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Concept Development for Quantifying Pollution Reductions through ITS

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Executive summary

The main objective of the work described in this report is the development of a tool to measure the impact of pollution reduction resulted from implementation of ITS measures compared to a base-line reference.

In order to quantify improvements resulted from ITS measure implementation with concern of their impact on the environment, assessment of emission level by appropriate vehicle fleets before and after ITS application is required. Such an assessment is suggested to be carried out based on available emission prediction models suited for different types of vehicle fleets under consideration.

Modern road emission models, such as the ARTEMIS one, make the assessment of ITS environmental impact for the fleets, based on motor vehicles, possible, by using traffic conditions, route parameters and vehicle fleet data as an input. If that vehicle fleet includes significant amounts of electric vehicles, their influence on total vehicle fleet emissions should be assessed by use of appropriate available models, such as the TEVeS one. If the number of electric vehicles in the vehicle fleet under consideration is very low, their influence on pollutants emission will be negligible and may be ignored.

The influence of ITS on vehicle fleet emissions is reflected usually in its effect on vehicle traffic activity, travel mode and demand. The former is mainly influenced by changes in traffic conditions and possibly driving routes as well. Driving cycle and route parameters together with vehicle fleet data are performance indicators that should be known and serve as inputs of the emission prediction models mentioned above. Therefore, their change as a result of ITS effects will be reflected in an appropriate change in vehicle fleet emissions.

A list of main performance indicators is proposed to allow assessment of ITS environmental impacts. This list contains data on vehicle fleet, traffic conditions and driving routes. A total emission indicator and an indicator of greenhouse gas emissions are suggested to be used as a tool for integral assessment of environmental impact resulted from implementation of various ITS solutions.

1 Introduction

Globally, the transport sector was responsible for about 61% of world oil consumption and about 28% of total final energy consumption in 2007 [1]. The significance of transport contribution to air pollution is well acknowledged and discussed worldwide [2]. Modern European cities face numerous challenges associated with the use of urban transportation. Such problems include road congestion, energy expenditure and noise and air pollution. All of those degrade the quality of urban life. These, in turn, by diminishing the attractiveness of living and working at the city center contribute to the development of unsustainable suburbs.

Nevertheless, there is an increasing awareness that technology can contribute to a sustainable development of our cities. This should go through the adoption of a global approach, based on sociological, economical, environmental parameters. This way novel intelligent transport systems (ITS) could be implemented, which would alleviate the above-mentioned problems. It is clear that quantifying required improvements in ITS with concern of their impact on the environment is an important step towards improvement of city quality and its degree of attractiveness.

Sometimes air quality monitoring data are used, in order to assess environmental impacts of various ITS projects. It should be clearly noted that in case of using the measured air pollution data, it is a challenging task to distinguish between the pollution sources (industrial, vehicular, etc). Therefore, assessment of traffic induced urban air pollution, based on measured air quality monitoring data, is not always possible. At the same time, reliable models based on extensive measurements, which are available today (e.g. the ARTEMIS model) allow assessment of vehicle fleet emissions, as function of fleet composition, traffic activity, road data, fuel type etc. Therefore, quantifying ITS' environmental impacts can be done by using the modeling approach.

The main objective of the work described in this report is the development of a tool to measure the impact of pollution reduction resulted from implementation of ITS measures compared to a base-line reference.

The report is structured as follows: Section 2 investigates the assessment of emission level by vehicle fleets based on motor and electric vehicles. Subsection 2.3 tackles the problem of fuel effects on emissions. Section 3 deals with the performance indicators for assessment of ITS environmental impacts. Section 4 presents the methodology that has been developed to define a total emission indicator. Section 5 concludes the report, summarizing the concept developed for quantifying pollution reductions through ITS.

2 Assessment of Energy and Environmental Impacts

In order to quantify improvements resulted from ITS measure implementation with concern of their impact on the environment an assessment of emission levels by appropriate vehicle fleets before and after ITS application is required. Such an assessment is suggested to be carried out with the aid of available emission simulation models suited for different types of vehicle fleets under consideration.

2.1 Vehicle Fleet Based on Motor Vehicles

Direct energy demand (ED) calculation can be carried out to assess transport energy and environmental impacts, including greenhouse gas (GHG) emissions. ED in the road transport sector is calculated, according to Yan & Crooks [3], as a product of several important driving factors as shown by the following expression:

$$ED_y = \sum_{i,j} VP_{i,j,y} FAVDT_{i,j,y} FAFE^{-1}_{i,j,y} \qquad (1)$$

Where:
ED (MJ) - the direct energy demand
y - the calendar year
i - vehicle type
j - fuel type
$VP_{i,j,y}$ - the vehicle population of the fuel type *j* for vehicle type *i* in the year *y*
$FAVDT_{i,j,y}$ (km) - the fleet average annual vehicle distance traveled of the fuel type *j* for vehicle type *i* in the year *y*
$FAFE_{i,j,y}$ (km/MJ) - the fleet average on-road fuel economy of the fuel type *j* for vehicle type *i* in the year *y*. The term "fuel economy" (FE), which is introduced here, means distance in *km* that vehicle can be driven per unit of energy consumed.

$VP_{i,j,y}$ is calculated by the following expression:

$$VP_{i,j,y} = \sum_v VP_{i,j,y,v} = \sum_v (Sales_{i,v} Survival_{i,y-v} FShare_{i,j,v}) \quad (2)$$

Where:
v - The vintage (i.e., the year when a vehicle is put into use)
$VP_{i,j,y,v}$ - the remaining stock in the year *y* for vehicles with fuel type *j*, vehicle type *i* and vintage *v*
$Sales_{i,v}$ - the number of new vehicles added for the vehicle type *i* in the year *v*
$FShare_{i,j,v}$ - the share of fuel type *j* within the Sales for vehicle type *i* in the year *v*
$Survival_{i,y-v}$ - the fraction of vehicles surviving after *y*–*v* years for vehicle type *i*.
For example, the remaining stock of gasoline passenger cars (PC) sold in 2005, in calendar year 2015, will be the Sales of PC in 2005, the share of gasoline vehicles within that sale and the fraction that survive 10 years (2015–2005).

$FAVDT_{i,j,y}$ is calculated by the following expression:

$$FAVDT_{i,j,y} = \sum_v (VP_{i,j,y,v} VDT_{i,j,v}) / VP_{i,j,y} \quad (3)$$

Where $VDT_{i,j,v}$ (km) is the average annual vehicle distance traveled during the lifetime for vehicles with fuel type *j*, vehicle type *i* and vintage *v*.

$FAFE_{i,j,y}$ is calculated by the following expression:

$$FAFE_{i,j,y} = \sum_v (VP_{i,j,y,v} FE_{i,j,v}) / VP_{i,j,y} \quad (4)$$

Where $FE_{i,j,v}$ (km/MJ) is the average on-road fuel economy during the lifetime for vehicles with fuel type *j*, vehicle type *i* and vintage *v*. Vehicle's fuel economy (FE) is usually defined as a vehicle distance traveled per unit of energy (or fuel amount) consumed.

Variety of parameters in (1) – (4) can be borrowed from the corresponding literature. Fuel economy data, for example, can be mainly determined by using available data on fuel economy research, including [4-6]. Vehicle's FE is improved gradually due to technology development and implementation of mandatory FE regulations [7]. It is assumed that FE for those commercial vehicle types using gasoline, diesel, compressed natural gas (CNG) or liquefied petroleum gas (LPG) will have an average annual improvement rate of 0.3% from 2007 to 2030. This rate is set in China [7] to: 0.3% for motorcycles, 1.5% for diesel passenger cars and minivans and 1.3% for gasoline, CNG or LPG fueled passenger cars and minivans during the same period. For other alternative vehicles and fuels FE data are set based on their advantages over conventional gasoline and diesel vehicle as described in [8,9]. The FE for those vehicles using bio-fuel and coal-based fuel is assumed to be the same as that of their substituted fuel during the scenario period. Demand for bio-diesel and coal-derived oil fuels must be estimated according to the government's target and scenario settings. Gasoline and diesel demand are calculated by assuming that all of the gasoline and diesel vehicles used only pure gasoline and diesel and then subtracting the amount substituted by the alternative fuels, respectively.

If the motor vehicle fleet under consideration is a property of any transportation company, average FE data are usually measured and available for single vehicle, selected fleet segments and vehicle fleet as a whole. If a fleet of private passenger cars is considered, the appropriate average data on FE may be gathered, in addition to the available information on fuel economy research, from the publications of National Statistics Office.

The analysis similar to the given above coupled with the others is incorporated in elaborated complex Road Emission Models, for instance, the ARTEMIS (Assessment and Reliability of Transport Emission Models and Inventory Systems) model [*10*]. The models usually contain a Fleet Module that allows the user to setup the necessary fleet composition with an appropriate segmentation for a particular region or country, for one or several years. The ARTEMIS model uses, for example, the following fleet segmentation: first of all, the fleet is divided in various vehicle categories (passenger cars, two- or three-wheeled vehicles, heavy goods vehicles, etc.); each vehicle category is further divided to subcategories subdivided in "segments", which are vehicle groups of equal size and fuel types. These segments are further split into sub-segments according to different emission concepts, etc.

An Emission Factor Module allows the access to the emission factor database and calculates weighted emission factors for particular traffic situations using the user specified fleet composition resulting from the Fleet Module. Finally, Road Emission Models contain an Emission Module that calculates the overall emissions either on an aggregate basis for the particular country or region, or for a specific network. The Emission Module refers to the user specified description of the traffic activity and the emission factors incorporated in the Fleet and Emission Factor Modules, respectively.

2.2 Vehicle Fleet Based on Electric Vehicles

Currently, pure battery electric vehicles (EVs) have significantly higher energy efficiency than conventional gasoline and diesel vehicles do, while hybrid electric vehicle (HEV) technologies can improve fuel efficiency by 15%, 30% and 50% in the form of mild-, full- and plug in-form, respectively. As an essential assumption, the share of the distance traveled in the electricity mode may be set to a potential of 40% for future plug-in capable vehicles. The drawback of the present-day EV designs is a relatively low battery energy capacity and, correspondingly, a low driving range. In [11] the parameters data are presented for simplified classification of electric vehicles - see Table 1. It is very important to evaluate the electric power consumed by the vehicle fleet. This will make possible, in addition to the assessment of EV energy impact, the estimation of their environmental influence. However this information varies from model to model and depends heavily on vehicle driving conditions.

Table 1: Simplified classification for the electric vehicles

Size	Capacity (kWh)	Range (km)	Consumption (kWh/100 km)
Cars			
Small	10	100	10.00
Mid-size	20	130	15.38
Large	35	180	19.44
Light duty vehicles	20	100	20.00

In the occasions, where a vehicle fleet is based on EVs and the vehicle driving behavior at various traffic conditions is known or may be assessed, some available simulation tools (for example, TEVeS model developed by the Technion in the framework of Cybercar, Cybermove and Citymobil EC projects [12,13]) can be used to assess ITS energy and environmental impacts. Brief description of the TEVeS model is given below.

A theoretical model was developed for evaluating the performance of electric vehicles based on the relations between the electrical motor efficiency and load factor $P = P_{mot} / P_{mot.\max}$ (here: P_{mot} – motor power, $P_{mot.\max}$ – maximal motor power), so as between the battery/ies efficiency/ies and depth of discharge (DOD) for driving and regenerative braking (RB) operation modes – Figures 1, 2. These analytical relations have been derived in the previous research work. Their form and set of required input parameters are based on published literature data. Known mechanical equations and expressions for the heat losses in the electrical circuit have been used too. The latter relation involves the load factor as an independent variable and is obtained based on the known electro-dynamic relations. The model does not presuppose using large data files for efficiencies: of the vehicle motor η_{mot}, of the transmission η_{tr}, of the inverter η_i, of the battery η_{bat}, and for driving and RB operational conditions of the engine. The model uses empirical equations for the vehicle motor and battery efficiencies.

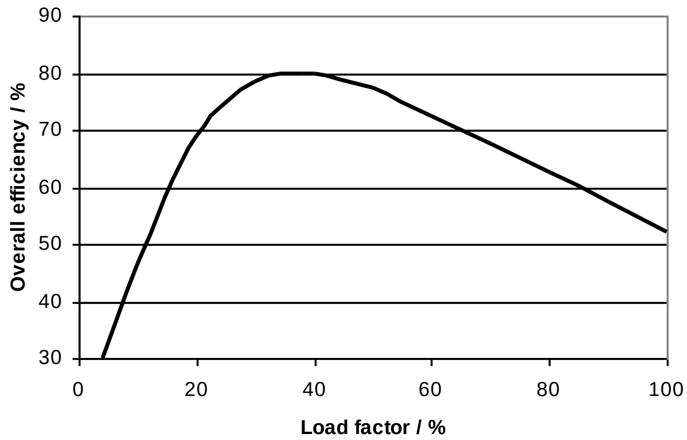

Figure 1: Load factor effect on the overall electrical motor efficiency [14]

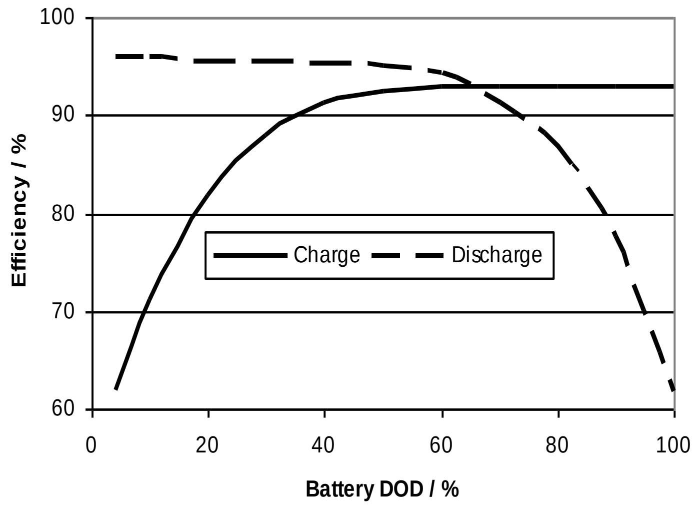

Figure 2: Battery efficiency dependence on the DOD

The following assumptions have been adopted. It is supposed that the motor efficiency dependence on the load factor *P* (for driving and regenerating modes) has a form similar to that shown in Figure 1. This assumption is justified, since in the discussed case the electric motor is only part of the propulsion system and its efficiency does not reflect heat losses (which cause a slope of the $\eta(P)$ curve at high loads). These heat losses occur mainly in batteries. Transmission efficiencies $\eta_{tr.dr}$, $\eta_{tr.reg}$, under driving and RB operation conditions, respectively, and that of the inverter $\eta_{i.dr}$, $\eta_{i.reg}$ – are constant. An effective ohm load resistance is used in the calculations of heat losses in the electrical circuit of the vehicle. The mechanical equations are taken from [15,16]. The approach suggested by Cole [16] was used to account for the effect of the wind direction and speed on the aerodynamic drag coefficient. The vehicle's total efficiency at loads close to a maximal motor power is assumed to be constant (near 0.5). The vehicle's route is divided into segments. On each segment the vehicle's speed and/or acceleration and the road gradient are constant.

This simulation tool was validated by using available measured data on EV energy consumption and used for an assessment of energy and environmental impacts of cybernetic transportation (CTS) and passenger rapid transit (PRT) systems.

On Figure 3 [13] an example of the tool usage for optimization of PRT vehicle parameters is shown. As can be seen, energy consumption of the PRT vehicle can be minimized by a selection of the appropriate maximal electric motor power. The model also allows an assessment of the influence of traffic and road conditions (vehicle average speed, road gradient, etc.) on energy consumption of EVs.

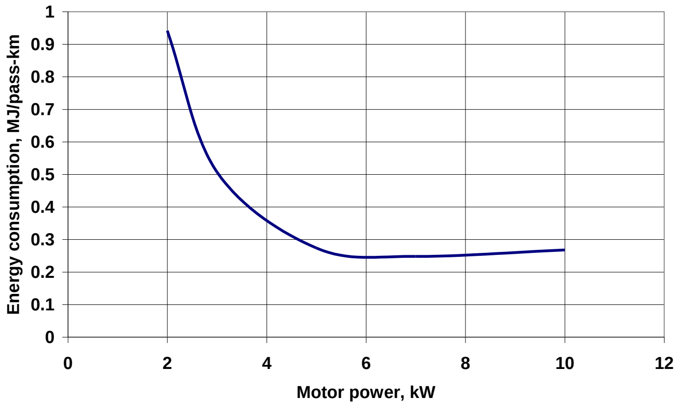

Figure 3: Effects of maximal motor power on energy consumption of the PRT vehicle [13]

Environmental impact of vehicle fleet based on EVs may be assessed by using the following algorithm:

- Derivation of data on total emissions EM_{tot} released in the considered region/country in the process of electricity production;
- Derivation of data on total electrical energy *EE* supply in the considered region/country;

- Calculation of specific emission *SEM* values per unit of electrical energy consumed:

$$SEM = EM_{tot} / EE \quad (5)$$

- Calculation of emissions per pass*km released due to EVs activity:

$$EM_i = E_{sp} * SEM_i \quad (6)$$

Here *i* is a pollutant type, such as CO, NO_x, PM, etc.

2.3 Fuel Effects on Emissions

Scenario analysis on road transport vehicles enables to turn to the analysis on fuels and emissions including the GHG one. The GHG emissions during the vehicle's operation stage are assumed to include CO_2 only (CO_2 is the dominant tailpipe GHG, though it is acknowledged that emissions of other GHG also occur). The GHG emission rate E_{GHG} (g CO_2/MJ) for a certain fuel type may be derived using a carbon balance method, as following. The heating value Q_{HV} for each specific fuel is known and usually measured in MJ/kg. So, the mass of fuel required to produce 1 MJ of energy can be easily calculated. The carbon content by mass C_{mass} for this fuel (%) may be assessed based on the known fuel type. Assuming that all of the carbon introduced with a fuel to the engine is fully oxidized to CO_2 an appropriate GHG emission rate can be calculated as following:

$$E_{GHG} = \frac{1000}{Q_{HV}} * C_{mass} * \frac{M_{CO_2}}{M_C} \quad (7)$$

Here M_{CO_2} = 44 (g/mol) is a molar weight of CO_2 and M_C = 12 (g/mol) is a molar weight of carbon.

The GHG emission rates for each fuel type are listed in Table 2 [1]. For an electric vehicle there are no tailpipe GHG and pollutant emissions when the vehicle is in EV mode, although emissions may be produced during generation of electricity consumed by EVs.

It must be noted, that a speed limit of 80 km/h leads to emission reduction of 5–30% for NO_x and 5–25% for PM10, as was presented in [17]. The limit with "strict enforcement" has been introduced in 2005 in zones of urban motorways in the Netherlands with an aim to reduce air pollution by NO_2 and PM10 along these motorways. Traffic data measured in Rotterdam and Amsterdam at the zones without and with speed management show that traffic dynamics have been significantly reduced as a result of speed management with strict enforcement. Reduction of traffic dynamics results in more free-flowing traffic with relatively less NO_x and PM10 emissions compared to congested traffic, i.e., stop-and-go traffic.

Table 2: Carbon content by weight and GHG emission rate for each fuel type [1]

Fuel type	Heating value	Carbon content by mass	GHG emission rate
	MJ/kg	%	g CO_2/MJ
Gasoline	42.5	84.6	73.2
Diesel	42.7	86.5	74.3
LPG	47.3	82	63.6
CNG	43.0	75	64.0
Bio-ethanol	27.0	52.2	70.9
Bio-diesel	38.0	77.3	74.6
Coal-derived methanol	19.7	37.5	69.8
Coal-derived oil	42.7	86.5	74.3

Requirements for fuel quality and aftertreatment technology, while taking into consideration the reduction of emissions, have become more rigorous with time. For example, sulfur content in diesel fuels has been reduced from 1300 ppm for Euro 1 vehicles to 10 ppm only for Euro 5 modern ones. For an assessment of particular fuel effects on harmful emissions the corresponding regression equations are normally used. The following equations for the emissions calculation depending on fuel parameters were suggested in the ARTEMIS project [18]. The example of equations for assessment of diesel fuel effects on emissions is given hereafter:

$CO = 2.24407 - 0.00111D + 0.00007P - 0.00768C - 0.00087T95$, g/kWh;

$HC = Exp(5.32059 - 0.1875CN + 0.001571CN^2 - 0.0009809T10 - 0.002448T50 - 0.1880CD + 0.003507CN*CD)$, g/kWh;

$NO_X = Exp(0.50628 - 0.002779CD + 0.002922A + 1.3966G - 0.0004023T50)$, g/kWh

$PM = (0.06959 + 0.00006D + 0.00065P - 0.00001C)*[1 - 0.000086(450 - S)]$, g/kWh, Where:

D- density, kg/m^3; G – specific gravity; P – poly-aromatic content, % m;
M – mono-aromatic content, % m; A – total aromatic content, % vol;
C – cetane number; CN – natural cetane number; S – sulfur content, ppm;
CD – cetane difference due to acidizing; OX – oxygen content, % m;
T10 – temperature at which 10% of gasoline is evaporated, C;
T50 – temperature at which 50% of gasoline is evaporated, C;
T95 – temperature at which 95% of gasoline is evaporated, C.

These equations allow an assessment of possible ITS emission reductions by introduction of advanced fuels. The mentioned above ARTEMIS model makes possible an estimation of fuel effects on vehicle emissions by using the mentioned above equations.

3 Performance Indicators for Assessment of ITS Environmental Impacts

3.1 The approach

It is suggested that available transport emission models should be used for quantifying possible air pollution reduction through ITS. The influence of ITS on vehicle fleet emissions is reflected usually in its effect on vehicle traffic activity and demand. The former is mainly influenced by changes in traffic conditions and, may be driving routes, as well.

Traffic conditions can be explained normally by so called typical driving cycle presenting typical speed of a vehicle considered as a function of driving time. The main parameters describing a vehicle’s driving cycle are:

- Average speed
- Maximal speed
- Number of stops
- Maximal acceleration/deceleration

Sometimes detailed data on a vehicle’s traffic activity, especially its driving cycle, are not available. Normally, emission prediction models (e.g. the ARTEMIS one) are built to allow a forecast of pollutant emissions also based on limited available input data, such as vehicle average speed only and traffic general classification (stop-and-go, free flow, etc.), together with detailed data approach. Important parameters of a driving route are its length and topography (road gradients).

If a vehicle fleet includes significant amounts of EVs, their influence on the total vehicle fleet emissions should be assessed by the use of appropriate available models, such as TEVeS model mentioned above. It is clear that EVs have zero tailpipe emissions, but they may affect urban air quality through increase in emissions by electric utilities, due to the growth of electricity production. Sometimes a study about the potential of extensive introduction of electric vehicles and its environmental and energy impact may be requested by cities. If the number of EVs in the vehicle fleet under consideration is very low, their influence on pollutants emission will be negligible and may be ignored.

3.2 Suggested performance indicators

Driving cycle and route parameters together with vehicle fleet data are performance indicators (PI) that should be known and serve as inputs of the emission prediction models mentioned above. Therefore, their change as a result of ITS effects will be reflected in an appropriate change in the vehicle fleet emissions. Of course, an assessment of typical driving cycle (or vehicle average speed) before and after implementation of ITS measures is required. Table 3 presents a list of main PIs that should be available, in order to allow an assessment of ITS environmental impacts.

Table 3: List of main performance indicators

Fleet data
Fleet composition by vehicle category by fuel type
Age distribution for each vehicle category
Traveled distance by age for each vehicle category
Traffic conditions
Traffic volume by time of a day by vehicle category
Number of stops by vehicle category
Average speed by vehicle category
Maximal allowed speed
Average passenger load by vehicle category
Average parking time by vehicle category
Route data
Average gradient
Number of signalized junctions

If the urban vehicle fleet under consideration contains a significant amount of EVs and their influence on emissions can not be ignored, the following PIs should be available to make possible an assessment of EVs environmental impact – Table 4.

Table 4: List of performance indicators for assessment of EVs environmental impact

Vehicle data
Weight
Height and width
Passengers capacity
Battery type
Battery weight
Maximal power of electric motor
Data on electricity production
Total amount of electricity generated
Total emissions due to electricity production

3.3 Availability of data

Normally, the fleet data, as it appears in Table 3, is published by the National Statistics Office. If public or goods transport is taken under consideration, the appropriate fleet data may be available from transport companies and public transport vendors.

Main potential sources of data on traffic conditions are:

- results of field data collection, which is carried out periodically;
- transport demand models;
- positioning systems;
- surveys;
- enforcement cameras

Route data may be provided by:

- results of field data collection;
- positioning systems;
- city traffic control center;
- etc.

Of course, other data sources may be used, as well.

If the environmental impact of EVs is planned to be evaluated, the appropriate vehicle data (Table 4) should be made available by local transportation companies and/or vehicle manufacturers. Normally the data on electricity production, as it appears in Table 4, is published by the National or Regional Statistics Office or/and other responsible Governmental organization.

3.4 Air pollution assessment

If a change in air pollution level at the considered area of interest should be assessed, the appropriate complicate atmospheric dispersion models must be used. Atmospheric dispersion modeling is the mathematical simulation of how air pollutants disperse in the ambient atmosphere. It is performed with computer programs that solve the mathematical equations and algorithms which simulate the pollutant dispersion. The dispersion models are used to estimate or to predict the downwind concentration of air pollutants or toxins emitted from sources such as industrial plants, vehicular traffic or accidental chemical releases [19]. The dispersion models vary depending on the mathematics used to develop the model, but all require the input of data that may include:

- Meteorological conditions such as: wind speed and direction, the amount of atmospheric turbulence, the ambient air temperature, cloud cover, solar radiation etc.
- Source term (the concentration or quantity of toxins in emission or accidental release source term) and temperature of the material
- Emissions or release parameters such as source location and height, type of source (i.e., fire, pool or vent stack) and exit velocity, exit temperature and mass flow rate or release rate.
- Terrain elevations at the source location and at the receptor location(s), such as nearby homes, schools, businesses and hospitals.
- The location, height and width of any obstructions (such as buildings or other structures) in the path of the emitted gaseous plume, surface roughness or the use of a more generic parameter “rural” or “city” terrain.

The atmospheric dispersion models sometimes are called also as atmospheric diffusion models, air dispersion models, air quality models or air pollution dispersion models. There is a wide variety of such models available. Amongst the models that are used for an assessment of air pollution caused by vehicular traffic, the OSPM [20] and AERMOD [21] models may be mentioned.

Air pollution levels in cities are normally measured by various monitoring stations. Such data is available for about 50 European cities participating in the CITEAIR II EC project [22] and many other cities, as well. It should be clearly noted that in case of using the measured air pollution data, it is a challenging task to distinguish between the pollution sources (industrial, vehicular, etc). Therefore, an assessment of traffic induced urban air pollution, based on measured air quality monitoring data, is not always possible.

4 Development of a total emission indicator

The results of emission values produced by a vehicle fleet before or after implementation of ITS measures may be further processed, in order to provide a so called total emission indicator (TEI). The latter can be used as a tool for an integral assessment of environmental impact resulted from implementation of various ITS solutions.

It is suggested to define TEI as a sum of normalized emission values of different pollutants. It can be calculated by using the following formula:

$$TEI = c_{cor}\Sigma(EM_i/TLV_i) \qquad (8)$$

Where:

EM_i - emission value of pollutant *i*, [g/km] or [g/pass*km];

TLV_i –threshold limit value for pollutant *i*, [mg/m^3];

c_{cor} – correction coefficient aimed at providing dimensionless value of TEI.

The values of TLV_i can be taken, for example, from the ACGIH TLVs and BEIs [23]. Some relevant values of TLV_i are presented in Table 5.

Table 5: TLVs for selected pollutants [23]

Pollutant	TLV [mg/m^3]
Nitrogen dioxide NO_2 (for normalization of NO_x emissions)	5.6
Carbon monoxide CO	28.5
Hexane C_6H_{14} (for normalization of HC emissions)	176
Particulates matter PM	0.05

The indicator of GHG emissions EIGHG is proposed to be defined as an absolute difference between CO_2 emissions by a vehicle fleet before and after implementation of ITS measures. It can be calculated by using the following formula:

$$EIGHG = (EM_{CO2})_{before} - (EM_{CO2})_{after} \quad (9)$$

Where:

$(EM_{CO2})_{before}$ – baseline CO_2 emission value before implementation of ITS measures;

$(EM_{CO2})_{after}$ - CO_2 emission value after implementation of ITS measures.

5 Conclusions

It is suggested that available transport emission models should be used for quantifying possible air pollution reduction through ITS. The influence of ITS on vehicle fleet emissions is reflected usually in its effect on vehicle traffic activity and demand. The former is mainly influenced by changes in traffic conditions and, may be driving routes, as well.

A list of main performance indicators is proposed and should be available, in order to allow an assessment of ITS environmental impacts. This list contains data on the vehicle fleet, traffic conditions and driving routes.

Normally the fleet data are published by the National Statistics Office. If public or goods transport is taken under consideration, the appropriate fleet data may be available from transport companies and public transport vendors. Main potential sources of data on traffic conditions and driving routes are: results of field data collection, which is carried out periodically; transport demand models; positioning systems; surveys; enforcement cameras; city traffic control center etc. Other data sources may be used, as well.

Modern road emission models, such as the ARTEMIS one, allow an assessment of ITS environmental impact for the fleets based on motor vehicles by using traffic conditions, route parameters and vehicle fleet data as an input.

If a vehicle fleet includes significant amounts of EVs, their influence on total vehicle fleet emissions should be assessed by the use of appropriate available models, such as the TEVeS one.

If the number of EVs in the vehicle fleet under consideration is very low, their influence on pollutants emission will be negligible and may be ignored.

If a change in air pollution level at the considered area of interest, as a result of ITS implementation, should be assessed, the appropriate complicate atmospheric dispersion models must be used. There is a wide variety of such models available. Between the models that used for assessment of air pollution caused by vehicular traffic, so called OSPM and AERMOD models may be mentioned.

In case of using the measured air pollution data, it is a challenging task to distinguish between the pollution sources (industrial, vehicular, etc). Therefore, an assessment of traffic induced urban air pollution, based on measured air quality monitoring data, is not always possible.

The GHG emission rate (g CO_2/MJ) for a certain fuel type may be derived using a carbon balance method. For electric or hybrid vehicles there are no tailpipe GHG emissions when the vehicle is in EV mode, although GHG emissions may be produced during the generation of electricity consumed by EVs.

For an assessment of fuel effects on harmful emissions the corresponding regression equations are normally used. These equations allow an assessment of possible ITS emission reductions by introducing advanced fuels.

Total emission indicator and indicator of GHG emissions are proposed and can be used as a tool for integral assessment of environmental impact resulted from implementation of various ITS solutions.

References

1. Ou XM, Zhang XL, Chang SY. Scenario analysis on alternative fuel/vehicle for China's future road transport: Life-cycle energy demand and GHG emissions. Energy Policy 2010; 38(8):3943–56.

2. Key World Energy Statistics 2009. Paris: OECD/International Energy Agency (IEA); 2009.

3. Yan XY, Crookes RJ. Reduction potentials of energy demand and GHG emissions in China's road transport sector. Energy Policy 2009; 37:658–68.

4. Barnitt R, Chandler K. New York City transit hybrid and CNG transit buses – final evaluation results. Golden (CO): National Renewable Energy Laboratory (US); 2006. Report No.: NREL/TP-540-40125.

5. Davis SC, Diegel SW. Transportation Energy Data Book. 28th ed. Oak Ridge National Laboratory; 2009.

6. Yan XY, Crookes RJ. Energy demand and emissions from road transportation vehicles in China. Progress in Energy and Combustion Science 2010; 36:651-76.

7. People's Republic of China. General Administration of Quality Supervision, Inspection and Quarantine (AQSIQ). Standardization Administration (SAC). Limits of fuel consumption for light duty commercial vehicles. Beijing: National Standard of the PRC; 2007. Standard No.: GB 1997-2007.

8. China Automotive Energy Research Center. Annual report of China automotive energy research. Beijing: Tsinghua University; 2009.

9. Energy Research Institute. Scenario Research on Low Carbon Development by 2050 in China. Beijing: NDRC; 2009.

10. Boulter P, McCrae I, editors. Assessment and reliability of transport emission models and inventory systems. ARTEMIS Project funded by the European Commission within

the 5th Framework Research Program, DG TREN Contract No. 1999-RD.10429, Deliverable No. 15. Wokingham (Berkshire): Transport Research Laboratory Ltd (UK); 2007 Oct. Final report No.: UPR/IE/044/07.

11. Perujo A, Ciuffo B. The introduction of electric vehicles in the private fleet: Potential impact on the electric supply system and on the environment. A case study for the Province of Milan, Italy. Ispra (VA): European Commission—Joint Research Center, Institute for Environment and Sustainability (Italy); 2010 April.

12. Zvirin Y, Aronov B, Tartakovsky L, Bekhor S, Baibikov V. A tool to choose the energy system and dimension of the vehicle fleet of CTS systems. CYBERMOVE Project "Cybernetic transport systems for the cities of tomorrow" funded by the European Commission within the 5th Framework Research Program, Project EESD EVK4-2001-00050, Deliverable CM D4.2. Haifa (IL): Technion – Israel Institute of Technology; 2004 Dec.

13. Tartakovsky L, Aronov B, Zvirin Y. Evaluation of energy and environmental impacts of automated road transport. CITYMOBIL project "Towards advanced transport for the urban environment" funded by the European Commission within the 6th Framework Research Program, Contract No. N. TIP5-CT-2006-031315, SP 5, WP 5.4. Haifa (IL): Technion – Israel Institute of Technology; 2010 Oct.

14. Nicol BD, Rand DAJ. Power Sources for Electric Vehicles. Amsterdam: Elsevier; 1984.

15. Automotive Handbook. 7th ed. Robert Bosch GmbH. Chichester, West Sussex, England: John Wiley & Sons Ltd; 2007.

16. Cole GH. SIMPLEV: A simple electric vehicle simulation program – version 2.0. Idaho Falls (ID): Idaho National Laboratory; 1993. Report No.: DOE/ID–10293-2.

17. Keuken MP, Jonkers S, Wilmink IR, Wesseling J. Reduced NO_x and PM10 emissions on urban motorways in The Netherlands by 80 km/h speed management. The Science of the Total Environment 2010; 408(12):2517-26.

18. Zvirin Y, Tartakovsky L, Aronov B, Veinblat M, Gutman M. Fuel Effects on Emissions by Heavy Duty Vehicles. ARTEMIS Project funded by the European Commission within the 5th Framework Research Program, DG TREN Contract No. 1999-RD.10429, WP 400. Haifa (IL): Technion – Israel Institute of Technology; 2003.

19. Atmospheric dispersion modeling. Wikipedia – The Free Encyclopedia [Internet]. 2010 [updated 2010 Dec 16; cited 2011 March 7]. Available from: http://en.wikipedia.org/wiki/Atmospheric_dispersion_modeling

20. Wang G, van den Bosch FHM, Kuffer M. Modeling urban traffic air pollution dispersion. In: The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences; XXXVII(B8); 2008; Beijing, China.

21. Cimorelli AJ, Perry SG, Venkatram A, Weil JC, Paine RJ, Wilson RB et al. AERMOD: Description of Model Formulation. Research Triangle Park (NC): United States Environmental Protection Agency (US); 2004 Sept. 85 p. Report No.: EPA-454/R-03-004.

22. CITEAIR II (Common Information to European Air) Project. Co-funded under the European Commission INTERREG IVC Program, 2008 – 2011 [Internet]. 2011 [updated 2011 Jan; cited 2011 March 7]. Available from: http://www.citeair.eu/

23. 2010 Threshold Limit Values and Biological Exposure Indices. Cincinnati, Ohio, United States: American Conference of Governmental Industrial Hygienists; 2010.