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A multi-objective nonlinear optimization approach to designing effective air quality control policies[☆]

Claudio Carnevale, Enrico Pisoni*, Marialuisa Volta

Department of Electronics for Automation, University of Brescia, Via Branze 38, 25123 - Brescia, Italy

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Abstract

This paper presents the implementation of a two-objective optimization methodology to select effective tropospheric ozone pollution control strategies on a mesoscale domain. The objectives considered are (a) the emission reduction cost and (b) the Air Quality Index. The control variables are the precursor emission reductions due to available technologies. The nonlinear relationship linking air quality objective and precursor emissions is described by artificial neural networks, identified by processing deterministic Chemical Transport Modeling system simulations. Pareto optimal solutions are calculated with the Weighted Sum Strategy. The two-objective problem has been applied to a complex domain in Northern Italy, including the Milan metropolitan area, a region characterized by frequent and persistent ozone episodes.

Keywords: Multi-objective optimization; Modeling; Artificial neural networks; Nonlinear control; Environmental control

1. Introduction

Tropospheric ozone originates, through nonlinear reactions, from precursor emissions (mainly VOC — volatile organic compounds and NO_x — nitrogen oxides) and high solar radiation. Decision Makers are interested in developing air quality plans, acting in terms of precursor emission reductions. Due to nonlinearities bringing to formation and accumulation of ozone, 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 cost implementation.

In the literature the following methodologies, based on Integrated Assessment Modeling, are available to evaluate alternative emission reductions: (a) scenario analysis (Thunis et al., 2007), (b) cost-benefit analysis (Rabl, Spadaro, & Zwaan, 2005; Reis, Nitter, & Friedrich, 2005) (c) cost-effectiveness analysis (Carslon, Haurie, Vial, & Zachary, 2004; Shih, Russell, & McRae, 1998) and (d) multi-objective analysis (Carnevale, Pisoni, & Volta, 2007; Guariso, Pirovano, & Volta, 2004). 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 appeared in the literature, due to the difficulties to include the nonlinear dynamics involved in ozone formation in the optimization problem. The pollution-precursor relationship can be simulated by deterministic 3D modeling systems, describing chemical and physical phenomena generating tropospheric ozone. Such models, due to their complexity, require high computational time and are not implementable in an optimization problem. The identification of simplified models synthesizing the relationship between the precursor emissions and ozone

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* Corresponding author. Tel.: +39 030 3715510; fax: +39 030 380014.
E-mail addresses: carneval@ing.unibs.it (C. Carnevale), enrico.pisoni@ing.unibs.it (E. Pisoni), lvolta@ing.unibs.it (M. Volta).

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concentrations, therefore, is required. In the literature, source-receptor relationships have been described using ozone isopleths (Shih et al., 1998), or with reduced form models such as (a) simplified photochemical models, adopting semi-empirical relations calibrated with experimental data (Venkatram, Karamchandani, Pai, & Goldstein, 1994), and (b) statistical models, identified on the results of complex 3D Chemical Transport Models (Friedrich & Reis, 2000; Guariso et al., 2004; Ryoke, Nakamori, Heyes, Makowski, & Schöpp, 2000).

In this paper, an integrated assessment methodology is proposed. It is focused on the mesoscale to better interpret the specific features of the area, the local meteorological and chemical conditions, the contribution of regional and local precursor emissions. It solves a two-objective (air quality and cost) optimization to select effective abatement strategies. The nonlinear relations between control variables (precursor emissions reduction) and Air Quality Index, defining the air quality objective, are described by artificial neural networks, identified processing long-term 3D deterministic multi-phase modeling system simulations. Emission reduction costs are described by deriving polynomial functions from a detailed technology dataset compiled by IIASA (Amann et al., 2004a). This paper is organized as follows. In Section 2 the methodology is proposed, focusing at first on the control variables used in the problem, then describing the air quality objective and the cost objective. Section 3 presents the applications of this approach on a case study, focusing on the Pareto boundary calculation and results. The conclusions (Section 4) stress the benefits of this kind of approach.

2. Problem formalization

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

$$\min_{\theta} f_o(\theta) \quad o = 1, \ldots, O_{\text{obj}} \tag{1}$$

$$\text{subject to :} \quad g_\lambda(\theta) = 0 \quad \lambda = 1, \ldots, \Lambda$$
$$h_\phi(\theta) \le 0 \quad \phi = 1, \ldots, \Phi$$

where f_o is the oth objective function, θ is the vector of control variables that represents a solution, O_{obj} is the number of objectives, while $g_\lambda(\theta)$ and $h_\phi(\theta)$ are the set of equality and inequality constraints applied.

The target of this study is to control ozone exposure at ground level. This can be achieved by formulating a two-objective mathematical programming problem. The solutions of such a problem are the efficient emission control policies in terms of air quality and emission reduction costs. The problem can be formalized as follows:

$$\min_{\theta} J(E,\theta) = \min_{\theta} [AQI(E,\theta); \quad CPI(E,\theta)]$$
$$\theta \in \Theta \tag{2}$$

where $J(E,\theta)$ is the vector function that has to be optimized, E represents the precursor emissions for the reference case, θ are the control variables (namely the emission reductions) constrained to assume values in Θ, $AQI(E,\theta)$ and $CPI(E,\theta)$ are the Air Quality Index (AQI) and Cost of Policy Index (CPI), both depending on precursor emissions and emission reductions. To depict the results of the two-objective problem, the concept of Pareto Boundary can be used; this represents the set of non-dominated solution obtained considering the two defined objectives (AQI and CPI). Each point of the Pareto Boundary is calculated solving an optimization problem, through an iterative approach. Neural Networks are needed to calculate the AQI for each iteration step in each optimization problem; in this way, the environmental control of the considered system can be identified (an example of environmental control is shown in Carslon et al. (2004)). In the following sections, control variables and constraints are presented (Section 2.1), the distributed parameter system models used to reconstruct ozone exposure and the Air Quality Index are shown (Section 2.2), the methodology to derive cost functions and the cost index is defined (Section 2.3) and at the end the methodology to solve the optimization problem is depicted (Section 2.4).

2.1. Control variables and constraints

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

(1) public power, co-generation 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 percentage emission reductions $\theta = \{\theta^{p,s}\}_{s\in S}^{p\in P}$, for each ozone precursor p and CORINAIR macrosector $s = \{1, \ldots, 11\}$; being NO_x and VOC the precursors of ozone, there are in principle 22 control variables for the control problem. The control variables are subjected to:

$$0 \le \theta^{p,s} \le \Theta^{p,s} \quad \forall p, s \tag{3}$$

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