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Receptor Modelling for Particulate Matter: Review of Indian Scenario

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Abstract: The ambient particulate matter is characteristically regulated by its kind and local weather conditions. The kind of particulate matter is significantly related to its source. Hence, evaluation and measurement of airborne particulates and its sources assist in generating an abstract model for source apportionment (SA). SA means a method to recognize responsible sources of ambient particulate matter and its influence on the basis of species data for receptor locations. On the basis of mass balance theory and specific hypothesis, various numerical models are established to effectively enumerate sources of particulates. Nevertheless, in Indian perspective, receptor models have been used for majority of SA studies and, therefore, these models are the emphasis of this paper. Current paper discusses various source apportionment models and their application in Indian scenario.

Key words: Principal component analysis, positive mass factorization, factor analysis, chemical mass balance.

Introduction

Air quality all over the world has reached alarming situation due to concentrations of certain pollutants exceeding applicable norms, particularly in developing countries. Particulate matter (PM) is considered to be one of the key pollutants due to its harmful influence on human beings. In order to control the particulate matter concentration in cities, a number of norms have been proposed. However, to devise an effective abatement programme and formulate policies for reducing particulate matter concentration in ambient air, it is vital to have precise data about air pollution origin and its corresponding involvement.

Source apportionment (SA) implies methods that are used to compute different source contributions to atmospheric PM concentration. SA of ambient particulate matter basically computes the influence of discrete sources to particulate matter contribution depending on the characteristics of the receptor as well as source and, type of pollutants. This can be achieved by examining explicit tracer markers by using filter analysis or by numerical analysis of a particular marker with prevalent weather condition or using emission record data along with dispersal models. The basic SA methods existing are: (a) chemical conveyance models, (b) receptor-oriented models and (c) emission data with dispersal models. There is extensive literature available on SA involving dispersal models and monitoring data. However, a substantial amount of research work has been undertaken using receptor models. Such models are explicitly termed as receptor models because variable information about the composition of particulates is taken from receptor site.

The significant output of RM is percentage contribution of an individual source to the concentration of pollutant. Such models are predominantly useful at places where comprehensive emissions data is

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not accessible. RMs are utilised for identifying the origin and individual source contributions of ambient particulates.

Source Apportionment

The chief clusters of source apportionment methods are:

(a) Chemical transport models working on pollutant speciation depending on meteorological variables and assessment of observed data. (Banerjee et al, 2011; Belis et al., 2013). Handling of elementary information is required to recognize the origin. Examples are: (1) Identifying source locations by using association of wind pathway with measured pollutant concentration; (2) Identifying source association by using relationship between gaseous contaminants and particulate constituents; (3) Identifying the contributions from regional/city background by deducting local backdrop pollutants from those existing in urban cities or at roadsides and (4) Deducting particulate concentration at local backdrop site from those at urban backdrop sites to quantify natural PM contributions. The key benefit of this method is simplicity and subsequent small influence of mathematical equations owing to proper handling of data.
(b) Emission data and dispersal models used for simulation of pollutant discharge, creation, conveyance, and dumping. (Balachandran et al., 2000; Srivastava et al., 2008). Such prototypes need exhaustive discharge data which might not be easily accessible and might be restricted by emission data precision.
(c) Receptor models based on statistical assessment and analysis of PM data collected from receptor sites (Banerjee et al., 2011).

Several SA studies for various atmospheric pollutants are available in India and majority of them have used receptor type of models working on an observed concentration of particulate matter and its origin contour. Depending on the type of particle attributes used for simulation, receptor models are generally categorized into two types as microscopic receptor models and chemical receptor models. Microscopic RM analyses structural aspects of ambient particulate matter using electron microscope or automated SEM that are adequately competent to characterise pollutants in mixing states. However, microscopic RM limits are not applicable on a large scale since it doesn't yield quantitative results in most cases and produces only qualitative results (Pant et al., 2012). While chemical receptor models classify and recognise explicit PM sources by carrying out the chemical configuration of particulates. Several models used in this study are Chemical Mass Balance analysis, Enrichment Factor analysis, multivariate factor analysis containing Principal Component Analysis, UNMIX, Positive Matrix Factorization, and Multilinear Engine analysis.

Receptor Models

The essential proposition for receptor model is to assume conservation of matter and use mass equilibrium theory to classify and recognise particulate matter sources. A mass balance equation is used to consider all chemical types (m) in samples (n) as involvement from individual sources (p).

$$X_{ij} = \sum_{p=1}^{P} g_{ip} f_{jp} + e_{ij} \quad (1)$$

where X_{ij} is observed quantity of j^{th} type in the i^{th} sample, f_{jp} is the quantity of j^{th} type in substance discharged from origin p, g_{ip} is the quantity of p^{th} origin to i^{th} sample, P is total number of sources and e_{ij} is measurement share that the model cannot identify. In F matrix, RMs utilise experimental data of receptor species quantification in source discharge as input; this is usually termed to be source profile. Also, RMs can obtain receptor species concentrations in the matrix (F) by iteration method, which is usually referred as a factor profile.

The basic presumptions behind mass balance analysis equation are:

(1) Source profiles don't alter considerably with time or they alter in a replicable way so as the system is pseudo-stationary. (2) Receptor species don't undergo chemical reactions or phase separation (solid or gas and solid or liquid) from origin to receptor transport (they augment linearly). The additional inherent presumptions being (i) Information represents geographical area under study and depends on abstract model and (ii) Corresponding investigative methods can be applied for receptor sites for entire study and source profile classification.

Source Profiles Known – Chemical Mass Balance (CMB)

If numbers and nature of sources in the region are known, the only unidentified variable is the contribution of matter of individual origin to the individual sample. Such values are calculated by applying regression

analysis. Winchester and Nifong (1971) initially proposed Chemical Mass Balance model in 1971 followed by Miller in 1972. This method uses least square method of variance to solve a problem.

The basis of CMB method is conservation of matter which assumes that signature markers don't transform chemically while travelling to the receptors from the source. It considers the concentration of receptor to be a direct summation of a source profile and may be calculated when suitable indeterminate estimations are existing. CMB uses profile of source and receptor along with a suitable indeterminate estimate to be input to generate discrete source involvement with rational indeterminacy using multiple linear least square regression algorithms. However, source profile choice shall evade linearity and probability of identical geographic areas; or else the model relevance shall reduce considerably. To decrease the linearity of source profiles, it is recommended combining like a group of sources together. CMB is one of the unconventional receptor model techniques and is suitable when limited monitoring data is obtainable. Accessibility of comprehensive data about source profile reduces requisite samples; however, a smaller dataset probably escalates the level of uncertainty. CMB is represented by equation (2) shown below:

$$C_{ik} = \sum_{n=1}^{N} F_{in} S_{kn} \tag{2}$$

where C_{ik} is the airborne quantity of i^{th} species from k^{th} source observed at receptor location and S_{kn} is influenced from k^{th} source. F_{in} is identified source profile and S_{nk} is source influence of measured quantity (C_{ik}) at the receptor site. The linear equation shown above can be solved using the least square method of weighted variance.

CMB method uses certain presumptions that certainly cannot be accomplished totally because as particulate elements react with one another, source configuration cannot be constant and may vary based on prevailing conditions. Since, particulate while travelling to receptor from source is likely to endure chemical alteration, Winchester (1971) presented coefficient of fractionation to Eq. (3)

$$C_{ik} = \sum_{n=1}^{N} a_{iN} F'_{in} S_{nk} \tag{3}$$

where F'_{in} denotes configuration of pollutant at source location while F_{in} is receptor configuration. The calculation of a_{iN} is particularly intricate practically. The indeterminacy related to the source is evaluated using variance weights and is shown by Eq. (4)

$$(\omega_e)_{ii} = \frac{1}{\sigma_i^2} + \sum_{n=1}^{N} \sigma^2 ms^2 n \tag{4}$$

where σ_i is observed indeterminacy of contaminant quantity, x_i, and σ_{in} is the observed indeterminacy of i species released by n source.

Unidentified Source Profile

Owing to the absence of native origin related discharge data and alteration in source discharge fundamental profiles, development of the new method is vigorous when the profile of source is unknown. Such methods are termed as factor analysis, where the problem is extended to source profiles resolution and contribution for a sample set. The elementary equation is expressed as

$$X = GF' \tag{5}$$

where the matrix of source contribution is G and source profile transpose matrix is F'.

Enrichment Factors (EF)

Enrichment factor (EF) method can be used for source apportionment of particulates along with know-how of source profile for suggesting emission source. EF is utilised to evaluate predictable species origin and magnitude of human-induced events linked with the discharge of particulates. It is one of the elementary receptor models that suggests occurrence or absenteeism of specific markers. It also gives elementary information associated with the creation of secondary particulates. EF associates comparative ratio of the basic configuration of predictable elements to a reference element in the sample to the equivalent ratio in the normal backdrop configuration.

$$\text{Enrichment factor} = \frac{\left(C_x / C_b\right)\text{sample}}{\left(C_x / C_b\right)\text{background}} \tag{6}$$

If EF is greater than one, natural or human-induced sources are expected to be predominant. If a particular source is governing, EF analysis is done by direct regression analysis or constituent configuration ratio. EF offers partial data regarding discrete sources and is incapable to enumerate discrete influence from a source for composite group. EF analysis uses: (1) variable regression algorithmic rule, (2) boundaries of a 2D dispersion plot and (3) influence ratios of the intended

marker and tracer element in airborne particulates monitored for a specific time interval when a sole source is predominant. EF analysis provides influence of individual source species measured in the analysis. EF analysis is simple and if elementary presumptions of mass balance are satisfied, EF method may be used for selection of information or backing presumptions for receptor sources if inadequate data is accessible. Thus, results from EF analysis should always be inferred with care.

Factor Analysis (FA)

Primary applicability of this method is to decrease variables for a definite set of data. Furthermore, FA is also utilised for eliminating repetitiveness for a data set of interrelated variables. It is regularly utilised for investigating data structure, reducing data groups to a suitable numeral and inferring results from initial data group. FA is an imperative numerical technique for finding accurate results by utilising the flexible system and isolates the origin of particulates on the basis of observation at a receptor location. SA studies involving FA are beneficial as data associated with source profile is redundant but helps in differentiating like sources (Pant and Harrison, 2012). Hence, outcome requires subjective explanation before finally drawing conclusions. These limitations can be overcome by using confirmative methods of factor analysis such as UNMIX and PMF, wherein the modeller predetermines the explicit constraints on the basis of hypothetical expectancy.

Exploratory Factor Analysis – Principal Component Analysis (PCA)

Amid various factor analysis methods, PCA is regularly utilised to be an investigative technique that syndicates factor analysis with multilinear regression to compute source involvement of particulates. The basic equation that governs PCA is mass balance equation. The chief objective of PCA is to transform a number of possibly interrelated variants into a group of linearly uncorrelated variants, termed as principal components (PCs). These components are successively inferred by the modeller as potential source profiles. PCA uses suitable orthogonal breakdown such that the first principal component accounts for as much of the variability in data as possible, and every succeeding component, in turn, has maximum variance possible under the restraint that it shall be uncorrelated with previous component. Thus PC with maximum variance is inferred as utmost dominant source while each successive PC, in turn, has maximum variance. Within every set of components greater correlation occurs while between individual PCs minimum or no correlation exists (Singh et al., 2012). In PCA, loading factors connect discrete variables to different components with orthogonal rotations like Varimax.

To overcome the effects of mean-centering of PCA scores, PCs are uncentered by subtracting a zero-valued pseudo-sample and regressing against the total PM mass. This method is called Absolute Principal Components Analysis (APCA). It is used to produce quantitative apportionments. The initial PCA outcomes are rotated and component scores are uncentered (relative to a zero pollution reference case), to provide scaling coefficients for both the component scores (related to source impacts) and component loadings (related to source profiles). Hence optimization of results is done to describe influence information variability without limiting adequate constituent of matter. This result reduces independent rotations since it utilises orthogonal rotation. The equation for APCA is given as:

$$X_i = \sum_{k=1}^{p} z_k APCS_{Ki} \tag{7}$$

where X_i is mass of PM observed for i^{th} observation, $APCS_{ki}$ is rotated absolute score for k component for i^{th} observation, and z_k is regression coefficient between PCs and pollutant mass.

Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis is like PCA method, but has the basis as hypothesis prototype and may produce a solution that can be physically inferred and assessed. Confirmatory analysis methods include UNMIX and Positive Matrix Factorization (PMF). The confirmatory analysis puts a limitation on potential source influence results and necessitates them to follow some physical constraints like non-negative source impacts.

Positive Matrix Factorization (PMF)

PMF is the one most advanced factor analysis tools, accessible for source apportionment of PM. Positive Matrix Factorization is a multivariable analysis method similar to Principal Components Analysis; however, it eliminates total non-positive items. Moreover, in spite of complete reliance on the arithmetic relationship of data group, it practices minimum square reduction to associate input factors. PMF basically differentiates particulate species data group to a diverse matrix such as numeral of factors, the influence of factor and their profiles. This data straightaway relates to sources if a

severe group of presumptions is satisfied. Furthermore, it deals every datapoint discretely to control discrete contribution on the basis of confidence interval measurement. Investigational indeterminacy is utilised as input for resolving weighted factorization and permit discrete handling of elements.

Various factor analysis methods utilise eigenvalue analysis depending on sole value disintegration (SVD). PMF uses a dissimilar method to solve a problem. X Matrix is expressed as

$$X = USV' = \overline{USV'} + E \tag{8}$$

where U and V are initial columns of matrices U and V Matrix, Matrix U and V are derived using eigenvector analysis of matrix $X'X$ and XX'. As shown on the right-hand side of Eq. (9) the next term estimates X by the least-square method to produce least probable value.

$$\sum_{i=1}^{m}\sum_{j=1}^{n} e_{ij}{}^2 = \sum_{i=1}^{m}\sum_{j=1}^{n}\left[x_{ij} - \sum_{p=1}^{P} g_{ip} f_{ip} \right] \tag{9}$$

Thus, eigenvalue investigation is an inherent least-square study which minimises the total of squared residuals. For PCA, data is scaled by row/column for normalizing it, and data scaling cause misrepresentations of the study. Furthermore, an optimal ranking of information shall be to rank every datapoint discretely to generate accurate data with greater influence on results rather than data points having larger indeterminacy. Though, exhaustive proportion provides a proportionate data matrix which might not be replicated by a regular factor analysis method. Thus, PMF uses the methodology of a clear least-square method that decreases the objective function:

$$Q = \sum_{j=1}^{n}\sum_{i=1}^{m} \left| \frac{X_{ij} - \sum_{p=1}^{P} g_{ip} f_{ip}}{S_{ij}} \right|^2 \tag{10}$$

where s_{ij} is indeterminacy assessment of j^{th} variable observed for i^{th} sample. The problem of FA then reduces Q (E) in relation to G and F with a constriction that every G and F element shall be non-negative. PMF holds similar benefits like PCA, however, PMF has the surplus benefit of treating missing data or data which is at a level below detection. But this method necessitates a big data group, rather greater than the number of associated elements and a weighted factor related to every observation must be allotted.

UNMIX

The basic philosophy for this method is to enforce minimum presumptions, thus allowing information communicate for itself. This model has an innovative and arithmetically exhaustive program to assess numeral of sources. For a given amount of sources, UNMIX utilises PCA to decrease the dimensions of data sets. UNMIX model solves mass balance equivalence by applying eigenvector analysis to decrease dimensions of the data group by not centering the initial data. UNMIX produces a group of principal components, having covariance receptor classes, that are consequently inferred by modeller as probable origin profiles.

Some features of this model are the ability to substitute lacking information and capability to approximate huge numeral of sources by utilising dual perception for RMs. It assesses indeterminacy in origin configuration by applying a blocked bootstrap method which considers sequential interrelation of data. This model doesn't integrate inaccuracies in the study, however, restriction of UNMIX is that it doesn't generate a precise answer for mass balance equation. UNMIX is capable to solve maximum powerful sources but the fragile sources generally display low compliance of anticipated and assessed source involvement. Additionally, UNMIX shall be simply utilised for locations for which exhaustive origin profile information is not accessible. The below equation is used for this model,

$$C_{\bar{v}} = \sum_{i=1}^{p}\left(\sum_{k=1}^{p} U_{ik} D_{ki} \right) V_{ij} + E_{ij} \tag{11}$$

where U, D, and V are $n\times p$, $p\times p$ diagonal, and $p\times m$ matrix, respectively. E_{ij} is inaccuracy comprising total variance in C_{ij} not calculated by initial principal component (p). The utility of this model necessitates great numeral of variants and dataset larger than 100, to generate an articulate result.

Hybrid Models

The theory of hybrid model combines CMB and positive factor analysis and offers superior regulation of concluding result. Two groups of hybrid models are used: (i) Constrained receptor models; and (ii) Trajectory receptor models. The trajectory model utilises contaminant concentration, wind direction and wind speed observed near the receptor location. This method utilises multivariable factor analysis and uses clear overview of supplementary data (along with wind

and its paths) to decrease the rotation uncertainty of the result.

Constrained Physical Receptor Model (COPREM)
COPREM syndicates the aspects of CMB and FA. The model can be resolved by decreasing a c2 function by means of a dual stage iteration process. The modeller can utilise the backdrop knowhow to deviate the reiteration towards a coherent solution. For instance, selecting trajectories that are relative to recognized source profiles, and by picking up restraints that keep a portion or entire profile as constant and thereby preventing undesirable mingling of source trajectories. Model output is a source power matrix, a profile matrix, function c2 and degrees of freedom (n). A single factor study is done on residuals to divulge a probable overlooked source. The indeterminacy in the source profiles is assessed using a precise model by linear regression. The estimated indeterminacy, however, denotes lower bound values, since rotation indeterminacy and independent variable indeterminacies are ignored.

It is a multivariable receptor model using linear model and weighted data deduction rule with restrains which permits to offer improved origin separation with measured indeterminacy. It primarily generates a matrix for origin profile by means of origin trajectories and consequently augments extra restraints to decrease mingling of origin profiles. Further, an overview of restraints assists to control not-physical result such as non-positive source profile and it provides profile constituents in continual ratio. Hence, choice of suitable constraint is particularly crucial and can be selected on the basis of appropriate data of initial source configuration. This model offers feasibility of integrating backdrop knowhow to control the undesirable mingling of sources. COPREM needs huge data with comprehensive information about source profile which occasionally restricts its applicability.

Extended Factor Analysis
The conventional linear factored analysis implemented on a two-dimension sample matrix by receptor elements is expanded to resolve additional composite multilinear equivalence by utilising multilinear engine (ME) platform. ME produces a table which stipulates the study and resolves it by Conjugate Grade Program. In this type of model, the rotation uncertainty of FA is decreased by incorporating supplementary constraints like identified origin profile, acknowledged source influence and meteorology variants. The flexibility of ME is subjugated to produce dataset explicit models and to develop diverse information such as particulate configuration and its size classification.

Extended factor analysis model solves different multilinear and pseudo-multilinear problem by including constraints. ME is backdrop algorithm utilised for running PMF. The problem is denoted by a group of equivalence, where every equivalence estimates sole data signifying diverse indeterminate. Indeterminates are mentioned for diverse data as per the model configuration and positive restraints are involved to decrease the probability of non-positive source distribution. It gives a general setup for numerous ME models together with bilinear or trilinear and multilinear model that improvises its flexibility. In sums-of-products form this model is shown below

$$x_i = y_i + e_i = \sum_{k=1}^{Kf} \pi f_i + e_i \quad (i = 1, 2.....M) \tag{12}$$

where i index indicates the equivalence for the model, every equivalence relates to a single observed value (X_i), M denotes numeral of equivalences which is total of numeral of observations and ancillary equivalences, if any, built-in value y_i for every data point x_i is designated as total of multiplication of all factors, K_i specifies the numeral of product terms in every equivalence. The enclosure of diverse data groups, particulate classification, particle size distributions, meteorology variants, and indeterminacy with the flexibility to alter the input as per requirement are some of the benefits of ME model.

Source Apportionment Studies in India

There is significant literature available for source apportionment studies in India. Most of the research work has been carried out using receptor models. PCA is one of the utmost frequently used methods. The vital reason for using multivariable modelling technique is the non-presence of native source profiles. Kumar et al. (2015) has used EF analysis independently for Tamilnadu and Lakhani et al. (2008) for Agra. EF analysis has been applied to various studies, in combination with correlation by Meena et al. (2015) for Kota and Haritash et al. (2007) for Hissar in Haryana. Bhanuprasad et al. (2008) has used PMF analysis for Indian Ocean cruise rather than city level. Numbers of studies have compared results from diverse models. For example, PCA in conjunction with Cluster Analysis has been used by Raina Pal et al. (2014) for Moradabad city and for Kolkata by Reshmi Das et al. (2015). Majority of

the studies have been done in New Delhi (Suryawanshi et al., 2016; Dahiya et al., 2015; Chaudhari et al., 2015) using PCA method whereas Rajaram et al. (2014) used PCA in combination with Enrichment factor analysis. PCA was also used by Srivastava et al. (2008) for Delhi city. Studies for heavy metals in the particulate matter have been conducted by Kushwaha et al. (2016); Gajghate et al. (2012) using Correlation for Chennai and by Karthikeyan et al. (2011) for dumpsites in Chennai.

Habil et al. (2013) examined PM sizes and heavy metals at the roadside and residentially located schools in Agra using PCA and Enrichment factor analysis whereas Lakhani et al. (2008) used only enrichment factor. Bhattacharya et al. (2011) studied heavy metal concentrations in street dust from five major roadways in Anand using PCA and Correlation coefficient analysis. Basha et al. (2007) conducted airborne particulate observation for Alang-Sosiya, ship-breaking yard at Gujarat by applying PCA and EF analysis. Srinivasa Rao et al. (2015) analyzed concentrations of ten trace elements collected from Gajuwaka Industrial Hub of Visakhapatnam and applied PCA-CA method. Bhanu Pandey et al. (2014) used PCA to identify the major sources of air pollutants in the area for mining areas in Jharia.

Dubey et al. (2012) studied ambient concentrations of trace metals measured for Dhanbad, Jharkhand by adopting PCA in conjunction with EF. PCA along with correlation was used by Mohammed et al. (2013) for investigating the distribution of heavy metals in atmospheric aerosols (PM10) of Kakinada city. Das et al. (2015) measured PM2.5 and PM10 along with heavy metals at different locations in Kolkata and applied PCA and EF analysis. Karar et al. (2006) also applied PCA and Correlation study for Kolkata. Statistical analysis by Pearson's correlations, enrichment factor, and principal component analysis was used by Meena et al. (2015) for investigating seasonal variations in average concentrations of metals in free fall dust samples in Kota, India. Basha et al. (2010) investigated heavy metal concentrations in the suspended particulate matter and carried outsource apportionment using PCA-EF for Mithapur, Gujarat. Pal et al. (2014) assessed the concentration of PM10 and trace metals for Moradabad and used PCA-EF and correlation study to identify source components. Roy et al. (2012) analyzed elemental concentrations of PM10 for Talher, Orissa and used Correlation and PCA, for source classification to recognize potential sources of PM10 and trace marker elements.

Discussions

In India, receptor models have been used for source apportionment of particulate matter across various cities. Most of the studies have applied multivariate statistical methods to generate factors that are characterised by permutations of elemental and ionic constituents. The results of CMB model analysis are influenced intensely by the availability of source profiles. This preferably should be from the area where the receptor is located and it should be in sync with the existing ambient air measurements. The sensitivity of CMB to source profile collinearity obstructs the mathematical solution of mass balance, so it often becomes essential to combine sources into groups in order to yield composite profiles. EF analysis is simple and elementary assumptions of mass balance equation are fulfilled. EF study is used in data screening and supporting assumptions for receptor species and sources where information is accessible. But, the presence of exclusive source tracers is very unusual; hence results from EF analysis shall be always inferred with restraint.

PCA is sensitive to relative scaling of original variables. For PCA, a dataset normally distributed is the elementary hypothesis. But this may not be the case for environmental concentration data. Artificial location of the variance in the initial few components can be partly solved by orthogonal rotations (e.g., varimax). UNMIX does not integrate errors into the analysis but it has some of the concerns, similar to PCA. Limitation of UNMIX is that it is not possible to find a mathematical solution for the mass balance equation always. UNMIX is capable to determine most intense sources while weak sources show poor accord between expected and estimated source contributions. The use of PCA which is unweighted model causes less acceptable factor resolution as compared to PMF which is a recent weighted model.

PMF needs no previous knowledge of source composition, but any data related to source emissions characteristics helps to differentiate like sources. It needs a considerable number of discrete air samples (at least 50) and gives the best result with the big dataset. To combine the advantages and reduce the disadvantages of CMB and factor analysis hybrid models have been developed like COPREM and Multilinear Engine. With a constrained physical receptor model COPREM, an initial profile matrix with the main characteristics of known sources as columns is used, and a prior knowledge about the character of the sources can be used to achieve a solution with a sufficient number of

sources. The multilinear engine can solve multilinear problems with the possibility of implementing many kinds of constraints using a script language. To restrain the model Multilinear Engine program permits to use source composition data.

Conclusion

Source apportionment study using various receptor models has been used in India for about past two to three decades. The study began with the use of enrichment factor analysis, then shifting to use of Principal Component Analysis and finally culminating in use of Positive Matrix Factorisation model. PMF has gained impetus due to its ability to handle input and output data uncertainties. However, a PCA model still performs better when applied for initial assessment or qualitative study. Over the past few years, Chemical Mass Balance method has gained new stimulus, due to its suitability for application of studies involving molecular markers.

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