Formalizing and solving the PM10 control problem

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Abstract: Atmospheric Particulate Matter (PM10) control is at the moment a great challenge for air quality management, due to the strong non linearities that affect formation and accumulation of this pollutant. This work presents the formalization and application of a two-objective methodology to select effective particulate matter control strategies on a mesoscale domain. The two considered objectives are emission reduction costs and the PM10 exposure index. The decision variables are the precursor emission reductions due to ablation technologies. The nonlinear relationships linking air quality objective and precursor emissions are described by neuro-fuzzy models, identified through the processing of simulations of the TCAM deterministic multiphase modeling system, performed in the framework of the CityDelta-CAFE Project (EU 6th Framework Program). The two-objective problem has been applied to a complex domain in Northern Italy, including the Milan metropolitan area, a region characterized by high emissions and frequent and persistent secondary pollution episodes.

1. INTRODUCTION

The Particulate Matter is one of the most important pollutants in Europe, in particular in high industrial and urban area like northern Italy due to its profound impact on human health and ecosystem. This is particularly true if the particulate matter with diameter lower than 10 μm (PM10) is considered. Moreover, PM10 formation and accumulation in troposphere are strongly nonlinear processes, related to meteorological condition and to the emissions of its precursors: volatile organic compounds (VOC), nitrogen oxides (NO_x), ammonia (NH_3), primary particulate matter (PPM) and sulfur oxides (SO_x). Controlling PM10 concentrations means to abate the precursor emissions taking into account the nonlinear processes involving the precursors and the costs of emission ablation technology. There are different techniques to assess the effect of emission reductions, as (a) scenario analysis (Haurie et al. (2004), Lim et al. (2005)); (b) cost-benefit analysis (Reis et al. (2005), Schrooten et al. (2006)); (c) cost-effectiveness analysis (Schöpp et al. (1999), Amann et al. (2004)); (d) multi-objective optimization (Guariso et al. (2004), Carnevale et al. (2007)). The multi-objective approach allows, calculating alternative optimal emission reduction scenarios, to consider the trade-off among different targets, for example considering both air quality improvement and cost, due to the implementation of a particular emission reduction policy. The multi-objective analysis has rarely been tackled in literature, due to the difficulties to include in the optimization problem the non-linear dynamics involved in particulate matter formation. In fact in the multi-objective approach the pollution-precursor relationship can not be simulated by deterministic 3D modeling systems, due to their high computational costs: the identification of simplified models capturing the relationship between the precursor emissions and secondary pollutant concentrations is required. For this purpose, source-receptor relationship has been implemented using isopleths (Flagen and Seinfeld (1988), Loughlin (1998)), and reduced form models such as (a) simplified models, adopting semi-empirical relations calibrated with experimental data as in Venkatram et al. (1994), or (b) statistical models, identified on the results of complex 3D transport-chemical models as in Schöpp et al. (1999), Friedrich and Reis (2000), Volta (2003), Guariso et al. (2004).

This work formalizes and applies a two-objective problem to select effective emission abatement strategies, considering (a) an air quality objective (the yearly mean PM10 concentrations), and (b) a cost objective (the costs due to the reduction of PM10 precursor emissions). The methodology has been applied to Lombardia Region, the most populated and industrialized area in Northern Italy, regularly affected by high PM10 concentrations.

2. PROBLEM FORMULATION

The particulate matter control problem can be formulated as a two-objective mathematical programming problem, including the effectiveness of emission reduction policies on an Air Quality Index (AQI) and their costs (RC). The problem can be formalized as follows:

$$\min_{\theta} J(E(\theta)) = \min_{\theta} [AQI(E(\theta)) \quad RC(E(\theta))] \quad (1)$$
$$\theta \in \Theta$$

where E represents the precursor emissions, θ are the decision variables, namely the emission reductions, constrained to assume values in Θ, $AQI(E(\theta))$ is the air quality objective and $RC(E(\theta))$ are the reduction costs, both depending on precursor emissions and emission reductions. In this section the formalization of the the control variables (2.1),

the air quality (2.2) and the cost objectives (2.3) will be presented.

2.1 Control Variables

A comprehensive problem formulation should consider separately each emission source as a decision variable, but this assumption leads to an unfeasible computational problem, due the high number of control variables. For this reason, it is natural to consider as decision variables a common percentage of reduction for groups of pollutant activities. This work assumes the CORINAIR emission classification in the following 11 macrosectors (EMEP/CORINAIR, 1999):

(1) public power, cogeneration and district heating plants;
(2) commercial, institutional and residential combustion plants;
(3) industrial combustion;
(4) production processes;
(5) extraction and distribution of fossil fuels;
(6) solvent use;
(7) road transport;
(8) other mobile sources and machinery;
(9) waste treatment and disposal;
(10) agriculture;
(11) nature.

The control variables of the decision problem are the emission percent reductions $\theta = \left\{ \theta^{p,s} \right\}_{s \in S}^{p \in P}$, for each PM precursor $p = \{VOC, NO_x, NH_3, PM, SO_x\}$ and CORINAIR macrosector s; so in principle there are 55 control variables (emission reductions).

2.2 Air quality objective

The precursor-PM relationship virtually should be given by the simulation of deterministic 3D modeling systems. Such models require so high computational time that are not of practical use in an optimization problem. For this reason simplified source-receptor models have been identified through the processing of simulations performed by a deterministic modeling system.

Air quality index   The air quality objective is a PM exposure index over a grid domain. Such exposure index is a function both of emissions (control variables) and meteorological parameters (that cannot be handled). The daily cell emissions are expressed with respect to a reference situation and split into the CORINAIR macrosectors (EMEP/CORINAIR, 1999). Since a regional Authority can impose different reduction to different emission macrosectors, the air quality index (AQI) can be expressed stressing the emission dependance of the exposure index function (Ψ) for cell (i,j), as follows:

$$AQI(E(\theta)) = \Psi\left(E_{i,j}^{p,s}(\theta^{p,s}) \right) \qquad (2)$$

where $E_{i,j}^{p,s}$ is the emission of the p precursor species for macrosector s in the cell (i,j);

Deterministic approach   PM10 concentrations are typically simulated by three-dimensional deterministic modeling systems. In this work the Gas Aerosol Modeling
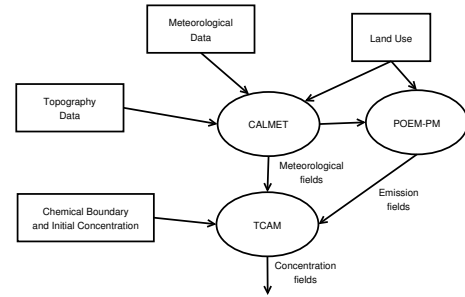

Fig. 1. The GAMES modeling system.

Evaluation System (GAMES) (Volta and Finzi, 2006) has been used. It consists of three main modules as shown in Figure 1: (a) the multi-phase Eulerian 3D model TCAM (Carnevale et al., 2008); (b) the meteorological pre-processor CALMET (Scire et al., 1990); (c) the emission processor POEM-PM (Carnevale et al., 2006).

Source-receptor approach   Simplified models based on neuro-fuzzy approach are identified through the processing of input and output of several runs of the GAMES deterministic modeling system.

In the neuro-fuzzy approach (Figure 2), neural networks are used to tune the membership functions of the fuzzy system, and to extract fuzzy rules from the identification dataset (Shing and Jang, 1993). In this work, a 4 layer neuro-fuzzy network is considered, as implemented in MATLAB® Fuzzy Logic Toolbox (MathWorks, 2006a).

The first layer computes the value of the membership function (MF) $\xi_{A_{h,d}}(v_d, \alpha_{h,d}, \beta_{h,d})$ (where the dependence to parameter $\alpha_{h,d}$ and $\beta_{h,d}$ to be identified during the training process is stressed) of each component of the input vector $v \in \mathbb{R}^D$, where $A_{h,d}$ is the $h-th$ linguistic variable of the $d-th$ input vector component.

In the second layer, the antecedent of each of the Z rules has been computed by means of a T-norm function and normalized:

$$w_z = T\left(\xi_{A_{h,d}}(v_d) \right) \qquad \forall A_{h,d} \in Ant_z \qquad (3)$$

$$\overline{w_z} = \frac{w_z}{\sum_{z=1}^{Z} w_z} \qquad (4)$$

where:

- D is the input vector cardinality (i.e. the number of the network inputs);
- H is the number of linguistic variable;
- T is the chosen T-norm function (min, and);
- Ant_z is the set of antecedents of the $z-th$ rule;
- $Z = H^D$ is the number of fuzzy rules in the second layer.

The third layer performs the computation of the consequent parameter of the rules, following the Takagi-Sugeno approach:

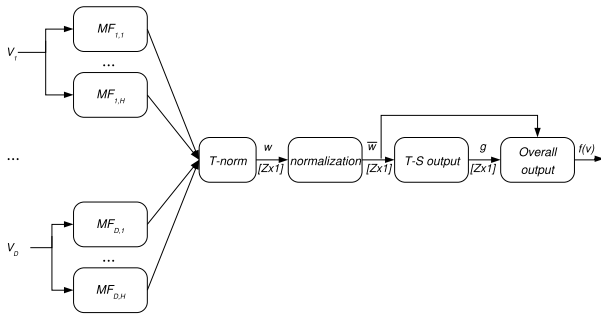$$g_z = w_z \cdot \left(\sum_{d=1}^{D} (p_{d,z} \cdot v_d) + r_z \right) \qquad (5)$$

Fig. 2. Scheme of the Neuro-Fuzzy Network.

Finally, the overall output is computed as the weighted mean of the output membership functions g_z:

$$f(v) = \sum_{z=1}^{Z} \overline{w_z} \cdot g_z \qquad (6)$$

During the learning process the membership function parameters $\alpha_{h,d}$, $\beta_{h,d}$, $p_{d,z}$ and r_z are tuned, using a back-propagation algorithm.

2.3 Cost objective

The cost objective of PM10 control can be formulated as follows:

$$RC(\theta) = \sum_{p} \sum_{s} RC^{p,s}\Big(E^{p,s}(\theta^{p,s}), uc^{p,s}(\theta^{p,s})\Big) \qquad (7)$$

where:

- $RC^{p,s}$ represents the total cost associated to reduction of precursor p in macrosector s;
- $E^{p,s}$ is the total annual emission of the p precursor species for macrosector s in the reference case;
- $uc^{p,s}$ represent the cost functions, that link emission reductions and unit cost, for each p precursor species and macrosector s.

More details about the methodology to derive cost objective are provided in Carnevale et al. (2007).

3. CASE STUDY

To apply and test the two-objective methodology the Lombardia region domain has been selected ($300 \times 300 km^2$). The domain has 10 million inhabitants, is one of the most industrialized in Italy, and is characterized by high traffic emissions. Furthermore in this area there are adverse atmospheric circulation, with stagnant conditions, low mixing height and low wind speed, that cause PM10 concentrations to be higher than the european standard specifications. The highest $PM10$ concentrations are reached in winter. Experimental data (Putaud et al., 2004), (Lonati et al., 2007) and modeling studies (Cuvelier et al., 2007), (Carnevale et al., 2008) show that the secondary fraction is extensive all over the domain (up to 70%).

In the following subsections control variables selection (3.1), air quality objective (3.2) and cost objective (3.3), formalized in Section 2, will be presented for the selected case study.

3.1 Control variables

As already stated, the considered control variables are the emission reductions for each CORINAIR macrosector. For $PM10$ in principle the problem should consider 55 control variables, eleven for each of $PM10$ precursor emission reductions, that is to say VOC, NO_x, NH_3, primary PM and SO_2. Indeed, the optimization problem solution does not consider the reduction of all the decision variables, due to the fact that in some CORINAIR macrosectors it is not possible to reduce emissions (i.e. biogenic emissions in macrosector 11 can not be abated), or there are no emissions on a particular macrosector. In Table 1, this information is summarized. $\Theta^{p,s}$ is the maximum feasible reductions allowed by the available technologies for pollutant p in the CORINAIR macrosector s (in the Table 1 'N.A.' means 'not applicable'). This means that i.e. the best $PM10$ technologies for macrosector 2 can reduce a maximum of 59% of current emissions. Furthermore it means that the NH_3 reductions are feasible only for macrosector 10, PM reductions for macrosectors 1, 2, 3, 4, 7, 8 and 9, SO_2 reductions for macrosector 1, 2, 3, 4, 7 and 8, etc...

It is important to underline the case of macrosector 7 and 8. Technologies of these macrosectors can reduce at the same time VOC, PM and NO_x. To take into account this fact, in the optimization problem NO_x reductions are taken into consideration as decision variables, while VOC and PM emission reductions are constrained to NO_x ones using polynomial functions linking VOC to NO_x and PM to NO_x abatement efficiencies (Carnevale et al., 2007).

3.2 Air quality objective

For this application neuro-fuzzy precursor models have been identified through the processing of GAMES simulations performed in the frame of the CAFE (Clean Air For Europe) CityDelta II project (Cuvelier et al., 2007). To evaluate different PM emission scenarios, the advantage in using simplified models instead of complex deterministic models, in terms of computational requirements, is significant. In fact the run of a yearly simulation with

Table 1. Maximum feasible reductions allowed by techonologies, for $PM10$ precursors).

CORINAIR macros.	$\Theta^{VOC,s}$	$\Theta^{NO_x,s}$	$\Theta^{NH3,s}$	$\Theta^{PM,s}$	$\Theta^{SO_2,s}$
1	N.A.	0.76	N.A.	0.24	0.72
2	0.68	0.39	N.A.	0.59	0.56
3	N.A.	0.34	N.A.	0.09	0.60
4	0.19	0.80	N.A.	0.40	0.80
5	0.33	N.A.	N.A.	N.A.	N.A.
6	0.33	N.A.	N.A.	N.A.	N.A.
7	0.47	0.29	N.A.	0.41	0.76
8	0.06	0.25	N.A.	0.39	0.59
9	0.06	N.A.	N.A.	0.82	N.A.
10	N.A.	N.A.	0.58	N.A.	N.A.
11	N.A.	N.A.	N.A.	N.A.	N.A.

Table 2. Neuro-fuzzy network architecture.

NF features	Value
H: Number of MF for input	2
$\mu_{A_{h,d}}(v_d)$: Input MF	$\left(1 + exp\left(-\frac{v_d - \beta_{h,d}}{\alpha_{h,d}}\right)\right)^{-1}$
$Z = H^D$: Number of fuzzy rules	2^5
g_z: Output MF	r_z
N_{tr}: Training set	843
N_{val}: Validation set	252

neuro-fuzzy models need 15 seconds to be performed on a Pentium IV - 3.8 GHz with 1 GB RAM machine. For the same simulation-machine GAMES modeling system requires 26 days.

The neuro-fuzzy identification and validation series have been selected processing the GAMES simulation results obtained considering basecase, CLE (Current LEgislation) and MFR (Most Feasible Reduction) scenarios of the Citydelta project (Cuvelier et al., 2007). Each GAMES simulation covers a period from January to December. The validation set (N_{val}) has been yielded extracting, from the simulation pattern, the third week of each month. The original GAMES simulations have a 5x5 km^2 resolution; about neuro-fuzzy, one network has been identified for each group of 36 GAMES domain cells (aggregating contiguous squares of 6x6 GAMES cells) identifying a modeling system with resolution of 30x30 km^2.

The neuro-fuzzy input data are the daily VOC, NO_x, NH_3, PM and SO_2 emissions estimated for each group of 6x6 cells. The neuro-fuzzy target data are the $PM10$ long-term mean concentrations computed by the GAMES system. It is important to stress that GAMES simulation results, used to identify neuro-fuzzy models, have been validated in a previous study (Carnevale et al., 2008).

The Air Quality Index considered is defined as a $PM10$ mean value over the considered time period, as defined by European Union Directive (Communities, 1999).

$$AQI_{i,j}^{MeanPM}(E_{i,j}) = \frac{\sum_n PM_{i,j}^{NF}(E_{i,j}(t))}{N} \quad [\mu g/m^3]$$
(8)

where:

- n are the days in the considered temporal period (in this case from January to December);
- $PM_{i,j}^{NF}(E_{i,j}(t))$ are the PM10 concentrations computed by neuro-fuzzy models for the cell (i,j), depending on time n and emissions E;
- N is the length of the temporal period considered.

The identified nets are characterized by the features shown in Table 2.

The scatter plot and the normalized mean error map between neuro-fuzzy and GAMES results, for the validation phase, are shown in Figure 3 and 4.

The scatter plot shown in Figure 3 confirms that the neuro-fuzzy system ensures capability to simulate the nonlinear source-receptor relationship between $PM10$ mean concentration and the emission of its precursors. For concentration lower than 30 $\mu g/m^3$ the system underestimates the
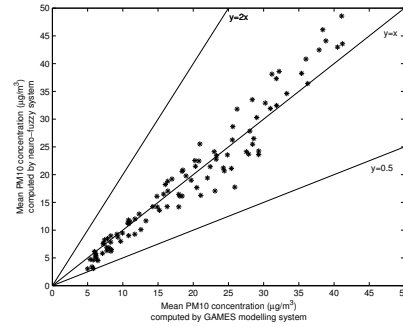

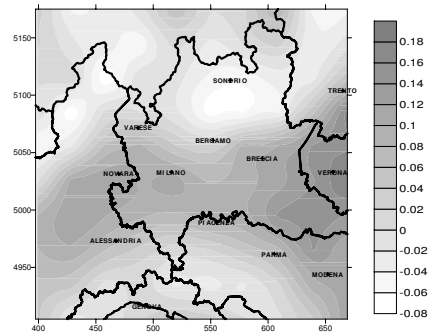Fig. 3. Neuro-fuzzy versus GAMES $PM10$ concentrations on each grid point of the domain.

Fig. 4. Normalized error between neuro-fuzzy system and GAMES simulated mean concentrations for the validation dataset.

target values up to 5 $\mu g/m^3$. On the contrary the system overestimates the concentration higher than 30 $\mu g/m^3$ up to 5 $\mu g/m^3$. The normalized mean error between $PM10$ mean concentrations computed by neuro-fuzzy system and GAMES (Figure 4) shows that the simplified models are able to reproduce the mean concentration over the domain, in particular in the area where the concentrations are higher (Po Valley/Milan urban area).

3.3 Cost objective

The abatement cost curves have been estimated on the basis of a large data set collected for Italy by IIASA (http://www.iiasa.ac.at). An emission abatement cost function for each macrosector has been estimated within zero and the maximum removal efficiency of technologies, with the constraint of identifying monotonically increasing and convex functions. Furthermore polynomial functions linking VOC to NO_x efficiency, and PM to NO_x efficiencies have been estimated, to update during optimization VOC and PM removal efficiency using NO_x removal efficiency of macrosector 7 and 8 (see Section 3.1). The cost function identification is described in Carnevale et al. (2007).

4. RESULTS AND DISCUSSION

The multi-objective optimization problem has been solved implementing the Weighted Sum Strategy (Ehrgott, 2000) using MATLAB® Optimization Toolbox (MathWorks, 2006b). Each single objective optimization problem derived by this approach has been solved by the Sequential

Quadratic Programming (SQP) method (Han, 1963). Figure 5 shows the result of the optimization methodology for the considered case study. The set of non-dominated solutions represents efficient reduction policies that can be implemented by the Decision Maker.
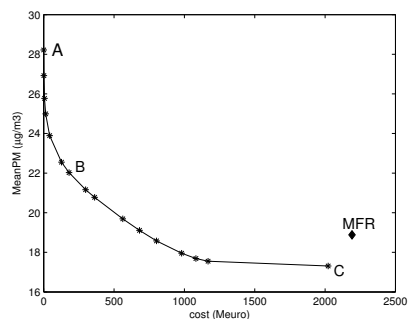

Fig. 5. The Pareto boundary.

In Figure 6 the Pareto boundary is rescaled with respect to the maximum feasible variation.
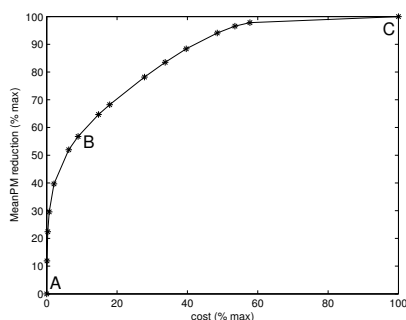

Fig. 6. The set of PM reduction non-dominated solutions rescaled with respect to the maximum feasible variation.

The extreme scenarios are highlighted:

- no technologies application (point A in Figures 5 and 6);
- PM index most reducing scenario (point C in Figures 5 and 6)
- MFR (Most Feasible Reduction) scenario implementing maximum emission reductions (point MFR in Figure 5)

The basecase emission scenario (point A) implies no costs and produces a maximum exposure PM index over the domain. Adopting the PM10 index most reducing technologies (point C), maximum emission reduction cost is associated to a minimum exposure PM index over the domain. The MFR scenario achieved by implementing maximum emission reductions is a dominated solution of the decision problem. The most interesting portion of the Pareto curve is the part characterized by strong slope, where an improvement in one objective does not imply a strong worsening of the other. For instance, the solution that corresponds to about 60% of the maximum air quality improvement (point B in Figures 5 and 6) can be attained with only about 10% of the maximum possible cost.

The two-objective problem solution suggests the values of decision variables needed to attain a particular PM exposure reduction. In Figure 7 and 8 i.e. this information is depicted for the case of NO_x and PM emission reductions.
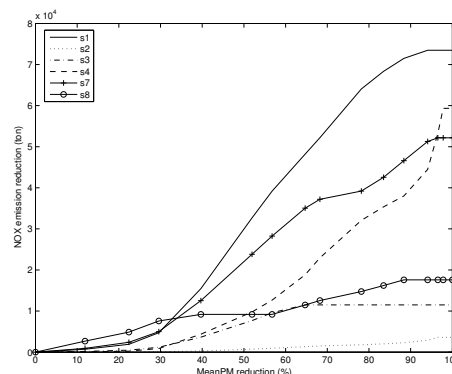

Fig. 7. NO_x emission reduction (ton), for each macrosector, to generate PM optimal solutions.
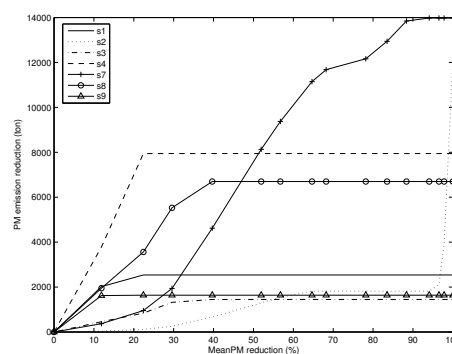

Fig. 8. Primary PM emission reduction (ton), for each macrosector, to generate PM optimal solutions.

In the case of NO_x (Figure 7) power plants (macrosector 1) and road transport (macrosector 7) have both to be reduced strongly to achieve the Air Quality Objective reduction. For PM emission (Figure 8) the main reductions have to be implemented in residential combustion (macrosector 2) if low Air Quality Objective are requested, in road transport (macrosector 7) for high Air Quality Objective reductions.

5. CONCLUSIONS

A multi-objective optimization approach to control PM10 concentration at the mesoscale has been formalized; it allows to consider trade-offs between two conflictual objectives, i.e. the air qualiy effectiveness and the costs of precursor emission reductions. The approach has been applied over a Northern Italy domain, a region often affected by high PM10 concentrations. The first objective is estimated processing neuro-fuzzy source-receptor models, tuned by GAMES long-term simulations performed in the frame of CityDelta II-CAFE EU Project. The second objective is computed by means of cost functions, estimated starting from IIASA reduction technology database. The multi-objective problem has been solved drawing the non-dominated curve. The analysis of the Pareto boundary allows to assess the priorities that an air quality manager

should first take into consideration, to reduce PM10 exposure in an efficient way.

6. ACKNOWLEDGMENTS

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