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A decision methodology for large scale systems: the case of the air quality planning

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Abstract: The paper describes a multi-objective optimization approach to define efficient air quality control policies at regional scale. Air Quality and Cost of policy implementation are the two ingredients considered in the methodology. Both seasonal (for ozone) and yearly (for PM10) models are applied to simulate the Air Quality Index, based on Artificial Neural Networks. Results are shown at first in terms of Air Quality models performances, and then in terms of optimal policies suggestions, over a Northern Italy domain.

Keywords: Optimal air quality control policies, multi-objective approach, regional scale.

1 INTRODUCTION

Integrated Assessment Models (IAMs) are important tools able to support the Decision Makers needing to improve air quality in a cost-effective way. In particular, Decision Makers can act on emissions (precursors of air pollutants) and their measures eventually are able to reduce human and ecosystem exposure to pollutants. One of the most outstanding examples of these kind of tools is the RAINS/GAINS [Wagner et al., 2007] model, applied since a number of years at International/European level to determine cost-efficient policies to reduce emissions and achieve target for given air quality indicators (e.g. acidification, eutrophication, tropospheric ozone, primary and secondary particulate). Apart from European Scale, some national IAMs exist (RAINS-Italy as in D'Elia et al. [2009], RAINS-Netherlands as in Aben et al. [2003], FRES-Finland as in Syri et al. [2002], UK-IAM as in Oxley and ApSimon [2007], Belgium-IAM as in Deutsch et al. [2008]). Based on similar approaches to GAINS, these models can then be used to optimize emission reductions within a given country at the regional level. At the local/urban scale few IA models have been developed and applied [Mediavilla-Sahagun and ApSimon, 2003]; these have generally been used for non-reactive species. Many regional/local air quality managers therefore use simpler approaches (typically scenario analysis) applying, if detailed data are available on the local meteorology and emissions, complex multiphase air pollution models to estimate pollutant concentrations at each point in time and space through simulation [Finzi et al., 2000; Cuvelier et al., 2002; Sokhi et al., 2006; Carnevale et al., 2008].

The aim of this paper is to present and discuss the application of an IAM developed at regional scale.The main goal of this tool is to identify the most efficient mix of local policies required to reduce tropospheric ozone and particulate matter, in compliance with National and International air quality regulations (e.g. EU directives), while accounting for local peculiarities in terms of emissions, meteorology and technological, financial and social constraints. Due to different seasonal phenomenology during the formation and accumulation of ozone and PM10 in the atmosphere, the evaluation has been performed using both seasonal (for ozone) and yearly (for PM10) ANNs. The methodology has been applied to Northern Italy, a very polluted and challenging (from the Decision Maker point of view) area.

2 METHODOLOGY

The proposed metodology implements and solves a multi-objective problem, for selecting effective policies to control population exposure to primary and secondary pollutants. To do so, the methodology requires a) current and prospective emission reductions technologies and related costs (derived by GAINS [Wagner et al., 2007]); b) regional activities and emission data (from the regional emission inventory); c) source-receptor (S/R) models, developed for the specific regional environment (that is to say, the surrogate of a larger and more detailed chemical transport model, as described in Carnevale et al. [2012]). In the following Sections the procedure is described in detail.

2.1 The decision problem

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:

$$min\ [P(E(\theta))\ \ C(E(\theta))] \tag{1}$$

where E represents the precursor emissions; $P(E(\theta))$ is the air pollution index considered; $C(E(\theta))$ represents the implementation costs of pollution reduction measures, and both objectives depend on precursor emissions through a set of decision variables θ.

2.2 The decision variables

The total emission reduction for a pollutant p, due to the application of a set of technologies, can be calculated as the sum of the emission reductions over all the macrosector-sector-activity triples (these triples are defined as in the GAINS model nomenclature [Wagner et al., 2007]):

$$E_p = \sum_{ijk} E_{ijkp} \tag{2}$$

The decision variables are the application rates of the emission reduction technologies. The reduced emissions are computed as follows:

$$E_{ijkp} = \sum_{t \in T_{ijk}} A_{ijk} \cdot ef_{ijkp} \cdot eff_{ijktp} \cdot X_{ijkt} \tag{3}$$

where:

- E_{ijkp} are the emissions [kton] of the pollutant p, in the macrosector, sector, activity, ijk triple, remaining after the application of a set of technologies.
- T_{ijk} are the technologies that can be applied in the macrosector, sector, activity ijk triple.

- A_{ijk} are the activity levels of a macrosector, sector, activity ijk triple.
- ef_{ijkp} represents the unabated emission factor [kton/Act.Unit] for a macrosector, sector, activity ijk triple, for a particular pollutant p.
- eff_{ijktp} is a measure of the efficiency of technology t. More precisely, it is the fraction (between 0 and 1) of pollutant p remaining after the application of a particular technology t, to the activity ijk.
- X_{ijkt} represents the application rate (between $\underline{X}_{ijkt}$ and $\overline{X}_{ijkt}$, respectively minimum and maximum value) of a macrosector, sector, activity, technology $ijkt$ quadruple.

2.3 The objectives

The **Air Quality objectives** considered in this work are a) the annual mean PM10 concentration and b) the seasonal AOT40 (ozone concentrations accumulated over a threshold of 40 ppb). The relationship between the decision variables and the indexes is modelled by Artificial Neural Networks, identified processing long-term simulations of the TCAM Chemical Transport Model (see i.e. [Carnevale et al., 2012] for more details on this step).

The Cost Objective is calculated as follows. For each activity i in sector j, macrosector k, the cost of applying all technologies is computed as:

$$C_{ijk} = \sum_{t \in T_{ijk}} C_{ijkt} \cdot A_{ijk} \cdot X_{ijkt} \tag{4}$$

where:

- C_{ijk} are the abatement costs [Meuro] for macrosector, sector, activity, ijk triple.
- C_{ijkt} are the unit costs [Meuro] of application of technology t.
- A_{ijk} and T_{ijk} and X_{ijkt} are the Activity Level (A) and the set of technologies (T) that can be applied for a certain sector-activity.

So the total costs [Meuro] are:

$$C = \sum_{ijk} C_{ijk} \tag{5}$$

In practice the two-objective optimization problem is solved following the ϵ-Constraint Method [Ehrgott, 2000]: the Air Quality objective is minimized using the Sequential Quadratic Programming approch [MathWorks, 2010], while the Cost objective is included in the set of constraints with a parametric threshold, i.e.:

$$\underset{X_{ijkt}}{min}\ P(X_{ijkt}) \tag{6}$$

$$C(X_{ijkt}) \leq L,\ 0 \leq L \leq \overline{L} \tag{7}$$

where $\overline{L}$ is the cost of a full application of all the available technologies. This is the same form of a standard cost-effectiveness analysis: a problem that the Decision Maker may be interested to solve, when the budget L is known.

2.4 The constraints

The problem constraints are the following:

- technology feasibility (control variables are constrained to remain between minimum and a maximum value):

$$X_{ijkt}^{CLE} \leq X_{ijkt} \leq \overline{X}_{ijkt},\ \forall ijkt \tag{8}$$

- emission conservation (for each sector-activity, and for each precursor, you can apply emission reductions to a maximum of 100 % of available emissions):

$$\sum_{t \in T_{ijk}} X_{ijkt} \leq 1 \tag{9}$$

3 APPLICATION

3.1 Case study domain

The methodology has been applied on a Northern Italy domain, characterized by high level of pollution concentrations both in winter (pm) and summer (ozone). The domain is shown in Figure 1. It is possible to notice, looking at the orography of the area (shown in the Figure) that the region is a basin, with a really low wind circulation, that brings to accumulation and reaction of secondary pollution.

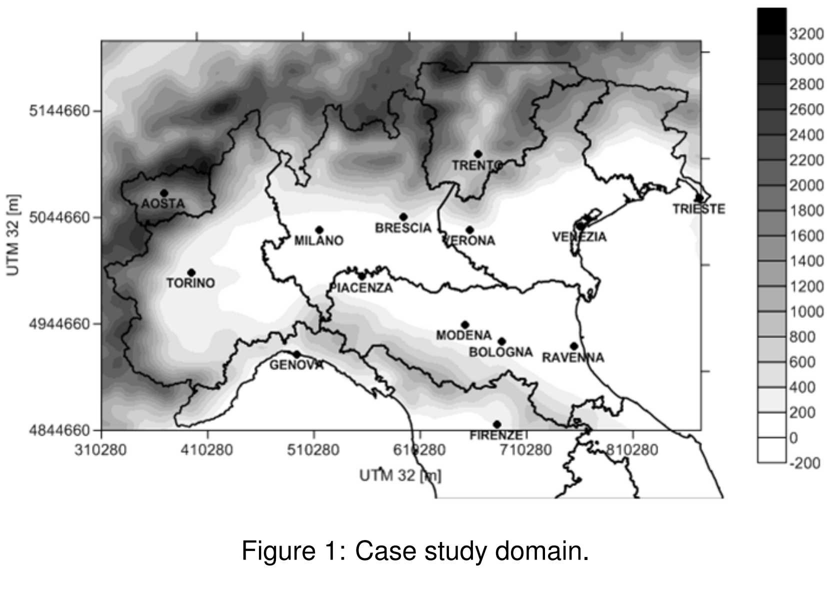


Figure 1: Case study domain.

3.2 Air Quality models

Artificial Neural Networks (ANNs) have been identified to link control variables (through emissions) to concentrations on the study domain. Starting from a number of simulations performed with a Chemical Transport Model (CTM), ANNs have been identified and validated, so that the surrogate of the full CTM can then be used in the optimization methodology. The whole procedure has been already presented in detail in Carnevale et al. [2012]; here we only show some relevant results. After having tested different ANNs configurations, the best one (in terms of mean squared error) has been selected, for each of the Air Quality Index considered in this work, that is to say AOT40 with seasonal emissions (**aot-sea**) and PM10 with yearly emissions (**pm10-yea**). The need to consider seasonal emissions for AOT40 models is related to the fact that ozone is a summer pollutant, and so the application of yearly (instead of seasonal) emission-based model could cause inconsistencies in optimization results. The best ANNs, as shown in Table 1, share the same features, both for ozone and PM indexes.

Table 1: Configuration for the best ANNs, for the two considered Air Qualiy Indexes.

	aot40-sea	**pm10-yea**
ANN type	feedforward	feedforward
TF1	Logsig	Logsig
TF2	Purelin	Purelin
Neurons ##	20	20
Epochs ##	300	300

In terms of statistical indicators (Table 2) all the ANNs show good performances, both in terms of correlation and errors, with higher correlations for PM10 ANNs, but lower normalized errors for ozone.

Table 2: Performances for the best ANNs, for the two considered Air Qualiy Indexes.

	aot40-sea	**pm10-yea**
corr	0.96	0.98
nmae	0.07	0.11
mae	3814.11	1.18
nmse	0.01	0.02
rmse	5086.26	1.7
maxe	0.46	1.91

3.3 Optimal policies

After having identified and validated the ANNs, two optimizations have been performed considering as Air Quality index both AOT40 (for ozone) and PM10. Figure 2 shows the optimal solutions computed through the multi-objective optimization procedure. In particular considering on the x-axis the cost of the policies, with values normalized to the Maximum Optimal Cost; and on y-axis the air quality relative improvement for the two considered optimizations. The two curves start at a value equal to 1; this value represents the CLE (Current LEgislation) values (for each single Air Quality Index) normalized at

1, and is the starting point to realize what happens if, with a predefined budget (on x-axis) we try to improve air quality. The highest improvement is (in % values) for ozone, that decreases its AQI value of 35%, in comparison to its initial value. For the PM the improvement is limited to 20%. This comment however does not take into account all the chain of impacts on ecosystem and health of the considered indexes, that are quite different for the two pollutants (in fact external costs associated to different pollutants can vary a lot, and the same comment in terms of ”effects” improvement could be very different).

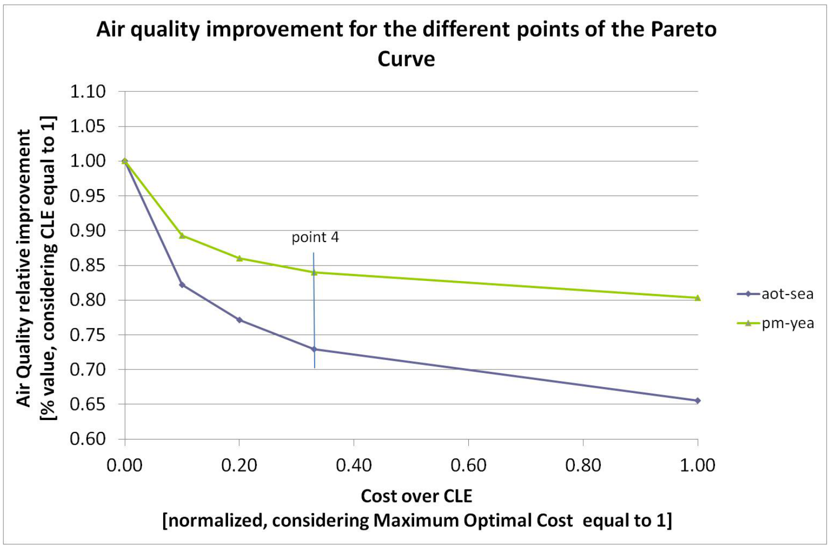
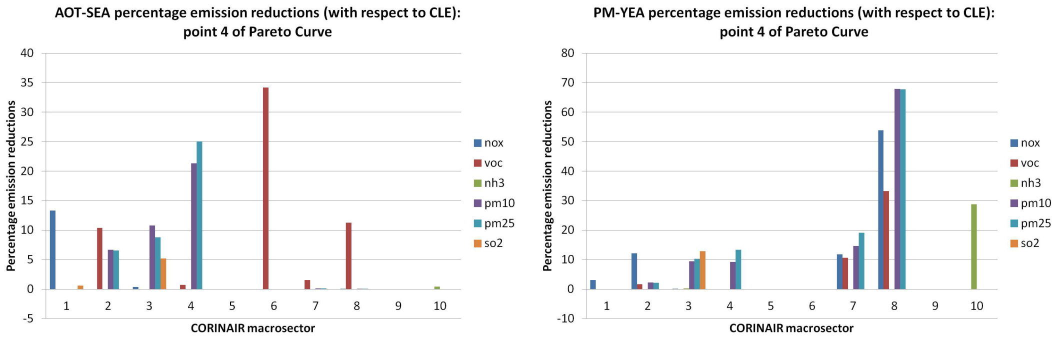


Figure 2: Comparison of optimal solutions computed through the multi-objective optimization procedure. In particular the x-axis shows the cost of the policies, normalizing its value to the Maximum Optimal Cost. The y-axis represents the air quality relative improvement for the two considered optimizations (the starting point is the Current LEgislation, normalized to 1). Point 4 of the Pareto curve (that will be considered in the final part of the paper) is also shown.

In terms of optimal policies, Figure 3 shows the percentage emission reductions (with respect to CLE emissions) for the 4th point of the Pareto curve (see Figure 2 to define this point), for the ozone (left Figure) and PM (right Figure) cases. The two cases are characterized by important differences. In particular, for the ozone case, the % emission reductions are mainly focused on macrosector 6 (solvent use) for VOC emissions, and macrosector 4 (production processes) on PM emissions, while for PM optimization the main reductions are on macrosector 8 (other mobile sources and machinery) for all emissions except NH3 ones, and macrosector 10 (agricolture) on NH3 emissions. These results show how the two Air Quality Objectives (ozone and PM) are in conflict (the 2 optimizations suggest different reduction priorities) and so that a multi-AQI optimization approach should be implemented, to find a trade-off among different measures. An important comment is related to macrosector 7 (road trasport). In the proposed optimization approach, new technologies can be applied only when there are emissions that are ”not controlled” (that is to say, some emissions are completely uncontrolled and no measures are applied on them). The case of macrosector 7 is quite peculiar, because almost 90% of emissions in this macrosector are already controlled (via the different EURO standars on cars) and so new measures can be applied only on a small fraction of the total emissions. For this reason, even if it is well-known that traffic emissions play an important role on PM10 concentrations, the suggested optimal percentage emission reductions are only between 10 and 20 % (depending on the considered pollutant).



(a) (b)

Figure 3: Percentage emission reductions, with respect to CLE emissions, for point 4 of the Pareto curve, for AOT-SEA (a) and PM-YEA (b) optimization.

4 CONCLUSIONS

In the frame of a multi-objective optimization approach, this paper presents the comparison of two possible configurations of the problem: considering AOT40 and considering PM10 as Air Quality Objectives. The correspondent ANNs have been identified and validated, and two optimizations have been performed. The results show how the percentage possible improvement on ozone Air Quality Index are higher than the one that can be obtained on PM10 Air Qualilty Index. Also the paper shows how the percentage emission reduction priorities differ between the ozone and PM optimizations. This last aspect stresses the conflict between ozone and PM emission reduction measures, and underlines how it is important to extend the proposed optimization approach to deal with multi-AQIs objectives, to properly look for a trade-off among different air quality measures.

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