Energy Policy 85 (2015) 253–270

Contents lists available at ScienceDirect

Energy Policy

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

A system dynamics approach to scenario analysis for urban passenger transport energy consumption and CO_2 emissions: A case study of Beijing

Xue Liu, Shoufeng Ma, Junfang Tian*, Ning Jia, Geng Li

Institute of Systems Engineering, College of Management and Economics, Tianjin University, Tianjin 300072, China

HIGHLIGHTS

- The creation of a Beijing urban transport carbon model using system dynamics.
- The effect of different policies on energy conservation and emission reductions.
- The cumulative effect of different individual policies.
- The optimal sequence of individual policy implementation in comprehensive policy.

ARTICLE INFO

Article history:
Received 23 February 2015
Received in revised form
27 April 2015
Accepted 2 June 2015
Available online 18 June 2015

Keywords:
Urban passenger transport
Energy conservation
Emission reduction
System dynamics
Scenario analysis

ABSTRACT

With the accelerating process of urbanization, developing countries are facing growing pressure to pursue energy savings and emission reductions, especially in urban passenger transport. In this paper, we built a Beijing urban passenger transport carbon model, including an economy subsystem, population subsystem, transport subsystem, and energy consumption and CO_2 emissions subsystem using System Dynamics. Furthermore, we constructed a variety of policy scenarios based on management experience in Beijing. The analysis showed that priority to the development of public transport (PDPT) could significantly increase the proportion of public transport locally and would be helpful in pursuing energy savings and emission reductions as well. Travel demand management (TDM) had a distinctive effect on energy savings and emission reductions in the short term, while technical progress (TP) was more conducive to realizing emission reduction targets. Administrative rules and regulations management (ARM) had the best overall effect of the individual policies on both energy savings and emission reductions. However, the effect of comprehensive policy (CP) was better than any of the individual policies pursued separately. Furthermore, the optimal implementation sequence of each individual policy in CP was TP→PDPT→TDM→ARM.

1. Introduction

In response to oil shortages, air pollution and climate change, an increasing number of governments have begun to set goals for energy savings and emission reductions (Zhang et al., 2014, 2011a, 2011b; USEPA, 2012). More than half of the world's population currently lives in cities. What is more, their Greenhouse Gas (GHG) emissions accounted for more than 80% of the world's total GHG emissions (Feng et al., 2013). In China, approximately 18% of the population lives in the 35 largest cities, but they brought in vast energy consumption and CO_2 emissions, which accounted for more than 40% (Dhakal, 2009). Therefore, energy savings and emission reductions at the city level played a vital role in the process of fulfilling existing overall energy conservation and emission reduction targets (Chen and Chen, 2012; Zhang et al., 2012; Chun et al., 2011; Li et al., 2010). In addition, energy consumption and CO_2 emissions from urban passenger transport played an important role at the city level; therefore, energy conservation and emission reductions in urban passenger transport became important measures by which to achieve low-carbon development goals (Litman, 2013a, 2013b; Geng et al., 2013; Chiou et al., 2013).

Currently, there are many researchers interested in urban transport energy conservation and emissions reduction measures (AASHTO, 2009; Ross Morrow et al., 2010; Gross et al., 2009;

* Corresponding author. Fax: +86 22 2740 4446.
E-mail address: jftian@tju.edu.cn (J. Tian).

http://dx.doi.org/10.1016/j.enpol.2015.06.007
0301-4215/

Seckin et al., 2013). Substantially, these measures can be divided into two categories: a clean vehicles strategy, which reduces energy consumption and emissions of vehicles or other automotive devices per kilometer using related technical improvements for vehicles or fuel; and a mobility management strategy, which reduces traffic volume through a variety of measures. However, there have been many debates regarding which strategy is optimal overall. Researchers who support a clean vehicles strategy usually think that mobility management is difficult to implement because there is great uncertainty and the potential for great harm to residents' utility and the urban economy (Cox and Moore, 2011; Hartgen et al., 2011; McKinsey, 2007; Moore et al., 2010). Others who support a mobility management strategy argue that the effect of mobility management on energy conservation and emissions reduction is more economical and efficient (TRB, 2009; USDOT, 2010; Gross et al., 2009). The mentioned measures are not absolutely negative or positive in principle. But comprehensive energy conservation and emission reduction policy should include various mobility management policies both in developed countries and developing countries (Litman, 2013a, 2013b). What is more, there is a high-income elasticity of demand for cars in developing countries. It means that car ownership will grow faster in the nearest future (Dargay and Gately, 1999). Thus, the motorization of developing countries will put a strain on global efforts to cut carbon emissions from transport. At the same time, developing countries lack the financial resources and governance system for achieving low-carbon transport target. Fortunately, the mobility management strategy can help cities in developing countries on the path toward a more low-carbon future (Santos et al., 2010). So we primarily analyze mobility management measures.

An urban passenger transport system is typically an open complex giant system that contains several subsystems. In such a complex system, a tiny change in societal, economic or environmental factors can lead to enormous changes to urban passenger transport development or energy consumption and emissions. For these reasons, it is vital for us to comprehend the structures and the relationships between different subsystems of the urban passenger transport system. Consequentially, quantitative analyses of behavioral characteristics and the dynamic mechanisms involved in urban passenger transport have become important areas of investigation.

In the past few years, a large number of studies have delved into the problem of urban transport energy consumption and emissions. These researches can primarily be divided into three types: top-down, bottom-up and hybrid methods.

(1) Top-down methods mainly include CGE, MACRO, GEM-E3, 3Es-Model, and so on. For example, Schafer and Jacoby (2005) analyzed how promoted new automobile technologies enter the automobile market and influence climate change under policy constraints using the CGE Model. Small (2012) assessed the effectiveness and cost of different energy policies for light motor vehicles using the National Energy Modeling System. Rentziou et al. (2012) forecasted urban passenger transport volume, energy consumption and CO_2 emissions based on the simultaneous equations Model. On the whole, top-down methods are good at providing economic analyses, but not do well in describing technology concretely. These methods generally underestimate the potential for technological progress (Nakata, 2004).
(2) The bottom-up approach primarily includes MARKAL, MESSAGE, EFOM, LEAP model, and so on. For example, Pressley et al. (2014) utilized a life cycle assessment methodology to evaluate the conversion of U.S. municipal solid waste to liquid transportation fuels via gasification and Fischer–Tropsch. Contreras, et al. (2009) analyzed the change in hydrogen energy vehicles' market share in road traffic using the MARKAL model. Cortés et al. (2008) developed an object-oriented simulation platform using a Java program to analyze urban traffic network energy consumption and emissions. On the whole, bottom-up methods perform economic analyses poorly, providing useful detailed descriptions of technology. These analyses generally overestimate the potential for economic progress (Nakata, 2004).
(3) Hybrid methods mainly include NEMS, POLES, PRIMES, POLES model, and so on. For example, Messner and Schrattenholzer (2000) analyzed an energy supply situation according to demand changes for different passenger and cargo transport units using an IIASA-CEC E3 model. Hickman et al. (2010) built the transport and carbon simulation model and investigated a series of potential policy packages that could reduce the emission's effect in London. Yang et al. (2009) built Long-term Evaluation of Vehicle Emissions Reduction Strategies and researched how to reach the target of reducing CO_2 emissions by 80% by 2050 in California. On the whole, hybrid methods combine the advantages of top-down and bottom-up methods. Not only are their functions more complete, but they also have a more complex structure. Therefore, they are more suitable to the simulation of complex giant systems.

Past research using hybrid methods normally assumed that the evolution structures of urban transport energy consumption and emissions were known; therefore, they reflected the dynamic process of energy consumption and emissions poorly and had difficulty conveying the uncertain behaviors of the primary issues associated with urban transport systems. Conversely, SD combines qualitative analysis with quantitative analysis and uses system synthesis reasoning to describe these undefined behavioral characteristics, making SD a better choice in dealing with nonlinear, high order complex time-varying systems. For these reasons, we chose the SD model to evaluate urban passenger transport energy consumption and CO_2 emissions in Beijing.

SD was first proposed for the analysis of a complex dynamic feedback system by J. W. Forrester in 1956 (Zhao et al., 2011). Based on computer simulation technology, this visual tool can analyze relationships among various factors, simulate quantitative data and obtain information on the feedback structure, function and behavior of the system. This makes it easier for us to understand the system overall and formulate various relevant policy scenarios to control the system's dynamic evolution mechanism (Yuan et al., 2008).

Currently, SD has been widely applied in various research fields, including societal and economic systems research (Forrester, 1969, 1971), ecosystem research (Saysel and Barlas, 2001), transportation research (Suryani et al., 2010) and so on. For instance, in the field of energy management, SD was widely applied to national energy policy-making and evolution (Ford, 1983; Naill, 1992; Qudrat-Ullah, 2005; Barisa et al., 2015). In addition, SD was also used extensively in energy efficiency assessments (Dyner et al., 1995) and the development of the energy industry (Bunn and Larsen, 1992; Chyong Chi et al., 2009). In the field of transportation, SD was applied to research into the operational management of the public transport enterprise (Bivona and Montemaggiore, 2010), the operational management of roads and infrastructure networks (Fallah-Fini et al., 2010), the usage of low emission cars such as electric vehicles and hydrogen vehicles (Walther et al., 2010), and the relationship between land usage and urban transport (Pfaffenbichler et al., 2010). Recently, Vafa-Arani et al. (2014) built an SD model that included urban transportation and air polluting industries subsystems to research urban air pollution in Tehran, Iran. However, in spite of these findings, there is still little literature in the field of the urban passenger transport energy and

emissions.

Just as other cities in developing countries that are undergoing rapid development, Beijing is in a transition period in which the population and economy are growing rapidly, and the city is experiencing continuous expansion, resulting in increasing pressure on the urban passenger transport system (Yuan et al., 2008; Dong et al., 2012). In recent years, Beijing has implemented a series of measures to alleviate urban traffic congestion and explore the possibility of urban passenger transport energy conservation and emission reductions. Research into urban passenger transport in Beijing can help identify solutions to problems associated with urban passenger transport energy conservation and emission reduction during urbanization in the developing countries.

Using Beijing as a case study, we focus on the effect of energy savings and emission reductions resulting from different policies, especially a mobility management strategy. The second section introduces the Beijing urban passenger transport carbon model (BUPTCM) and related data acquisition, and then constructs policy scenarios based on specific parameters. The third section provides the share rates for different transport modes, as well as energy consumption and emissions under different scenarios. The fourth section discusses the cumulative effect of each individual policy and the implementation sequence of each individual policy in the CP scenario. Finally, key conclusions are presented, policy implications are drawn and future research opportunities are identified.

2. Methods

In this study, we built a BUPTCM using Vensim (DSS) which is a simulation software for improving the performance of real systems. Vensim provides causal tracing of structure and behavior, and has Monte Carlo sensitivity, optimization and sub-scripting capabilities (Zhan et al., 2012).

We analyzed data from 2002 to 2020. First, we calibrated the parameters and verified that the simulation was consistent with the actual situation from 2002 to 2010.[1] Based on the simulation, we investigated Beijing's urban passenger transport energy consumption and CO_2 emissions from 2011 to 2020.

2.1. Causal loop diagram

To analyze the characteristics of Beijing's urban passenger transport system and clarify the relationships of the main variables in the system, we built a causal loop diagram (CLD) of the urban passenger transport energy consumption and CO_2 emissions. This diagram describes the mutual influences and interactional relationships among the system's variables, as shown in Fig. 1. Positive links are denoted with a "+", and negative links are denoted with a "−". A positive link means that two variables change in the same direction, while a negative link means that two variables change in the opposite direction. For instance, the increase in annual trip volumes per capita resulted in an increase in total trip volumes, and vice versa. A positive reinforcement loop, labelled by ⊕, has an even number of negative links. For instance, bus trip volumes → income → number of buses → frequency of bus service → maximum waiting time → bus service level → bus attraction was a typical positive feedback loop. The positive feedback loop has a self-reinforcing feature.[2] In contrast to the positive feedback loop, a negative feedback loop has an uneven number of negative links.

2.2. Flow diagram

Although the CLD could describe the basic structure of feedback relationships, it could not distinguish the differences among the various variables. Therefore, we built a flow diagram (FD) to explain the accumulated reactions for different levels of variables. In the SD model, Level variable (L) describes the cumulative effect of the system, which can react to the accumulation of material, energy and information over time. This variable is denoted with symbol "□". Rare variable (R) describes the speed of the system's cumulative effect and reflects the changes of Level variables over time, representing the speed of change in the system or the amplitude of a decision. It is denoted with the symbol"⟶⧖⟶". Auxiliary variables (A) are the intermediate variables, which run through the entire decision-making process. The BUPTCM consisted of 4 subsystems and included 7 level variables (L), 8 rate variables (R) and 70 auxiliary variables (A).

2.2.1. Economy subsystem

Due to rapid economic development in recent years, more and more people have purchased personal vehicles. The number of incremental cars in developing countries in Asia is significantly more than that in developed countries during the same period (Nakamura and Hayashi, 2013). This phenomenon has resulted in a transition from a reliance on non-motorized to motorized vehicles. This finding also shows that high speed development of the economy, especially the rapid growth of the GDP per capita, can greatly influence the transport system. For this reason, we built a FD of the economy subsystem, as shown in Fig. 2. Specific equations are identified in Appendix A. We assumed that Beijing's GDP growth rate was 8% for 2011–2015 and 6% for 2016–2020.[3]

2.2.2. Population subsystem

Population scale and structure are all important factors that affect urban passenger transport (Pettersson and Schmöcker, 2010). In Beijing, a large floating population plays a significant role in urban development. At the same time, they also put enormous pressure on the urban passenger transport system. Therefore, we built a FD of the population subsystem, as shown in Fig. 3. Specific equations can be found in Appendix A. For this subsystem, we assumed that Beijing's resident population growth rate was 9‰ for 2011–2015 and 8‰ for 2016–2020.[4]

2.2.3. Transport subsystem

The past decade has witnessed explosive growth in Beijing's population. However, the change in total trip volumes has not been so obvious, as it has hovered approximately 19 billion person time passengers in recent years. On the contrary, annual trip volumes per capita fell by about 3.24% due to the population's

[1] "The Tenth Five-Year Plan for National Economic and Social Development of the People's Republic of China" was promulgated in 2001. This policy specifically encourage families to buy cars in China. It brought huge impact on the share rate of different transport modes, trip volumes, trip volume per capita and other key elements of urban transport system. Taking the above mentioned policy and the availability of relevant data into consideration, we just use data from 2002 to 2010.

[2] If the maximum waiting time could be shortened, bus appeal would improve, which would lead to an increase in bus trip volume, followed by an increase in income and the number of buses generated. Eventually, the maximum waiting time would reduce and bus service level would enhance.

[3] Initial GDP and GDP growth rate for 2002–2010 can be obtained through the China Statistical Yearbook. In addition, we set GDP growth rate to 8% for 2011–2015, according to *"Beijing's the twelfth five-year plan"*. Because GDP growth rate would be reduced GDP growth rate will be 6% for 2016–2020.

[4] Initial transient population, initial resident population and resident population growth rate for 2002–2010 were obtained through the China Statistical Yearbook. In addition, we assumed that resident population growth rate for 2011–2020, according to the relevant policy of *"reasonable population scale, guide the population reasonable layout"* in *"Beijing's the twelfth five-year plan"*.

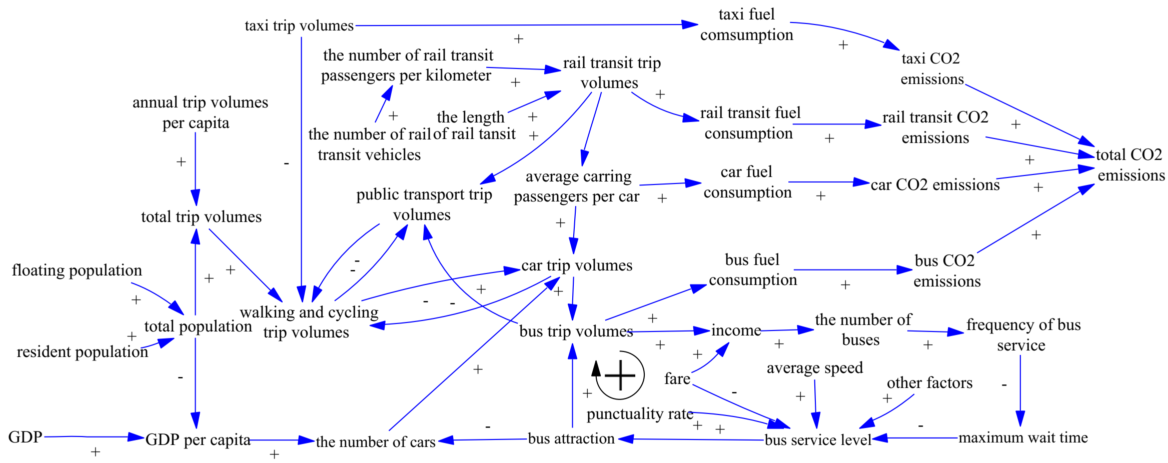

Fig. 1. The causal loop diagram of BUPTCM.

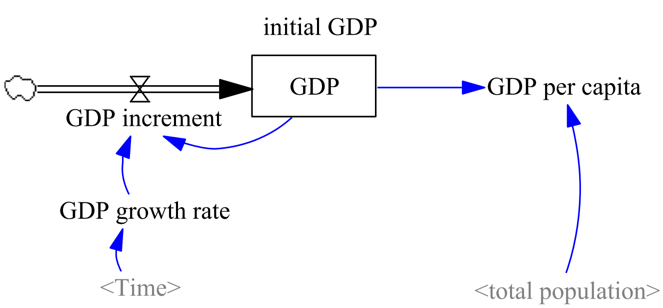

Fig. 2. The flow diagram for the economy subsystem.

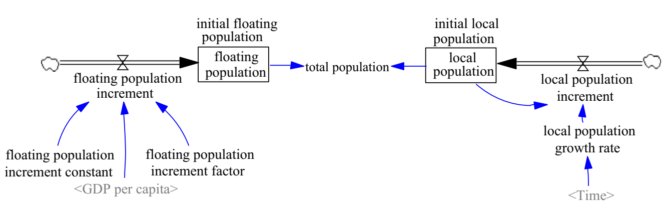

Fig. 3. The flow diagram for the population subsystem.

explosion. Overall, urban residents have completed the transition from walking and cycling to motorization, which typically includes usage of public transport and car. The share rate of walking and cycling decreased from 52.6% in 2002 to 26.5% in 2010, and the share rate of motorization rose from 47.4% in 2002 to 73.5% in 2010. Nevertheless, considering the following factors, like the stickiness of travel choice (Innocenti et al., 2013), the individual preferences and requirements on the travel efficiency (Tertoolen et al.,1998), and comfort and convenience (Bamberg et al., 2003), safety and some other factors (Wu and Ying, 2011; Hensher, 2001), we think that citizens will still give priority to choose car or public transport rather than walking and cycling in Beijing in the future. To research changes of transport mode, we constructed a FD of the transport subsystem, which is shown in Fig. 4.

The quantity of cars has a huge impact on urban transport congestion, energy consumption and CO_2 emissions (Li and Hensher, 2012; Pongthanaisawan and Sorapipatana, 2010; Chiou et al., 2009). Car trip volumes were determined based on the number of cars, average passengers per car[5] and car trip volumes decrement.[6]

Beijing's bus system plays a vital role in the urban passenger transport system (BBS, 2012). Its trip volumes accounted for 82.7% of the entire public transport trip volumes in 2002. Although Beijing's rail transit was undergoing rapid development at that time, bus trip volumes still played a leading role and accounted for 66.6% of the public transport trip volumes in 2010. In the recent years, bus trip volumes reached their saturation point. To understand further urban residents' perceptions of buses in Beijing and to identify problems and shortcomings, we surveyed a sample population using a questionnaire via the website platform (http://www.sojump.com/). A total of 214 effective questionnaires were received. Through this survey, we identified that 5 points residents worried about most in the process of bus operation and weighted those concerns successively as follows: punctuality (0.268); maximum waiting time (0.266); average speed (0.2053); fare (0.187); and others (0.074).[7] The survey also found that people who preferred cars might consider abandoning car and traveling by bus when bus service level increased by 76.7%.

Rail transit has become an effective way to ease urban traffic congestion and reduce transport energy consumption and CO_2 emissions (Nakamura and Hayashi, 2013).

Specific equations are identified in Appendix A. Initial number of cars, initial bus trip volumes, initial number of buses, initial length of rail transit, initial rail transit trip volumes, the number of rail transit vehicles for 2002–2010, annual trip volumes per capita for 2002–2010 and taxi trip volumes for 2002–2010 were all obtained through the China Statistical Yearbook. We assumed that operating subsidies were 0,[8] the ratio of operating income to total income was 1/3, the equipment update fee rate was 3.5%, the bus unit price was 500,000 RMB, the bus scrap rate was 1‰, the bus maintenance rate was 5%, average operating time was 40 min, average number of runs was 20 times, and the time interval was 1 h based on surveys and research of the Beijing public transport group. Moreover, we assumed that punctuality was 88%, average speed was 28 km per hour, other factors were 70, and bus attractive factor was 1.304 according to questionnaire results and calculations.

[5] We assumed that average passengers per car decrease with the growth of rail transit trip volume, presented as a concave curve with right high and left low.

[6] Car trip volume decrement was a variable quantity based on passengers' (footnote continued) choice to ride public transport due to improvement of service levels and abandoned cars.

[7] The other factors included the walking distance between the different transfer stations, transfer convenience, safety, degree of crowding, comfort, cleanliness, equipment status, noise conditions, reminder service for stops, and degree of bus driver civility.

[8] Existing subsidies were calculated using the ratio of operating income to total income.

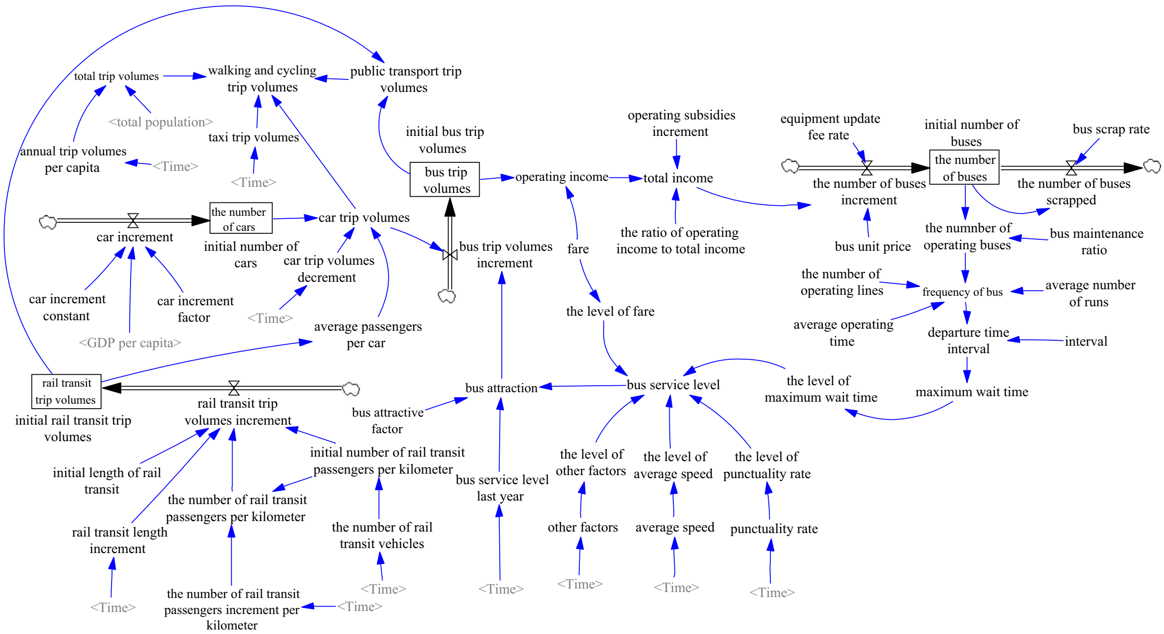

Fig. 4. The flow diagram for the transport subsystem.

We assumed that annual rail transit length increment was 30 km, the number of rail transit vehicles increment was 100 and the number of rail transit passengers increment per km was 300,000 per year for 2011–2020.[9]

Annual trip volumes per capita and taxi trip volumes were obtained through the China Statistical Yearbook. It should be noted that no new taxi licenses will be issued in the future, according to the *"Beijing transportation development report"*. Finally, according to historical data trends, we assumed that annual trip volumes per capita for 2010–2020 are progressively decreasing by 2% per year.

2.2.4. Energy consumption and emissions subsystem

Most existing studies estimated energy consumption and emissions from urban passenger transport using vehicle population, vehicle kilometers travelled (VKT), and fuel economy/emission rates (He et al., 2005; Wang et al., 2007; Huo et al., 2011). However, this method was subject to a few constraints or difficulties: (1) It did not consider the influence of the residents' travel behavior. (2) It ignored the difference between registered vehicle numbers and actual vehicles on the road. (3) The city-wide average travel distance was often inaccurate or unavailable (He et al., 2013; Wang et al., 2011). For these reasons, we developed a new methodology to quantify energy consumption, and which could link comprehensive policy scenarios with energy consumption via travel behavior changes.[10] The specific equation was as follows:

$$EC_{i,j} = C_{i,j} \times D_i \times T_i \quad (1)$$

where i are the modes of transport, j is the energy type; $EC_{i,j}$ is the energy consumption for energy type j by modes of transport i; $C_{i,j}$ is the energy consumption coefficient per capita[11] for energy type j by modes of transport i; D_i was driving distance per capita[12] for modes of transport i and T_i was annual trip volumes by modes of transport i.

CO_2 emissions were calculated using fuel consumption and electricity power consumption produced by various modes of transport (Cai et al., 2012). The specific equation was as follows:

$$CE_{i,j} = EC_{i,j} \times EF_j \quad (2)$$

where $CE_{i,j}$ represents CO_2 emissions for energy type j by modes of transport i; EF_j is the emission factor[13] from energy consumption j to CO_2 emissions.

Finally, we calculated total energy consumption and energy consumption per capita. The specific equations were as follows:

$$TEF = \sum_{i,j} EC_{i,j} \times ECC_j \quad (3)$$

$$ECPC = TEF \div TP \quad (4)$$

where TEF is the total energy consumption; ECC_j is the conversion coefficient[14] from energy type j to standard coal. $ECPC$ is energy consumption per capita and TP is the total population.

The specific equations for total CO_2 emissions and CO_2 emissions per capita were as follows:

$$TCE = \sum_{i,j} CE_{i,j} \quad (5)$$

$$CEPC = TCE \div TP \quad (6)$$

where TCE represented total CO_2 emissions and $CEPC$ represented CO_2 emissions per capita.

[9] Annual rail transit length and the number of rail transit vehicles was obtained from *"Beijing's 'Twelfth Five-Year' Transportation Development and Construction Plan"* (BMCT and BMCDR, 2012) and *"Beijing Transportation Development Report"*. Rail transit passengers increment per km was obtained from investigation into the existing Beijing rail transit passenger per kilometer, combined with rail transit trip volume incubation periods to correct expectations.

[10] To simplify analyses and calculations, we assumed that cars, taxis and buses all burned gasoline, while rail transit consumed electricity power. Then, the fuel consumption and electricity power consumption were converted into standard coal consumption.

[11] We set the energy consumption coefficient per capita with reference to Zhang (2010a, 2010b).

[12] We set driving distance per capita with reference to Huang et al. (2008).

[13] We set the emission factor from energy consumption to CO_2 emissions according to related data from the IPCC.

[14] We set the conversion coefficient from energy to standard coal according to related data from the IPCC.

2.3. Model tests

To make the BUPTCM consistent with reality, the model was verified using an authenticity test, a dimensional consistency test and a sensitivity test. It was convenient for the VENSIM to carry out the dimensional consistency test. Although there were some parameters with no realistic meaning, the model could still maintain dimensional consistency.

The authenticity test analyzed the error rate for 7 Level variables of numerical changes between simulation and reality. Specific results are shown in Table B.1 (Appendix B). It is worth mentioning that Severe Acute Respiratory Syndromes (SARS) broke out in Beijing in 2003. This accidental interference had a major effect on bus trip volumes, leading to an error rate of 24.28% in 2003. Therefore, we ignored this disturbance. The error rates of other indicators were within 20%. Furthermore, the error rates for GDP per capita, population quantity, total trip volumes and rail transit trip volumes were all within 5%. These indicators fully met the requirements of the authenticity test. Thus, with no obvious changes in system structure in the future, the BUPTCM can be used to analyze changes in Beijing's urban passenger transport energy consumption and CO_2 emissions.

To realize optimal control of the system and find out which parameters in the system have subtle effects on the system's behavior, we carried out a sensitivity test on the model. Specific test parameters, test scope and the effect of some elements are presented in Table B.2 (Appendix B). As observed from the results of the sensitivity analysis, the GDP growth rate and annual trip volumes per capita had greater influence on total trip volumes; and the GDP growth rate, car driving distance per capita and car energy consumption coefficient per capita had greater influence on the total energy consumption and total CO_2 emissions. In the bus subsystem, equipment update fee rate, average number of runs, punctuality, average speed and other factors had major influences on bus trip volumes. In the rail transit subsystem, rail transit length increment and the number of rail transit passengers increment per kilometer had major influences on rail transit trip volumes and rail transit power consumption. The above elements represent the potential policy variables that needed to be investigated further.

2.4. Policy scenarios

Based on the results of the sensitivity analysis and the current classification of the main policy tools, we established six policy scenarios, namely, Business as usual (BAU) scenario, Priority to the development of public transport (PDPT) scenario, Travel demand management (TDM) scenario, Technical progress (TP) scenario, Administrative rules and regulations management (ARM) scenario and Comprehensive policy (CP) scenario. In individual policy, PDPT, TDM and ARM represent typical mobility management strategies, while TP was a clean vehicle strategy. Specific technical parameters are shown in Table 1.

2.4.1. BAU scenario

The BAU scenario was set in accordance with the current development situation, without any additional policies. Settings related to the economy subsystem, population subsystem, transport subsystem, energy consumption and CO_2 emission subsystem were the same as above.

2.4.2. PDPT scenario

The development goal in this scenario was that the attractiveness of public transport would be obviously enhanced and the travel structure would be further optimized, based on *"Beijing's 'Twelfth Five-Year' Transportation Development and Construction Plan"* (BMCT and BMCDR, 2012). The concrete targets included three aspects: (1) The proportion of traveling by public transport accounted for 50%. (2) The proportion of traveling by car accounted for less than 25%. (3) The proportion of traveling by bicycle remained at approximately 18% in the central city.

2.4.3. TDM scenario

Since 2004, Beijing has implemented a systematic multi-stage traffic demand management plan and policy. Recently, Beijing is firmly determined to build a new transportation system characterized by "Humanistic Transportation, High-tech Transportation and Green Transportation" and turn into a "public transportation friendly city" (BMCT and BTRC, 2010). As a result, Beijing will attempt reforms based on the following plans to reduce car use in the future: (1) Establish urban multi-centers that meet different daily life needs to the utmost extent to reduce trip volumes. (2) Advocate and guide residents to change modes of travel and utilize more public transport. (3) Enhancement of the existing fuel tax or charge congestion fees is being planned.

2.4.4. TP scenario

In recent years, Beijing has made many efforts in technology to realize energy savings and emission reductions. Since 2000, Beijing has accelerated the elimination of vehicles which are high in emissions or have high pollution rates (i.e. "yellow label vehicles" which did not reach the Chinese national standard I for gasoline or national standard III for diesel). Beijing improved its emission standards from Europe I to Europe II in 2004. Then the European III standard was implemented in 2008. In addition, Beijing, as a representative of Chinese cities, completed an upgrade in its emissions standard from Chinese national standard IV to V in advance of the deadline. What is more, the Beijing municipal

Table 1
The concrete measure in different scenarios.

Scenarios	Measures
BAU	Operating subsidies increment was 0 Yuan, average number of runs was 20 times, punctuality rate was 88%, average speed was 26 km/h, other factors were 70, rail transit length increment was 30 km, the number of rail transit passengers increment per kilometer was 300,000 person time/km/year, the number of rail transit vehicles increment was 100 vehicles.
PDPT	Operating subsidies increment was 250 million Yuan, average number of runs rose by 5%, punctuality rate rose by 1%, average speed rose by 2 km/h, other factors rose to 75. In 2011–2015, rail transit length increment rose to 60 km, the number of rail transit passengers increment per kilometer rose to 600,000 person time/km/year, the number of rail transit vehicles increment rose to 200 vehicles. In 2016–2010, rail transit length increment rose to 80 km, the number of rail transit passengers increment per kilometer rose to 800,000 person time/km/year, the number of rail transit vehicles increment rose to 300 vehicles.
TDM	Car driving distance per capita declined by 30%, taxi, bus, rail transit driving distance per capita rose by 20%.
TP	Car, taxi, bus, rail transit consumption coefficient per capita declined by 2%, fuel consumption CO_2 emission factor declined by 5%.
ARM	Transient population increment limit of 300,000 people per year, car increment limit of 240,000 per year, car trip volume declined by 20% by limit of travel on weekday.
CP	Includes all control measures from BAU, PDPT, TDM, TP, and ARM.

commerce commission formally issued *"The notice about implementation of 5th stage automotive gasoline and diesel standards in Beijing"* in May 7, 2012. Beijing had carried out the new automotive gasoline and diesel standard (Jing V) by May 31, 2012. The adjusted standard was stricter than the national standard's recommended indexes in the 5th stage, which was the same as the European standard for the same stage. Comparing to technologies for emission reductions, the development of technology for energy savings went through a relative lag. *"Automobile fuel consumption marking"* was not officially launched until June 22, 2009.

2.4.5. ARM scenario

In the past few years, Beijing has effectively coped with urban passenger transport problems by restricting car purchases and use, controlling the excessive growth of the population and so on. First, Beijing formally announced *"the interim provisions on passenger car quantity regulation of Beijing"* in December 23, 2010 (commonly known as the "limit acquisition rule (LAR)"). According to LAR, Beijing carried out a restraining policy on the annual incremental cars. Annual incremental car purchase credits numbered 240,000, and individual demand accounted for 88% of credits. Credits were distributed by free lottery. In addition, cars whose licenses were not native were banned when driving within the fifth ring road during peak hours to reduce the rebound effect. Second, according to "*Beijing's municipal circular of restrict traveling on weekday at peak hours*", vehicle licenses would be divided into 5 groups from April 10, 2011 to April 10, 2012, based on the last number on the license. The city then implemented regional motor vehicle restrictions during peak weekday hours. At present, the vehicle restriction policy on travel is still in practice. The Beijing municipal transportation committee said that whether they continue to implement this policy depends on the actual situation. Third, the population of Beijing reached 19.619 million in 2010. The floating population reached 7.047 million with an incremental increase of 905,000 people from the year before. The population has reached its highest record level so far. The explosive growth in population has placed huge pressure on the urban passenger transport system in Beijing. Therefore, we suggest limiting the influx of floating populations by balancing development of medium cities and small towns, gradually reducing or even cancelling special benefits obtained from Beijing's Household Registration.

2.4.6. CP scenario

The comprehensive policy scenario was the integration of the above four scenarios, the PDPT, TDM, TP, and ARM scenarios.

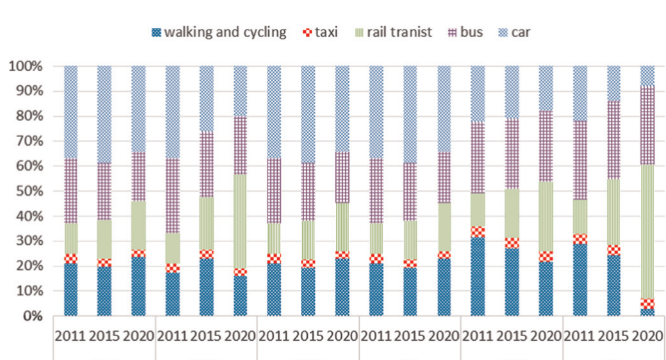

Fig. 5. The changes in share rate of different transport modes.

3. Results

3.1. Transport mode

Changes in the share rate of different transport modes were obtained using the BUPTCM model, as shown in Fig. 5.

In the BAU scenario, the share rate of rail transit shows a rising trend, up from 12.3% in 2011 to 19.5% in 2020. In addition, although the absolute value of bus trip volumes is on the rise, its share rate presents a downward trend from 26% in 2011 to 20% in 2020. At the same time, the share rate of cars continues to decline as the share rate of public transport increases. It will decrease from 37% in 2011 to 34.3% in 2020. What is more, the share rate of walking and cycling will slightly decline and the share rate of taxis will rise slightly. From what has been discussed above, the Beijing urban passenger transport structure can undergo a certain degree of optimization with the development of public transport where rail transit is a major leading component.

In the PDPT scenario, the share rate of rail transit rises sharply, and the share rate of cars drops significantly. Meanwhile the share rate of buses presents a slight decline, though it has a small rise in absolute trip volumes. In addition, the share rate of walking and cycling shows a declining trend in ways to travel from non-motor to motorized vehicles. In general, the share rate of public transport will rise sharply more than 60% in 2020. Under this scenario trip structure is optimized in all individual policies.

Similar to the BAU scenario, due to the development of public transport system that cannot meet travel demand for more long distance and more comfortable options, the falling share rate of the car will slow in the TDM and TP scenarios. It will still be close to 35% by 2020.

In the ARM scenario, purchase and use of a car is governed by tight restrictions, and the share rate of cars declines sharply. Overall, the share rate of rail transit will steadily increase, while the share rate of cars will continue to decline, with urban passenger transport structure trends that are more reasonable.

In the CP scenario, the share rate of cars is low in the beginning, and then will continue to decline from 21.9% in 2011 to 8.1% in 2020 with the development of public transport. The share rate of public transport will rise sharply, up from 45.3% in 2011 to 85.1% in 2020.

In all scenarios, the development of motorized transport is rapid, combined with the continued decline in walking and cycling. The result is that urban residents will seldom travel by foot or bike in the coming years. These modes of transport will only be used as supplements to motorized transport to meet the needs of short distance travel.

3.2. Energy consumption and CO_2 emissions

In the BAU scenario, the contribution rate of different transport modes to energy consumption and CO_2 emissions is shown in Table 2. The contribution rate of cars to energy consumption is always maintained above 88% in this scenario. Energy consumption of cars will rise from 6.41 million tce in 2011 to 9.26 million tce in 2020, with an average annual growth rate of 4.44%. In this scenario, car is the most significant contributor to energy consumption. Similarly, the CO_2 emissions of cars also play a leading role. They will rise from 13.61 million tonnes in 2011 to 19.65 million tonnes in 2020, with an average annual growth rate of 4.44%. The contribution rate of cars to CO_2 emissions will also rise from 89% in 2011 to 90.6% in 2020. To sum up, the energy consumption and CO_2 emissions of cars is a primary cause of existing energy consumption and CO_2 emissions associated with urban passenger transport in Beijing and will inevitably become the focus of any process geared toward realizing a low-carbon

Table 2
The contribution rate of different transport modes to energy consumption and CO_2 emissions.

	Mode	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Energy consum-piton	Car	88.1%	88.9%	89.2%	89.3%	89.5%	89.6%	89.4%	89.1%	89.2%	89.1%
	Taxi	7.0%	6.5%	6.2%	6.1%	5.9%	5.8%	5.9%	6.0%	5.9%	5.8%
	Bus	3.9%	3.7%	3.5%	3.5%	3.4%	3.3%	3.4%	3.4%	3.4%	3.4%
	Rail	1.0%	1.0%	1.0%	1.1%	1.2%	1.3%	1.4%	1.5%	1.6%	1.7%
CO_2 emissions	Car	89.0%	89.8%	90.2%	90.3%	90.6%	90.7%	90.7%	90.5%	90.6%	90.6%
	Taxi	7.0%	6.5%	6.3%	6.2%	6.0%	5.9%	5.9%	6.1%	6.0%	5.9%
	Bus	4.0%	3.7%	3.5%	3.5%	3.4%	3.4%	3.4%	3.5%	3.4%	3.4%
	Rail	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

transport system of the future.

The changes in total energy consumption under different scenarios are shown in Fig. 6(a). In the TP scenario, the fall of total energy consumption is minimal. In the TDM scenario, the decline in total energy consumption happens earlier and is greater in the beginning. However, it appears to surge once again as time passes. In the PDPT scenario, total energy consumption shows a declining trend in the beginning, but evidences a slightly upward trend after 2016. In the ARM scenario, total energy consumption has the largest decline of all of the individual policies in the beginning and maintains a lower level of consumption continuously until 2020. Through the above different scenarios analyses, it is obvious that the ARM and TDM policies are both highly effective ways to reduce the energy consumption of urban passenger transport in the short term. In the CP scenario, total energy consumption is lowest in the beginning and then declines continuously. Whether in the short or long-term, the result of energy reduction in CP is best among all policies.

The changes in total CO_2 emissions under different scenarios are shown in Fig. 6(b). In the TP scenario, the implementation of "Chinese national standard V" for motor vehicle emissions and the "Jing V standard" of fuel, as well as the elimination of "yellow label vehicles", will lead to a relatively larger decline in CO_2 emissions than energy consumption. In spite of this, the total CO_2 emissions still present a rising trend because of the increase in urban residents' travel. The change in total CO_2 emissions is similar to energy consumption in other scenarios, so we do not repeat the discussion here.

Changes in energy consumption per capita under different scenarios are shown in Fig. 6(c). In the TP scenario, energy consumption per capita declines slightly. The main reason is that the energy economy around urban transport is difficult to make great progress in the short term, due to limitations in capital and technology. In TDM scenario, energy consumption per capita

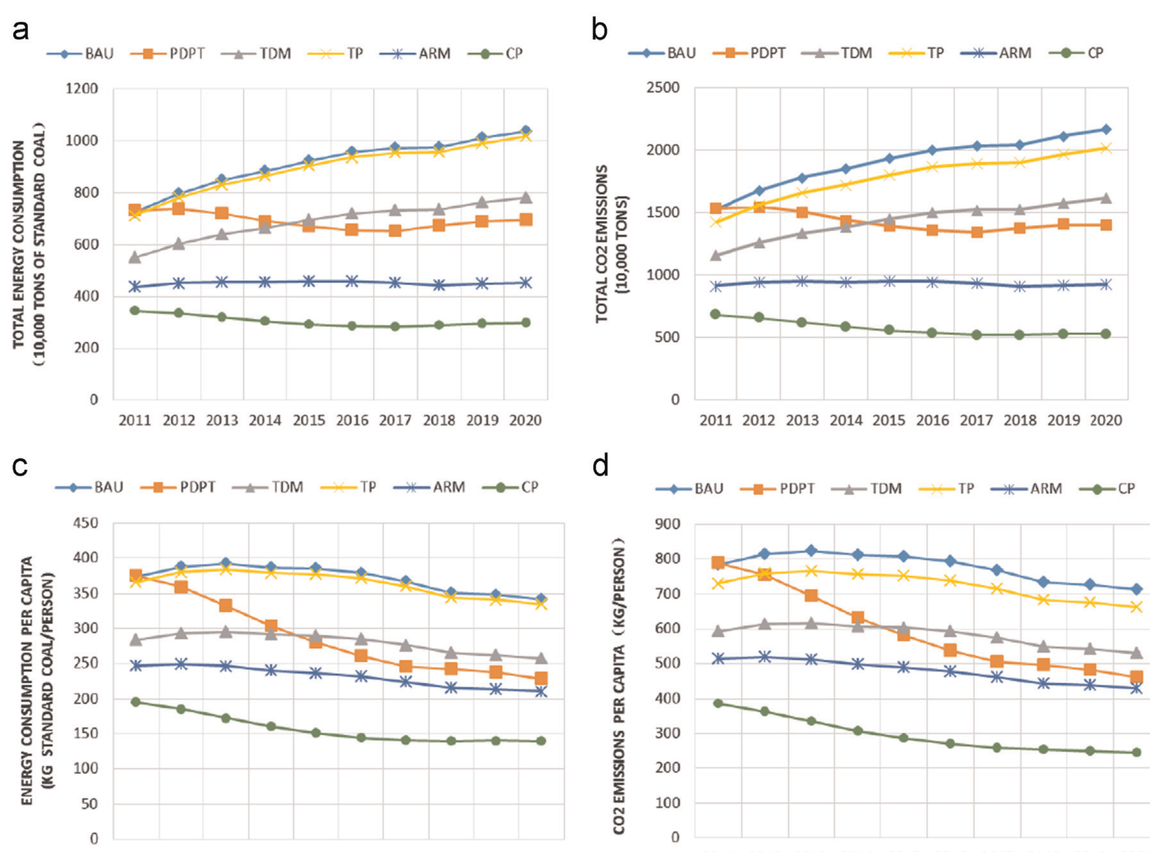

Fig. 6. (a) Beijing urban passenger transport total energy consumption in the different scenarios. (b) Beijing urban passenger transport total CO_2 emissions in the different scenarios. (c) Beijing urban passenger transport energy consumption per capita in the different scenarios. (d) Beijing urban passenger transport CO_2 emissions per capita in the different scenarios.

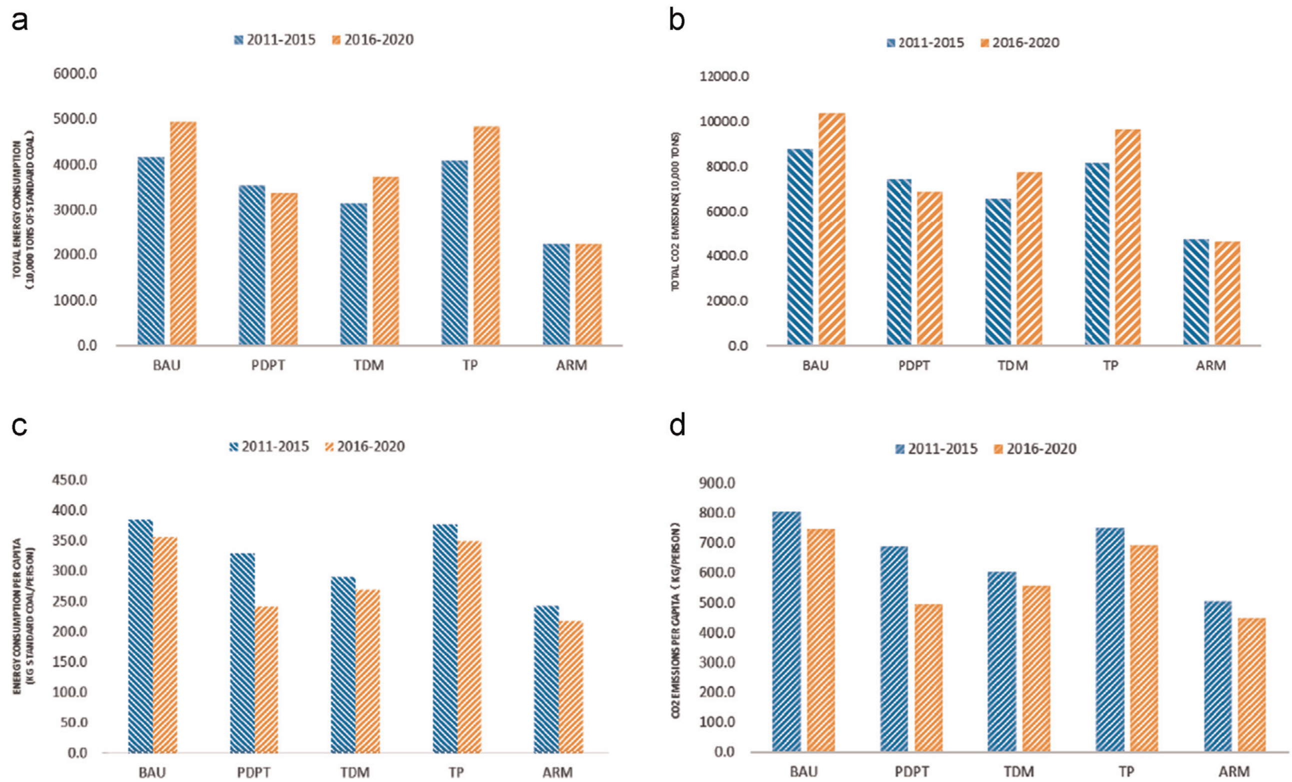

Fig. 7. (a) The cumulative effect of total energy consumption in different scenarios. (b) The cumulative effect of total CO_2 emissions in different scenarios. (c) The cumulative effect of energy consumption per capita in different scenarios. (d) The cumulative effect of CO_2 emissions per capita in different scenarios.

shows a slow decline in the beginning, and then its decline becomes more rapid. In the PDPT scenario, energy consumption per capita shows a sharp downward trend, but the pace of decline slows down gradually. Energy consumption per capita in the ARM scenario is the lowest of all individual policies, but the amplitude of decline is much smaller than in the PDPT scenario throughout the entire period. Compared with different scenarios, the ARM and TDM policies have a huge initial drop in energy consumption per capita. However, the PDPT policy will result in a dramatic decrease in energy consumption per capita on the whole. Therefore, it presents an important way to fundamentally reduce energy consumption from urban passenger transport. In the CP scenario, energy consumption per capita shows a level low in the beginning and continuously falling, with a rate of decline that begins quickly and slows over time.

Changes in CO_2 emissions per capita under different scenarios are shown in Fig. 6(d). There is little difference between the changes in CO_2 emissions per capita and changes in energy consumption per capita for the TDM, PDPT, ARM, and CP scenarios, with the exception of the relative larger changes in CO_2 emissions per capita in TP, due to stricter emissions standards.

4. Discussion

4.1. The cumulative effect of policies

To discuss the effect of the PDPT, TDM, TP, and ARM scenarios on energy savings and emissions reductions, the simulated time was divided into two periods: 2011–2015 and 2016–2020. Specific cases are shown in Fig. 7.

It is obvious that of all of the individual policy scenarios, ARM always has the best effect on both energy savings and emission reductions. A comparison of Fig. 7(a) and (b) shows that TP's contribution to emission reduction is superior to energy savings both in absolute value and relative percentage. Although TDM policies take effect quickly, their effect on energy savings and emission reduction in the second five-years is significantly weaker than in the first five-years. In addition, the energy consumption per capita and CO_2 emissions per capita in the PDPT scenario in the second five-year period is significantly lower than that in the first five-year period, as seen in Fig. 7(c) and (d). This phenomenon reflects that the PDPT policy has a certain lag time before it becomes effective. Thus, we assume that PDPT will play a more important role in energy conservation and emission reductions in the future.

4.2. The optimal sequence of policy implementation

Comparing CP with the individual policies, it is easy to find that implementing CP is always more effective than implementing any individual policy in the terms of energy savings and emissions reduction. To explore the role of each individual policy in the CP, we investigated the effect of each individual policy under different conditions. According to the analysis in Section 3.2, it is obvious that there is not much difference among PDPT, TDM, TP and ARM in terms of energy savings and emission reduction.[15] In addition, Chinese government is under great pressure to reduce emissions to response to global climate change (Gan, 2003; Zhang, 2010a, 2010b). As a result, we just discuss effects on emissions reduction from each individual policy. Specific calculation methods are shown in Table B.3 (Appendix B).

In Fig. 8(a), the effect of PDPT−(TDM+TP)[16] is most significant,

[15] Kahn Ribeiro et al. (2007) also pointed out that actual changes in the trend of energy consumption and CO_2 emissions are basically consistent. Empirical results for China suggest a unidirectional Granger causality running from energy consumption to carbon emissions in the long run (Zhang and Cheng, 2009).

[16] PDPT−(TDM+TP) presents the changes of emissions reduction resulting from the implement of PDPT after the former implementation of TDM and TP. Other

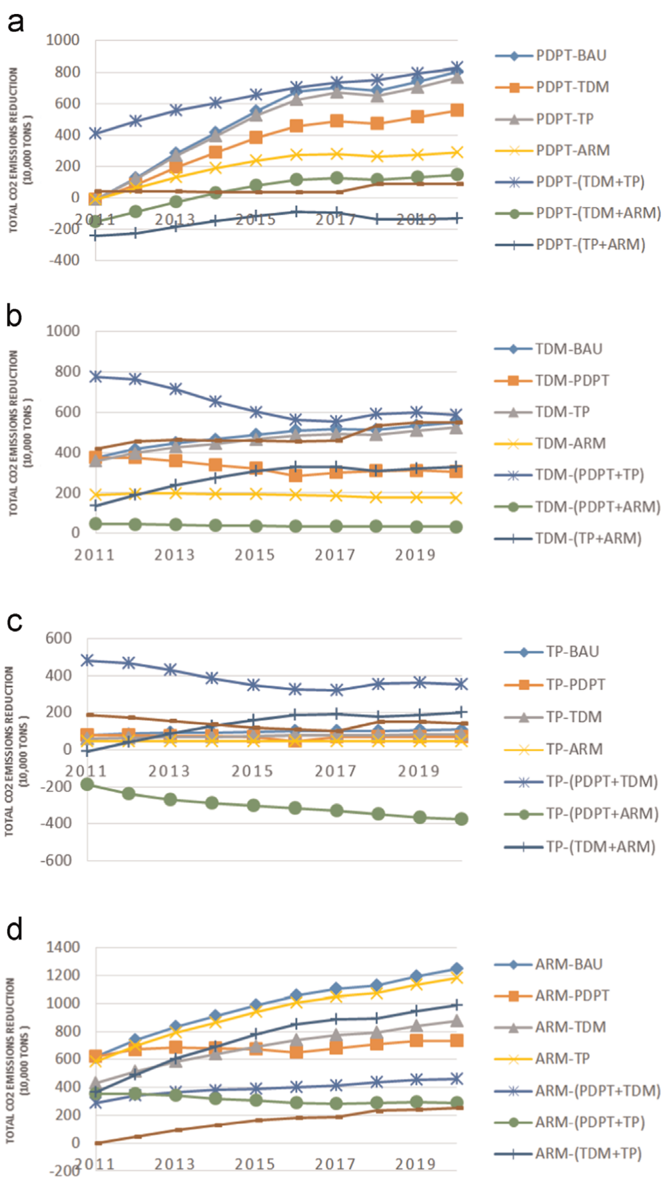

Fig. 8. (a) The CO_2 emissions reduction change from PDPT implementation under different conditions. (b) The CO_2 emissions reduction change from TDM implementation under different conditions. (c) The CO_2 emissions reduction change from TP implementation under different conditions. (d) The CO_2 emissions reduction change after ARM implementation under different conditions.

which indicates that the effect of PDPT will be best after the implementation of TDM and TP. Comparing PDPT – TDM, PDPT – TP with PDPT – ARM, we find that the PDPT scenario will be most impactful only after the implementation of TP. What is more, PDPT – (TP + ARM) is always negative; PDPT – (TDM + ARM) is also negative before 2014, while PDPT – (TDM + TP + ARM) is always positive. These conflicts illustrate that the implementation of ARM has a serious influence for the effect of PDPT. Therefore, PDPT should be implemented before ARM. In short, the best policy implementation sequence to maximize the effects of PDPT is TP → TDM → PDPT → ARM.

Fig. 8(b) demonstrates that the effect of TDM – (PDPT + TP) is best, indicating that the implementation of TDM will be most effective after the implementation of PDPT and TP. Comparing TDM – PDPT, TDM – TP with TDM – ARM, we reach the following conclusions: TDM will be enhanced after TP; however, the effect of TDM will be weakened after the implementation of ARM. In addition, the effect of TDM – (PDPT + TP + ARM) is prominent, which shows that TDM provides effective measures to solve the traffic problem at any time and should be practiced unremittingly. Therefore, the best policy implementation sequence to maximize the effects of TDM is TP → PDPT → TDM → ARM.

Fig. 8(c) illustrates that the effect of TP – (PDPT + TDM) is most significant, which suggests that ARM should be implemented after TP in order for TP to be most effective. Comparing TP – PDPT, TP – TDM with TP – ARM, we find that PDPT should be implemented first, then TDM, followed by ARM. To sum up, the best policy implementation sequence to maximize the effects of TP is PDPT → TDM → TP → ARM.

Fig. 8(d) demonstrates that ARM should be implemented first to obtain the best effect of ARM – BAU. However, the ARM policy has a strong crowding-out effect on PDPT, TDM and TP. As a result the ARM policy should be implemented last to leave space for the effects of PDPT, TDM and TP policies. The effect of ARM – TP is second-most prominent; thus, TP should be implemented first. Comparing ARM – PDPT with ARM – TDM reveals that the effect of ARM – PDPT is more substantial than ARM – TDM early on; however, it become worse later. In addition, PDPT has a certain lag time, while TDM requires good public transport conditions as a prerequisite. All in all, the best policy implementation sequence to maximize the effects of ARM is TP → PDPT → TDM → ARM.

From the above, the best policy implementation sequence to maximize the effect of all individual policy in CP is TP → PDPT → TDM → ARM.

5. Conclusions and policy Implications

5.1. Key conclusions

In this study, we constructed a BUPTCM. Through an authenticity test and a dimensional consistency test, we demonstrated that BUPTCM is reliable and effective. Based on a sensitivity analysis, we simulated Beijing urban passenger transport energy consumption and CO_2 emissions and changes in the share rate of transport mode in BAU, PDPT, TDM, TP, ARM and CP scenarios.

In terms of transport structure optimization, Beijing should rely primarily on the development of the public transport system with a focus on rail transit. In addition, walking and cycling will be an effective complement to public transport to meet the requirements of short distance travel.

In terms of transport energy consumption and CO_2 emissions, PDPT has a positive effect. However, PDPT has a certain lag time, so its effect on energy conservation and emissions reduction will be revealed gradually over time. TDM reveals results quickly and has excellent short-term effects. It can account for the lag in the effect of the PDPT policies when the two are pursued in tandem. In terms of emissions reductions, TP's contribution is much stronger here than in the area of energy savings. ARM can achieve the stated goals most quickly and with the largest drop in numbers. The effect of CP is better than each individual policy pursued separately. However, its cost is the highest, as well.

5.2. Policy implications

To achieve the goal of urban passenger transport energy conservation and emissions reduction and to realize the development of low-carbon transport modes in the future, we recommend a series of policies and measures based on the PDPT, TDM, TP, ARM

(*footnote continued*)
variables in Fig. 8 are similar to PDPT – (TDM + TP). The last upcoming policy is in front of the " – ", while the policies having been implemented are located after the " – ".

and CP scenarios.

Specifically, PDPT is an effective way to solve urban passenger transport problems in cities like Beijing, which is a megacity with large populations. There is no doubt that public transport, which is dominated by rail transit, should be developed as soon as possible in Beijing and other megacities with large populations. Furthermore, we also need to improve the travel environment for walking and cycling by setting up special driveways, increasing the lanes' greening, and encouraging new ways of walking and cycling, such as electric bicycles, to enhance the share rate of walking and cycling.

The mechanism design for TDM is more important. The related departments should forecast ahead and consider a variety of possible loopholes to this policy. The various possible impacts of urban development and layout on travel from TDM should be considered at the beginning of the city planning effort.

TP still has a great potential to be discovered. At present, the effect produced by TP on emission reduction is better than that on energy savings in Beijing. From the point of practical experience, technology research and development require a large number of inputs and have a much longer investment payback period. Therefore, vehicle manufacturers and energy providers usually lack the motivation to research such technologies. This urges the government to formulate and promulgate more strict technical standards as soon as possible. What is more, providing certain compensation through different incentives, such as deductions and tax exemptions, may be significantly more substantial compensation, which will help realize ultimate goal.

In general, ARM relies on the government's coercive power to implement the related policies, so the government needs to consider both fairness and efficiency in the implementation process. In addition, the related departments should provide explanations about ARM policies to obtain support and understanding from the residents to reduce the rebound effect. What is more, a supervisory mechanism and exit mechanism are also important parts of these policies. Taking Beijing as an example, the effect of ARM on energy conservation and emission reduction is obviously very positive. However, Beijing has already changed car quotas from its original 240,000 vehicles per year to 150,000 vehicles per year in 2014, including 20,000 quotas which are set aside for new energy car.[17]

There is no doubt that the energy conservation and emission reduction effect of CP is the best solution of all policies and measures analyzed here. Within this, we propose that the optimal policy implementation sequence in CP is TP → PDPT → TDM → ARM.

5.3. Future works

The conclusion of this article confirms the views that technological and regulatory solutions should be implemented first followed by economic ones (Nakamura and Hayashi, 2013). However, without considering the characteristics and development stage of different cities from the time dimension, it is unknown whether this sequence for policy implementation is only suitable to Beijing or applicable in other cities as well. Furthermore, the implementation cost of each policy was not taken into account in this analysis. These conditions need to be studied further. Governments should choose the appropriate policy portfolio to achieve the most significant energy savings and emission reductions in practice, according to each city's own characteristics and development stage and considering the cost of implementation and the applicable scope of different policies.

[17] The new energy car is pure electric car which is included in the "*Beijing demonstration in new energy passenger car production enterprises and products catalogue*".

Acknowledgments

We are grateful to Professor Guoguang He and Huibin Du for fruitful discussions and suggestions about the work presented in this paper. We would also like to give sincere thanks to the anonymous reviewers for their helpful comments and suggestions. This research was supported by the National Natural Science Foundation of China (NSFC) (71431005, 71271150 and 71401120) and Tianjin social science planning project (TJGL13-015).

Appendix A.

The principal equation of the economy subsystems are as follows:

L GDP = INTEG (GDP increment) + initial GDP, unit: 10000*Yuan, note: the INTEG is integral sign.

R GDP increment = GDP*GDP growth rate, unit: 10,000*Yuan/year

A GDP per capita = GDP/total population, unit: Yuan/persons

A GDP growth rate = WITH LOOKUP (Time), Initial Value ([(2002, 0.02)–(2020, 0.25)], (2002, 0.16041), (2003, 0.2049), (2004, 0.15519), (2005, 0.16476), (2006, 0.21299), (2007, 0.12879), (2008, 0.0339), (2009, 0.16132), (2010, 0.1515), (2011, 0.08), (2012, 0.08), (2013, 0.08), (2014, 0.08), (2015, 0.08), (2016, 0.06), (2017, 0.06), (2018, 0.06), (2019, 0.06), (2020, 0.06)), unit: %/year, note: The GDP growth rate is table function of simulate time.

The principal equation of the population subsystems are as follows

L floating population = INTEG (floating population increment) + initial floating population, unit: 10,000*persons, note: the INTEG is integral sign

L resident population = INTEG (resident population increment) + initial resident population, unit: 10,000*persons, note: the INTEG is integral sign

R floating population increment = GDP per capita*floating population increment factor + floating population increment constant, unit: 10,000*persons/year, note: $R^2 = 0.974$, DW = 3.408, Prob (*F*-statistic) = 0R resident population increment = resident population*resident population growth rate, unit: 10,000*persons/year

A total population = floating population + resident population, unit: 10,000*persons

A floating population increment constant = −58.8476, unit: 10,000*persons/year, note: It is calculated by the regression in which GDP per capita as independent variable and floating population increment as the dependent variable.

A floating population increment factor = 0.001957, unit: 10,000*persons*persons/Yuan/year, note: It is calculated by the regression in which GDP per capita as independent variable and floating population increment as the dependent variable.

A resident population growth rate = WITH LOKUP (Time), Initial Value ([(2002, 0)–(2020, 0.02)], (2002, 0.012321), (2003, 0.01088), (2004, 0.01212), (2005, 0.01508), (2006, 0.01411), (2007, 0.01294), (2008, 0.0135), (2009, 0.01276), (2010, 0.00907), (2011, 0.009), (2012, 0.009), (2013, 0.009), (2014, 0.009), (2015, 0.009), (2016, 0.008), (2017, 0.008), (2018, 0.008), (2019, 0.008), (2020, 0.008)), unit: %/year, note: The resident population growth rate is table function of simulate time.

The principal equation of the transport subsystems are as follows:

L the number of cars = INTEG (car increment) + initial number of cars, unit: vehicle, note: the INTEG is integral sign.

L bus trip volumes = INTEG (bus trip volumes increment) + initial bus trip volumes, unit: 10,000*person*time

L the number of buses = INTEG (the number of buses increment − the number of buses scrapped) + initial number of buses, unit: vehicle

L rail transit trip volumes = INTEG (rail transit trip volumes increment) + initial rail transit trip volumes, unit: 10,000*person*time

R car increment = GDP per capita*car increment factor + car increment constant, unit: vehicle/year, note: $R^2 = 0.987$, DW = 0.970, Prob (F-statistic) = 0R bus trip volumes increment = bus attraction*car trip volumes, unit: 10,000*person*-time/year

R the number of buses increment = total income*equipment update fee rate/bus unit price, unit: vehicle/year

R the number of buses scrapped = bus scrap rate*the number of buses, unit: vehicle/year

R rail transit trip volumes increment = rail transit length increment*the number of rail transit passengers per kilometer + initial length of rail transit*(the number of rail transit passengers per kilometer − initial number of rail transit passengers per kilometer), unit: 10,000*person*time /year

A car increment constant = −242,605, unit: vehicle/year, note: It is calculated by the regression in which GDP per capita as independent variable and car increment as the dependent variable.

A car increment factor = 11.3291, unit: person*vehicle/Yuan/year, note: It is calculated by the regression in which GDP per capita as independent variable and car increment as the dependent variable.

A average passengers per car = WITH LOOKUP (rail transit trip volumes), Initial Value ([(0, 0)–(1.3e+006, 0.6)], (47,258, 0.4023), (47,690, 0.566), (60650, 0.4529), (65,488, 0.2569), (67,994, 0.4246), (70,298, 0.3053), (104,346, 0.2557), (146654, 0.2257), (210,157, 0.1818), (250,000, 0.16), (300,000, 0.13), (350,000, 0.11), (400,000, 0.09), (500,000, 0.07), (600,000, 0.06), (800,000, 0.05), (1e+006, 0.04), (1.3e+006, 0.035)), unit: 10,000*person*time/vehicle, note: The average passengers per car is table function of simulate time.

A car trip volumes = average passengers per car*the number of cars − car trip volumes decrement, unit: 10,000*person*time

A car trip volumes decrement = WITH LOOKUP (Time), Initial Value ([(2002, 0), (2020, 60,000)], (2002, 10.81), (2003, 8.75), (2004, 11.65), (2005, 72.35), (2006, 64.31), (2007, 59.99), (2008, 143.13), (2009, 154.13), (2010, 142.5), (2011, 1257), (2012, 1363), (2013, 1428), (2014, 1457), (2015, 1498), (2016, 1521), (2017, 1515), (2018, 1485), (2019, 1511), (2020, 1518)), unit: %/year, note: The car trip volumes decrement is table function of simulate time.

A operating income = fare*bus trip volumes, unit: 10,000*Yuan

A total income = operating income/the ratio of operating income to total income + operating subsidies increment, unit: 10,000*Yuan

A operating subsidies increment = 0, unit: 10,000*Yuan

A the ratio of operating income to total income = 1/3, unit: %

A equipment update fee rate = 3.5, unit: %/year

A bus unit price = 50, unit: 10,000*Yuan/vehicle

A bus scrap rate = 1, unit: ‰/year

A the number of operating buses = the number of buses * (1 − bus maintenance ratio), unit: vehicle

A bus maintenance ratio = 5, unit: %

A frequency of bus = (the number of operating buses*average number of runs/the number of operating lines)/average operating time, unit: vehicle*time/line/min

A the number of operating lines = 620, unit: line

A average operating time = 40, unit: min

A average number of runs = 20, unit: time

A Departure time interval = interval/frequency of bus, unit: min

A interval = 60, unit: min

A maximum wait time = 0.75*1*Departure time interval + 0.2*2*Departure time interval + 0.05*3*Departure time interval, unit: min

A the level of maximum wait time = IF THEN ELSE (maximum wait time ≦ 1, 9, IF THEN ELSE (maximum wait time ≦ 3, 7, IF THEN ELSE (maximum wait time ≦ 5, 5, IF THEN ELSE (maximum wait time ≦ 9, 3, 1)))), unit: Dmnl, note: IF THEN ELSE (a, b, c) is selection function, when condition a is satisfied, the function value is b, otherwise, the function value is c. We determine the maximum waiting time nodes and corresponding utility value according to the results of the questionnaire.

A fare = 1, unit: Yuan/person/time

A the level of fare = IF THEN ELSEIF THEN ELSE (fare < 1, 9, IF THEN ELSE (fare ≦ 2, 7, IF THEN ELSE (fare ≦ 5, 5, IF THEN ELSE (fare ≦ 10, 3, 1)))), unit: Dmnl, note: IF THEN ELSE (a, b, c) is selection function, when condition a is satisfied, the function value is b, otherwise, the function value is c. We determine the fare nodes and corresponding utility value according to the results of the questionnaire.

A punctuality rate = WITH LOOKUP (Time), Initial Value ([(2002, 0)–(2020, 1)], (2002, 0.8), (2003, 0.81), (2004, 0.82), (2005, 0.83), (2006, 0.84), (2007, 0.85), (2008, 0.86), (2009, 0.87), (2010, 0.88), (2011, 0.88), (2012, 0.88), (2013, 0.88), (2014, 0.88), (2015, 0.88), (2016, 0.88), (2017, 0.88), (2018, 0.88), (2019, 0.88), (2020, 0.88)), unit: %, note: The punctuality rate is table function of simulate time.

A the level of punctuality rate = IF THEN ELSEIF THEN ELSE (punctuality rate < 0.7, 1, IF THEN ELSE (punctuality rate < 0.8, 3, IF THEN ELSE (punctuality rate < 0.9, 5, IF THEN ELSE (punctuality rate < 0.95, 7, 9)))), unit: Dmnl, note: IF THEN ELSE (a, b, c) is selection function, when condition a is satisfied, the function value is b, otherwise, the function value is c. We determine the punctuality rate nodes and corresponding utility value according to the results of the questionnaire.

A average speed = WITH LOOKUP (Time), Initial Value ([(2002, 0)–(2020, 40)], (2002, 40), (2003, 38), (2004, 36), (2005, 34), (2006, 32), (2007, 31), (2008, 30), (2009, 29), (2010, 28), (2011, 28), (2012, 28), (2013, 28), (2014, 28), (2015, 28), (2016, 28), (2017, 28), (2018, 28), (2019, 28), (2020, 28)), unit: km/h, note: The average speed is table function of simulate time.

A the level of average speed = IF THEN ELSE (average speed ≦ 25, 1, IF THEN ELSE (average speed ≦ 30, 3, IF THEN ELSE (average speed ≦ 35, 5, IF THEN ELSE (average speed ≦ 40, 7, 9)))), unit: Dmnl, note: IF THEN ELSE (a, b, c) is selection function, when condition a is satisfied, the function value is b, otherwise, the function value is c. We determine the average speed nodes and corresponding utility value according to the results of the questionnaire.

A other factors = WITH LOOKUP (Time), Initial Value ([(2002, 0)–(2020, 100)], (2002, 60), (2003, 60), (2004, 60), (2005, 65), (2006, 65), (2007, 65), (2008, 70), (2009, 70), (2010, 70), (2011, 70), (2012, 70), (2013, 70), (2014, 70), (2015, 70), (2016, 70), (2017, 70), (2018, 70), (2019, 70), (2020, 70)), unit: Dmnl, note: The other factors is table function of simulate time.

A the level of other factors = WITH LOOKUP (other factors), Initial Value ([(0, 0)–(703, 10)], (60, 1), (70, 3), (80, 5), (90, 7), (100, 9)), unit: Dmnl, note: The level of other factors is table function of simulate time. We determine the level of other factors nodes and corresponding utility value according to the results of the questionnaire.

A bus service level = the level of other factors*0.074 + the level of punctuality rate*0.268 + the level of average speed*0.2053 + the level of maximum wait time*0.266 + the level of fare*0.187, unit: Dmnl

A bus attraction = ((bus service level − bus service level last year)/bus service level last year)*bus attractive factor, unit: 1/year

A bus service level last year = WITH LOOKUP (Time), Initial Value ([(2002, 0)–(2020, 10)], (2002, 4.958), (2003, 4.958), (2004, 4.958), (2005, 4.621), (2006, 4.621), (2007, 5.153), (2008, 4.816), (2009, 4.816), (2010, 4.816), (2011, 4.81), (2012, 4.81), (2013, 4.81), (2014, 4.81), (2015, 4.81), (2016, 4.81), (2017, 4.81), (2018, 4.81), (2019, 4.81), (2020,4.81)), unit: Dmnl, note: The bus service level

last year is table function of simulate time.

A bus attractive factor = 1/0.767, unit: 1/year, note: We determine bus attractive factor according to the results of the questionnaire.

A rail transit length increment = WITH LOOKUP (Time), Initial Value ([(2002, −10)–(2020, 120)], (2002, 0), (2003, 0), (2004, 0), (2005, 0), (2006, 2), (2007, 58), (2008, 28), (2009, 108), (2010, 36), (2011, 30), (2012, 30), (2013, 30), (2014, 30), (2015, 30), (2016, 30), (2017, 30), (2018, 30), (2019, 30), (2020, 30)), unit: km, note: The rail transit length increment is table function of simulate time.

A the number of rail transit passengers increment per kilometer = WITH LOOKUP (Time), Initial Value ([(2002, −200)–(2020, 180)], (2002, −3), (2003, 93), (2004, 51), (2005, 16), (2006, −27), (2008, 147), (2009, 16), (2010, 74), (2011, 30), (2012, 30), (2013, 30), (2014, 30), (2015, 30), (2016, 30), (2017, 30), (2018, 30), (2019, 30), (2020, 30)), unit: 10000*person*time/km/year, note: The rail transit length increment is table function of simulate time.

A the number of rail transit passengers per kilometer = initial number of rail transit passengers per kilometer + the number of rail transit passengers increment per kilometer, unit: 10,000*person*time/km/year

A the number of rail transit vehicles = WITH LOOKUP (Time), Initial Value ([(2002, 0)–(2020, 6000)], (2002, 641), (2003, 692), (2004, 892), (2005, 968), (2006, 967), (2007, 1130), (2008, 1714), (2009, 2014), (2010, 2463), (2011, 2850), (2012, 2950), (2013, 3050), (2014, 3150), (2015, 3250), (2016, 3350), (2017, 3450), (2018, 3550), (2019, 3650), (2020, 3750)), unit: vehicle, note: the number of rail transit vehicles is table function of simulate time.

A initial number of rail transit passengers per kilometer = WITH LOOKUP (the number of rail transit vehicles), Initial Value ([(641, 0)–(5050, 2000)], (641, 331), (692, 328), (892,421), (967, 488), (968, 472), (1130, 461), (1714, 608), (2014, 624), (2463, 550), (2850, 589), (2950, 620), (3050, 650), (3150, 680), (3250, 710), (3350, 740), (3450, 770), (3550, 800), (3650, 830), (3750, 860)), unit: 10000*person*time/km/year, note: the initial number of rail transit passengers per kilometer is table function of simulate time.

A annual trip volumes per capita = WITH LOOKUP (Time), Initial Value ([(2002, 0)–(2020, 2000)], (2002, 1456), (2003, 1172), (2004, 1336), (2005, 1302), (2006, 1034), (2007, 955), (2008, 1040), (2009, 1048), (2010, 984), (2011, 934), (2012, 915), (2013, 897), (2014, 879), (2015, 861), (2016, 844), (2017, 827), (2018, 811), (2019, 795), (2020, 779)), unit: time, note: the annual trip volumes per capita is table function of simulate time.

A total trip volumes = total population*annual trip volumes per capita, unit: 10,000*person*time

A taxi trip volumes = WITH LOOKUP (Time), Initial Value ([(2002, 0)–(2020, 80,000)], (2002, 50,766), (2003, 54,468), (2004, 64,378), (2005, 71,072), (2006, 64,121), (2007, 64,111), (2008, 69,000), (2009, 68,000), (2010, 69,000), (2011, 69,000), (2012, 69,000), (2013, 69,000), (2014, 69,000), (2015, 69,000), (2016, 69,000), (2017, 69,000), (2018, 69,000), (2019, 69,000), (2020, 69,000)), unit: 10,000*person*time, note: the taxi trip volumes is table function of simulate time.

A public transport trip volumes = bus trip volumes + rail transit trip volumes, unit: 10,000*person*time

A walking and cycling trip volumes = total trip volumes − public transport trip volumes − car trip volumes − taxi trip volumes, unit: 10,000*person*time

The principal equation of the energy consumption and emissions subsystems are as follows:

A car driving distance per capita = WITH LOOKUP (Time), Initial Value ([(2002, 0)–(2020, 15)], (2002, 10.11), (2003, 10.32), (2004, 10.53), (2005, 10.75), (2006, 10.97), (2007, 11.19), (2008, 11.41), (2009, 11.64), (2010, 11.87), (2011, 12.11), (2012, 12.35), (2013, 12.6), (2014, 12.85), (2015, 13.11), (2016, 13.37), (2017, 13.64), (2018, 13.91), (2019, 14.19), (2020, 14.48)), unit: km, note: the car driving distance per capita is table function of simulate time.

A car energy consumption coefficient per capita = 678, unit: l/(10,000*person*time*km)

A taxi driving distance per capita = WITH LOOKUP (Time), Initial Value ([(2002, 0)–(2020, 20)], (2002, 7.2), (2003, 7.34), (2004, 7.49), (2005, 7.64), (2006, 7.8), (2007, 7.96), (2008, 8.12), (2009, 8.28), (2010, 8.45), (2011, 8.62), (2012, 8.79), (2013, 8.96), (2014, 9.14), (2015, 9.33), (2016, 9.51), (2017, 9.7), (2018, 9.9), (2019, 10.1), (2020, 10.3)), unit: km, note: the taxi driving distance per capita is table function of simulate time.

A taxi energy consumption coefficient per capita = 734, unit: l/(10,000*person*time*km)

A bus driving distance per capita = WITH LOOKUP (Time), Initial Value ([(2002, 0)–(2020, 20)], (2002, 7.61), (2003, 7.77), (2004, 7.92), (2005, 8.09), (2006, 8.25), (2007, 8.42), (2008, 8.59), (2009, 8.76), (2010, 8.94), (2011, 9.11), (2012, 9.3), (2013, 9.48), (2014, 9.67), (2015, 9.87), (2016, 10.06), (2017, 10.26), (2018, 10.47), (2019, 10.68), (2020, 10.89)), unit: km, note: the bus driving distance per capita is table function of simulate time.

A bus energy consumption coefficient per capita = 57, unit: l/(10,000*person*time*km)

A rail transit driving distance per capita = WITH LOOKUP (Time), Initial Value ([(2002, 0)–(2020, 40)], (2002, 11.89), (2003, 12.13), (2004, 12.38), (2005, 12.63), (2006, 12.89), (2007, 13.15), (2008, 13.41), (2009, 13.68), (2010, 13.95), (2011, 14.23), (2012, 14.52), (2013, 14.81), (2014, 15.11), (2015, 15.41), (2016, 15.72), (2017, 16.03), (2018, 16.35), (2019, 16.68), (2020,17.01)), unit: km, note: the rail transit driving distance per capita is table function of simulate time.

A rail transit energy consumption coefficient per capita = 178.15, unit: kw*h/(10,000*person*time*km)

A car fuel consumption = car driving distance per capita*car energy consumption coefficient per capita*car trip volumes, unit: l

A taxi fuel consumption = taxi energy consumption coefficient per capita*taxi driving distance per capita*taxi trip volumes, unit: l

A bus fuel consumption = bus driving distance per capita*bus energy consumption coefficient per capita*bus trip volumes, unit: l

A rail transit power consumption = rail transit driving distance per capita*rail transit energy consumption coefficient per capita*rail transit trip volumes, unit: kw*h

A fuel consumption CO_2 emission factor = 2.466, unit: kg/l

A power consumption CO_2 emission factor = 0, unit: kg/(kw*h)

A car CO_2 emissions = car fuel consumption*fuel consumption CO_2 emission factor, unit: kg

A taxi CO_2 emissions = taxi fuel consumption*fuel consumption CO_2 emission factor, unit: kg

A bus CO_2 emissions = bus fuel consumption*fuel consumption CO_2 emission factor, unit: kg

A rail transit power consumption = rail transit driving distance per capita*rail transit energy consumption coefficient per capita*rail transit trip volumes, unit: kg

A total energy consumption = taxi fuel consumption*fuel and standard coal conversion coefficient + car fuel consumption*fuel and standard coal conversion coefficient + bus fuel consumption*fuel and standard coal conversion coefficient + power and standard coal conversion coefficient*rail transit power consumption, unit: kg standard coal

A total CO_2 emissions = taxi CO_2 emissions + car CO_2 emissions + bus CO_2 emissions + rail transit emissions, unit: kg

Appendix B

See Table B.1–B.3.

Table B.1
Authenticity test results.

Years	GDP per capita/Yuan		Error/%	Total population/10,000 person		Error/%
	Actual value	Simulation value		Actual value	Simulation value	
2002	30,730	30,319	−1.34	1423.2	1423.2	0.00
2003	34,777	34,828	0.15	1456.4	1437.7	−1.28
2004	40,916	41,337	1.03	1492.7	1459.5	−2.22
2005	45,993	46,598	1.32	1538.0	1495.7	−2.75
2006	51,722	52,516	1.54	1601.0	1545.7	−3.45
2007	60,096	61,292	1.99	1676.0	1606.5	−4.14
2008	64,491	66,030	2.39	1771.0	1683.3	−4.95
2009	66,940	64,915	−3.02	1860.0	1770.2	−4.83
2010	73,856	71,970	−2.55	1961.9	1854.3	−5.48
Years	Total trip volumes/10,000 person time		Error/%	The number of cars/10,000 vehicle		Error/%
	Actual value	Simulation value		Actual value	Simulation value	
2002	2,072,767	2,072,179	−0.03	728,800	729,000	0.03
2003	1,706,206	1,684,969	−1.24	984,000	829,882	−15.66
2004	1,993,979	1,949,910	−2.21	1,166,800	981,846	−15.85
2005	2,002,275	1,947,342	−2.74	1,405,200	1,207,548	−14.07
2006	1,655,820	1,598,302	−3.47	1,675,700	1,492,854	−10.91
2007	1,600,722	1,534,236	−4.15	1,993,700	1,845,213	−7.45
2008	1,842,682	1,750,640	−5.00	2,356,100	2,296,987	−2.51
2009	1,948,485	1,855,219	−4.79	2,883,000	2,802,440	−2.79
2010	1,930,761	1,824,641	−5.50	3,631,300	3,295,269	−9.25
Years	Bus trip volumes/10,000 person time		Error/%	The number of buses/vehicle		Error/%
	Actual value	Simulation value		Actual value	Simulation value	
2002	471,555	471,555	0.00	15,070	15,687	4.09
2003	379,434	471,566	24.28	18,667	16,662	−10.74
2004	453,223	471,575	4.05	20,819	17,635	−15.29
2005	457,630	471,586	3.05	20,345	18,608	−8.54
2006	397,919	471,659	18.53	19,522	19,580	0.30
2007	4,22,645	471,723	11.61	19,395	20,551	5.96
2008	470,863	471,783	0.20	21,507	21,521	0.06
2009	516,517	471,926	−8.63	21,716	22,490	3.56
2010	505,144	472,080	−6.55	21,548	23,458	8.87
Years	Rail transit trip volumes/10,000 person time		Error/%			
	Actual value	Simulation value				
2002	47,690	47,690	0.00			
2003	47,248	47,258	0.02			
2004	60,653	60,650	0.00			
2005	67,976	67,994	0.03			
2006	70,306	70,298	−0.01			
2007	65,493	65,488	−0.01			
2008	121,660	104,346	−14.23			
2009	142,268	146,654	3.08			
2010	184,645	210,157	13.82			

Table B.2
Sensitivity test results.

Test parameters	Test range	Unit	The influence of some elements in the system
GDP growth rate	2–20	%	Total trip volumes (more sensitive, and the sensitivity increases with time) Total energy consumption (more sensitive, and the sensitivity increases with time) Total CO_2 emission (more sensitive, and the sensitivity increases with time)
Resident population growth rate	0.5–2	%	Total trip volumes (less sensitive, but the sensitivity increases with time) Total energy consumption (not sensitive, but the sensitivity increases with time) Total CO_2 emission (not sensitive, but the sensitivity increases with time)
Annual trip volumes per capita	500–2000	time	Total trip volumes (very sensitive, and the sensitivity increases with time)
Operating subsidies increment	0–50	100 million Yuan	Bus trip volumes (less sensitive, and the sensitivity is not generally affected by time)
Equipment update fee rate	1–10	%	Bus trip volumes (very sensitive, and the sensitivity increases with time) Total energy consumption (Not sensitive, but the sensitivity increases with time) Total CO_2 emission (Not sensitive, but the sensitivity increases with time)
Average number of runs	10–30	time	Bus trip volumes (very sensitive, and the sensitivity increases with time) Total energy consumption (not sensitive, but the sensitivity increases with time) Total CO_2 emission (not sensitive, but the sensitivity increases with time)
Punctuality rate	0.6–0.99	%	Bus trip volumes (very sensitive, and the sensitivity increases with time) Total energy consumption (not sensitive, but the sensitivity increases with time) Total CO_2 emission (not sensitive, but the sensitivity increases with time)
Average speed	20–60	km/h	Bus trip volumes (very sensitive, and the sensitivity increases with time) Total energy consumption (not sensitive, but the sensitivity increases with time) Total CO_2 emission (not sensitive, but the sensitivity increases with time)
Other factors	40–80	dmnl	Bus trip volumes (more sensitive, and the sensitivity increases with time) Total energy consumption (not sensitive, but the sensitivity increases with time) Total CO_2 emission (not sensitive, but the sensitivity increases with time)
Bus attractive factor	0.5–1.8	1/year	Bus trip volumes (more sensitive, and the sensitivity increases with time) Total energy consumption (not sensitive, but the sensitivity increases with time) Total CO_2 emission (not sensitive, but the sensitivity increases with time)
Rail transit length increment	0–100	km	Rail transit power consumption (very sensitive, and the sensitivity increases with time) Rail transit trip volumes (very sensitive, and the sensitivity increases with time)
The number of rail transit passengers increment per kilometer	0–100	10,000*person*time/(km*year)	Rail transit power consumption (very sensitive, and the sensitivity increases with time) Rail transit trip volumes (very sensitive, and the sensitivity increases with time)
The number of rail transit vehicles	500–4000	vehicle	Rail transit power consumption (more sensitive, and the sensitivity increases with time) Rail transit trip volumes (more sensitive, and the sensitivity increases with time)
Car driving distance per capita	2000–5000	km	Total energy consumption (very sensitive, and the sensitivity increases with time) Total CO_2 emission (very sensitive, and the sensitivity increases with time)
Taxi driving distance per capita	2000–3000	km	Total energy consumption (Not sensitive, and the sensitivity is not generally affected by time) Total CO_2 emission (not sensitive, and the sensitivity is not generally affected by time)
Bus driving distance per capita	2000–4000	km	Total energy consumption (not sensitive, and the sensitivity is not generally affected by time) Total CO_2 emission (Not sensitive, and the sensitivity is not

Table B.2 (*continued*)

Test parameters	Test range	Unit	The influence of some elements in the system
			generally affected by time)
Rail transit driving distance per capita	3000–6000	km	Total energy consumption (not sensitive, and the sensitivity is not generally affected by time) Total CO_2 emission (Not sensitive, and the sensitivity is not generally affected by time)
Car energy consumption coefficient per capita	600–750	l/(10,000 person*time*km)	Total energy consumption (more sensitive, and the sensitivity increases with time) Total CO_2 emission (more sensitive, and the sensitivity increases with time)
Taxi energy consumption coefficient per capita	700–800	l/(10,000 person*time*km)	Total energy consumption (not sensitive, and the sensitivity is not generally affected by time) Total CO_2 emission (not sensitive, and the sensitivity is not generally affected by time)
Bus energy consumption coefficient per capita	20–100	l/(10,000 person*time*km)	Total energy consumption (less sensitive, but the sensitivity increases with time) Total CO_2 emission (Less sensitive, but the sensitivity increases with time)
Rail transit energy consumption coefficient per capita	100–250	kw*h/(10,000 person*time)/km	Total energy consumption (not sensitive, and the sensitivity is not generally affected by time) Total CO_2 emission (not sensitive, and the sensitivity is not generally affected by time)

Table B.3
Emissions reduction effect from individual policy implementation under different conditions.

Policy	Calculation	Note
PDPT	PDPT − BAU = ΔPDPT	The effect on emission-reduction from the implementation of PDPT after the former implementation of BAU
	PDPT − TDM = Δ(PDPT + TDM) − ΔTDM	The effect on emission-reduction from the implementation of PDPT after the former implementation of TDM
	PDPT − TP = Δ(PDPT + TP) − ΔTP	The effect on emission-reduction from the implementation of PDPT after the former implementation of PT
	PDPT − ARM = Δ(PDPT + ARM) − ΔARM	The effect on emission-reduction from the implementation of PDPT after the former implementation of ARM
	PDPT − (TDM + TP) = Δ(PDPT + TDM + TP) − Δ(TDM + TP)	The effect on emission-reduction from the implementation of PDPT after the former implementation of TDM and TP
	PDPT − (TDM + ARM) = Δ(PDPT + TDM + ARM) − Δ(TDM + ARM)	The effect on emission-reduction from the implementation of PDPT after the former implementation of TDM and ARM
	PDPT − (TP + ARM) = Δ(PDPT + TP + ARM) − Δ(TP + ARM)	The effect on emission-reduction from the implementation of PDPT after the former implementation of TP and ARM
	PDPT − (TDM + TP + ARM) = ΔCP − Δ(TDM + TP + ARM)	The effect on emission-reduction from the implementation of PDPT after the former implementation of TDM, TP and ARM
TDM	TDM − BAU = ΔTDM	The effect on emission-reduction from the implementation of TDM after the former implementation of BAU
	TDM − PDPT = Δ(PDPT + TDM) − ΔPDPT	The effect on emission-reduction from the implementation of TDM after the former implementation of PDPT
	TDM − TP = Δ(TDM + TP) − ΔTP	The effect on emission-reduction from the implementation of TDM after the former implementation of PT
	TDM − AR = Δ(TDM + ARM) − ΔARM	The effect on emission-reduction from the implementation of TDM after the former implementation of ARM
	TDM − (PDPT + TP) = Δ(PDPT + TDM + TP) − Δ(PDPT + TP)	The effect on emission-reduction from the implementation of TDM after the former implementation of PDPT and TP
	TDM − (PDPT + ARM) = Δ(PDPT + TDM + ARM) − Δ(PDPT + ARM)	The effect on emission-reduction from the implementation of TDM after the former implementation of PDPT and ARM
	TDM − (TP + ARM) = Δ(TDM + TP + ARM) − Δ(TP + ARM)	The effect on emission-reduction from the implementation of TDM after the former implementation of TP and ARM
	TDM − (PDPT + TP + ARM) = ΔCP − Δ(PDPT + TP + ARM)	The effect on emission-reduction from the implementation of TDM after the former implementation of PDPT, TP and ARM
TP	TP − BAU = ΔTP	The effect on emission-reduction from the implementation of TP after the former implementation of BAU
	TP − PDPT = Δ(PDPT + TP) − ΔPDPT	The effect on emission-reduction from the implementation of T TP after the former implementation of PDPT
	TP − TDM = Δ(TDM + TP) − ΔTDM	The effect on emission-reduction from the implementation of T TP after the former implementation of TDM
	TP − ARM = Δ(TP + ARM) − ΔARM	The effect on emission-reduction from the implementation of TP after the former implementation of ARM
	TP − (PDPT + TDM) = Δ(PDPT + TDM + TP) − Δ(PDPT + TDM)	The effect on emission-reduction from the implementation of TP after the former implementation of PDPT and TDM
	TP − (PDPT + ARM) = Δ(PDPT + TP + ARM) − Δ(PDPT + ARM)	The effect on emission-reduction from the implementation of TP after the former implementation

Table B.3 (*continued*)

Policy	Calculation	Note
		of PDPT and ARM
	TP − (TDM + ARM) = Δ(TDM + TP + ARM) − Δ(TDM + ARM)	The effect on emission-reduction from the implementation of TP after the former implementation of TDM and ARM
	TP − (PDPT + TDM + ARM) = ΔCP − Δ(PDPT + TDM + ARM)	The effect on emission-reduction from the implementation of TP after the former implementation of PDPT, TDM and ARM
ARM	ARM − BAU = ΔARM	The effect on emission-reduction from the implementation of ARM after the former implementation of BAU
	ARM − PDPT = Δ(PDPT + ARM) − ΔPDPT	The effect on emission-reduction from the implementation of ARM after the former implementation of PDPT
	ARM − TDM = Δ(TDM + ARM) − ΔTDM	The effect on emission-reduction from the implementation of ARM after the former implementation of TDM
	ARM − TP = Δ(ARM + TP) − ΔTP	The effect on emission-reduction from the implementation of ARM after the former implementation of TP
	ARM(PDPT + TDM) = Δ(PDPT + TDM + ARM) − Δ(PDPT + TDM)	The effect on emission-reduction from the implementation of ARM after the former implementation of PDPT and TDM
	ARM − (PDPT + TP) = Δ(PDPT + TP + ARM) − Δ(PDPT + TP)	The effect on emission-reduction from the implementation of ARM after the former implementation of PDPT and TP
	ARM − (TDM + TP) = Δ(TDM + TP + ARM) − Δ(TDM + TP)	The effect on emission-reduction from the implementation of ARM after the former implementation of TDM and TP
	ARM − (PDPT + TDM + TP) = ΔCP − Δ(PDPT + TDM + TP)	The effect on emission-reduction from the implementation of ARM after the former implementation of PDPT, TDM and TP

ΔPDPT, ΔTDM, ΔTP, ΔARM, Δ(PDPT + TDM), Δ(PDPT + TP), Δ(PDPT + ARM), Δ(TDM + TP), Δ(TDM + ARM), Δ(TP + ARM), Δ(PDPT + TDM + TP), Δ(PDPT + TDM + ARM), Δ(PDPT + TP + ARM), Δ(TDM + TP + ARM), ΔCP is emissions reduction amount which is PDPT, TDM, TP, ARM, (PDPT + TDM), (PDPT + TP), (PDPT + ARM), (TDM + TP), (TDM + ARM), (TP + ARM), (PDPT + TDM + TP), (PDPT + TDM + ARM), (PDPT + TP + ARM), (TDM + TP + ARM), CP relative to BAU.

References

AASHTO, 2009. Real Transport ation Solutions for Greenhouse Gas Emissions Reductions. American Association of State Highway Transportation Officials, ⟨www.transportation1.org/RealSolutions/index.html⟩.

Bamberg, S., Rölle, D., Weber, C., 2003. Does habitual car use not lead to more resistance to change of travel mode? Transportation 30 (1), 97–108.

Barisa, A., Romagnoli, F., Blumberga, A., et al., 2015. Future biodiesel policy designs and consumption patterns in Latvia: a system dynamics model. J. Clean. Prod. 88, 71–82.

BBS (Beijing Bureau of Statistics), 2012. Beijing Statistical Yearbook 2012. China Statistics Press, Beijing.

BMCT (Beijing Municipal Commission of Transport) and BMCDR (Beijing Municipal Commission of Development and Reform), 2012. Beijing "Twelfth Five-Year" Transportation Development and Construction Plan. ⟨http://zhengwu.beijing.gov.cn/ghxx/sewgh/t1237237.htm⟩.

BMCT (Beijing Municipal Commission of Transport) and BTRC (Beijing Transportation Research Center), 2010. A Perspective on Beijing Transportation – An Analysis of Strategic Issues Within Beijing's Transportation System.

Bivona, E., Montemaggiore, G.B., 2010. Understanding short-and long-term implications of "myopic" fleet maintenance policies: a system dynamics application to a city bus company. Syst. Dyn. Rev. 26, 195–215.

Bunn, D., Larsen, E., 1992. Sensitivity reserve margin to factors influencing investment behavior in the electricity marker of England and Wales. Energy Policy 29, 420–429.

Cai, B., Yang, W., Cao, D., et al., 2012. Estimates of China's national and regional transport sector CO_2 emissions in 2007. Energy Policy 41, 474–483.

Chen, S.Q., Chen, B., 2012. Network environ perspective for urban metabolism and carbon emissions: a case study of Vienna, Austria. Environ. Sci. Techn. 46, 4498–4506.

Chiou, Y.C., Lan, L.W., Chang, K.L., 2013. Sustainable consumption, production and infrastructure construction for operating and planning intercity passenger transport systems. J. Clean. Prod. 40, 13–21.

Chiou, Y.C., Wen, C.H., Tsai, S.H., et al., 2009. Intergrated modeling of car/motorcycle ownership, type and usage for estimating energy consumption and emissions. Transp. Res. Part A 43, 665–684.

Chyong Chi, K., Nuttall, W.J., Reiner, D.M., 2009. Dynamics of the UK natural gas industry: system dynamics modelling and long-term energy policy analysis. Techn. Forecast. Soc. Change 76, 339–357.

Chun, M., Mei-ting, J., Xiao-chun, Z., Hong-yuan, L., 2011. Energy consumption and carbon emissions in a coastal city in China. Procedia Environ. Sci. 4, 1–9.

Contreras, A., Guervós, E., Posso, F., 2009. Market penetration analysis of the use of hydrogen in the road transport sector of the Madrid region, using MARKAL. Int. J. Hydrog. Energy 34, 13–20.

Cortés, C.E., Vargas, L.S., Corvalán, R.M., 2008. A simulation platform for computing energy consumption and emissions in transportation networks. Trans. Res. Part D 13, 413–427.

Cox, W., Moore, A., 2011. Reducing Greenhouse Gas Emissions from Automobiles. Reason Foundation. ⟨www.reason.org⟩ at: ⟨http://reason.org/news/show/reducing-greenhouse-gases-from-cars⟩ (accessed 06 .06.14.).

Dargay, J., Gately, D., 1999. Income's effect on car and vehicle ownership, worldwide: 1960–2015. Transp. Res. Part A 33, 101–138.

Dhakal, S., 2009. Urban energy use and carbon emissions from cities in China and policy implications. Energy Policy 37, 4208–4219.

Dong, C., Huang, G.H., Cai, Y.P., et al., 2012. An inexact optimization modeling approach for supporting energy systems planning and air pollution mitigation in Beijing city. Energy 37, 673–688.

Dyner, I., Smith, R.A., Peña, G.E., 1995. System dynamics modeling for energy efficiency analysis and management. J. Oper. Res. 46, 1163–1173.

Fallah-Fini, S., Rahmandad, H., Triantis, K., et al., 2010. Optimizing highway maintenance operations: dynamic considerations. Syst. Dyn. Rev. 26, 216–238.

Feng, Y.Y., Chen, S.Q., Zhang, L.X., 2013. System dynamics modeling for urban energy consumption and CO_2 emissions: a case study of Beijing, China. Ecol. Model. 252, 44–52.

Ford, A., 1983. Using simulation for policy evaluation in the electric utility industry. Simulation 40, 85–92.

Forrester, J.W., 1969. Urban Dynamics. The MIT Press, Cambridge.

Forrester, J.W., 1971. World Dynamics. Wright-Allen Press, Cambridge.

Gan, L., 2003. Globalization of the automobile industry in China: dynamics and barriers in greening of the road transportation. Energy Policy 31 (6), 537–551.

Geng, Y., Ma, Z., Xue, B., et al., 2013. Co-benefit evaluation for urban public transportation sector–a case of Shenyang, China. J. Clean. Prod. 58, 82–91.

Gross, R., Heptonstall, P., Anable, J., et al., 2009. What Policies Are Effective at Reducing Carbon Emissions from Surface Passenger Transport? A Review of Interventions to Encourage Behavioral and Technological Change. Report for UKERC, March. UKERC Technology and Policy Assessment.

Hartgen, D.T., Fields, M.G., Moore, A., 2011. Impacts of Transportation Policies on Greenhouse Gas Emissions in U.S. Regions: Comparing the Cost and Effectiveness Transportation-related Policies Aimed At Reducing CO_2 Emissions. Reason Foundation.

He, K., Huo, H., Zhang, Q., et al., 2005. Oil consumption and CO_2 emissions in China's road transport: current status, future trends, and policy implications. Energy Policy 33, 1499–1507.

He, Dongquan, Liu, Huan, He, Kebin, et al., 2013. Energy use of, and CO_2 emissions from China's urban passenger transportation sector – carbon mitigation scenarios upon the transportation mode choices. Transp. Res. Part A 53, 53–67.

Hensher, D.A., 2001. The sensitivity of the valuation of travel time savings to the specification of unobserved effects. Transp. Res. Part E: Logist. Transp. Rev. 37 (2), 129–142.

Hickman, R., Ashiru, O., Banister, D., 2010. Transport and climate change: simulating the options for carbon reduction in London. Transp. Policy 17, 110–125.

Huang, Shu-sen, Rui, Song, Yuan, Toa, 2008. Behavior of urban residents travel mode choosing and influencing factors—taking Beijing as an example. Commun. Stand. 9, 124–128 in Chinese.

Huo, H., Yao, Z., He, K., et al., 2011. Fuel consumption rates of passenger cars in China: labels versus real-world. Energy Policy 39, 7130–7135.

Innocenti, A., Lattarulo, P., Pazienza, M.G., 2013. Car stickiness: Heuristics and biases in travel choice. Transp. Policy 25, 158–168.

Kahn Ribeiro, S., Kobayashi, S., Beuthe, M., et al., 2007. Transport and its

infrastructure. Clim. change, 323–385.
Li, L., Chen, C.H., Xie, S.C., et al., 2010. Energy demand and carbon emissions under different development scenarios for Shanghai, China. Energy Policy 38, 4797–4807.
Li, Z., Hensher, D.A., 2012. Congestion charging and car use: a review of stated preference and opinion studies and market monitoring evidence. Trans. Policy 20, 47–61.
Litman, T., 2013a. Are Vehicle Travel Reduction Targets Justified? Evaluating Mobility Management Policy Objectives Such As Targets To Reduce VMT And Increase Use Of Alternative Modes. Victoria Transport Policy Institute. ⟨www.vtpi.org/vmt_red.pdf⟩ (accessed 06.06.14.).
Litman, T., 2013b. Comprehensive evaluation of energy conservation and emission reduction policies. Trans. Res. Part A 47, 153–166.
McKinsey, 2007. Reducing U.S. Greenhouse Gas Emissions: How Much At What Cost. McKinsey and Company.⟨www.mckinsey.com⟩ and The Conference Board.
Messner, S., Schrattenholzer, L., 2000. MESSAGE-MACRO: linking an energy supply model with a macroeconomic module and solving it iteratively. Energy 25, 267–282.
Moore, A.T., Staley, S.R., Poole, R.W., 2010. The role of VMT reduction in meeting climate change policy goals. Transp. Res. Part A 44, 565–574.
Naill, R., 1992. A system dynamics model for national energy policy planning. Syst. Dyn. Rev. 8, 1–19.
Nakamura, K., Hayashi, Y., 2013. Strategies and instruments for low-carbon urban transport: an international review on trends and effects. Transp. Policy 29, 264–274.
Nakata, T., 2004. Energy—economic models and the environment. Progr. Energy Combust. Sci. 30, 417–475.
Pettersson, P., Schmöcker, J.D., 2010. Active ageing in developing countries? – trip generation and tour complexity of older people in Metro Manila. J. Transp. Geogr. 18, 613–623.
Pfaffenbichler, P., Emberger, G., Shepherd, S., 2010. A system dynamics approach to land use transport interaction modelling: the strategic model MARS and its application. Syst. Dyn. Rev. 26, 262–282.
Pongthanaisawan, J., Sorapipatana, C., 2010. Relationship between level of economic development and motorcycle and car ownerships and their impacts on fuel consumption and greenhouse gas emission in Thailand. Renew. Sustain. Energy Rev. 14, 2966–2975.
Pressley, P.N., Aziz, T.N., DeCarolis, J.F., et al., 2014. Municipal solid waste conversion to transportation fuels: a life-cycle estimation of global warming potential and energy consumption. J. Clean. Prod. 70, 145–153.
Qudrat-Ullah, H., 2005. MDESRAP: a model for understanding the dynamics of electricity supply, resources, and pollution. Int. J. Glob. Energy 23, 1–14.
Rentziou, A., Gkritza, K., Souleyrette, R.R., 2012. VMT, energy consumption, and GHG emissions forecasting for passenger transportation. Transp. Res. Part A 46, 487–500.
Ross Morrow, W., Gallagher, K.S., Collantes, G., et al., 2010. Analysis of policies to reduce oil consumption and greenhouse-gas emissions from the U.S. transportation sector. Energy Policy 38, 1305–1320.
Santos, G., Behrendt, H., Teytelboym, A., 2010. Part II: policy instruments for sustainable road transport. Res. Transp. Econ. 28 (1), 46–91.
Saysel, A.K., Barlas, Y., 2001. A dynamic model of salinization on irrigated lands. Ecol. Model. 139, 177–199.
Schafer, A., Jacoby, H.D., 2005. Technology detail in a multi-sector CGE model: transport under climate policy. Energy Econ. 27, 12–24.
Seckin, C., Sciubba, E., Bayulken, A.R., 2013. Extended energy analysis of Turkish transportation sector. J. Clean. Prod. 47, 422–436.
Small, K.A., 2012. Energy policies for passenger motor vehicles. Transp. Res. Part A 46, 874–889.
Suryani, E., Chou, S.Y., Chen, C.H., 2010. Air passenger demand forecasting and passenger terminal capacity expansion: a system dynamics framework. Expert Syst. Appl. 37, 2324–2339.
Tertoolen, G., van Kreveld, D., Verstraten, B., 1998. Psychological resistance against attempts to reduce private car use. Transp. Res. Part A: Policy Pract. 32 (3), 171–181.
TRB, 2009. Strategies for Reducing the Impacts of Surface Transportation on Global Climate Change. NCHRP 20-24. Transportation Research Board, ⟨www.ruraltransportation.org/uploads/nchrp20-24 (59).pdf⟩ (accessed 06.06.12.).
USDOT, 2010. Transportation's Role in Reducing U.S. Greenhouse Gas Emissions, vol. 1. Report to Congress. U.S. Department of Transportation. ⟨www.dot.gov⟩ at: ⟨www.dot.gov/affairs/2010/dot7510.htm⟩ (accessed 06.06.12.).
USEPA, 2012. Climate Change Action Plans. U.S. Environmental Protection Agency, ⟨http://epa.gov/statelocalclimate/state/state-examples/action-plans.html⟩.
Vafa-Arani, H., Jahani, S., Dashti, H., et al., 2014. A system dynamics modeling for urban air pollution: A case study of Tehran, Iran. Transp. Res. Part D 31, 21–36.
Walther, G., Wansart, J., Kieckhäfer, K., et al., 2010. Impact assessment in the automotive industry: mandatory market introduction of alternative powertrain technologies. Syst. Dyn. Rev. 26, 239–261.
Wang, C., Cai, W., Lu, X., et al., 2007. CO_2 mitigation scenarios in China's road transport sector. Energy Convers. Manag. 48, 2110–2118.
Wang, H., Fu, L., Bi, J., 2011. CO_2 and pollutant emissions from passenger cars in China. Energy Policy 39, 3005–3011.
Wu, Z., Ying, Y., 2011. A Survey and analysis of low-carbon awareness and capability of low-carbon living in China. In: Proceedings of the Fourth International Conference on Business Intelligence and Financial Engineering (BIFE), IEEE, pp. 549–552.
Yang, C., McCollum, D., McCarthy, R., 2009. Meeting an 80% reduction in greenhouse gas emissions from transportation by 2050: a case study in California. Transp. Res. Part D 14, 147–156.
Yuan, X.H., Ji, X., Chen, H., et al., 2008. Urban dynamics and multiple-objective programming: a case study of Beijing. Commun. Nonlinear Sci. Numer. Simul. 13, 1998–2017.
Zhao, W., Ren, H., Rotter, V.S., 2011. A system dynamics model for evaluating the alternative of type in construction and demolition waste recycling center—The case of Chongqing, China. Resour. Conserv. Recycl. 55, 933–944.
Zhan, S.F., Zhang, X.C., Ma, C., et al., 2012. Dynamic modelling for ecological and economic sustainability in a rapid urbanizing region. Procedia Environ. Sci. 13, 242–251.
Zhang, L., Feng, Y., Chen, B., 2011a. Alternative scenarios for the development of a low-carbon city: a case study of Beijing, China. Energies 4 (12), 2295–2310.
Zhang, X., Ma, C., Zhan, S., et al., 2011b. Assessing powder emission risk on large open-air yard of coal energy. Energy Procedia 11, 3047–3053.
Zhang, Tieying, 2010a. Study on Different Urban Transport Modes' Energy Consumption (Master thesis). Beijing Jiao Tong University (in Chinese).
Zhang, X., Myhrvold, N.P., Caldeira, K., 2014. Key factors for assessing climate benefits of natural gas versus coal electricity generation. Environ. Res. Lett. 9 (11), 114022.
Zhang, X.C., Ma, C., Zhan, S.F., et al., 2012. Evaluation and simulation for ecological risk based on emergy analysis and pressure-state-response model in a coastal city, China. Procedia Environ. Sci. 13, 221–231.
Zhang, X.P., Cheng, X.M., 2009. Energy consumption, carbon emissions, and economic growth in China. Ecol. Econ. 68 (10), 2706–2712.
Zhang, Z., 2010b. The US proposed carbon tariffs and China's responses. Energy Policy 38 (5), 2168–2170.