Potential for low transport energy use in developing Asian cities through compact urban development

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Abstract

Global reliance and continued growth in oil demand is likely to persist in future as a result of high growth in vehicle ownership from emerging affluence in developing economies. The outcome will lead to growing oil price risks along with increasing greenhouse gas emissions. We show the importance of compact city development to the projected per capita energy use in developing cities. Policies that address the decline in city density during the transition from emerging to affluent cities are shown to provide substantial long-term transport energy savings.

We formulate an improved estimation of vehicle ownership and unit vehicle travel using a refined saturation derivation. We combine our vehicle ownership and unit travel model with a vehicle fleet model to predict consumer preference and the rate of diffusion of alternative vehicle technologies. In this analysis, preventing the decline in urban compactness reduces per capita transport energy use in developing cities by up to 50% in 2050. Quantitative models and statistical data are used to assess the impact of city compactness on projected urban transport energy use for developing Asian APEC cities to 2050.

Keywords Vehicle projection, urban density, urban transportation, vehicle diffusion, energy policy

Introduction

It is widely recognized that how cities are designed can have a big impact on their transportation energy use. Specifically, compact city design could offer both energy savings and a healthier, more pleasant lifestyle for their residents [1, 2, 3]. But how big an impact could urban design have on energy use? The question is an especially critical one for developing Asian cities, as these cities are expected to grow very rapidly over the next few decades and there are real choices to be made about how they will be designed.

By 2050 the global urban population is expected to increase by over 80% or by approximately 2.8 billion people [4]. Approximately 90% of the growth in urban population is expected from developing cities alone. Within Asian APEC developing cities the urban population is expected to increase by over 600 million people [4]. The high rate of consumption and dependence on finite petroleum resources for transit mobility is an increasingly urgent issue in both developing and developed economies. For developing cities the combination of growing urban population combined with growing affluence leads to rapid growth in vehicle ownership and urban transport energy use. The consequences include increasing risk in oil security and oil price, along with traffic congestion, air pollution and greenhouse gas emissions. Research conducted at the Asia Pacific Energy Research Centre (APERC) suggests under a business-as-usual (BAU) policy based scenario road transport energy demand in developing APEC Asian economies[1] will increase 260% by 2035 or 4.1% per annum.

This paper seeks an approximate answer to the question of how big an impact urban design could have on urban transportation energy use in developing Asian cities. To answer the question, we apply a descriptive model linking urban design to urban transportation energy use.

A key link between urban design and urban transportation energy use appears to be urban population density. Figure 1 shows the relationship of urban transport energy use to metropolitan city compactness for cities within North America, Australia, Europe and Asia. Compact cities (to the right of Figure 1) such as Hong Kong have a per capita energy use up to 90% lower than sprawling low density cities (to the left of Figure 1).

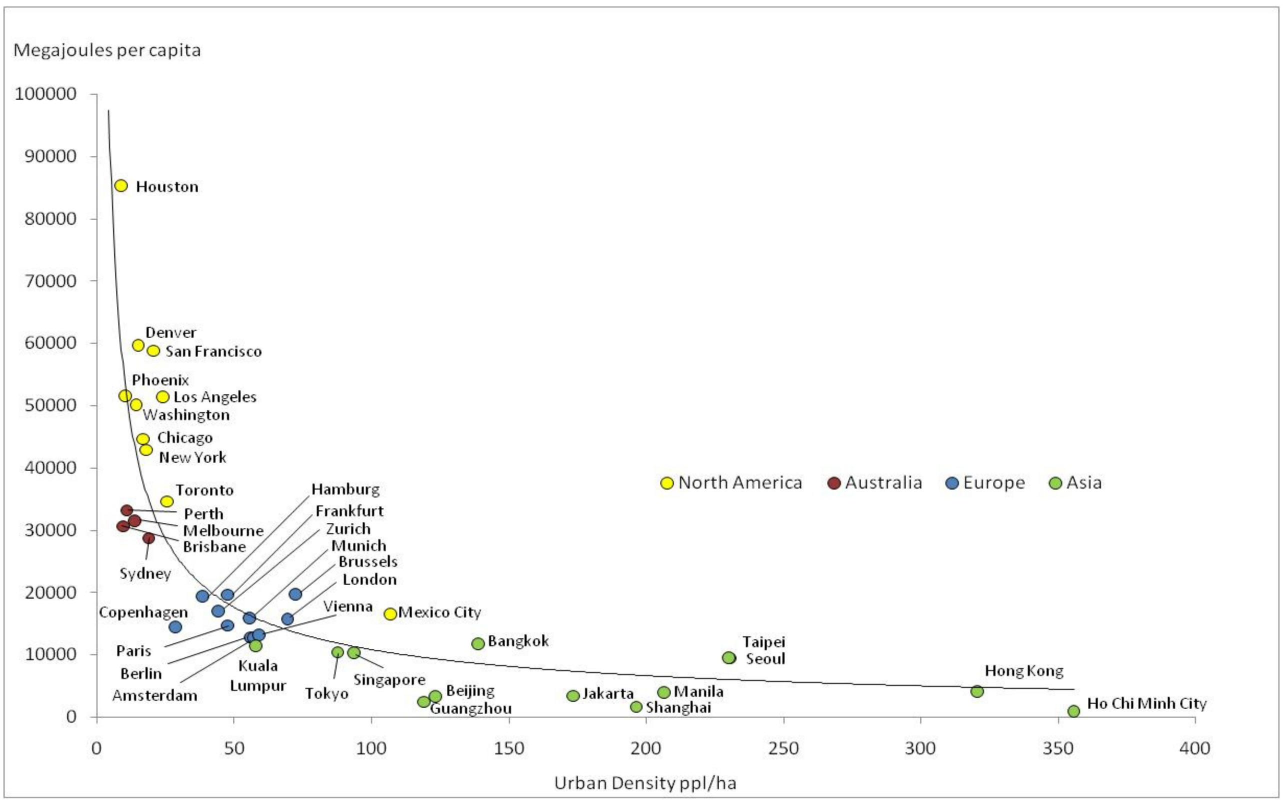


Figure 1 Transport energy use per capita relative to city compactness for affluent and non-affluent cities [5].

The correlation between transportation energy use and urban population density is clear and well-documented [2, 3, 6]. What is less clear are the underlying causes of this correlation. Certainly, compact cities will have shorter travel distances and their residents will, therefore, have less need for private vehicle travel. But compact cities may also *tend* to favor other transport energy-saving design features in greater abundance, including

- More mixed-use development so as to reduce the distances between housing, jobs, shopping, and community services

[1] Developing APEC Asian economies include China, Thailand, Vietnam, Philippines and Indonesia.

- more inter-connected streets for easier access to destinations
- Better facilities for walking and cycling
- Higher quality transit service, and more accessibility of destinations to transit
- A de-emphasizing of urban motorway and parking development, which tend to promote automobile use

Whether these other energy-saving design features are a consequence of higher population density (perhaps because their economics are more favorable where population density is high) or are themselves a cause of the higher population density is uncertain. In any case, they all tend to appear together and result in cities with significantly lower urban transport energy use.

For the purposes of building a descriptive model, we argue that precise causes of lower urban energy consumption may be put aside. Our model focuses on the simpler question of how energy use in developing Asian cities is likely to grow under two alternative assumptions. The first is that urban density in these cities continues to decline according to historical trends *and* the urban energy consumption becomes similar to affluent cities with a similar lower population density today. The alternative would be to assume that the cities follow 'smart growth' or 'compact city' urban design policies under which urban density ceases to decline *and* the urban energy consumption becomes similar to affluent cities with a similar higher population density today.

We find that substantial savings in urban transportation energy use can be achieved through compact urban development. In the four developing Asian cities examined in this paper the potential benefits in private transport energy reduction ranges from 30-50%. However once the cities are developed, the patterns of urban transport and urban transport energy use become much more difficult to alter. Therefore, developing Asian cities have a unique window of opportunity, which may be lost if the opportunities for better urban design are not implemented quickly.

Methodology

Urban city statistical indicators published in the Millennium cities database (MCD) are used in formulating our analysis [5]. The MCD was collected from 1995 census data for 100 global metropolitan cities including 38 APEC cities. The calculation of urban density in the MCD uses a standardized approach to urban land area which avoids error from the comparison of varying land uses between cities.

In this study future urban transport energy use in developing cities is estimated by modeling the change in private vehicle ownership and unit vehicle travel to the change in city compactness and income. The level of transport energy use in affluent cities across a compactness index defines the expected energy use trend of developing cities. As developing cities become more affluent in the future, the level of private transport energy use per capita is expected to approach that of current affluent economies with a similar urban compactness index. The improvement in vehicle efficiency, switching to lower carbon fuels and growth of alternative vehicles is considered in the model. Without expected technological improvements, future growth in transport energy demand would be considerably higher than the 4.1% growth prediction to 2035. Two independent models were developed and linked in unison to model the behavior of consumer choice and projecting consumer dependence for private transit in response to changes in economic wealth and the urban built environment.

Urban metropolitan density has a long standing history of decline in both developing and developed cities. A recent United Nations (UN) study assessed the trend in urban density for over 3900 global cities. The study concluded that urban density has been declining at an average rate of 1.7% during the last decade, with the decline rate for developing cities up to three times higher than developed cities [7]. Figure 1 shows the change in urban density relative to the urban population size (bubble dimension) and to the average real gross domestic product (GDP) per capita for APEC cities.

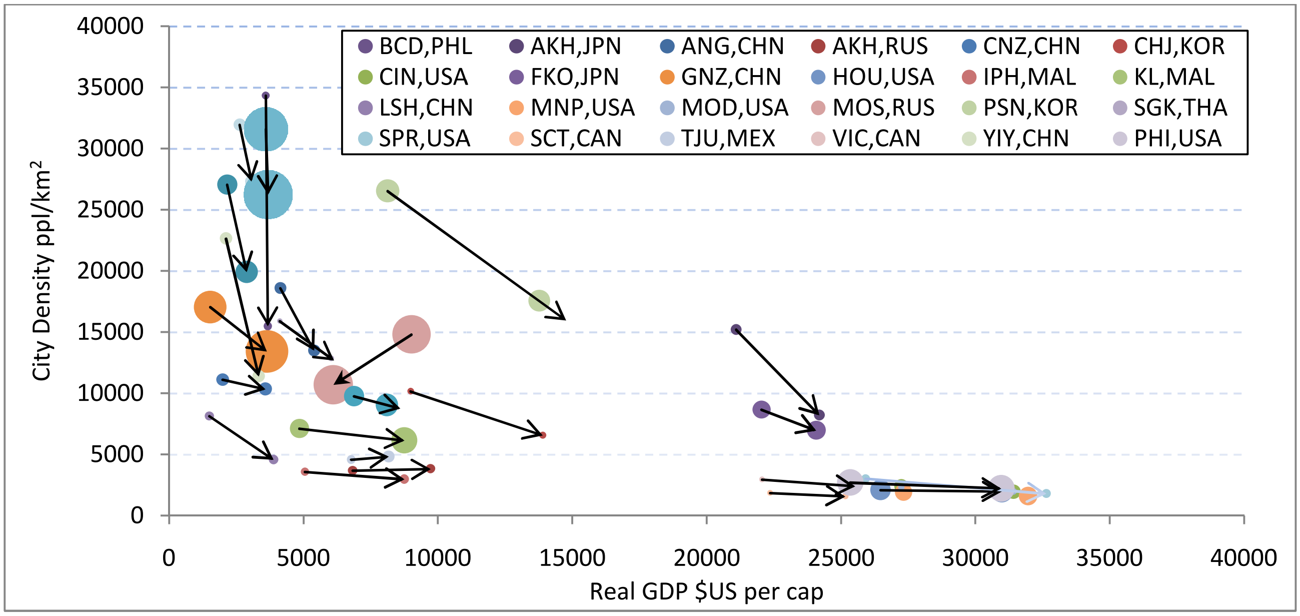


Figure 1 Trend in urban density for APEC cities relative to the size of population and growth in GDP per capita discretely within 1984-2002.

The majority of metropolitan cities in Figure 1 show a decline in urban density with growing per capita GDP. The decline is particularly rapid for developing cities where small changes in per capita GDP result in rapid changes in urban population density. Two scenarios are modeled in this analysis to assess the effects of urban density to transport energy. We classify these two scenarios as follows:

(i) Business as Usual (BAU) – Urban compactness continues to decline at 1.7% per annum through to 2050 for all cities

(ii) Alternative Policy (ALT) – Urban density is maintained at a constant 2008 level for the projected outlook period to 2050

Formulation

We define the urban transport energy use as the multiplication of vehicle ownership per capita, *V*, by the average travel per vehicle, *T,* by the average fuel efficiency per km, *FE,* by the urban population *UP*. Equation (1) shows the calculation of transport energy use for a given year, *t,* and metropolitan city, *i.*

$$Private\ Transport\ Energy\ Use_{it} = V_{it} \times T_{it} \times FE_{it} \times UP_{it} \tag{1}$$

The following derivation details the models used to project transport energy use in developing cities. The main causes for increasing energy use in developing cities is growing affluence which often leads to explosive demand for private mobility. The functional form of the equation used to model the long run interaction of income to vehicle growth is given by the S-shaped Gompertz function given in equation (2) [8].

$$\mathrm{V_t}' = \gamma \mathrm{e}^{\alpha \mathrm{e}^{\beta GDP_t}} \tag{2}$$

Where V' is the long run equilibrium vehicle ownership (per 1000 people) and GDP as the per-capita income (expressed in real $PPP). γ is the saturated level of vehicle ownership (per 1000 people) and α and φ are shape variables with negative coefficients [8]. The shape elasticity factor φ_i is specific to each city which essentially defines the income level at which saturation is reached and is estimated using historical data. Equation (2) is modified with a partial adjustment variable c (0<c<1) to account for irregularities between income growth and vehicle growth equilibrium [8]. Since income per capita growth is positively projected in all developing cities in future, this variable is assumed constant. The vehicle ownership algorithm is shown in equation (3) where the adjustment factor is used to calibrate the long run equilibrium ownership model in equation (2).

$$V_t = V_{t-1} + \mathrm{c}(\mathrm{V_t}' - \mathrm{V_{t-1}}) \tag{3}$$

Substituting (2) into (3) vehicle ownership (per 1000 people) is given by in equation (4) [8].

$$V_t = \gamma \mathrm{c} \mathrm{e}^{\alpha \mathrm{e}^{\varphi GDP_t}} + (1-\mathrm{c})\mathrm{V_{t-1}} \tag{4}$$

The determination of vehicle saturation has a high level of influence on model projections [8]. Traditional estimates of countrywide vehicle saturations use broad indicators of population density and urbanization which often neglect the urban built environment [8]. An improved estimate for vehicle saturation within cities is illustrated using the city urban compactness indicator as a variable to model the dependence on private vehicles use. In this model, we let the vehicle saturation vary dynamically in time and independently for each metropolitan city in response to changes in the compactness indicator. This assumption uses the vehicle ownership of affluent cities as a saturation benchmark, as the change in vehicle ownership with high per capita GDP is small. This methodology is contained in equation (5) where for affluent cities we assume a minimum average per capita GDP of US$20,000.

$$\gamma_{it} \cong \mathrm{f}[\mathrm{CI_{it}}]\ for\ GDP_{it} > \frac{USD\$20{,}000}{capita} \mathrm{since} \left[\frac{\partial V}{\partial t}\right]_{it} \rightarrow small \tag{5}$$

Where CI is the city compactness indicator defined as the number of inhabitants per hectare. The vehicle saturation is given in equation (6) and the constants ω and δ are derived from the statistical data set of affluent global cities (refer to Figure 3).

$$\gamma_{it} = \omega e^{\delta CI_{it}} \quad r^2{=}0.63 \tag{6}$$

For developing cities the strongest factor in the projection of vehicle travel per vehicle is the vehicle ownership which is intrinsically dependant on GDP per capita as detailed in equation (2) [8]. As per capita wealth increases the share of households with two vehicles increases, however the unit vehicle travel decreases with a reducing share of single vehicle dependant households. We model the saturation effect of this phenomenon as in the vehicle ownership model using affluent cities as a benchmark from the statistical data set. Equations (7) and (8) show the assumptions and derivation of the saturation in vehicle travel per vehicle. As in equation (6) the constants *b* and *d* in equation (8) are derived from the statistical data of affluent global cities (refer to Figure 4).

$$T_{sat_{it}} \cong \mathrm{f}[\mathrm{CI_{it}}]\ for\ GDP_{it} > \frac{USD\$20{,}000}{capita}\ \mathrm{since}\left[\frac{\partial V}{\partial t}\right]_{it} \rightarrow small \tag{7}$$

$$T_{sat_{it}} = (b \ln CI_{it} + d) \quad r^2=0.475 \tag{8}$$

Average unit vehicle travel is more volatile to external factors such as the oil price and fuel economy among others [9, 10]. We calculate a simple model adjustment to the average unit vehicle travel to changes in the oil price, *OP,* and the fleet fuel economy. The elasticity coefficients θ for the adjustment variables are constant and estimated from published research [9, 10]. Since $T_{it} \equiv f(V_t)$, we calculate T_{it} from the convergence of $T_t \propto T_{sat}$ by equating this to the negative of the growth rate between $V_t \propto V_{sat}$ multiplied by the adjustment to fuel price and fuel economy. We formulate T_{it} in the form shown in equation (9).

$$T_{it} = \left[\left(\frac{(\gamma_{it}-V_{it})}{\gamma_{it}} - 1\right) \times \left(T_{i(t-1)} - T_{sat_{it}}\right) + T_{i(t-1)}\right] \times \left(\Delta OP^{\theta_1} \Delta FE^{\theta_2}\right) \tag{9}$$

Substituting equation (8) and (6) into (9) we arrive at equation (10).

$$T_{it} = \left[\left(\frac{(\omega e^{\delta CI_{it}}-V_{it})}{\omega e^{\delta CI_{it}}} - 1\right) \times \left(T_{i(t-1)} - (b \ln CI_{it} + d)\right) + T_{i(t-1)}\right] \times \left(\Delta OP^{\theta_1} \Delta FE^{\theta_2}\right) \tag{10}$$

Substituting equations (4), (6) and (10) into equation (1) we can define urban transport energy use for developing cities as given in equation (11).

$$EU_{it} = \left(\omega e^{\delta CI_{it}} \mathrm{c} \mathrm{e}^{\alpha \mathrm{e}^{\varphi GDP_t}} + (1-\mathrm{c})\mathrm{V_{t-1}}\right) \times \left(\left(\frac{(\omega e^{\delta CI_{it}}-V_{it})}{\omega e^{\delta CI_{it}}} - 1\right) \times \left(T_{i(t-1)} - (b \ln CI_{it} + d)\right) + T_{i(t-1)}\right) \times \left(\Delta OP^{\theta_1} \Delta FE^{\theta_2}\right) \times FE_{it} \times (UP_{it-1} + \Delta UP) \tag{11}$$

The average fuel efficiency of the vehicle fleet can be estimated from simple top down econometric modeling using energy intensity reduction estimation. However, with rapid improvements in alternative vehicle technology and volatile energy prices, consumer preference in vehicle sales is an important mechanism to consider [11, 12]. Here, we utilize a consumer choice model to asses both economic and non economic attributes which affect consumer behavior when purchasing a new vehicle [13, 14]. For each city in each year the average fleet fuel efficiency is calculated using a harmonic average of the vehicles in use as given in equation (12).

$$FE_{it} = \left(\sum_{a=0}^{MA} \sum_{j=1}^{N} \frac{n_{aj}}{\frac{n_{aj}}{f_{aj}}}\right)_{it} \tag{12}$$

The fuel economy f_{aj} for vehicle type *j* of age *a* is exogenously specified for the existing vehicle fleet in operation and endogenously projected into the future [14]. The formulation for the number of vehicles n_{aj} of type *j* and age *a* in operation is given in equation (13).

$$[n_{aj}]_{it} = \sum_{a=1}^{MA} \sum_{j=1}^{N} \left(n_{aj} - R_{aj}\right)_{it} + n_{0jit} \tag{13}$$

Where R_{ajit} is the number of vehicle retirements of vehicle type *j* of age *a* during year *t* and n_{0jit} is the number of new vehicles (age = 0) entering the vehicle fleet of each vehicle type *j* at year *t*. Total new vehicle sales in year *t* are calculated by multiplying the change in vehicle ownership by the change in urban population plus net retirements. The sales share for each vehicle type is calculated using the consumer choice conditional logit model. The new vehicle additions for each vehicle type *j* are given in equation (14).

$$[n_{0j}]_{it} = \left(\left[\frac{\partial V}{\partial t}\right]_{it} \times \left[\frac{\partial UP}{\partial t}\right]_{it} + \sum R_{ajt}\right)_{i} \times [S_j]_{it} \tag{14}$$

S_{jit} is the new vehicle sales share allocation for each vehicle technology which is determined from rational economic and non economic variables in the conditional logit model [14]. The condition form of the logit decision model is shown to provide a more realistic projection for the interaction of consumer behavior than the standard form [13, 14, 15]. The conventional vehicles include petrol/diesel internal combustion engine vehicles (ICEVs) and hybrid electric vehicles (HEVs). Alternative fuelled vehicles include liquid petroleum and compressed natural gas (LPGVs and CNGVs) hydrogen fuel cell (FCVs), battery electric (EVs) and plug-in hybrid electric vehicles (PHEVs). The conditional logit is defined in equation (15).

$$[S_j]_{it} = \frac{exp\left(\beta_{FC}U_{FCj}+\beta_{PP}U_{PPj}+\beta_{DR}U_{DRj}+\beta_{CMDD}U_{CMDDj}+\beta_{PLDD}U_{PLDDj}+\beta_{CV}U_{CVj}\right)}{\sum_k \exp\left(\beta_{FC}U_{FCk}+\beta_{PP}U_{PPk}+\beta_{DR}U_{DRk}+\beta_{CMDD}U_{CMDDk}+\beta_{PLDD}U_{PLDDk}+\beta_{CV}U_{CVk}\right)} \tag{15}$$

The utilities *U* are the important variables to consumer preference which are weighted accordingly by the coefficients β_j. The variables defined by utility coefficients include the fuel cost (FC), purchase price (PP), driving range (DR), convenient medium distance destinations (CMDD), possible long distance destinations (PLDD) and vehicle diffusion rate (CV) [13, 15]. Further sub sector vehicle features such as engine size, turbo use and detailed attributes can be modeled into the vehicle categories using a nested conditional logit with associated utility coefficients.

Research indicates the consumers tend to value the upfront cost of vehicle more than the potential saving in the fuel cost [16]. Other factors such as the driving range and refueling convenience are factors which negatively affect electric and fuel cell vehicles.

Results and Analysis

Figures 3 and 4 show the corresponding cities vehicle ownership and unit vehicle travel relative to the city compactness for affluent and developing cities. We define a best least square fit for affluent cities under the assumption that vehicle ownership is near saturation.

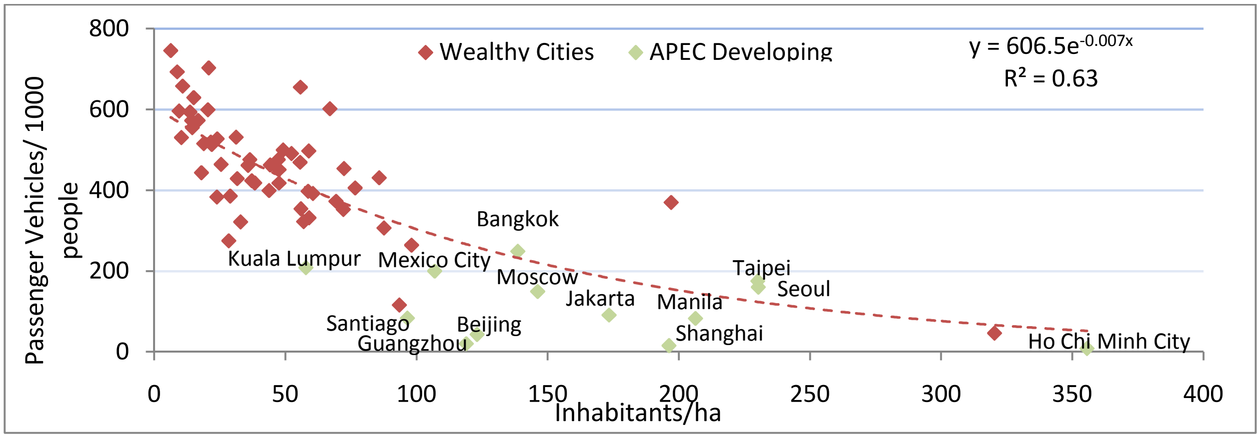


Figure 3 Private car vehicle ownership per 1000 people relative to the number of inhabitants per hectare.

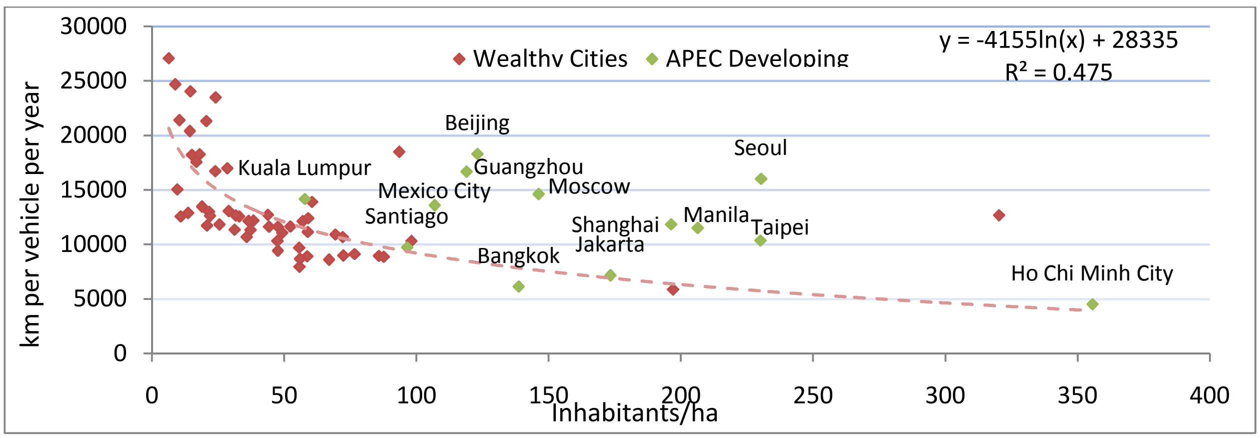


Figure 4 Passenger vehicle travel per year per vehicle relative to the number of inhabitants per hectare.

The removal of two outliers from each statistical data set improves the r-squared values of the equations in Figures 3 and 4 from 0.63 and 0.475 to 0.77 and 0.55 respectively. The uncertainty in the data is skewed toward the higher density cities since the number of affluent high density cities is limited. In contrast the number of affluent low density cities in the statistical data is relatively high. In Figure 3, low density cities have high per capita vehicle ownership. In comparison with Figure 3, low density cities also have higher unit vehicle travel than more compact cities. The very high transport energy use differences between sprawling and compact cities in Figure 1 can be explained by the correlation between unit vehicle travel and vehicle ownership per capita.

In Figure 5 we show the implementation of the consumer choice model in equation (15) to the vehicle diffusion in the light vehicle fleet for the example Guangzhou China. In Guangzhou there is increasing use of hybrid and plug-in hybrid technology and more efficient conventional fuelled vehicles such as those fuelled on diesel, LPG and CNG. Fuel cell vehicles also have a moderate market share from 2040. The makeup of the vehicle fleet in Guangzhou between 2030 and 2050 is shown in Table 1.

Table 1 Vehicle fleet share projection by technology in Guangzhou 2030-2050.

Year	2030	2040	2050
ICE Petrol	*79.9%*	*58.3%*	*38.1%*
Diesel	*5.9%*	*11.8%*	*14.5%*
HEV Petrol	*6.0%*	*9.0%*	*10.4%*
HEV Diesel	*1.0%*	*2.1%*	*2.8%*
Petrol PHEV - 50km	*3.3%*	*8.1%*	*11.6%*
Diesel PHEV - 50km	*0.9%*	*3.0%*	*4.7%*
EV 200km Range	*0.9%*	*1.5%*	*2.0%*
FCV	*0.2%*	*2.3%*	*9.1%*
LPG and CNG	*1.8%*	*3.9%*	*6.9%*

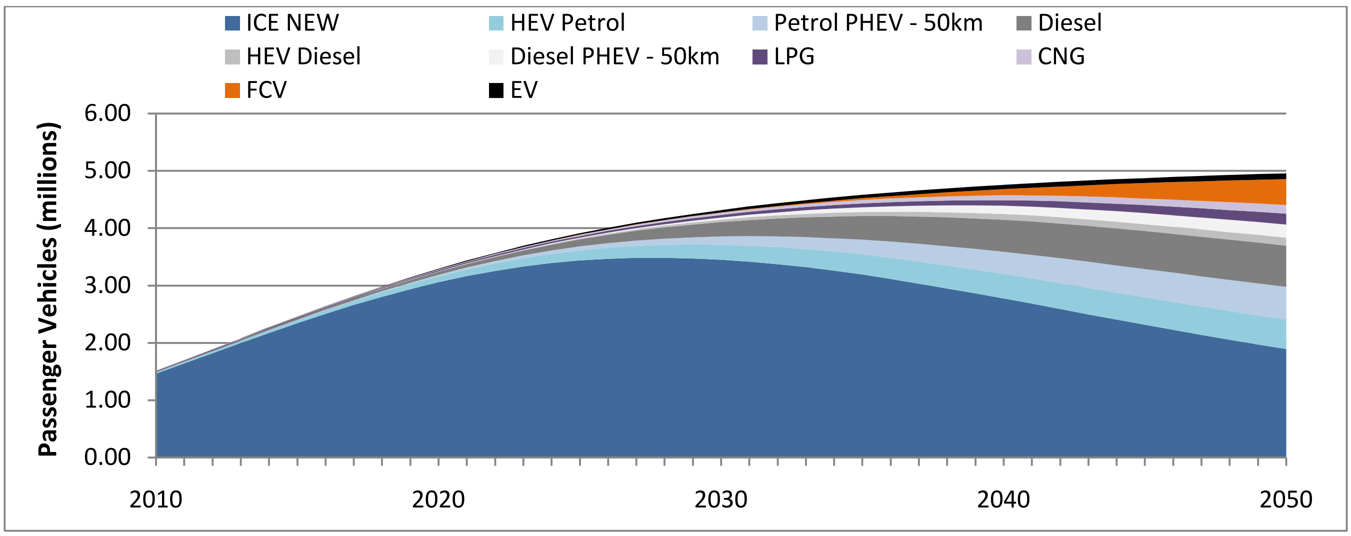
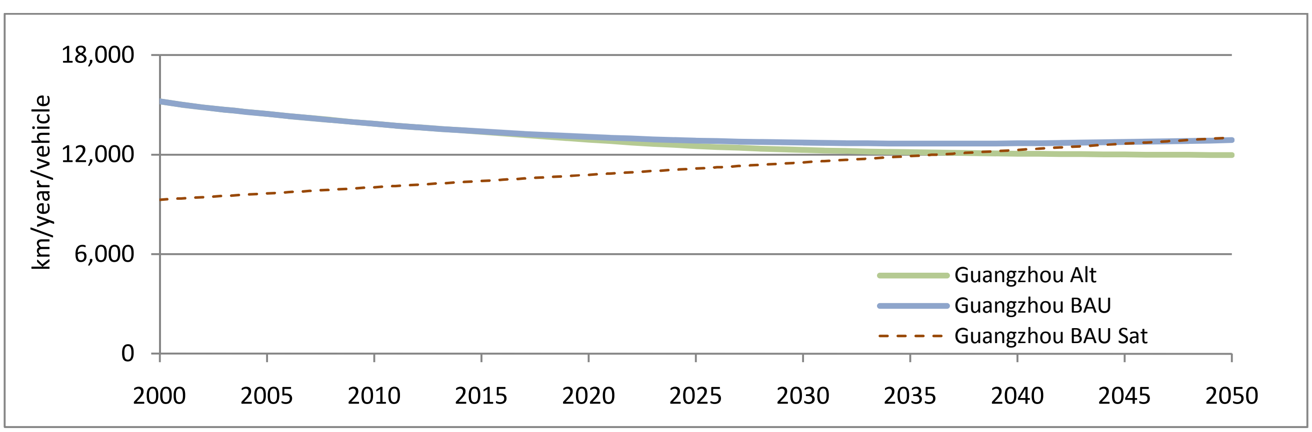


Figure 5 BAU Light vehicle fleet projection by vehicle technology diffusion for the city of Guangzhou China.

By 2050 we expect that alternative vehicles will reach a market share of 35%. Electric vehicles with a 200km range reach a market share of approximately 2% in 2050. The principal barrier to the adoption of electric vehicles is the short time frame that consumers demand for payback of additional capital cost through fuel savings [12]. From the formulation shown in equations (2) – (10) the projected vehicle ownership and unit vehicle travel for the BAU and ALT policy scenarios are shown in Figure 6 for the example of Guangzhou China.



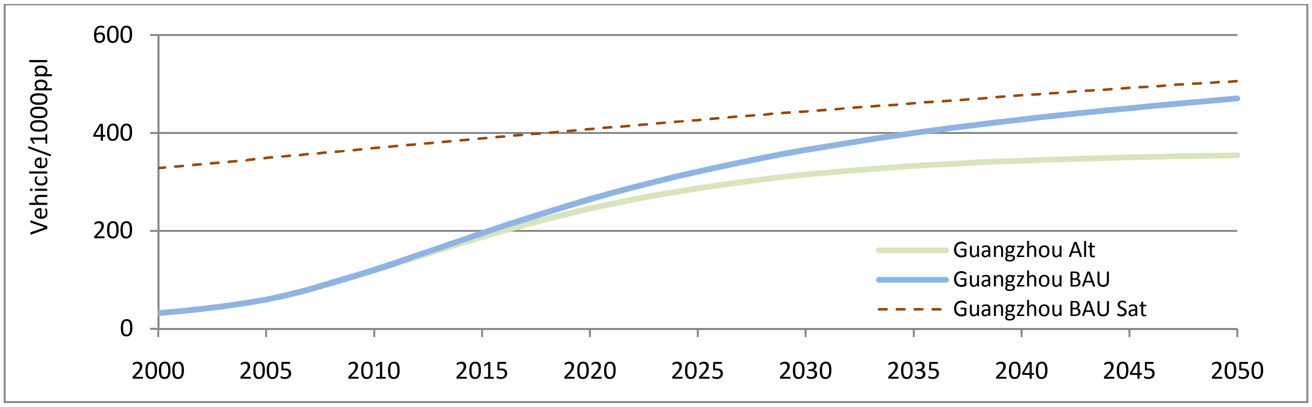
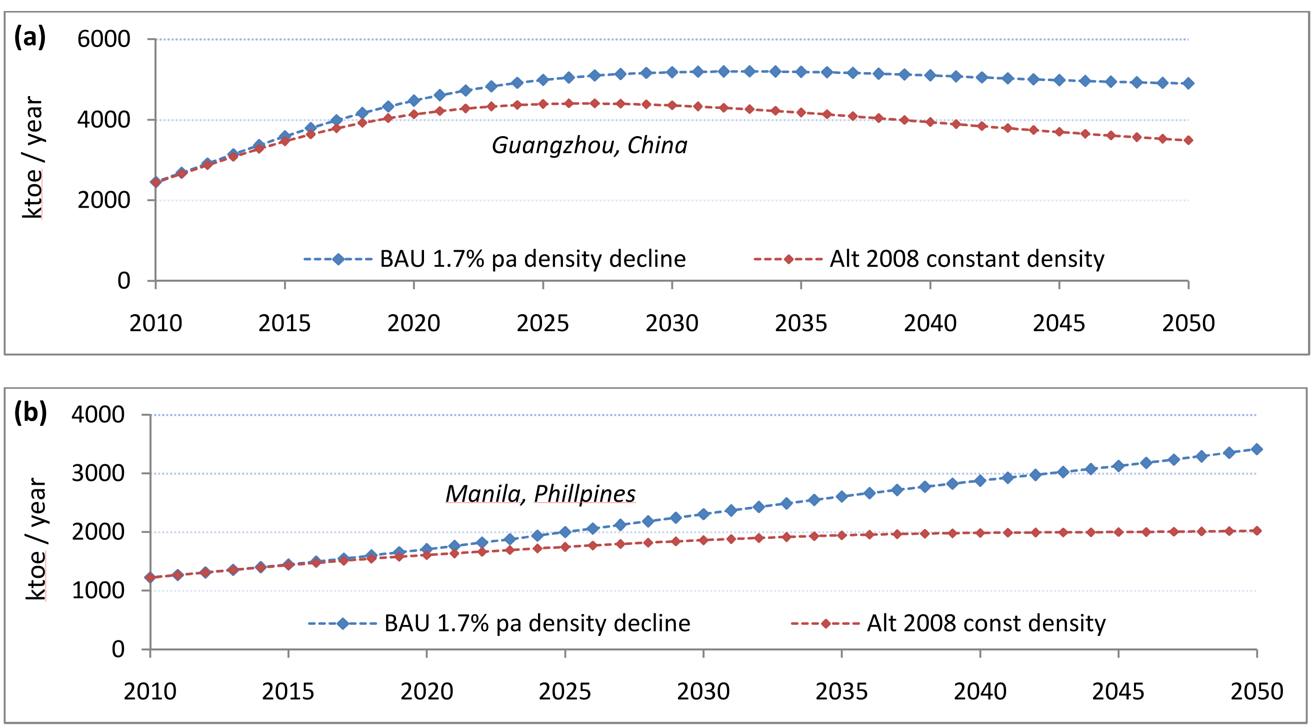
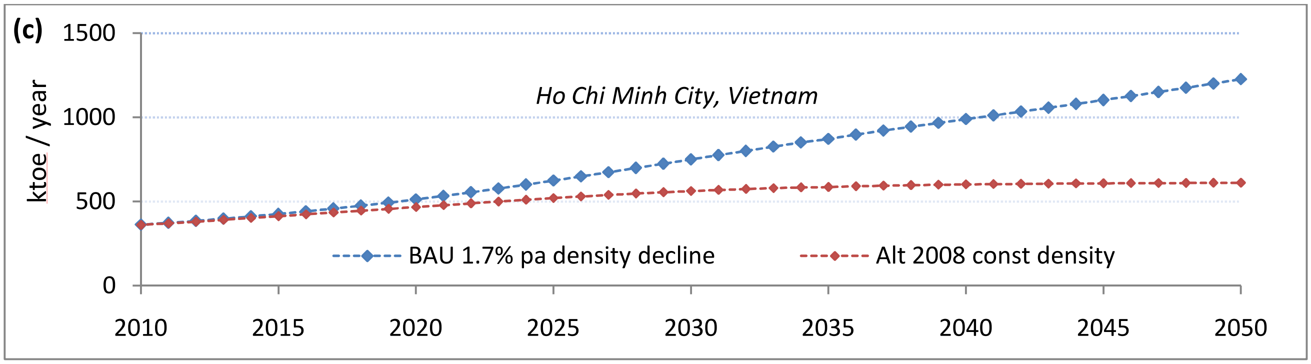


Figure 6 Projection of unit vehicle travel, vehicle ownership relative to the BAU saturation limit under BAU and ALT policy scenarios for the city of Guangzhou China.

In Figure 6 under the BAU scenario vehicle ownership is approximately 33% higher and unit vehicle travel is 7.5% higher than in the ALT scenario. From Figure 6, as per capita income increases vehicle ownership increases which results in a corresponding decrease in unit vehicle travel. The saturation level of vehicle ownership has a greater influence on vehicle growth at high per capita income. In contrast, during the developing stages, low per capita income is the most restrictive influence to vehicle growth. Once income poses less of a barrier to vehicle growth city compactness becomes the limiting factor to vehicle demand. A comprehensive list of key indicators and assumptions for each city projection is provided in Appendix A.

Figure 7 (a-d) shows the projected urban transport energy use for each scenario from 2010 to 2050 for the cities of Guangzhou, China; Manila, Philippines; Bangkok, Thailand; and Ho Chi Minh, Vietnam respectively. The expected savings in urban transport energy use range from between 30-50% by 2050 when maintaining the existing level of urban city compactness in selected developing Asian cities.





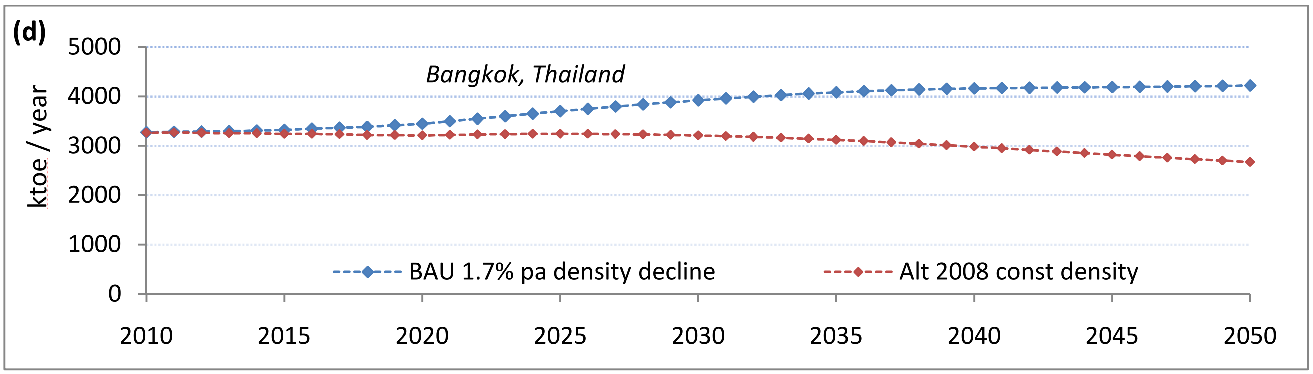


Figure 7 Private transit energy use comparison for BAU and alternative scenarios for the cities of Guangzhou, Manila, Ho Chi Minh and Bangkok.

The fleet average fuel efficiency in 2050 is slightly higher in the BAU scenario than for the ALT scenario as a result of higher vehicle growth resulting in higher growth in the number alternative vehicles in use. The improvement in the average vehicle efficiency under BAU is more than offset with higher vehicle ownership and higher unit vehicle travel. The reduction in transport energy use by 2050 in the ALT scenario compared to BAU for Guangzhou, Manila, Ho Chi Minh and Bangkok was 29%, 42%, 50% and 31% respectively. The potential for transport energy savings is higher for cities which have a high initial level of urban density such as the cities of Manila (160 ppl/ha) and Ho Chi Minh (275 ppl/ha).

Conclusions

Better urban design is shown to have a major impact on future urban transport energy use. We expect the demand for transport from growing urban population and increasing affluence will continue the trend of growing demand for transport. The patterns of transport use are strongly impacted by how cities are built. Of the four developing Asian cities examined in this paper the potential benefits in private transport energy reduction ranges from 30-50% in the alternative policy compared to business as usual. We find that once cities are built, the patterns of urban transport and transport energy use become very difficult to change.

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Appendix A: Projected model indicators for the cities of Guangzhou China, Manila Philippines, Bangkok Thailand, Ho Chi Minh Vietnam.

Table A1 Guangzhou China

Year	*1995*	2010	2015	2020	2030	2040	2050
Urban Population Projection [million ppl]	*11.5*	12.7	13.1	13.4	13.7	13.9	14
GDP US$2005 PPP Projection	*$6,641*	$19,470	$26,346	$33,693	$47,571	$61,377	$75,036
GDP PPP [City/Rural Ratio] Projection	*361%*	288%	263%	239%	190%	165%	165%
Density BAU [ppl/ha]	*119*	92	84	78	65	55	46
Density ALT [ppl/ha]	*119*	93	93	93	93	93	93
Vehicle BAU Sat Projection [veh/1000 ppl]	*306*	369	389	408	444	477	506
Km per Vehicle per year BAU Sat Projection	*8,919*	10,041	10,415	10,789	11,537	12,285	13,034
Vehicle Ownership BAU [veh/1000ppl]	*20*	120	195	264	365	427	470
Vehicle Ownership ALT [veh/1000ppl]	*20*	120	188	245	315	343	354
Km per vehicle per year BAU	*16,671*	13,853	13,392	13,067	12,719	12,683	12,870
Km per vehicle per year ALT	*16,671*	13,853	13,372	12,901	12,282	12,053	11,969

Table A2 Manila Philippines

Year	*1995*	2010	2015	2020	2030	2040	2050
Urban Population Projection [million ppl]	*9.5*	11.9	12.9	13.9	15.7	17.5	19.3
GDP US$2005 PPP Projection	*$5,615*	$10,869	$11,803	$12,866	$14,863	$16,765	$18,665
GDP PPP [City/Rural Ratio] Projection	*353%*	322%	303%	284%	246%	226%	226%
Density BAU [ppl/ha]	*206*	160	146	134	113	95	80
Density ALT [ppl/ha]	*206*	165	165	165	165	165	165
Vehicle BAU Sat Projection [veh/1000 ppl]	*167*	231	253	275	319	361	400
Km per Vehicle per year BAU Sat Projection	*6,518*	7,640	8,014	8,388	9,137	9,885	10,633
Vehicle Ownership BAU [veh/1000ppl]	*57*	92	112	137	192	249	304
Vehicle Ownership ALT [veh/1000ppl]	*57*	92	111	130	162	186	204
Km per vehicle per year BAU	*11,509*	9,857	9,644	9,525	9,502	9,698	10,051
Km per vehicle per year ALT	*11,509*	9,857	9,623	9,360	8,990	8,854	8,803

Table A3 Bangkok Thailand

Year	*1995*	2010	2015	2020	2030	2040	2050
Urban Population Projection [million ppl]	*10.7*	12.1	12.4	12.7	13.1	13.3	13.6
GDP US$2005 PPP Projection	*$15,948*	$18,974	$21,989	$25,371	$32,966	$40,705	$48,564
GDP PPP [City/Rural Ratio] Projection	*283%*	244%	232%	219%	194%	191%	191%
Density BAU [ppl/ha]	*139*	107	98	90	76	64	54
Density ALT [ppl/ha]	*139*	111	111	111	111	111	111
Vehicle BAU Sat Projection [veh/1000 ppl]	*267*	332	353	373	412	448	480
Km per Vehicle per year BAU Sat Projection	*8,252*	9,374	9,748	10,123	10,871	11,619	12,367
Vehicle Ownership BAU [veh/1000ppl]	*249*	275	296	320	367	410	447
Vehicle Ownership ALT [veh/1000ppl]	*249*	274	287	298	313	320	322
Km per vehicle per year BAU	*6,126*	7,481	7,904	8,320	9,132	9,927	10,708
Km per vehicle per year ALT	*6,126*	7,481	7,884	8,154	8,428	8,529	8,566

Table A4 Ho Chi Minh Vietnam

Year	*1995*	2010	2015	2020	2030	2040	2050
Urban Population Projection [million ppl]	*6.7*	8.2	8.6	9.0	9.7	10.3	10.9
GDP US$2005 PPP Projection	*$3,462*	$6,911	$8,765	$10,885	$16,137	$21,466	$26,855
GDP PPP [City/Rural Ratio] Projection	*285%*	246%	234%	221%	195%	193%	193%
Density BAU [ppl/ha]	*356*	275	252	232	195	164	139
Density ALT [ppl/ha]	*356*	285	285	285	285	285	285
Vehicle BAU Sat Projection [veh/1000 ppl]	*60*	104	122	141	181	224	268
Km per Vehicle per year BAU Sat Projection	*4,143*	5,265	5,639	6,013	6,762	7,510	8,258
Vehicle Ownership BAU [veh/1000ppl]	*8*	16	28	46	99	159	214
Vehicle Ownership ALT [veh/1000ppl]	*8*	16	24	36	61	79	89
Km per vehicle per year BAU	*4,500*	4,872	5,161	5,484	6,182	6,911	7,653
Km per vehicle per year ALT	*4,500*	4,872	5,154	5,356	5,553	5,626	5,653