Transportation Research Part D 56 (2017) 68–84

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Electric vehicles for greenhouse gas reduction in China: A cost-effectiveness analysis

Han Hao, Xiang Cheng, Zongwei Liu, Fuquan Zhao*

State Key Laboratory of Automotive Safety and Energy, Tsinghua University, Beijing 100084, China

ARTICLE INFO

Keywords:
Battery electric vehicle
Greenhouse gas emissions
Cost-effectiveness analysis
Life cycle assessment
China

ABSTRACT

There have been ongoing debates over whether battery electric vehicles contribute to reducing greenhouse gas emissions in China's context, and if yes, whether the greenhouse gas emissions reduction compensates the cost increment. This study informs such debate by examining the life-cycle cost and greenhouse gas emissions of conventional vehicles, hybrid electric vehicles and battery electric vehicles, and comparing their cost-effectiveness for reducing greenhouse gas emissions. The results indicate that under a wide range of vehicle and driving configurations (range capacity, vehicle use intensity, etc.), battery electric vehicles contribute to reducing greenhouse gas emissions compared with conventional vehicles, although their current cost-effectiveness is not comparable with hybrid electric vehicles. Driven by grid mix optimization, power generation efficiency improvement, and battery cost reduction, the cost-effectiveness of battery electric vehicles is expected to improve significantly over the coming decade and surpass hybrid electric vehicles. However, considerable uncertainty exists due to the potential impacts from factors such as gasoline price. Based on the analysis, it is recommended that the deployment of battery electric vehicles should be prioritized in intensively-used fleets such as taxis to realize high cost-effectiveness. Technology improvements both in terms of power generation and vehicle electrification are essential in improving the cost-effectiveness of battery electric vehicles.

1. Introduction

With rapid economic and population growth, China's vehicle market scale has been increasing dramatically over the past decade, from 2.09 million in 2000 to 23.49 million in 2014, accounting for about 26% of global vehicle sales (State Council, 2000). However, as the vehicle ownership in China is relatively low (125 vehicles/1000 people in 2015) compared with developed countries (300–500 vehicles/1000 people), great growth potential is expected for China's vehicle market.

The rapid growth of China's vehicle market leads to considerable increases of oil consumption, pollutant emissions and greenhouse gas (GHG) emissions (Wang et al., 2015). China's dependence on oil import increased from 30.0% in 2000 to 59.6% in 2014 (National Bureau of Statistics of PRC, 2000). According to McKinsey, China's dependence on oil import will be higher than 70% in 2020, raising concerns about China's national energy security (Krieger et al., 2012). Hundreds of pollutants exist in the emissions of vehicles, threatening the health of urban residents (Pathak et al., 2016). Vehicles are considered to be the primary sources of particulate matter (PM) in most densely populated cities in China. In addition, China was responsible for 27.5% of the world's CO_2 emissions in 2014, ranking the highest globally (Amoco, 2015). GHG emissions from passenger vehicles accounted for roughly 5% of China's total GHG emissions in 2014 (Hao et al., 2015). However, as the growth rate of the vehicle industry is faster than the national

* Corresponding author.
E-mail address: zhaofuquan@tsinghua.edu.cn (F. Zhao).

http://dx.doi.org/10.1016/j.trd.2017.07.025

economy, this proportion will increase as a result of the growth of China's vehicle ownership in the future.

To cope with the issues of national energy security and emissions caused by passenger vehicles, China's policy makers have been seeking alternatives to conventional vehicles, including hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), and battery electric vehicles (BEV). Among the alternative technologies, BEVs are generally considered to be a promising option (Yuan et al., 2015). BEVs offer the benefits of replacing oil consumption and there is no emission during the use stage (Zhang and Yao, 2015). Therefore, BEV deployment contributes to addressing the energy security issue from the national level and reducing pollutant emissions in densely populated cities (Wu et al., 2015). With the aim of promoting BEV penetration, the Chinese government has launched a series of policy initiatives, including financial subsidies and tax exemptions. Besides, China has established an ambitious target of 5 million cumulative BEV sales by 2020, implying great growth potential for China's BEV market (State Council, 2012).

Regarding the impact of BEV deployment on GHG emissions in China, extensive studies have been conducted. However, no consensus has been reached yet. Most studies concluded that BEVs have the benefit of reducing GHG emissions in China. However, their results are scattered. Ou et al. estimated GHG emissions of BEVs charged from China's coal electricity, concluding that even if coal electricity is used, BEVs can still reduce life-cycle GHG emissions compared with conventional gasoline vehicles (Ou et al., 2010). Under China's current generation mix, the GHG emissions reduction effect of BEVs is believed to be higher. Zhou et al. compared CO_2 emissions of BEVs in the contexts of several regional power grids in China (Zhou et al., 2013). Their results showed that BEVs reduce GHG emissions by 17.1% at the national level in 2009. On the regional level, the reduction depends heavily on the regional power grids. Huo et al. studied CO_2 emissions of BEVs in 2008 and 2030 (Huo et al., 2010). Their results showed that BEVs do not promise much benefit in reducing CO_2 emissions in China in 2008. In the future, the CO_2 reduction effect of BEVs is expected to be improved. Shi et al. estimated potential of BEVs in reducing GHG emissions in China (Shi et al., 2013). They concluded that from the life cycle perspective, BEVs can reduce GHG emissions by 56% in China. However, a certain studies reached an opposite conclusion that BEVs will increase GHG emissions. Wang et al. conducted a life cycle assessment of internal combustion engine and BEVs in China (Wang et al., 2013). According to their results, BEVs increase GHG emissions by 16.5% in 2009 compared with conventional vehicles. In 2020, they estimated that BEVs will still increase GHG emissions by 11.3%.

In contrast, the GHG reduction potential of BEVs in many developed countries is larger than that in China, mostly because of the domination of coal electricity in China. For instance, Huo et al. compared the GHG emissions of BEVs between China and the U.S. (Huo et al., 2015). According to their results, EVs in California and the northeast states in the U.S. have 30–60% lower GHG emissions than EVs in China. JongRoul Woo et al. estimated the GHG emissions of BEVs in different countries (Woo et al., 2017). Their results showed that BEVs in China have 30% higher GHG emissions than global average.

In spite of the different conclusions from existing studies, it is widely accepted that BEVs have the potential of reducing GHG emissions under cleaner electricity generation. However, the evaluation of GHG emissions reduction needs to be balanced from the economic point of view. Although BEVs may reduce GHG emissions with a cleaner power grid, it probably have higher total cost than conventional vehicles. As there are numerous technologies in reducing GHG emission, it is still in doubt whether BEV is the most economic technology pathway (Ruan et al., 2016; Rezvani et al., 2015). Therefore, total cost analysis of the vehicles is also essential in providing a comprehensive evaluation. Several studies have been conducted on the total cost of BEVs. Wu et al. estimated the total cost of BEV ownership in China from the consumer perspective under nine cases (Wu et al., 2015). The results indicated that the total cost of BEV ownership is highly influenced by driving distance and vehicle class. Under the long driving distance case, BEVs cost less than gasoline vehicles for all vehicle classes. Hao et al. used real-world data to compare the levelized costs of conventional vehicles and BEVs in Beijing (Hao et al., 2015). They concluded that with average driving profiles and an assumed 8-year vehicle lifetime, the levelized cost for conventional vehicles is 1.40 yuan/km while 1.44 yuan/km for BEVs. Zhao et al. estimated the cost of BEVs from both the consumers and society perspectives in China (Zhao et al., 2015). Their results indicated that even with subsidies from the government, the life-cycle cost of BEVs is still about 40% higher than comparable internal combustion engine vehicles. They also predicted that BEVs will not become economically competitive in China until around 2030.

Based on the literature review, it is widely believed that currently the total cost of BEVs is higher than conventional vehicles. The basic rationale behind BEV deployment is realizing lower GHG emissions than conventional gasoline vehicles with higher cost. Under such a circumstance, cost-effectiveness analysis is required to assess BEV's GHG emissions reduction effect more comprehensively. However, few studies have covered this topic. Bickert et al. estimated both the GHG emissions and total private cost of BEVs in Germany (Bickert et al., 2015). According to their study, total GHG emissions can be reduced by BEV deployment in Germany, but the total private cost of BEVs exceeds the cost of conventional vehicles in 2015. Their study is a valuable reference for this study for China. Vliet et al. studied the cost-effectiveness of BEVs in Europe and concluded that the cost in reducing GHG emissions is currently above 1900 €/ton and will drop below 300–800 €/ton in the future (Van Vliet et al., 2011). Their research provided the method framework for conducting cost-effectiveness analysis for BEVs. However, their conclusions can not reflect China's specific situation.

With the aim of filling such a gap, the cost-effectiveness of deploying BEVs for reducing GHG emissions in China's context is estimated. Due to the nonconformity of existing researches on BEVs' GHG emissions, the GHG emissions of BEVs are evaluated from the life-cycle perspective. Afterwards, the life-cycle costs and cost-effectiveness of different vehicles are evaluated under China's localized situation. Moreover, single factor analysis is conducted to get a better understanding of the impacts from the influencing factors. These influencing factors include the coal power share, coal power efficiency, energy density of the battery, learning rate of the battery, vehicle use intensity and gasoline price. Afterwards, three scenarios are defined and compared to present the uncertainty of the results. This paper is organized as follows. The next section describes the research method and data. Following that, the cost-effectiveness estimations under the reference scenario and multiple scenarios are presented. The subsequent section proposes the policy implications for BEV deployment. The final section provides the conclusive remarks.

2. Methods and data

This section describes the method and data in the study. Section 2.1 shows the vehicle models to be compared in the study. Section 2.2 discusses the method in calculating GHG emissions of vehicles. Following that, the method in calculating the total cost of vehicles are presented. In Section 2.4, the definition of cost-effectiveness are explained.

2.1. Vehicle models to be compared

According to the literature review, the differences in the conclusions of existing studies are partially caused by different assumptions on the parameters of vehicle models. In order to avoid uncertainties caused by such factors, real-world vehicle models from China's vehicle market are selected to be compared. The vehicle technologies compared in this study include conventional gasoline vehicle, mild hybrid electric vehicle (MHV), heavy hybrid electric vehicle (HHV), EV100 (with a range capacity of 100 km), EV200 (with a range capacity of 200 km) and EV300 (with a range capacity of 300 km). The conventional gasoline vehicle is chosen as the baseline vehicle.

BAIC (Beijing Automotive Industry Corporation) EV200 is chosen as the reference BEV model considering its leading position in China's BEV market. By referring to official data, the battery capacity of BAIC EV200 is 30.4 kWh, and the weight of the battery system is 276 kg (BAIC BJEV, 2017). Accordingly, the specific energy of the battery system is 110 Wh/kg. Moreover, the electricity consumption rate of BAIC EV200 under New European Driving Cycle (NEDC) is 15.2 kWh/100 km and the range capacity is 200 km (BAIC BJEV, 2017).

The parameters of BEVs with different range capacities (100 km, 200 km, 300 km) are assumed based on the parameters of BAIC EV200 and the method presented below. The curb weights (the weight of a fully equipped vehicle) of BEVs can be derived from Eq. (1):

$$m_i = m_{EV200} - (BC_{EV200} - BC_i)/SE \tag{1}$$

where m_i is the curb weight of BEV type i (i = 1, 2, 3) with a range capacity of (100 ∗ i) km (kg); m_{EV200} is the curb weight of BAIC EV200 (kg); BC_{EV200} is the battery capacity of BAIC EV200 (kWh); BC_i is the battery capacity of EV type i (kWh); SE is the specific energy of the battery system (Wh/kg), which equals 110 Wh/kg in this case.

The electricity consumption rates of BEVs depend heavily on the curb weight. According to data from real Chinese market, a fixed coefficient of 0.009 kWh/(kg·100 km) are introduced in estimating the electricity consumption rates of BEVs with different range capacities. The relationship between electricity consumption and curb weight in China's vehicle market is derived through Eq. (2).

$$\mathrm{EC}_i = 0.009m + C \tag{2}$$

where EC_i is the electricity consumption rate under NEDC (kWh/100 km); m is the curb weight of the vehicle (kg); C is a constant based on vehicle characteristics (L/100 km), which is assumed to be 2.25 kWh/100 km in this study according to the data of BAIC EV200.

The range capacities of different BEVs are delivered through Eq. (3).

$$\frac{\mathrm{R}_i \times EC_i}{BC_i} = \frac{R_{EV200} \times EC_{EV200}}{BC_{EV200}} \tag{3}$$

where EC_i is the electricity consumption rate of BEV type i (kWh/100 km); EC_{EV200} is the electricity consumption rate of BAIC EV200 (kWh/100 km); R_i is the range capacity of BEV type i (km); R_{EV200} is the range capacity of Leaf (km), which equals 200 km in this case.

Based on Eqs. (1)–(3), the battery capacity and electricity consumption rate of BEVs with different range capacities can be calculated by adopting iteration method.

For baseline vehicles, a vehicle of similar size and chassis with BAIC EV200 is chosen from the Chinese market, which is BAIC D20 (BAIC, 2017). It is assumed that MHVs are equipped with an incremental integrated starter generator, and HHVs are equipped with a power-spit hybrid powertrain typified by the Toyota Corolla hybrid (Toyota China, 2017). The fuel consumption reduction effects of MHVs and HHVs are assumed to be 8.6% and 33% respectively, by referring to National Research Council (NRC) (National Research Council, 2011). The parameters of vehicle models compared in this study are listed in Table 1.

Table 1
Major properties of the vehicle models to be compared.

Vehicle model	Battery capacity (kWh)	Curb weight (kg)	Energy consumption (L/100 km for gasoline vehicles and kWh/100 km for BEVs)
Baseline vehicle	/	1091	6.5
MHV	/	1100	5.9
HHV	/	1191	4.4
EV100	14.0	1146	13.9
EV200	30.4	1295	15.2
EV300	50.0	1473	16.8

2.2. GHG emissions

The GHG emissions are calculated from the life cycle perspective. In other words, both the GHG emissions from vehicle manufacturing and the fuels are considered. The boundary of the life cycle for the vehicle is from the manufacturing stage to end of use. The boundary for the fuel is from the acquisition stage to the burning stage. Moreover, in this study, the GHG emissions are considered to include CO_2, CH_4 and NO_X.

2.2.1. Gasoline vehicles

During the vehicle manufacturing stage, the total GHG emissions of gasoline vehicles are approximately 6.5 t $CO_{2,e}$, by referring to the estimation of Hawkins et al. (2013). The GHG emissions of MHV and HHV from vehicle manufacturing are 6.6 t $CO_{2,e}$ and 6.8 t $CO_{2,e}$, respectively, based on the results of Li (2014).

As for emissions from the fuel, the GHG emissions intensities of baseline vehicles, MHVs and HHVs depend largely on their fuel consumption rates. As discussed above, the NEDC fuel consumption rate of baseline vehicles is 6.5 L/100 km in 2015. According to China's fuel consumption standards for passenger vehicles, the fuel consumption of the baseline vehicles is assumed to decline to 6 L/100 km in 2020 and 5.5 L/100 km in 2025. Fuel consumptions of MHVs and HHVs in the future are assumed to decline with the same rate.

The GHG emissions intensity of gasoline vehicles during the usage stage is calculated through Eq. (4).

$$\mathrm{GHG}_{GV} = GHG_G \times FCR \times \rho \times q_{L,g} \tag{4}$$

where GHG_{GV} is the GHG emissions intensity of the gasoline vehicle (g $CO_{2,e}$/km); GHG_G is the life-cycle GHG emissions intensity of gasoline (g $CO_{2,e}$/MJ), FCR is the fuel consumption rate of the vehicle (L/100 km); ρ is the density of gasoline (kg/L); $q_{L,g}$ is the low heat value (LHV) of gasoline (kJ/kg).

In this study, according to Ou et al. (2011), the life-cycle GHG emissions intensity of gasoline in China is estimated to be 98.9 g $CO_{2,e}$/MJ. The density of gasoline is 0.732 kg/L and the LHV is 43,070 kJ/kg (National Bureau of Statistics of PRC, 2015).

2.2.2. Electric vehicles

The GHG emissions of electric vehicles during the manufacturing process are calculated from Eq. (5).

$$\mathrm{GHG}_{m,EV} = BC \times GHG_{m,b} + GHG_{m,other} \tag{5}$$

where $\mathrm{GHG}_{m,EV}$ is the GHG emissions of BEVs during vehicle manufacturing stage (t $CO_{2,e}$); BC is the battery capacity of BEVs (kWh); $GHG_{m,b}$ is the GHG emissions of unit capacity battery during manufacturing stage (t $CO_{2,e}$/kWh); $GHG_{m,other}$ is the GHG emissions of BEVs except batteries during vehicle manufacturing stage (t $CO_{2,e}$).

In this study, the GHG emissions of unit capacity battery during manufacturing stage are assumed 0.10 t $CO_{2,e}$/kWh, by referring to Amarakoon et al. (2013). According to Hawkins et al. (2013), the GHG emissions of BEVs except batteries during the manufacturing stage are 8 t $CO_{2,e}$.

As for the usage stage, the GHG emissions intensity of BEVs depends on both the electricity consumption rate and power grid characteristics. According to Eq. (2), the electricity consumption rate of BEVs is calculated by using the vehicle weight. Considering the improvement of battery specific energy, the curb weight of the BEVs is expected to decrease in the future, which will lead to lower electricity consumption rate. In this study, the specific energy of the battery system is expected to increase linearly from 110 Wh/kg in 2015 to 250 Wh/kg in 2025, by referring to industrial plan of the Chinese government (Chinese State Council, 2015). Besides, an extra 1% annual decrease is also expected for the energy consumption rate of BEVs (Chinese State Council, 2015). The electricity consumption rate of BEVs is estimated by referring to Eqs. (1)–(3). The key parameters of the power grid include thermal power share, net coal consumption rate, transmission and charging efficiencies and GHG emissions intensity of coal. Therefore, the GHG emissions intensity of BEVs can be calculated by Eq. (6).

$$\mathrm{GHG}_{EV} = \frac{ECR}{\eta_c \times (1-\eta_t)} \times \alpha_t \times \lambda_{sc} \times q_{L,sc} \times GHG_C \tag{6}$$

where GHG_{EV} is the GHG emissions intensity of BEVs (g $CO_{2,e}$/km); ECR is the electricity consumption rate of BEVs (kWh/100 km); η_c is the charging efficiency; η_t is the national average line loss factor; α_t is the thermal power share of the grid; λ_{sc} is the net standard coal consumption rate (g/kWh); $q_{L,sc}$ is the LHV of the standard coal (kJ/kg), GHG_C is the life-cycle GHG emissions intensity of coal in China (g $CO_{2,e}$/MJ).

According to Yuan et al. (2015) and Van Vliet et al. (2011), the charging efficiency of the battery is assumed to be 90%. The national average line loss factor was 6.34% in 2014 (Chinese Electricity Council, 2015). It is assumed to decline linearly to 5% in 2025. The national thermal power share was 75.4% in 2014, which is expected to decline linearly to 60% in 2030 (Wu et al., 2012). The net coal consumption rate was 318 g/kWh in 2014, which is assumed to decline to 300 g/kWh in 2030 (China Electric Power Yearbook Editorial Board, 2014). The LHV of standard coal is 29,307 kJ/kg in China. The life-cycle GHG emissions intensity of coal is estimated to be 104.5 g $CO_{2,e}$/MJ, according to Ou et al. (2011).

2.2.3. Annual mileage travelled and vehicle lifespan

Numerous studies have been conducted on vehicle use intensity in China. Huo et al. (2012) reported that the annual mileage of China's private light-duty vehicles declined from 18,500 km in 2002 to 16,900 km in 2009. Due to insufficiency of official statistics, the estimation of reference Huo et al. (2012) is regarded as the major reference. Owing to the high population density in China, it is estimated that the vehicle use intensity will reach the level similar to Japan or Europe in the future, which is about 8000–12,000 km per year. In this study, the annual mileage travelled is expected to decline linearly to 11,000 km in 2050 under the reference scenario, similar to the projection by Hao et al. (2015).

Previous studies suggested that the annual distance travelled would decrease as vehicle age increases. In this study, a 3% annual decrease is assumed by referring to Hao et al. (2015). The vehicle lifetime is assumed to be ten years with a total mileage of around 150,000 km (Zhao et al., 2015; Hao et al., 2011).

2.3. Cost

In this study, the life-cycle cost includes three parts, which are vehicle cost, energy cost and maintenance cost. The tax and insurance costs are not included because the total cost is estimated from the social perspective.

2.3.1. Battery cost

Numerous studies have been conducted on the manufacturing cost of batteries, but generally with large uncertainties due to limited reliable data sources. According to references Nykvist and Nilsson (2015) and Diouf and Pode (2015), the battery cost reduction is most likely caused by mass production. Therefore, in this study, the battery cost is influenced by the cumulative production as well as the learning rate, as expressed in Eqs. (7) and (8).

$$\mathrm{C}_t = C_0\left(\frac{x_t}{x_0}\right)^b \tag{7}$$

$$\mathrm{LR} = 1-2^b \tag{8}$$

where C_t is the cost at time point t (yuan/kWh); C_0 is the cost at starting point 0 (yuan/kWh); x_t is the cumulative production at time point t (kWh); x_0 is the cumulative production at starting point 0 (kWh); b is the experience index and LR is the learning rate.

In reference Nykvist and Nilsson (2015), Nykvist comprehensively reviewed Li-ion battery pack costs, which is considered as a highly credible estimation. In this study, by referring to their estimation, the learning rate of the battery pack is assumed to be 9% in the next ten years. The industry-wide manufacturing cost of the battery system was $410 and the cumulative production is calculated to be 13,285 MWh in 2014 (Nykvist and Nilsson, 2015).

In order to make projections for the cumulative production of the battery in the future, both BEV's global sales and their average battery capacity are required. In this study, the global BEV projection is derived from IEA (2011). Based on the parameters of market-leading BEV models, the average battery capacity of BEVs is assumed to be 29.8 kWh. The cost is converted to Chinese yuan with the exchange rate of 6.14 between US dollar and Chinese yuan in 2014.

Based on Eqs. (7) and (8) and the prediction for the battery cumulative production, the industry-wide manufacturing cost for the battery system can be predicted, as shown in Fig. 1.

As for the difference between manufacturing cost and retail price, Vyas et al. (2000) estimated the price markup over manufacturing costs for in-house and outsourced components to be approximately 2.0 and 1.5, respectively. This cost markup includes R & D engineering, overhead costs, selling costs and profits. In this study, the battery system is assumed to be manufactured from outside suppliers and the price is estimated to be 1.5 times of the manufacturing cost.

2.3.2. Vehicle cost

The cost of baseline vehicles was 52, 800 yuan in 2015. It is assumed to increase in the future because of the strict fuel regulations. Based on our estimation, the average cost for reducing 1 L/100 km is approximately 5000 yuan in China. As for MHVs and HHVs, the NRC estimation is adopted in this study (National Research Council, 2011). Regarding BEVs, the retail price of BAIC EV200 in China

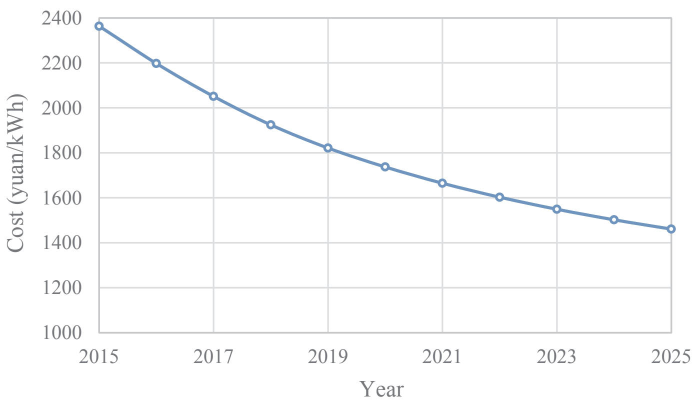

Fig. 1. Manufacturing cost of the battery system.

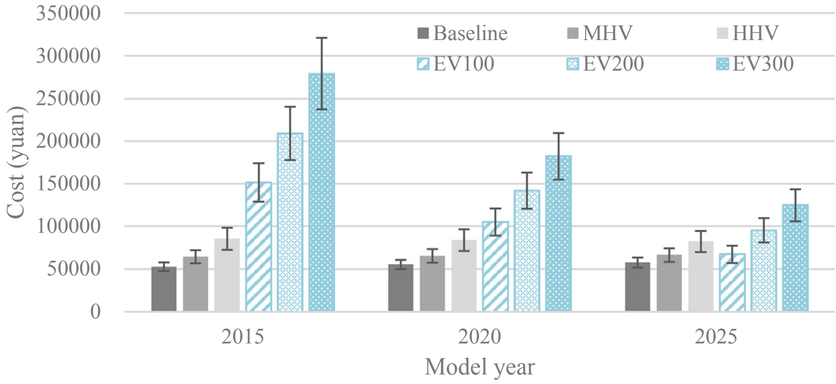

Fig. 2. Comparison of the vehicle cost estimations.

is 208, 900 yuan. BEV cost is separated into two parts: the cost of the battery system and the cost of other components. The cost of other components is assumed to be the same for all the BEVs compared. Battery system cost is determined by battery capacity. Based on these assumptions, the costs of EV100, EV200 and EV300 can be calculated. Due to the immaturity of China's BEV market, the prices of BEVs in China's market are much higher than in the U.S. market. Since China has no obvious disadvantage in terms of the battery cost, it can be concluded that the costs of BEVs in China will gradually decline to a similar level with the U.S. In this section, the cost unit is also converted into Chinese yuan. The vehicle cost estimations are presented in Fig. 2.

2.3.3. *Energy cost*

Gasoline and electricity costs are the energy costs for the gasoline vehicles and BEVs, respectively. Energy Information Administration (EIA) predicted Brent crude oil prices under three cases, which are high, reference and low price cases (EIA, 2014). The gasoline prices in the future are also derived based on the Brent crude oil price (EIA, 2014). China's gasoline prices are regulated by the government, which introduces relatively higher taxes. The gasoline price in China is assumed to be 40% higher than the EIA estimation based on historical data analysis. Moreover, China's electricity prices are also regulated by the government. For instance, Beijing adopted a stepped price for residential electricity from 0.49 yuan/kWh to 0.79 yuan/kWh in 2015. In this study, the price step of 0.54 yuan/kWh for 241–400 kWh/month is adopted as the reference case. China Electricity Council (CEC) expected an annual 2.7% increase for electricity price from 2015 to 2020 (Yang, 2012). In this study, the price is assumed to keep this increasing trend after 2020.

The assumptions for annual mileage and vehicle lifespan are the same with the assumptions above. In order to compare all costs on an equal basis, the net present value (NPV) method is applied for the energy cost. In this study, the cost in the future is converted into NPV in 2014 with the annual discount rate of 1.5%, which is estimated based on China's one-year certificate of deposit rate currently (Noori et al., 2015).

2.3.4. *Maintenance cost*

The maintenance cost is determined by the maintenance cost each time, the annual mileage travelled, maintenance requirement and the vehicle lifespan. It is generally believed that gasoline vehicles bear higher maintenance costs because of more complicated propulsion system configuration. According to data from the real market, the maintenance cost of BAIC D20 is 273 yuan for every 5000 km and an extra 205 for every 10,000 km. Compared with BAIC D20, the maintenance cost of BAIC EV200 is much lower, which is 440 yuan every 20,000 km.

2.4. *Cost-effectiveness*

In this study, the cost-effectiveness of deploying BEVs for reducing GHG emissions is defined to be the cost for unit GHG emissions reduced, as Eq. (9) shows. The results are used to determine the most economic technology pathway to reduce GHG emissions.

$$\mathrm{CE} = \frac{CI}{ER} \tag{9}$$

where CE is the cost-effectiveness for reducing GHG emissions (yuan/t $CO_{2,e}$), CI is the total cost increase compared with baseline vehicles (yuan), ER is the GHG emissions reduction compared with baseline vehicles (t $CO_{2,e}$).

3. Results and discussions

This section presented the results and discussions in the study. Section 3.1 shows the results under the reference scenario. Section 3.2 conducts a single-factor analysis to compare the influencing factors in the study. Section 3.3 presents the results under the most optimistic and pessimistic scenarios for BEVs.

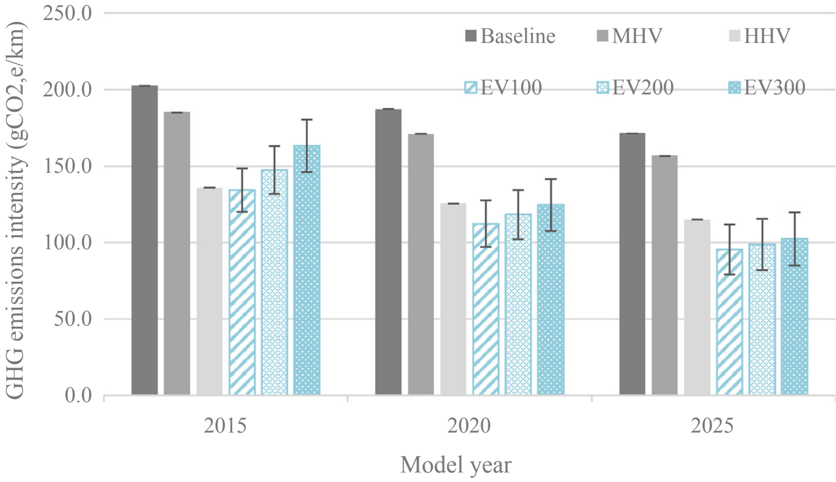

Fig. 3. GHG emissions intensities under the reference scenario.

3.1. Reference scenario

3.1.1. GHG emissions

Under the reference scenario, parameters are applied according to the data assumption above. The GHG emissions intensities of the vehicles during the usage stage are shown in Fig. 3. Based on the GHG emissions intensities, annual mileage travelled, the vehicle lifespan and the GHG emissions from the manufacturing stage, the life-cycle GHG emissions are calculated and presented in Fig. 4.

Currently, MHVs reduce the life-cycle GHG emissions slightly. However, HHVs are estimated to reduce GHG emissions much greater. As for BEVs, GHG emissions increase with the increase of range capacities. At present, the GHG emissions of EV100 are lower than HHVs. However, EV200 and EV300 have more GHG emissions than HHVs.

Driven by the fuel consumption regulations, the life-cycle GHG emissions of baseline vehicles are expected to decline considerably in the coming decade, from 37.7 t in 2015 to 30.4 t in 2025. The fuel consumption rates of MHVs and HHVs are assumed to keep the same improvement ratios to the fuel consumption rate of conventional vehicles. Mostly due to the improvement of China's power grid mix, the life-cycle GHG emissions of BEVs are expected to decrease rapidly in the next decade. Therefore, BEVs' effect of reducing GHG emissions will be improved in the future. EV200 are expected to have greater potential in reducing GHG emissions than HHVs in 2025.

3.1.2. Life-cycle cost analysis

The life-cycle costs of different vehicles in 2015 are presented in Fig. 5. The results are calculated under the reference scenario.

The vehicle cost of BEVs is higher than baseline vehicles, especially for BEVs with longer range capacities. Compared with baseline vehicles, the energy and maintenance costs of BEVs are lower, which can be attributed to the lower price of electricity and

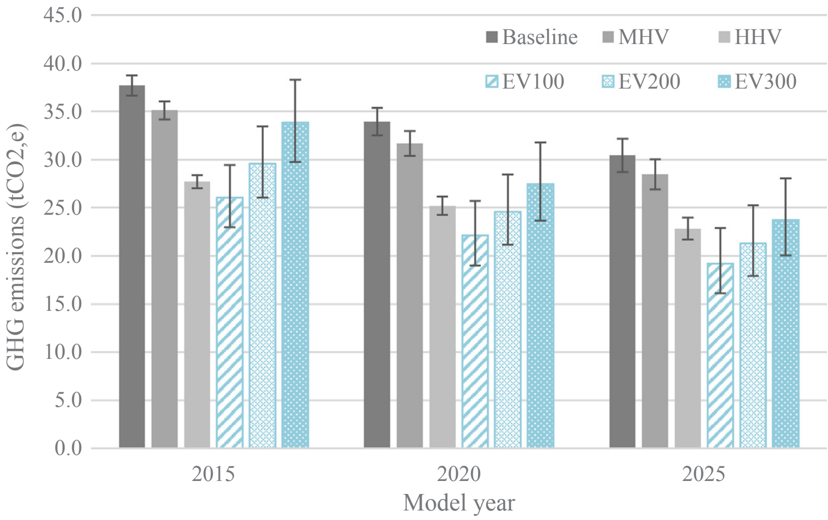

Fig. 4. Life-cycle GHG emissions under the reference scenario.

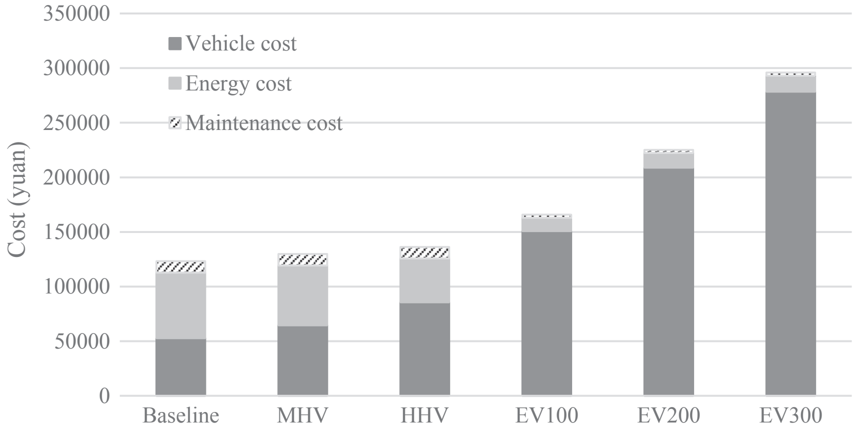

Fig. 5. Life-cycle costs in 2015 under the reference scenario.

the simplicity of the powertrain system. Overall, the lower usage cost of BEVs can only partially offset the high vehicle cost. As for the total cost, BEVs of three kinds are more costly in the current situation. Therefore, BEVs are not competitive enough in terms of cost in China. Moreover, a comparison among baseline vehicles, MHVs and HHVs reveals that the life-cycle costs of MHVs and HHVs are close to that of baseline vehicles but are still a little higher. In other words, the lower cost of HEVs during the usage stage is able to partially counteract the cost increment caused by the hybrid system. Based on the cost predictions, the life-cycle costs for different vehicle models in the future are presented in Fig. 6.

The life-cycle costs of baseline vehicles and HEVs are expected to decrease slightly in the future because of the improvement of the vehicle energy efficiency as well as the decline of annual mileage travelled. Meanwhile, as for BEVs, their life-cycle costs will experience a rapid decrease in the next decade, mostly due to the rapid decline of the vehicle cost. For instance, currently EV200 cost approximately 100,000 yuan more than baseline vehicles. However, in 2025, it is predicted to obtain an obvious cost advantage over baseline vehicles and HEVs.

3.1.3. *Cost-effectiveness analysis*

The cost-effectiveness of different vehicles for reducing GHG emissions are presented in Fig. 7. In this study, lower value of cost-effectiveness indicates lower cost for reducing each ton of GHG emissions, which implies a better economic performance.

The cost-effectiveness of MHVs and HHVs improves slightly over time, mostly due to the decreasing cost of hybrid systems. As for BEVs, their cost-effectiveness is not satisfying currently but will be considerably improved in the future. The cost-effectiveness of EV200 is worse than HEVs at present. However, it is expected to become much better over the next ten years, exceeding HEVs in 2025. In 2025, the cost-effectiveness of EV200 becomes negative, which indicates the vehicles contribute to reducing GHG emissions while saving cost. The cost-effectiveness of EV300 is quite poor at present. However, this poor cost-effectiveness is likely to be improved substantially in the future. It can be concluded that due to the fact that higher range capacities lead to more GHG emissions as well as higher costs, the cost-effectiveness of BEVs becomes worse as the range capacities increases. Moreover, it can be concluded

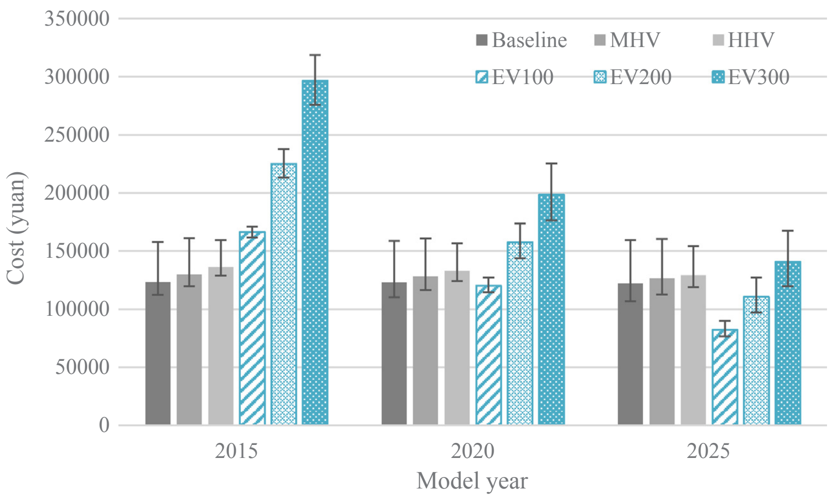

Fig. 6. Life-cycle costs in the future under the reference scenario.

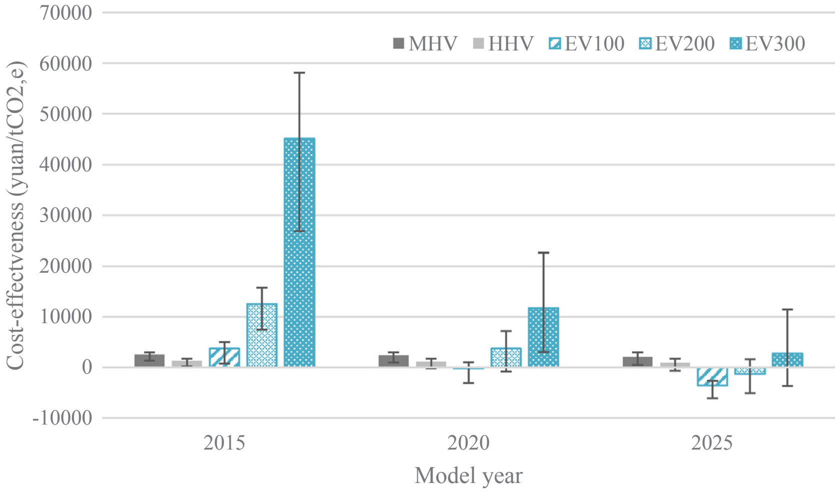

Fig. 7. Cost-effectiveness of different vehicles for reducing GHG emissions under the reference scenario.

that in 2025, EV300 become closer to EV100 in terms of cost-effectiveness than in 2015. However, the difference will still exist in the future due to more energy consumption and cost caused by larger batteries in EV300. Therefore, as the power generation process and battery technology are improving, longer range of BEVs will be more acceptable in the future.

3.2. Single-factor analysis

Multiple factors potentially influence the cost-effectiveness estimations. To address the possible uncertainties, a single-factor analysis is conducted in the following part to assess the impacts of various influencing factors on the cost-effectiveness. The influencing factors considered include coal power share, coal power efficiency, battery specific energy, battery learning rate, vehicle use intensity and gasoline price. In consideration of the representativeness of the results, EV200 is chosen as the BEV model to be compared in the analysis.

3.2.1. Coal power share

By referring to Casals et al. (2016), coal power share is a key parameter that decide the effect in reducing GHG emissions of BEVs. In the past few decades, China's coal power share has experienced fluctuations and began to decrease after 2010 (National Bureau of Statistics of PRC, 2000). By referring to historical data and the study by Ou et al. (2011), three coal power share scenarios are assumed, under which the coal power share is expected to decline linearly to 55%, 60% and 65% in 2030, respectively. These three scenarios are named as conservative, reference and radical scenarios, as presented in Fig. 8.

Cost-effectiveness under different coal power share scenarios are compared in Fig. 9. As coal power shares have little influence on the cost-effectiveness of MHVs and HHVs, it is not considered in the study.

The coal power shares have relatively small influence on the cost-effectiveness of BEVs. Conservative assumption on the coal power share worsens the cost-effectiveness of EV200. It has an influence of 6.5%, 9.4% and 12.6% in 2015, 2020 and 2025 on the cost-effectiveness numbers, respectively. In contrast, under the radical scenario, owing to lower coal power shares, the cost-

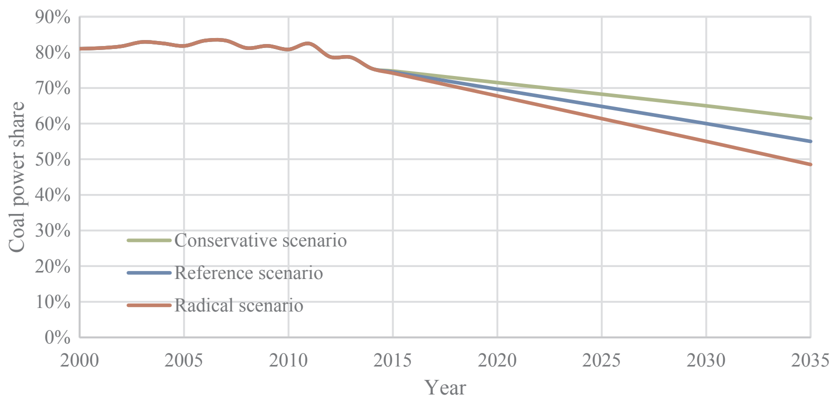

Fig. 8. Assumptions of coal power share under different scenarios.

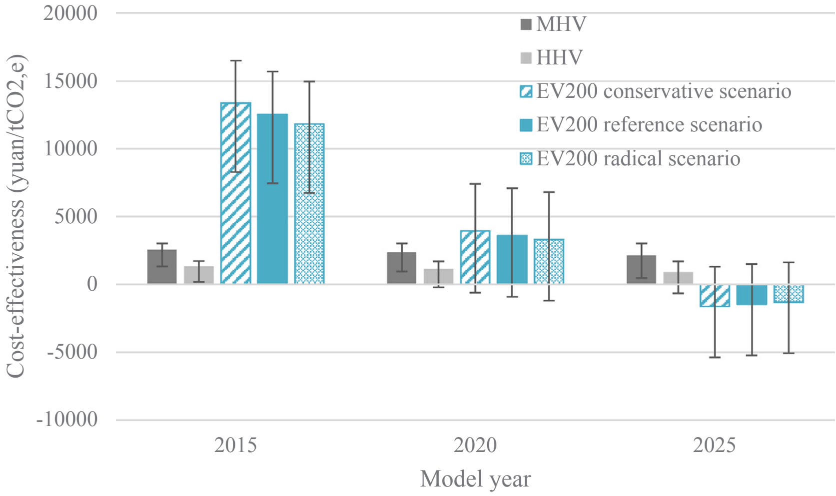

Fig. 9. Cost-effectiveness under different coal power share scenarios.

effectiveness of BEVs is improved. The cost-effectiveness numbers are influenced by 5.8%, 7.9% and 10.1% in 2015, 2020 and 2025, respectively.

As presented in Fig. 9, the cost-effectiveness results of BEVs become negative after 2025. Therefore, a different analyzing method is required in this study. When analyzing negative results, both the life-cycle GHG emissions and costs are required to be explained. As the life-cycle cost of BEVs is not affected by coal power share, reducing more GHG emissions leads to less absolute value of cost-effectiveness. As the absolute values under the radical scenario are the least after 2025, the cost-effectiveness under the radical scenario is still considered the best. Similar explanations can be adopted for the conservative scenario.

3.2.2. *Coal power efficiency*

Net coal consumption rate, which is defined as the coal consumption for per unit of electricity transmitted to the grid, is used as the proxy for coal power efficiency. Based on reference China Electric Power Yearbook Editorial Board (2014), the net coal consumption rate declines with the increase of the capacity of the power units. The net coal consumption rate for power units over one million kilowatts is about 290 g/kWh, which is the lowest at the current technology level. Under the reference scenario, the net coal consumption rate is assumed to decline linearly to 300 g/kWh in 2030 and maintain the decreasing trend afterwards. Under the radical scenario, the net coal consumption rate will be 295 g/kWh in 2030. Under the conservative scenario, the net consumption rate is expected to reach the level of 305 g/kWh in 2030. The net coal consumption rates under different scenarios are presented in Fig. 10.

The influence of net coal consumption rate on the cost-effectiveness is presented in Fig. 11. Compared with reference scenario, the conservative scenario worsens the cost-effectiveness by 1.3%, 1.9% and 2.3% in 2015, 2020 and 2025, respectively. In contrast, the cost-effectiveness under the radical scenario is improved by 1.4%, 1.8% and 2.2% in 2015, 2020 and 2025. It is concluded that with lower net coal consumptions of coal power plants, the cost-effectiveness for reducing GHG emissions will improve accordingly.

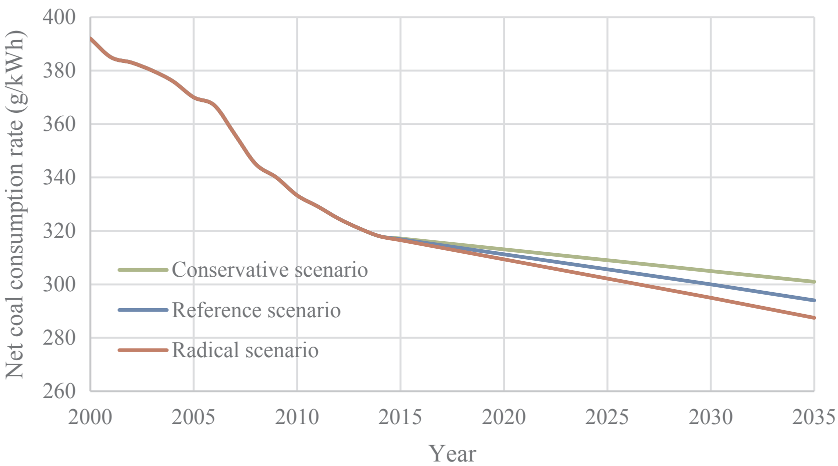

Fig. 10. Assumptions of net coal consumption rate under different scenarios.

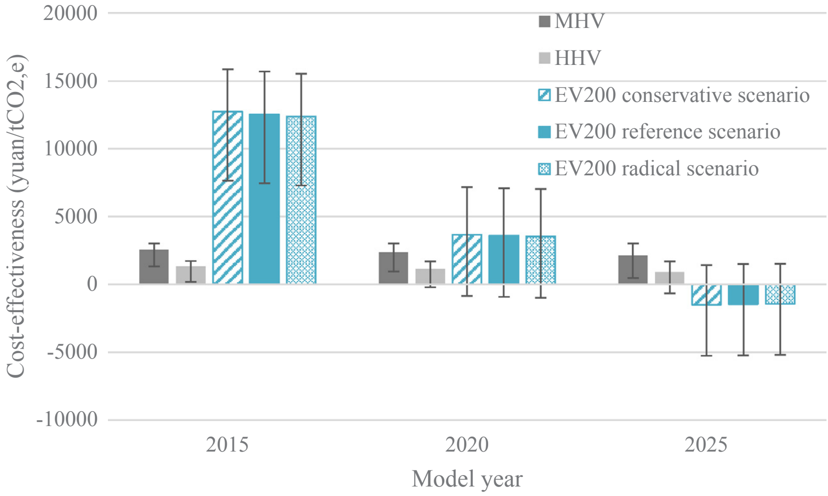

Fig. 11. Cost-effectiveness under different coal power efficiency scenarios.

However, the influences on the results are quite limited.

3.2.3. Battery specific energy

The specific energy of li-ion battery range from 100 Wh/kg to 150 Wh/kg currently (Etacheri et al., 2011). However, batteries of new systems are expected to have higher specific energy as technology develops. Under the reference scenario, according to the plan of Chinese government, the specific energy of the battery system is assumed to increase to 250 Wh/kg in 2025 (Chinese State Council, 2015). China's industrial plan is in accordance with plans of other countries like the U.S. and Japan (Åhman, 2006). However, as there have been controversies on the predictions for battery specific energy, conservative and radical scenarios are introduced. Under the conservative scenario, the specific energy of battery system is expected to increase linearly to 200 Wh/kg in 2025. While under the radical scenario, the specific energy of the battery system will increase linearly to 300 Wh/kg in 2025.

The battery specific energy has an influence on the cost-effectiveness, as presented in Fig. 12. As the increase of battery specific energy, the cost-effectiveness of BEVs will be improved. However, the influences of the battery specific energy on the results are not significant. For instance, under the conservative scenario, the cost-effectiveness result of BEVs will be reduced by 6.6% in 2020 and 9.4% by 2025.

3.2.4. Learning rate of batteries

According to Nykvist and Nilsson (2015), the learning rate of the battery pack is estimated to be 9% for the whole industry and 6% for market leaders. In this study, 9% is considered to be the learning rate under the reference scenario. And the learning rate of 6% for market leaders is assumed to be the case under the conservative scenario. As for the radical scenario, the learning rate is assumed to be 12%.

The cost forecasts for the battery pack under different scenarios are presented in Fig. 13, in which the cost is assumed to decline to

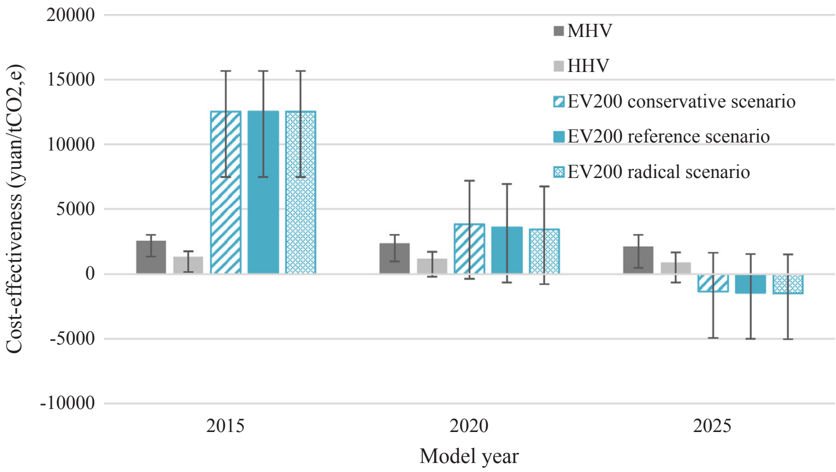

Fig. 12. Cost-effectiveness under different battery specific energy scenarios.

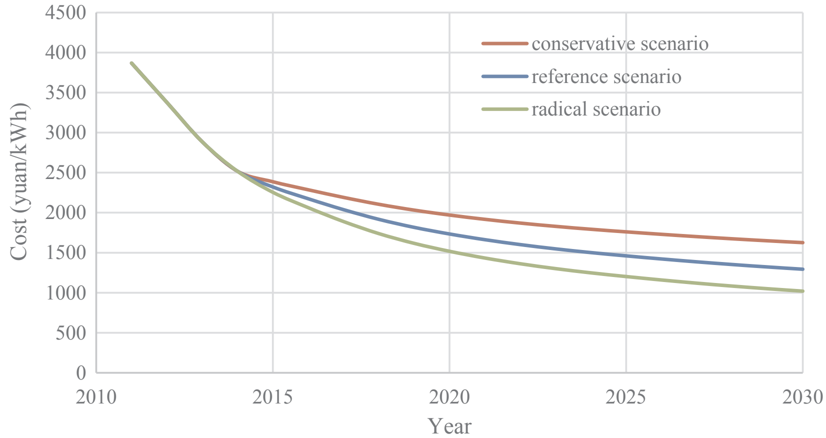

Fig. 13. Assumptions of battery pack cost under different scenarios.

1627, 1294, 1021 yuan/kWh in 2030, respectively. The cost-effectiveness for reducing GHG emissions can be figured out based on the cost forecasts and are shown in Fig. 14. As the cost for battery packs takes a large proportion of the total cost, the learning rate of the batteries has a considerable influence on the cost-effectiveness. Compared with reference scenario, the conservative scenario worsens the cost-effectiveness by 28.9% in 2020 and 56.9% in 2025. And under the radical scenario, the cost-effectiveness of BEVs will be improved by 25.3% in 2020 and 35.0% in 2025.

3.2.5. Vehicle use intensity

As discussed above, under the reference scenario, the annual mileage travelled for passenger vehicles is expected to decline linearly to 11,000 km/year (about 30 km/day) in 2050. By referring to Hao et al. (2015), the annual mileage is assumed to be 9000 km/year (about 25 km/day) in 2050 under low use intensity scenario. Under high use intensity scenario, the annual mileage will decline to 13,000 km/year in 2050. The annual mileage travelled in the future under different scenarios are presented in Fig. 15.

The cost-effectiveness under different scenarios is presented in Fig. 16. Generally, higher use intensities lead to better cost-effectiveness of BEVs and HEVs. Under low use intensity scenario, the cost-effectiveness for reducing GHG emissions is worse. Besides, it can be concluded that the influence of use intensity is greater on BEVs than on HEVs. This is mainly caused by the fact that the price of electricity is much lower than gasoline. Therefore, BEVs benefit more from higher use intensities.

3.2.6. Gasoline price

There are great uncertainties on the gasoline price in the future. EIA forecasted three scenarios for the gasoline price, which are high, reference and low scenarios (EIA, 2014). And the predictions are adopted in the study. Besides, in China's specific situation, 40% increment is assumed. Predictions for China's gasoline price are shown in Fig. 17.

The cost-effectiveness under different gasoline price scenarios is shown in Fig. 18. It is concluded that the results are greatly influenced by the gasoline price. Under the high gasoline price scenario, the cost-effectiveness of HEVs and BEVs are greatly

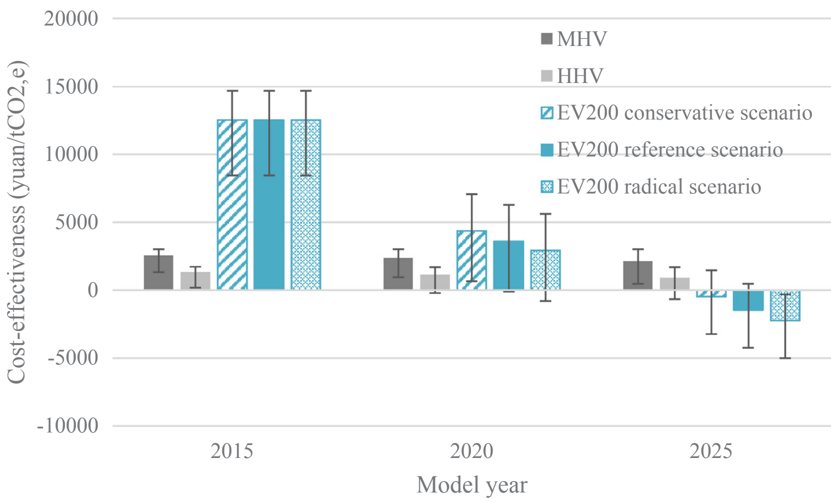

Fig. 14. Cost-effectiveness under different learning rate scenarios.

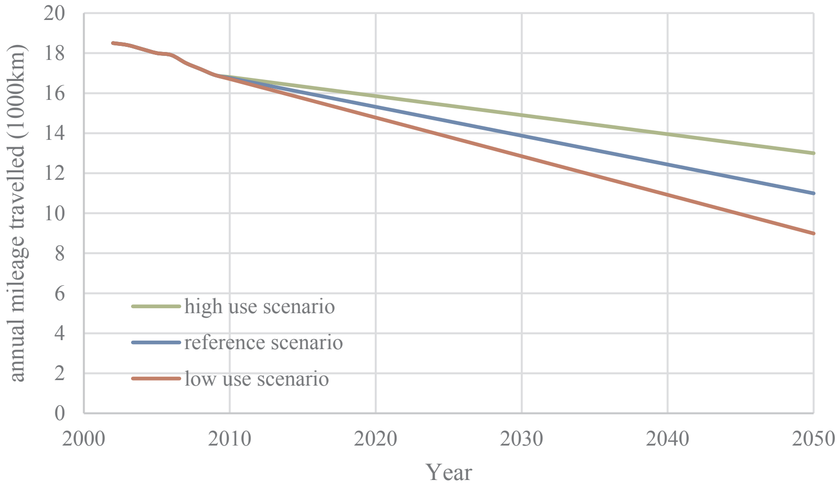

Fig. 15. Annual mileage travelled in the future under different scenarios.

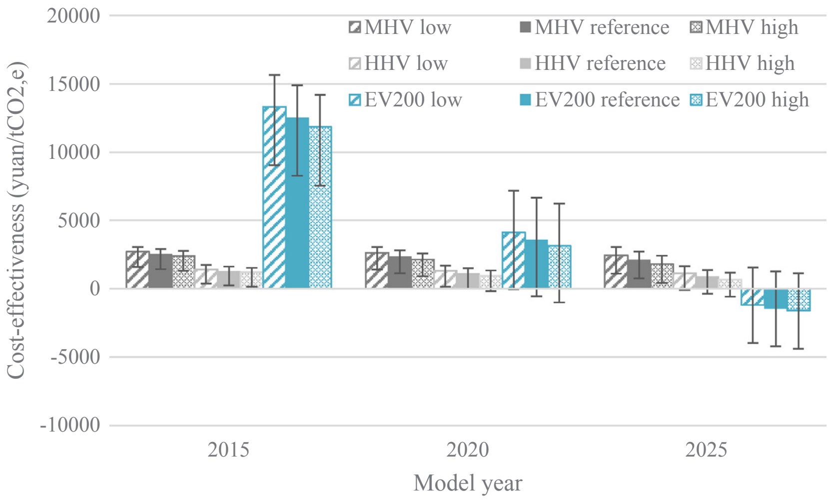

Fig. 16. Cost-effectiveness under different use intensity scenarios.

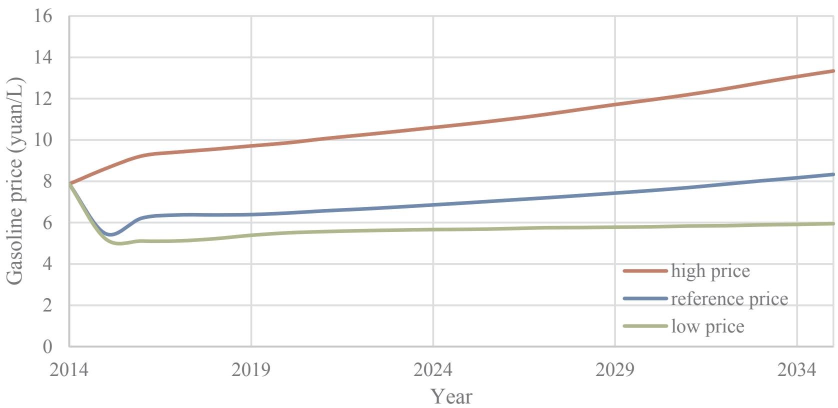

Fig. 17. Assumptions of gasoline price under different scenarios.

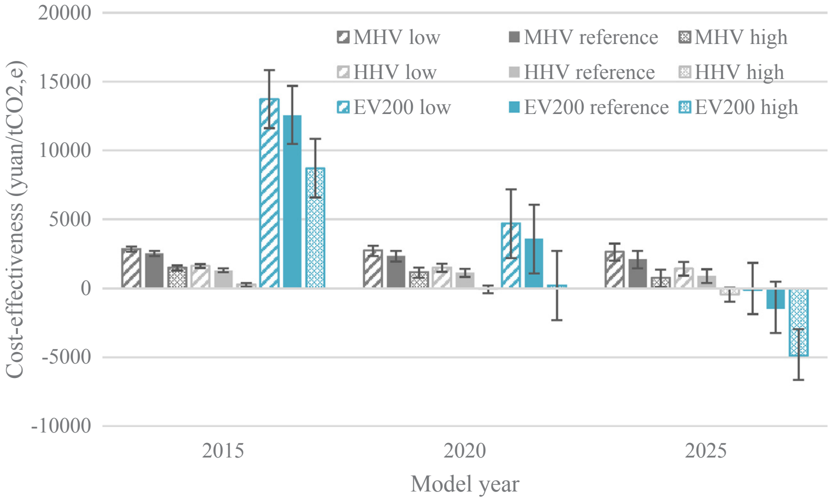

Fig. 18. Cost-effectiveness under different gasoline price scenarios.

improved. Besides, the influence of gasoline price on BEVs is much greater than on HEVs.

3.2.7. Comparison among influencing factors

In the sections above, the impacts from the six influencing factors are discussed separately. In this section, comparative analysis among these influencing factors is conducted to identify the most significant influencing factors. The differences of cost-effectiveness of EV200 between high and low scenarios in 2025 are summarized in Fig. 19.

It can be found that the gasoline price has the greatest influence on the cost-effectiveness of BEVs. This is because the gasoline price is the most variable factor among all the factors. For example, in 2030, the gasoline price ranges from 5.8 yuan/L under the low price scenario to 11.9 yuan/L under the high price scenario.

Apart from the gasoline price, the learning rate of the battery also has considerable influence on the results. The reason is the cost of the battery takes a large proportion in the life-cycle cost of the vehicle. Meanwhile, the learning rate of the battery has a great influence on the battery cost. For instance, in 2030, the battery cost is 1021 yuan/kWh under the radical scenario and 1626 yuan/kWh under the conservative scenario.

Alternatively, the impacts from the other factors, including coal power share, coal power efficiency, battery specific energy and vehicle use intensity, are relatively limited. The reason is that these factors have smaller variation ranges and smaller influence on the life-cycle GHG emissions or cost of the vehicle, compared with the former two factors.

3.3. Most optimistic and pessimistic scenarios for BEVs

By adopting the best and worst assumptions for BEVs in all the six scenarios above, the most optimistic and pessimistic scenarios for BEVs are figured out, as presented in Fig. 20.

Under the most optimistic scenario for BEVs, the cost-effectiveness of BEVs will be greatly improved. For example, EV200 are expected to have a lower total cost than conventional gasoline vehicles. Therefore, the cost-effectiveness of EV200 will be negative

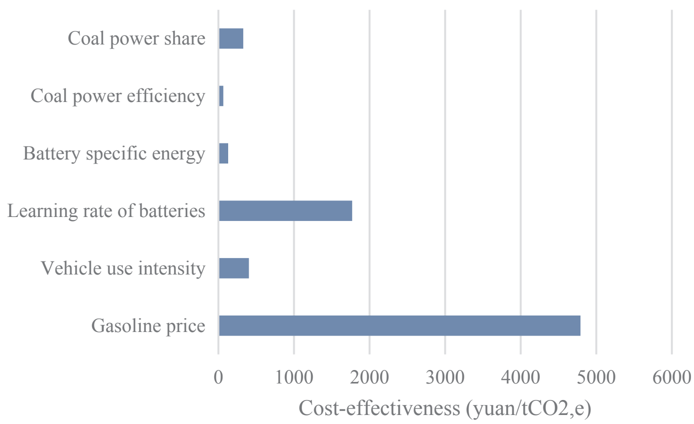

Fig. 19. Differences of cost-effectiveness of EV200 between high and low scenarios in 2025.

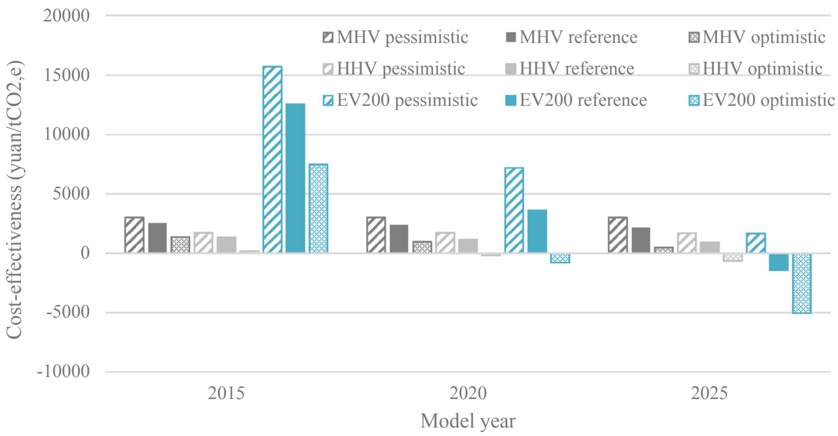

Fig. 20. Most optimistic and pessimistic scenarios for BEVs.

after 2020. Moreover, EV200 are expected to obtain an obvious advantage over MHVs and HHVs after 2020. Therefore, under the most optimistic scenario for BEVs, EV200 will be the most promising technology pathway in reducing GHG emissions after 2020.

However, under the most pessimistic scenario for BEVs, BEVs will be less competitive in reducing GHG emissions. For example, in 2025, the cost-effectiveness of EV200 will still be positive. This indicates that EV200 will still cost more than conventional vehicles in 2025. Meanwhile, under the most pessimistic scenario for BEVs, HHVs are expected to be the most effective technology pathway in the next ten years.

4. Policy implications

According to the analysis, BEVs offer the potential of reducing GHG emissions in China's context both at present and in the future. The Chinese government's efforts in promoting BEVs can be justified. However, more efforts are required in order to expand the GHG emissions reduction advantage of BEVs in the coming decades. For example, the coal power share in China is relatively high compared with some European and American countries, which weakens the advantage of BEVs in reducing GHG emissions in China. Moreover, it should be stressed that BEVs possess bigger advantage besides reducing GHG emissions, when considering their impact on national oil security and local pollutant reduction.

Currently, the life-cycle costs of BEVs are relatively higher compared with baseline vehicles and HEVs, which weakens their market competitiveness. Subsidies, tax exemptions and other preferential policies for BEVs are needed to reduce the life-cycle cost of BEVs and enhance their market competitiveness. However, as BEVs are expected to possess lower life-cycle costs in the foreseeable future, it is recommended that the financial subsidies should be determined following the technology changes.

Numerous factors have influences on BEVs' cost-effectiveness for reducing GHG emissions. Among the factors, gasoline price and learning rate of the battery have the biggest influence on the results. Extremely low price of gasoline is considered disadvantageous for the cost-effectiveness of BEVs. As the gasoline price in China is regulated by the government, extremely low gasoline price should be avoided, which helps to maintain the market competitiveness of BEVs. The cost of battery takes a large proportion in the total cost of BEVs. Therefore, the learning rate of battery has considerable influence on the cost-effectiveness of BEVs. Therefore, the government should encourage the technology development of the battery and prompt the return-to-scale effect in order to reduce the cost of battery. Moreover, the cost-effectiveness of BEVs is improving as the vehicle use intensity increases. Therefore, heavily used vehicles such as taxis are advised to be preferentially equipped with electric powertrains to realize high cost-effectiveness. Other factors such as coal power share and battery specific energy are also essential in improving the cost-effectiveness of BEVs. However, the influence of these factors are smaller than the gasoline price and learning rate of batteries.

5. Conclusive remarks

There exist studies that focus on the cost-effectiveness of BEVs for reducing GHG emissions. These studies discussed both the GHG emissions and cost of different vehicles, which provided the method framework for this study. However, few studies are conducted based on China's situation. As China is developing into the biggest BEV market worldwide, a detailed study on China is necessary. With the aim of filling such a gap, in this study, the cost-effectiveness of deploying BEVs for reducing GHG emissions in China's context is estimated. Moreover, multiple factors potentially influence the cost-effectiveness results. Therefore, a single factor analysis is also conducted in this study. From the single factor analysis, the most important factors can be identified and policies can be adjusted to optimize the cost-effectiveness of BEVs.

In this study, we discussed the life-cycle GHG emissions and cost of ICEVs, HEVs and BEVs. Afterwards, the cost-effectiveness of different technology pathways in reducing GHG emissions are compared. Based on the research, BEVs have the potential of reducing life-cycle GHG emissions in China currently. In the next ten years, the GHG emissions of BEVs are expected to decrease as a result of the improvement of power generation structure and coal power efficiency. As for the life-cycle cost, the cost of BEVs is higher than baseline vehicles at present. Owning to the rapid decline of the vehicle cost, the life-cycle cost of BEVs is expected to decrease rapidly in the future. In terms of the cost-effectiveness for reducing GHG emissions, it is concluded that BEVs don't have an obvious advantage over HEVs at present. However, in the next decade, the cost-effectiveness of BEVs is expected to improve considerably, mostly due to the rapid decline of the total cost.

A single factor analysis is also conducted in this study. The influencing factors include coal power share, coal power efficiency, battery specific energy, battery learning rate, vehicle use intensity and gasoline price. The results indicate that gasoline price and learning rate of batteries have the greatest influences on the cost-effectiveness of BEVs. Moreover, the cost-effectiveness results are quite different under the most optimistic and pessimistic scenarios for BEVs. Under the most optimistic scenario, the total cost of BEVs will be lower than conventional vehicles after 2020 and BEVs will be the most effective technology pathway. However, under the most pessimistic scenario, the cost-effectiveness of BEVs will be greatly weakened.

This study still have its limitations. Firstly, the GHG emissions of the production process of battery is assumed constant in this study. This assumption is due to a lack of reliable data. However, this factor will probably decrease in the future, which will raise the potential of BEVs in reducing GHG emissions. Secondly, the GHG emissions of electricity is based on the share of different energy sources in China. However, different electricity grid regions have different energy source structures. Taking this into account will increase the practical significance of the results. Thirdly, this article is mainly discussed in China's context. The results cannot show the differences among China and other developed countries.

Acknowledgement

This study is sponsored by the National Natural Science Foundation of China (71403142, 71690241), State Key Laboratory of Automotive Safety and Energy (ZZ2016-024), Young Elite Scientists Sponsorship Program by CAST (YESS20160140), China Automotive Energy Research Center of Tsinghua University (CAERC), Beijing Natural Science Foundation (9162008).

References

Åhman, M., 2006. Government policy and the development of electric vehicles in Japan. Energy Policy 34 (4), 433–443.
Amarakoon, S., Smith, J., Segal, B., 2013. Application of Life-cycle Assessment to Nanoscale Technology: Lithium-ion Batteries for Electric Vehicles.
Amoco, B.P., 2015. BP statistical review of world. Energy.
BAIC, 2017. Parameters of BAIC D20. < http://d20.senova.com.cn/ > (in Chinese).
BAIC BJEV, 2017. Parameters of BAIC EV200. < http://www.bjev.com.cn/car/ev200 > (in Chinese).
Bickert, S., Kampker, A., Greger, D., 2015. Developments of CO_2-emissions and costs for small electric and combustion engine vehicles in Germany. Transp. Res. Part D: Transp. Environ. 36, 138–151.
Casals, L.C., Martinez-Laserna, E., García, B.A., et al., 2016. Sustainability analysis of the electric vehicle use in Europe for CO_2 emissions reduction. J. Clean. Prod. 127, 425–437.
China Electric Power Yearbook Editorial Board, 2014. China Electric Power Yearbook 2014. China Electric Power Press, Beijing.
Chinese Electricity Council, 2015. Situation of China's Electricity Industry. Beijing. < http://www.cec.org.cn/guihuayutongji/gongxufenxi/dianliyunxingjiankuang/2015-02-02/133565.html > .
Chinese State Council, 2015. Made in China 2025.
Diouf, B., Pode, R., 2015. Potential of lithium-ion batteries in renewable energy. Renewable Energy 76, 375–380.
EIA, 2014. Annual Energy Outlook 2014. Secondary Annual Energy Outlook 2014. < http://www.eia.gov/forecasts/archive/aeo14/ > .
Etacheri, V., Marom, R., Elazari, R., et al., 2011. Challenges in the development of advanced Li-ion batteries: a review. Energy Environ. Sci. 4 (9), 3243–3262.
Hao, H., Wang, H.W., Ouyang, M.G., Cheng, F., 2011. Vehicle survival patterns in China. Sci. Chin. Technol. Sci. 54(3), 625e9.
Hao, H., Wang, M., Zhou, Y., et al., 2015. Levelized costs of conventional and battery electric vehicles in China: Beijing experiences. Mitig. Adapt. Strat. Glob. Change 20 (7), 1229–1246.
Hao, H., Liu, Z., Zhao, F., et al., 2015. Scenario analysis of energy consumption and greenhouse gas emissions from China's passenger vehicles. Energy 91, 151–159.
Hawkins, T.R., Singh, B., Majeau-Bettez, G., et al., 2013. Comparative environmental life cycle assessment of conventional and electric vehicles. J. Ind. Ecol. 17 (1), 53–64.
Huo, H., Zhang, Q., Wang, M.Q., et al., 2010. Environmental implication of electric vehicles in China. Environ. Sci. Technol. 44 (13), 4856–4861.
Huo, H., Zhang, Q., He, K., et al., 2012. Vehicle-use intensity in China: current status and future trend. Energy Policy 43, 6–16.
Huo, H., Cai, H., Zhang, Q., et al., 2015. Life-cycle assessment of greenhouse gas and air emissions of electric vehicles: a comparison between China and the US. Atmos. Environ. 108, 107–116.
IEA, 2011. Technology Roadmap: Electric and Plug-in Hybrid Electric Vehicles.
Krieger, A., Wang, L., Radtke, P., Malorny, C., 2012. Recharging China's Electric Vehicle Aspirations: A Perspective on Revitalizing China's Electric Vehicle Industry. McKinsey & Company. April 2012.
Li, S., 2014. Life-cycle Assessment and Environmental Benefits Analysis of Electric Vehicles. Jilin University.
National Bureau of Statistics of PRC, 2000. China Statistical Yearbook 2000–2014. China Statistics Press, Beijing.
National Bureau of Statistics of PRC, 2015. China Energy Statistical Yearbook.
National Research Council (NRC), 2011. Assessment of Fuel Economy Technologies for Light-duty Vehicles.
Noori, M., Gardner, S., Tatari, O., 2015. Electric vehicle cost, emissions, and water footprint in the United States: development of a regional optimization model. Energy 89, 610–625.
Nykvist, B., Nilsson, M., 2015. Rapidly falling costs of battery packs for electric vehicles. Nat. Clim. Change 5 (4), 329–332.
Ou, X., Yan, X., Zhang, X., 2010. Using coal for transportation in China: life cycle GHG of coal-based fuel and electric vehicle, and policy implications. Int. J. Greenhouse Gas Control 4 (5), 878–887.
Ou, X., Xiaoyu, Y., Zhang, X., 2011. Life-cycle energy consumption and greenhouse gas emissions for electricity generation and supply in China. Appl. Energy 88 (1), 289–297.
Pathak, S.K., Sood, V., Singh, Y., et al., 2016. Real world vehicle emissions: their correlation with driving parameters. Transp. Res. Part D: Transp. Environ. 44, 157–176.
Rezvani, Z., Jansson, J., Bodin, J., 2015. Advances in consumer electric vehicle adoption research: a review and research agenda. Transp. Res. Part D: Transp. Environ. 34, 122–136.
Ruan, J., Walker, P., Zhang, N., 2016. A comparative study energy consumption and costs of battery electric vehicle transmissions. Appl. Energy 165, 119–134.

Shi, X., Li, X., Yang, J., 2013. Research on carbon reduction potential of EVs for low-carbon transportation and its influence factors. Environ. Sci. 34 (1), 386–389.
State Council, 2000. China Automotive Industry Yearbook. 2000–2014.
State Council, 2012. Notice about Enacting Energy Efficient and Alternative Energy Vehicles Industry Development Plan. < http://www.gov.cn/zwgk/2012-07/09/content_2179032.htm > . (in Chinese).
Toyota China, 2017. Parameters of Corolla Hybrid. < http://www.toyota.com.cn/technology/hev/ > (in Chinese).
Van Vliet, O., Brouwer, A.S., Kuramochi, T., et al., 2011. Energy use, cost and CO_2 emissions of electric cars. J. Power Sources 196 (4), 2298–2310.
Vyas, A., Santini, D., Cuenca, R., 2000. Comparison of Indirect Cost Multipliers for Vehicle Manufacturing. Center for Transportation Research, Argonne National Laboratory, Argonne, IL April.
Wang, D., Zamel, N., Jiao, K., et al., 2013. Life cycle analysis of internal combustion engine, electric and fuel cell vehicles for China. Energy 59, 402–412.
Wang, H., Zhang, X., Ouyang, M., 2015. Energy consumption of electric vehicles based on real-world driving patterns: a case study of Beijing. Appl. Energy 157, 710–719.
Woo, J.R., Choi, H., Ahn, J., 2017. Well-to-wheel analysis of greenhouse gas emissions for electric vehicles based on electricity generation mix: a global perspective. Transp. Res. Part D: Transp. Environ. 51, 340–350.
Wu, Y., Yang, Z., Lin, B., et al., 2012. Energy consumption and CO_2 emission impacts of vehicle electrification in three developed regions of China. Energy Policy 48, 537–550.
Wu, X., Freese, D., Cabrera, A., et al., 2015. Electric vehicles' energy consumption measurement and estimation. Transp. Res. Part D: Transp. Environ. 34, 52–67.
Wu, G., Inderbitzin, A., Bening, C., 2015. Total cost of ownership of electric vehicles compared to conventional vehicles: a probabilistic analysis and projection across market segments. Energy Policy 80, 196–214.
Yang, F., 2012. CEC Projects Higher Electricity Prices. Secondary CEC Projects Higher Electricity Prices.
Yuan, X., Li, L., Gou, H., et al., 2015. Energy and environmental impact of battery electric vehicle range in China. Appl. Energy 157, 75–84.
Zhang, R., Yao, E., 2015. Electric vehicles' energy consumption estimation with real driving condition data. Transp. Res. Part D: Transp. Environ. 41, 177–187.
Zhao, X., Doering, O.C., Tyner, W.E., 2015. The economic competitiveness and emissions of battery electric vehicles in China. Appl. Energy 156, 666–675.
Zhou, G., Ou, X., Zhang, X., 2013. Development of electric vehicles use in China: a study from the perspective of life-cycle energy consumption and greenhouse gas emissions. Energy Policy 59, 875–884.