ARTICLE IN PRESS

STOTEN-24353; No of Pages 10

Science of the Total Environment xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

A non-linear optimization programming model for air quality planning including co-benefits for GHG emissions

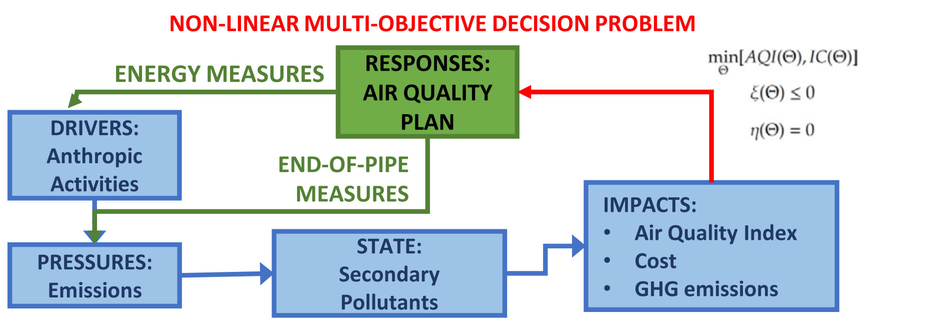
Enrico Turrini*, Claudio Carnevale, Giovanna Finzi, Marialuisa Volta

DIMI, University of Brescia, via Branze 38, Brescia 25123, Italy

HIGHLIGHTS

- A new Integrated assessment methodology based on a multi-objective approach to support air quality planning;
- Methodology able to be applied at different scale, from national to urban sites;
- Methodology assessing the effectiveness of end-of pipe, energy and fuel switch measures, including behavioral changes;
- Methodology assessing GHG emission variation due to changes in fuel consumption arising from energy measures application.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 19 July 2017
Received in revised form 2 October 2017
Accepted 13 October 2017
Available online xxxx

Editor: D. Barcelo

Keywords:
Air quality
Decision support systems
Integrated assessment modelling
Environmental modelling
Optimization
Control strategy
Particulate matter

ABSTRACT

This paper introduces the MAQ (Multi-dimensional Air Quality) model aimed at defining cost-effective air quality plans at different scales (urban to national) and assessing the co-benefits for GHG emissions. The model implements and solves a non-linear multi-objective, multi-pollutant decision problem where the decision variables are the application levels of emission abatement measures allowing the reduction of energy consumption, end-of pipe technologies and fuel switch options. The objectives of the decision problem are the minimization of tropospheric secondary pollution exposure and of internal costs. The model assesses CO_2 equivalent emissions in order to support decision makers in the selection of win-win policies. The methodology is tested on Lombardy region, a heavily polluted area in northern Italy.

1. Introduction

Particulate matter (*PM*), NO_2 and Ozone, can heavily affect population health and ecosystems. In particular, according to World Health Organization (WHO, 2008), the exposure to high concentrations of small *PM* fractions, can cause several diseases to cardiovascular and respiratory systems (Kelly and Fussell, 2015; WHO, 2013). Also the vegetation can be affected from these pollutants: *PM* can interfere with photosynthesis, whereas high concentrations of ground-level ozone can damage leaves, reduce forest growth and crop yields.

To prevent these impacts, the 2008 European Air Quality Directive (AQD) (2008/50/EC) provides that Member States should design air

* Corresponding author.
E-mail address: enrico.turrini@unibs.it (E. Turrini).

https://doi.org/10.1016/j.scitotenv.2017.10.129
0048-9697/

Please cite this article as: E. Turrini et al., A non-linear optimization programming model for air quality planning including co-benefits for GHG emissions, Science of the Total Environment (2017), https://doi.org/10.1016/j.scitotenv.2017.10.129

quality plans for areas where air quality does not comply with the limit values.

Given the importance of the secondary component for *PM*), NO_2 and Ozone, the main challenges, that Environmental Authorities have to face while building air quality plans, are to assess in the decision process the non-linear phenomena involving precursors (VOC, NO_x, NH_3, primary *PM* and SO_2) in accumulation and transport, the health and economic impacts of the policies and the co-benefits for greenhouse gases.

Integrated assessment modelling (Guariso et al., 2016) is a methodology aiming at supporting the decision makers in the selection of effective air quality strategies. Such methodology can be based on different approaches (Thunis et al., 2016b), such as scenario analysis (Thunis et al., 2016a; Duque et al., 2016), source-apportionment analysis (Viana et al., 2008; Belis et al., 2013), cost-benefit analysis (Rotaris et al., 2010; Schrooten et al., 2006), cost-effectiveness analysis (Amann et al., 2011; Carnevale et al., 2016a) and multi-objective optimization (Miranda et al., 2016; Carnevale et al., 2014).

The MAQ (Multi-dimensional Air Quality) model, presented in this paper, is a multi-objective decision model that differs from what is reported in literature (Viaene et al., 2016) as it includes surrogate models describing the non-linear processes that lead to the production and accumulation of tropospheric pollutants; the decision problem is non-linear both in the objectives and in the constraint set; taking into account at the same time end-of-pipe and energy measures, MAQ is able to estimate how air quality policies impact on GHG emissions, allowing the decision maker to identify an effective set of measures to reduce both secondary pollutants and GHGs (win-win policy).

The proposed methodology has been tested to Lombardy region in Northern Italy, characterized by a complex orography and high anthropogenic emissions. An area that is frequently affected by tropospheric pollutant concentrations above the limits set by EU legislation.

2. The decision problem

The multi-objective problem implemented in MAQ aims at minimizing, in a given domain, one or more **Air Quality Indexes** (**AQIs**), representing the impacts on air quality of a policy, namely a set of measures (decision variables) and its implementation **cost** (**IC**), while satisfying a set of **constraints**. The problem can be formalized as follows:

$$\begin{aligned} &\min_{\Theta} J(\Theta) = \min_{\Theta}[AQI(\Theta), IC(\Theta)] \\ &\text{subject to} \qquad \xi(\Theta) \le 0 \\ &\qquad\qquad\qquad \eta(\Theta) = 0 \end{aligned} \tag{1}$$

where

- J is the objective function;
- Θ is the set of decision variables, i.e. the feasible emission reduction measures, as defined in Section 2.1;
- AQI is the Air Quality Index, that depends on the decision variables affecting the precursor emissions $E(\Theta)$, as described in (Section 2.2);
- IC is the cost due to abatement measures implementation, namely the policy cost (Section 2.3);
- ξ and η constraint the decision variable in a feasible set, as defined in Section 2.4.

The solution of the problem is a set of non-dominated policies (Pareto Curve) optimizing all the objectives simultaneously. In this case, the objective functions are said to be conflicting, and an infinite number of Pareto optimal solutions exists.

In this work, the decision problem, presented in Eq. (1), is solved by means of the weighted sum method (Marler and Arora, 2010).

The solutions are further analyzed to assess the co-benefits for GHG emission reduction (see Section 2.5).

2.1. Decision variables

The decision variables considered in the problem are the penetration levels (in %) of abatement measures (**application rates**). The application of these measures leads to the variation of precursor emissions on the considered domain.

Two main classes of measures are accounted:

- the end-of-pipe measures are technologies reduce the amount of precursor emissions without affecting the energy consumption of the anthropic activities.
- the energy measures directly affect energy consumptions by varying the activity levels(i.e. the presence and extension of an anthropic activity on the domain) expressed in energy consumption. In this work, the activity level is defined as the energy consumption of the activity.

  This class is divided in 2 sub-classes: (i) Fuel consumption measures, that reduce the activity levels and (ii) fuel switch measures aiming at substituting a certain percentage of an activity with another, less energy consuming, one (i.e. substituting a certain amount of fireplaces with gas boilers for domestic heating).

According to these definitions, the decision variable set is defined as the union of three sets: $\Theta = [\{\Gamma\}, \{\Psi\}, \{\Phi\}]$. Γ is the set of all the **end-of-pipe** control variables γ_m where γ_m is the penetration level of end-of-pipe measure m.

Ψ is the set of all the **fuel consumption** control variables ψ_f, where ψ_f is the penetration level of fuel consumption measure f.

Finally, Φ is the set of all the **fuel switch** control variable, where ϕ_s is the penetration level of fuel switch measure s.

A switch measure s is always modelled as a couple of measures: the active one decreases fuel consumption in an activity, whereas the passive one proportionally increases the fuel consumption in another activity (e.g. the active measure decreases the use of coke for domestic heating, whereas the active one could increase gas for domestic heating).

2.2. Objectives: Air Quality Index

The AQI is an aggregated value describing the state of air pollution over a specific domain.

To minimize Eq. (1), a set of models describing the link between AQIs and decision variables ($\frac{\partial AQI}{\partial \Theta}$)is required. This relation can be also formalized explicating the link with precursor emissions:

$$\frac{\partial AQI}{\partial \Theta} = \frac{\partial AQI}{\partial E} \cdot \frac{\partial E}{\partial \Theta} \tag{2}$$

The first term ($\frac{\partial AQI}{\partial E}$) represents the relation between precursor emissions and Air Quality Indexes. This can be ideally provided by three-dimensional deterministic multiphase models, but, due to their high computational times, these models can not be used in an optimization problem. For this reason, surrogate models are applied. (Castelletti et al., 2012; Carnevale et al., 2009).

The second factor ($\frac{\partial E}{\partial \Theta}$) represents the effect that abatement measures have on precursor emissions.

If no measures are applied, the emissions, for a precursor $p \in P$, where $P = \{NO_x, VOC, NH_3, PM_{10}, PM_{2.5}, SO_2\}$, in a cell d of the