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Horizon 2020

Societal Challenge: Improving the air quality and reducing the carbon footprint of European cities

Project: 690105 – ICARUS

Full project title:

Integrated Climate forcing and Air pollution Reduction in Urban Systems

MS8: Methodology for using source apportionment for estimating concentrations caused by emission changes

WP3: Integrated emission modelling at the regional and urban scales

Lead beneficiary: USTUTT

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Executive summary

Aim: An approach was developed to identify sources of air pollutants by evaluating PM and PAH measurements in the ambient air at three different types of measurement sites: traffic sites, urban and rural background sites. Different approaches are available which require more or less detailed input data into the source apportionment model. With the help of the Lenschow approach, the PMF (positive matrix factorization) and the PCA (principal component analysis) approach shall be applied in the six cities.

Details of progress: The PM and PAH measurements are carried out during two measurement periods. One in winter 2017 and the other in summer 2017. The expected difference of the results are in lower concentrations in summer time and less contribution of sources caused by combustion for heating purposes.

Main results: Results available up to now is the approach that will be applied. Further, apart from the PM and PAH analysis for the 6 participating cities (Athens, Thessaloniki, Madrid, Stuttgart, Ljubljana, Brno) are available yet. After the complete data set will be available, the above mentioned approaches will be applied on the data set in order to identify the sources causes the PM and PAH air pollution at the different measurement sites.

List of abbreviations

CMB	Chemical Mass Balance
GHG	Greenhouse gases
LA	Lenschow Approach
PCA	Principal Component Analysis
PMF	Positive Matrix Factorization

1 Main objectives

The main objective in WP 3.2 is the development of an approach to link changes in emissions of local sources, like traffic, industries, caused by ICARUS policy/measures to concentrations using source apportionment techniques for the six participating cities, which means Athens (Greece), Brno (Czech Republic), Ljubljana (Slovenia), Madrid (Spain), Stuttgart (Germany) and Thessaloniki (Greece). There are many different source apportionment (SA) techniques available, varying by their requirements and the output. The most well-known approaches are the Lenschow Approach (LA), the mass closure method, a tracer based approach and receptor models like the Positive Matrix Factorization (PMF), the Principal Component Analysis (PCA) and the Chemical Mass Balance (CMB). To apply these methods, there is much data needed, which can be extracted on the one hand from the public measurement stations in the cities. On the other hand, data gaps can be filled by field campaigns during winter and summer periods, so that a whole year will have been climatically well covered. The necessary data could also be taken from airborne/satellite and other remote sensing sources. These results can be used to predict the ground level concentrations of all pollutants and GHG’s after implementing the ICARUS policies.

Based on the results a friendly user guidance tool to authorities will be developed. This guidance tool will include recommendations on the application of SA for the assessment of the effectiveness of abatement measures/policies of air quality and CFP.

2 Introduction

The main purpose or aim of the Source apportionment (SA) models is to reconstruct the impacts of emissions from different sources of atmospheric pollutants [1]. There are three main groups of SA techniques:

(a) Methods based on the evaluation of monitoring data. Basic numerical data treatment is used to identify sources [1].

(b) Methods based on emission inventories and/or dispersion models to simulate aerosol emission, formation, transport and deposition. These models require detailed emission inventories [1].

(c) Methods based on the statistical evaluation of PM chemical data acquired at receptor sites (receptor models). The fundamental principle of receptor modelling is that mass and species conservation can be assumed and a mass balance analysis can be used to identify and apportion sources of airborne PM in the atmosphere [1]. Focusing on the most spread and widely used methods, the Chemical Mass Balance (CMB) is frequently employed when a very detailed knowledge of sources and emission profiles is available. On the other hand, Positive Matrix Factorization (PMF) is the first in line when relatively little quantitative knowledge of sources and emission profiles are available, even though they do require initial qualitative knowledge of the sources present in the study area [2]. When a first approach or understanding is needed and chemical composition data for the major compounds as well as emission inventories for the corresponding areas are available, the apportionment according to the relative shares through the Lenschow approach for the emissions of each environment can be carried out [3].

Some multivariate receptor models are based on the analysis of the correlations between measured concentrations of chemical species, assuming that highly correlated compounds come from the same source. One commonly used multivariate receptor model is the Principal Component Analysis (PCA) that has already been often applied in several studies. However PCA is not a convenient tool for quantifying source contributions. Therefore several

Source Apportion Tools will be used, like the PMF that has been specially developed in order to address this problem.

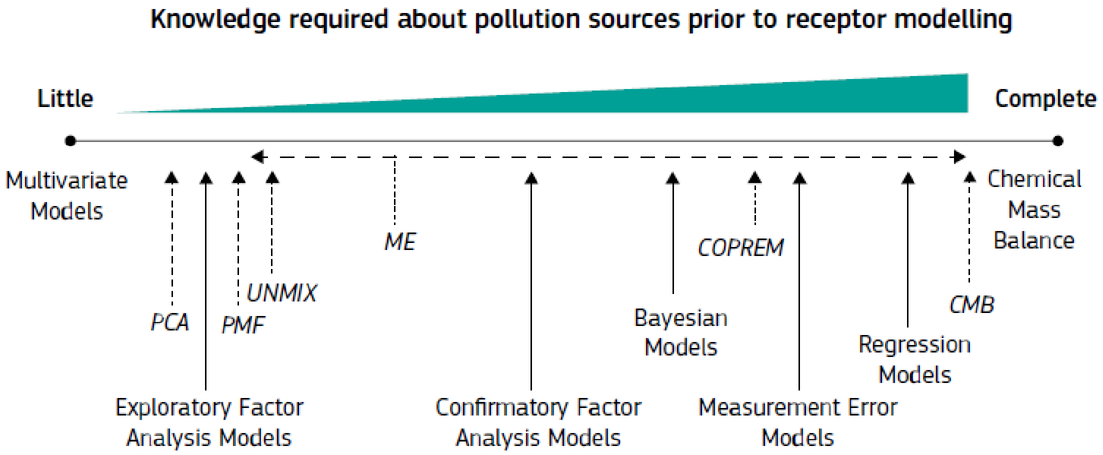

Figure 1 knowledge required about pollution sources prior to receptor modelling [4]

In WP 3.2 we propose and apply a methodology for determining particulate emission sources and their concentrations at 3 sites, for example in Stuttgart for the traffic site “Hohenheimer Straße”, for the urban background “Bad Cannstatt” and for the regional background “Schwäbische Alb”. The following tree step process will be implemented:

1. Collection of PM2.5 samples with low (or high) volume samplers and corresponding quartz filters on the receptor site and the chemical composition of each sampler was measured with several analytic methods of the different laboratories. After several pre-treatments a data matrix of chemical compounds concentrations in each sampler was selected. This step had been done for the winter campaign. The summer campaign is pending.
2. PCA will be applied to this data matrix and the standardized principal components were rotated, in order to identify possible sources of the different sites.
3. After step 2, PMF will be applied to the same data matrix and the results will be normalized so that we can find components with physical interpretations (the concentration of each source in each particle sampler).

Both steps are necessary because they are independent but the results of step 2 will be used to validate the results of step 3. [7]

3 Source apportionment approaches

A number of different methods and models can be found to apportion particle contributions to a specific source or source group. It is not possible to say that there is just one perfect method to be employed. As it has been already mentioned, one approach is preferred among other depending on the type of available data, the computational effort required and if previous knowledge on the field of study (source profiles, emission compositions, emission inventories, etc) is needed. It is also relevant to mention that the output results may vary between the two different methods, but in general it can be said that the different approaches contribute in the identification of major sources agree in their trends [3].

3.1 The Lenschow approach

In most PM characterization studies the composition of PM are measured for background, urban, and kerbside sites of the same region and they are compared by decomposing. Using the Lenschow methodology, a simple source apportionment analysis is carried out (see Figure 2) by considering the scenario of an urban background as an ‘‘island’’ of elevated PM-levels arising from a regional background, and on top definite peak concentrations due to traffic hotspots at kerbside sites. Consequently, for this method measurements performed have to be divided in these three typical locations (regional background, urban background and kerbside sites) [6]. The basic data required to perform the source apportionment consist in chemical composition for the major compounds as well as emission inventories for the corresponding areas. With these measured compounds concentrations the apportionment is done according to the relative shares of the corresponding emissions for each environment [3]. The main advantage of this strategy is the simplicity of the method and the consequent low mathematical treatment required for the data processing.

It directly relates measured PM levels to source categories listed in official emission inventories. The local increment measured at a traffic site, is considered to be exclusively caused by the local traffic emissions, if chemical composition does not indicate otherwise.

The validity of the results depends on the accuracy and completeness of the emission registers [3]. For some source types, the distribution depends on assumptions made that may have a high degree of uncertainty.

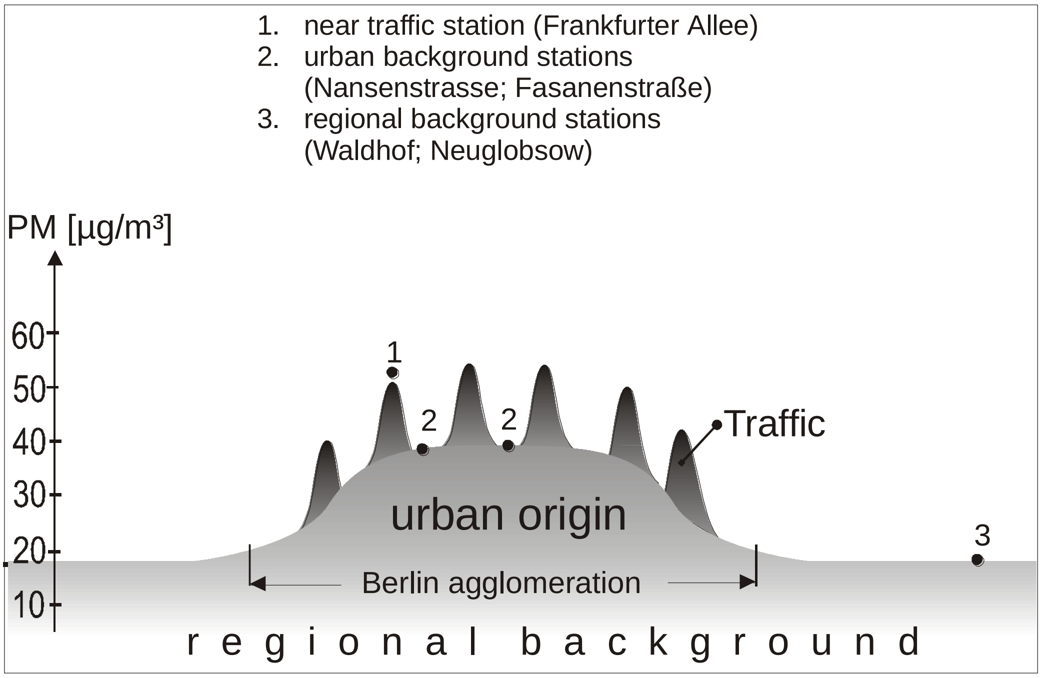

Figure 2 Schematic horizontal profile of the ambient PM10 concentration according to the Lenschow approach

One of the most relevant assumptions made within this method is that natural sources as well as contributions by transboundary long-range transport are usually not included, which may cause overestimation of the relative contributions by national emission sources [3].

After the main components are determined from the measured concentrations sampling analysis process, an emission data inventory and previous knowledge about the emissions help deriving, discriminating and determining the partitioning of the source contributions of the three previously classified factors, attributing each one of the species to the sources.

At first glance, the major differences between the emitting sources should be evident, like for example if it is considered that the traffic station can be attributed mainly to carbonaceous material, assuming that it stems mainly from the exhaust emissions of vehicles, tyre abrasion and resuspension of road dust [7].

Regarding the urban background, for example depending on the height of stack emissions and dispersion calculations, it could be assumed how much percentage must be attributed to this kind of source. Also agglomerations could be contributing to this classification, but at the end all of this information can be concluded when the measurements for the specific case study are analyzed.

3.2 Chemical Mass Balance (CMB)

One of the biggest advantages that this model can offer is that it can work on a single sample if the source data is known while on the other hand multivariate methods require a series of samples [4].

CMB consists of a least square solution to a set of linear equations which express each receptor concentration of a chemical species as a linear sum of products of source compositions (fractional amount of the species in the emissions from each source type) and source contributions [4]. In order to be able to employ this method, the following a priori information is required as input data: Concentration of the different species, source profiles and the correspondent uncertainties.

The output basically consists in the amount contributed by each source type to each chemical species. The model also provides as an output the uncertainties for those inputs. The uncertainties introduced as an input contribute to weight the importance of the input data in the solution and to calculate the uncertainties of the source contributions [4].

3.2.1 CMB Model Assumptions

1. *Compositions of source emissions are constant over the period of ambient and source sampling.*
2. *Chemical species do not react with each other* (reactive species such as Ammonium, Nitrate, Sulfate and elemental Carbon are then apportioned to chemical compounds rather than directly to sources - Secondary emitters).

3. *All sources with a potential for significantly contributing to the receptor have been identified and have had their emissions characterized.*
4. *The source compositions are linearly independent from each other (from 5 to 7 sources are linearly independent of each other in most cases).*
5. *The number of sources or source categories is less than or equal to the number of chemical species.* (In some cases the number of sources turns out to be larger than the number of species that can be measured. In those situations it is necessary to group sources into source-types of similar compositions).
6. *Measurement uncertainties are random, uncorrelated, and normally distributed.* (A log-normal distribution is employed since it does not allow negative values and due to the fact that ambient concentrations can never be negative. For small errors is not important (< 20%), for large errors is important)

On a real basis, these assumptions will not be accomplished 100%, but the model is able to tolerate some deviations, however this increases the stated uncertainties of the source contribution estimates. *Test improves and the magnitude of source contribution errors diminishes if the number of species and sources are increased [6]*.

3.2.2 Mathematical work

The mathematical work behind the CMB Model has the following expression as the starting point [6]:

$$S_j = D_j * E_j \qquad (1)$$

Where:

Sj: Measured concentration due to a source j

Dj: Dispersion Factor, which has a dependence on the wind velocity (u), atmospheric stability (σ), and the location of source j with respect to the receptor (x_j). Taking into account that all of these parameters vary with time, this factor must be an integral over time period T. For the CMB model, this parameter does not have to be fully known.

E_j: Constant emission rate

The total mass measured at the receptor site, will be a linear sum of the contributions from the individual sources [6].

$$C = \sum_{j=1}^{J} Sj \qquad (2)$$

The concentration of elemental component i, C_i is expressed as [6]:

$$C_i = \sum_{j=1}^{J} F_{ij} * S_j \qquad (2)$$

Where:

F_{ij}: is the fraction of source contribution S_j of element i.

The number of chemical species (I) must be greater than or equal to the number of sources (J) for a unique solution of this equations [6].

For the solution of the CMB equations and taking into account that it has to be constrained to obtain positive values and/or it might be necessary to add a non-zero constant intercept term, the “Ordinary weighted least square solution” is the preferred method, but nowadays the CMB Software is applying the “Effective variance least squares solution” because it provides realistic estimates of the uncertainties of the source contributions and it gives greater influence to chemical species with higher precisions [6].

This method consists in minimizing the weighted sums of the squares of the differences between the measured and calculated values of C_i and F_{ij}. An iterative procedure proceeds, calculating a new set of S_j based on the S_j estimated from the previous iteration [6].

Procedure:

(1) The initial estimation of the source contributions is set equal to zero

$$S_j^{k=0} = 0 \quad j = 1, \ldots, J \qquad (4)$$

S: $(S_{1\ldots}S_j)^T$ a column vector with S_j as the *j*th component.

(2) Calculate the diagonal components of the effective variance matrix V_e. The rest of the components of this matrix are also set to zero.

$$V_{e_g}^k = \sigma_{C_i}^2 + \sigma(S_j^k)^2 * \sigma_{f_g} \qquad (5)$$

σ_{Ci} = One standard deviation precision of the C_i measurement.

(3) Calculate the k+1 value of S_j

$$S^{k+1} = (F^T (V_e^k)^{-1} F^T)(V_e^k)^{-1} C \qquad (6)$$

C: $(C_{1\ldots}C_I)^T$ a column vector with C_i as the i^{th} component

F: An I x J matrix of F_{ij}, the source composition matrix.

(4) Test the $(k+1)^{th}$ iteration of the S_j against the k^{th} iteration. If they differ by more than 1 percent, then perform the next iteration. If all differ by less than 1 percent, then terminate the algorithm.

$$If\ \frac{\left|s_j^{k+1} - s_j^k\right|}{s_j^{k+1}} > 0.01, go\ to\ step\ 2 \qquad (3)$$

$$If\ \frac{\left|s_j^{k+1} - s_j^k\right|}{s_j^{k+1}} \leq 0.01, go\ to\ step\ 5$$

(5) Assign the (k+1)th iteration to S_j and σ_{Sj}. All the other calculations are performed with this final values.

$$\sigma_{s_j} = \left[F^T (V_e^{k+1})^{-1} F_{jj}\right]^{-1/2} \qquad (8)$$

3.2.3 CMB Input/Output

Inputs

- *Concentrations of the species* C_i*,*
- *Fractional amount of the species in each source-type emission (Source Profile)* F_{ij}*.*

- *Uncertainty estimations of σ_{Ci} and σ_{Fij} also as an input* (as already mentioned, to weight the importance of input data values in the solution and to calculate the uncertainties of the source contributions).

Outputs

- *Source contributions estimates (S_j) of each source type.*
- *Standard errors of these source contribution estimates.*
- *Amount contributed by each source-type to each chemical species.*

3.3 Positive Matrix Factorization (PMF)

PMF is a multivariate factor analysis tool that decomposes a matrix of speciated sample data into two matrices: factor contributions (G) and factor profiles (F). These factor profiles need an interpretation by the user to identify the source types that may be contributing to the sample employing measured source profile information, emissions or discharge inventories [5].

With this model the main constraint that has to be accomplished is that no sample can have significantly negative source contributions. PMF requires as an input the sample concentrations and user-provided uncertainty associated with each sample data to weight individual points.

Factor contributions and profiles are derived by the PMF model minimizing the objective function Q [5]:

$$Q = \sum_{i=1}^{n} \sum_{j=1}^{m} \left[\frac{x_{ij} - \sum_{k=1}^{p} g_{ik} f_{kj}}{u_{ij}} \right]^2 \qquad (9)$$

Where:

x_{ij}: Data matrix X of i by j dimensions, in which i number of samples and j chemical species were measured

f_{kj}: Species profile of each source

g_{ik}: Amount of mass *g* contributed by each factor to each individual sample

u_{ij}: Uncertainties

Q turns out to be a critical parameter for the PMF model and two versions of Q are displayed for the model runs [5]:

> *$Q_{(true)}$ is the goodness-of-fit parameter calculated including all points.*
>
> *$Q_{(robust)}$ is the goodness-of-fit parameter calculated excluding points not fit by the model, defined as samples for which the uncertainty-scaled residual is greater than 4.*

PMF Model developed by the Environmental protection Agency (EPA) requires multiple iterations by means of the Multilinear Engine (ME) algorithm, in order to identify the most optimal factor contributions and profiles. The best solution is usually identified by the lowest $Q_{(robust)}$ value along the path (i.e., the minimum Q). To maximize the chance of reaching the global minimum, the model should be run at least for 20 times developing a solution and 100 times for a final solution, each time with a different starting point [5]. If the data provide a stable path to the minimum, the $Q_{(robust)}$ values will have little variation between the runs [5].

The lowest $Q_{(robust)}$ value is used by default since it represents the most optimal solution.

Variability in the PMF solution can be estimated using three methods [5]:

1. *Bootstrap (BS)* analysis is used to identify whether there are a small set of observations that can disproportionately influence the solution.
2. *Displacement (DISP)* is an analysis method that helps the user understand the selected solution in finer detail, including its sensitivity to small changes. Data uncertainty can directly impact DISP error estimates.
3. *BS-DISP (a hybrid approach)* error intervals include effects of random errors and rotational ambiguity. It is more robust than DISP.

3.4 Principal Component Analysis (PCA)

The PCA can be carried out using numerous statistical software packages. The computation of source contributions with the PCA is characterised by a fast source identification where no specific software is required and it is a relatively time-consuming source contribution estimation. PCA is an exploratory receptor modelling tool for urban air quality management, i.e. for the design of air pollution mitigation strategies.

There are several model performance indicators available when applying PCA [4]:

1. A correlation between the modelled and the measured PM mass.
2. The chemical mass closure: the sum of the estimated source contributions and the comparison with the total measured PM mass.
3. There is an average absolute error (AAE): the average of the absolute percentage differences between the estimated and the experimental PM mass data, when different numbers of sources or factors are considered (Chow et al., 2007, Table B10.2).
4. The correlation between modelled and measured known sources: the most commonly used source for this test is the marine source, calculated as the sum of the chemically determined Na and Cl in study areas with no other major sources of the elements.

4 Field campaigns

The necessary data can possibility been taken from an extensive monitoring field campaign, that is taking place in all the 6 cities: (Athens, Thessaloniki, Madrid, Stuttgart, Ljubljana, Brno) at 3 sites (traffic hot spot, urban background, regional) which are part of the monitoring network of the city and are equipped by additional instrumentation (PM2.5 sampler). The duration of every campaign (winter/summer) will last 1 month per season (30 days of sampling).

4.1 Measurement sites

Table 1 Overview measurement sites

Cities (responsible partner)	Monitoring sites		
	Traffic hot spot (NO_X, O_3, BC, SO_2, Benzol, PM10) + 1 Sampler for PM2.5 (quartz filter)	Urban background (NO_X, O_3, BC, SO_2, Benzol, PM10) + GHG + 1 Sampler for PM2.5 (quartz filter)	Regional (NO_X, O_3, BC, SO_2, Benzol, PM10) + GHG + 1 Sampler for PM2.5 (quartz filter)
Athen (NCSRD)	**Aristotelous** Excl.: BC, Benzol, O_3	**Ag. Paraskevi** Excl.: BC	**Aliartos** Distance from city center: 101 km Excl.: BC, SO_2, Benzol
Thessaloniki (AUTH)	**1) Egnatia** **2) University campus**	**1) Stavroupoli** **2) Eptapyrgio**	**Neochorouda**
Stuttgart (USTUTT)	**Hohenheimer Straße** Excl.: BC, SO_2	**Bad Cannstatt** Excl.: BC	**Schwäbische Alb** Distance from city center: 47 km Excl.: BC
Madrid	**E. Aguirre station**	**Farolillo station**	**Casa de Campo station**

(ISCIII)	Excl.: BC	Excl.: BC	Excl.: BC
Brno **(MU)**	**Brno-Svatoplukova** Excl.: O_3, BC, SO_2, benzol	**Brno-Lány** Excl.: BC, Benzol, GHG	**Košetice** Distance from city center: 130 km Not hourly data: BC, Benzol, GHG
Ljubljana **(JSI)**	**MOL – Vosnjakova** Excl.: O_3, BC	**ARSO – Bezigrad** Excl.: BC, Benzol	**TETOL – Zadobrova** Distance from city center: 7 km Excl.: BC, Benzol, GHG

4.2 Sampling

4.2.1 Devices

There are low volume and high volume samplers used, that differs in the diameter of the sampling filter.

4.2.2 Sampling filters

A filter type is used that is appropriate for all the chemical analysis that will be performed (OC/EC, Ions, PAHs and HM): 47mm Tissue Quartz 25000 QAO PALL membrane filters (Pall) or the corresponding WHATMAN filter for low volume samplers (precipitator head 2,3m^3/h). For high volume samplers the corresponding filter is used.

4.2.3 Methodology

The methodology for preparing the filters, sampling and conditioning afterwards is described in the EN 12341:2004.

4.2.4 Further processing of the filters

The sampled filters were appropriate divided into 3 pieces using a surgical scalpel in order to be analyzed for all the proposed species. Every cut part is weighted in order to exactly quantify the distribution of particles onto these 3 pieces. A quarter of the filter will be used for the OC/EC analysis, one quarter for the ions analysis and one half for the heavy metals (first using XRF – nondestructive method) and then for the PAHs).

4.3 Species to analyze

There are 4 groups of most important species that will be used in the source apportionment: ions, organic carbon / elemental carbon (OC / EC), Benz[a]Pyrene (B[a]P), heavy metals (HM). This group will be analyzed from the gravimetric measurements. The greenhouse gases (GHG) will be measured by a light manned aircraft.

4.3.1 Anions

The group of the anions contain the following species:

Table 2 Anions to be analyzed

Symbol	Species
Cl	Chlorine
Br	Bromine
SO_4^{2-}	Sulfuric acid
NO_3^-	Nitrate
PO_4^{3-}	Phosphate

4.3.2 Cations

The group of the cations contain the following species:

Table 3 Cations to be analyzed

Symbol	Species
Na^+	Sodium
K^+	Potassium
Mg^{2+}	Magnesium
Ca^{2+}	Calcium
NH^{3+}	Ammonia

4.3.3 Carbon

The group of carbon includes the organic carbon (OC) and the elemental carbon (EC).

4.3.4 Heavy metals

The group of the heavy metals contain the following species:

Table 4 Heavy metals to be analyzed

Symbol	Species
Pb	Lead
Ni	Nickel
Cu	Copper
Cr	Chromium
Mn	Manganese
Fe	Iron
Co	Cobalt
Zn	Zinc
Mg	Magnesium
Si	Silicon
S	Sulfur
Cl	Chlorine
K	Potassium
Ca	Calcium
Ti	Titanium
V	Vanadium
Ge	Germanium
Br	Bromium
Rb	Rubidium
Sr	Strontium
Sb	Antimony

4.3.5 PAHs

The PAH analysis is only performed for one site because of several reasons: the PAHs are not a priority species for the approached source apportionment techniques. Due to their low concentrations in the ambient air (usually in ng/m³) they have a higher uncertainty in comparison to the other species used in the source apportionment. Also PAHs usually reveal the combustion sources, which can be also revealed by other species or a combination of them. Another responsible reason is the high analytical procedure and cost. That results in analyzing PAHs only in one site (e.g. traffic site) per city for 30 days.

4.4 Analytical effort

Table 5 Analytical effort

Partner	Number of samples to be chemically analyzed				
	Ions	**OC/EC**	**B[a]P**	**HM**	**GHG**
PM2.5	6 cities x 3 sites x 60 samples (30 warm + 30 cold period)	6 cities x 3 sites x 60 samples (30 warm + 30 cold period)	6 cities x 1 sites x 30 samples (15 warm + 15 cold period)	6 cities x 3 sites x 60 samples (30 warm + 30 cold period)	6 cities x 2 sites (UB) x 20 samples (10 warm + 10 cold) x 2 years
TOTAL	**1080**	**1080**	**180**	**1080**	**480**
NCSRD	540 (Athens, Madrid, Ljubljana)	-	30 (Athens, Brno)	360 (Athens, Ljubljana)	480 (all cities)
AUTH	540 (Thessaloniki, Stuttgart, Brno)	-	30 (Thessaloniki)	360 (Thessaloniki, Brno)	
ISCII	-	1080 (all cities)	30 (data from Madrid city)	120 (data from Madrid city)	
USTUTT	-	-	30 (data from Stuttgart city)	180 (data from Stuttgart city)	

JSI			60 (Ljubljana, Brno)			

5 Source apportionment tools

For PCA there is no specific software needed, also for the Lenschow Approach .

To apply the PMF the EPA software tool *“PMF 5.0”* will be used. EPA’s Positive Matrix Factorization (PMF) Model is a mathematical receptor model developed by EPA scientists that provides scientific support for the development and review of air and water quality standards, exposure research and environmental forensics. The PMF model can analyze a wide range of environmental sample data: sediments, wet deposition, surface water, ambient air, and indoor air. EPA’s PMF model reduces the large number of variables in complex analytical data sets to combinations of species called source types and source contributions. The source types are identified by comparing them to measured profiles. Source contributions are used to determine how much each source contributed to a sample. In addition, EPA PMF provides robust uncertainty estimates and diagnostics.

The users of EPA’s PMF model provide files of sample species concentrations and uncertainties, and also the number of sources. The model calculates the source profiles or fingerprints, source contributions, and source profile uncertainties. The PMF model results are constrained to provide positive source contributions and the uncertainty weighted difference between the observed and predicted species concentration is minimized. The PMF model software uses graphical user interfaces that ease data input, visualization of model diagnostics, and exporting of results. The model is free of charge, and does not require a license or other software to use. Algorithms used in the PMF model have been peer reviewed by leading air and water quality management scientists. [5]

6 Conclusions

In every of the 6 cities, there are 3 sites (traffic, rural background, regional background) where PM2.5 is measured for summer and winter campaign (30 days per campaign). There are sampling devices used following the methodology described in EN 12341:2004. After the measurement period, the filters were sent to the different partner laboratories and the chemical analysis followed. With the results of the chemical analysis, the source apportionment can be applied. First starting with the PCA and then the second step PMF. The results of the PCA will be used to validate the results of the PMF. Results of the source apportionment are estimations of source profiles from different measurement stations (traffic, rural background, regional background).

7 References

[1] Viana, M.: Source apportionment of particulate matter in Europe: A Review of methods and results. Barcelona: Journal of Aerosol Science (2008), Vol. 39.

[2] Viana, M.: Inter-comparison of receptor models for PM source apportionment: Case Study in an industrial area. Barcelona: Atmospheric Environment (2007), Vol. 42.

[3] Quass, U, John, A.C., Kuhlbusch, T. A. J.: Urban Air Quality in Europe. Berlin. Springer Berlin Heidelberg (2012).

[4] Belis Claudio, A., et al. European Comission (2014). Online document: [Cited: June 16, 2016]. http://www.jrc.ec.europa.eu. ISBN 978-92-79-32513-7 (pdf) / ISBN 978-92-79-32513-7 (pdf).

[5] Duvall, R., Norris, G.: Environmental Protection Agency, Positive Matrix Factorization Model for environmental data analyses (2014). Online document: [Cited August 9, 2016]. https://www.epa.gov/sites/production/files/2015-02/documents/pmf_5.0_user_guide.%20pdf.%20EPA/600/R-14/108

[6] K., Hopke Philip. Receptor Modeling for Air Quality Management (1991). Amsterdam: Elsevier.

[7] Chavent, M. et al.: PCA and PMF based methodology for air pollution sources identification and apportionment. Environmetrics, Wiley, 2009, 20, pp.928-942.