PETROL, DIESEL OR ELECTRIC? AN EXTENSION OF PASSENGER TRANSPORT MODELS FOR DIFFERENTIATING CAR TRAVEL DEMAND

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MOTIVATION

Transport models can quantify the impact of policy measures and increasingly also address the issues of energy and environment. Traffic-related greenhouse gas emissions are particularly important in global warming and climate change. For any sizeable reduction of emissions to be achieved in the coming decades, the transportation system will also have to undergo significant changes. For this, an increasing number of new technologies have been developed and their impact on the transportation system and its (CO_2-) emissions has to be assessed. However, modeling new technologies is often difficult. For instance, the emergence of electric vehicles (EVs) and uncertainty regarding future fuel prices further complicate the forecasting of traffic-induced environmental effects. Can our models answer such questions?

Typically, traffic-related emissions and energy consumption are closely related to the vehicle miles traveled (VMT). Total VMT then acts as input for energy and emission models, e.g. MOVES (*1*) in the US and TREMOD (*2*) in Germany. As each vehicle type has its own emission profile, the result is more accurate if VMT are differentiated according to vehicle types. Usually, macroscopic transport demand models calculate overall VMT and subsequently divide it into the necessary categories according to statistical data. This is sufficient for forecasts only if vehicle emission and consumption profiles do not drastically change. New propulsion technologies and changing fuel prices may prevent this, however.

This paper presents a model extension which aims to rectify these shortcomings and provide a method for forecasting differentiated VMT values for passenger cars. It is based on a four-step transport demand model and uses input from a vehicle fleet model, with vehicle-type choice added as an extension using a nested logit structure. The approach is used to estimate VMT values for 2030 in Germany at national level for two scenarios, with vehicles being grouped into five fuel-type categories.

METHODOLOGY

German National Transport Model

The starting point for calculating differentiated car transport demand is the German National Transport Model (GNTM). The GNTM consists of two distinct models, one for short-distance (≤ 100 km) and one for long-distance trips. This separation is necessary due to the differences in trip purposes, available transport modes, zoning system etc. As the extension considered here is almost identical for both models, we will discuss the new approach for the short-distance trips model only. The case study described below includes results from both models.

The short-distance trips model is a variation of the "EVA (German: *Erzeugung, Verteilung, Aufteilung* – trip generation, distribution, mode choice)-model". Vrtic et al. (*3*) describe this approach extensively. It employs a simultaneous calculation of trip distribution and mode choice in a triple-constrained model environment. A specific feature of this approach is the mode share constraint for the base-year calculation, which generates the alternative specific constants for forecasts. The EVA approach does not restrict the usage of deterrence f and utility functions V, i.e. any known function $f(V)$ can be employed. The GNTM employs an exponential deterrence function $f(V) = \exp(V)$.

The EVA model provides origin-destination (OD) matrices for all considered modes, including overall car transport demand. The matrices (of all short- and long-distance trips) can be assigned to the network model to calculate congestion and update travel times, thus delivering realistic input back into the demand model.

At this point it should be noted that the specification and estimation of the GNTM were carried out prior to the development of the model extension presented below. The model estimation was based on the recent national household travel survey for Germany “Mobilitaet in Deutschland 2008, MiD” (*4*). Thus, the GNTM was by itself a fully functional and sensitive transport demand model, using average costs for the calculation of overall car transport demand. It was, however, not capable of producing differentiated car transport results.

Vehicle Fleet Model

To differentiate car transport demand according to vehicle types, the results of a vehicle fleet model (VFM) are required. VFMs ideally run on the same zoning system as the transport demand model, providing detailed information about car (type) ownership for each traffic zone.

For the model application presented here, the results of an aggregate VFM for Germany were used. This model predicts total vehicle numbers by fuel type owned by the German population. It is spatially aggregate as it does not use a zoning system; however it does distinguish between three land-use settings compatible to the GNTM (urban, mixed and rural).

Vehicle-Category-Differentiation Model Extension

Concept

The GNTM and the VFM cannot provide detailed information about the choice of vehicle types for single trips. Consequently, the necessary details for calculating reliably differentiated VMT are lacking. Therefore, an extension of the travel demand model had to be derived. This new Vehicle-Category-Differentiation Model Extension (VCDME) is a sub-model of the GNTM combining the results of the travel demand and vehicle fleet models and generating OD matrices and VMT values for different vehicle categories. This permits a more detailed assessment of policy measures affecting only some vehicle types (e.g. free parking only for EVs). The emergence of new propulsion technologies (e.g. EVs and fuel cell vehicles) will also influence the overall car transport demand; the VCDME helps to estimate such effects using a methodic link and feedback between the GNTM and VCDME (nested logit structure).

FIGURE 1 schematically illustrates the model structure and interdependencies between the transport demand model, the fleet model and the VCDME.

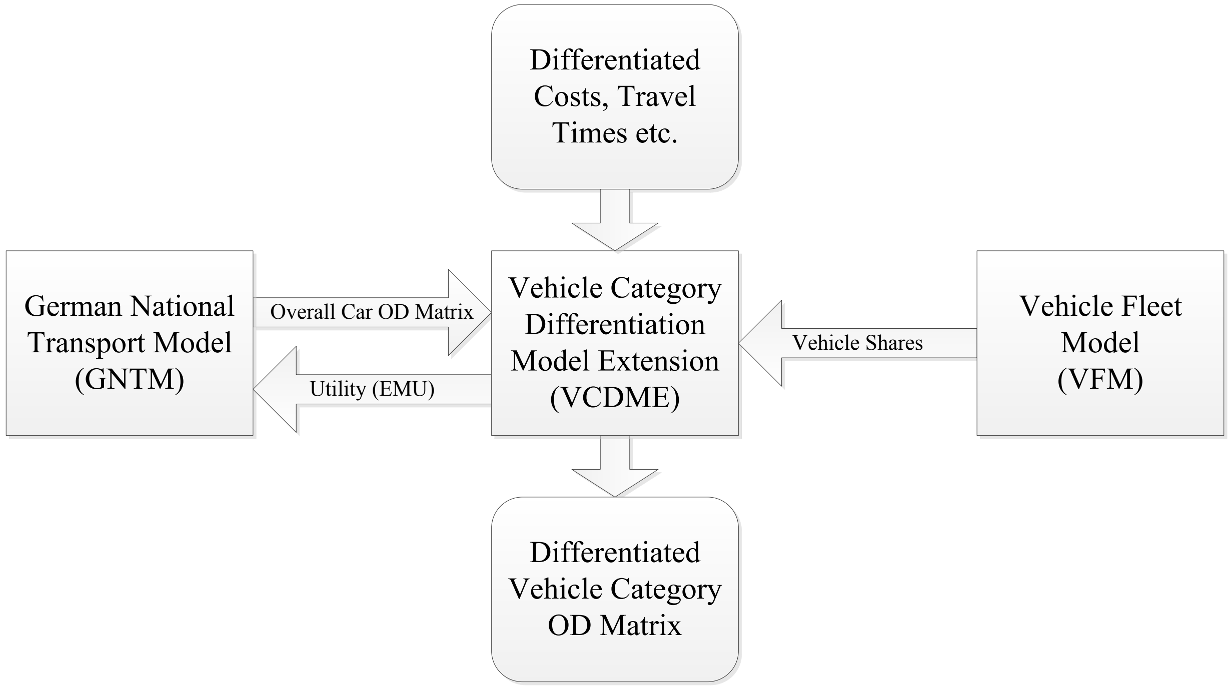

FIGURE 1 VCDME context.

The link between the GNTM and the VCDME works in both directions. It is set up using a nested logit model structure, with the vehicle categories in the VCDME forming the lower nests and the modes and destinations defining the upper hierarchies in the GNTM. FIGURE 2 illustrates this structure.

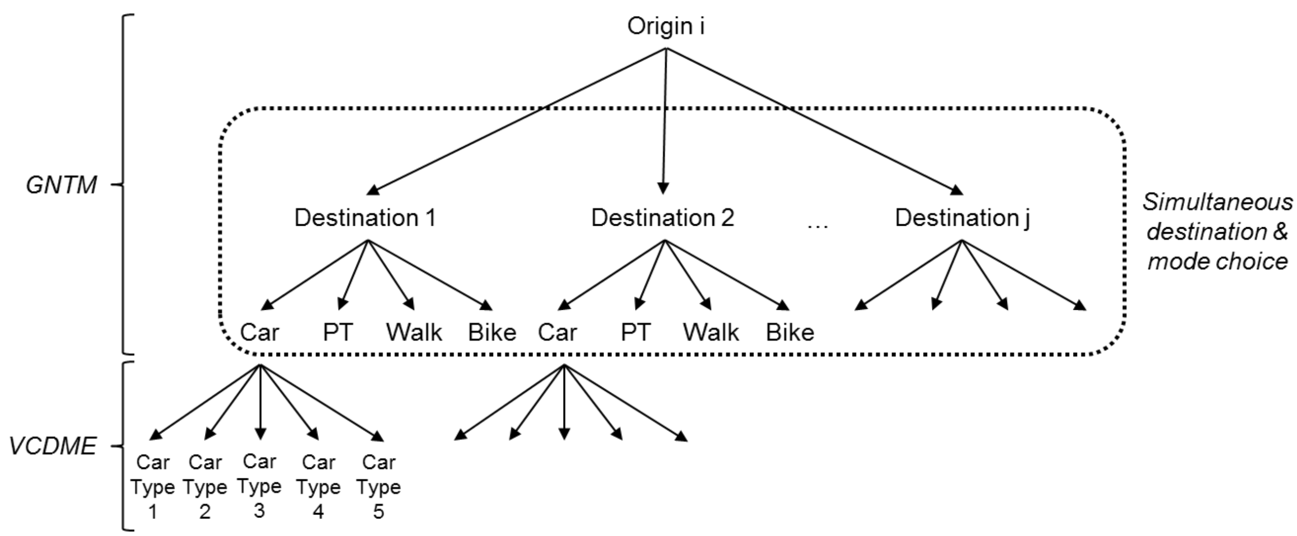

FIGURE 2 Nested logit structure

Firstly, the VCDME is used to generate the individual utility V_{VC} for each vehicle category and calculate the total car utility V_{car} over all categories using the logsum formula (1) as a measure of the expected maximum utility (EMU) over all vehicle alternatives (see e.g. (*5*)).

$$V_{car} = E[\max_{VC} V_{VC}] = \frac{1}{\mu} \ln \sum_{VC} \exp(\mu\, V_{VC}) \tag{1}$$

where:
μ scale parameter

The EMU is used in the higher-level GNTM to substitute those components of the original car utility which are assumed to be variable between the vehicle categories. Using this replacement, travel demand for all modes and destinations can be calculated in the GNTM. The resulting overall car OD matrices then go back into the VCDME where they are split into the different vehicle categories, thus providing separate results for each vehicle category. For this, the individual utilities V_{VC} are used within a standard logit approach:

$$T_{VC} = \frac{\exp(\mu\, V_{VC})}{\sum_{VC}(\exp\,(\mu\, V_{VC}))} T_{Car} \tag{2}$$

where:
T_{VC} trips using vehicle category VC
T_{car} total car trips

The utility function in the VCDME has the following form:

$$V_{VC} = f(time, costs, others) + \beta_{ca}\, f(ca_{VC}) \tag{3}$$

where:
β_{ca} car availability utility parameter

The first part of the utility function comprises every attribute which differs from one vehicle category to another. It can include separate costs per km, parking costs, access and egress times (e.g. reserved parking spots for EVs), and travel times (infinite travel times for prohibited OD relations, e.g. emitting vehicles not allowed inside the city center, range restrictions etc.). The car availability component ca_{VC} is discussed in the next section.

Model Estimation and Parameter Definition

Estimating the model parameters in the absence of revealed- and/or stated-preference data is difficult. Due to the vehicle-market dynamics and rapidly emerging technologies, reliable nationwide data on vehicle-type usage is not yet available. The parameters and deterrence functions in the VCDME were therefore on the one hand derived from the GNTM and on the other hand set manually using specific assumptions.

It seems reasonable to suppose that individual preferences for travel times, costs and other relevant impedance categories do not vary between the different vehicle types, thus we can transfer the corresponding parameters and deterrence functions from the GNTM, where they have already been estimated. This means that no additional model estimation is required for the VCDME for these parameters.

The nested logit approach, however, requires the definition of a scale parameter. For the present model implementation, the EMU scale parameter μ in equation (1) was set to 1, as there were no reliable means of estimating this parameter. This turns the nested logit approach into a joint logit. However, the EMU-based V_{car} should be approximately equal to the overall car utility calculated with (real) average costs in the GNTM. As correlation in a nested logit model is captured with the scale parameter, setting $\mu = 1$ requires a different approach to ensure compatibility between the VCDME and the GNTM, i.e. to cope with the IIA problem. The approach discussed here makes use of the car availability variable to deal with this issue.

Car availability ca_{total} is given as the proportion of trips originating in a traffic zone, for which using one's personal car is possible. Considering the fleet composition as a proxy for the vehicle category car availability ratios results in:

$$ca_{VC} = \frac{fleet\ size_{VC}}{fleet\ size_{total}} ca_{total} \ \forall\, VC \text{ with } \sum_{VC} ca_{VC} = ca_{total} \tag{4}$$

In the VCDME utility function in equation (3), the deterrence function chosen for car availability is a logarithmic function.

$$f(ca_{vc}) = \ln(ca_{vc}) \tag{5}$$

With $0 \le ca_{VC} \le 1$ the utility component becomes $-\infty \le f(ca_{VC}) = \ln(ca_{VC}) \le 0$. In other words, a low vehicle category share lowers its utility as well. This also reduces V_{car}. While this is not a rigorous estimation of model parameters, it does provide reasonable results with a simple approach. Furthermore, the parameter β_{ca} attached to car availability offers the possibility of adjusting the influence of this component on utility.

The calibration of vehicle-category shares in the VCDME requires comparing the results (VMT shares) to statistical data. This might often be difficult due to data availability at regional or national level. While overall VMT figures should easily be obtainable, separate values might not be available at the required level of differentiation (e.g. VMT by vehicle size or fuel type). The problem is compounded by emerging propulsion technologies (e.g. EVs) for which there is no statistical data available at all. If the share of some vehicle categories appears too large, the weight of car availability in the utility function could be adjusted. In our model application, we set $\beta_{ca} = 1$ as the results appeared realistic (see next section).

Originally, the GNTM was set up and validated to run with overall car impedances (overall availability, average cost and travel time etc.). As the EMU-based V_{car} in equation (1) is not exactly equal to the utility components it replaces in the GNTM, a different mode-share result might occur when employing the VCDME. In such a case, recalibrating the model by slightly adjusting the mode choice parameters might be necessary.

CASE STUDY RESULTS

The following case study illustrates the VCDME approach. The aim was to estimate spatially disaggregated mode shares and VMT values at national level for Germany. The VCDME was applied to both the short- and the long-distance trips model. Car transport was differentiated into five vehicle categories according to their propulsion technology and fuel type used. The following five vehicle categories were considered:

- Petrol
- Diesel
- Plug-In Hybrid Electric (PHEV)
- Battery Electric(BEV)
- Gas (LPG and CNG)

To illustrate the VCDME approach, two scenarios forecasting transport demand in 2030 were calculated and compared. Scenario 1 is derived from the official Federal Transport Forecast of the German Ministry of Transportation and includes an assumption about rising fossil-fuel taxes. Scenario 2 is an alternate scenario, very similar to Scenario 1 but without the increase of fossil-fuel tax, thus leading to lower costs per km for fossil-fuel-powered vehicles. The difference in costs per km, as shown in TABLE 1, is the only distinction between the two scenarios. Input data for all other modes and other car attributes are identical.

TABLE 1 Cost per Km in Scenarios 1 & 2

Vehicle Category	**Scenario 1**	**Scenario 2**
	in Euro cent per km	
Petrol	13.3	9.3
Diesel	10.0	7.5
PHEV-electric	5.8	5.8
PHEV-petrol	13.4	9.3
BEV	5.5	5.4
Gas	6.4	6.8

Using the VCDME approach, we expect two main differences in the scenario results. Firstly, because overall car costs per km are lower in Scenario 2, we expect a (slightly) larger car mode share compared to the other modes in the GNTM and higher car VMT values. Secondly, as the cost advantage of alternative fuel vehicles falls in Scenario 2, we expect a shift towards petrol and diesel vehicles within overall car demand. TABLE 2 shows the model results calculated with the VCDME.

TABLE 2 Combined Result of VCDME for Both Models

	Scenario 1	**Scenario 2**
Overall Car Mode Share	58%	62%
Overall Car VMT *(in bn km)*	1,039.2	1,161.1
VMT Shares		
Petrol	34%	45%
Diesel	40%	42%
PHEV	20%	11%
BEV	2%	1%
Gas	4%	2%

Overall car mode share increases from 58% in Scenario 1 to 62% in Scenario 2. The overall car VMT also increase drastically by ca. 12%, because conventional fuel vehicles form the bulk of the fleet, so a decrease of 25-30% in their cost per km will affect a large proportion of car demand. In Germany, demand for public transportation and non-motorized modes (walking, cycling) is also significantly higher as they represent realistic alternatives for (short-distance) trips. Therefore, the impact of changing car costs will be higher than in countries where car is the predominant mode of transport.

The shift towards conventional fuel vehicles is also evident in TABLE 2. It is important to note that the difference in VMT shares also originates from the different vehicle fleets estimated using the Vehicle Fleet Model for both scenarios. Using the same vehicle fleet shares in both scenarios would lead to much smaller differences in the VCDME results. Accurately modeling the effects on the vehicle fleet composition is an important requirement for the VCDME to estimate realistic results. Discussing the results of the VFM is, however, not the object of this study.

CONCLUSION

This paper presents an approach to differentiate demand for car transport according to vehicle type. This method splits results from a transport demand model into different vehicle categories using a nested logit-structured model extension (VCDME).

The purpose of the VCDME is to provide a reliable method for car travel differentiation sensitive to policy measures. This is especially required for long-term forecasts assessing the environmental impact. Calculating VMT for different vehicle types leads to more accurate estimates of transport-related emissions and energy requirements. The VCDME can also model the impact of emerging technologies such as electric or fuel-cell vehicles. This approach enables the implementation of various policy measures ranging from general issues such as costs per km to origin-destination-specific or even network-related ones. Because the VCDME is directly linked to the transport demand model, the resulting vehicle-category OD matrices can be assigned to the network, thus enabling demand for a specific vehicle type to be localized on the network. Applications for this include determining the optimal location of charging stations for EVs and modeling air quality in congested cities.

The VCDME was used in a case study to forecast national transport demand in Germany for two scenarios. The results show that the VCDME delivers plausible results when quantifying the impact of a cost differential. As expected, overall car demand increased in Scenario 2, while VMT shares were also responsive. Further work is required to identify more robust ways of deriving the model parameters, including the value of the scale parameter in the logsum formula.

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