SCENARIO ANALYSIS AND OPTIMIZATION APPROACH IN AIR QUALITY PLANNING: A CASE STUDY IN NORTHERN ITALY

Claudio Carnevale
Giovanna Finzi
Anna Pederzoli
Enrico Turrini
Marialuisa Volta
Department of Mechanical and Industrial Engeneering
University of Brescia
Via Branze 38, 25123 Brescia, Italy
E-mail: claudio.carnevale@unibs.it

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ABSTRACT

Secondary pollution derives from complex non-linear reactions involving precursor emissions, namely VOC, NOx, NH3, primary PM and SO2. Due to difficulty to cope with this complexity, Decision Support Systems (DSSs) are key tools to support Environmental Authorities in planning cost-effective air quality policies that fulfill EU Directive 2008/50 requirements.
The objective of this work is to formalize and compare the scenario analysis and the multi-objective optimization approach for air quality planning purposes. A case study of Northern Italy is presented.

INTRODUCTION

Particulate Matter (PM) usually originates, through nonlinear phenomena, from precursor emissions (primary PM10, ammonia, nitrogen oxides, sulfur dioxied and organic compound). The key problem of air quality Decision Makers is to develop suitable emission control strategies, aiming to the selection of the available technologies to limit the concentration of PM10 in atmosphere.
Due to non linearities bringing to formation and accumulation of PM10, it is very challenging to develop sound air quality policies. This task is even more difficult when considering at the same time air quality improvement and policy implementation cost.
In literature, the following methodologies are available to evaluate alternative emission reductions: (a) scenario analysis (Thunis et al., 2007), (b) cost-benefit analysis (Reis et al., 2005) (c) cost-effectiveness analysis (Carslon et al., 2004) and (d) multiobjective analysis (Carnevale et al., 2008). Scenario analysis is performed by evaluating the effect of an emission reduction scenario on air quality, using modeling simulations. Cost-benefit analysis monetizes all costs and benefits associated to an emission scenario in a target function, searching for a solution that maximizes the objective function. Due to the fact that quantifying costs and benefits of non material issues is strongly affected by uncertainties, the cost-effective approach has been introduced. It searches the best solution considering non monetizable objectives as constraints (non internalizing them in the optimization procedure). Multi-objective analysis selects the efficient solutions, considering all the targets regarded in the problem in an objective function, and stressing possible conflicts among them.
The multi-objective analysis has rarely been faced in literature, due to the difficulties to include the non-linear dynamics involved in PM10 formation in the optimization problem.. The pollution-precursor relationship can be simulated by deterministic 3D modeling systems, describing chemical and physical phenomena involved in pollutant formation and accumulation. Such models, due to their complexity, require high computational time and can not be implementable in an optimization problem, which needs thousands of model runs to find solutions. The identification of surrogate models synthesizing the relationship between the precursor emissions and PM10 concentrations, therefore, can be a solution. (Carnevale et al., 2008).
In this work, scenario and multi-objective approach are applied and compared for a highly polluted region of Northern Italy, where the production of secondary PM10 is significant, up to 50% and beyond (Carnevale et al., 2010).

METHODOLOGY

Scenario analysis

This is the approach mainly used nowadays to design "Plans and Programmes" at regional/local scale. Emission reduction measures (Policies) are selected on the basis of expert judgment or Source Apportionment and then they are tested through simulations of an air pollution model. This approach does not guarantee that Cost Effective measures are selected, and only allows for "ex-post evaluation" of costs and other impacts. This decision pathway can be easily interpreted in the light of the classical DPSIR (Drivers-Pressures-State-Impacts-Responses) scheme, adopted by the EU (EEA, 1999) as presented in Figure 1.

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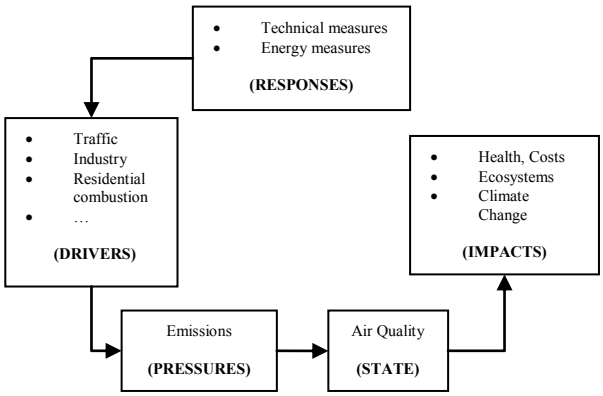

Figure 1: DPSIR Scheme for Scenario Analysis

The scenario analysis approach allows to assess the variations of the air quality indexes due to the application of a set of policies chosen a priori by the user. The problem can be formalized as follows:

$$AQI_n = f(E(\theta)) \qquad with\ n = 1, \dots, N$$

where:
θ are the application levels of the considered technologies;
E represents the precursor emissions;
$AQI_n(\theta)$ are the Air Quality Indexes concerning different pollutants. Each Index depends on precursor emissions through emission reductions.
The decision variables θ are constrained to assume values between two extreme values:

- the CLE level, that represents the level of application for each measure as provided by european legislation for the year considered in the analysis;
- the MFR level, that is the maximum technically feasible reduction of one measure, for the year considered in the analysis.

In this approach impacts of the can be evaluated by someone that, based on its experience, acts on decision variables in order to create a more efficient scenario that can be tested again through scenario analysis.

Optimization approach

This approach, according to the DPSIR scheme, can be presented as shown in Figure 2. It faces the AQ problem defining a decision problem solved by means of optimization algorithms.
In this case the feedback from impacts is evaluated by an optimizer and, though thousands of iterations, the optimal solution is found.

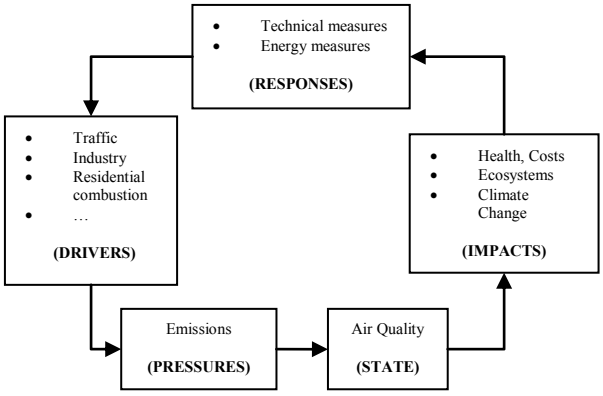

Figure 2: DPSIR Scheme for Optimization Approach

A Multi Objective problem consists of a number of objectives to be simultaneously optimized while applying a set of constraints. The problem can be formalized as follows:

$$\min \mathrm{J}(\theta),$$

$$\mathrm{J}(\theta): \mathrm{R}^{\mathrm{T}} \rightarrow \mathrm{R}^{\mathrm{O_{obj}}}$$

subject to:

$$\theta \in \Theta$$

where $\mathrm{J}(\theta)$ is the objective function
T is the number of considered technologies,
$\mathrm{O_{obj}}$ is the number of the objectives,
θ are the decision variables constrained to assume values in the feasible decision variable set Θ.

The target of the proposed problem is to control secondary pollution at ground level. The solutions of the Multi Objective problem are the efficient emission control policies in terms of air quality and emission reduction costs. The problem can be formalized as follows:

$$\min_{\mathrm{x}} \mathrm{J}(\theta) = \min_{\mathrm{x}} [\mathrm{AQI_n}(\theta)\ \ \mathrm{C}(\theta)],$$

$$\text{with } \mathrm{n} = 1, \dots, \mathrm{N}$$

where

- E represents the precursor emissions;
- $\mathrm{AQI_n}(\theta)$ are (maximum N) Air Quality Indexes concerning different pollutants;
- $\mathrm{C}(\theta)$ represents the emission reduction costs;
- θ is a vector containing the application rates of the reduction measures, constrained to be included in the feasible set Θ.

The decision problem complexity can then be reduced to a two objectives, considering a single Air Quality Index (AQI) obtained as a linear combination of the various Air Quality Indexes AQIn (plus the Cost index).

These various AQIs can be aggregated through linear combination of normalized AQIs.
Finally, the previous equation can be re-written as:

$$\min_{\theta} J(\theta) = \min_{\theta}[AQI(\theta) \quad C(\theta)],$$

The Multi Objective optimization problem is solved following the ε-Constraint Method: the Air Quality objective is minimized, while the emission reduction cost objective is included in the set of constraints. In this configuration, the Multi Objective approach has the same features of the Cost Effectiveness analysis, where the Figure of Merit is

$$\min_{\theta} J(\theta) = \min_{\theta} AQI(\theta)$$

and the second objective is included in the constraints:

$$C(\theta) \leq L \qquad 0 \leq L \leq \bar{L}$$

where L can assume different values in the defined range. In this way a set of effective solutions is computed and a Pareto curve can be drawn.

Air Quality objective
The Air Quality objective may consider a number of indexes related to PM10, PM2.5, ozone (eg. SOMO35, AOT40) and NOx. The case study presented in this work is focused on PM10.
All the indexes can be computed over different domains, and can be related to i.e. yearly, winter or summer periods. Starting from the local value, computed cell by cell, an aggregation function is applied, to get the scalar variable (AQI) that has to be optimized. The aggregation function can be:

- spatial Average;
- population weighted average;
- number of cells over threshold

Decision variables
The decision variables are the application rates of the emission reduction measures. In particular, two classes are considered: the end-of-pipe technologies (or technical measure)s and the efficiency (or non-technical measures). Such latter measures reduce the enrgy consumption and as consequence the emissions. Examples of this class of measures are the behavioural changes (like the use of bicycle instead of cars for personal mobility or the reduction of temperature in buildings) or the energy saving technologies.
Applying the measures, the reduced emissions of pollutant p, due to the application of measures in sector k and activity f, are computed as follows:

$$E_{k,f,p} = \sum_{t \in T_{k,f}} (A_{k,f} \cdot ef^{p}_{k,f}) X_{k,f,t} \cdot eff^{p}_{k,f,t} + \sum_{t \in Z_{k,f}} (A_{k,f} \cdot ef^{p}_{k,f}) Z_{k,f,t} \cdot eff^{p}_{k,f,t}$$

where:
$X_{k,f,t}$: is the application rate (bounded in $[\bar{X}_{k,f,t}; \underline{X}_{k,f,t}]$) of technical measure t to sector k and activity f;
$Z_{k,f,t}$: is the application rate (bounded in $[\bar{Z}_{k,f,t}; \underline{Z}_{k,f,t}]$) of efficiency measure t to sector k and activity f;
$A_{k,f} \cdot ef^{p}_{k,f}$: is the pollutant p emission due to sector k and activity f;
$X_{k,f,t} \cdot eff^{p}_{k,f,t}$: is the overall technical measure t removal factor with respect to sector k, activity f and pollutant p;
$Z_{k,f,t} \cdot eff^{p}_{k,f,t}$: is the overall efficiency measure t removal factor with respect to sector k, activity f and pollutant p.

The total emission reduction beyond CLE scenario for a pollutant p, due to the application of a set of measures, can be calculated as the sum of the emission reductions over all the <sector-activity> pairs:

$$E_p = \sum_{k,f} E_{k,f,p}$$

Emission reduction costs
The emission reduction costs are calculated first for each sector-activity:

$$C_{k,f} = \sum_{t \in T_{k,f}} c_{k,f,t} \cdot A_{k,f} \cdot X_{k,f,t} + \sum_{t \in T_{k,f}} c_{k,f,t} \cdot A_{k,f} \cdot Z_{k,f,t}$$

where:
$c_{k,f,t}$ is the unit cost [M€/year] for sector, activity, technology k,f,t;
$C_{k,f}$ is the total cost [M€/year] for sector, activity k,f;
$T_{k,f}$ are the technologies that can be applied in a defined sector activity.

Then, the total emission reduction cost [M€/year] is computed as:

$$C = \sum_{k,f} C_{k,f}$$

Constraints
The first constraint concerns the emission reduction cost, which cannot be greater than the available budget L.
The following constraints hold for *technical measures*.
When the substitution of old technologies is admitted, the following constraints are applied:

- to ensure the application feasibility:

$$0 \leq X_{k,f,t} \leq \bar{X}_{k,f,t} \quad \forall\, k \in K, f \in F_k, t \in T_{k,f};$$

- to ensure the mutual exclusion of technical measures application (for each activity and each primary pollutant, i.e. for each activity and each precursor):

$\sum_{t \in T_{k,f}: eff^{p}_{kft} > 0} X_{k,f,t} \leq 1 \quad \forall\, k \in K, f \in F_k, p \in P;$

- to ensure that the emission reduction achieved according to the optimal solution are at least those guaranteed by the application of the technologies imposed by the Current LEgislation (for each activity and each primary pollutant):

$$\sum_{t \in T_{k,f}: eff^{p}_{kft} > 0} X_{k,f,t} \cdot eff^{p}_{k,f,t} \geq \sum_{t \in T_{k,f}: eff^{p}_{kft} > 0} X^{CLE}_{k,f,t} \cdot eff^{p}_{k,f,t}$$

$\forall\, k \in K, f \in F_k, p \in P;$

- to ensure that the emissions controlled according to the optimal solution are at least those controlled applying the technologies at the lower bounds imposed by the Current LEgislation:

$\sum_{t \in T_{k,f}: eff^{p}_{kft} > 0} X_{k,f,t} \geq \sum_{t \in T_{k,f}: eff^{p}_{kft} > 0} X^{CLE}_{k,f,t} \;\; \forall\, k \in K, f \in F_k, p \in P;$

Concerning *efficiency measures*:

- to ensure the application feasibility:

$Z^{CLE}_{k,f,t} \leq Z_{k,f,t} \leq \bar{Z}_{k,f,t} \quad \forall\, k \in K, f \in F_k, t \in NT_{k,f};$

Moreover, when both technical and efficiency measures are applied, the global conservation of mass constraints have to be stated explicitly (for each activity and each primary pollutant):

$$\sum_{t \in T_{k,f}: eff^{p}_{kft} > 0} X_{k,f,t}\, eff^{p}_{kft} + \sum_{t \in NT_{k,f}: eff^{p}_{kft} > 0} Z_{k,f,t} eff^{p}_{kft} \leq 1$$

$$\forall k \in K, f \in F_k, p \in P$$

TEST APPLICATION RESULTS

Case study

In these section, the proposed approaches are applied and compared to the test case of Lombardia region in Northern Italy. This is one of the most polluted regions in Europe due to three main factors: high level of emissions, stagnant meteorological conditions (low wind speed and temperature inversions) and a complex topography that prevents access to strong winds. For these reasons, unless the European legislation is applied, high levels of parti culate matter are still a major concern in the region. The geographical domain was discretized with a 6 x 6 km^2 grid and comprises roughly 6000 cells (see Figure 3).

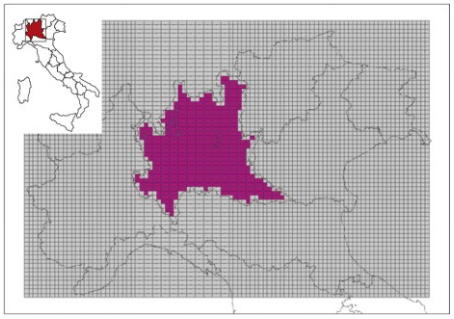

Figure 3: Lombardia region Domain.

The air quality index (AQI) is the yearly average of PM10. The relationship between such index and the decion variables, namely the annual emissions of the precursors (NOx, VOC, NH3, PM10, PM2.5, SO2) for each domain cell, is modelled by Artificial Neural Networks (ANNs). The ANNs are identified processing long-term simulations of TCAM model. Such simulations are selected assessing of nonlinear relationship between the precursor emissions and PM concentrations. Such analysis has been performed implementing the Factor Separation Analysis (Canevale et al., 2010) and has produced 20 scenarios varing emissions between CLE2010 and MFR2020.

A quadrant shape input configuration has been used, as shown in the Figure 3:

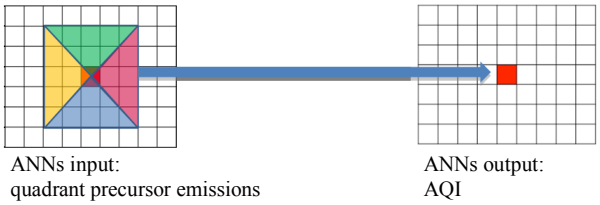

Figure 3: Quadrant Shape input Configuration.

This shape of input allows considering the prevalent wind directions over the domain: the North-South direction follows the Po Valley axes and the East-West direction is the breezes axes. So to simulate the Air Quality Index on a particular cell, 48 input data are considered:

- the 6 emissions precursor under study (NOx, VOC, NH3, PM10, PM25 and SO2);
- the 4 quadrants;
- the 2 emission levels: *low* for areal emissions and *high* for point sources.

The dimension of the input quadrants is 24km.
The source-receptor models are Feed Forward Artificial Neural Networks, with one hidden layer. To select, the best ANN structure, the following tests have been performed:

- number of neurons of the hidden layer: 10 or

20;

- transfer functions of the first and hidden layer: linear, tangent-sigmoid, logarithmic sigmoid;
- number of epochs (100, 200, 300, 400);

The identification dataset contains the 80% of the TCAM simulation cells, while the 20% of the cells (spatially uniformly distributed) is kept for validation.
The ANN structure with lower Mean Squared Error is selected and used in the next phase of the work.

Traffic Scenario (TS) analysis

An emission reduction scenario has been performed considering the application of the new EURO standard to the all vehicles (EURO V and VI) substituting the older standars. And, in addition to this, the application at the maximum possible level, of three efficiency measures (efficiency measures):

- bus investment;
- construction of new bicycle paths;
- lowered speed on highways.

The simulation of this scenario has been performed using the RIAT+ tool (Carnevale et al. in press) and shows that, starting from a CLE 2010 scenario with a PM10 yearly average of 27.3 µg/m^3, the application of these technologies would cost 170M€, allowing a mean reduction of 6% in the PM10 average concentrations over the domain. A reduction of 6% in health costs, due to the months of life lost, has been estimated using ExternE approach (Bickel et al. 2005).

Table 1: Traffic Scenario (TS) features.

Impacts	CLE	TS
Emission reduction costs [M€/year]	0	170
PM10 [µg/m^3]	27.3	- 6%
Health costs (due to months of life lost) [€]		- 6%

In Figures 4 and 5, the spatial distribution of the yearly PM10 concentrations is shown for CLE2010 and TS. It is clear that the latter scenario is reducing PM10 particulary in the central most populated and industrialized cells between the cities of Milano, Bergamo and Brescia.

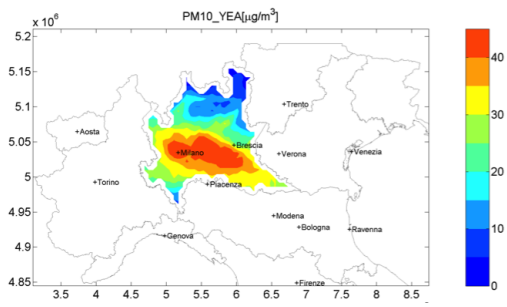

Figure 4: PM10 yearly average [µg/m^3] map for CLE2010.

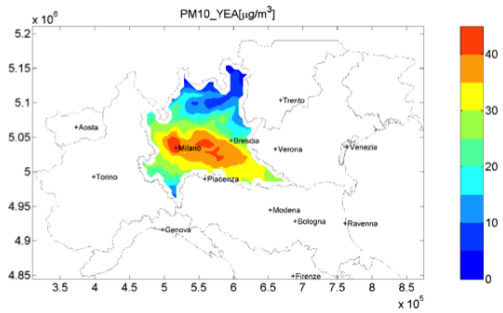

Figure 5: PM10 yearly average [µg/m^3] map for TS.

Figure 6 shows the emission reductions in each macrosector for TS. The selected measures are reducing more than 35000 Kton/year of NOx emissions and around 10000 Kton/year of VOC emissions.

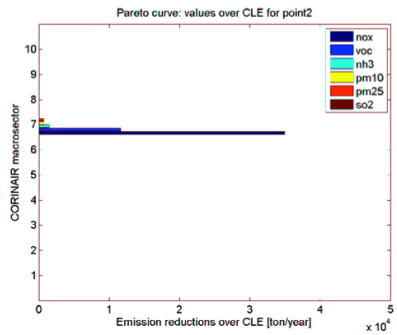

Figure 6: Emission Reductions [ton/year] in each Macrosector for TS.

Optimization approach

Applying a Cost-Effectiveness analysis at the same cost of the Traffic Scenario (170M€), an Optimized Scenario (OS) has been computed. It represents the most performing scenario applying the most effective measures. Both the PM10 mean concentrations and the health costs have a significant reduction, going respectively from 6% to 21% and from 6% to 19%, as shown in summary Table 2.

Table 2: Traffic Scenario (TS) and Optimized Scenario (OS).

Impacts	CLE	TS	OS
Emission reduction costs [M€/year]	0	170	170
PM10 [mg/m3]	27.3	- 6%	- 21%
Health costs (due to months of life lost) [€]		- 6%	- 19%

Figure 7 depicts the Pareto curve (emision reduction cost objective vs. mean PM10 concentrations) that results form the Multi Objective optimization. Starting from CLE scenario, the curve shows the optimal

solutions at different costs. In particular two points are highlited: Traffic Scenario (green triangle) and the Optimized Scenario (red square).

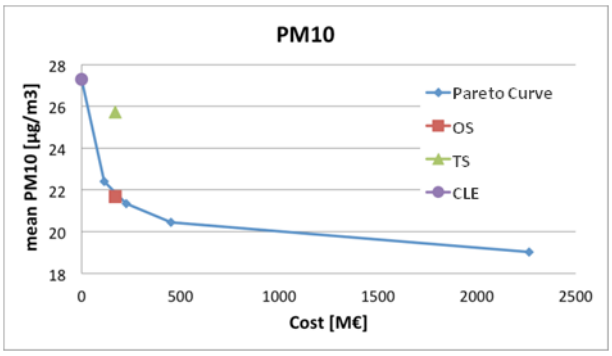

Figure 7: Pareto curve, TS (green triangle) and OS (red square).

Figure 8 shows the map of the yearly PM10 concentrations for OS. The highest concentrations are essentially disappeared over the industrialized area between Milano and Brescia.

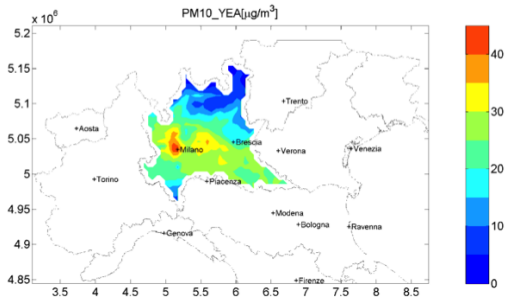

Figure 8: PM10 yearly average [µg/m^3] map for the optimized scenario.

Figure 9 shows the costs in each macrosector for OS. More than 140M€ over the total (170M€) are allocated for macrosector 10 (Agricolture). Macrosector 7 (Transports) and 2 (Non industrial combustion) are relevant. Figure 10 shows the emission reductions in each macrosector for the same scenario. The measures for Agriculture allow to reduce a great amount of NH3 emissions, but also the limided budget invested in macrosectors 7 and 8 (Transports and Other Mobile Sources) allows to reduce great amounts of emissions, in particular NOX emissions.

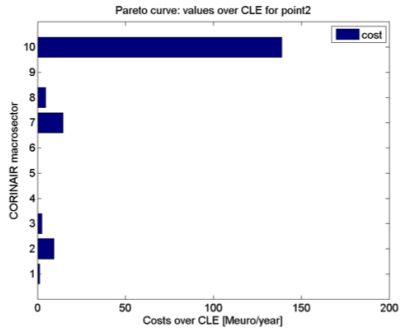

Figure 9: Costs [M€/year] in each Macrosector for OS.

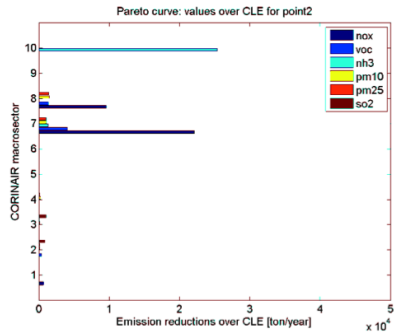

Figure 10: Emission Reductions [ton/year] in each Macrosector for OS.

CONCLUSIONS

In this paper the comparison between two approaches for air quality planning is presented. The first one is the scenario approach; it allows to assess the variations of the air quality indexes due to the application of a set of policies chosen by the user. Since the possible technological or non technological measures that can be implemented to reduce air pollution are hundreds, this approach does not guarantee that the most efficient combination of measures is identified, even though a large number of scenarios are assessed.

The Multi Objective approach optimizes a number of objectives simultaneously while applying a set of constraints. It allows to find the most efficient set of measures that garentees to achieve the higher reduction of secondary pollution over the domain , at minimun costs.

The case study presented shows that the scenario analysis focused the trafic emission macrosector is not efficient. The optimization approach, taking into account hundreds of different measures, is able to find air quality polices that are more effective on air quality, and consequently on health effects, and emission reduction costs.

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AUTHOR BIOGRAPHIES

CLAUDIO CARNEVALE is Assistant Professor at University of Brescia since 2006. He holds a Ph.D. in Information Engineering (University of Brescia) and he has been involved in a number of National and International projects (QUITSAT, RIAT, OPERA, APPRAISAL). He is author or co-author of around 80 scientific papers.
E-mail: claudio.carnevale@unibs.it

GIOVANNA FINZI is Full professor in Environmental Modelling and coordinates the ESMA research team, working on environmental decision support systems. She has been national delegate in the MC of several COST Actions, in EMEP TFMM and in TF-HTAP (UNECE LRTAP Convention) and member of IFAC, AGU, IEEE. She is in the Steering Group of the APPRAISAL project. She co-authored several peer-reviewed scientific papers.
E-mail: giovanna.finzi@unibs.it

ANNA PEDERZOLI is currently working at DIMI, University of Brescia. Her main research interests concern atmospheric physics and chemistry and the evaluation of the impact of air quality control policies. She is involved in a number of national and international projects.
E-mail: anna.pederzoli@unibs.it

ENRICO TURRINI is Research Fellow and Ph.D. student in Technology for Healh at University of Brescia since 2013. He has been involved in a number of national and international projects concerning optimal policy selection.
E-mail: enrico.turrini@unibs.it

MARIALUISA VOLTA is Associate Professor in Environmental Modelling, with a Ph.D. in Information Engineering. She has been involved in several national and European Projects, in particular as Project Leader of RIAT JRC project, chair of the OPERA LIFE+ project Steering Group, and coordinator of the APPRAISAL FP7 project. She is a national delegate at UNECE-TFIAM, a member of NIAM and of IFAC Technical Committee on Modelling and Control of Environmental Systems. She is author or co-author of around 120 scientific papers (65 peer-reviewed papers).
E-mail: marialuisa.volta@ unibs.it