ENVIRONMENT-RESPONSIVE TRAFFIC CONTROL

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ABSTRACT

This article describes some fundamentals for an environment-responsive traffic control. It starts with a brief description of the reasons to consider environmental aspects in urban traffic control, focusing on particular matters (PM), and nitrogen oxides (NOx). The current approaches to evaluate the effect of traffic control measures on the roadside pollution concentration are described. Some relevant aspects regarding the physical and chemical characteristics of the pollutants are presented as well as the influencing parameters on urban pollution concentration.

In the next section, a new approach to assess short-term and mid-term effects of traffic control measures is developed. The approach uses high resolution input data of traffic and meteorological parameters in order to consider appropriately the influence of volatile parameters such as traffic flow conditions. A linearized regression model is used to explain measured roadside pollution concentrations and to assess the influence of the different input variables. With the influence of traffic-related input variables, the maximum potential and the typically realizable potential can be estimated.

The article closes with potential investigation areas to improve the developed modelling approach and with recommendations for data collection and processing regarding an integrated environment-responsive traffic control.

Keywords: Traffic signal control; Environmental aspects; Roadside Pollution Modelling

1. INTRODUCTION

After introducing legal thresholds for particulate matter in 2005, people had to face environment-related traffic restrictions and realized more and more one imminent goal conflict in traffic engineering: Accessibility versus environmental impacts. Further goal conflicts come up with the secondary effects of many measures, e.g. by shifting traffic and environmental problems to suburban areas or other parts of the road network.

These goal conflicts gain even more weight, since the implemented measures often implicate harsh restrictions for individual motorized traffic, and therefore, have negative impacts on the efficiency of transport and the corresponding economical processes. Since the measures mostly are of static nature, they are effective also in times when the environmental situation (e.g. due to weather conditions or low traffic volumes) does not require them.

The mentioned developments are indicating clearly, that traffic control should support the needs of mobility as well as the needs of environmental protection by selecting the control measures under consideration of the actual situation of traffic and environment. First implementations, such as in the German town of Hagen (Ludes et al., 2008), show that in many cases dynamic measures can be very advantageous to deal with the mentioned goal conflicts as well as to avoid unnecessary restrictions for the users of the urban road network.

The following contribution focuses on the development of such an environment-responsive traffic control, which dynamically considers the impact of changed traffic parameters on the local roadside pollution concentration. Potential traffic control measures which could be integrated in an environment-responsive traffic control are

- traffic signal control to coordinate traffic and to meter accessing traffic streams,
- access restrictions for certain parts of the network and for certain user groups,
- speed limits to reduce the emissions of certain pollutants and
- dynamic routing to shift traffic from critical parts of the network to less critical parts.

Since there are several categories of measures, several spatial levels on which these measures can be activated, and a lot of factors influencing the impact of these measures, it is vital to have a precise assessment of their effects. Currently applied assessment methods, which mostly involve modelling tools, show an uncertainty in a range much bigger than the reduction potential of many traffic control measures. Very often, one reason for this uncertainty is inaccurate input data. Another reason may be data aggregation levels which do not consider the high volatility of traffic parameters.

In the following, a high-resolution empiric statistical approach for assessing the short-term (minutes) and mid-term (hours) effects of traffic signal control on the emission concentration of particulate matter and nitrogen oxides is presented.

At first, a brief overview of currently applied assessment methods (which of course can be also applied for the assessment of other traffic measures) is given. Then, the examined pollutants and their important characteristics, which should be considered for short-term and mid-term assessment, are discussed. An overview of the main influencing parameters and the state of research regarding their impact is given. Based on this background, the development and the application of the modelling approach is described. Finally, in the conclusions, the further potential of the model in the context of an environment-responsive traffic control is discussed, and further research needs are addressed.

2. METHODS TO ASSESS THE EFFECT OF MEASURES ON PARTICULATE MATTER AND NITROGEN OXIDES

Pollution concentration is being influenced by several factors (traffic emissions, meteorology, etc.). To predict the effectiveness of traffic related measures, even to assess them, models are required. There are three different approaches to this topic, which are shown in Figure 1.

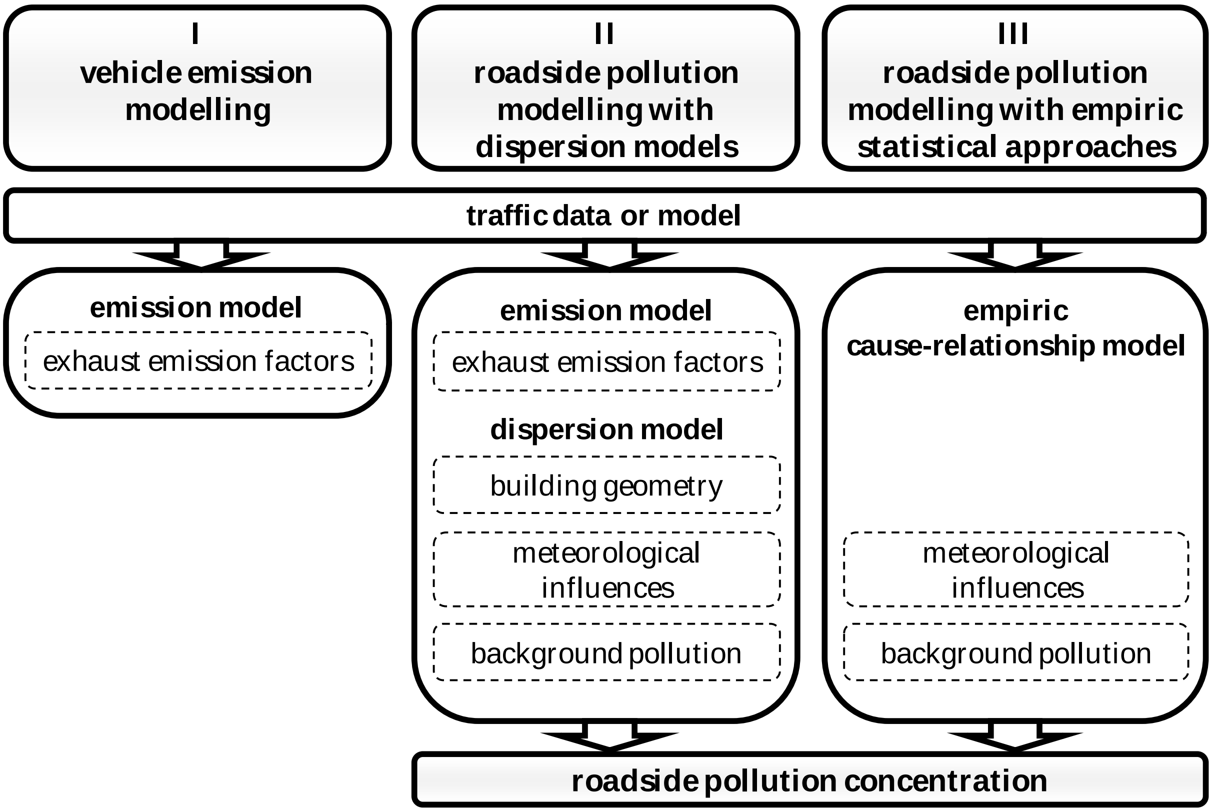

Figure 1 – Common methods to evaluate the effect of measures on air quality

The first approach "Vehicle Emission Modelling" gives an isolated view on the influence of traffic parameters. Yet it is not directly relevant for the discussed topic since it is the roadside pollution concentration that is in the focus of regulated thresholds.

The second approach "Roadside Pollution Modelling with Dispersion Models" currently dominates the evaluation of measures in Germany and Austria. Usually, screening tools or microscale dispersion models are used to assess the impact of different influencing factors on pollution concentration. While screening tools are used for a rough assessment of typical situations, microscale dispersion tools try to model the dispersion of different emission sources under the exact consideration of building geometry, atmospheric stability, and vehicle induced turbulences. The applied models in the different products are box models, Gaussian plume or puff models, Langrangian and Eulerian models, as well as models from computational fluid dynamics. Despite the high required efforts for the inclusion of building geometry and other parameters, there is still a remarkable uncertainty in the results (e.g.

Bächlin et al.; 2003, Diegmann et al., 2009) which is a multiple of the expected reduction potential of certain traffic control measures[1].

The third approach "Roadside Pollution Modelling with Empiric Statistical Approaches" uses gathered time series of all kinds of influencing parameters as explaining variables in a statistical model. This model may reach high prediction quality, but of course spatial transfer of the model is not ensured. Research in this field has been done e.g. by Shi and Harrison (1997), who used an autoregressive quasi-linear model to estimate NO_X-concentrations in London and achieved a high coefficient of determination (R^2=0.92). Aldrin and Haff (2005) used generalized additive models to explain urban pollution concentrations, and achieved a good fit, as well (R^2 up to 0.80 for NO_X). Hrust et al. (2009) used neural networks as a tool for data analysis, and they achieved a coefficient of determination of 0.87 for NO_X.

Yet, none of the investigated approaches uses data with a higher time resolution than one hour. Since traffic signal control nowadays tries to assess the current traffic state in a time resolution of about five minutes (Friedrich, 2009), it seems that some very volatile traffic parameters (such as number of stops or cue length) as well as their influence on pollution concentration are not considered appropriately.

3. CHARACTERISTICS OF THE EXAMINED POLLUTANTS

In order to assess the short-term and mid-term potential of traffic control measures to reduce pollution, it is important to have a closer look at some characteristics of the regulated parameter "PM_{10} mass concentration" and at the chemical properties of nitrogen oxides.

3.1. Particulate Matter

Particulate matter (PM) is usually distinguished by size because size determines the effect on health as well as on processes of coagulation, deposition, and sedimentation. The following fractions are commonly used:

- TSP (totally suspended particles) with an aerodynamic diameter of less than 57 micrometer,
- PM_{10} with an aerodynamic diameter of less than 10 micrometer,
- $PM_{2,5}$ with an aerodynamic diameter of less than 2,5 micrometer,
- PM_1 with an aerodynamic diameter of less than 1 micrometer and
- UFP (ultrafine particles) with an aerodynamic diameter of less than 0,1 micrometer.

[1] E.g. investigations of Hirschmann and Fellendorf (2009) show a reduction potential of 11% for NO_X and of 14% for engine related PM_{10} emissions with an optimized signalization.

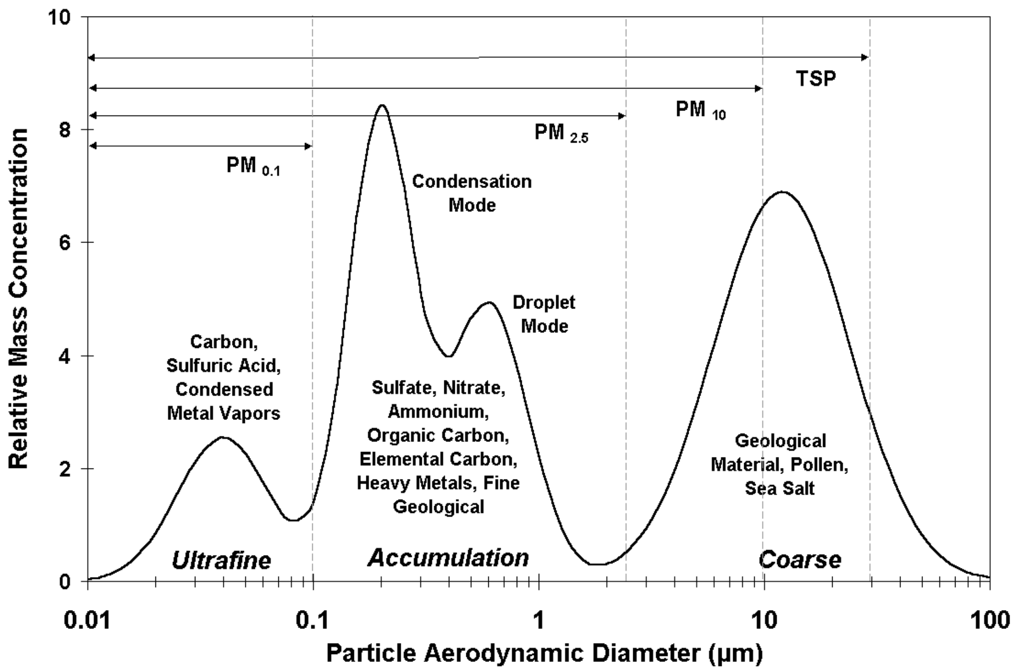

Figure 2 – Particle size - mass fraction diagram for particulate matter in urban air (Central Pollution Control Board, 2005)

While the primary engine exhaust emissions usually are allocated to the ultrafine particles, road dust resuspension is contained in the fraction bigger than $PM_{2,5}$ and smaller than PM_{10}. As Figure 2 indicates, the UFP-fraction is of minor share in the PM_{10} mass concentration. Actual source apportionment studies state a share of traffic emissions of about 20 % related to the whole PM_{10} emissions (Umweltbundesamt, 2009), of which at least 50 % are road dust resuspension (Diegmann, 2009).

The fraction from 0,1 µm to 2,5 µm contains mostly secondary particles which are derived from the oxidation of primary gases, such as sulphur and nitrogen oxides. Because of its long dwell time in atmosphere, this fraction has only minor relevance for short-term and mid-term measures.

Regarding the above-mentioned facts, it seems questionable, if short-term and mid-term effects of traffic control measures, which do not include harsh access restrictions, can be measured at all in the PM_{10} mass-concentration.

3.2. Nitrogen oxides

Only small amounts of nitrogen dioxide are emitted directly. Mostly, it is nitrogen monoxide which is emitted during combustion processes and then reacts with oxygen to nitrogen dioxide. If ozone is present, it may react with nitrogen monoxide to nitrogen dioxide, as well. The third way of NO_2 formation is the reaction between nitrogen monoxide and peroxide radicals under the influence of solar radiation. On the other hand, solar radiation can also initiate the decomposition of nitrogen dioxide to nitrogen monoxide and ozone.

Regarding these formation and decomposition reactions, it seems suitable to use NO_X as the sum of nitrogen monoxide and nitrogen dioxide as an indicator for the short-term effects of traffic control measures. Conclusions on the NO_2-effects can be drawn according to FGSV (2005), by applying an NO_X/NO_2-regression.

4. INFLUENCING FACTORS ON POLLUTION CONCENTRATION

Generally, the following influencing factors on pollution concentrations have to be considered when assessing the effects of measures:

- building density and longitudinal grade, road condition and surface type,
- vehicle type, engine type (petrol or diesel), and vehicle emission class,
- vehicle speed and traffic flow condition,
- wind speed and wind direction,
- humidity and rainfall,
- temperature,
- air pressure and atmospheric layering,
- solar radiation and ozone concentration.

In the context of the applied statistical approach, it seems feasible to neglect static parameters such as building density, longitudinal grade, road condition, and surface type. Furtheron, there is currently no possibility for an online detection of the vehicle emission class, and therefore, this parameter has to be neglected, as well. Regarding the remaining parameters, extensive research has already been done to assess their influence.

The influence of the *vehicle type* can be (roughly) assessed by using the Handbook for Emission Factors (Keller et al., 2004), at least for the exhaust emissions. The non-exhaust (particle) emissions have been investigated by Düring et al. (2004) and further works of this research team. Yet, the researchers make clear that there is still a lot of research to be done in this field. Currently, the non-exhaust emissions are considered in a very general way, depending on road surface condition (good/bad) and vehicle type (light vehicle/heavy vehicle).

For *vehicle speed* and *traffic flow* a lot of research has been conducted. But since in urban road networks both parameters are closely connected, it seems difficult to draw clear conclusions. The general tendencies which can be deduced from literature research are: Increased speed generates higher (exhaust and non-exhaust) emissions. Smooth traffic flow (less stops) generates fewer emissions with speed being less important than smoothness of traffic flow (bast, 2008). The optimization of parameters which are closely connected to the number of acceleration and deceleration processes, like number of stops or cue length, will probably bring higher emission reduction then the optimization of waiting time (Galatioto and Zito 2007, Unal et al. 2003).

Regarding *wind speed*, it is quite clear that increased wind speed leads to decreased pollution concentration. Wind speed often is calculated as a reciprocal value (FGSV, 2007). Nonetheless, increase of wind speed in steady wind conditions may lead to an increase of non-exhaust particle emissions (Baum, 2008). The *wind direction* has high influence on the regional transport of pollutants, and therefore, it is a dominating factor for the background pollution. At roadside measurements the wind shifts vehicle emissions towards the measurement device or away from it. Windward and leeward measurements are often conducted in parallel for this reason.

While *humidity* shows only minor effect on PM_{10}- and NO_X-concentrations (Schulze, 2002), *rainfall* reduces PM_{10}-concentration significantly during the next 3 to 5 days (Klingner et al., 2006). Probably, the reason for this effect is the reduced dust load of the road surface.

Temperature seems to have no direct influence on PM_{10}- and NO_X-concentrations. Yet, its effect is significant. During winter, low temperature leads to increased household heating and increased winter gritting, and with this to higher PM_{10}-concentrations. During summer, a positive correlation between PM_{10}-concentrations and temperature occurs. This may be an indirect effect, as well, because of changed air convection (bast, 2008).

Air pressure influences the pollution concentration mainly indirectly via its influence on *atmospheric layering*. Low atmospheric layers lead to high pollution concentrations because of reduced air convection. Klingner and Sähn (2005) show a negative linear relationship between mixing layer height and PM_{10}-concentrations.

As already explained above, *solar radiation* and *ozone* have high influence on the chemical reactions of nitrogen oxides. Therefore, the nitrogen dioxide concentration depends on the availability of the potential reactants. E.g., Kurtenbach et al. (2008) have done some research on this subject.

5. ASSESSING THE SHORT-TERM AND MID-TERM EFFECTS OF TRAFFIC CONTROL MEASURES

5.1. Methodology and results

In the following, the developed method to assess the short-term and mid-term effects of traffic control measures is described. Some sub-chapters of the methodical approach contain also results from one field measurement campaign.

General approach

The basic idea of the developed assessment methodology is to use high resolution input data of traffic parameters and meteorological parameters in order to consider appropriately the influence of volatile parameters such as traffic flow conditions. Thereby, a higher modelling power should be achieved, compared to conventional aggregation levels. Furthermore, the model should use easy-to-interpret traffic parameters instead of emission factors which are derived from abstract traffic situations and often considered as a main source of errors in dispersion modelling (Richter and Schmidt, 2006).

For the further investigations, the following hypothesis is put forward:

While the *daily cycle* of the roadside pollution concentration depends
on the daily cycle of meteorological, chemical, and urban traffic processes,
the *short-term-variance* of the pollution concentration
is dominated by the influence of volatile traffic parameters.

Therefore, a two-way approach seems suitable (visualized by Figure 3):

1. Developing an explanatory model for the *daily cycle* of the roadside pollution concentration, that is comparable to the described state-of-art approaches.
2. Developing an explanatory model for the *short-term variance* of the roadside pollution.

In the following, the investigations of the daily cycle are tagged with the term *"low-frequent"* while the investigations of the short-term variance are tagged with the term *"high-frequent"*.

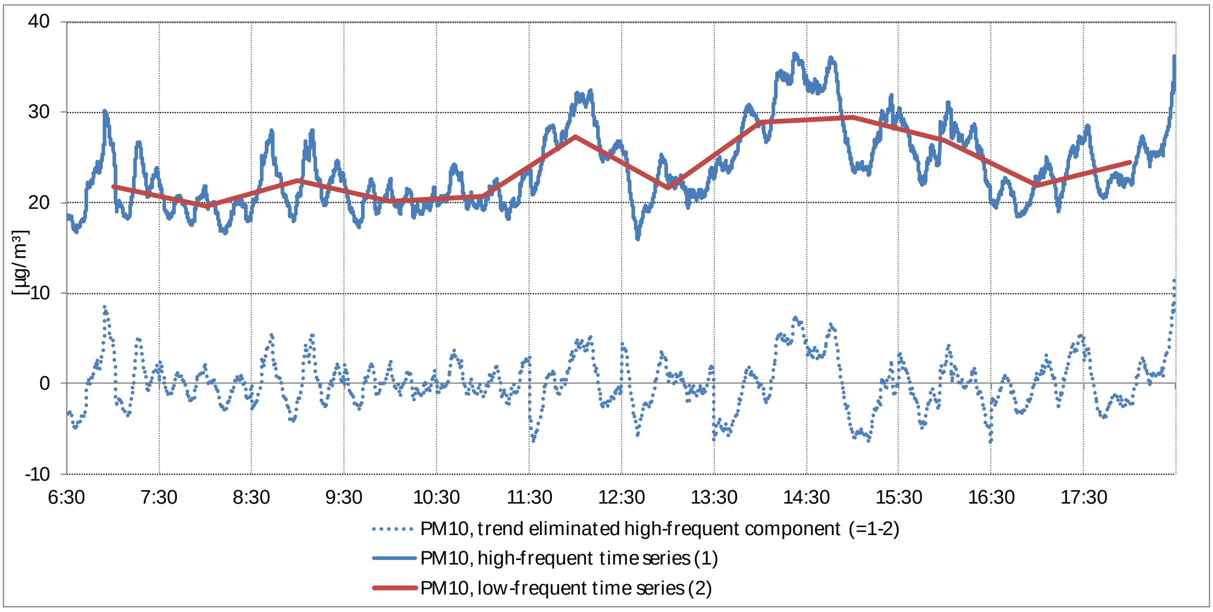

Figure 3 – Exemplary PM_{10} low-frequent time series (as aggregated 1 h average values), corresponding high-frequent 7.5 min time series and trend-eliminated high-frequent time series.

The first approach should provide a good fit for the low frequent pollution concentration at the measurement site and should include the main influencing factors as explained above. It should be comparable to other approaches as described in the second chapter, as well.

The second approach should describe the high-frequent variations in traffic parameters on the roadside pollution concentration.

For both approaches the following five steps are applied:

1. Data collection
2. Data validation and data processing
3. Hypothesis testing
4. Identification of the relevant influencing parameters and quantification of their influence
5. Quantifying the reduction potential of traffic control measures

1. Data collection

Field measurements which are presented in this contribution were conducted in the City of Hamburg (Germany). The measurement site was in a street canyon, about 60 meters in front of the stop line of a signalized intersection, and about 200 meters away from one PM_{10} and NO_2 hotspot. The measurements have been conducted for two weeks during working days, from 6:30 am to 6:30 pm.

PM mass concentration has been measured with optical particle counters (type “Grimm Environmental Dust Monitor 107”). NO_X mass concentration has been measured with chemoluminescence method (type “Horiba NO_X Monitor APNA370”). Local meteorological data has been collected by the outdoor housing for the Grimm measurement device with connected meteorological sensors for humidity, air pressure, temperature, wind speed, and wind direction. Traffic data has been collected manually. All these local measurements were conducted with a time resolution of five seconds. Furthermore, existing on-site measurement devices for local and regional meteorological and pollution parameters have been included.

The following list shows the collected and deduced data.

Pollution parameters

- NO_X
- NO_2
- PM_{10}
- $PM_{2,5}$
- $PM_{10-2,5}$
- O_3

Meteorological parameters

- wind speed & direction
- temperature
- humidity
- air pressure
- solar radiation
- water vapour ratio

Traffic parameters

- traffic volume
- heavy vehicle share
- starting cars
- passing through cars

(all traffic parameters have been differentiated by six different vehicle types and by lanes)

2. Data validation and data processing

In the phase of data validation the collected data has been checked for several criteria such as missing data, systematic errors in the data, and outliers.

After data validation, some data processing had to be done in order to prepare the data analysis:

- According to the chosen model (as described in step 4), the input variables have been log-transformed.
- Several data aggregation levels were calculated:
    - Aggregation to hourly values for the low-frequent daily cycle
    - Aggregation to the smallest common multiple of the different cycle times that were used in the different signal programs (about 10 min. average values)
    - Aggregation to the current cycle time that was used in the current signal program (60 s, 75 s, 90 s).
    - Aggregation to 5 s time resolution.
- According to the described hypothesis and the two-way approach, the input variables have been trend-eliminated by subtracting the low-frequent daily cycle from the high-frequent data (Figure 3).

3. Hypothesis testing

At first, a fundamental test should show if the formulated hypothesis can be sustained. This test should show coherence between the trend-eliminated (high-frequent) traffic data and the trend-eliminated (high-frequent) pollution data. While standard regression analysis procedures need independent and normally distributed data for full explanatory power (not fulfilled by the raw data), frequency analysis seems to be the better method. By transforming the different variables from time view to spectral view (using Fourier analysis), it is possible to check for corresponding periodicities in environmental and in traffic time series. The Fourier transformation produces a spectrum from which the original function can be reconstructed by an inverse transformation, which means that no information is discarded during transformation. Similar work has been done by Tchepel and Borrego (2009), but with lower resolution in time and space.

Figure 4 shows the trend-eliminated NO_X variable for one morning 7:00 am to 12:30 pm as a time series (upper diagram), and the results of a cross-correlation analysis between NO_X and traffic volume in a spectral view (lower diagram).

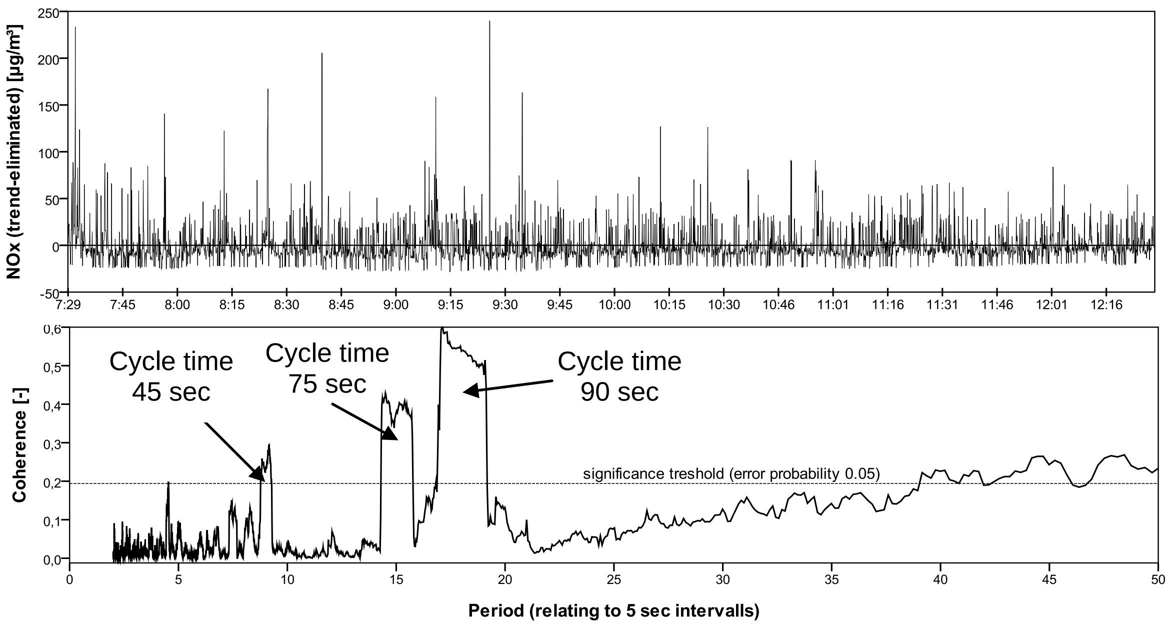

Figure 4 – Physically measured high-frequent NO_X component from 7:30 am to 12:30 pm, on June 4th, 2008 in the City of Hamburg. The upper diagram shows the time series, the lower diagram shows the coherence (the spectral coefficient of determination) between NO_X and traffic volume in spectral view.

While the upper diagram is dominated by noise and makes a visual analysis impossible, the lower diagram shows significant correlation for the cycle time which was activated between 7:30 am and 10:00 am and with this, during the peak hour. A smaller correlation is visible for the period of 75 s, which was the cycle time activated between 10:00 am and 12:30 pm. Another small correlation peak is also visible for the period of 45 s, which corresponds to the cycle length at a pedestrian traffic light which is demand-activated and is located some 100 meters in front of the intersection.

4. Identification of relevant influencing parameters and quantification of their influence

An extensive correlation analysis is done in order to identify significant influencing factors on roadside pollution concentration. A regression model is used to quantify the influence of the identified influencing factors. Linear Regression seems appropriate because of its easy handling and its high transparency. Advanced approaches, such as neural networks, can be applied in further steps. The regression model used was already applied by Shi and Harrison (1997). It contains an autoregressive component in order to solve the problem of autocorrelation, which may lead to inefficient ordinary least squares (OLS) coefficient estimates. The regression model is described in equations 1 to 4.

$$C_{Poll,t} = F(X_1, \dots, X_k) = e^{B1} X_2^{B2} \dots X_k^{Bk} \qquad (1)$$

For a linear regression the formula can be converted as follows:

$$\ln(C_{Poll,t}) = B_1 + B_2 \ln(X_2) + \cdots + B_k \ln(X_k) \qquad (2)$$

with

$C_{poll,t}$:	Pollution concentration at time t
B:	Regression coefficient
X:	Influencing factor

An autoregressive process of first order (C at time t depends strongly on C at time t-1), can be considered as follows:

$$\ln(C_t) = \beta_1 + \beta_2 \ln(X_{2,t}) + \cdots + \beta_k \ln(X_{k,t}) + \beta_{k+1} Lag1_t + e_j \qquad (3)$$

with

$$\mathrm{Lag1_t} = \ln(C_{t-1}) - B_1 - \sum_{i=2}^{k} B_i \ln(X_{i,t-1}) \qquad (4)$$

β_k:	Adjusted regression coefficient
e_j:	Independent residual
$\mathrm{Lag1_t}$:	Autoregressive component (residual at time t-1)

The identified influencing factors were used as input variables for the regression when they increased the fit of the regression model. Influencing factors were discarded from the model when they were strongly correlated to other influencing factors (e.g. temperature and humidity) in order to eliminate collinearity and suppression effects.

As explained, the low-frequent concentration (the daily cycle) of the pollutants and its high-frequent component were modeled separately. The following list shows influencing factors which were used as input variables and the direction of their influence.

NO_X low-frequent (daily cycle)

- wind speed (-)
- temperature (-)
- air pressure (-)
- global radiation(+)
- ozone (-)
- HGV volume (+)
- number of starting cars (+)

PM_{10} low-frequent (daily cycle)

- wind speed (-)
- air pressure (-)
- PM_{10} background (+)
- number of passing through cars (+)

NO_X high-frequent component

- wind speed (-)
- HGV volume (+)
- number of starting cars (+)

PM_{10} high-frequent component

- wind speed (-)
- HGV volume (+)
- number of passing through cars (+)

The regression model was applied to the measured data. The quality of the model is being scrutinized by several criteria from which some are shown in Table 1 for each model and each measuring week. Figure 5 shows the time series of the observed and the modeled NO_X pollution concentration.

Table 1 – model quality criteria for the different regression models

Regression parameter	Week	NO_X low-frequent (daily cycle)	PM_{10} low-frequent (daily cycle)	NO_X high-frequent component	PM_{10} high-frequent component
coefficient of determination R^2	1	0.82	0.79	0.40	0.28
	2	0.81	0.70	0.34	0.51
rel. std. error[2]	1	12 %	9 %	37 %	44 %
	2	21 %	13 %	41 %	14 %
Durbin Watson	1	1.90	2.10	2.07	2.03
	2	1.86	1.89	2.09	2.20

The coefficient of determination reaches a good fit for the low-frequent models. The standard error is between 9 % and 21 %, related to the average measured concentration level which seems satisfying. The Durbin Watson value around 2.0 indicates that the residuals are not autocorrelated which means that the ordinary least square estimation *is* efficient. For the NO_X-model, slight collinearity effects occur for wind speed and the traffic parameters. Since these are no causal relationships, the parameters are used, nevertheless. The residuals are normally distributed. The signs of the coefficients seem plausible according to the described influences. The visual analysis shows a good match between the observed and modeled time series.

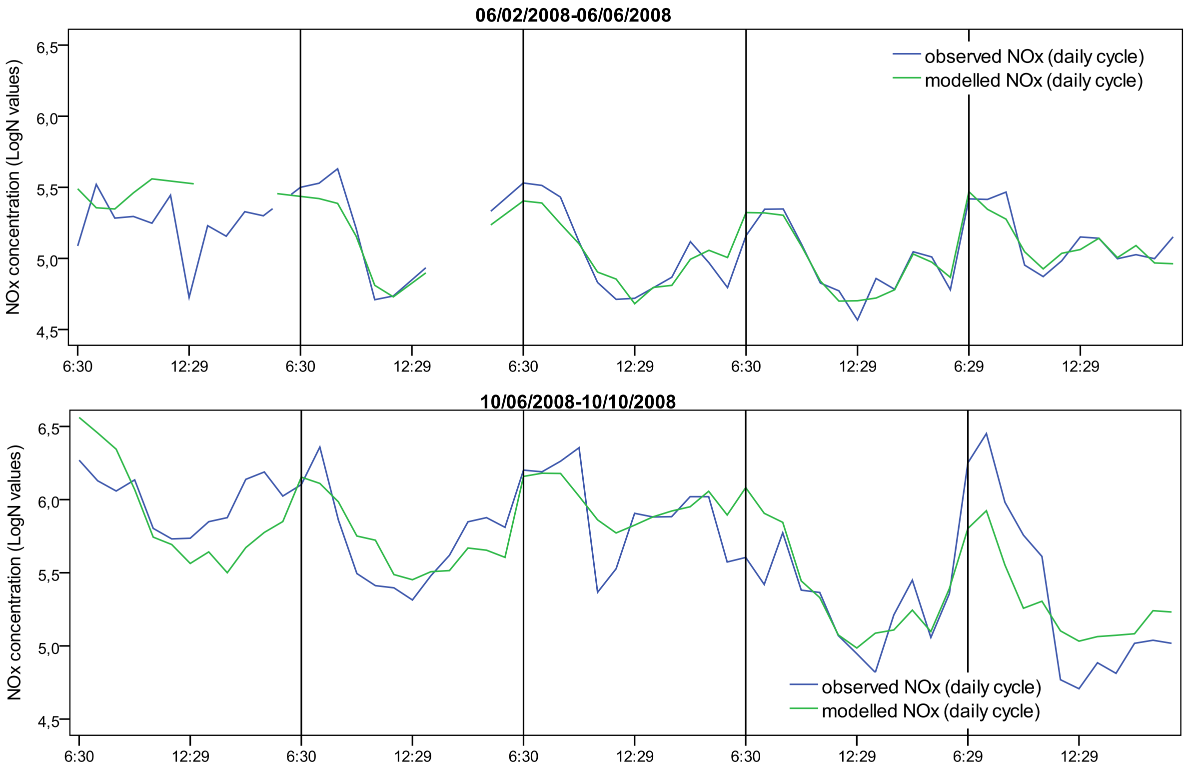

Figure 5 – Regression of the low-frequent NO_X-concentration (daily cycle): modelled time series vs. observed time series

[2] The relative standard error related to the average measured concentration during each week for the low-frequent models and related to the doubled standard deviation of trend-eliminated high frequent models.

Regarding the high-frequent component, about 30 % to 50 % of the NO_X-variance can be explained with only three input parameters. The various residual checks indicate no weakness in the explaining power of the models, and collinearity does not occur. The (subjective) visual analysis (figure 6) shows, at least for NO_X, a good match between the observed and modeled time series. Nearly all peaks are corresponding; only the amplitude seems to be underestimated by the model. This of course leads to the quite high error as displayed in Table 1. A nonlinear approach might improve the results.

Regarding the high-frequent *PM_{10}-model*, the visual analysis (not displayed) shows that the *model has only minor quality*. Many Peaks in the observed time series are not reproduced by the model and the explaining input variables often are only significant in one of the two measurement weeks. Yet it has to be mentioned that the counted passing through cars explain more of the PM_{10}-variance than the starting cars, probably due to dust resuspension. The PM_{10}-modelling results support the assumption which was stated at the beginning of this contribution, that the impact of traffic control measures on the particle number concentration is probably much higher than on particle mass concentration.

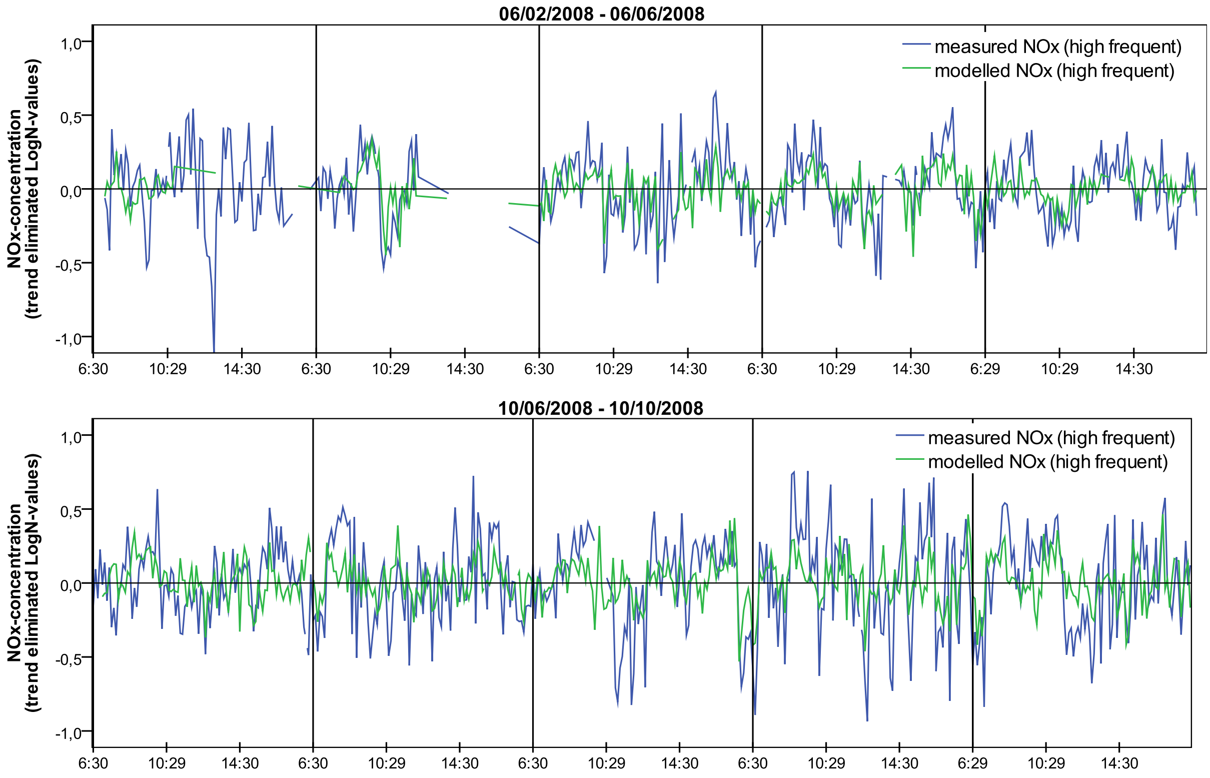

Figure 6 – Regression of the high-frequent NO_X-component: modelled time series vs. measured time series

5. Quantifying the reduction potential of traffic signal control

With the regression model, the influence of the different input variables can be estimated.

The practically achieved reduction due to traffic control measures can be assessed by measuring or by modelling (using micro-simulation) the relevant traffic parameters. These optimized traffic parameters can be used as input values for the regression model, and the environmental impact for the investigated hotspot can be estimated (of course, only if the optimized traffic parameters have significant weight in the model). Regarding traffic signal control, these measures can include the metering of accessing traffic (reduced traffic volume) and/or an improved coordination at the hotspot (reduced number of stops).

Due to space restrictions, the following text only describes the estimation of the maximum potential of traffic signal control measures. The maximum potential is estimated by using the 5% percentile values of measured traffic volume and the number of stops as input variables for the regression model while all other input variables are fed with average values. The modelled logarithmic value is then retransformed to absolute pollution concentrations, and the difference to the average measured value shows the maximum potential for the current measurement site. Figure 7 shows the environmental effect of the minimized number of stops and the minimized traffic volume in relation to the average measured pollution concentration for the low-frequent model (in the chart labeled as “mid-term potential”) and for the high-frequent model (in the chart labeled as “short-term potential”).

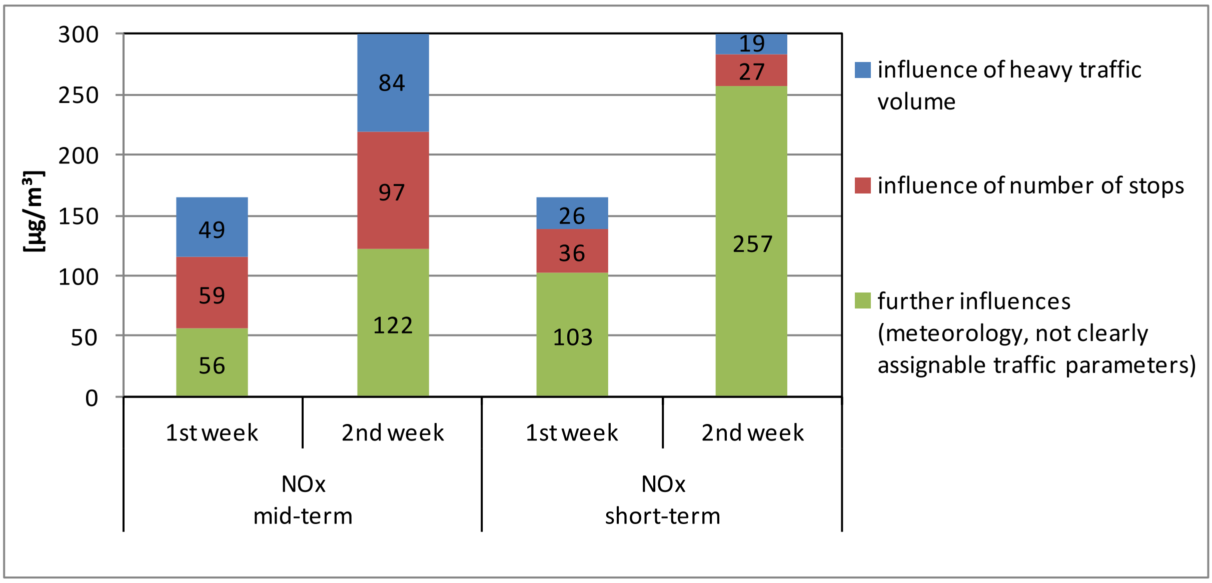

Figure 7 – Maximum NO_X reduction potential for the investigated location by minimizing heavy traffic volume and number of stops, related to the measured average pollution concentration, differed by the mid-term potential and the short-term potential.

For NO_X, the model shows a plausible share for the weight of the traffic parameters. Although the meteorological conditions were very different in the two measurement periods so that considerably higher pollution concentration occurred in the second measurement week, the modelled share of the traffic parameters shows a similar dimension for both weeks. Since the measured traffic parameters indicate nearly identical traffic situations in both weeks, this seems plausible, as well.

For PM_{10} (not displayed), the model shows only small influence of the traffic parameters. According to the mentioned source apportionment studies, this may be plausible. Yet, further investigations regarding time lag (see next sub-chapter), particle number concentration and the possibility that a better traffic signal coordination (fewer stops and more passing through cars) leads to higher road dust resuspension, will be conducted by the authors.

Limitations

First, with only 10 days of field measurement it is not possible to develop a fully valid and sound pollution concentration model, since seasonal changes in influencing factors cannot be considered at all, and pseudo-correlations cannot be identified for sure. Second, the particle model shows no significant influence of the measured traffic parameters. As already mentioned, the characteristics of traffic-related particle emissions indicate that there is a significant time lag between the emission and the perceptibility in the particle mass concentration. Of course, this effect can be investigated and quantified by using lagged variables, but for this investigation, time series without gaps are needed. Since the field measurements took place from 6:30 am to 6:30 pm, this requirement is not fulfilled.

6. CONCLUSIONS

The investigations conducted in this research clearly indicate that a strong consideration of environmental impacts in traffic control is useful and necessary. Regarding NO_X, the reduction potential by smoothening traffic flow and reducing the number of stops ranges above 10 %, which could be a significant contribution to stay within given limits of pollution. Regarding PM_{10}, the (short-term) potential seems to be small, but further investigations are needed, also to learn more about the effectiveness of already applied measures.

On the one hand, this study clearly motivates to apply the established principles of improving traffic signal control by proper signal program design, e.g. minimizing the number of stops by signal coordination (green waves). The need to reduce pollution should also motivate investments to allow a modern and efficient traffic signal control. Appropriate strategies should be developed on how to deal with existing goal conflicts (e.g. environmental protection vs. accessibility; public transport priority vs. reduction of pollution from other vehicle traffic).

On the other hand, the investigations clearly confirmed that environmental pollution with NO_X and PM is not constant in nature, but highly dynamic and dependent on several influencing factors. Therefore, traffic restrictions with mostly static nature generally seem not to be the best solution. In many cases of applied traffic restrictions, such as limitations of the road network for heavy vehicles, major disadvantages are caused permanently (less efficient use of the road infrastructure, additional transport costs due to deviations, less attractive locations due to worse accessibility) while the advantages of reducing the pollution level are only relevant in short time periods (e.g. unfortunate meteorological conditions, high back-ground pollution level). We must also reflect that the pollution level may differ significantly between different locations in one area. Consequently, for the future, there is a need to develop dynamic signal control strategies which consider not only the current traffic situation but also the actual environmental situation, and which allow a network-wide optimization. This leads to several further research and development needs.

Regarding the knowledge about the actual environmental situation, more comprehensive and precise information on the relevant environmental parameters is needed. Hotspot measurements only will not be sufficient, but the pollution level must be mapped throughout the road network. To gain such information, economical considerations will probably lead to a combination of roadside measurements and modelling. The relevant measured values and the required measuring quality have to be specified. The measurement technologies have to be improved significantly regarding their accuracy and costs, and they should provide more dynamic data to fulfil the need of dynamic traffic control. Regarding the modelling, major developments are needed to integrate environmental models and traffic models.

To develop appropriate measures and signal control strategies, further fundamental research of the cause-effect-relationship between the various influencing factors and the exposition to pollutants and also to noise is needed. The potentials of traffic-related measures to improve the exposition have to be quantified, and the sensitivity of the impacts to the influencing factors must be investigated in detail. This includes careful considerations on which measures strengthen each other, which measures suppress each other, or show overlapping effects. A consequent validation of the appropriateness of measures must include an assessment of the negative impacts on accessibility and economical processes. Fundamental recommendations on the handling of goal conflicts have to be developed. Based on these findings, detailed algorithms for dynamic, environment-responsive traffic control can be developed and implemented.

Finally we can state that the development of an environment-responsive traffic control has just begun. An intensive teamwork between experts in traffic engineering, in environmental aspects, and in software engineering will help to master the challenge of fulfilling mobility needs and protecting our environment at the same time.

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