UNDA Seventh Tranche

Project E:

Development and implementation of a monitoring and assessment tool for CO_2 emissions in inland transport to facilitate climate change mitigation

Concept document on the contents and structure of the ForFITS model

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Introduction

The UNECE Transport Division, together with all UN Regional Commissions, initiated a new project to enhance international cooperation and planning toward sustainable transport policies that facilitate climate change mitigation.

The project is funded by the UN Development Account (UNDA) for 3 years, from January 2011 to December 2013.

The objective of the project is to develop a uniform methodology for calculating detailed transport CO_2 emissions on the basis of existing assessment models, streamlined according to UN requirements, terminology, definitions and classification of vehicles, transport modes, etc. The project shall also provide a robust and transparent framework capable of analysing alternative strategies for the development of sustainable transport, establishing links with transport policy-making decisions through the estimation of transport policy impacts with respect to CO_2 emission mitigation.

This tool focuses on the inland transport sector (road, rail and inland waterways). CO_2 emissions caused by international aviation and maritime transport are excluded from its scope.

Since the tool is meant to pave the way for future inland transport systems, it was named ForFITS.

This document provides essential information on the model requirements and features, as well as the methodology for the development of the ForFITS tool. In addition, it highlights the main challenges that exist and proposes solutions with the aim to achieve a good compromise between the degree of detail required and the information that is likely to be available for this sort of assessment.

Model characteristics

Requirements

The ForFITS model shall be developed as a software tool and to be freely available for users (e.g. national and local governments, general public). It shall be able to perform the assessment of CO_2 emissions, as well as the evaluation of the impact of transport policies for CO_2 mitigation. In addition, it will be instrumental in the analysis of the policy implications of using different mitigation techniques and measures in the land transport sector. The ForFITS model shall take into consideration not only the continued growth of road vehicle fleets (including the different types of propulsion), changes in the transport infrastructure and the availability of sustainable energy sources, but also railway and inland waterway transport, as well as the development and use of Intelligent Transport Systems (UNECE, 2011).

In short, the ForFITS modelling tool shall provide a robust and transparent framework capable of analyzing alternative strategies for the development of sustainable transport and linking these strategies with transport policy-making decisions.

Main parameters

In order to fulfil its objectives, the model needs to perform the following main operations:

- evaluate fuel consumption from transport activities and vehicle characteristics;
- convert information on fuel consumption into emission estimates;
- estimate the total transport activity and fuel consumption (especially relevant for projections).

The fulfilment of these operations requires the analysis of a large amount of data and information and projecting them into the future on the basis of assumptions characterising a few main drivers.

Estimation of CO_2 emissions

For the evaluation of CO_2 emissions, the model will need to build on information concerning transport activity, vehicle and fuel characteristics, and fuel usage.

On the vehicle side, the information needed includes the number of vehicles circulating by mode, class and powertrain group, their consumption per km, their average annual travel and their average load (resulting, for freight, from the average load on laden trips and empty running).

In addition, it is important to know data on the vehicle sales, the evolution of vehicle travel once the vehicle age increases, the average scrappage rate of vehicles over time and the average maximum scrappage age.

On the fuel side, it is necessary to acquire information on the types and the amounts of fuels and other energy carriers used, as well as their technical characteristics in terms of tank-to-wheel and well-to-tank emissions per unit energy consumed.

The whole analysis can be improved by complementary inputs on parameters like the average travel time, or (for passenger travel) the average number of trips per day and the average trip length.

Finally, variables providing demographic, macroeconomic, geographic information, as well as data concerning prices, are extremely important for the accurate model characterisation. Even if they do not contribute directly to the calculation of CO_2 emissions, they have a fundamental role for the definition of the socio-economic context where they take place and for the characterisation of policy inputs.

Estimation of policy impacts

For the evaluation of policies, the model will require a wider range of inputs. Such data would not only encompass the past and current timeframes, but also the future, since policy measures need to be evaluated for their expected effects after introduction.

This sort of information includes:

- historical figures and projections of demographic, macroeconomic, and geographic characteristics, as well as projections of the same variables in the future;

- historical data characterising the vehicle stock and sales from a technical point of view (fuel consumption, load capacities, production cost for each powertrain group) and in terms of activity (average travel and average loads), as well as projections of the same variables in the future;
- historical data characterising networks with respect to their extension, speed limits and congestion components, as well as projections on their future development;
- inputs related to the current and expected vehicle and fuel production costs;
- information capable of characterising the policy measures that need to be evaluated, such as:
    - the current and expected vehicle and fuel taxes;
    - the variation of vehicle travel due to measures like travel or access restriction to some areas of the transport network;
    - the effects, in terms of modal shares of passenger km, associated to measures favouring modal shifts;
    - the introduction of legislation regulating the fuel consumption of new vehicles (whose impact is diluted by the inertia of the unchanged fleet of existing vehicles);
    - the development of transport networks (e.g. due to the construction of new infrastructure or the conversion of existing transport connections).

Model methodology

Estimating fuel consumption and emissions from transport activity

Fuel consumption

The evaluation of fuel consumption from existing information on transport activity and vehicle characteristics can be effectively performed using an approach based on the decomposition of Fuel use into transport Activity, energy Intensity and Structural components, such as the type of transport service (passenger vs. freight), mode, vehicle class and powertrain group. Such approach is generally called ASIF (Activity · Structure · Intensity = Fuel consumption)

In particular, the ASIF methodology builds on the idea of "Laspeyres identities", widely used in the analysis of energy efficiency indicators.

The following identity illustrates its main equation:

$$\sum_i F_i = A \sum_i \left(\frac{A_i}{A}\right)\left(\frac{F_i}{A_i}\right) = A \sum_i S_i I_i = F$$

Where:

F and F_i A and A_i

$\frac{A_i}{A} = S_i$	total energy use in the sector (e.g. given by a specific service, mode, vehicle class and powertrain group) i
$\frac{F_i}{A_i} = I_i$	represent (respectively) the total activity (expressed in vkm) and the activity in the sector i
represent (respectively) the energy (fuel) use and the	represents the sectoral structure (by service, mode, vehicle class and powertrain group)
	is the energy intensity, expressed in energy required per vehicle km, of each vehicle category i (e.g. average fuel consumption per km of vehicles performing a given type of service and belonging to a given mode, a given vehicle class and a given powertrain group)

The ASIF approach is based on parameters and variables that have strong linkages to measurable variables. As a result, it is an effective instrument to avoid black-box modelling shortcuts, since all the information flow that characterises it is fully traceable.

The ASIF approach is also coupled with decomposition analysis, a proven approach that helps identifying the main factors behind changes in energy consumption widely used in the field of energy efficiency indicators.

In the field of transport, energy and climate change, the ASIF approach has been adopted in models like the SMP model of the World Business Council for Sustainable Development (WBCSD, 2004a), the IEA Mobility Model (IEA, 2009), and the World Bank EFFECT model (World Bank, 2011).

It is for these reasons that the ASIF structure was chosen as the main underlying structure for the joint evaluation of transport activity, vehicle characteristics and fuel consumption in the ForFITS model.

CO_2 emissions

The assessment of emission estimates from fuel consumption can be addressed effectively by the multiplication of the amounts of energy used by appropriate emission factors, eventually expressed as a function of parameters like the average vehicle speed, the ambient temperature and the number of trips per day (in order to introduce a parameter capable of representing inputs relevant for cold start emission factors), to information concerning the fuel consumption.

Most of the uncertainties about CO_2 emissions estimates are due to the limitations associated with the precise evaluation of fuel consumption. In ASIF analyses, the uncertainties associated with Activity, Structure and Intensity parameters are the main reasons for the limited precision of fuel consumption estimates. Among these uncertainties, the main issues are typically found for data on transport activity, even if fuel consumption is also strongly affected by changes in driving conditions (e.g. because of traffic or driving styles) or load factors (as discussed earlier). Contrary to pollutant emissions, changes in changes in ambient temperatures and cold-start transient conditions have very limited effects on the emission factors of CO_2.

Contrary to pollutant emissions, changes in driving conditions and cold start have very limited effects on the emission factors of CO_2. According to the IPCC (Intergovernmental Panel on Climate Change), emissions of CO_2 are best calculated on the basis of the amount and type of fuel combusted. In particular, CO_2 emission factors for fuel combustion are based on the carbon content of the fuel and should represent 100% oxidation of the fuel carbon (IPCC, 2006). In other words, unlike other emissions (like those of some pollutants, as well as greenhouse gases like CH_4 and N_2O), CO_2 emission factors are strongly correlated with fuel consumption.

In addition, since CO_2 emission factors are one order of magnitude larger than the order of magnitude of other GHG (GreenHouse Gas) emissions deriving from fuel combustion (i.e. CH_4 and N_2O), and since uncertainties on fuel properties like the net calorific value far exceed the amounts related to the emission of non-CO_2 GHGs from the combustion of fuels even without catalytic converters (IPCC, 2006), the initial approach adopted in ForFITS for the evaluation of emission factors is relying exclusively on CO_2 emissions.

These considerations can be combined with those concerning the ASIF approach outlined earlier. The synthesis of these two elements is best summarized by the ASIF equation extended to include emission factors, summing also across the different energy carriers when more energy carriers are in use (this is the case of the ForFITS model):

$$\sum_i F_i EF_i = A \sum_i \left(\frac{A_i}{A}\right)\left(\frac{F_i}{A_i}\right)\left(\frac{EF_i}{F_i}\right) = A \sum_i S_i I_i EF_i = E$$

With:

$$EF_i = \sum_j \left(\frac{EF_{ij}}{F_{ij}}\right)\left(\frac{F_{ij}}{F_i}\right)$$

Where:

E	represents the total emissions
F, F_i and F_{ij}	represent (respectively) the energy use, the total energy use in the sector i, and the use of the energy carrier j in the sector i
A and A_i	represent (respectively) the total activity (expressed in vkm) and the activity in the sector i
$\frac{A_i}{A} = S_i$	represents the sectoral structure (by service, mode, vehicle class and powertrain group)
$\frac{F_i}{A_i} = I_i$	is the energy intensity of the sector i (i.e. for the service, mode, vehicle class and powertrain group)
EF_{ij}	is the emission factor per unit of energy for the energy carrier or fuel j used in the sector i.

Model structure and main variables

The ASIF equation extended to CO_2 emissions, calibrated on the classification of vehicles based on type of transport service, mode, the vehicle class and powertrain group (also including information on age of vehicles by powertrain group, via the definition of their characteristics in different vintages), constitutes the main basis of the ForFITS model structure (the blue boxes in Figure 1 provide a simplified illustration of this).

In addition, in ForFITS, the vehicle-based extended ASIF approach has to be combined with other measurable parameters (namely load factors, trips per day, trip duration, network extension, network usage, through average speed in different traffic conditions, average share of time spent in different traffic conditions, and average extension on the different traffic conditions on the network) to represent passenger and freight transport, as well as some fundamental characteristics of the transport network and its usage.

Vehicle, passenger and freight activity, their energy use and the respective estimations of CO_2 emissions stem from the combination of all the information contained in the vehicle-based ASIF approach extended to CO_2 emissions and the complementary parameters characterising the model.

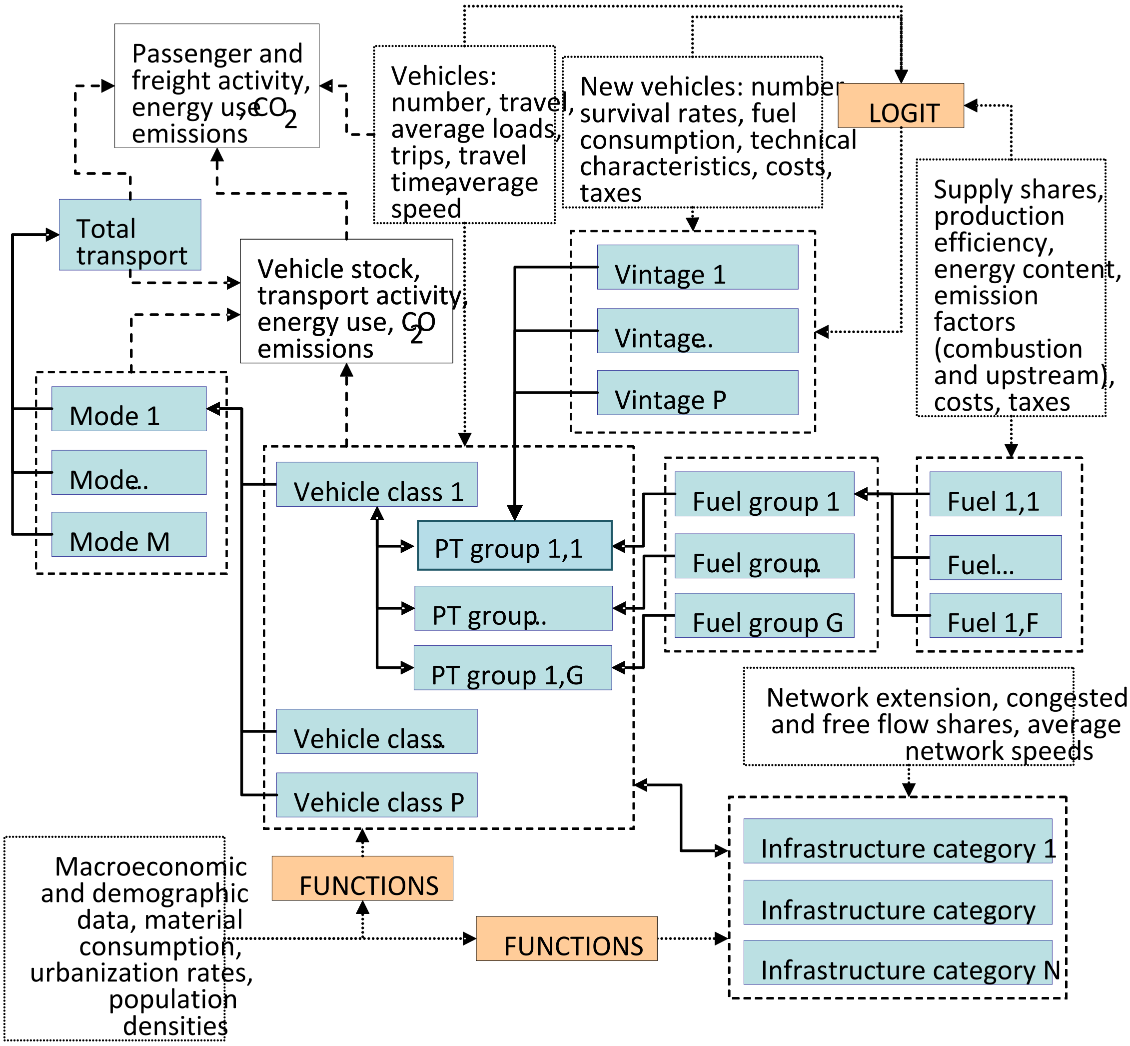


Figure 1: Graphical representation of the ForFITS model structure

The main variables that shall be included in the ForFITS modelling framework comprise:

- macroeconomic and demographic variables (including GDP, population), to represent the socio-economic context where transportation takes place;
- urbanisation rate and urban population densities, to provide information on the environment where urban passenger transport takes place;
- the size and characteristics of existing vehicle fleets and new vehicles entering the market (including the types of propulsion systems they rely on, their specific fuel consumption and their costs), to represent the role of vehicle technology in the transport sector, as well as information liked to regulatory policies;
- information on the travel activity (including parameters like the number of trips per capita per day, the average trip length and the relevant modal choice for passenger transport, the average vehicle load; for freight, parameters capable of identifying the characteristics of the logistical system, like the share of empty running, the average vehicle load on laden trips, and handling factors), to define further the context characterising passenger and freight transport;

- the characteristics of the transportation infrastructure (such as the size of the transport network for each mode, as well as information on congestion levels and average speeds, ultimately linking the network extension with the network usage rates), to take into account the capacity of the transportation networks and their degree of development;
- the energy sources, their properties (like production efficiencies and emission characteristics) and their costs (including production and transportation costs), to provide information on the technical and economic characteristics of transport fuels;
- energy consumption and CO_2 emissions in transport (at least as an aggregate, and possibly by fuel, by mode and in further disaggregation);
- information on fiscal parameters (to be represented through specific instruments, including taxation rates on vehicles, fuels and travel) to allow the representation of some of the instruments subject to changes in policy measures.

Evaluating future transport activity

The vehicle-based ASIF approach extended to account for CO_2 emissions can be applied to different scopes:

- the assessment of transport activity, transport-related energy use and CO_2 emissions in historical years (by requiring assuring coherence amongst modelling inputs);
- the estimation of the same variables in the future (via the formulation of projections);
- the evaluation of the impact of transport policies for CO_2 mitigation, typically achieved by comparing different scenarios resulting from the evaluation of projections using different modelling inputs.

In order to work on projections, however, the vehicle-based ASIF approach described earlier needs to be complemented by relationships that link economic parameters to transport-related ones (such as changes in the cost of travel to variations of travel per vehicle, or changes in the income per capita to variations of vehicle ownership), as well as other specific methodologies (like choice models) that apply only to specific sub-sets of the data.

In ForFITS, this will be the case for the sections of the model that perform:

- the evaluation of transport activity in the future (requiring information on size of vehicle stocks, the average travel per vehicle and the average vehicle load), when macroeconomic and demographic data are used as the main modelling inputs;
- the evaluation of new vehicle sales and the selection amongst different powertrain groups for the new vehicles entering the rolling stock, for each vehicle class
- the definition of the fuel mix used for different powertrain groups.

The evaluation of transport activity in different transport modes is expected to rely on a number of parallel approaches that depend on the vehicle class considered.

Vehicle stocks, average vehicle travel and average loads

Motorized personal passenger transport vehicles

For motorized personal passenger transport vehicles (namely cars and motorcycles), the **vehicle stock** is expected to be estimated using the approach, based on Gompertz curves describing vehicle ownership as a function of GDP per capita, urbanisation rates and densities, similar to those described by Dargay et al. (2007) for the whole vehicle fleet.

The **average vehicle travel** per year in the same type of vehicle class (cars and motorcycles) is going to be estimated on the basis of the variation of the cost of travel (cost per km), considering the variation of fuel prices as the input variable, via price elasticities, building on published information. Income elasticities, linking GDP per capita to travel, are also especially relevant in case of recessions, when the reduction of vehicle km per capita is not due to a strong contraction of the existing fleet because of increased scrappage (the scrappage rate is actually more likely to be lower), but rather due to a reduction of the travel per vehicle. In case of economic recession, income elasticities are also going to be accounted for in the estimation of the average travel per vehicle.

The **average vehicle load** is going to be assumed constant, using historical data as reference. Exogenous corrections of this assumption are going to be possible.

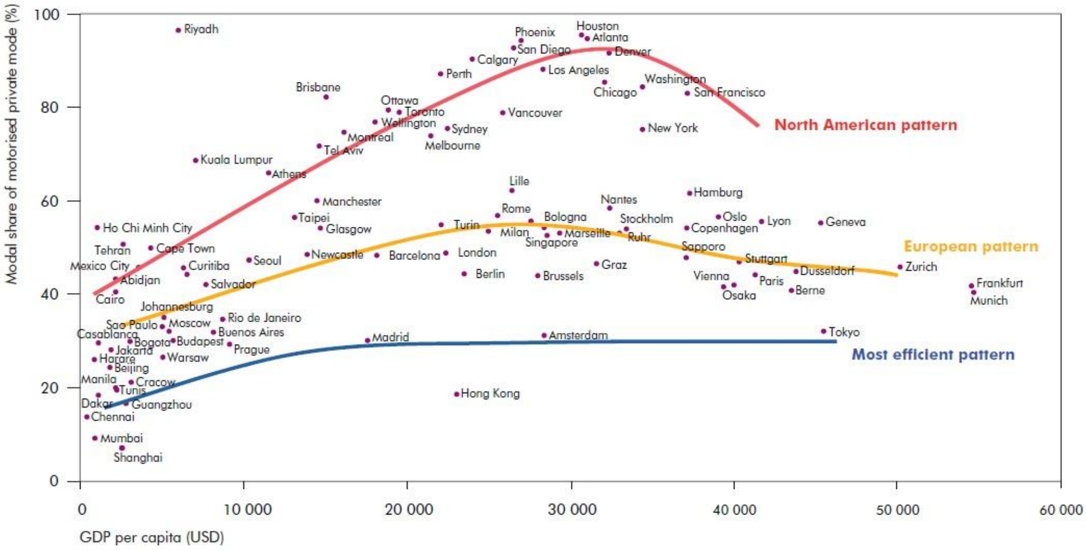
Collective passenger transport vehicles

For collective passenger transport vehicles (vehicles for mass transit purposes), the evolution of the **vehicle stock** is going to be estimated distinguishing urban and non-urban areas.

In all cases, the expected vehicle stock is expected to result from the estimation of the total passenger travel (pkm) on collective passenger transport vehicles, the average vehicle load (p/v) and the average travel per year of the vehicles (km/v).

For urban areas, the future total passenger travel on collective passenger transport vehicles is expected to be derived from the share of travel of public transport, expressed as a function of parameters like the GDP per capita, and the average population density and the density of the mass transit network, building on published information like those shown in Figure 2, complemented by specific indicators and statistics. For non-urban areas, default values describing a limited provision of collective passenger transport services will be used.

For historical years (including the base year), the passenger km will be estimated on the basis of the stock of collective passenger transport vehicles, the average passenger load and the average travel per year of each vehicle.



Source: UITP (2006) in IEA (2008)

Figure 2: GDP per capita and modal shares of motorised private passenger vehicles

The share of passenger travel on different vehicle classes (e.g. relative to road and rail vehicles) is going to be evaluated on the basis of historical data. The shares are going to be evaluated assuming constant travel times for passengers, taking into account the increased ownership of personal vehicles, as well as changes in the average speed of the different modes (e.g. due to improved infrastructures for public transport or congestion for personal light duty vehicles).

Information on the **average vehicle loads** of collective passenger transport vehicles is also going to be extracted from historical figures. By default, the average vehicle load is going to be assumed constant. This reflects the need to recover costs by assuring services having a certain ridership rate. It will be possible, however, to correct this assumption exogenously. In the future, this assumption may also be replaced by improved approaches, e.g. capable of taking into account changes of the fare prices, subsidies to public transport, and changes in the quality of service.

The **average travel per vehicle** per year for public transport is going to be evaluated on the basis of exogenous inputs concerning the average vehicle speed and assuming that the average time of service is constant over time. In the future, this assumption may be refined and possibly linked to changes in the fare prices, subsidies to public transport, and changes in the quality of service.

Freight vehicles

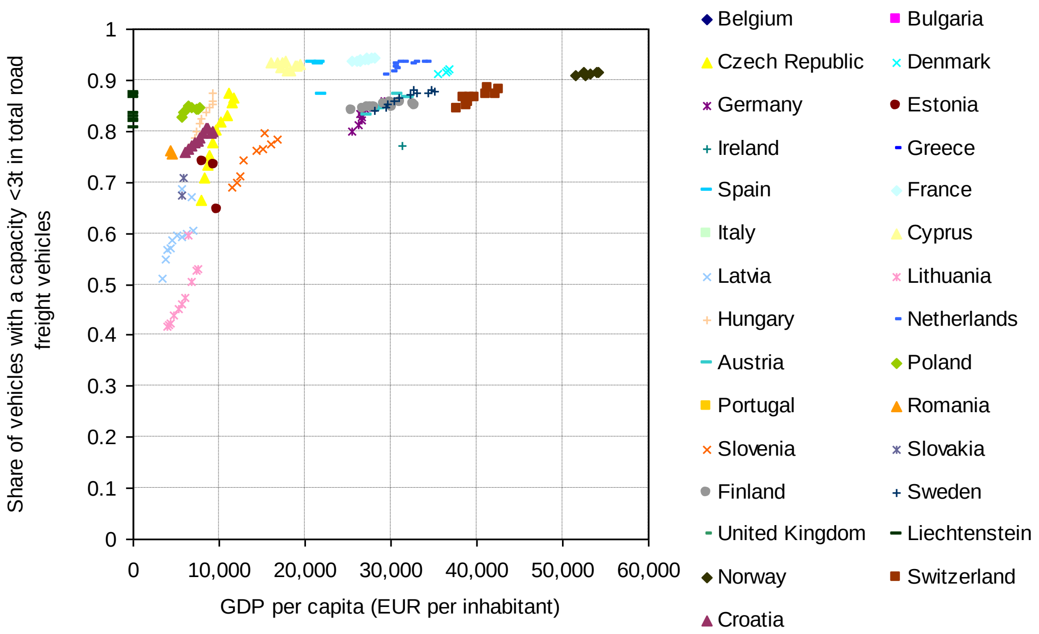
For freight vehicles (vehicles for the transport of goods), the **vehicle stock** is going to be estimated on the basis of the total freight travel (tkm) on freight vehicles, the average vehicle load (t/v) – encompassing the effects of loads on laden trips and empty running – and the average travel per year of the vehicles (km/v).

Initially, the total freight travel is expected to be evaluated from economic growth. This is consistent with the idea that growth in total freight travel tends to closely follow the growth of GDP, without clear signs of decoupling of transport volume growth from economic growth (as highlighted for instance in EEA, 2008)[1].

The evaluation of the total freight travel (tkm) can also be associated with the evaluation of transport volume (tonnes lifted) through the average haul length and the handling factor (i.e. an indicator of the number of times a unit of mass is ‘lifted’ onto a vehicle), which represents a crude measure of the number of links in a supply chain and is one of the parameters that can give an indication of the efficiency of the logistic system.

The share of freight travel on different modes (e.g. rail vs. road) is going to be estimated on the basis of exogenous inputson the modal tkm shares (constant and equal to historical values, by default).

Within each mode, the share of vehicles belonging to different classes is deducted from historical trends. The share of small freight vehicles in the total freight vehicle stock, for instance, is expected to be evaluated from statistical data like those reported in Figure 3.



Source: Eurostat (2011)

Figure 3: Share of vehicles with a load capacity lower than 3 t in total road freight vehicles

The **average vehicle load** within each class in projected years is going to be assumed constant, on the basis of historical data. However, it is going to be possible to correct this assumption exogenously, in order to evaluate the effects of changes in the efficiency of the logistical system. In the future, improvements taking into account variations of average loads on the basis of exogenous variables shall be considered. Key parameters to be taken

[1] In the future, accounting for the possibility of decoupling between GDP and the total freight travel (a phenomenon that can result from the declining weight of goods in the economy, the increase of their value, or a combination of both these elements) shall be included in the modelling approach. McKinnon (2006) provides an initial conceptual framework to address this issue.

into account include fuel prices, as well as the average value of goods transported (even though they are difficult to characterise for each vehicle class).

The **average travel per vehicle** per year for freight is going to be evaluated using price elasticities, as in the case of passenger vehicles. As in the case of motorized personal passenger transport vehicles, income elasticities shall also be considered in the event there is an economic recession.

New vehicle sales

Future vehicle sales are going to be estimated (for all modes and transport service types) on the basis of the expected ownership in the relevant vehicle class, the vehicle sales in the same class in previous years (either coming from historical data or projected estimates), and vehicle mortality, calculated using Winfrey S3 survival curves (as defined in the equation below). Such curves are calibrated on the average maximum vehicle scrappage age ($age_{scrappage}$) and considering zero vehicle retirements during the first few years (age_0), as follows:

$Survival\ rate = 1$ if $age \leq age_0$ (and $age < age_{scrappage}$)

$Survival\ rate = \left(1 - \frac{(age - age_0)^2}{(age_{scrappage} - age_0)^2}\right)^3$ if $age_0 < age < age_{scrappage}$

Powertrain selection

The sales mix of new vehicles by powertrain group and within each vehicle class, for each mode and transport service type (passenger and freight), is going to be estimated on the basis of a discrete choice approach using a multinomial logit model (where the options selected are represented by different powertrain groups, and the selection is made by one single average individual), combined with inputs on the availability of the different powertrain technologies on the vehicle market.

Multinomial logit

In the multinomial logit model (Ben Akiva and Lerman, 1985), the probability that a decision maker *n* selects the element *i* in the total set of choices C_n is expressed as:

$$P_n(i) = \frac{e^{\mu V_{in}}}{\sum_{j \in C_n} e^{\mu V_{jn}}}$$

$P_n(i)$ is such that $0 \leq P_n(i) \leq 1$, and $\sum_{i \in C_n} P_n(i) = 1$.

This formulation assumes that the utility of the choice *i* made by the decision maker *n*, U_{in}, results from a deterministic component, V_{in}, and an unknown disturbance, ε_{in}:

$U_{in} = V_{in} + \varepsilon_{in}$.

This formulation also assumes that all the disturbances ε_{in} are independently and identically Gumbel-distributed[2], with a location parameter η (which is assumed to be zero in this case, indicating that in the absence of disturbances the utility corresponds to its deterministic component) and a scale parameter μ.

The multinomial logit approach requires the definition of the characteristics of all different options (the powertrains groups in each vehicle class, in this case) in order to characterise the utility of the individuals that have to select one of the choices.

The utility parameter that shall be maximised by the discrete choice approach is the expected amount of savings derived from the selection of one option with respect to the others. Such savings are determined on the basis of the actualized cost of travelling[3].

The estimation of the average cost of travelling for each powertrain technology is going to be based on:

- a personal discount rate for future expenditures that ranges between 10% and 20%;
- the vehicle purchase price of vehicles, including taxes;
- the expected purchase price of fuel, including the costs due to the fuel production, transport, distribution and refuelling, as well as the commercial mark-up and the fuel taxation (assumed by default to remain at the same level of the last known value, i.e. the level of the last available year);
- the expected average vehicle life, evaluated on the basis of the survival curve described earlier;
- the expected average vehicle travel within a class, assuming, in particular, that:
    - the average annual travel per vehicle does not change because of future changes in fuel cost (this means that it is assumed that people assume that fuel prices will remain constant when they decide which powertrain group they prefer);

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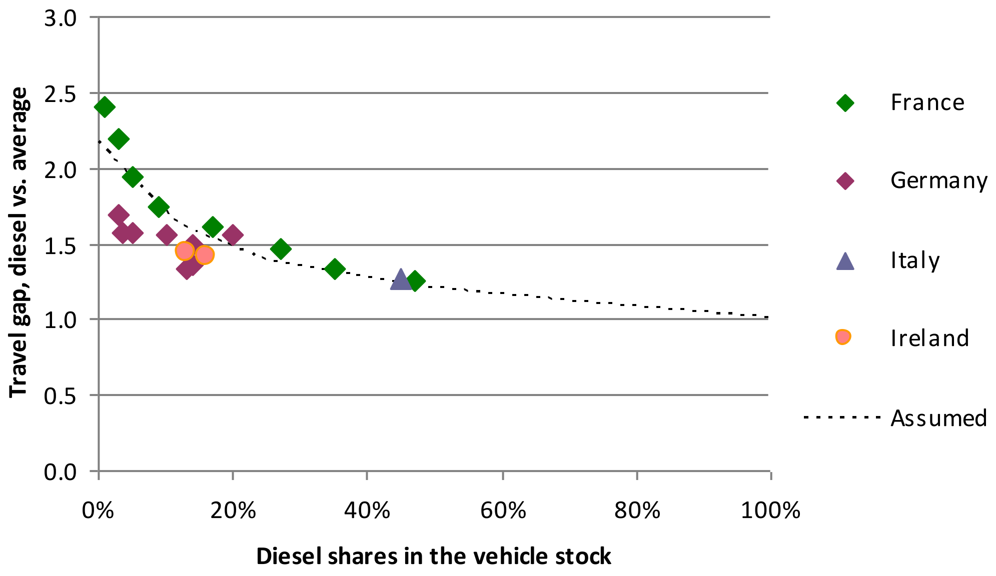
[2] The assumption of a Gumbel distribution is used for reasons of analytic convenience, mainly due to the availability of an explicit formulation of the probability $P_n(i)$ associated with it. The Gumbel distribution is not a major limitation of this approach and can be defended as as an approximation of the normal distribution. On the other hand, the assumption of independently and identically distributed disturbances is a more important restriction, especially for innovative technologies.

[3] The restrictions imposed by this assumption are acceptable in this specific case (powertrain group selection), since it is conceivable that the disturbances characterising the utility resulting from the adoption of different powertrains do not change significantly for most powertrain options, especially if they are associated to similar performances. However, it must be noted that the limitations associated to the assumption of independently and identically distributed disturbances become more relevant for powertrains having performance characteristics that tend to differ more (e.g. because of important gaps in terms of range, refuelling time and availability of refuelling points) in comparison with conventional alternatives. This is the case, for instance, for electric motors and fuel cells. In the future, improvements to this approach may be needed. One possibility is to differentiate amongst different categories of individuals selecting the different options, e.g. in order to address the emergence of new types of ownership patterns. Another possibility is to include additional parameters in the deterministic component of the utility.

- the average vehicle travel decreases with vehicle age, according to a profile defined exogenously and set, by default , to a decline linearly up to a 30% reduction in the last year of vehicle life;
- technologies representing an alternative to the conventional spark-ignition powertrain fuelled with a gasoline-based blend are characterised by an average annual amount of travel that is more than double the mileage per vehicle if their market share is close to zero, while the travel gap narrows to zero when they represent the great majority of the fleet (Figure 4).



Sources: various datasets and publications, including Bodek and Heywood (2008), Eurostat (2011), Howley et al. (2007), Caputo et al. (2008).

Figure 4: Travel gaps diesel and gasoline vehicles (1990-2010)

The scale parameter μ is proportional to the inverse of the mean deviation of the disturbances from the mean value of their Gumbel distribution (σ):

$$\mu = \frac{\pi}{\sigma\sqrt{6}}, \text{ since } \quad \sigma^2 = \frac{\pi^2}{6\mu^2}.$$

The effect on the choice probabilities of the scale parameter is definitely not irrelevant (Adamowicz et al., 1998). The higher the mean deviation from the location parameter of the Gumbel distribution (i.e. the location of the maximum of the distribution), the lower the scale parameter, and the least extreme the choice coefficients. Vice-versa, the lower the mean deviation from the location parameter, the higher the scale parameter.

In the case considered here, the utility determines the selection of the available options, and it is given by the sum of a deterministic component and an unknown disturbance. The growth of the scale parameter μ means that the mean value of the unknown disturbances becomes increasingly negligible with respect to the value of its deterministic component.

This leads to a choice that is increasingly characterised by the deterministic component of the utility.

On the other hand, a decreasing value of μ (towards zero) implies that the mean deviation of the distribution of the disturbances tends to grow, increasing also the mean magnitude of the disturbances with respect to the value of the deterministic component of the utility. This results in a decreasing relevance of the deterministic component of the utility for the choice of one option rather than another. In this case, all choices tend to have the same probability of being selected because they are increasingly influenced by the non-deterministic component.

In the ForFITS model, μ is going to be set in a way that corresponds to a mean deviation of the unknown disturbances of the utility of roughly 10% of the total cost of travelling estimated for the cheapest option.

Availability of the different powertrain technologies on the vehicle market

ForFITS is going to combine the choices resulting from the application of the choice model with exogenous inputs that shall represent the level of technology availability on different models within the same vehicle class.

This goal reflects the fact that, in the case of some new technologies like hybrid, fuel cell or electric powertrains (or in case of specific market characteristics, like for instance in the United States, where compression ignition powertrains are not commonly available on light duty vehicles), only a fraction of all models within a given vehicle class are offered with one or more motorisation options that is based on the advanced technologies.

The use of exogenous inputs described earlier is intended to provide a framework for the definition of the feasible alternatives to conventional spark-ignition powertrains powered by a gasoline fuel blend, helping the analyst to define the set of options available to the consumer for its choice (whose selection is then addressed with the multinomial logit approach).

Fuel mix

Each powertrain group can be powered by a number of different fuels. Spark-ignition engines may use a blend of petroleum gasoline and ethanol, for instance. Ethanol may be obtained from several different primary feedstocks, like sugar cane, corn and wooden biomass. Similarly, compression ignition powertrains may be fuelled by petroleum diesel fuel, as well as biodiesel obtained from different feedstocks (like vegetable oil, coal, natural gas or woody biomass) through different conversion processes.

As in the case of powertrain groups, the selection of different fuel shares in ForFITS is going to be estimated on the basis of a discrete choice approach using a multinomial logit model where the options to be selected are represented by different fuel production, transport and distribution pathways.

For fuels, the utility parameter that shall be maximised by the discrete choice approach is the expected amount of savings derived from the selection of one fuel option with respect to the others. Such savings are determined on the basis of the cost of production, transport and distribution of each fuel.

In addition, the multinomial logit model is going to be complemented by exogenous inputs that characterise the availability of the different fuels (linked to the availability of their feedstocks). This is especially relevant for feedstocks (like sugar cane, for instance), whose availability is limited to specific regions of the world (and eventually extended to other regions through trade).

Infrastructure and the estimation of congestion

The previous sections of the model shall be linked to a section that focuses on infrastructure and leads to the estimation of congestion.

The vehicle travel for each vehicle class and powertrain group needs to be allocated to different network types (e.g. urban roads, rural roads, or highways) by exogenous inputs on the percentage of time spent in different network types.

Each network type needs to be characterised with information on its total extension and its average speed. This is going to be linked to the average speed in congested areas, the average speed in free-flow traffic (assumed to be close to 90% of the speed limit on the corresponding network type), the average share of time spent in congested traffic by network type, as well as assumptions and estimates on:

- the portion of time spent in the free flow traffic conditions, which is assumed to be a quadratic function of the share of time spent in congested and traffic: if the share of time spent in congested traffic is χ, the share of time spent in free flow traffic is $(1-\chi)^2$;
- the percentage of time spent in non-congested and non-free flow traffic conditions, assumed to be the complement to 1 of the two others;
- the average speed in non-congested and non-free flow areas (assumed as the average of the two extremes).

The above mentioned information can lead to the estimate of the average share of km of congested traffic in each network type. This is going to be assumed to be proportional to the total vehicle activity per km of network.

Projected congestion level would then depend on the balance between the evolution of the network capacity on one hand, and the total vehicle activity on the other. Reversing the relationships amongst the parameters mentioned earlier, the expected average network speeds would then be determined as a function of the evolution of these two parameters.

One limitation of this approach lies in the assumption that changes in the vehicle activity per km of network affect all network types in the same manner. Ideally, information shall be acquired for each network type. The solution adopted here is a compromise dictated by the limited availability of data (and it is already rather data-intensive, even if some of the data requirements may be simplified by limiting the level of disaggregation of different network types).

Classification of vehicles, fuels and networks: compromising between accuracy and the availability of statistics

The ForFITS model has the capacity to adapt to different levels of data availability (with a likely trade-off in terms of data accuracy) and it is suitable for progressive developments and information disaggregation.

The vehicle and network classification which is actually going to be selected will play an important role in this regard. The idea is to build on results stemming from an overview of statistical data available to identify a good compromise in terms of disaggregation of data amongst different fuels, network types, and vehicle classes, and powertrain groups.

The aim is to select the classification so that all key categories and technological solutions can be adequately represented, without excessive data requirements. This would limit the need to “create” ad hoc statistical information using the (less detailed) data that are actually available.

The key guidance in the determination of the classification that will be adopted in ForFITS is best represented by a good balance between the accuracy requirements on one hand, and the actual data availability on the other.

Time span

The time span covered by the first version of ForFITS is expected to range between 20 and 30 years.

Model improvements

The current model focuses on the assessment of CO_2 emissions, as well as the evaluation of the impact of transport policies for CO_2 mitigation. At this stage, it does not address transport externalities like local pollution and noise, and it does not attempt to evaluate the external costs due to congestion.

In the future, however, it may be extended to include, progressively, the ability to take into account these externalities. The future development of the model, including the classification choices, will be carried out in order to open up new development possibilities that could improve its usefulness for users.

The model outlined for freight transport will require a number of improvements. Two important elements that will need to built on observed relationships are the modal tkm share selection and the estimation of average vehicle loads within each class. The latter is expected to benefit from the analysis of information on the haul length (the longer the haul, the higher the incentive to avoid empty running and low loads) and travel costs.

Other refinements of the model can take advantage of the significant amount of information contained in the ASIF structure. In regards to emission factors, model refinements can use the available information (as well as additional inputs) for the definition of more detailed approaches, such as those used in emission models like the USEPA MOVES or MOBILE models, or the EEA’s COPERT, i.e. models that are targeting mainly the emission of pollutants. The scope of the model built according to this methodology can also be extended to estimate the emissions of local pollutants.

Learning curves may also be fully incorporated into the model. They would be especially relevant to improve the characterisation of vehicle and fuel costs.

Finally, the current structure takes into account powertrain selection on the basis of the expected purchase price of fuel, assuming that it would remain at the same level of the last known value, i.e. the level of the last available (or projected) year. Future developments of the model may refine this approach, possibly offering the option to base powertrain group selection on the basis of the expected fuel price profile in forthcoming years.

Modelling environment

The ForFITS model will be developed using the Vensim software (from Ventana Systems) and modelling environment, based on the ideas of system dynamics.

This choice builds on the following elements:

- the Vensim modelling environment targets specific issues that concern processes evolving over time;
- it allows the development of models that interact with data sheets (including Excel files) for their characterisation;
- it has been developed in a way that allows different functionalities, including the development of models on one hand (requiring to purchase a license) and their use (not requiring the software purchase, but a free software download);
- unlike other tools, it does not require the full- fledged creation of software applications (allowing greater for greater focus on the development of the model for which we have the capacity, eliminating time losses due to the development of interfaces and the communication across different files);
- in the field of energy, climate change and transport policy analysis, it has been used for the development of models like the World Energy Model (laying behind the IEA World Energy Outlook) and the POLES model of the European Commission, proving to be a reliable and solid choice and making its selection as modelling environment strategically sound for the UNECE (partnerships, cooperation, data sharing);
- it has already been used (by IIASA, on a model aimed at analysis of development policies targeting countries like Botswana, Namibia and Mozambique) in a way that allowed the free download and use of the model in a “model reader”, demonstrating effectiveness in this respect.

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