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Exploring trade-offs between air pollutants through an Integrated Assessment Model

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HIGHLIGHTS

- RIAT+ is a methodology and tool for Integrated Assessment Modeling at local scale.
- It selects optimal air quality policies, considering a multi-pollutant framework.
- It shows possible trade-offs among policies devoted to different pollutants.
- It is applied over Alsace Region, for joint NO_2 and O_3 control.

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ABSTRACT

When designing air pollution reduction policies, regional decision makers face a limited budget to choose the most efficient measures which will have impacts on several pollutants in different ways. RIAT+ is a regional integrated assessment tool that supports the policy maker in this selection of the optimal emission reduction technologies, to improve air quality at minimum costs. In this paper, this tool is formalized and applied to the specific case of a French region (Alsace), to illustrate how focusing on one single pollutant may exacerbate problems related to other pollutants, on top of conflicts related to budget allocation. In our case, results are shown for possible trade-offs between NO_2 and O_3 control policies. The paper suggests an approach to prioritize policy maker objectives when planning air pollution policies at regional scale.

1. Introduction

In the regional/local contexts, the design of air quality strategies is a complex task for local authorities. They must enforce the respect of air quality standards by decreasing local precursor emissions for different air pollutants and greenhouse gases, through a set of actions within a constrained budget. The definition of efficient strategies requires accurate and detailed information on the local situation, and fast and simple tools to process it. One of the most commonly used approaches in EU regions to deal with such problems, at the local scale, is the scenario analysis. This methodology makes use of deterministic chemical transport models (CTMs) to evaluate the effects on air quality of a limited number of emission reduction policies (selected by experts or on the basis of source-apportionment studies), accounting for regional (Cuvelier et al., 2002; Vautard et al., 2007; Cheng et al., 2012), local, and/or street level scales (Giannouli et al., 2011). Because of the limited number of simulations that can be performed (CTMs are computationally very demanding), this approach does not allow for the determination of the most effective actions, in terms of implementation costs or in terms of air quality levels.

On the contrary, Integrated Assessment Models (IAMs) account for both the policy implementation costs and the impacts of abatement measures, in order to select the best available options (in terms of efficiency) to improve air quality (Fronza and Melli, 1984). IAMs are based on a wide spectrum of techniques of which the most frequently used are cost–benefit analysis (Schrooten et al., 2006; Vlachokostas et al., 2009), cost-effectiveness (Atkinson, 1974; O'Ryan, 1996; Amann

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et al., 2011), multi-criteria (Vlachokostas et al., 2011) and multi-objective approaches (Ellis, 1988; Pisoni and Volta, 2009; Carnevale et al., 2011, 2012b).

Usually, regional/local IAM applications are based on the assumption that a single indicator representative of air quality can be defined a-priori. Such an indicator can either be expressed in physical terms (e.g. the statistical parameters prescribed by the EU legislation on pollutant concentrations, like *SOMO*35) or in economic terms (e.g. through the evaluation of external costs, as proposed by ExternE and similar projects) (Bickel and Friedrich, 2005). In practice, this is not so straightforward, and local decision makers have to deal with several pollutants at the same time, through a number of actions related to multiple emission reduction technologies, each impacting the pollutants of interest. Due to the complex nature of physical–chemical processes leading to the production of secondary pollutants in the atmosphere, some abatement measures may even be counter-productive: i.e. the decrease of one pollutant concentration may be counterbalanced by the unavoidable increase of another (this is the case for instance of nitrogen oxides and ozone, which are part of the same chemical reactive process). This complex dynamics, together with the obvious need that the overall cost be subdivided among different actions, underlines the necessity of tools that may rapidly illustrate the potential trade-offs among alternative air quality plans.

This study presents the methodology and application of one of these tools, called RIAT+ (Regional Integrated Assessment Tool Plus), partly developed in the frame of the EU financed LIFE+ project OPERA (Operational Procedure for Emission Reduction Assessment, www.operatool.eu).

In terms of methodology, the main advances of RIAT+ in comparison to the state-of-the-art are related to the:

- multi-pollutant (vs single-pollutant) framework;
- use of seasonal (vs yearly) source–receptor models;
- general formulation of the decision problem, that can include efficiency (non-technical) measures as well as land use policies (not adopted in the following case study).

RIAT+ extends the approach applied i.e. to the Lombardy region (in Italy) and described in a previous work (Carnevale et al., 2012b) to a multi-pollutant case (and to an extended set of measures).

The main goal of the proposed approach is to identify the most efficient mix of local policies for reducing pollution exposure, at a level which complies with EU and national air quality regulations. To this end, the tool solves an optimization problem in which Pollution Indices (PIs) are minimized together with the implementation costs of measures needed to achieve these PIs. An additional key feature of such system is the substitution of the CTM with a suitable nonlinear surrogate model, allowing for a fast repetitive evaluation of the PIs with accuracy close to the one obtained with a full CTM (Carnevale et al., 2012a). The RIAT+ package requires an emission inventory, a set of feasible emission reduction measures and surrogate model(s) as input. It has already been successfully applied to various regions and is freely available on the LIFE+ OPERA project website (www.operatool.eu), since September 2013.

In terms of application, this paper proposes the computation of optimal policies for air quality improvement in Alsace, focusing on nitrogen oxides and ozone exposure. Three different RIAT+ settings are presented, considering at first single pollutant optimizations (to improve exposure to NO_2 or O_3 separately), and then a multi-pollutant case (optimizing NO_2 and O_3 at the same time). The goal is to identify the trade-offs between alternative emission reduction plans, and to show how integrated assessment tools can support decision makers in correctly setting priorities for improving air quality.

2. Methodology

To evaluate and compare alternative air quality plans and correctly define a decision problem, the impact of air pollution over a given territory must be evaluated in terms of a few aggregated values. This means that it is necessary to combine point hourly or daily concentration values (those normally corresponding to actual measurements or to the output of a CTM) into some indicators or an indicator, usually in the form of a spatial integral over a longer time span, normally one year. The definition of such an indicator is thus relatively critical. As for the time integration, the set of statistics proposed by the European Environmental Agency or by the US EPA provides temporally aggregated indicators, e.g. *SOMO*35 or *AOT*40 are helpful to describe ozone effects on human health and on vegetation, respectively. The spatial integration is less standard and necessarily assumes that the territory under consideration can be subdivided into a number of homogeneous parcels (normally a grid cell with a surface that may go from hundred square meters to hundred square kilometers) depending on the scale of the study. The spatial integration may vary from a simple average over all cells belonging to the area of interest, to a weighted average (for instance, using population density), or to a subset of cells in which exceedance of a concentration threshold is reached.

Another essential point in air quality planning is to define a set of measures (decisions) that can be considered, and where these can be implemented. Decision makers must therefore define an action space, which might represent a subset of all possible emission reduction measures (e.g. a given decision maker's responsibility may be limited to some activity sectors), and/or specific portions of the domain (e.g. decisions may concern only urban environments). This aspect is particularly critical because air pollution and particularly secondary pollution are strongly influenced by emissions even tens of kilometers away from the region under study. The impact of emission abatement policies in a given region can thus be analyzed only if the evolution of air quality in the surrounding areas is accounted for.

Whatever the case, the computation of the effects of a given emission change always starts from the underlying emission inventory. The emission $E_p(x, y)$ of pollutant p from a certain activity $A(x, y)$, in cell x, y of the domain under study, is the product of some measure of the activity itself times a reference emission factor $\underline{ef}_p$ (sometimes called unabated emission factor), i.e.:

$$E_p(x,y) = A(x,y) \cdot \underline{ef}_p. \tag{1}$$

Only three options are considered for emission reduction:

- Technical (end-of-pipe) measures. Emission factors are reduced by application of suitable filtering technologies that decrease the amount of pollutant released to the atmosphere, with a negligible impact on the corresponding activities. The application of electric precipitators or DeNOx systems is an example of this type of measures. Each of these technologies i has the ability to reduce emission of a pollutant p by a given percentage (called removal efficiency, re_{pi}), but may be applied only to a fraction of the total activities, so that the application rate (ar_i) of technology i may vary within a range, possibly 0_1 or min_i _ 1 (in case for instance of a minimum technology application, min_i, is required by the norms in force). For a set of measures, the reduced emission factor ef_p becomes:

$$ef_p = \underline{ef}_p \cdot \left(1 - \sum_i re_{pi} \cdot ar_i\right) \tag{2}$$

  For some pollutant–activity couples, the summation is limited to a single measure, while in some other cases various actions may be undertaken. On the other side, application of a given technology i may reduce more than one pollutant. In the previous equation, only the term ar_i is the result of some decision, while all others directly derive from the physical characteristics of the considered activity or technology under consideration.
- Efficiency (non-technical) measures. They are characterized by a reduction of the polluting activity, generally through a lower

amount of fuel used. The modal shift from private cars to public transportation or the application of heat pumps for domestic heating is a measure of this class. In principle, application of such measures should not modify the overall performance of the related activity. If this is obvious for domestic heating (it is indeed easy to compare the efficiency of two heating methods supplying the same amount of heat but with different amounts of fuels), it may be much more difficult for other cases. Indeed, it is possible to compute the quantity of energy (fuel) used by two modes of transportation, but it is not straightforward to assess when the same service is supplied in the two cases. The adoption of efficiency measures can be formalized by introducing another decision variable ar_j (smaller than one) that multiplies the activity value. The emission remaining after the application of the efficiency measure j is thus:

$$E_p(x,y) = ar_j \cdot A(x,y) \cdot \underline{ef}_p \tag{3}$$

or

$$E_p(x,y) = ar_j \cdot A(x,y) \cdot ef_p \tag{4}$$

depending whether technical measures are applied in addition.

- Land planning measures. These measures apply when the localization of an activity is switched to another place, while keeping the activity level unchanged. Building a new highway (i.e., increasing the emissions in certain cells, possibly reducing them in others) or urbanizing agricultural land is a well-known decision belonging to this class. Compared with the other two classes, measures in this category normally take place on much longer time horizons, and are therefore of reduced interest when air quality needs to be improved on a short time scale. In formal terms, the variable ar_j introduced above may depend on the spatial location, with: $ar_j(x, y) = 0$ meaning that the activity disappears from cell (x, y); while $ar_j(x, y) > 1$ represents an expansion of activity j.

Not all measures will fit exactly in one of these three categories. Indeed, some measures may belong to more than one class. A well-known example is the shift to higher EURO class cars or tracks, which can be seen as a classical technical measure (emission per kilometer decreases) but can also be interpreted as an efficiency measure (as the associated amount of fuel per kilometer driven also decreases). A similar example is fuel change, say from oil to gas; even if the actual activity does not change in practice, to fit into the preceding scheme, it must be considered as the closing of an activity and the opening of another because it may entail a change of the pollutants emitted and not simply their reduction.

Each measure can in principle be characterized by a cost per unit of emission reduction. The evaluation of such a cost is quite a difficult task, since it involves the estimation of the duration of the investment, of the depreciation rate, of the economies of scale. Additionally, it can be estimated with some reliability only for small changes around the current situation and disregarding the cost of scrapping old technologies to install new ones. Whatever approach is taken for its estimation (see for instance: Amann et al. (2011)), such a cost must be considered only as an indication of the effort of the society in decreasing emissions, more than an actual sum to invest (even the entity that should bare these costs is often undefined). As such, it can be useful to select the most efficient technological options, but resources needed to implement these options cannot be easily compared with actual budgets, for instance, the investment of a regional authority in air quality plans.

This paper does not deal with land planning measures and assumes that activities are fixed in terms of geographical location. Technical and efficiency measures alone can nevertheless constitute a set of hundreds of decisions to be possibly adopted over a given territory. Starting from the large set of available technical measures categorized for instance by the GAINS model for many European and non-European countries (Amann et al., 2011) and from a limited number of local non-technical measures, the user needs to select those which are relevant for her/his specific regional situation. Some activities might not be operating, some measures are not applicable to all plants (for instance, because they are unsuitable or inefficient for very small plants), other measures may be already in place via local regulations. At the end, the space for local decisions is constrained within two boundaries: on one side, the minimum application rate (min_i) imposed by the regulation in force (often called Current Legislation, or CLE) and on the other side the maximum application rate possible considering current scientific and technical knowledge (referred as Maximum Feasible Reduction, or MFR). Air quality conditions associated to CLE are somehow guaranteed and cannot be worsen, whereas the MFR constitutes the best or utopic situation where all technical measures are applied to the maximum degree, regardless of their cost. Thus,

$$ar_i^{MFR} \geq ar_i \geq ar_i^{CLE}. \tag{5}$$

Additional constraints might appear (as shown in Carnevale et al. (2012b)) if the replacement of old technologies is considered. It is important to note that both the MFR and the CLE are time dependent, as the legislation evolves over time, with stricter emission norms usually being imposed, as demonstrated for example by the evolution of EURO specifications for gasoline engines. For both CLE and MFR it is thus necessary to specify the year they refer to.

All these being defined, a multi-objective problem can be formulated, aiming at minimizing a pollution index synthetizing the impacts (on health, ecosystems, etc.) of one or more pollutants. This index will depend on the reduced emissions, themselves depending on the implemented application rates ar_i and ar_j of each technology/efficiency measure. To represent the actual impacts of air pollution over a certain region, the pollution index may be constructed as a combination of indicators related to more than one pollutant. For instance, one index may be a combination (a weighted sum) of some indicators I_p related to Ozone (say $SOMO35$) and NO_x (say, the average yearly concentration of NO_2). The weights within this sum represent the relative importance assigned to these different (and sometimes conflicting) pollution problems by the decision makers. These indicators I_p cannot, however, be directly combined into a single quantity since they might be characterized by different units or range of values (average NO_2 concentrations may be two or three orders of magnitude smaller than the $SOMO35$). It is thus essential to normalize all indicator values prior to any aggregation, as follows:

$$I_p^* = \frac{I_p - I_p^{CLE}}{I_p^o - I_p^{CLE}} \tag{6}$$

where:

- I_p is the current indicator value for pollutant p;
- I_p^{CLE} is the indicator value when applying measures dictated by the Current Legislation (CLE);
- I_p^o is the best value of the same indicator when each indicator is optimized separately (note that this value may not coincide with that obtained when applying MFR since that may not be the best for a specific pollutant); and finally
- I_p^* is the standardized value of the indicator.

Thus a pollution index PI is computed as:

$$PI = \alpha_1 I_1^* + \alpha_2 I_2^* + \ldots + \alpha_P I_P^* \tag{7}$$

$$\text{with} \sum_p \alpha_p = 1 \tag{8}$$

where weights α_p must be chosen by the decision makers and, if only one weight is equal to 1, the pollution index coincides with the indicator of a specific pollutant. Note that *PI* as defined here does not have a specific physical meaning, neither a unit of measurement and only serves to discriminate between possible alternative plans in terms of their efficiency.

The air quality planning problem can finally be written as

$$min|PI, C| \tag{9}$$

where:

$$I_p = M_p\left(\left(ar_j \cdot A(x,y) \cdot ef_p \cdot \left(1 - \sum_i re_{pi} ar_i\right)\right)\right) \tag{10}$$

$$I_p^* = \frac{I_p - I_p^{CLE}}{I_p^o - I_p^{CLE}} \tag{11}$$

$$PI = \alpha_1 I_1^* + \alpha_2 I_2^* + \ldots + \alpha_P I_P^* \tag{12}$$

$$C = \sum_{x,y} A(x,y)\left(\sum_i c_i \cdot ar_i + \sum_j c_j \cdot ar_j\right) \tag{13}$$

subject to the constraints previously specified.

$M_p(\cdot)$ in Eq. (10) represents a model linking the domain grid-cell emissions to the pollution indicator; c_i and c_j are the unit application costs for the *i*-th (*j*-th) technical (efficiency) measure and *C* is the total cost. The solution of such a problem can be illustrated by the classical Pareto frontier, i.e. the set of non-dominated alternatives which represents all the efficient trade-offs between pollution impact and abatement measure costs.

As anticipated, the model M_p cannot be a classical CTM, but must be substituted by a faster surrogate model, in order to solve the problem in a reasonable time. This may be implemented through a simple mathematical structure (a polynomial, a neural network), calibrated with a limited number of CTM simulations. These simulations must be chosen to cover a suitable range of emission reductions, to closely replicate the results obtained with the CTM itself (see Carnevale et al. (2012a), for details). In general, these surrogate models can be developed with a limited set of input variables (e.g., not all cell emissions, but only a subset is considered) while preserving relevant features of the pollution pattern (for e.g. the spatial distribution). As illustrated later calculation of the indicator I_p is performed in two steps: first, a parameter is computed for each cell based on local emissions; secondly, these values are combined in a single indicator for the entire domain.

3. The case study domain

The RIAT+ approach (described in the previous section) has been applied to the Alsace Region. Alsace is situated in north-eastern France, alongside Switzerland and Germany, in the geographical and historical region of the Upper Rhine Valley. The valley, embanked between the Vosges mountains and the Black Forest, generates winds and frequent temperature inversions in winter, which lead to high pollutant concentrations. Periods of calm wind and heat often lead to high ozone concentrations in summer, with stagnation in some sensitive areas caused by valley breezes.

As a German–French frontier area, high traffic emissions are generated in Alsace Region. In addition to traffic, important industrial activities, varying from large industrial sites to small and medium enterprises, are present. The Alsace plain is very densely populated. This configuration leads to air pollution problems mainly along the traffic axes and in the three major cities (Strasbourg, Colmar, Mulhouse). Urban motorways are currently the main source of pollution and the air quality NO_2 limits have been exceeded frequently between 2000 and 2009 (ASPA, 2009), both at urban traffic and background locations. Exceedances of the air quality O_3 target have also been registered during the past ten years. Finally, industrial emissions caused occasional episodes of pollution with exceedance of the alert threshold (ASPA, 2009).

4. The surrogate model creation

The link between emissions and concentrations, usually described through deterministic CTMs, has to be re-written in the context of the Integrated Assessment, to be more efficient in terms of CPU demand. The procedure to create surrogate models follows these steps:

(1) Definition of the surrogate model structure;
(2) Design of Experiments;
(3) Chemical transport model simulations;
(4) Surrogate model training and validation.

4.1. Definition of the surrogate model structure

The purpose of the surrogate model(s) is to approximate the CTM. The first step to define their structure is the identification of all relevant actions the decision-maker can test and the indexes of interest. The relevant actions are the input of the surrogate model whereas the indices are the output. As the focus of this work is related to O_3 and NO_2 interacting in a non-linear manner, Artificial Neural Networks (ANNs) are selected as surrogate modeling approach, to represent the link between precursor emissions and concentrations. In particular, a feed-forward neural network has been adopted, with a type of structure that has shown good performance in previous similar studies (Wahid et al., 2013; Jiang et al., 2004). Two different networks are constructed:

- the first ANN computes for each grid cell *SOMO*35 as a function of the NO_x and *VOC* precursor emissions in the current and the adjacent cells;
- the second ANN computes for each cell yearly NO_2 average as a function of all precursor emissions (shown in the first row of Table 1) in the current and the adjacent cells.

Emission values have additionally been split into areal and point sources to consider separately the effects of control actions on these two types of pollution emission. More details on the input structure for ANNs can be found in Carnevale et al. (2012a). It must be emphasized that these surrogate models are not supposed to compute hourly

Table 1
Emission reduction percentages (in comparison to the base case) for scenarios S1 to S21, for six pollutants. These scenarios, in addition to the base case (S0), represent the set of emission reductions used for training and validation of the surrogate models.

Scenario	NO_x	*VOC*	NH_3	SO_x	*PM*10	*PM*2.5
S1	−34.5%	−17.3%	−19.0%	−25.1%	−28.3%	−32.5%
S2	−62.3%	−31.6%	−36.2%	−46.5%	−51.8%	−59.1%
S3	−62.3%	−17.3%	−19.0%	−25.1%	−28.3%	−32.5%
S4	−34.5%	−31.6%	−19.0%	−25.1%	−28.3%	−32.5%
S5	−34.5%	−17.3%	−36.2%	−25.1%	−28.3%	−32.5%
S6	−34.5%	−17.3%	−19.0%	−25.1%	−51.8%	−59.1%
S7	−34.5%	−17.3%	−19.0%	−46.5%	−28.3%	−32.5%
S8	−62.3%	−31.6%	−19.0%	−25.1%	−28.3%	−32.5%
S9	−62.3%	−17.3%	−36.2%	−46.5%	−51.8%	−59.1%
S10	−62.3%	−17.3%	−36.2%	−25.1%	−28.3%	−32.5%
S11	−62.3%	−17.3%	−36.2%	−46.5%	−28.3%	−32.5%
S12	−1.4%	−0.1%	−0.4%	0.4%	−0.1%	−0.1%
S13	−2.5%	−0.2%	−0.8%	0.6%	−0.2%	−0.2%
S14	−2.5%	−0.1%	−0.4%	0.6%	−0.2%	−0.2%
S15	−1.4%	−0.1%	−0.4%	0.6%	−0.1%	−0.1%
S16	−2.5%	−0.1%	−0.4%	0.6%	−0.1%	−0.1%
S17	−64.8%	−31.8%	−37.0%	−45.9%	−52.1%	−59.3%
S18	−64.8%	−17.4%	−36.6%	−45.9%	−52.1%	−59.3%
S19	−35.8%	−17.4%	−19.4%	−45.9%	−28.4%	−32.7%
S20	−64.8%	−17.4%	−36.6%	−45.9%	−28.4%	−32.7%
S21	−64.8%	−31.8%	−19.4%	−24.7%	−28.4%	−32.7%

concentrations in each cell (as is the case of CTM models and for other common source–receptor relationships) but rather directly to evaluate a local pollution indicator aggregating concentrations over time. ANNs will thus be calibrated and tested against those aggregated indicators computed with the CTM model.

4.2. Design of Experiments

The Design of Experiment (DoE) phase is devoted to the definition of the minimum set of CTM simulations, required to provide data for the surrogate model calibration and validation. The main factors in terms of emission influencing pollution concentrations have been detailed in previous works (Gabusi et al., 2008; Carnevale et al., 2010) and result in the selection of a series of 22 emission reduction scenarios (Table 1). Given the high flexibility of the surrogate model structure adopted in this work, this limited set of simulations allows identifying the ANN parameters with sufficient accuracy. In scenarios 1 to 11 (Table 1) areal emissions are reduced, whereas in S12 to S16 only point emission changes are considered. The split of scenarios into low and high level sources is motivated by the different dispersion behaviors in the atmosphere of these two types of sources, leading to different impacts on air quality (Thunis et al., 2010). For each precursor emission and source (areal/point), three emission levels are considered and combined (see again Table 1): the 2010 CLE + 15% (upper bound), the 2020 MFR − 15% (lower bound) and the average between these two extremes, to provide surrogate models with an intermediate point between CLE and MFR (for more details on the methodology used to create this table, the reader is referred to Gabusi et al. (2008); Carnevale et al. (2010)). It must be noted that the same surrogate model is applied hundreds of times on different sets of data (once for each training cell in the domain) which allows a robust estimation of ANN parameters.

4.3. Chemical transport model simulations

The air quality model simulations have been performed with the WRF/CHIMERE system. The configuration of the system has been based on the Atmo-RhenA System (MM5/CHIMERE) designed by ASPA, using Global Land Cover Facilities database to describe the land use, and MODIS data to estimate the vegetation fraction. WRF is driven by FNL-AVN NCEP global meteorological data for the reference year 2005. It has been set up on three nested domains (see Fig. 1 (a)) with a horizontal resolution of 45, 15 and 3 km side-length centered on Western Europe, France and the Upper-Rhine area, respectively. The vertical resolution is stretched along 27 levels from surface up to 50 hPa. This Upper-Rhine area covers the Alsace Region, one part of Lorraine and Franche-Comté regions on the French side, Rhineland-Palatinate and west Baden-Württemberg on the German side and Basel region in Switzerland as illustrated in Fig. 1 (b). The main physical WRF parameterizations (for details refer to NCAR (2012)) have been set up to:

- Noah-LSM for the surface scheme;
- RRTM-Duhia for the radiation scheme;
- MM5 Monin-Obukhov for the turbulence scheme;
- YSU for the mixing layer scheme;
- Greel-Devenyi Ensemble for the cumulus scheme;
- Graupel for the cloud microphysics scheme.

A nudging has been used for temperature, relative humidity and wind speed.

The CTM CHIMERE was run over the two nested grids centered on Western Europe and France, with emissions derived from the EMEP database. The vertical distribution of the emissions followed the work of Bieser et al. (2011) and Terrenoire et al. (2013). Over the Upper-Rhine area, local emission inventories for year 2005 have been collected and gridded by ASPA using the Manag'Air tool, over the Alsace Region. One specificity of this local emission inventory is the assumed speciation, based on local information collected per activity sectors. For other regions, local inventories issued from several sources (with different levels of detail for the different gridded emissions) have been used, as shown in Fig. 1 (b). Boundary conditions of the lowest resolved grid domain are taken from monthly mean of the global CTM LMDz-INCA. The gaseous chemistry is computed using Melchior 2.

Table 2 shows comparisons of the WRF/CHIMERE simulations with measurements collected by the ASPA monitoring network, for the 2005 (basecase) validation year. Besides this scenario, 22 air pollution simulations have been performed on the Upper-Rhine domain, corresponding to the list in Table 1.

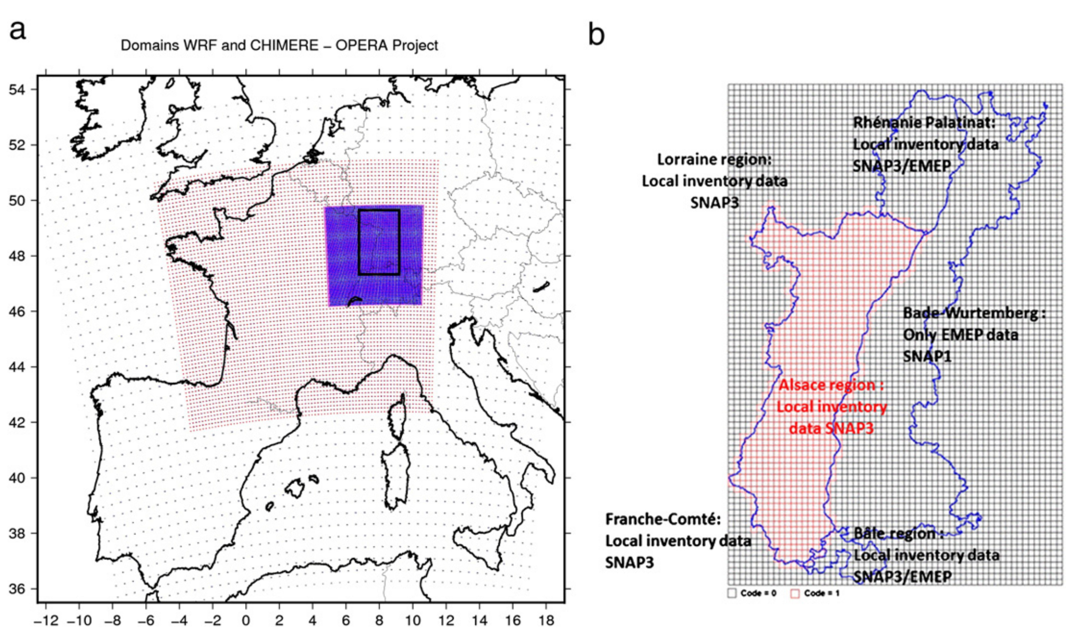

Fig. 1. Grid domains: (a) WRF grid domains on Western Europe, France, and Eastern France, with a respective resolution of 45, 15, 3 km (CHIMERE grid over the Alsace Region highlighted in a black box); (b) detail on Upper Rhine domain.

Table 2
Comparisons (for the year 2005) of the average hourly concentrations of ozone and nitrogen dioxide simulated by WRF/CHIMERE over the Alsace Region, with measurements of the ASPA monitoring network. Bias (model-measurement) and RMSE are given in μg/m^3. Corr is the correlation coefficient.

Stations	NO_2 bias	NO_2 RMSE	NO_2 corr	O_3 bias	O_3 RMSE	O_3 corr
Nord-Est-Alsace	2.0	17.1	0.55	14.9	26.6	0.78
STG-Centre	10.7	24.1	0.58	1.1	21.9	0.76
STG-Centre-2	7.6	22.7	0.62	1.0	21.9	0.77
STG-Clemenceau	−10.8	27.4	0.54	…	…	…
STG-Nord	11.3	21.3	0.66	2.8	20.0	0.83
STG-Est	13.4	22.7	0.68	2.4	19.4	0.81
STG-Ouest	15.7	28.0	0.55	−3.0	24.6	0.74
Colmar-Centre	−3.7	21.9	0.37	…	…	…
Colmar-Est	5.3	20.9	0.50	5.2	26.2	0.70
Mulhouse-Sud-II	17.6	25.1	0.63	−0.1	22.1	0.77
Mulhouse-Est	11.8	19.6	0.60	−3.1	23.1	0.74
Mulhouse-Nord	4.8	20.1	0.61	…	…	…
C-C-3-Frontières	19.7	27.4	0.64	−1.1	23.5	0.76
Vosges-du-Nord	−2.8	9.1	0.63	6.5	21.0	0.78
Vosges-Moyennes	−0.7	4.2	0.64	−3.0	18.4	0.77
Hautes-Vosges	5.5	10.3	0.29	−8.2	22.5	0.63
Chalampé	10.8	30.7	0.43	…	…	…

4.4. Training and validation of the surrogate models

The study domain is characterized by a grid of 86 × 59 square cells, 3 × 3 km^2. The pollution indicators computed with the CTM on 80% of the cells (randomly chosen) have been used for the ANNs training, while the remaining 20% served for their validation. Results have been computed for O_3 and NO_2, and for each of these, three time aggregations have been considered: yearly, summer and winter. Only results for yearly average NO_2 and summer *SOMO*35 (the two indicators that will be considered in the following optimizations) are discussed here. The comparison between the results obtained with CHIMERE and with surrogate models (ANN) for each validation cell is illustrated in Fig. 2. The correlation between the values obtained with the two approaches is very high (0.92 for *SOMO*35, 0.95 for NO_2), showing the capacity of the ANN approach to properly mimic the deterministic model behavior, and so being an adequate substitute within the Integrated Assessment Model.

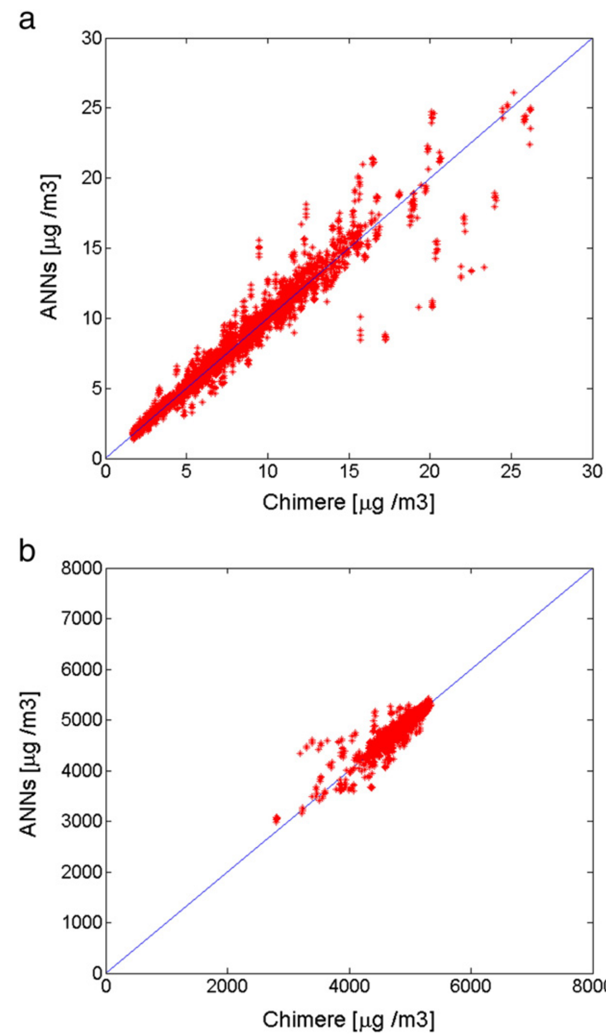

Fig. 2. Surrogate model validation scatter plots, for (a) yearly NO_2 and (b) summer *SOMO*35 indicators. The value simulated by the CHIMERE deterministic model is on the horizontal axis, and that obtained with the ANN surrogate model is on the vertical axis.

5. The computation of optimal policies

5.1. Configuration setting

The CTM simulations and the derived ANNs represent in a way the physical environment on which local authorities have to act. Their responsibility may however be limited to a subdomain where they can set regulations, provide incentives, and/or forbid activities. For Alsace, two subdomains have been identified: the four "European reporting zones" and the "sensitive zone", as defined in the SRCAE (Schéma Régional Climat Air Énergie Alsace), a strategic document on air quality and climate protection released in June 2012 (DREAL, 2012). The sensitive zone of the SRCAE represents the priority area for air quality, and encloses about 29% of the territory and 63% of the population. This sub-domain is shown in Fig. 3 and has been considered in this paper as the area in which the air quality improvements should be concentrated. Other important choices for this case study are:

- the reference year for the optimization is 2010, meaning that the optimal results will suggest which measures should be applied on top of the CLE 2010, assuming that boundary emissions have been modified accordingly.;
- it is possible to replace old technologies with new ones, in macrosector 2 and macrosector 7. This option allows for the replacement of old heating systems with new ones, and old EURO traffic standards with more advanced ones (this is implemented without taking into account the lost "lifetime" of the replaced measure). For other macrosectors, technologies foreseen by legislation in force are supposed to remain in place;
- the definition of Pollution Indicators is based on population weighted averages for NO_2 (to stress the importance of NO_2 levels in densely populated areas), and on summer average for *SOMO*35.

Having chosen these options, three different configurations have been considered, minimizing respectively:

- population weighted average yearly NO_2;
- average summer *SOMO*35;
- a joint index composed by NO_2 and *SOMO*35 assuming, as an example, NO_2 "three times more important" than *SOMO*35.

In terms of emission reduction measures (and relative removal efficiencies and costs), both the end-of-pipe technology datasets developed by IIASA for the GAINS EUROPE model, and some local non-technical measures, have been used. The GAINS dataset for France includes the measures available for the Gothenburg protocol revision ("CIAM1/2011 march, goth_nat_baseline_rev1" scenario, available at http://gains.iiasa.ac.at/gains). In terms of local measures, four efficiency measures have been considered:

- car sharing;
- reduced road speed on highways;
- eco driving;
- thermal renovation of buildings.

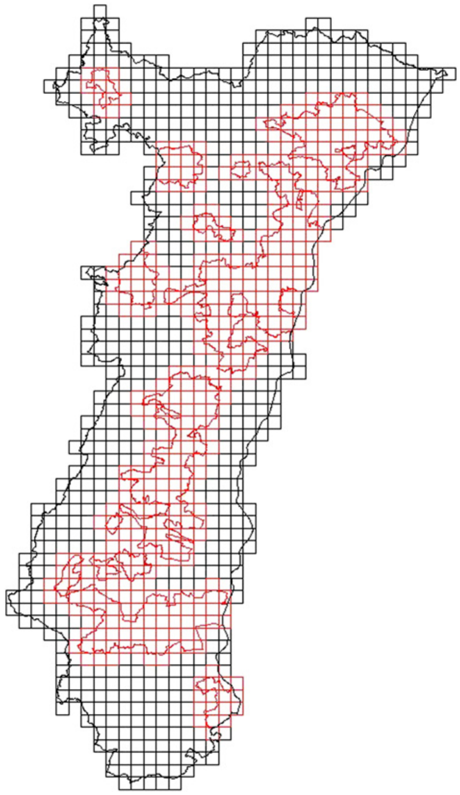

Fig. 3. Sensitive zones (in red) according to SCRAE, considered for the RIAT+ optimization.

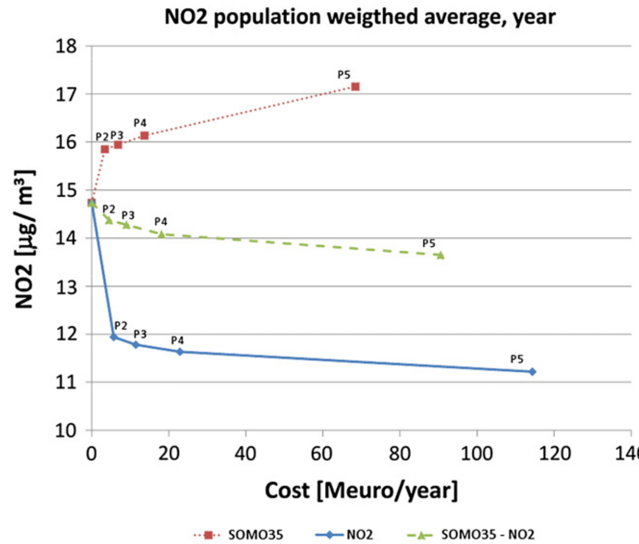

Fig. 4. Pareto optimal policies computed considering the three selected optimizations, with cost of policy implementation (horizontal axis) and NO_2 population weighted yearly average (vertical axis). The blue line corresponds to the NO_2 optimization, the red dotted line to the *SOMO*35 optimization, and the green dashed line to the multi-pollutant case.

For these measures, costs and efficiencies have been estimated based on the values collected within the above mentioned OPERA project.

5.2. Results and discussion

Figs. 4 and 5 show the policy outcomes computed with the Pollution Indices described above. Yearly average NO_2 concentrations obtained with an optimization focused on NO_2 only (Fig. 4, blue curve) obviously provides the maximum NO_2 indicator reduction, whereas an optimization focusing on *SOMO*35 only would lead to the worst NO_2 indicator value (red curve). This result can be explained by the choice of the specific area to be considered for the air quality computation, shown in Fig. 3. In fact, the area is mainly *VOC*-limited, and this means that for these cells, a reduction in NO_2 can cause ozone increasing, with a clear clash between the two objectives. A similar analysis can be done for *SOMO*35 (Fig. 5). Again, the maximum *SOMO*35 reduction is reached for an optimization focusing on this indicator, whereas an optimization based on NO_x emissions would lead to the worst results. For a pollution index constructed as a weighted average between the *SOMO*35 and NO_2, an intermediate solution is obtained (green line). This compromise solution allows a slight improvement of NO_2 (Fig. 4) without worsening *SOMO*35 (Fig. 5). Fig. 6 details these optimal solutions in terms of decision variables aggregated per CORINAIR macro-sector. The left side panels show emission reductions beyond CLE, and the right side ones the cost beyond CLE, entailed by the optimal policy related to the point P4 of the previously depicted Pareto curve. For the yearly NO_2 optimization (Fig. 6 (a) and (b)) emission reductions should be applied to macro-sectors 7 and 8 (road transport and other mobile sources, respectively) even if the costs are mainly related to macro-sector 2 (non-industrial combustion). This is explained by the fact that, although cost-free (no costs are considered for substitutions) and allowed for macro-sectors 2 and 7, the replacement of old technologies is mainly applied to macro-sector 7. On the contrary, actions (i.e. emission reductions) are more efficient in macrosectors 2, 6 and 8 for *SOMO*35 (Fig. 6 (c), (d)) with higher costs in macro-sector 2. For the multi-pollutant weighted optimization, the emission reduction policy is similar to the *SOMO*35 one but at reduced cost (Fig. 6 (e), (f)). The main difference between the *SOMO*35 and the multi-pollutant optimization case lies in the reduced emissions for macro-sector 2, with VOC emission reductions recommended in the case of a *SOMO*35 optimization, whereas the effort is mostly on NO_x emissions in the weighted optimization case.

In the case of the NO_2 focused optimization (taken as an example to study the measures' detail, in Fig. 7) emission reduction efforts should mainly be on improving EURO standard, reducing road speed on highways and improving car sharing (points P2 and P3 on the Pareto

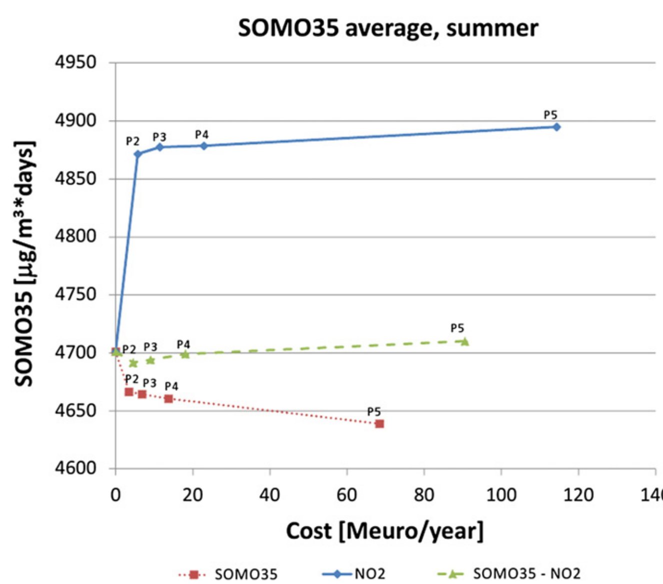

Fig. 5. Pareto optimal policies computed considering the three selected optimizations, with cost of policy implementation (horizontal axis) and *SOMO*35 summer values (vertical axis). The blue line corresponds to the NO_2 optimization, the red dotted line to the *SOMO*35 optimization, and the green dashed line to the multi-pollutant case.

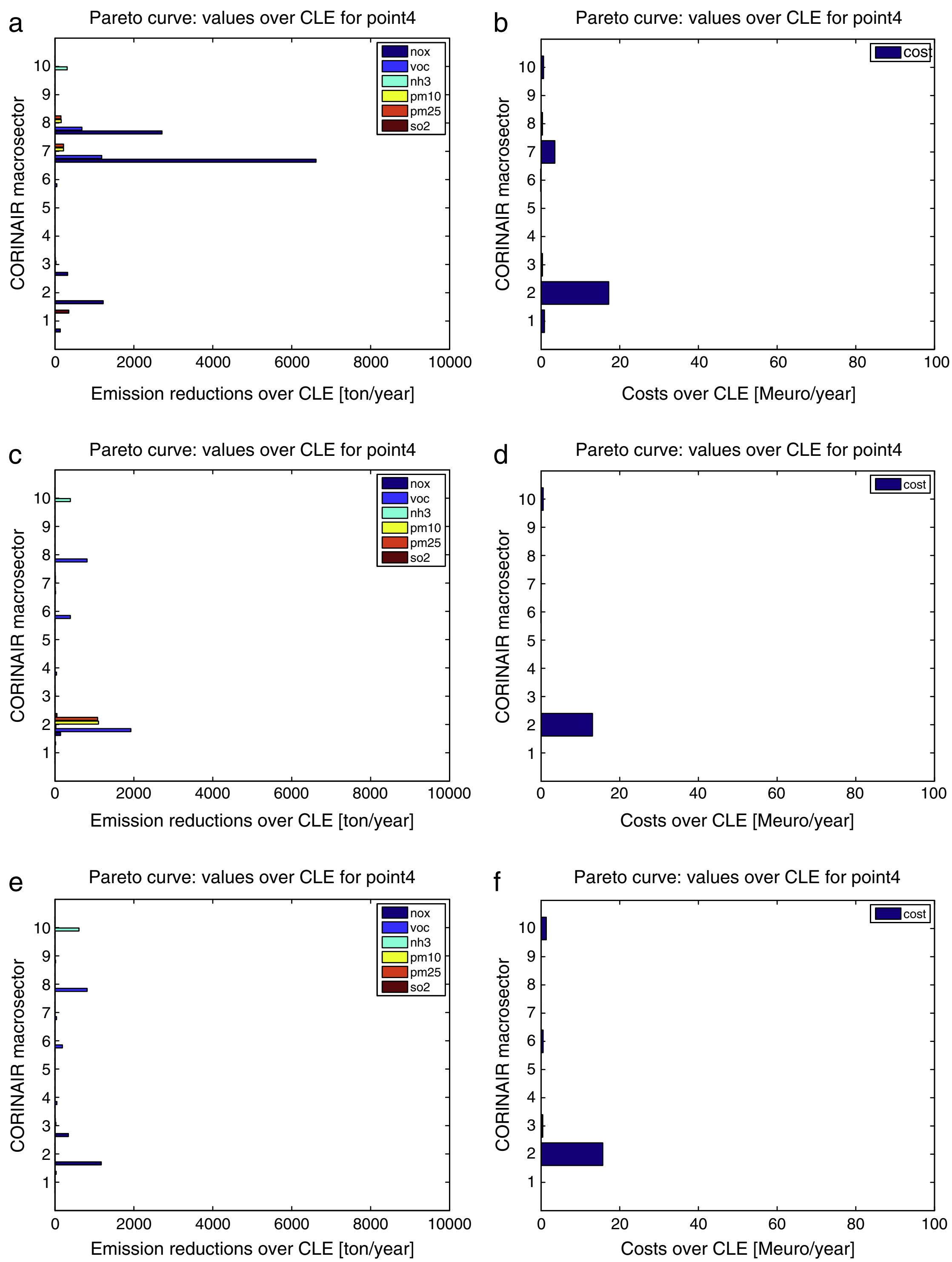

Fig. 6. Emission reductions (left column) and costs (right column) beyond CLE, corresponding to the optimal policies computed for point P4 of the Pareto curve, for (a, b) yearly NO_2 optimization; (c, d) summer $SOMO35$ optimization; (e, f) joint NO_2 and $SOMO35$ optimization.

curve) for the lower range of costs. In the higher cost range (points P4 and P5), emission reduction measures in the residential–commercial sector become efficient as well (e.g. shift to gas combustion and thermal renovation of buildings).

So far the multi-pollutant optimization has been solved considering pre-defined weights for NO_2 and $SOMO35$ pollutants (in particular, considering $PI = 3I^*_{NO_2} + I^*_{SOMO35}$). However, it is also possible to analyze how the optimal solutions set (Pareto curve) depends on the assumed weights for the two indices. Fig. 8 shows a view of such solution. In particular, considering as an example a cost of policy implementation of 20 M euro/year, it shows the efficient compromise solutions of the multi-objective problem of minimizing both $SOMO35$ (on x-axis) and of NO_2 (on y-axis). These can be obtained solving the multi-objective problem for many different couples of α_p weights. From this curve it is possible to appreciate that:

- the relative weights of the two indicators affect the optimization results, and should therefore be a key aspect to be considered by policy

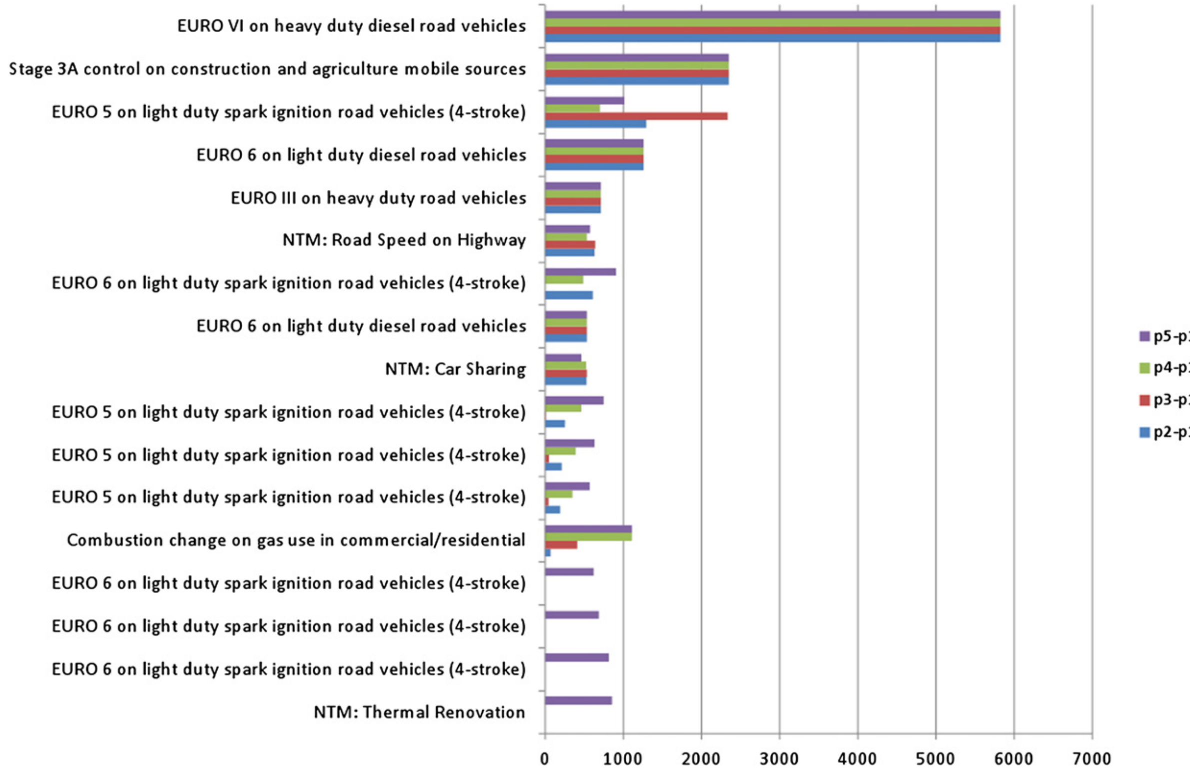

Fig. 7. Main NO_x emission reduction measures, in the case of NO_2 optimization, for different points of the Pareto curve. Bars are related to the reductions beyond CLE (i.e. point P1) for the different points from P2 to P5 (i.e. P3–P1 represent the emission reduction needed to move from CLE to the third point of the curve).

makers when designing optimal policies regarding on more than one pollutant;

- in the particular case considered, the difference between the minimum and maximum indicator values is quite small, meaning that the possible control of air pollution by local authorities is limited. This is especially true for *SOMO*35, as O_3 concentrations are largely affected by boundary conditions (contrary to NO_2 that is more directly related to local emissions);
- the set of actions corresponding to CLE is already very close to the Pareto Frontier (red dot in the figure), meaning that actions at the local level will have a very limited impact on air quality, regardless of the cost incurred.

The results of the integrated modeling approach presented in this paper can be affected by uncertainties on different issues. These should be carefully considered to demonstrate the robustness and usability of the proposed air quality plans. More in detail, as for all modeling exercises, uncertainties are related to input data and to the modeling approach itself. As for input data, in the case at hand, they are the emissions and measure inventories on one side and the meteorology adopted for the CTM on the other. As explained above, emission inventories are based on a very simple formulation; and indeed a recent survey among European researchers and planners (www.appraisal-fp7.eu) resulted in more than half thinking that their emission inventory is the source of most uncertainty. As for the meteorology, it is more a problem of representativeness than of uncertainty. The year used in this study, 2005, was an average year. The French average temperature was only slightly warmer (0.5 °C) than the past two decades. It can thus represent the expected mean conditions of few years to come. One may however want to test most stringent conditions, such as the heat wave of Summer 2003 (more than 3 °C warmer) or the cold Winter of 2009 (almost 4 °C colder in January), thus obtaining more conservative (and probably more expensive) solutions. The uncertainties of the modeling approach have basically three components: the CTM itself, its approximation through the surrogate models and the optimization setting. The first two aspects can be analyzed by traditional techniques on the basis of performance indicators such as those shown in Table 2 and Fig. 2, while the last aspect is more critical since there is no absolutely optimal solution to compare with. Future work will thus be devoted to further explore suitable qualitative and quantitative techniques (Saltelli et al., 2008) to determine the robustness of the proposed solution and/or its sensitivity to the optimization setting.

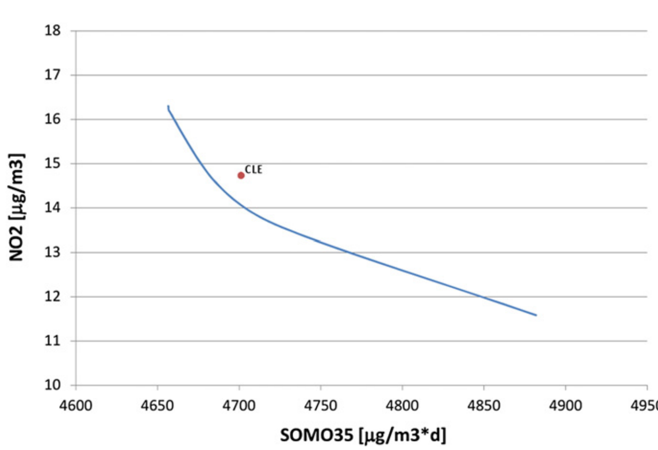

Fig. 8. Pareto curve showing the optimal results in terms of *SOMO*35 (x-axis) and NO_2 (y-axis), for an implementation cost of 20 M euro/year. The red dot represents 2010 CLE conditions.

6. Conclusions

As a contribution to air quality planning at the regional scale, this paper shows how trade-offs among atmospheric pollutants can be analyzed using the Integrated Assessment Model RIAT+. This tool allows for a) optimizing jointly different pollutants; b) computing various air quality indices on different time intervals; and c) including measures made compulsory by legislation for different time horizons. Other features of RIAT+ are currently under development and will extend the tool to estimate: the greenhouse gas associated to an air quality policy, to determine air quality and climate change win–win actions; and the external costs related to a particular policy application.

The presented application of RIAT+ to the Alsace Region has led to the following conclusions. Firstly, reductions of the NO_2 concentrations will be achieved mainly through actions on traffic and domestic sectors, but there could be conflicts with *SOMO*35 policies; decision makers so should correctly prioritize objectives, when designing air quality plans. Secondly, there is a little scope for local actions, and so measures at the national–international scale should be fostered simultaneously, to achieve significant air quality improvement.

From the discussions held with local decision makers on this preliminary application, a practical problem appeared: the impossibility of implementing some of the RIAT+ suggested proposed measures. Indeed, some of these measures (e.g. heavy truck standards) can only be tackled at the national or European level. Nevertheless, the application of RIAT+ helped to set priorities for local level actions, identifying measures which should be implemented at the national level. RIAT+ is presently used to evaluate other air quality objectives, to complete the future Alsace action plans.

Conflict of interest

This paper is the result of a LIFE+ project (OPERA, www.operatool.eu) that has been performed jointly by the co-authors of this paper. In particular the paper presents the methodological development and a case study on Alsace Region (FR), one of the two case studies considered in the project. As far as I know, no conflict of interest issue is applicable for this work.

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