VEHICLE OWNERSHIP AND TRIP GENERATION MODELLING – A Case Study of Thailand –

Pattarathep SILLAPARCHARN

Research Student
Institute for Transport Studies
University of Leeds
Leeds, UK

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This paper aims to address some important issues of a rapid growth in vehicle ownership, how different types of vehicles interact and how these growths affect a number of trip generations, especially in a country undergoing fast economic development, such as Thailand. The forecasts of such growth are important for strategic transport decision-making, travel demand forecasts and other policy issues at both regional and national levels. For these reasons, a series of vehicle ownership models, which include: (1) car, (2) motorcycle, (3) truck and heavy goods vehicle and (4) bus and coach models, are proposed together with a trip generation model. These models are built upon the limited aggregate data, both time series and cross sectional and disaggregated spatially by province, using non-log-linear weighted least squares regression for motor vehicle ownership models and exponential modelling for a trip generation model. The inputs required are basically forecasted gross provincial products per capita and population level. All proposed models have good statistical properties, i.e. all statistically significant coefficients and high adjusted R squared value and very good fits which are within 12% of observed values during the base years. The car ownership model also gives reasonable car ownership elasticities with respect to income and a sensible saturation level when compared with other studies. The forecast for a case of increasing income shows that the car and truck ownership level will increase together with the trip generation level. However, as people own more cars, the motorcycle and bus ownership levels will decrease as there might be a switch to car ownership.

Key Words: Aggregate data, Vehicle ownership model, Trip generation model, Thailand vehicle ownership

1. INTRODUCTION

The transportation-related problems of many of today’s cities stem from a number of interrelated factors. Growing urban populations and increasing household incomes have led to a rise in motor vehicle ownership, which in turn has created a greater propensity for travel and a demand for more roads. Increasing business and industrial activity have sent more service vehicles onto city streets and has produced more freight traffic. The dispersed form of many cities has also resulted in a demand for more roads, which translates into longer journeys, more congestion, and yet more fuel consumption and pollution1.

This paper aims to address some important issues of a rapid growth in vehicle ownership, how different types of vehicles interact and how these growths affect a number of trip generations, especially in a country undergoing fast economic development, such as Thailand. The forecasts of such growth are important for strategic transport decision-making, emissions forecasts and energy use forecasts and other policy issues at both regional and national levels.

In addition, the forecasts of such growth are also important for decision-making in trip frequency, trip distribution, modal choice and route choice, as in general people who own a car tend to travel more frequently, make longer journeys and are reluctant to switch to other modes. These issues are in turn important for making forecasts of traffic and travel demand at the national level.

Moreover, the research has an ultimate aim to develop national transport modelling capabilities with a case study of Thailand. However, motor vehicle ownership and its availability are not presently covered in the existing Thai national transport model (NAM), which is built using the conventional aggregate four-stage modelling approach2. As a result, the proposed model will be to expand the focus of the modelling efforts beyond the four-step process to include a more detailed consideration of motor vehicle ownership and its availability in the context of a national transport model. Here, the term “motor
vehicle” refers to car, motorcycle, goods vehicle, and bus and coach. Motorcycles are included in the proposed national model because they account for more than 60% of the motor vehicle population in Thailand, and lower income people, who cannot afford to buy a car, can pay for a motorcycle.

In this paper, a series of good quality car or vehicle ownership models are reviewed in Section 2. A series of vehicle ownership models, which include: (1) car, (2) motorcycle, (3) truck and heavy goods vehicle and (4) bus and coach models, and a trip generation model are proposed in Section 3. After that, the proposed vehicle ownership and trip generation models are used to make forecasts at a national level and the forecasts are compared with those from other countries to ensure sound logic in Section 4. Finally, conclusions are then made in Section 5.

2. LITERATURE REVIEW

In order to develop a vehicle ownership model, the model structure is considered as it might be determined by:
- the data available, and
- the outputs that are required from the model.

In Thailand, most of the data available are collected at an aggregate zonal level - either at the provincial level or national level. Finer detailed disaggregate data, such as from national transport survey at household level, is rarely collected. As data collection is very expensive, many developing countries including Thailand may not consider spending their limited budget on it and therefore, a model that requires less data, such as an aggregate model, is more appropriate.

Most vehicle ownership models from developed countries use disaggregate logit choice models, e.g. car ownership models used in the UK national transport model and in the Dutch National Transport Model, which are considered to be superior in terms of behavioural richness and data use efficiency. However, this model structure may not be practical to use in developing countries where there are many limitations and constraints such as lack of availability of suitable data, of resources available for study and of levels of training and skill of analysts. For these reasons, an aggregate model structure such as multiple regression form, e.g. Dao and Duc’s motorcycle ownership model for Vietnam, is popular and still in use in many parts of world, though there are many criticisms and concerns about this modelling method.

The outputs required from the vehicle ownership model for Thailand are mainly dependent on the current transport policy and as in many developing countries, the Thai government still focuses more on a “predict and provide” policy - future traffic volumes are predicted and measures to deal with these predicted levels are then devised. The government might also focus on measures to deal with an increase in vehicle ownership via different forms of taxes and charges – which could be used to fund additional investment in roads and road maintenance. Therefore, a model that can predict the growth in total vehicle ownership using policy variables is considered appropriate. In addition, as the vehicle ownership model would provide inputs to the proposed national transport model, which originally has 76 provincial zones, the vehicle ownership forecasts are required at a provincial level rather than national level.

A series of car or vehicle ownership models, such as models used in the UK and Dutch national transport models and models developed by Khan and Willumsen and Dargay and Gately were reviewed. The key findings from which are described here; a full review can be found in Sillaparcharn.

The overall structure of the UK car ownership model assesses the household’s decision to own zero, one, two or three or more vehicles by way of three binary logit models. The Dutch model considers the car ownership choices of a household conditional on its licence holding using binary logit models. These two models are considered inappropriate due to the data unavailability. Khan and Willumsen developed policy-sensitive models for car ownership and use using a log linear regression model (Equation 1) and Dargay and Gately developed an econometrically estimated model that explains the growth of the car/population ratio (car ownership) as a function of per-capita income using a Gompertz function.

\[
\log C1000 = -361 + 70.5 \log GNPH -0.373 \log PURTAX -2.58 \log OWNTAX -0.682 \log IMPDUTY -29.4 \log FUELPR -2.04 \log POPDEN \quad (1)
\]

\[R^2 = 0.86\]

where:
- C1000 = the number of cars per 1000 inhabitants,
- GNPH = the gross national product per capita,
- PURTAX = the purchase tax associated with cars,
- OWNTAX = the associated ownership tax (road license),
- IMPDUTY = the import duty for cars,
- FUELPR = the price per litre of fuel, and
- POPDEN = the population density.
Moreover, models predicting changes in motorcycle ownership using different functional forms are also reviewed. Most of them are developed for Asian countries. Hsu commented that the S-shaped curve is not suitable for the motorcycle ownership modelling in selected East Asian Countries (China, Japan, Malaysia, Taiwan and Vietnam) as it gives the unreasonable curve fitting. He also found that the Gompertz model is not appropriate for countries with fast growing economies like China and Vietnam, as it cannot find the searching saturation level. However, Dao and Duc found that multiple linear regression (Equation 2) is appropriate for forecasting the motorcycle ownership level at the national level for Vietnam. Other forms such as the disaggregate choice model were used in the Malaysian and UK models. In the Malaysian model, Leong and Ahman Farhan use disaggregate choice models using multinomial logistic regression for motorcycle ownership for individual ownership and household ownership, whilst, the structure of the UK motorcycle ownership model is a disaggregate hierarchical logit model, with structural parameters to measure the sensitivity of choice of engine size relative to motorcycle ownership.

\[ m_{cy} = -7192516.765 + 0.020804096 \times \text{pop} + 6447.490353 \times \text{ppp} + 8110.564977 \times \text{urb} \]  
\[ R^2 = 0.98 \]  
where:  
m_{cy} = \text{total number of motorcycles},  
\text{pop} = \text{total population},  
\text{ppp} = \text{purchasing power parity per capita}, \text{ and }  
\text{urb} = \text{urbanisation rate}.

In conclusion, due to data availability in Thailand, the disaggregate modelling form is considered inappropriate. However, the log linear regression car ownership model due to Khan and Willumsen (Equation 1) seems to satisfy the modelling requirements in terms of data availability and output requirements and it also seems applicable to Thailand. Even though it is a car ownership model, it can be extended and modified in order to model other vehicle ownership levels. In addition, a regression model, similar to the Vietnam motorcycle ownership model from Dao and Duc (Equation 2), may be suitable if it is extended to include some policy variables. However, both models in Equations 1 and 2 produce a forecast at the national level. The proposed vehicle ownership model for Thailand is required to produce a forecast at the finer provincial level, which has never been made in any earlier models reviewed.

The car ownership model together with other vehicle ownership models, such as motorcycle, truck and heavy goods vehicle and bus and coach models, will provide an input to a trip generation model and therefore be included in the proposed national transport model for Thailand and the inclusion of motorcycle ownership forecasting has never been made in any earlier national models reviewed.

For Thailand, the following data are available: (1) the number of registered vehicles per 1000 inhabitants and (2) the population density, POPDEN. The gross national product per capita, GNPH, is rarely forecasted and therefore, the gross domestic product, GDP, per capita and the gross provincial product, GPP, per capita will be used instead. This data were collected at both national and provincial level from 1998-2002 whilst the Khan and Willumsen model used data at only the national level. FUELPR term is not easily accessible and TAX and DUTY terms are not straightforward to estimate and therefore will be ignored at this stage. As a result, the vehicle ownership model for Thailand will be proposed at the provincial level using limited data from 1998-2002.

### 3. PROPOSED MOTOR VEHICLE OWNERSHIP AND TRIP GENERATION MODELS

In this section, motor vehicle ownership models for the different modes are developed based on provincial data and are used in forecasting at the national level. Due to page constraints, only final models are presented and more information on the proposed car ownership model can be found in Sillaparcharn and the proposed motorcycle ownership model in Sillaparcharn.

#### 3.1 Car ownership model

Considering Equation 1 above with the data availability in Thailand, the proposed car ownership model may contain an income term (GPPpH) and a population density term (POPDEN). The gross national product per capita, GNPH, is rarely forecasted and therefore ignored. It was found that the log POPDEN was not statistically significant and was then ignored, whilst a linear distance term (Distance) was found to be significant and is then included in the proposed model. The distance term does not necessarily imply a level of urbanisation of the regional cities but implies a transportation cost of petrol from Bangkok to regional provinces, e.g. in Thailand, the retailed petrol price is relatively lower in Bangkok and vicinities than in other provinces. Further
distances away from Bangkok may face higher transportation costs and hence the higher petrol price (e.g. Mae Hong Son, which is 924 km from Bangkok, has a 1.00 Baht per litre higher petrol retail price). The transportation cost of petrol is relatively constant during the base year data (1998-2002). However, if the crude oil price increases significantly, this term will need to be calibrated. In addition, there is evidence from major UK cities that show a higher population density may not necessarily lead to higher car ownership e.g. in 2001, households in London and other urban areas were least likely to have a car, whereas households in rural areas, and particularly in the south, were the most likely. Therefore, the population density is not included in the proposed models.

The log linear model (Equation 1) implies a constant income elasticity with respect to car ownership which is not desirable. As one might expect, higher income provinces have a lower income elasticity compared to lower income provinces. In order to solve this problem, a saturation level was introduced to the proposed model. Different saturation levels, such as 400, 600, 800 and 1,000 cars per 1,000 inhabitants, were tested and it was found that the saturation level of 600 cars per 1,000 inhabitants fits the data best and was therefore included in the proposed model (Fig. 1).

Finally, when using the proposed models to make forecasts, a homoscedasticity problem was found. When forecasting car ownership for each province, the population term comes to have an effect as the higher population levels will lead to larger differences between the predicted and observed values: Bangkok and Vicinities, which has about 10 million inhabitants (15% of the country’s population) has contributed 76-130% of such differences. In order to solve this problem, a weighted least squares (WLS) modification was applied as it might help in improving the model results by: (1) stabilising the variance of errors to satisfy the standard regression assumption of homoscedasticity; and (2) limiting the influence of outliers on the regression analysis. The weight variable was selected as a population in terms of thousands ($POP1000$) and the final model is shown in Equation 3 below.

\[
\log\left(\frac{C_{1000i}}{600 - C_{1000i}}\right) = -4.919 + 0.921 \cdot \log GPP_{pH_i} - (1.23E^{-4}) \cdot Distance_i \quad (3)
\]

Subscript $i$ for Province $i$

Weight variable = $POP1000_i$

Adjusted $R$-squared = 0.815

The proposed car ownership model has desirable statistical properties, i.e. high $R$-squared and all coefficients are statistically significant, are of expected sign and have a sensible value. In addition, it also gives a reasonable car ownership elasticity with respect to income ranging from about 0.4 for high income provinces to 0.9 for low income provinces (Fig. 2), which is more theoretically sound than a constant elasticity value as from a model without a saturation level. Moreover, the saturation level selected, 600 cars per 1,000 inhabitants, seems plausible as it is similar to 0.62 cars per capita as estimated by Dargay and Gately from a wide range of countries ranging from lowest income countries such as Pakistan, China

![Fig. 1 Number of cars per 1,000 inhabitants with different saturation levels](image-url)
and India, to highest income countries such as USA, UK and Japan. Finally, the proposed model produces a good fit, within 10% of the observed values (see later).

### 3.2 Motorcycle ownership model

Similar to the proposed car ownership model, a motorcycle ownership model development was started from Khan and Willumsen’s Equation 1. It was found that the log POPDEN was again not statistically significant and was therefore ignored. The Distance term was still significant and was then included in the proposed model. However, the log linear model with only log GPPpH and Distance terms gives very low R-squared (less than 0.40). In order to improve the model’s goodness of fit to the observed data, a log car ownership level (log C1000) was introduced as it might be positively related with motorcycle ownership. A log quadratic income term, log GPPpH2, also helps in improving R-squared.

There is some evidence from Australia17 and New Zealand18 showing that despite income increases, motorcycle ownership level might decrease. In Japan, motorcycle ownership was first growing with the economy and then started to decline when income reached a certain level19. However, car ownership will keep on growing until it approaches the saturation level. Therefore, how to predict the decreasing level of motorcycle ownership is an important issue9 and the additional log quadratic car ownership level, log C10002, helps the model to predict a decline in motorcycle ownership. The final proposed model is still subject to WLS modification in which POP1000 was selected as a weight variable. The final model is shown in Equation 4 below.

\[
\log \text{MC1000}_i = -1.599 + 0.685 \cdot \log \text{GPPpH}_i - (7.125 \times 10^{-2}) \cdot (\log \text{GPPpH}_i)^2 + (2.044 \times 10^{-4}) \cdot \text{Distance}_i + (0.242 \cdot \log \text{C1000}_i - 0.349 \cdot (\log \text{C1000}_i)^2
\]  

(4)

MC1000i = the number of motorcycles per 1000 inhabitants for Province i

Weight variable = POP1000

Adjusted R-squared = 0.741

The proposed model has desirable statistical properties, i.e. high R-squared and all coefficients are statistically significant, are of expected sign and have a sensible value. When comparing with Vietnamese model developed by Dao and Duc5 (see Equation 2), the Vietnamese model above did give a higher adjusted R-squared value (R2 = 0.98) as it was easier to fit fewer points of national data than the proposed model for Thailand which uses provincial data. The ppp term from the Vietnam model is comparable to GPPpH term in the proposed model as both are an income term. The population term was used as a weighted variable in the proposed WLS model rather than the independent variable. Therefore, the proposed model has captured most important variables. The additional linear car ownership, C1000, improved the model fitness and its quadratic term, C10002, helped the model to predict a decline in motorcycle ownership. In addition, the model forecasts a maximum level of about 350 motorcycles per 1,000 inhabitants (Fig. 3). This number is similar to a saturation level of 339 estimated for a neighbouring country, Malaysia, which was estimated using the Gompertz model by Hsu9.

### 3.3 Truck and HGV ownership model

In this section, only the total number of larger sized trucks will be modelled; automobile-sized trucks or pick-ups are included in the car ownership model. Following a similar procedure to that applied for modelling motorcycle ownership, it was found that the log GPPpH and the linear Distance terms were statistically significant and thus included in the model. Although the log car ownership level, log C1000, was significant, it is not included in the model because no strong evidence was found to support the idea that the larger sized truck ownership was associated with car ownership. The final model is shown in Equation 5 below.

\[
\log \text{T1000}_i = -0.158 + 0.285 \cdot \log \text{GPPpH}_i - (3.968 \times 10^{-4}) \cdot \text{Distance}_i
\]  

(5)
T1000i = the number of trucks and HGVs per 1000 inhabitants for Province i
Weight variable = POP1000i
Adjusted R Squared = 0.792

The final proposed model has high R-squared and all coefficients were statistically significant, were of expected sign and have a sensible value.

3.4 Bus and coach ownership model

Similar to the previous sections, Khan and Willumsen’s6 model (Equation 1) was modified to forecast bus and coach ownership level. The log GPPpH and Distance terms were included in the model as they were found to be statistically significant. A log car ownership level, log C1000, and a quadratic log income, log GPPpH2, were also included as they enable the model to capture bus users switching to cars bringing about a decline in bus ownership; see Equation 6:

\[
\log B1000i = -4.720 + 1.524 \cdot \log GPPpHi - 0.139 \cdot (\log GPPpHi)^2 + (1.603 \cdot 10^{-3}) \cdot \text{Distance} + 0.465 \cdot \log C1000i
\]

B1000 = the number of buses and coaches per 1000 inhabitants
Weight variable = POP1000
Adjusted R Squared = 0.724

The final proposed model has a high R-squared and all coefficients were statistically significant, were of expected sign and have a sensible value.

3.5 Trip generation model

Daly20 compared different trip generation modelling forms and concluded that a logit choice model appeared to offer the best approach as it addressed the data correctly and was consistent with utility maximisation. The exponential model represents a close approximation to the logit model when trip rate is low and can be properly estimated only using aggregate data. Other model forms, such as linear regression models, category analysis, elasticity models were rejected because they either lack consistency with utility maximisation or were unable to incorporate an accessibility variable. In a more recent paper, Daly and Miller21 showed that the exponential model had the same expectation of the forecast number of trips as a logit model in which two model components were identical and it thus has a secure a basis in utility theory. Therefore, considering the data availability, the exponential trip generation model is considered the best option and is proposed for Thailand at a provincial level using 1998 trip end data. The final model becomes:

\[
\ln t1000i = 3.092 + (5.000 \cdot 10^{-3}) \cdot C1000i - (7.996 \cdot 10^{-4}) \cdot \text{Distance};
\]

\(t1000i = \) the number of trip generations per 1000 inhabitants for Province i
Weight variable = POP1000i
Adjusted R Squared = 0.618

The final model is theoretically sound and has desirable statistical properties, i.e. high R-squared and all coefficients were statistically significant, were of expected sign and have a sensible value. It also produces a very good fit which is within 4% of observed value during a base year (Table 1). In addition, the relationship found from the proposed model (Fig. 3), which implies a saturation level in the number of trip generations, is comparable with those from US Department of Transportation22, which published a trip generation analysis manual, that described in detail the development of a recommended trip generation procedure including the development of relationships between trips and income and car ownership. Therefore, the model is considered appropriate.

4. VEHICLE OWNERSHIP FORECASTS AT A NATIONAL LEVEL

In this section, the series of proposed vehicle ownership models will be used to forecast vehicle ownership first at the provincial level and then aggregated to the national level.

The results are summarised in Table 2. It can be seen that all proposed vehicle ownership models give good fits as they are within 12% of the observed values during the base years, 1998-2002. Therefore, the models are considered appropriate to use in forecasting vehicle ownership levels for selected future years (see Table 3). The input assumptions such as GDP growth and population growth are similar to the Transport Master Plan23, as these are acknowledged by the Thai Ministry of Transport and are widely used by various agencies under its control. Three different per capita GDP growth assum-

<table>
<thead>
<tr>
<th>Table 1 Observed and modelled trip generation levels</th>
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<tr>
<td>Predicted Total</td>
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<td>Observed Total</td>
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<tr>
<td>Difference</td>
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<tr>
<td>% Difference</td>
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### Table 2 Observed and modelled motor vehicle ownership levels

<table>
<thead>
<tr>
<th>Year</th>
<th>Cars</th>
<th>Motorcycles</th>
<th>Trucks and HGVs</th>
<th>Buses and Coaches</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Predicted Total</td>
<td>Observed Total</td>
<td>Difference</td>
<td>% Difference</td>
</tr>
<tr>
<td>1998</td>
<td>5,577,049</td>
<td>5,428,473</td>
<td>148,576</td>
<td>2.74%</td>
</tr>
<tr>
<td>1999</td>
<td>5,733,184</td>
<td>5,876,082</td>
<td>142,898</td>
<td>2.43%</td>
</tr>
<tr>
<td>2000</td>
<td>5,899,529</td>
<td>6,004,207</td>
<td>104,678</td>
<td>1.74%</td>
</tr>
<tr>
<td>2001</td>
<td>5,993,772</td>
<td>6,336,201</td>
<td>342,429</td>
<td>5.40%</td>
</tr>
<tr>
<td>2002</td>
<td>6,265,757</td>
<td>6,918,054</td>
<td>652,297</td>
<td>9.43%</td>
</tr>
</tbody>
</table>

### Table 3 Forecast motor vehicle ownership levels for selected future years

<table>
<thead>
<tr>
<th>Year</th>
<th>Population</th>
<th>Cars</th>
<th>Motorcycles</th>
<th>Trucks and HGVs</th>
<th>Buses and Coaches</th>
<th>Total Motor Vehicles</th>
<th>Trip Generation</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>64,521,460</td>
<td>7,149,357</td>
<td>15,972,450</td>
<td>707,072</td>
<td>110,612</td>
<td>23,967,490</td>
<td>2,513,962</td>
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<tr>
<td>2011</td>
<td>66,556,575</td>
<td>8,432,656</td>
<td>17,511,659</td>
<td>777,846</td>
<td>115,996</td>
<td>26,880,869</td>
<td>2,976,633</td>
</tr>
<tr>
<td>2016</td>
<td>68,729,058</td>
<td>9,902,086</td>
<td>18,986,969</td>
<td>856,713</td>
<td>118,596</td>
<td>29,926,437</td>
<td>3,538,088</td>
</tr>
<tr>
<td>2021</td>
<td>71,050,379</td>
<td>11,570,752</td>
<td>20,372,338</td>
<td>954,771</td>
<td>122,529</td>
<td>33,092,437</td>
<td>4,211,301</td>
</tr>
<tr>
<td>2026</td>
<td>73,533,080</td>
<td>13,456,172</td>
<td>21,637,720</td>
<td>1,042,743</td>
<td>128,951</td>
<td>36,366,714</td>
<td>5,013,669</td>
</tr>
</tbody>
</table>

### Equations

\[ V_{1000} = C_{1000} + MC_{1000} + T_{1000} + B_{1000} \]  

\[ V_{1000} = \text{the total number of motor vehicles per 1000 inhabitants} \]

To ensure sound logic under the proposed models, the vehicle ownership levels from other countries are considered and compared with the forecast results (see Table 4). All forecasted vehicle ownership levels are considered reasonable. As seen from Figure 3, for a case of increasing income, the overall forecast shows that the car ownership level will increase together with the number of trip generations. However, as people own more cars, the motorcycle and bus ownership levels will decrease as there might be a switch to car ownership.
level. The car ownership will keep on growing until it approaches the saturation level. This is similar to what is observed in EU countries from Table 4. In addition, for Thailand, the saturation level selected is 600 cars per 1,000 inhabitants, which is comparable to 0.62 cars per capita as estimated by Dargay and Gately 7 for a group of countries from lowest to high income countries. From Figure 3 and Table 4, the truck and HGV ownership level will also grow with the economy. For the motorcycle ownership level, Figure 3 shows that it will initially grow and then decline when the income reaches a certain level, which is similar to what was observed in Japan as mentioned earlier in Section 3.2. In addition, the proposed model forecasts a maximum of about 350 motorcycles/1,000 inhabitants, which is comparable to a saturation level of 339 for a neighbouring country, Malaysia, which was estimated using the Gompertz model by Hsu 9. However, there is no motorcycle data from the EU available for comparison. Similar to the motorcycle ownership level, as people own more cars, the proposed model predicts a decline in bus ownership level (Fig. 3). However, the observed data from Table 4 does not show the expected decline in a group of either EU15 or EU25. When considered at the finer national level, the decline in bus ownership level was found during 1990 and 2000 in 9 of 25 countries: Belgium, Czech Republic, Denmark, Germany, Estonia, Hungary, Poland, Slovak Republic and Sweden24.

Table 4 Motor vehicle ownership levels for other countries (Vehicles per 1,000 inhabitants)

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<tr>
<td>EU25</td>
<td>-</td>
<td>-</td>
<td>21.94</td>
<td>47.84</td>
<td>53.30</td>
<td>63.23</td>
<td>65.75</td>
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<tr>
<td>EU15</td>
<td>-</td>
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<td>30.02</td>
<td>43.42</td>
<td>51.30</td>
<td>60.23</td>
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Source: European Commission Directorate-General for Energy and Transport24

Note: (-) means data unavailable.

EU25 includes Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, The Netherlands and United Kingdom.

EU15 includes countries in EU25 except Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovak Republic and Slovenia.

Fig. 3 Relationship between different forecast vehicle ownership levels (Distance = 500 km)
5. CONCLUSIONS

In this paper, a series of vehicle ownership models, which include: (1) car, (2) motorcycle, (3) truck and heavy goods vehicle and (4) bus and coach models, were proposed together with a trip generation model. These models were built upon limited aggregate data, both time series and cross sectional and disaggregated spatially by province, using non-log-linear weighted least squares regression for motor vehicle ownership models and exponential modelling for a trip generation model. It was found that all proposed models have desirable statistical properties, i.e. high R-squared and all coefficients were statistically significant, were of expected sign and have a sensible value. The car ownership model also has a reasonable income elasticity with respect to car ownership and a sensible saturation level. The weighted least squares modification was applied to all proposed models in order to solve the homoscedasticity problem and all WLS models produced good fits, within 12% of the observed values. The vehicle ownership forecasts were compared with those observed from other countries and for the case of trip generation model, the forecasts were checked with the US Department of Transportation’s trip generation analysis manual to ensure that sound logic is obtained.

The proposed vehicle ownership models are useful in forecasting the vehicle ownership level at both provincial and national levels which is important for road building, traffic management, strategic transport decision-making, emissions forecasts, energy use forecasts and other policy issues. It is also important for decision making in trip frequency, trip distribution, modal choice and route choice and therefore, the models are recommended to be implemented as a part of the national transport model for Thailand. Moreover, as the model structure is limited by the data availability, when other data such as fuel price, vehicle tax and duty are available, these variables should be introduced to the model. The availability of more disaggregate data, for example, at the household level, would allow a disaggregate model to be developed which could then be compared with aggregate approach adopted in this paper. Moreover, as the model structure has little Thai-specific content, it could be applied easily in any other country.

REFERENCES


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