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Minimizing external indirect health costs due to aerosol population exposure: A case study from Northern Italy

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A B S T R A C T

Environmental Agencies require Decision Support Systems, in order to plan Air Quality Policies considering the cost of emission reduction measures and the human health effects (with related social costs). The use of Decision Support Systems is also useful to spread information to general public, explaining the effectiveness of proposed air quality plans. In this paper, a multi-objective approach to control PM10 concentration at a regional level is presented. The problem considers both the internal costs (due to the implementation of emission reduction measures) and the external costs (due to population exposure to high PM10 concentrations). To model PM10 concentrations, a single surrogate model is used for the entire domain, allowing the implementation of a very efficient optimization procedure. The surrogate model is derived through a set of 10 simulations, performed using a Chemistry Transport Model fed with different emission reduction scenarios. The methodology is applied to Northern Italy, a region affected by very high PM10 concentrations that exceed the limit values specified by the EU legislation.

1. Introduction

Human exposure to high PM10 concentrations causes increasing of morbidity and mortality (Curtis et al. (2006), Rabl (2006) and Pope et al. (2002)). These health effects can be assessed (Moschandreas et al., 2002) by estimating the mean PM concentration over a domain, and then applying consistent dose–response functions. To estimate ambient PM concentrations different approaches are presented in literature. In the first approach ambient air pollution monitoring (Chow et al., 2002) sites are used to estimate exposure for human health studies (Bell, 2006; Kyrkilis et al., 2007)). This approach uses real measured data to estimate health effects. Even though it has two main limitations, due to the small number of available monitoring station over a domain, and to the possible lack of representativeness of the monitoring network when considering larger areas, this approach is still widely used (Chen et al. (2007), Zhang et al. (2007), Viana et al. (2008)). A second possible approach is to use statistical models to spatially interpolate measured PM concentrations (Yanosky et al. (2008), (Wu et al. (2006)). In this way it is possible to overcome the limitation of the scarce availability of monitoring station, but statistical models do not contain the representation of the physics and chemistry of PM10 formation and accumulation. Furthermore spatial interpolation techniques to estimate secondary pollutants contain large uncertainties for areas at large distances from monitoring stations (Tong et al., 2009). A third approach consists in using Chemical Transport Models (CTMs) to reconstruct PM10 concentrations over a study domain (Cuvelier et al. (2007)). Even if also model simulations are affected by uncertainties, the use of air quality models addresses several important limitations faced by monitor based approaches; i.e. with models it is possible to cover large regions without measurement stations and the capture of PM10 concentrations variability through detailed description of emission sources, topography and implementation of chemical and physical processes (Tong et al., 2009). Moreover, models can assess the effectiveness on Air Quality (and consequent health effects) of emission reduction policies.

Models in the frame of air quality policy support are defined as Integrated Assessment Models. These models, that evaluate the effects and costs of emission reduction strategies, are typically used in:

- *Scenario analysis* (Carnevale et al., 2009a), performed by assessing the effect of an emission reduction scenario on air quality, using deterministic modeling simulations;
- *Cost-benefit analysis* (Schöpp et al. (1999)) that monetizes all costs and benefits associated to an emission scenario in a target function, searching for a solution that maximizes the objective function;

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- *Cost-effective analysis* (Schöpp et al. (1999), Mediavilla-Sahagun and ApSimon (2003)), introduced in order to take into account the high uncertainty affecting the quantification of costs and benefits of non material issues. This approach looks for the best solution considering non monetizable objectives as constraints. The most comprehensive research project in the Integrated Assessment Modeling, based on a cost-effective analysis and focused mainly at a European scale, is RAINS/GAINS system (Amann et al., 2004a);
- *The multi-objective analysis* (Pisoni et al., 2009) (Castelletti et al., 2010), that performs a selection of the efficient solutions, considering in a vector function all the planning targets, assessing conflicts and synergies among them.

In this paper, an integrated assessment model based on a two-objective analysis (Pisoni et al., 2009) is proposed. This approach considers in the optimization procedure both internal costs, due to implementation of emission reduction policies, and external costs, due to health effects caused by high PM10 concentrations. This work is an extension of the Pisoni et al. (2009) paper, in particular dealing with (in comparison to the previous work):

- a much better data set for training neural networks (now 10 scenarios are used, instead of 2);
- the optimization of external and internal costs, rather then exposure index and internal costs;
- the use of a single artificial neural network over the entire domain, instead of a different neural network for each cell, allowing faster optimizations.

The proposed methodology, based on a limited number of control variables (emission reduction per pollution-activity macrosector), provides useful support in designing effective air quality policies mainly in those situations in which, due to time or money constraints, few input data can be collected (i.e. no detailed list of emission reduction technologies have been compiled for a particular domain).

A case over the Po Valley Area, in Northern Italy, is presented. This is a very polluted area that, in spite of actions taken by local authorities of the region to limit emissions, has PM10 levels often exceeding the EU limit value established for health protection (i.e. the daily limit of 50 $\mu g/m^3$, not to be exceeded more than 35 times per year, has been exceeded in 2009 in all Lombardy region main cities, except Varese (RSA, 2010)). This is due to high emissions of the area, peculiar orography and meteorological conditions, that play an important role in determining stable atmospheric conditions, low dispersion of pollutants, and consequently high PM concentrations (Carnevale et al., 2009a).

The paper is organised as follows: Section 2 describes the proposed methodology, Section 3 the case study results and Section 4 the conclusions.

2. Methodology

2.1. The decision problem

The aim of the proposed methodology is to plan Air Quality Control Policies over a regional domain, taking into account both cost of emission reductions and cost in terms of health effects. The problem can be formulated as:

$$\begin{aligned}&\min_{\theta} J(\theta) = \min_{\theta}(\alpha \cdot \mathrm{IC}(E(\theta)) + (1-\alpha)\cdot \mathrm{EC}(E(\theta)))\\&0 \le \alpha \le 1\\&\theta \in \Theta\end{aligned} \tag{1}$$

where E represents the precursor emissions for the reference case, θ are the decision variables (namely the precursor emission reductions), $\mathrm{EC}(E(\theta))$ and $\mathrm{IC}(E(\theta))$ are the External and Internal Costs respectively, both depending on precursor emissions and emission reductions, and α is the factor used to aggregate the two index (IC and EC) to get the final J value. J is so optimized for different α values, obtaining at the end the complete set of efficient solutions.

2.2. The decision variables

The decision variables are the percentage emission reductions ($\theta = \theta^{p,k}$) for each PM10 precursor (p) and CORINAIR macrosector (k). Five are the precursors for PM10 (NOx, VOC, SO2, NH3 and primary PM) and 11 the CORINAIR macrosectors; so there are in principle 55 decision variables in the control problem. The decision variables are subjected to the constraints:

$$0 \le \theta^{p,k} \le \Theta^{p,k} \tag{2}$$

where $\Theta^{p,k}$ are the maximum feasible reductions for precursor p and macrosector k.

2.3. Internal costs

The internal cost (IC) objective is related to the cost of implementation of a particular emission reduction scenario. Polynomial functions, linking technology ablation efficiency to reduction unit cost (Carnevale et al., 2008b), are used to estimate the internal cost index $\mathrm{IC}(E(\theta))$ as follows:

$$\mathrm{IC}(E(\theta)) = \sum_{p=1}^{P}\sum_{k=1}^{K}\mathrm{TC}^{p,k}\left(E^{p,k}\left(\theta^{p,k}\right),\mathrm{UC}^{p,k}\left(\theta^{p,k}\right)\right) \tag{3}$$

where:

- $\mathrm{TC}^{p,k}$ represents the total cost associated to reduction of precursor p in macrosector k;
- $\mathrm{E}^{p,k}$ is the total annual emission of the p precursor species for macrosector k in the reference case;
- $\mathrm{UC}^{p,k}$ represent functions linking emission reductions and unit cost, for each precursor species p and macrosector k.

The data used to identify these functions are derived by IIASA database (Amann et al. (2004b)). More details about the procedure to compute internal costs can be found in Pisoni et al. (2009).

2.4. External costs

The methodology implemented to estimate health effects and external costs (EC) is based on ExternE approach (Bickel and Friedrich, 2005). This methodology is used to transform domain PM10 concentrations at first in Years of Lost Life, and then in external costs.

2.4.1. Health impact and societal cost

The health indicator considered to compute external cost is related to mortality caused by long term PM10 exposure. In particular the Years Of Lost Life (YOLL) is considered (Bickel and Friedrich, 2005), modeled through linear and without thresholds Exposure-response functions (Brizio and Genon, 2004).

The mortality YOLL index estimates the Years of Lost Life of population exposed to PM10 pollution. Assuming the population split in cohorts of 5 years, the total YOLL index for the domain population is calculated as (Bickel and Friedrich, 2005):