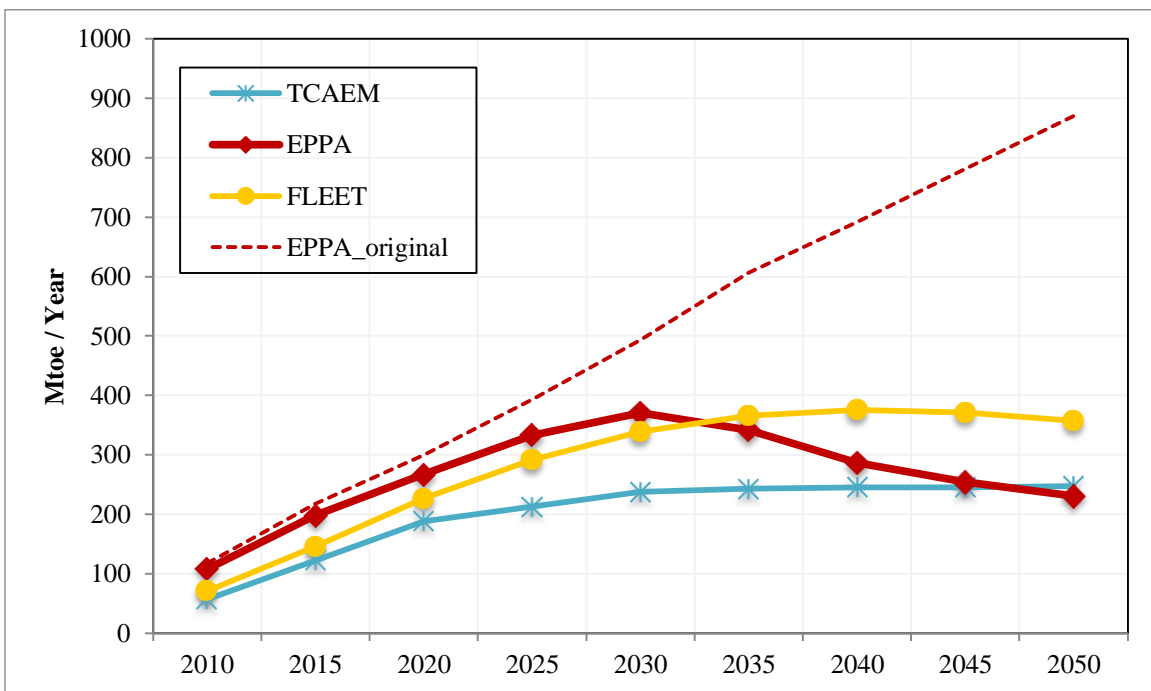


Figure 4-8 Comparison of energy demand after FC is adjusted for EPPA

The GHG emissions forecast comparison is similar in shape to the energy demand comparison and can be found in the Appendix. The reasons causing the difference in energy demand forecasts can explain the difference in GHG emissions since GHG emissions are derived from multiplying energy demand and emissions intensity factors in the three studies.

To conclude, the analysis shows that VDT/vehicle/year and FC improvement are crucial assumptions driving the forecasts of energy demand. EPPA is structurally and logically very

different from the other two models, but after applying the same FC assumptions, its result becomes quite similar to the other studies'. The analysis has also shown how the difference in these assumptions between FLEET and TCAEM explains the discrepancy for their energy demand forecasts.

Overall for the forecast results, the impacts are comparable, especially between FLEET and TCAEM. The EPPA results are relatively different, but they become similar after their assumptions are adjusted. These indicate that conclusions based on the models are robust to the input assumptions. There are clear differences in the level of details, model rationales and classification of data among the three studies. But the comparison enables the deconstruction of the models and a better understanding of the contributions of FC and VDT input parameters to their outputs.

Chapter 5 Assumptions and Data

This chapter presents the assumptions, data used, and modifications made for the China FLEET model. It first introduces the addition of micro-BEV into the model and the three scenarios. It then demonstrates the assumptions made for sales mix in different scenarios, vehicles distance traveled, fuel consumptions, and emissions intensity factors.

5.1 Micro-BEV's Share of Sales

The micro-BEV powertrain is added to the China FLEET model under the private and non-private car types. Because of the relatively large size of mini-truck and mini-bus, only regular-BEV is in these categories, but private and non-private cars have both regular and micro-BEVs.

The breakdown of sales between regular-BEVs and micro-BEVs is shown in Table 5-1 (ChinaEV100 2015). There has been some fluctuation of micro-BEV's share in total BEV sales in the past few years, but its share has been gradually rising.

Table 5-1 Shares of regular and micro-BEVs in total BEV sales

	Regular-BEV	Micro-BEV
2010	61%	39%
2011	33%	67%
2012	59%	41%
2013	36%	64%
2014	27%	73%

Despite the historical fluctuating trend, I assume that the share of micro-BEVs in total BEVs steadily increases by 0.35% annually and will reach 85% by 2050. The reasons for this logic include: (1) since there will be more cars in China, the problems of traffic congestion and limited parking space will escalate; therefore people choose to buy smaller cars; (2) micro-BEVs are cheaper and more fuel efficient, so people are incentivized to use them for both economic and

convenience factors; (3) the Chinese government starts to encourage the purchase of micro-BEVs, and stronger policies are assumed to further stimulate their development.

However, there are also counter-arguments to this logic, including: (1) as people become wealthier, the income effect will make them spend more on luxury goods such as expensive and bigger cars; (2) as the economy grows, people view luxury cars as symbols for their social status and would not be satisfied with smaller cars.

Both of these scenarios are likely, and I performed sensitivity analysis to see whether changing the ratio of micro-BEVs makes a big difference on fuel consumptions and emissions. The result is a small difference, and more details of the sensitivity analysis will be shown in Chapter 6.

Nonetheless, in the FLEET model I assumed that the first set of reasons prevails and especially that the government chooses to incentivize the purchasing of micro-BEVs. The forecast based on the annual increase rate of 0.35% for micro-BEV's share is shown in Table 5-2.

Table 5-2 Forecast of the shares of regular and micro-BEVs in total BEV sales

	Regular BEV	Micro BEV
2015	25%	75%
2017	24%	76%
2020	24%	76%
2025	22%	78%
2030	21%	79%
2040	18%	82%
2050	15%	85%

5.2 Scenarios

Three scenarios are designed to describe the different levels of electrified vehicles' (EVs) penetration in the light-duty passenger vehicle (LDV) fleet. Across the three scenarios, the market share inputs of PEVs (plug-in electric vehicles), including BEVs and PHEVs, vary by a great amount, while the market share of HEVs stays the same. The sales mix of the other

powertrains is adjusted based on the EV inputs. The contrast among scenarios is due to the different paces of technological advancement and changes in governmental policies. The three scenarios include a reference and two scenarios that make more aggressive and passive projection of the EV penetration.

The first one is a *sensible* scenario, describing the plausible development path of EVs. The assumptions of the future sales mix of powertrains in this scenario are based on historical trends as well as consultations from governmental mandates and other studies, with the belief that the government maintains its positive policies to develop the domestic EV industry. This scenario is designed to serve as a likely-to-happen reference scenario.

The second is an *aggressive* scenario, depicting the case where PHEVs and BEVs are developed much faster and sold much more, compared to the sensible scenario, because of the faster development in battery technologies, better establishment of the infrastructure, and stronger policy support for the development of EVs.

The *passive* scenario is where fewer PHEVs and BEVs will appear in the market than in the sensible scenario, assuming slow technology advancement, weak governmental support in new energy vehicles, and a lack of charging infrastructures.

5.3 Sales Mix across Scenarios

There are four types of passenger vehicles and seven powertrains in the FLEET model, and I made assumptions on the sales mix for each one of them in year 2015, 2017, 2020, 2025, 2030, 2040, and 2050. I lay out my assumptions in each scenario in the following sections.

5.3.1 Sensible Scenario

The sensible scenario assumes that (1) China's battery technology improvement is in line with international standards, resulting in relatively longer electric miles and shorter charging time, but these improvements are not enough to overcome the inconvenience factor of BEVs; (2) the

charging infrastructure is more comprehensive but not enough to meet the entire demand, so charging still has some limiting effect on BEVs; (3) the government gradually reduces the 2015-level PEV subsidy over time but maintains policies on promoting PEVs; so the momentum for the market to grow continues.

PHEV is considered to be more convenient than BEV because its capability of driving on both electricity and gasoline fuels leads to longer driving range and shorter recharging time. HEV is also more convenient than BEV, but because it is not considered as a new energy vehicle and not favored by governmental policies, it becomes less popular than PHEV and comparable with BEV in the long run.

Under these circumstances, as shown in Table 5-3, the share of PHEV sales is assumed to catch up with BEV's in around 2025 and reach 20% by 2050, 5% more than the share of BEV sales. HEVs will catch up with BEVs in 2035 and reach 15% by 2050 at the same level as BEVs. The breakdown of BEVs into regular and micro-BEVs is calculated based on Table 5-2. In 2050, the total share of PEVs will reach 35%.

Table 5-3 Sales mix for private and non-private cars in the sensible scenario

	ICE NA-SI	Turbo-SI	Diesel	HEV	PHEV	BEV – regular	BEV – micro	BEV (total)
2015	83.2%	14.9%	1.0%	0.3%	0.2%	0.1%	0.3%	0.5%
2017	78.9%	17.7%	1.0%	0.8%	0.5%	0.3%	0.8%	1.1%
2020	71.2%	21.4%	1.0%	2.1%	1.7%	0.6%	2.0%	2.7%
2025	56.8%	26.1%	1.0%	5.0%	5.6%	1.3%	4.4%	5.7%
2030	41.6%	31.8%	1.0%	7.8%	9.7%	1.7%	6.4%	8.1%
2040	26.8%	32.4%	1.0%	12.3%	16.0%	2.1%	9.4%	11.5%
2050	16.3%	32.7%	1.0%	15.0%	20.0%	2.3%	12.7%	15.0%

The EV sales mix in 2015 is determined based on the historical data, summarized in Table 5-4. The growth rate of PHEVs and BEVs exceeded 100% between 2013 and 2014; so the growth rate of over 100% is applied to determine the market shares in 2015.

Table 5-4 Historical market shares of HEV, PHEV, and BEV in total LDV sales

	HEV	PHEV	BEV
2010	0.02%	0%	0.01%
2011	0.01%	0%	0.04%
2012	0.06%	0%	0.07%
2013	0.02%	0.00%	0.09%
2014	0.04%	0.09%	0.24%

The original China FLEET model assumes that the market share of Turbo-SI gradually increases until it becomes twice the share of ICE by 2050. So in all vehicle type scenarios, the ratio of ICE and Turbo-SI shares will be 1:2 in year 2050. The diesel vehicle share trend stays the same as in Akerlind’s model; its share is high for mini-truck but is around 1% for other vehicle types.

The sales mix assumptions for powertrains are the same for both private and non-private cars. Some may argue that the share of PEVs might be higher in non-private cars because it is easier to promote EV usage in the governmental, business, rental, and taxi sectors. This could be true; however, because of the small and decreasing market share of non-private car sales (6.6% in 2015 and 4.5% in 2050), making them different from the private cars would not make a big difference. To avoid unnecessary complication, I assumed the private and non-private cars have the same market share inputs.

To better explain the rationales behind the sales mix assumptions, the growth rates of the sales mix for EVs and the sales mix forecast are plotted on the graphs. For example, Figure 5-1 shows the growth rate of sales mix for EVs in private and non-private cars. It is shown that the growth rate for all EVs gradually declines.

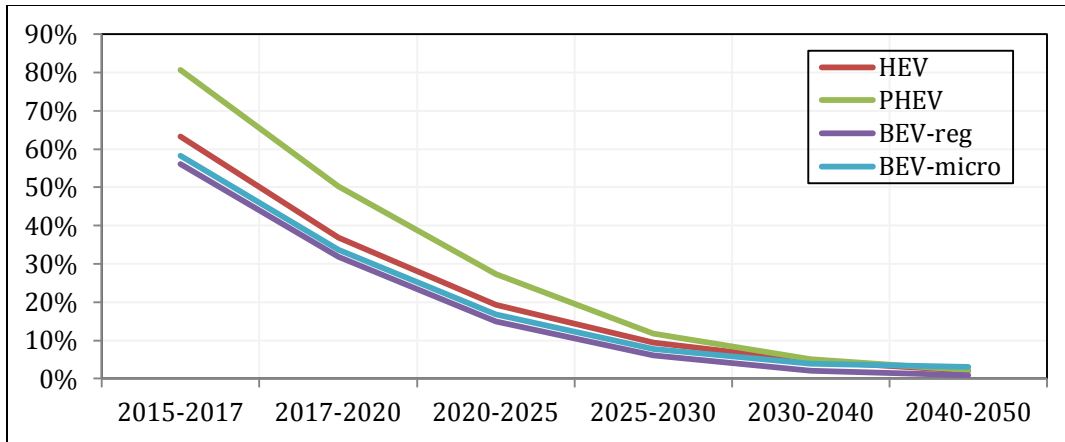


Figure 5-1 Growth rate of the EV sales mix for private and non-private cars in the sensible scenario

The forecasted market shares for private and non-private cars are shown in Figure 5-2, in order to graphically exhibit the underlying assumptions and to provide a comparison with the mini-bus and mini-truck. It is assumed that HEVs gradually reach a plateau of growth approaching 2050, while PHEVs and BEVs continue to grow and will not approach a plateau before 2050. The diffusion of new technologies normally follows a logistic growth model, which has an “S” shape, indicating three stages of new technology diffusion (China Automotive Energy Research Center Tsinghua University 2012). In the beginning stage, the vehicles grow very slowly; in the boom period, there is a rapid development; in the stable and final stage, the growth rate slows down and the development reaches a saturation level. FLEET’s EV diffusion follows the same pattern.

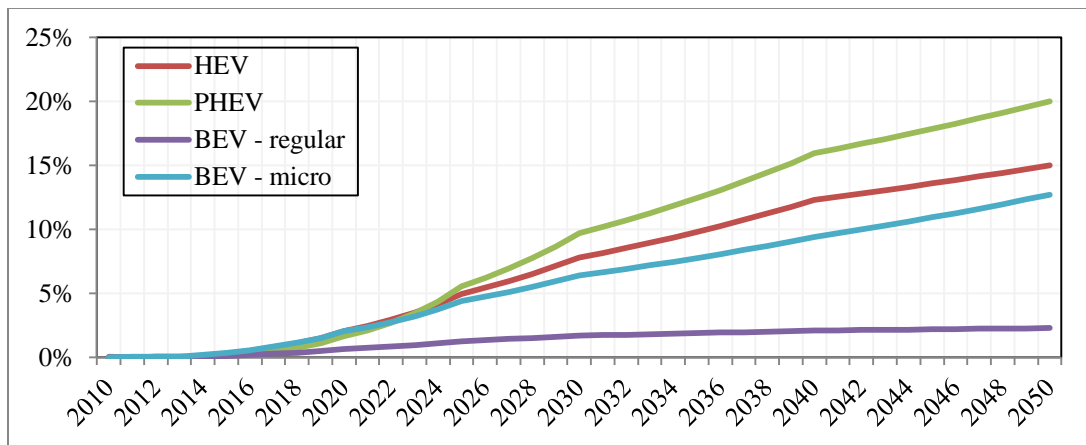


Figure 5-2 Forecast of the EV sales mix for private and non-private cars in the sensible scenario

Mini-trucks have a different sales mix profile. Due to considerations that SUVs (equivalent to mini-trucks in China) have more demanding schedules and people usually drive them for longer distances, it is assumed that the electrification adoption in mini-trucks is much gentler than that in cars. The share of PEVs in mini-truck sales is set to be half of that in car sales, while the share of HEVs stays the same. SUV’s robustness in capability would make it benefit from cheaper operation such as HEV over time. Therefore, under the sensible scenario, the share of HEV prevails in mini-trucks, staying at 15%, followed by PHEV at 10% and BEV at 7% in 2050, as shown in Figure 5-3.

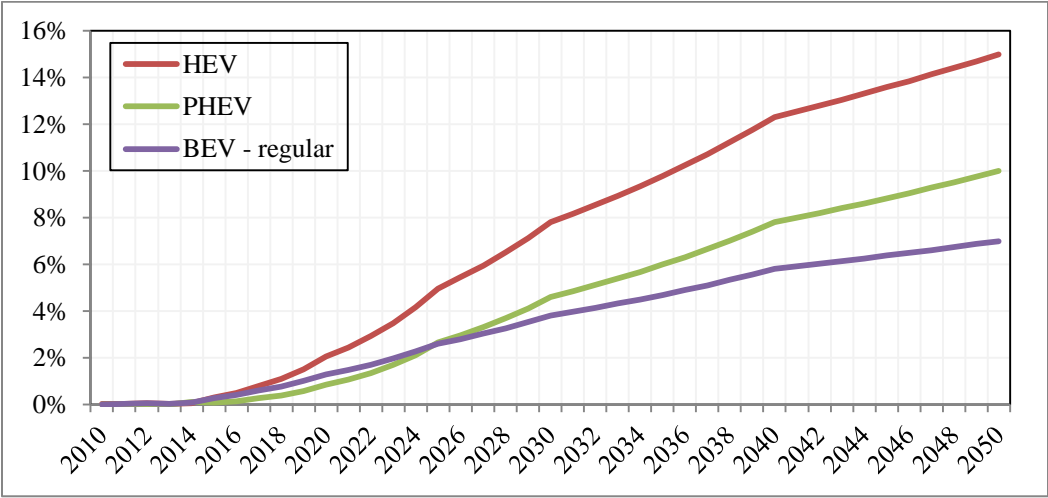


Figure 5-3 Forecast of the EV sales mix for mini-truck in the sensible scenario

Similarly, mini-buses are usually used in non-private circumstances. While they also have demanding schedules, they are not driven as intensively as mini-trucks. There are also more types of electric mini-buses than mini-trucks in the current Chinese market. Therefore, the model assumes that the PHEV share in the mini-bus segment will reach the same level as HEV, at 15% by 2050. The share of BEV is lower than both HEV and PHEV, reaching around 8.4% by 2050, as shown in Figure 5-4.

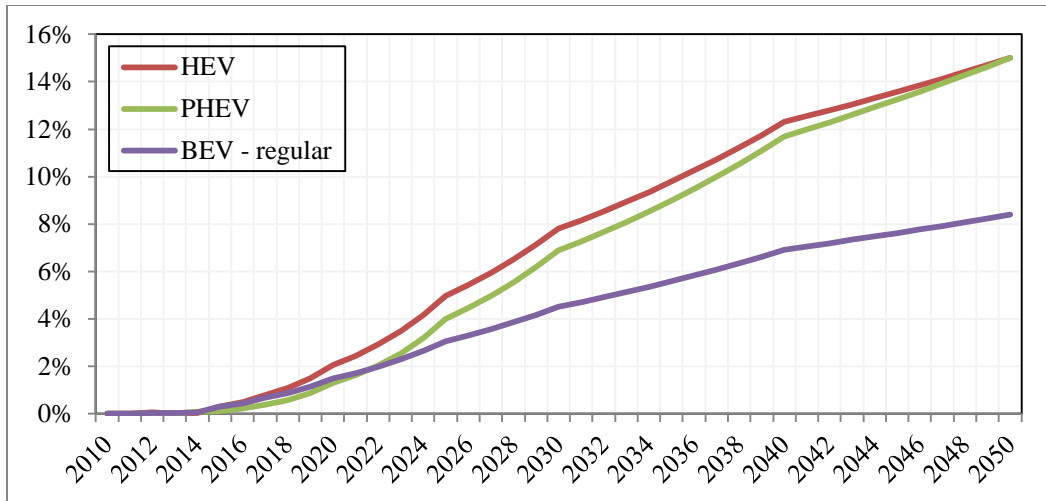


Figure 5-4 Forecast of the EV sales mix for mini-bus in the sensible scenario

5.3.2 Aggressive Scenario

The aggressive scenario assumes that (1) there are breakthroughs and outstanding improvements in BEV battery technologies, which will become cheaper, safer, and have higher energy density, leading to longer electric mileage and shorter recharging time; (2) the charging infrastructure in China will be steadily built up to meet the demand; (3) the government makes extra efforts to promote PEVs, slows down the rate of decreasing the 2015-level subsidy, and even makes more aggressive policies and mandates such as requiring car companies to have a high share of low-emissions vehicles.

One likely outcome of these assumptions is that the inconvenience factor of BEVs would be overcome, and BEVs will outpace PHEVs in their shares of the private and non-private cars due to their improved functionalities and their best potential for reducing emissions. This scenario still assumes that micro-BEVs serve as the majority of BEV sales due to their advantages in traffic and parking as well as the strong governmental supports.

As Table 5-5 indicates, the total share of PEVs will increase to 60% by 2050, with BEVs reaching 35%, 10% more than PHEVs' share, while the HEV assumption stays the same. The share of sales for micro-BEVs is the highest, reaching almost 30%. The ratio of ICE NA-SI and

Turbo-SI in 2050 will still be 1:2. The forecast of EV sales mix for private and non-private cars is shown in Figure 5-5.

Table 5-5 Sales mix of private and non-private vehicles in the aggressive scenario

	ICE NA-SI	Turbo-SI	Diesel	HEV	PHEV	BEV – regular	BEV – micro	BEV (total)
2015	83.1%	14.9%	1.0%	0.3%	0.3%	0.1%	0.3%	0.5%
2017	81.0%	15.2%	1.0%	0.8%	0.7%	0.3%	1.0%	1.3%
2020	75.4%	15.5%	1.0%	2.1%	2.2%	0.9%	3.0%	3.9%
2025	61.0%	15.8%	1.0%	5.0%	6.3%	2.5%	8.5%	11.0%
2030	45.8%	15.9%	1.0%	7.8%	11.0%	3.9%	14.6%	18.5%
2040	23.2%	16.0%	1.0%	12.3%	19.0%	5.2%	23.3%	28.5%
2050	7.9%	16.1%	1.0%	15.0%	25.0%	5.3%	29.7%	35.0%

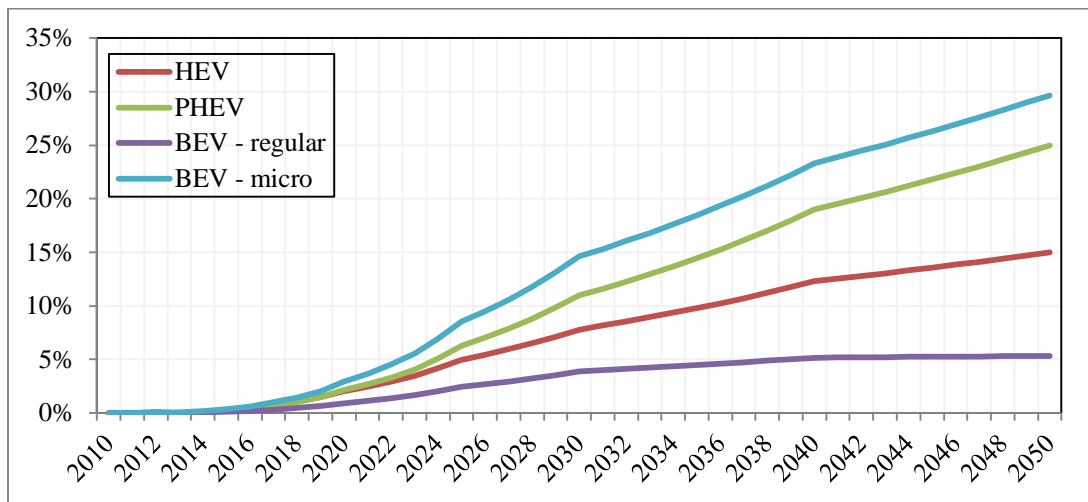


Figure 5-5 Forecast of sales mix for EV in private and non-private cars in the aggressive scenario

For mini-trucks however, due to their robustness, BEV is still unlikely to compete with PHEV and HEV. In the aggressive scenario, PHEV is assumed to have the highest share at 19%, followed by HEV at 15% and BEV at 13.5% in 2050. The forecast is shown in Figure 5-6.

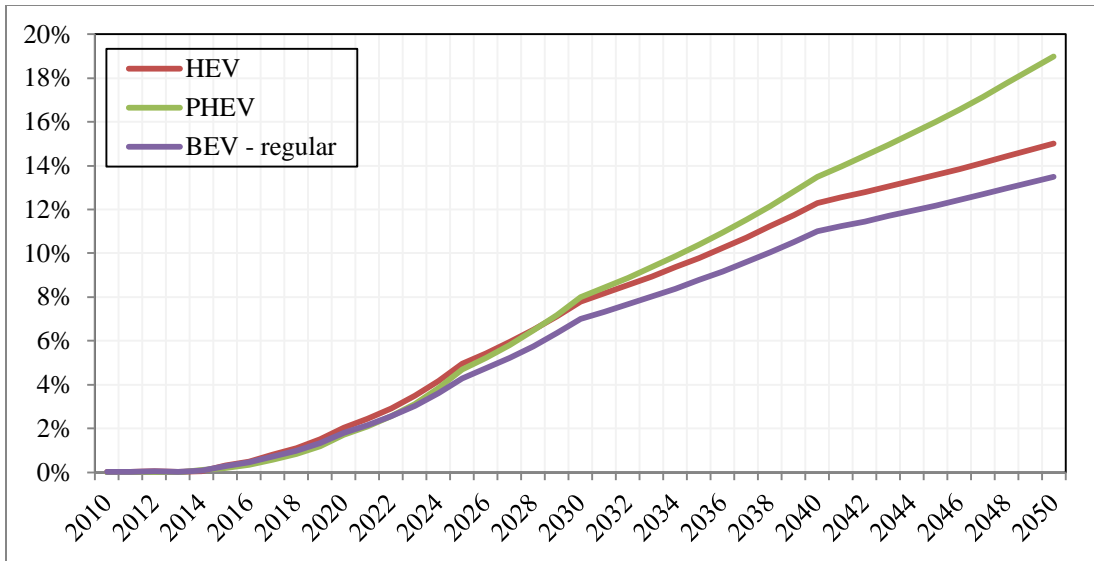


Figure 5-6 Forecast of sales mix for EV in mini-trucks in the aggressive scenario

For mini-buses, electrification is more likely than for mini-trucks. So the aggressive scenario assumes that PHEV leads the sales, reaching 25% by 2050; BEV gets to around 16%, slightly above HEV's share at 15%. The forecast is shown in Figure 5-7.

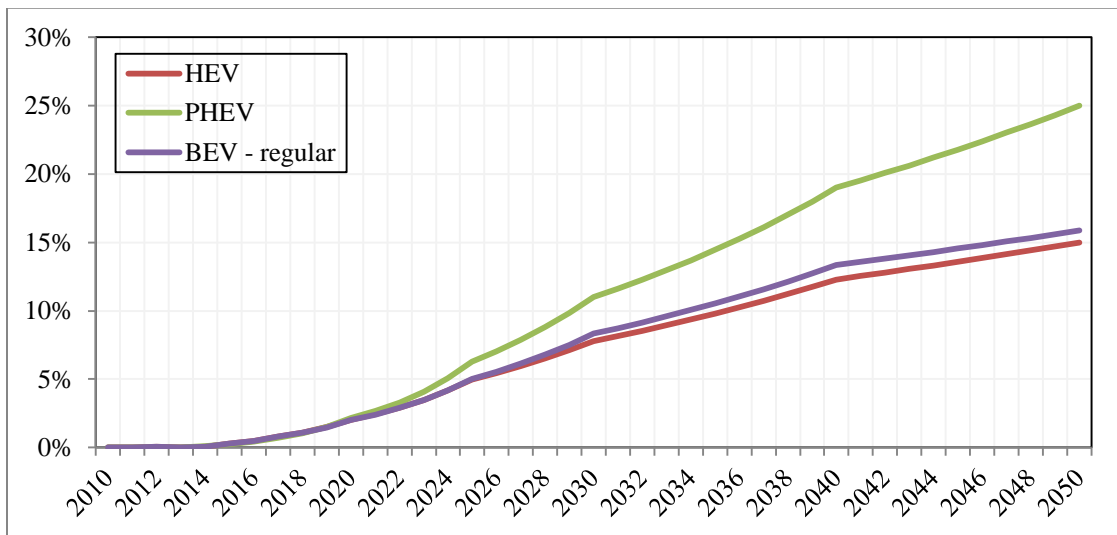


Figure 5-7 Forecast of sales mix for EV in mini-buses in the aggressive scenario

5.3.3 Passive Scenario

The passive scenario assumes that (1) the improvement of battery technology is slower than expected and the cost and safety problems are not well improved; (2) the charging infrastructure in China is limited, inadequate, and unable to catch up with the demand; (3) the government gradually withdraws policies from promoting new energy vehicles, and it greatly reduces the PEV subsidy after 2015, leading to a low enthusiasm for EVs among companies and citizens. Therefore the EV sales and development in China are much lower than those in the other two scenarios.

Under this scenario, HEVs prevail among all EV vehicle types, still reaching 15% by 2050. For private and non-private types of cars, the total share of PEVs will increase to only 10% by 2050, with the sales mix of PHEVs, micro-BEVs, and regular-BEVs reaching 7%, 2.5% and 0.5%. The sales mix for ICE NASI, Turbo-SI, and Diesel will reach 24.6%, 49.4%, and 1%. The growth of PEVs in this scenario, shown in Figure 5-8, is still in the starting stage of the “S” logistic curve.

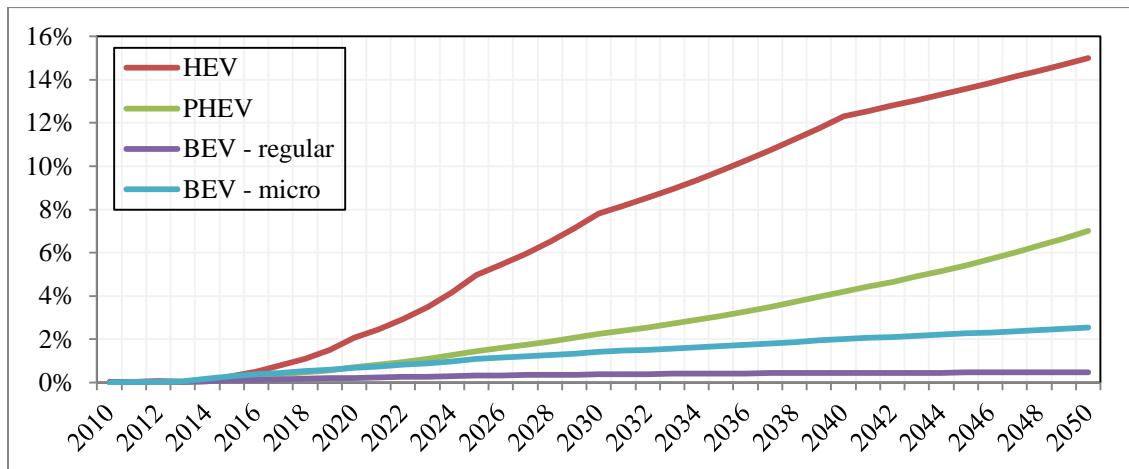


Figure 5-8 Forecast of sales mix for private and non-private cars in the passive scenario

For the other two vehicle types, the share of HEVs stays the same, while PEVs’ share will reduce by half for mini-trucks from that in cars, and mini-buses' share will be in the middle between its shares in mini-trucks and in cars. The forecast of sales mix for mini-trucks is shown in Figure 5-9. The forecast for mini-buses is similar and the details can be found in the Appendix.

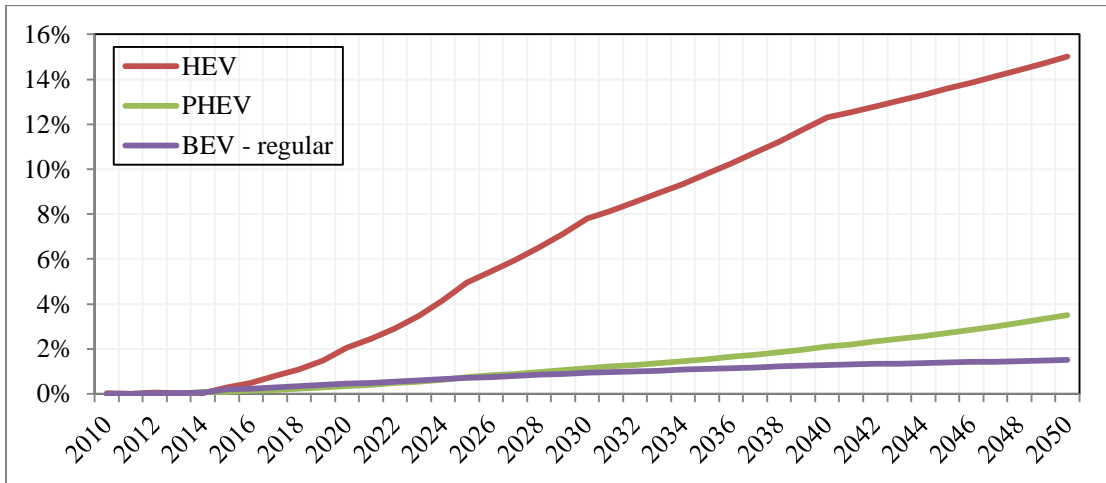


Figure 5-9 Forecast of sales mix for mini-trucks in the passive scenario

5.4 Vehicle Distance Traveled (VDT)

The VDT/year (abbreviated as VDT) in the FLEET model follows an exponential decay function. As introduced in Chapter 4, the decreasing trend of annual VDT is due to the assumptions that as more vehicles are sold resulting in more traffic congestions on the road, people will drive shorter distance. This is especially the case in China as traffic congestion becomes a serious problem.

The FLEET model assumes that new vehicle drives fewer miles than old vehicles at the same age, and the same vehicle drives shorter distance as it becomes older, after year 2010. Therefore, no matter what the new vehicle sales rate is, the average annual VDT would decrease. The assumption of the changes in VDT for different vehicle types was shown in Figure 4-5.

5.4.1 Micro-BEVs

The modification I made for VDT is to differentiate micro-BEV from other vehicle powertrains. I assumed the average annual VDT for micro-BEVs to be 33% less than the VDT of private and non-private cars. This is because people with micro-BEVs are likely to drive fewer miles due to their small size and limited range. Even regular BEVs may drive less distance than regular

gasoline vehicles, but because micro-BEVs constitute the majority of BEVs, I make micro-BEV's VDT different but leave regular-BEV the same as the rest of the powertrains.

Since very limited data can be found on the driving behaviors of BEVs or micro-BEVs in China, one can look into the behavior of micro cars. In the China Automotive Energy Outlook 2012 report, the Tsinghua group assumed that the difference in VDT between micro and small vehicles ranges from 13% to 46% between 2010 and 2050 (China Automotive Energy Research Center Tsinghua University 2012).

Therefore it is reasonable to set the assumption of a 33% reduction in average annual VDT for micro-BEVs in the FLEET model. Figure 5-10 exhibits the difference between the VDT of private and non-private BEVs and cars. The VDT for mini-trucks and mini-buses stays the same and is not shown here. The VDT for all the other powertrains under private and non-private car categories also stays the same.

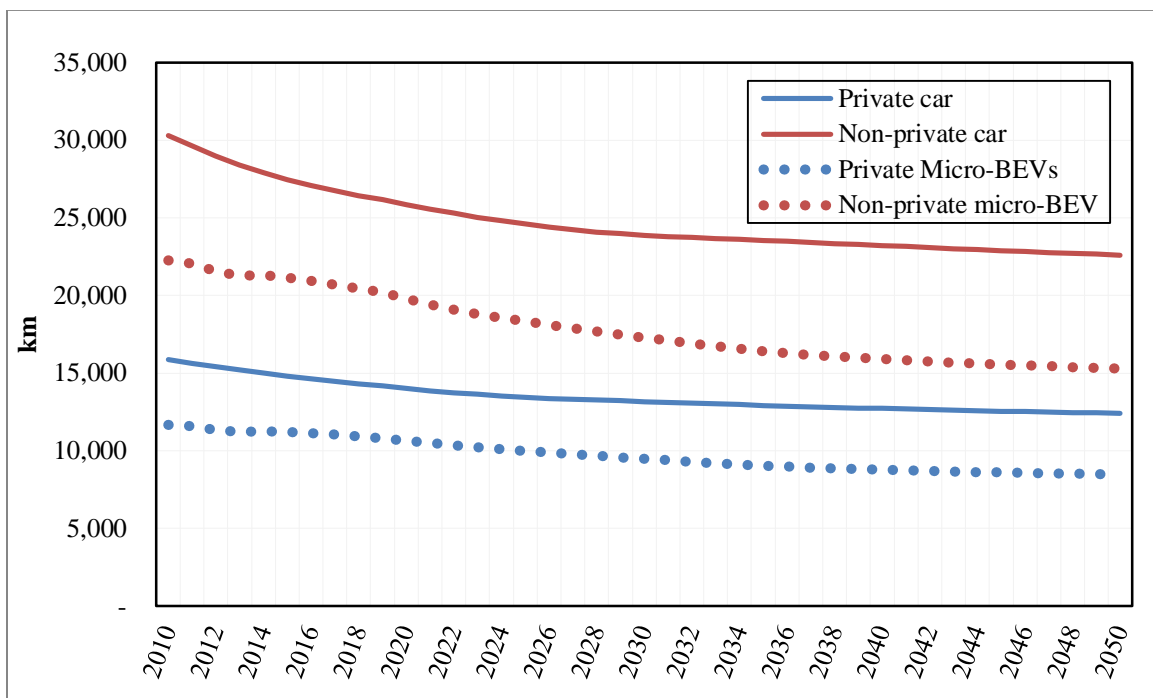


Figure 5-10 Comparison of average annual VDT between micro-BEVs and cars

5.4.2 Additional Scenario

The condition described in Section 5.4.1 is that the average annual VDT decreases for micro-BEVs, and along with that the total average VDT for the entire fleet would also decrease.

However, there might be a scenario where the total VDT stays the same. It is possible that as the VDT for micro-BEVs decreases, the other vehicles would have to drive more to compensate for the lost mileage. For example, people may use micro-BEVs for short daily trips, but would need rentals or additional cars for longer trips. This is because households have a certain fixed mileage need that needs to be met even if they choose to buy a micro-BEV.

Therefore, a scenario is designed to reflect the case where the total annual average VDT for the entire fleet stays the same as that in Akerlind's model. I distributed the lost mileage equally and added them to all other powertrains under private and non-private cars, except for micro-BEVs. In the sensitivity analysis section of Chapter 6, one would be able to see whether keeping total mileage the same affects GHG emissions significantly.

5.5 Fuel Consumption Improvement

5.5.1 Assumptions of Liquid Fuel Consumption

The FLEET model assumes that the liquid fuel consumption for different powertrains will gradually decrease over time, as shown in Figure 5-11.

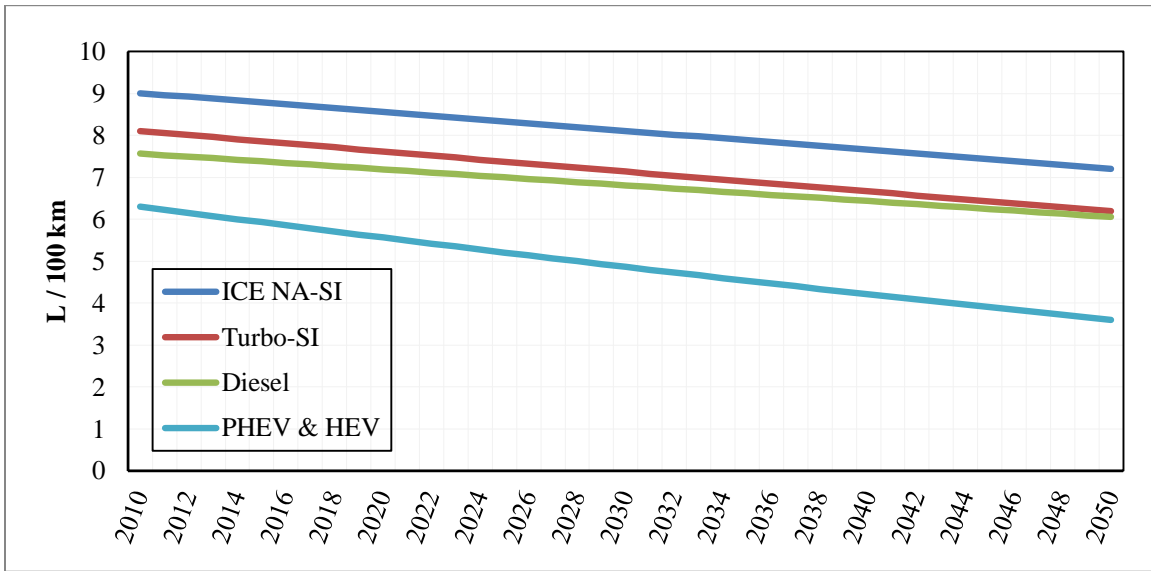


Figure 5-11 Projected liquid fuel consumption for each powertrain in the new vehicle fleet

The model assumes that the annual liquid fuel consumption of HEV and PHEV decreases from 5.93 to 3.6 L/100km between 2015 and 2050. Based on findings from Zoepf et al., the model also assumes that the utility factor of PHEV will increase from 35% to 60% between 2015 and 2050 (Zoepf et al. 2013).

The electricity efficiency for BEVs under private and non-private cars in the model will change from 0.15 to 0.089 kWh/km between 2010 and 2050, and the next section introduces the modification made for micro-BEVs.

5.5.2 Micro-BEVs' Electricity Efficiency

Micro-BEVs are expected to have higher electricity efficiency, due to their advantages of being small and light. The assumption implemented based on this feature is a 13.2% efficiency improvement for micro-BEVs.

Micro-BEVs weigh 1/3 less than regular private or non-private BEVs based on their average weights collected from the vehicle manufacturers. According to a 2012 report conducted by the

National Petroleum Council, a 2.5% increase in BEV mass leads to 1% increase in energy consumption per mile (National Petroleum Council 2012). Therefore, a 33% reduction in weight results in a 13.2% decrease in energy consumption per mile. Table 5-6 shows the different electricity consumption between regular and micro-BEVs implemented in the model.

Table 5-6 Comparison of electricity efficiency between regular and micro BEVs

(kWh/km)	Regular BEV	Micro BEV
2010	0.150	0.130
2030	0.113	0.098
2050	0.089	0.077

5.6 GHG Emissions Intensity (EI) Factors

The lifecycle GHG EI factors for different fuel sources remain the same as in Akerlind’s model, except for electricity. For example, the Well-to-Tank EI factor for gasoline and diesel are 98.6 g CO₂-e/MJ and 102.4 g CO₂-e/MJ. The EI for gasoline is assumed to stay the same between 2015 and 2050 in the China FLEET model, and this is similar to other studies’ assumptions; for example, Zhou et al. in their paper state that the carbon intensity for gasoline is relatively stable within a given period (G. Zhou, Ou, and Zhang 2013).

The GHG EI factor for electricity is derived from the Electricity Supply and Emissions Model (ESEM) introduced in Chapter 2. Table 5-7 shows the simplified version of the EI factors exported from ESEM. The annual data are imported into the China FLEET model to calculate the GHG impact of EVs. The annual EI data can be found in the Appendix.

Table 5-7 GHG emissions intensity factors for electricity demand in three scenarios

(g CO ₂ -e/MJ)	2010	2020	2030	2040	2050
Planned Scenario	235.4	188.5	154.9	132.3	120.8
More-RE Scenario	235.4	182.6	132.6	105.0	83.3
Less-RE Scenario	235.4	211.9	202.3	193.4	183.3

Chapter 6 Results and Discussions

This section discusses the major results and findings from running the ESEM and FLEET models along with different scenarios, including the three EV scenarios (sensible, aggressive, passive) depicting the different levels of EV penetration in the fleet, and the three electricity scenarios (planned, more-RE, less-RE) reflecting the adoption of renewable energy in the electric grid. The results, including the forecasts of vehicle stock, energy demand, and life-cycle GHG emissions, will be presented sequentially.

6.1 Vehicles Stock Forecast

The stock forecast of LDV fleet for different scenarios is the first output from the FLEET model. The total stock will reach 576 million by 2050, which is the same across different EV scenarios, while the stock breakdown is different across scenarios. The stock forecast for the sensible scenario, broken down by vehicle powertrains, is shown in Figure 6-1. EVs, including HEVs, PHEVs, and BEVs, will take up about 40% of the total vehicle stock by 2050. PHEVs have the highest share of the stock, reaching 16% of the total; micro-BEVs' share is half of that, reaching 8% of the total stock. PEVs, including PHEVs and BEVs, will have a share of 27.4% by 2050.

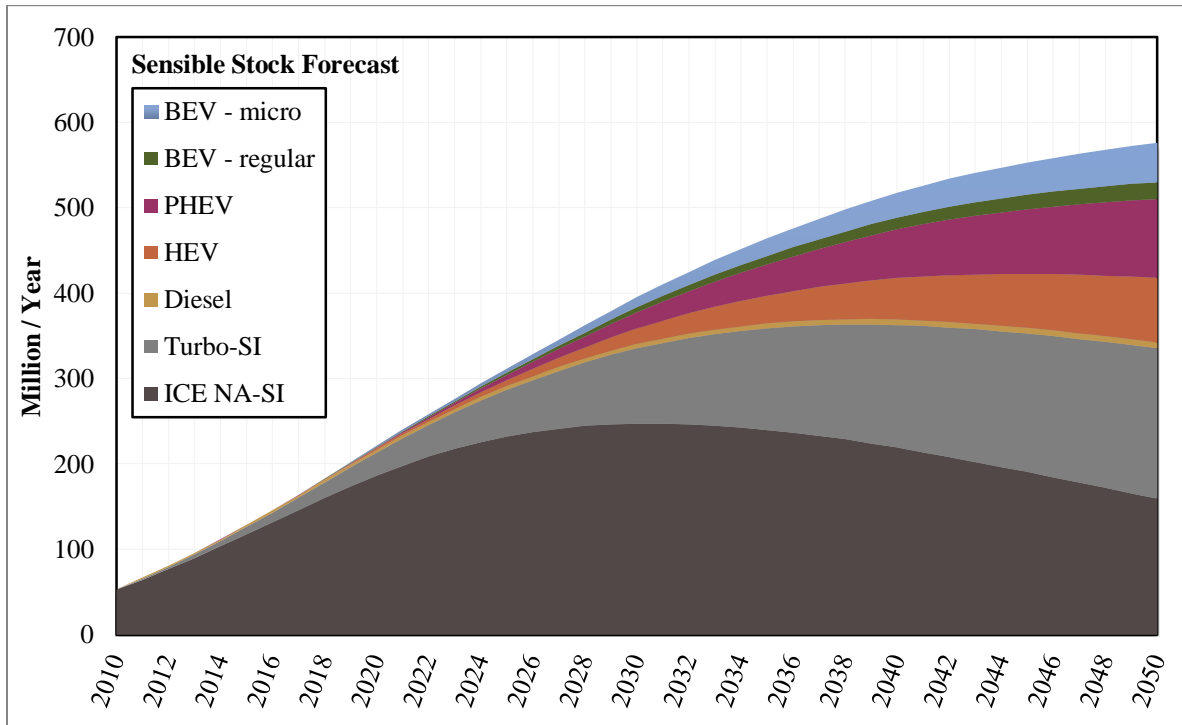


Figure 6-1 Stock forecast of LDVs under the sensible scenario

The share of PEVs in total sales was set to be 35% in 2050 (shown in Table 5-3). The difference between 35% and the previously noted 27.4% is due to a lag between sales and stock captured by the FLEET model. It takes time for old cars to be scrapped from the fleet, and therefore it takes time for the market share of sales to reach the same level of stock shared. The shares of PEVs in both sales and stock are plotted in Figure 6-2, showing a lag of six years on average for the LDV fleet in China.

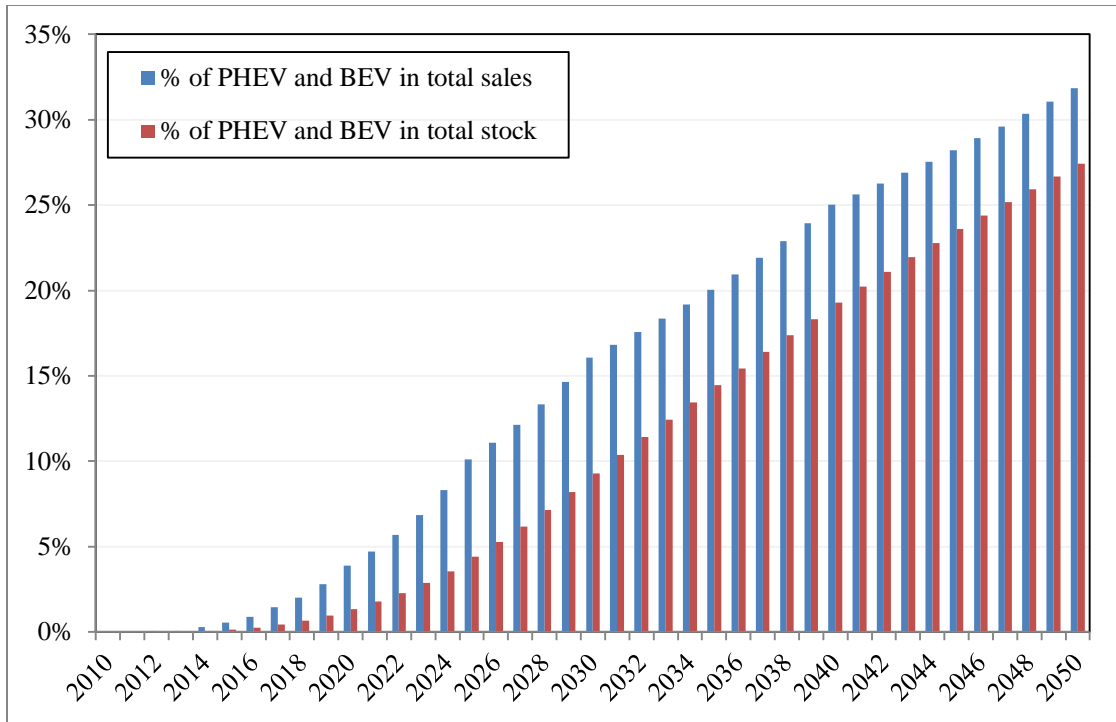


Figure 6-2 Lag between PEV shares in sales and stock (lag = 6 years on average)

The stock forecasts for the aggressive and passive EV scenarios are shown in Figure 6-3. Comparing the aggressive and passive scenarios, the EV share of stock in 2050 will be 60.5% versus 20.5%, and the PEV share 47.3% versus 7.3%.

In the aggressive scenario, both shares of PHEVs and micro-BEVs in total stock will reach around 20% by 2050. Micro-BEVs' fast growth in this scenario is mostly due to its high percentage in private car sales. In the passive scenario, only HEVs' share will reach 13.2% by 2050, while the shares of all other EVs will remain below 5%.

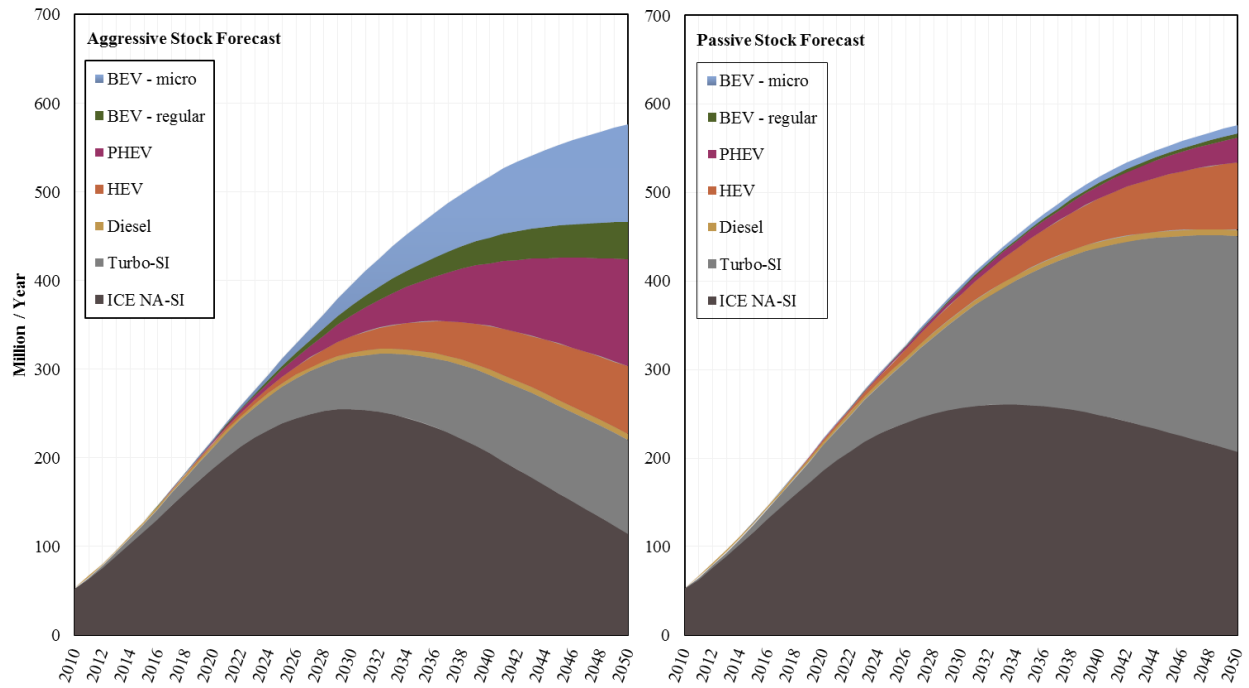


Figure 6-3 Vehicle stock forecast in the aggressive scenario (left) and passive scenario (right)

As shown in the summary Table 6-1, the aggressive scenario’s electrification level (47.3%) will be higher than the passive scenario’s (7.3%) by almost a factor of seven in 2050. This table presents the summary of the shares of PEVs in total LDV stock over time, comparing the level of electrification intensity in the fleet among the three scenarios.

Table 6-1 Comparison of PEV share of stock among three scenarios

	2015	2020	2030	2040	2050
Sensible	0.15%	1.3%	9.3%	19.3%	27.4%
Aggressive	0.16%	1.8%	14.7%	32.7%	47.3%
Passive	0.15%	0.7%	2.5%	4.7%	7.3%

6.2 Energy Demand Forecast

Due to the large difference of electrification in the fleet, the energy demand forecasts from the three scenarios vary significantly, as shown in Figure 6-4. The unit for energy demand is million tons of oil equivalent (Mtoe). In the sensible scenario, the total energy demand will peak at 340 Mtoe in year 2038 then decrease to 305 Mtoe in 2050. Comparing the aggressive and passive scenarios, the total energy demands will peak at 310 in year 2033 vs. 383 in 2042, and then decrease to 237 vs. 369 in 2050. Compared to the aggressive scenario, the sensible scenario demands 29% more energy and the passive scenario demands 56% more; the difference between the aggressive and passive scenarios in terms of their energy forecast will be 132 Mtoe in 2050, equivalent to 56% of the total demand in the aggressive scenario.

The reason for the low energy demand in the aggressive scenario is that more EVs displace the ICE and turbo-SI vehicles and less gasoline will be consumed. In addition, because EVs, especially BEVs, are more energy efficient than traditional powertrains, they require less energy as well, lowering the overall energy consumption of the fleet.

The dotted line in Figure 6-4 represents the additional scenario where the total mileage stays the same because other vehicles drive more to compensate for the reduced mileage by micro-BEVs; this is meant to provide some sensitivity analysis and contrast the sensible scenario which assumes that the total mileage decreases as micro-BEVs drive less (refer to section 5.4.2 for more details). The result indicates that keeping the total mileage the same only increases the energy demand modestly, by about 3%.

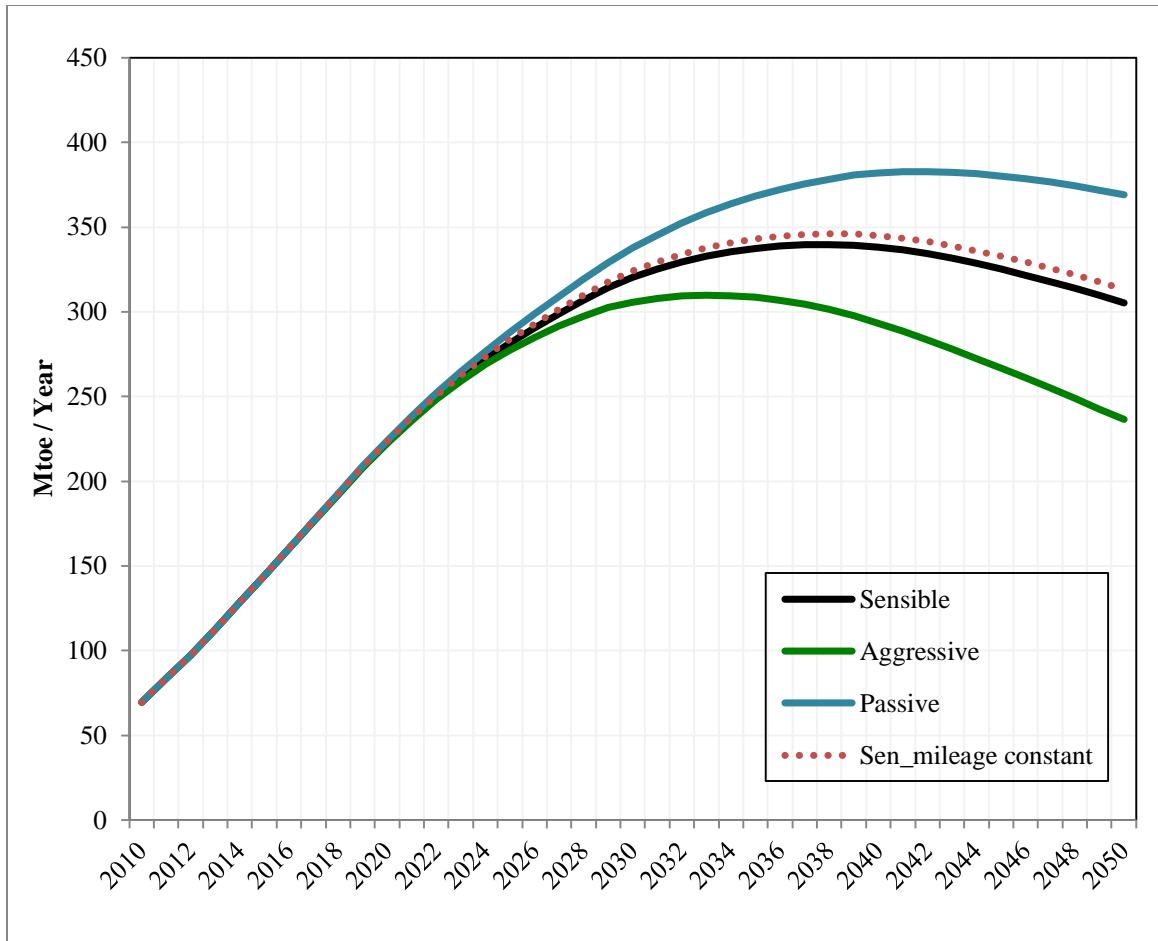


Figure 6-4 Comparison of the energy demand forecasts from four EV scenarios

In order to understand how electrification lowers energy demand, it is important to examine the energy demand forecast breakdown for each scenario. First, the forecasts of energy and fuel demand in the sensible scenario are shown in Figure 6-5. The energy demand is disaggregated by powertrains and the fuel demand disaggregated by fuel sources; they have the same total values.

It is shown that in 2050, 79% of energy demand will come from ICE and Turbo-SI powertrains, and 19% from EVs. HEVs' demand will reach 31.8 Mtoe by 2050, and this value does not change across scenarios, since its market share input assumptions were all the same. BEVs and PHEVs will take up 1.7% and 7% of the total energy demand by 2050, respectively.

Note that although BEVs' share of total vehicle stock will reach 11.4% in 2050, it will only demand 1.7% of the total energy. This indicates that BEV has a strong energy efficiency advantage.

The total electricity demand in 2050 will also be small, reaching 11 Mtoe, around 3.7% of the total fuel demand, as shown in Figure 6-5 (right). Out of the 3.7%, 1.7% comes from BEVs and 2% comes from PHEVs. Gasoline continues dominating the total fuel demand of the LDV fleet, reaching 257 Mtoe with a share of 84% in 2050.

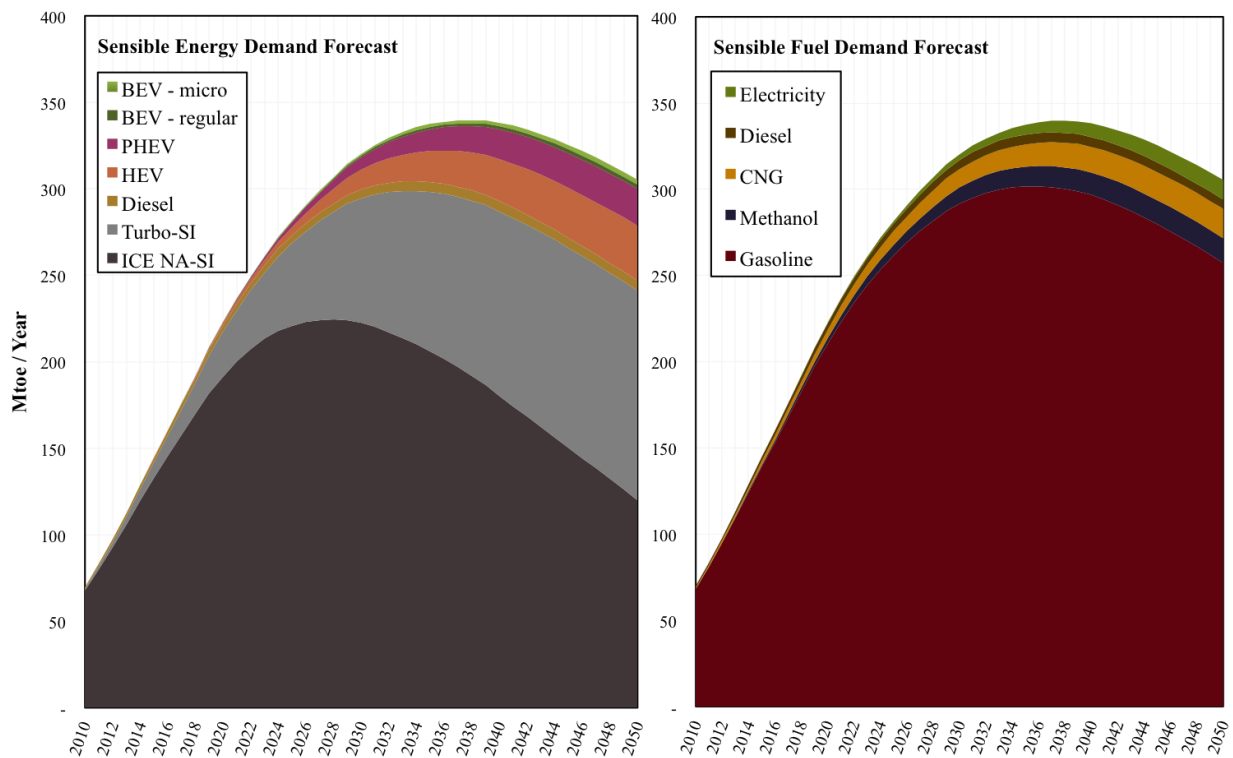


Figure 6-5 Projected energy demand (left) and fuel demand (right) in the sensible scenario

Aggressive electrification not only reduces the total energy demand, but it also significantly lowers the gasoline consumption, as shown in Figure 6-6. In 2050, the gasoline demand will be 211 Mtoe in the aggressive scenario, 149 Mtoe lower than that in the passive scenario. This could help mitigate the oil import dependence and energy insecurity problems faced by China.

In the aggressive scenario (Figure 6-6, left), micro-BEVs will account for only 2.9% of the energy demand by 2050, although it will take up around 20% of the total vehicle stock. This is because micro-BEVs are most energy efficient, and since they play a big role in the aggressive scenario, they successfully help reduce the total energy demand and gasoline demand of the fleet. Also shown is that in the aggressive scenario, the share of energy demand from ICE and Turbo-SI will be 67% in 2050, while the share of EVs 31%. PHEVs and regular-BEVs' share of demands will be 13.4% and 12.3% (3.3% for electricity), respectively.

The passive scenario (right) has much higher total energy demand since the PEVs' share of total vehicle stock will only reach 7.3% by 2050, and the fleet is dominated by traditional powertrain vehicles. In this scenario, ICE and turbo-SI will take up 88% of the total energy demand while PEVs only 2% in 2050. The total electricity demand will be 3 Mtoe, compared to 20 Mtoe in the aggressive scenario. Once again, it shows that electrification has a big impact in reducing the energy and especially gasoline consumption of the vehicle fleet.

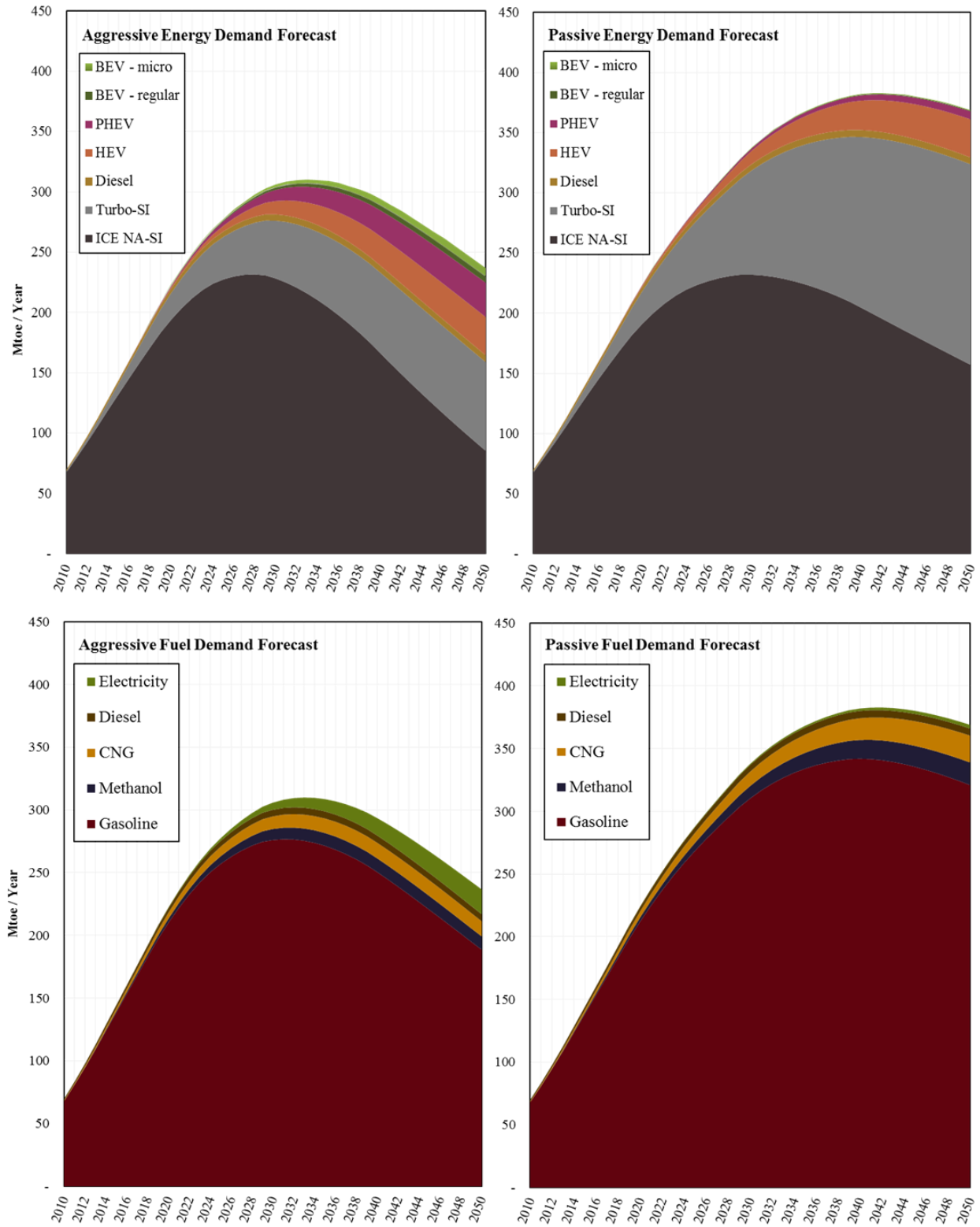


Figure 6-6 Energy demand forecasts in the aggressive (left) and passive (right) scenarios

6.3 Lifecycle GHG Emissions

6.3.1 Bring Everything Together

Electrification also has a significant impact on the reduction of vehicle fleet GHG emissions, as shown in Figure 6-7, which presents the GHG emissions forecasts for nine scenarios derived from combining three EV scenarios and three electricity scenarios. The unit is million metric tons (Mmt) CO₂-equivalent per year.

The *reference* in this graph is the black solid line, representing the *sensible* EV scenario adopting emissions intensity (EI) factors exported from the *planned* scenario of the Electricity Supply and Emissions Model (ESEM). The three sets of lines in the graph represent the different levels of aggressiveness of EV penetration in the fleet. The lower green lines show the *aggressive* EV scenario while the upper blue lines show the *passive* EV scenario. The three lines within each set of EV scenario represent the different levels of renewable energy (RE) adoption in the electricity grid, or, the “cleanness” of the grid. The middle line is the *planned* scenario, while the upper and lower lines are the *less-RE* and *more-RE* scenarios. The EI factors from these scenarios are fed into each EV scenario to derive the GHG emissions curves.

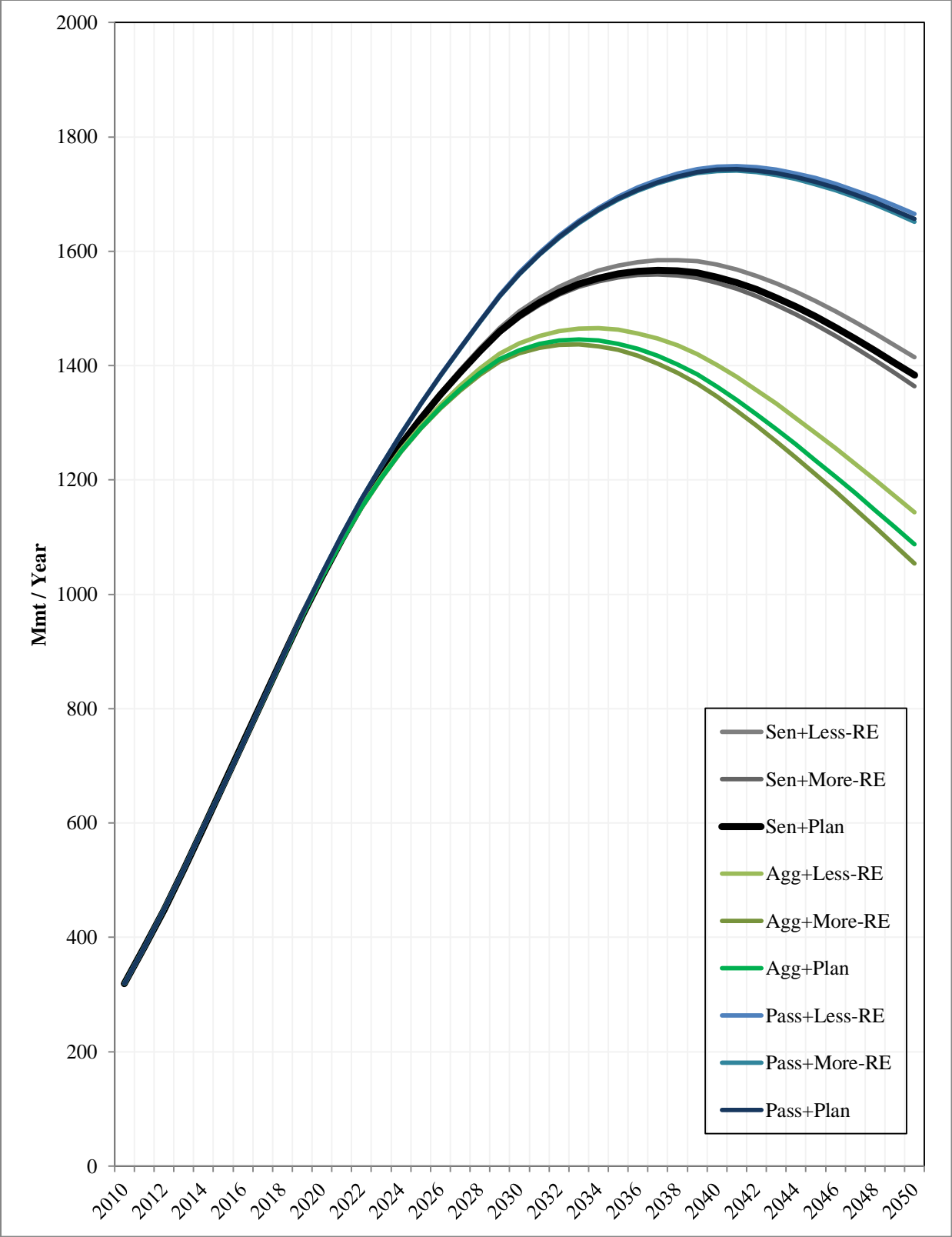


Figure 6-7 GHG emissions forecasts across nine scenarios

The dark green, black and blue lines in Figure 6-7 suggests that: under the planned electricity scenario, the GHG emissions forecasts from different EV scenarios vary significantly, indicating that electrification plays a big role in reducing emissions. In the reference, the GHG emissions will rise and peak at 1559 Mmt in 2037 before decreasing to 1383 Mmt by 2050. The aggressive and passive scenarios will emit 1087 and 1657 Mmt in 2050, respectively, resulting in a difference of 570 Mmt, a number equivalent to 52% of the total emissions in the aggressive scenario. The aggressive scenario's emission savings compared to the reference will be 296 Mmt in 2050, equivalent to 45% of the current (2015) emission level.

In contrast, the GHG emissions forecasts in different electricity scenarios vary less significantly. Take the aggressive EV penetration (the green lines), for example; in the planned electricity scenario, the GHG emissions will reach 1087 Mmt by 2050. In the less-RE and more-RE scenarios, the emissions will reach 1143 and 1054 Mmt by 2050, resulting in a difference of 89 Mmt. This indicates that the benefit of aggressively greening the grid rather than doing nothing is an 89 Mmt emissions saving for the LDV fleet, which is around six times smaller than the emissions savings for aggressive EV penetration. The emissions savings for more-RE adoption in the sensible and passive EV scenarios will be even smaller, with only 50 and 13 Mmt by 2050.

It seems that the aggressive EV penetration has a greater impact on reducing emissions than aggressively cleaning up the grid, since the GHG emissions saved from the former is about six times more than the emissions saved from the latter ($570/89 = 6.4$). However, this is not the entire picture. The difference among the constructions and attributes of scenarios affects the results. Referring to Table 2-8, the share of non-fossil electricity in More-RE and Less-RE scenarios differs by a factor of two, while referring to Table 6-1, the share of PEVs in aggressive and passive fleet scenarios differs by a factor of seven. Therefore, since the contrast of scenarios is much bigger for EV penetration in the fleet than for renewables penetration in the grid, it makes sense for aggressive EV expansion to have a bigger impact on the reduction of emissions.

The fact that the share of PEV in vehicle stock could vary widely across the three EV scenarios (Table 6-1) suggests that, relative to growing the RE contribution to the electricity supply system, there is greater potential for aggressive EV penetration to reach a significant percentage,

or, expanding EVs in the fleet can occur on a faster time scale. It is more difficult to clean up the grid that aggressively due to the long life cycle of power plants, and it is especially difficult to get rid of coal power plants in China because of its abundance of coal. But since the life cycle of vehicle is shorter and it is easier to substitute new vehicle technologies in the fleet, if EVs become more attractive relative to conventional gasoline vehicles, a highly aggressive EV penetration is less difficult to achieve in order to reduce the GHG emissions.

Changing the grid mix could help reduce the emissions of the LDV fleet when EVs occupy a significant share of the fleet. As shown in Figure 6-7, the emission-saving benefit starts to become evident after 2030, and the lines of less-RE and more-RE continue to diverge as they approach 2050 and beyond. The diverging trend indicates that if the government wants GHG emissions to go down, it would need to aggressively adopt the more-RE scenario. This is especially the case for the aggressive *EV* scenario; as shown in the figure, cleaning up the grid could achieve most emissions savings for the fleet when aggressive EV expansion takes place.

Cleaning up the grid is critical, as electricity generation accounts for the majority of the country's total energy demand and emissions. As shown in Figure 6-8, greening the grid can achieve enormous emissions savings for the power supply system. The total GHG emissions of the grid, derived from the ESEM, will reach 4109, 5960, and 9041 Mmt by 2050 for the more-RE, planned, and less-RE scenarios, respectively. The difference between *more-RE* and *less-RE* scenarios in terms of total grid GHG emissions will be around 5000 Mmt by 2050, which is almost nine times more than the LDV emissions savings expected from the *aggressive EV* penetration (570 Mmt). Therefore, cleaning up the grid could greatly reduce the overall emissions, and it would require both improving the efficiency of the electricity-generation technologies and developing more renewable energy for the grid.

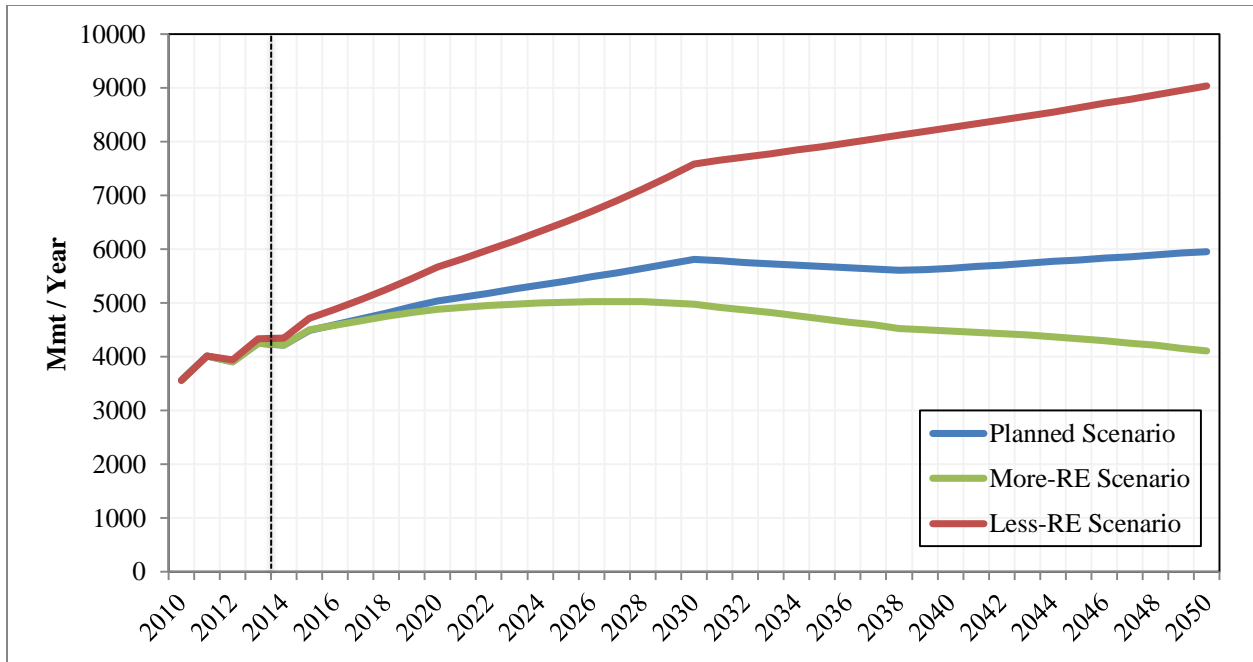


Figure 6-8 Forecast of GHG emissions from the electricity supply system for each electricity scenarios

Finally, both figures infer that in order to help China reverse the emissions trajectory by 2030, the government would need to adopt the two scenarios of aggressively expanding EVs in the fleet and adopting more renewables in the grid. As shown in Figure 6-7, under the more-RE scenarios, the peaking years and GHG emissions for the passive, sensible, and aggressive EV scenarios will be: 2041 (1741 Mmt), 2037 (1559 Mmt), and 2033 (1437 Mmt). Therefore, only the most aggressive EV and renewables adoption scenarios could enable the LDV fleet to reach its emissions peak as early as 2033. Interestingly, according to Figure 6-8, the total GHG emissions of the power supply system in the more-RE scenario will peak in 2027, which is the only scenario that could reverse the rising emission trajectory for the grid before 2030. So China would need the more-RE scenario in order to accomplish its emission reduction goal.

6.3.2 Emissions Breakdown Compared by Powertrains

Micro-BEV could achieve the most reduction of energy demand and GHG emissions per km, compared to traditional powertrains such as ICE, as shown in Table 6-2, which presents the

energy consumption and emissions per km for ICE, regular-BEV, and micro-BEV in year 2015 and 2050. This shows that although energy consumption per km for both ICE and BEV reduces over time, because the EI factor of ICE remains the same but changes for BEV, the latter will achieve greater reduction of emissions by 2050. For example, between 2015 and 2050, the energy consumption per km will reduce by 18% and 25% for ICE and micro-BEV respectively; however, in the same period, the emissions reduction will still be 18% for ICE but 64% for micro-BEV. This illustrates the importance of cleaning up the grid, since the EI improvement for BEV is due to the efficiency improvement of the power generating technologies for the planned scenario. If the more-RE scenario were applied here, an even greater reduction of emissions can be achieved by BEVs.

Another observation from this table is that there is a modest difference between regular-BEV and micro-BEV in terms of the energy and emissions savings per km. Because of the assumptions made for this study, such as a 13% energy consumption difference between regular and micro BEV, micro-BEV does not seem to have an outstanding advantage over regular-BEV in reducing the LDV fleet’s environmental impact.

Table 6-2 Comparison of GHG emissions per km between ICE and micro-BEV in 2015 and 2050

Year	2015			2050		
	ICE ⁸	Regular-BEV	Micro-BEV	ICE	Regular-BEV	Micro-BEV
Powertrains						
Energy consumption (MJ/km)	2.9	0.51	0.44	2.4	0.32	0.28
EI factors (g/MJ)⁹	98.6	209.3	209.3	98.6	120.8	120.8
GHG emissions (g/km)	289.3	106.1	92.3	237.4	38.7	33.7

Figure 6-9 shows the forecasts of life-cycle GHG emissions breakdown for each EV scenario, using EI factors from the planned electricity scenario. The emission breakdown for the reference (or the sensible EV scenario) is shown in the upper graphs. By 2050, out of the total GHG

⁸ A conversion of 33.4MJ/L is used.

⁹ The EI factor for micro-BEV is obtained from the planned scenario in ESEM; the EI factor for ICE is the assumption by the FLEET model

emissions, the share of BEVs, PHEVs, and HEVs' emissions will reach 2%, 7% and 10%, respectively, and the share of the emissions of total electricity consumption will reach 4.4%.

In the aggressive EV scenario shown in the lower left of Figure 6-9, out of the total GHG emissions by 2050, the share of micro-BEVs, regular-BEVs, PHEVs, and HEVs' emissions will reach 3.4%, 2.5%, 12% and 13%, respectively, and the electricity's contribution to total emissions will reach 9.9%. Gasoline vehicles' emissions (ICE and Turbo-SI) will still account for the majority of the total emission, at around 65% by 2050.

In the passive EV scenario shown in the lower right, out of the total GHG emissions by 2050, the share of PEVs' emissions will be below 3% and the share of HEVs' emissions will be around 8%. The electricity's contribution to the total emissions will be only 1%.

The comparison of the aggressive and passive scenarios suggests that the aggressive expansion of EVs can significantly lower the overall emissions of the LDV fleet, and their contribution to the LDV fleet's emissions will still be lower than the contribution from gasoline vehicles.

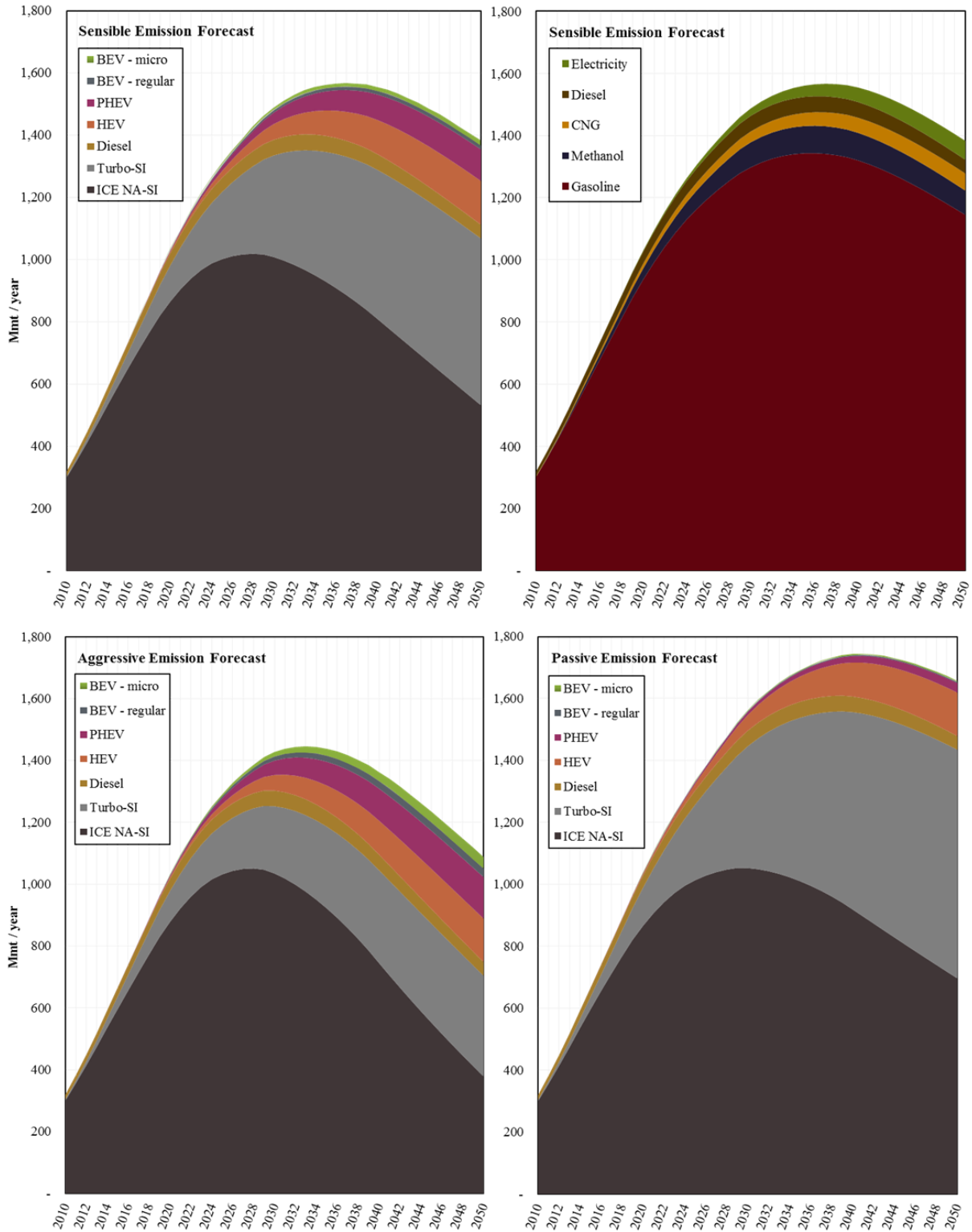


Figure 6-9 GHG emissions forecasts for the sensible scenario breakdown by powertrains (upper left) and fuel sources (upper right); emissions forecast for the aggressive scenario (lower left) and passive scenario (lower right). The EI factors for these scenarios come from the planned electricity scenario.

6.3.3 Sensitivity Analysis

A sensitivity analysis was performed to show how the forecast of total GHG emissions would change by varying some of the assumptions made for the China FLEET model.

The assumptions examined here are: (1) the share of micro-BEVs in total BEV sales; (2) whether the total mileage of the fleet stays the same; and (3) the efficiency improvement for micro-BEVs. Under (1), it assumes that the share of micro-BEVs in total BEV sales will only reach 12% by 2050, while in the original study the share of micro-BEVs was assumed to reach 85% by 2050. Under (2), this sensitivity analysis assumes that the total mileage of the fleet stays the same, compared to the original study where the total mileage reduces as micro-BEVs drive less. Under (3), this analysis assumes that micro-BEV is 40% more energy efficient than the regular private car, compared to 13.2% in the original study.

The sensitivity analysis for the sensible scenario is shown in Figure 6-10, where the *reference* represents the GHG emissions for the sensible EV and planned electricity scenarios in year 2020, 2030, 2040, and 2050. Adjusted assumptions (1), (2), and (3) are represented by *fewer micro-BEVs*, *constant mileage*, and *more efficient micro-BEVs* in the figure.

The results in Figure 6-10 show that (1) and (3) barely change the total emissions forecast of the LDV fleet, while keeping the mileage constant would increase the total emissions by a modest amount. The emissions for the mileage-constant scenario will be 1419 Mmt by 2050, only 3% higher than the reference. The reasons for such small variation in the forecast of GHG emissions might be due to the relatively small percentage of BEVs in the fleet. A sensitivity analysis was then conducted for the aggressive EV scenario.

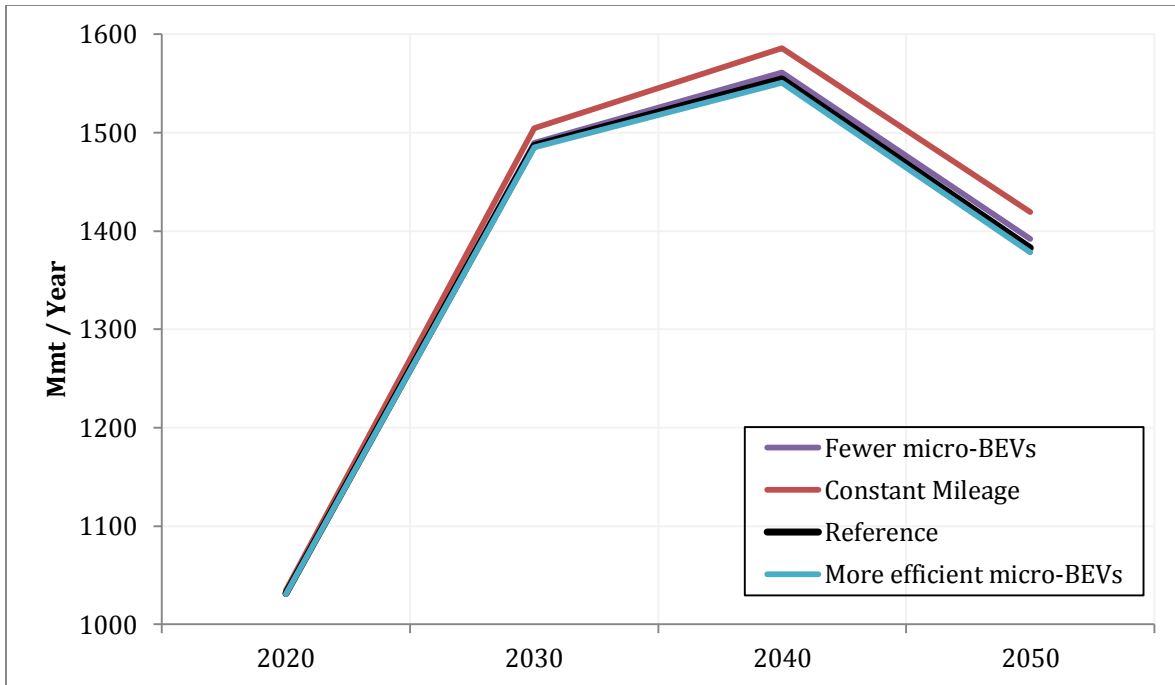


Figure 6-10 Sensitivity analysis of the total GHG emissions forecast for the sensible EV scenario

The sensitivity analysis for the aggressive scenario is shown in Figure 6-11, which exhibits much wider variations of the GHG emissions for the different modified assumptions. The *aggressive scenario* in the figure is the combination of the aggressive EV and planned electricity scenarios, and assumptions (1), (2), (3) stay the same as in the previous sensitivity analysis.

This result suggests that as micro-BEVs account for a more significant share of the fleet, their emissions saving benefit would become more evident, but not to a great extent. Also shown is that if other vehicles have to drive more to compensate for the reduced mileage from micro-BEVs, the emissions will increase by 6.5%. Overall, this sensitivity analysis indicates that the assumption of micro-BEV is not as important as the other assumptions made for the model, such as the vehicles distance traveled, PEV sales mix, and emission intensity factors of the grid.

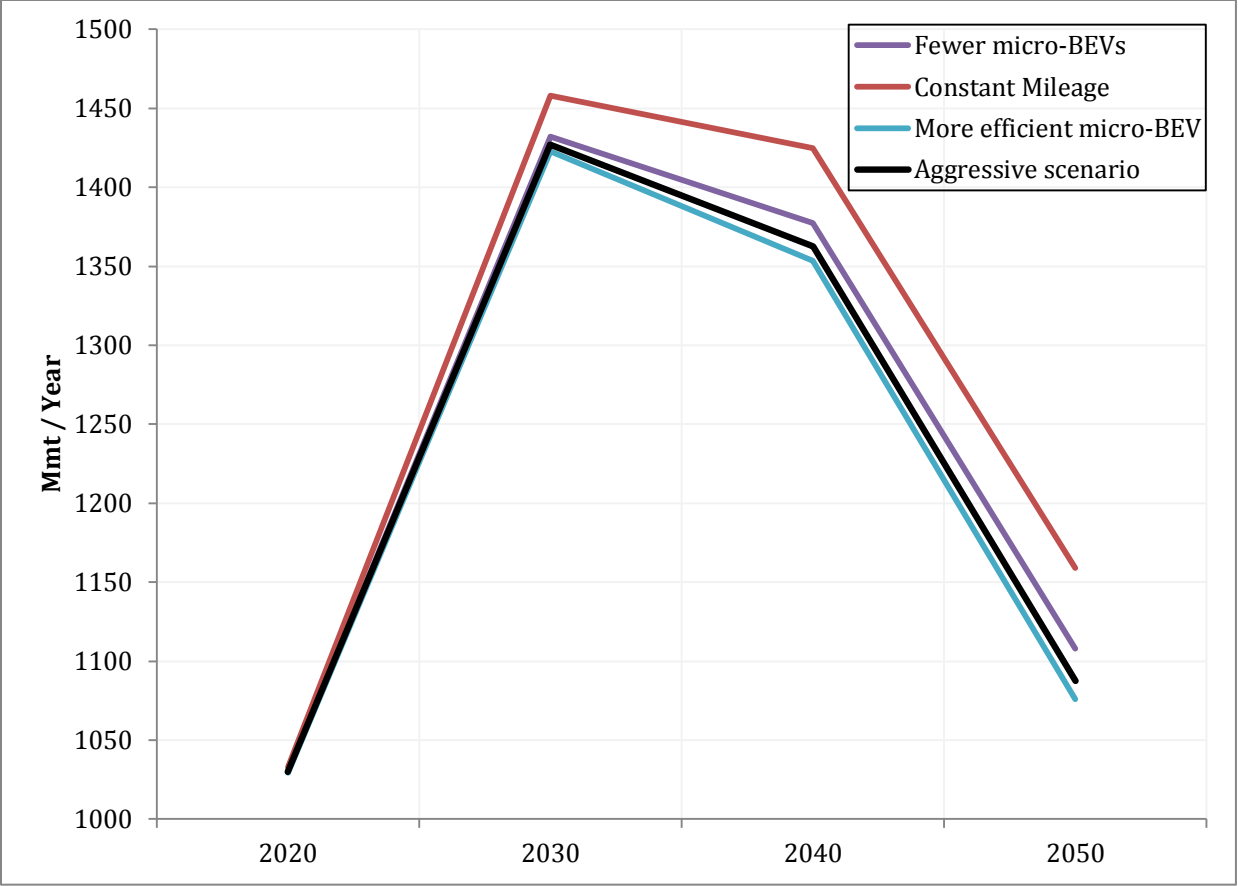


Figure 6-11 Sensitivity analysis of the total GHG emissions forecast for the aggressive EV scenario

Chapter 7 Concluding Remarks

As an overview, this study evaluates and forecasts the impact of electrification on China's light duty vehicle (LDV) fleet's energy demand and emissions, by varying the level of EV penetration and adoption of renewable electricity through different scenarios. Two models were developed for this purpose: the Electricity Supply and Emissions Model (ESEM) is used to forecast the GHG emissions intensity factors of the grid, and the China FLEET model is used to forecast the stock, energy demand, and GHG emissions of the LDV fleet until 2050. Three scenarios were developed for each model; for the ESEM, there are *planned*, *more-RE*, and *less-RE* scenarios that reflect the different levels of renewables adoption in the grid; for the China FLEET model, there are *sensible*, *aggressive*, and *passive* scenarios that reflect the different levels of EV expansion in the fleet. Detailed assumptions about various aspects of the LDV fleet were also made to reflect the reality. Together, the two models and a combination of scenarios show the relative impact, importance and inter-dependency of expanding EV use and cleaning up the grid.

In this chapter, I briefly summarize the major results of this study, and then conclude by highlighting the findings and implications as well as pointing out the limitations of the study. The major results are listed below.

- (1) In terms of the vehicle stock forecast, the share of plug-in electric vehicles (PEVs) in total stock will reach 7%, 27%, and 47% by 2050 in the passive, sensible, and aggressive scenarios, respectively. The fleet's electrification level in the aggressive scenario will be seven times higher than that in the passive scenario.
- (2) In terms of the electricity supply forecast, the share of non-fossil energy in total electricity generation by 2050 will reach 34%, 62%, and 45% in the more-RE, planned, and less-RE scenarios, respectively. The renewable adoption levels differ by almost a factor of two.
- (3) The reference (combining sensible and planned scenarios), which reflects what is likely to happen, shows that the automotive energy demand of the fleet will rise and peak at 340 million tons of oil equivalent (Mtoe) in year 2038 before decreasing to 305 Mtoe by 2050, and the GHG emissions of the fleet will rise and peak at 1559 Mmt in 2037 before decreasing

to 1383 Mt by 2050; these 2050 values will be about two to three times more than the current (2015) level of energy demand and emissions of the fleet.

- (4) In terms of the forecast of the automotive energy demand including electricity, the aggressive scenario will demand 132 Mtoe less than the passive scenario in 2050, a number equivalent to 56% of the total demand in the aggressive scenario. Compared to the aggressive scenario, the reference will demand 29% more energy and the passive scenario 56% more. The reason for such low energy demand in the aggressive scenario is that BEVs are very energy efficient; therefore a high electrification level of the fleet leads to great automotive energy consumption reduction.
- (5) Aggressive electrification can also lower the gasoline demand by an amount up to 149 Mtoe, which would help mitigate the problem of oil import dependence and energy insecurity.
- (6) The GHG emissions forecasts from the three main *EV* scenarios vary greatly, exhibiting a difference of 570 million metric tons (Mmt) between the aggressive and passive scenarios in 2050, equivalent to 52% of the total emissions in the aggressive scenario (the planned scenarios' EI factors are used here).
- (7) The GHG emissions forecasts in the different *electricity* scenarios vary less. Under the aggressive EV penetration, more-renewables adoption will reduce GHG emissions by 89 Mmt compared to less-renewables scenario in 2050; this difference is smaller than the difference between EV scenarios (570 Mmt) by a factor of six. This is partially due to the difference in the scenario design as shown in (1) and (2).
- (8) The scenarios of aggressive EV penetration and more renewables adoption in the grid could enable the LDV fleet to reach its emissions peak as early as 2033, which would contribute to China's effort of meeting the goal of reversing its emissions trajectory by 2030.

Four major highlights and policy implications can be drawn from the findings above. First, there is a significant potential for EV penetration to reduce the automotive energy demand, oil dependence, and GHG emissions of the LDV fleet. A highly aggressive electrification level of the fleet can mitigate the energy insecurity problem and achieve great emissions savings. This is because PEV powertrains such as BEVs are much more efficient than traditional gasoline vehicles, and as electricity becomes cleaner, the benefits become even greater.

In order to expand EV penetration, the government would need to incentivize the improvement of battery technologies, build adequate recharging infrastructures, and strengthen aggressive policies, mandates, and subsidies on promoting PEVs. These could help eventually overcome the inconvenience factors of PEVs, namely limited electric mileage, long recharging time, and inconvenient charging.

Second, compared to growing the renewable energy contribution to the electricity supply system, expanding the sales of EVs and building their share in the stock can occur on a faster time scale, provided that they become more attractive relative to conventional gasoline vehicles in the market. There is greater potential for aggressive EV penetration to reach a significant percentage, since it is easier to substitute new vehicle technologies in the fleet than to substitute renewables in the grid. Therefore, it is critical to promote EV penetration to an aggressive level to take advantage of the opportunity of greatly lowering the fleet's energy demand and emissions.

However, cleaning up the grid is also important for various reasons. Electricity generation accounts for a majority of the country's total energy demand, and greening the grid can achieve enormous emissions savings. The difference between more-RE and less-RE scenario in terms of the total GHG emissions of the grid will be 5000 Mmt by 2050, which is almost nine times more than the emissions savings expected from the aggressive EV penetration scenario. Furthermore, greening the grid also increases the positive impact of the aggressive EV expansion; if China continues the cleanup, the benefit of the fleet's emissions savings will be evident by 2030 and become more significant as we approach 2050 and beyond. In addition, substituting EV in the fleet has the effect of transferring pollution sources from vehicles to power plants, which may negatively impact the people in rural areas, and therefore it is important to clean up the grid. To achieve this, results from ESEM indicate that the government would need to improve the efficiency of the electricity-generating technologies and to develop renewables aggressively.

Fourth, to help China reverse the emissions trajectory by 2030, the aggressive EV scenario and the more-RE electricity scenario will likely be needed. In these scenarios, there will need to be 61% EVs of the total LDV stock, and the GHG emissions intensity (EI) factors of the grid will decrease to 300 g CO₂-e/kWh by 2050. The combination of these two scenarios will enable the

LDV fleet to peak its GHG emissions as early as 2033. Also, the more-RE scenario will enable the grid to peak its total GHG emissions before 2030, in as early as 2027, which could further help China meet the emissions reduction goal.

Finally, there are some areas that the study cannot address due to limited time and resources. One is that both the ESEM and FLEET models focus on the national level instead of the regional level. There is a wide difference among Chinese regions in terms of the coal dominance and the GHG EI of grid, which is not captured by this study. Also, at the national level, FLEET does not differentiate between rural and urban areas, which could also be important since more EV penetration tends to take place in urban areas.

Furthermore, for ESEM, only the average generation mix and EI of the grid are modeled. If more resources are available such as the hourly load profiles of the grid, it would be interesting to model the marginal EI, which could more accurately forecast the environmental impact of EVs. Further analysis can be conducted to describe the interaction between the two, studying the charging and storage impact of EVs on the grid.

Last but not least, although power generation constitutes the majority of the life-cycle GHG emissions from EVs, further analysis can be conducted to reflect the emissions of manufacturing EVs and building the EV charging stations, especially as more EVs will come into the market. All in all, this study indicates that the emissions savings from EV penetration at the national level will be significant, and future studies are needed to give a more comprehensive view of the emissions from the regional level and sources other than power generations.

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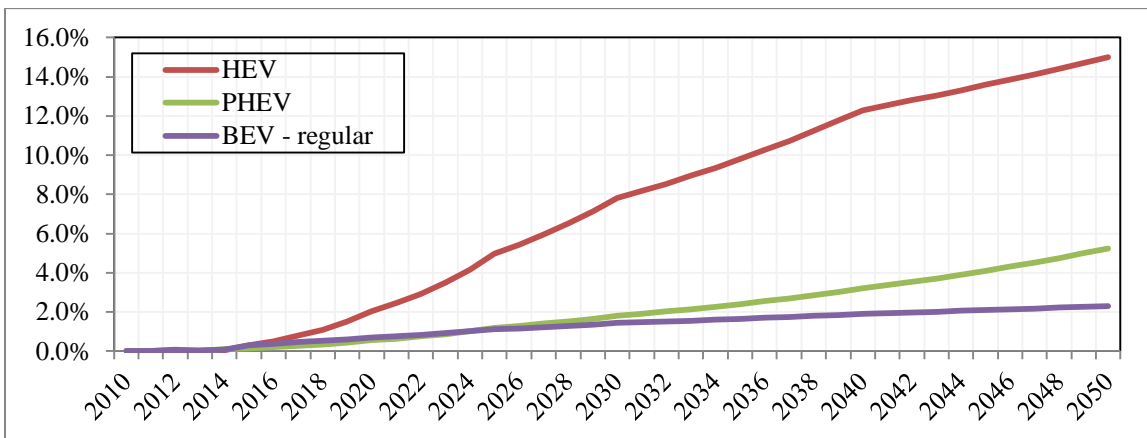
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Appendix

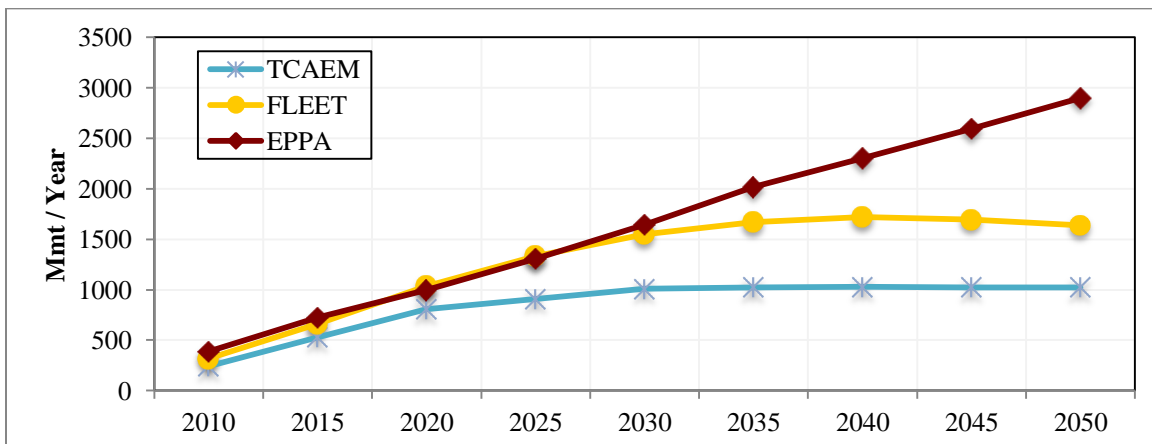
A – 1: Sales mix of private and non-private vehicles in the passive EV scenario

	ICE NA-SI	Turbo-SI	Diesel	HEV	PHEV	BEV – regular	BEV - micro	BEV (total)
2015	83.2%	14.9%	1.0%	0.3%	0.2%	0.1%	0.3%	0.4%
2017	78.8%	18.5%	1.0%	0.8%	0.4%	0.1%	0.4%	0.6%
2020	71.9%	23.4%	1.0%	2.1%	0.7%	0.2%	0.7%	0.9%
2025	60.9%	30.3%	1.0%	5.0%	1.5%	0.3%	1.1%	1.4%
2030	46.5%	40.7%	1.0%	7.8%	2.3%	0.4%	1.4%	1.8%
2040	33.3%	46.8%	1.0%	12.3%	4.2%	0.4%	2.0%	2.5%
2050	24.6%	49.4%	1.0%	15.0%	7.0%	0.5%	2.5%	3.0%

A – 2: Forecast of sales mix for mini-buses in the passive EV scenario



A – 3: Comparison of the GHG emissions forecasts for LDV fleet in China among three models



A – 4 Forecast of the lifecycle GHG emission intensity factors for the three different electricity scenarios in ESEM, served as inputs for the FLEET model

	Planned Scenario	More-RE Scenario	Less-RE Scenario
2015	4498	4506	4719
2016	4602	4592	4888
2017	4709	4674	5065
2018	4818	4752	5254
2019	4930	4823	5455
2020	5045	4885	5670
2021	5116	4921	5825
2022	5189	4954	5987
2023	5263	4982	6156
2024	5338	5004	6333
2025	5414	5021	6518
2026	5491	5030	6711
2027	5569	5031	6915
2028	5649	5024	7129
2029	5729	5006	7355
2030	5811	4976	7593
2031	5785	4926	7656
2032	5759	4874	7719
2033	5733	4821	7783
2034	5708	4766	7848
2035	5682	4710	7915
2036	5657	4653	7982
2037	5632	4595	8050
2038	5607	4535	8119
2039	5622	4505	8189
2040	5651	4485	8261
2041	5681	4462	8333
2042	5712	4436	8407
2043	5742	4408	8482
2044	5773	4376	8558
2045	5803	4341	8635
2046	5834	4302	8713
2047	5865	4260	8793
2048	5897	4214	8874
2049	5928	4163	8957
2050	5960	4109	9041