A Short-Term Air Quality Control for PM$_{10}$ Levels

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Abstract: In this work, the implementation and test of an integrated assessment model (IAM) to aid governments to define their short term plans (STP) is presented. The methodology is based on a receding horizon approach where the forecasting model gives information about a selected air quality index up to 3 days in advance once the emission of the involved pollutants (control variable) are known. The methodology is fully general with respect to the model used for the forecast and the air quality index; nevertheless, the selection of these models must take into account the peculiarities of the pollutants to be controlled. This system has been tested for particulate matter (PM$_{10}$) control over a domain located in Northern Italy including the highly polluted area of Brescia. The results show that the control system can be a valuable asset to aid local authorities in the selection of suitable air quality plans.

1. Introduction

In recent years, exposure to high particulate matter PM$_{10}$ concentrations has become one of the most relevant environmental problems [1] due to its known negative impacts on human health, ranging from pulmonary to cardio-vascular diseases [2,3]. Like other pollutants as nitrogen oxides and ozone, the formation and accumulation of PM$_{10}$ is driven by nonlinear phenomena occurring in atmosphere, including chemical reactions, physical transformation and thermodynamic equilibrium, thus making the evaluation of planning decisions extremely complex [4]. For this reason, a number of studies concerning the impact of emission control strategies have been performed [5–8]. Because of this complexity, international, national, regional and local authorities need tools to support the decision makers in taking their decisions [9]. Based on the problem they should tackle, these tools can be divided into:

- Monitoring Tools: to support the authorities in the evaluation of the current concentration levels in a defined area. They include tools related to the management of data from regional networks and novel/personal networks supported by low cost technology [10,11] and modelling tools able to integrate the gridded evaluation of the current state of the atmosphere with virtually any kind of available measurement [12,13];

- Forecasting Tools: to perform pollutant level forecasts in specific points or areas. These include statistical models [14], usually giving information on monitoring station locations, deterministic grid models [15,16] or models implementing a mixed approach [17] trying to integrate both the previous approaches;

- Planning/Management Tools: to support decision makers in the selection of suitable air quality control actions for a certain domain [18,19]. The most recent approaches allow to

take into account both air quality levels and emission abatement costs using cost-effectiveness and/or multi-objective approaches [20–23]. They are also referred to as integrated assessment models (IAMs).

This work is mainly focused on the introduction of a management tool for short-term policies definition. This is a quite challenging task as in literature a series of IAMs has been described, treating the problem in the long-term period and, for this reason, considering the atmosphere always in a steady-state condition for the control problem solution [20,23–25].

In this study, the implementation of a short-term integrated assessment model based on a receding horizon technique is proposed. This approach can be used in two different configurations:

- Scenario Mode: evaluation of the impact of a single set of actions on air quality;
- Optimization Mode: selection of a set of (optimal) actions.

The main advance with respect to literature is that considering the short-term (up to few days) control problem means that the strong non-linearity of the system, and in particular its dynamics, should be considered in control development. Moreover, to the authors knowledge, this is the first time the receding horizon technique [26] is used for the development of air quality control.

The implemented system has been tested on a domain in Northern Italy including Brescia city and its surroundings, an area often affected by high PM_{10} (and other pollutants) concentrations, trying to find an optimal set of actions to satisfy the PM_{10} concentration daily limits, minimizing, at the same time, the application cost.

2. Methodology

The short term IAM developed in this work is similar, in principles and structure, to existing long term ones (Figure 1). In this figure, it is possible to identify the two key elements that are needed in an IAM: a controller and a model, constituted by the comprehensive air quality model with eXtensions (CAMx) model, optimal interpolation and correction factor (CF) blocks.
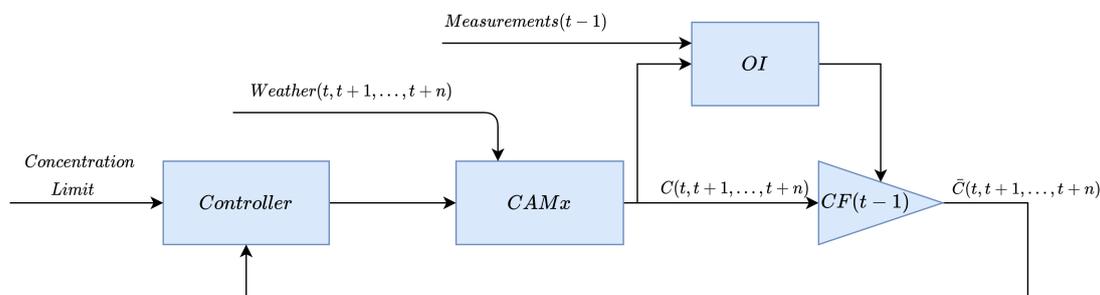

Figure 1. Overall System Scheme.

The choice of the CAMx [27] deterministic chemical transport model has been influenced by the fact that short-term forecasting is driven by the dynamic of the phenomena involved and it is usually strongly affected by uncontrollable variables, such as wind speed and precipitation rate. These facts make the use of surrogate models less appealing due to their ability to represent with good performances only the steady state of pollutants in atmosphere [28].

Furthermore, to increase the model performance, a reanalysis technique based on an optimal interpolation (OI) algorithm has been implemented. This allows to cope with input uncertainties and approximation in the modelling of the different phenomena considered the model. In practice, OI computes a correction factor (CF) by processing the last available measurements and model output to improve forecast accuracy. Since in our case the last available measurements usually date back to the day before the CTM forecast run, the only option is to hold the correction factor along the prediction horizon.

The controller has the goal to find a set of optimal emission abatement measures to be applied, with respect to two main objectives: an air quality index and a cost index [29].

2.1. Problem Formulation

Due to the nature of the involved phenomena, the control laws for the short-term air quality control problem can be considered as a sequence of decisions taken by a (national, regional and/or local) authority. In this work, the problem has been formalized through a multiple input, nonlinear receding horizon control technique [26] where the control law u^i acting on the horizon $[i, i + N - 1]$, with length N, is expressed as a sequence of M decisions (input):

$$u^i = \{u_{1,i}, ..., u_{M,i}, ..., u_{1,i+N-1}, .., u_{M,i+N-1}\} \tag{1}$$

At each time step i an optimal control problem has to be solved and the first step of the solution sequence u^i is applied:

$$\min_{u^i} V_N(x_k, u^i, \cdot) = \min_{u^i} \sum_{k=i}^{i+N-1} V(x_k, u_{1,k}, ..., u_{M,k}, \cdot)$$

s. t. $\tag{2}$

$$x_{k+1} = f(x_k, u_k, \cdot) \qquad k = i, ..., i + N - 1$$

$$u^i \in U$$

where:

- V_N is the objective function to be minimized, i.e., the sum of the objective functions V computed for each step. In this work, it includes both an air quality index and a cost index;
- $f(x_k, u_k, \cdot)$ is the air quality model, allowing to estimate the evolution of the concentration of different pollutants in the atmosphere as a function of the concentration values computed at previous steps, the input controlled variable (emissions) and the uncontrolled ones (meteorology);
- x_k is the state of the system, i.e., the concentration of each species in each cell of the computational domain;
- u^i is the control sequence, as defined in Equation (1);
- U is the feasible control set.

2.2. Control Sequence

The control sequence u^i represents the application of the different short term actions (STAs) considered in the problem. The actions that can be included in the problem are short term abatement measures that authorities/decision makers may implement to reduce atmospheric pollutant emissions. In this work STAs are always binary (i.e., the action can be fully applied or not applied at all).

STAs are defined in terms of:

- Abatement factor: percentage emission reduction resulting from the application of an action on a domain cell. This factor depends on where the measure is applied, due to the presence of different drivers (emission activities) in different locations, i.e., wood burning reduction and traffic limitations do not have the same effect if applied in city centres or rural areas.
- Application map: the area of application of an action. In order to keep considering u_k as a binary value array, if a measure is applied on different areas, it will be considered as two separate measures.
- Cost: implementing an STA has a cost that can be expressed both as a monetary or a social disappointment cost.

The pollutant emissions over the domain D are then a function of the control sequence u^i according to:

$$E^{d,p}(u^i) = E_0^{d,p}\left(1 - eff(u^i, p, d)\right)$$ (3)

where:

- $E^{d,p}$ is the emission value of pollutant p at cell $d \in D$.
- $E_0^{d,p}$ is the initial condition of the emission value, without the application of any of the abatement measures studied.
- eff is the effectiveness of the abatement measures applied for the control law u^i, it represents how much the measures manage to reduce the given pollutant p at cell d.

2.3. Objective Function

In Europe, in a typical short-term air quality management problem, a decision authority has the task to keep the daily concentrations of a number of pollutants below the European Directive thresholds, trying to minimize the impacts on the people affected by the application of the abatement measures. A modelling system designed to solve this problem must take into account both these aspects. Therefore, the objective function has to be composed by two functions to be minimized simultaneously: the number of concentration exceedances and the monetary/social cost to implement the emission abatement actions.

In general, the objective function $V(\cdot)$ at time i will be expressed as:

$$V(x_k, u^i) = \begin{bmatrix} \Gamma(x_k, u^i) \\ \Omega(x_k, u^i) \end{bmatrix}$$ (4)

where Γ and Ω are two real scalar functions allowing to compute the air quality index and the control action cost over the chosen horizon.

These values depend on the concentrations computed through the model, on the level of application of the different actions and on the social costs of each single action.

2.4. Air Quality Forecast

The most consistent way to proceed to define the function f that models the dynamic of the pollutants in atmosphere consists in the use of full chemical transport models, allowing to threat all the physical and chemical phenomena involved in emission, transport, accumulation and removal of chemical species.

In this work, the CAMx model [27] has been applied. CAMx is an open source chemical transport model, based on Fortran source code, describing the physical and chemical phenomena involved in the formation of pollutants solving the mass-balance Equation (5):

$$\frac{\partial C}{\partial t} = f_{Xtransport}(\cdot) + f_{Ytransport}(\cdot) + f_{Ztransport}(\cdot) + f_{XYdiffusion}(\cdot) + f_{Zdiffusion}(\cdot) +$$
$$+ f_{emission}(\cdot) + f_{deposition}(\cdot) + f_{chemistry}(\cdot)$$ (5)

where C ($\mu g/m^3$) is a vector composed by chemical species concentrations in (x, y, z) at time t and the different functions f_* are expressed in Equation (6):

$$
\begin{aligned}
f_{emission} &= f_{em\_mech}(E, \cdot) \\
f_{Xtransport} &= -\frac{1}{A_{yz}}\frac{\partial(uA_{yz}C)}{\partial x} \\
f_{Ytransport} &= -\frac{1}{A_{xz}}\frac{\partial(vA_{xz}C)}{\partial y} \\
f_{Ztransport} &= \frac{\partial(C\eta)}{\partial z} - C\frac{\partial^2 h}{\partial z\partial t} \\
f_{Zdiffusion} &= \frac{\partial}{\partial z}\left(\rho K_v \frac{\partial(C/\rho)}{\partial z}\right) \\
f_{XYdiffusion} &= \frac{\partial}{\partial x}\left(\rho K_x \frac{\partial(C/\rho)}{\partial x}\right) + \\
&\quad + \frac{\partial}{\partial y}\left(\rho K_y \frac{\partial(C/\rho)}{\partial y}\right) \\
f_{deposition} &= -\Lambda C \\
f_{chemistry} &= f_{chem\_mech}(\cdot)
\end{aligned}
\tag{6}
$$

where A_{yz} and A_{xz} (m^2) represent, for each species, the cross-sectional areas in the y-z and x-z planes respectively; the wind components in m/s on the horizontal plane are u (along direction x) and v (along direction y); K_x, K_y and K_z denote the turbulent diffusion coefficient along the three dimensions; Λ is the scavenging coefficients array $[1/s]$ for each species; finally, $f_{chem\_mech}(\cdot)$ is the nonlinear function illustrating the chemical transformations in atmosphere among the considered species according to a selected chemical mechanism.

As stated by Equation (6), a series of partial differential equation systems has to be solved. For this reason the model needs in input the initial condition X_0 and the boundary conditions x_{east}, x_{west}, x_{north}, x_{south}, x_{top} corresponding to the concentration values at the domain boundaries.

Equations (6) can be solved by the model through different algorithms. The configuration applied in this work is presented in Table 1.

Table 1. Selected configuration for CAMx model.

Feature	Options
Chemical Mechanism	CB05 [30,31]
Advection Solver	BOTT [32]
Drydep Model	WESELY [33]
Chemistry Solver	EBI [34]
Aerosol Approach	CF [27]
Inorganic Thermodynamic module	ISORROPIA [35]
Organic Aerosol module	SOAP [36]

In general, the aerosol modules allow to take into account the aqueous chemistry, the partitioning of inorganic aerosol constituents (sulphate, nitrate and ammonium) and gas-aerosol partitioning of organics, allowing to include the most important processes in the formation and accumulation of aerosol in atmosphere [27]. With these particular configurations, aerosol treatment is performed using a coarse/fine approach, splitting the species in two different granulometries: coarse, with diameters greater than 2.5 μ/m and fine, with diameters lower than 2.5 μ/m. The primary species (including elemental and organic carbon) can be coarse or fine, while secondary species (nitrates, sulphates, ammonium and secondary organic aerosols) are considered only as fine particles.

More details on air quality IAMs and CAMx can be obtained from [17,37]. Furthermore, an optimal interpolation based data assimilation technique [38] has been integrated to reduce the effects of input and model uncertainties on the system [39].

2.5. Optimal Interpolation

Optimal Interpolation [13] is a reanalysis technique used to merge model simulations and air quality measurements to obtain a more precise concentration field. The errors included in measurements and forecasts can be represented as:

$$C_b(t) = C_t(t) + \eta_b(t) \tag{7}$$
$$y_0(t) = \mathbf{H}(C_t(t)) + \varepsilon(t) \tag{8}$$

where:

- C_b is the background simulated field (first guess), in this case, the output of the deterministic model CAMx.
- C_t is the vector of true values.
- η_b represents the error of the simulated values.
- y_0 is the observation vector that contains all the measurements.
- $\mathbf{H}$ is a linear operator linking the grid field and the observations, typically bilinear interpolation is applied.
- ε represents the error of the observations.

This approach minimizes the error variance to compute a reanalyzed field $C_a(t)$ according to:

$$C_a(t) = C_b(t) + \mathbf{K}[y_0(t) - \mathbf{H}(C_b(t))] \tag{9}$$

where $\mathbf{K}$ is known as the Kalman Gain and it is calculated as:

$$\mathbf{K} = \mathbf{P}\mathbf{H}^T(\mathbf{H}\mathbf{P}\mathbf{H}^T + \mathbf{R})^{-1} \tag{10}$$

Based on the following statements:

- $\mathbf{P}$ is the simulation errors covariance matrix.
- $\mathbf{R}$ is the observation errors covariance matrix.
- $E[\eta_b] = 0$ and $E[\varepsilon] = 0$, thus both errors are unbiased.
- $E[\eta_b \varepsilon^T] = 0$, thus the simulation errors are independent from the measurement ones.

This methodology, according to [38] allows to obtain significant improvements in the precision of deterministic model output for the simulation of PM_{10} daily mean concentrations.

3. Optimization Problem Solution

This section describes in detail the procedure applied to solve the management problem described in the previous sections. Three issues significantly affect the resolution:

- to run the deterministic model CAMx is computationally expensive;
- the huge number of input variables and relationships involved in CAMx to describe the phenomena of formation and accumulation of atmospheric pollutants makes the function modelled through the CTM model too complex to be studied;
- the objective of the decision maker in the short-term period is to avoid/limit critical situation, i.e., the situation where the concentration values for a pollutant is higher than a critical threshold (usually defined at the legislative level).

These facts strongly affect the implementation of the optimization procedure. Before the presentation of the algorithm steps, three important features must be defined:

- Forecast Horizon Window: it determines how many steps ahead the pollutant concentrations are forecasted. A wide forecast window will increase the model uncertainty and the computational burden for each cycle. However, abatement measures usually have a higher impact if applied in advance;
- Application Interval Length: this determines for how many days, within the Forecast Horizon, the chosen actions are applied. In other words, it represents the actual control output length and the interval of time between subsequent IAM runs. This variable has a practical limitation, as its minimum value corresponds to running the IAM system and applying the optimal actions within the same day. This is highly unlikely to be obtained in a real life application for any authority. On the other hand, keeping this value as small as possible, allows the system to change the measures selection to cope with new, more accurate forecasts.
- Measure Drop Threshold: This threshold determines the maximum air quality index degradation allowed during the optimization process, with respect to the best index value obtainable with the maximum application of all the measures. Thus, lower values will increase the weight of the air quality objective, higher values, instead, will increase the weight of the cost. For this work this value was set to 1.

The optimization algorithm is based on a fast and simple heuristic procedure designed according to the following steps:

1. the control law u^i is computed only if the air quality limit value is exceeded within the forecasting horizon window $[i, i + N - 1]$;
2. the control law computation starts with all the actions simultaneously applied for all the application interval length;
3. each action is deactivated individually, and the impacts of these individual deactivations are assessed according to the following rules:

   - exceedance days should not increase. If the deactivation of an action results in an increase, then the STA cannot be deactivated;
   - the worsening of the air quality level, should be less than the value defined by the Measure Drop Threshold. If the worsening is higher, then the measure cannot be deactivated;
   - the action with the highest cost among the ones respecting the previous rules is dropped. If two actions have the same cost, then the one with the highest air quality worsening is deactivated.

4. the set of the resulting active STA is used as the base case for another iteration in order to deactivate other measures.
5. finally, when no deactivation respects the previous control rules, the optimal set of actions is found.

There is a special situation that needs extra consideration. When no air quality exceedances can be found within the forecast horizon, no action is applied. Since the lack of exceedances may be caused by prediction uncertainty then, the control system is run again the following day, without considering the Application Interval length.

4. Case Study

The methodology presented in the previous section has been applied to a particulate matter (PM_{10}) management case-study for the city of Brescia (Northern Italy) and its surrounding area. The simulations presented in the following tests refer to January 2011 in order to apply the model to

an adverse situation, as Winter months in the selected area are characterized by frequent exceedances of the daily average PM$_{10}$ European Legislation threshold of 50 μg/m^3.

4.1. Case Study Setup

The city of Brescia is one of the main urban centers in the Po valley basin and it is among the European areas with higher particulate levels. The modelling domain is a 108×138 km^2 area (Figure 2) including almost all Brescia province as well as the neighboring cities of Cremona and Bergamo. This area has been gridded into 3726 2×2 km^2 squared cells. The meteorological fields are computed by means of the weather research and forecasting (WRF) prognostic model [40], while the basecase emission data are collected from the regional inventory INEMAR [41]. The boundary conditions are obtained through a simulation performed with CAMx for the same period, but with a coarser 6×6 km^2 horizontal resolution over a domain covering the entire Northern Italy, following a one-way nesting procedure. In this last case, the boundary conditions are obtained interpolating the results of the Mozart global model [42]. More information and the validation of the simulation over the coarser grid can be found in [37].
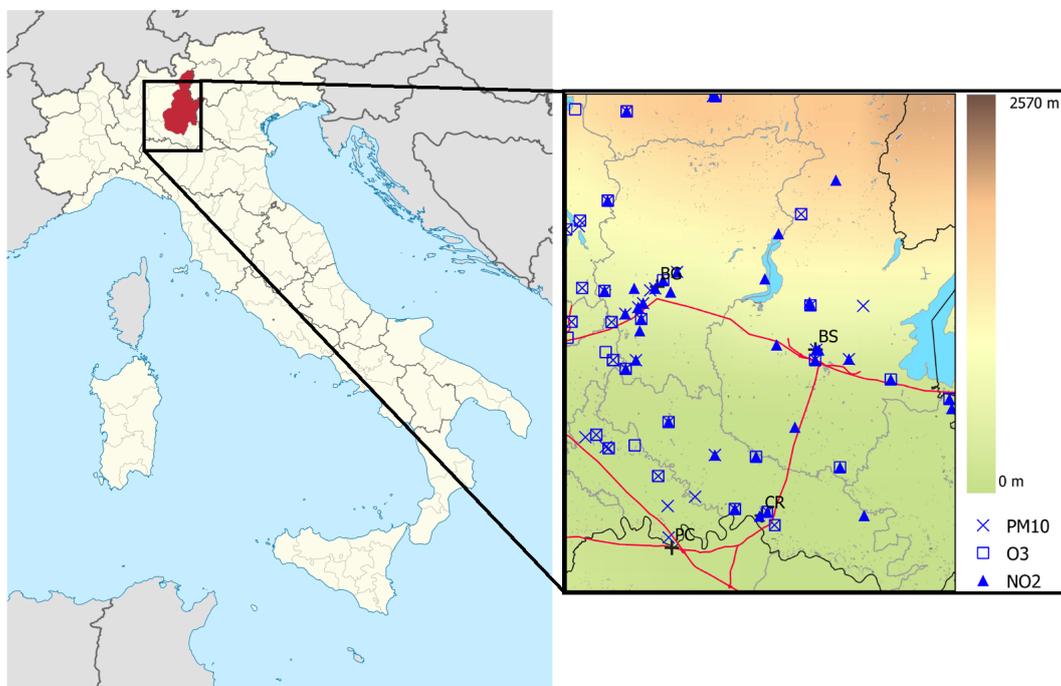
Figure 2. Modelling domain including the location of monitoring network stations.

4.2. Validation of Camx Model for PM$_{10}$ Concentration

A validation procedure has been applied in order to assess if CAMx can be used for the definition of the control law. This validation was performed by comparing the output of the model with data measured by the regional monitoring network (represented in Figure 2) following a Monte Carlo approach as presented in [12]. With this approach a set of 100 re-analyses was performed using, for each case, 80% of the stations for the optimal interpolation and the remaining 20% for the validation. Figure 3 shows through boxplots the correlation coefficients (Figure 3a) and the normalized mean absolute errors (Figure 3) computed for the validation stations on the domain. For the optimal interpolation case, the worst performance index computed for each station in the 100 re-analyses was considered. The results clearly showed the impact of the optimal interpolation techniques on the model performances, with the median of the correlation increasing from 0.7 to a value close to 1 and the median of normalized mean absolute error decreasing from 0.4 to less than 0.1. These figures

highlight that the performance of CAMx, without optimal interpolation, was not enough to apply the model for the definition of the control system, therefore, the following section will focus on the application of the system integrating both CAMx and optimal interpolation.
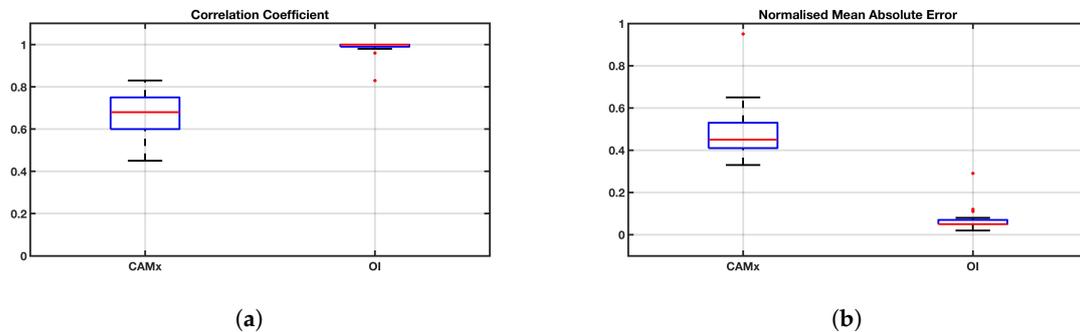

Figure 3. PM_{10} daily mean concentration correlation coefficient (**a**) and normalised mean absolute error (**b**) for CAMx model and CAMx + optimal interpolation system.

4.3. Actions

The actions considered in this work were specifically emission abatement measures focused on the reduction of PM_{10} concentrations. Since PM has a primary (directly emitted) and a secondary (formed in atmosphere) fraction, the measures included in the problem could affect directly primary PM_{10} emissions and/or other precursors of secondary PM_{10} such as nitrogen oxides (NO_x).

Each action was defined through three main variables:

1. precursor abatement efficiency;
2. application area;
3. cost.

In order to take into account the impact on PM_{10} concentrations in Brescia of the emission of the surrounding areas, the domain was divided in three application zones as represented in Figure 4. The smaller blue area included the cells belonging to the municipality of Brescia (Zone 1). The light blue ring included Area 1 municipalities (Zone 2) defined according Lombardy region directives and the outer yellow ring included Area 2 municipalities (Zone 3). Finally Zone 4 was composed by the cells including highways and main streets (black line in Figure 4). The orange surrounding cells highlight the whole province of Brescia, but were not considered for measure application in this work.
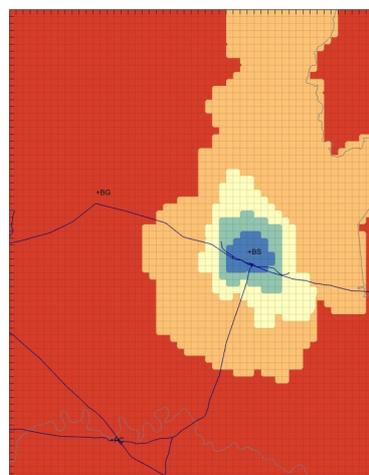

Figure 4. Application zone considered for the short term actions.

The actions included in this case study were:

- Traffic Limitation/Car Ban: Traffic is among the main pollutant activities in the area, emitting significant quantities of NO_x through internal combustion, primary PM from brakes and tires abrasion and particle re-suspension. In this short-term case study, traffic measures are applied with a limited time span (down to one day).

- Maximum Speed Reduction: This action, if applied to highways and main streets, proved, in previous studies, to be a viable option to obtain concentration reductions near the streets [43], despite little influence at higher scales.

- Heating Temperature Reduction: one degree reduction of indoor temperature. Even if the reduction factor is small, the area of application allows temperature reduction to cut a significant amount of emissions.

- Wood Burning Limitation in the area under study 98% of domestic heating emissions comes from biomass burning. Long term limitations are already in place, but further emergency limitations are expected to effectively contribute to particulate concentration reductions.

Table 2 presents all the measures considered with the values assigned to their properties. Application efficiency values have been extracted from INEMAR database [41]. Costs are extremely difficult to compute. In first instance, and in absence of better criteria, the cost of each action has been computed as a "dissatisfaction estimate" based on the amount of population affected by the measure.

Table 2. Abatement measures available.

Action	Zone	PM_{10} Reduction	NO_x Reduction	Cost
Traffic Limitation	1	42%	51%	2
Traffic Limitation	2	25%	52%	3
Traffic Limitation	3	25%	52%	5
Speed Reduction	4	23%	5%	2
Reduce Heating	3	5%	5%	2
Wood Burning Limitation	1	30%	4%	2
Wood Burning Limitation	2	50%	7%	3
Wood Burning Limitation	3	50%	7%	4

4.4. Objective Function and Control Law Definition

In this work, according to Equation (4), the selected objective function Γ is the number of the days, over Zone 1, with the daily mean concentration of PM_{10} higher than the legislation threshold of $50\ \mu g/m^3$ (European legislation index for PM_{10}). Ω objective function, taking into account the cost of the control law, is simply the sum of the daily costs of each selected action.

Following the decision to use a threshold index for air quality, the general optimization problem solution procedure was adapted in order to consider an action as a candidate for deactivation, not only if the resulting worsening of the concentration levels was under the Measure Drop Threshold, but also if the number of exceedance days did not increase after the deactivation. Moreover, a constraint related to the decision level was considered in the solution: in order to be activated for an outer zone, the action also had to be applied to the inner zones.

4.5. Results

The results obtained through the previous methodology were assessed by comparing avoided PM_{10} exceedances and daily average PM_{10} concentrations with a maximum reduction scenario (referred as Test Max in the following subsections) built by always applying all the measures available. Two different configurations of the system were tested:

- Test 1: applies the IAM (with control) with a three day forecast horizon and keeping the application of the resulting measures fixed for the next three days. Optimal interpolation is based on the measurements of the day before the IAM run. This test simulates a situation in which the decision maker cannot change the strategy every day;

- Test 2: applies the daily IAM (with control) with a three day forecast horizon. In this case the pool of measures applied varies every day. This is the standard implementation of the receding horizon technique, but it implies that the decision makers can impose every day different measures to the population. Optimal interpolation is based again on the measurements of the day before each IAM run;

The scheme in Figure 5 allows us to better appreciate the differences in the two configurations. Assuming that the decision maker required the computation of the control law at time $t-1$ (when the last measurement was available for optimal interpolation), both the systems performed a 3-days-ahead forecast in order to compute the control actions to be activated for each day in the interval $t \div t+2$. In the first case (Test 1), the solution was applied for the entire interval. In the second configuration (Test 2), the actions were applied for the first day of the interval and a new 3-days-ahead forecast was performed, once the correction factor was updated with new available measurements (day t). The second configuration (very similar to a classical receding horizon approach) ensured a better forecast thanks to the use of correction factors that were updated every day, but had a higher computational cost. It is, therefore, a good benchmark for the performances of the Test 1.
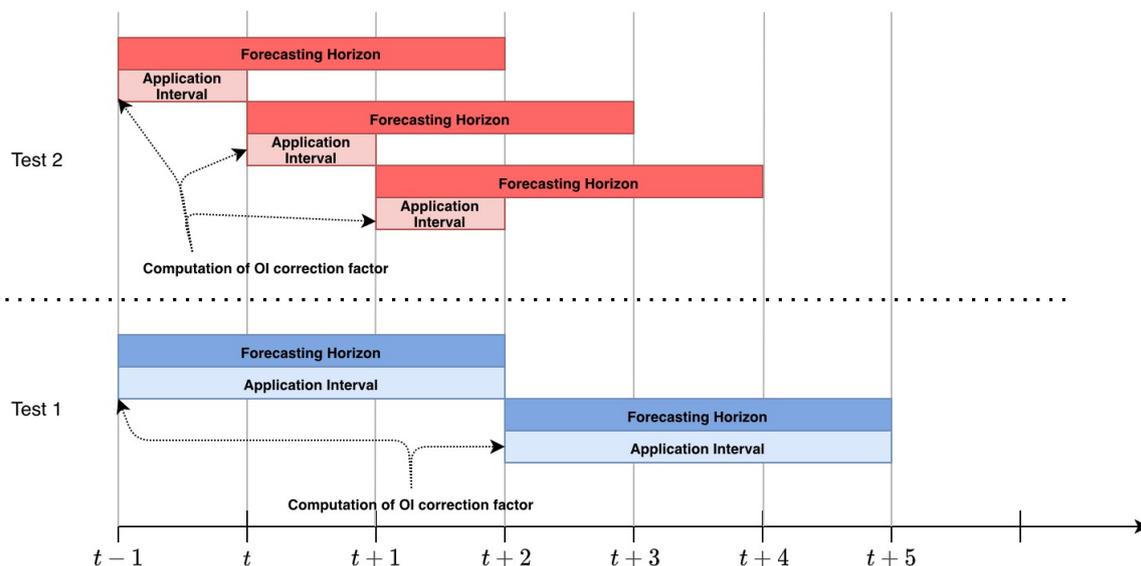

Figure 5. Differences between Test 1 and Test 2 configuration.

Figure 6 presents the daily mean PM_{10} concentrations for the 3 different tests over the period under study (January 2011). From the results of the Test Max configuration (the test performed with all the measures activated) it is possible to see that the problem was quite difficult to solve, since also in this potential application scenario, the reduction of the exceedance days was limited. Moreover, it seems that the impact of the selected actions was not enough to consistently change the dynamic of the phenomena and that a stronger carrier was affecting the system as an uncontrolled input. Nevertheless, in the three cases the controlled PM_{10} concentrations were very similar, with the exception of days 21–23. In these days, only the Test Max configuration was able to avoid any exceedance, while Test 1 and Test 2 could not always push the PM_{10} levels under the threshold. This is probably due to the fact that the the concentration values, in these days, were close to the threshold, thus, even a small forecast error could drastically change the behaviour of the optimization algorithm. For what the Test 1 and Test 2 is concerned, the main difference between the results of them was that the higher dynamic of Test 2 configuration allowed us to avoid an exceedance for day 23. Furthermore, on day 9, Test 1 (and Test Max) ensured a higher concentration reduction (around 20 $\mu g/m^3$) with respect to Test 2. This is due (1) to the fact that Test 2, due to its dynamic, was able to capture the concentration decrease for the following day and (2) to the optimization procedure aiming to reduce the exceedances
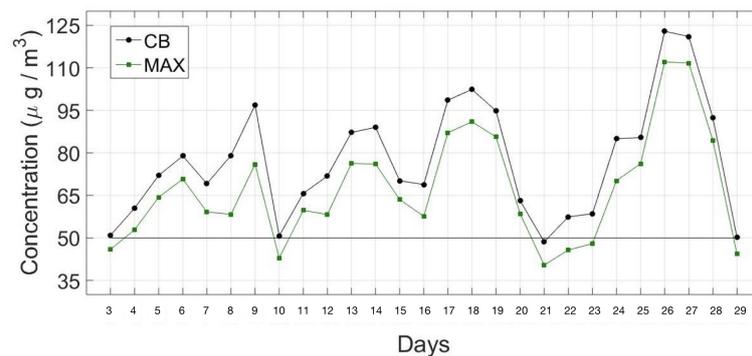
with the minimum effort, so, no action is taken when a non exceedance day was forecasted. In Test 1, instead, all the measures were kept in place due to the 3-day application constraint.
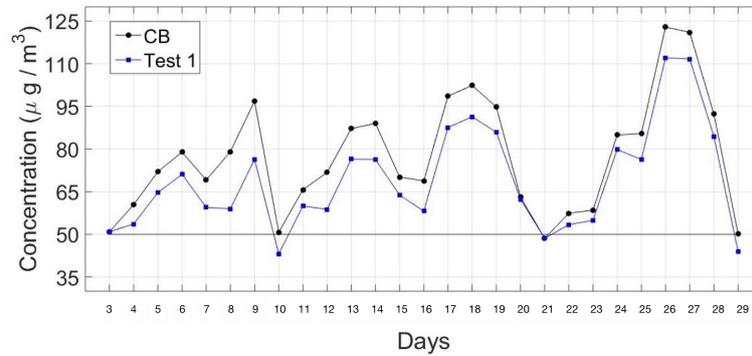
(**a**)
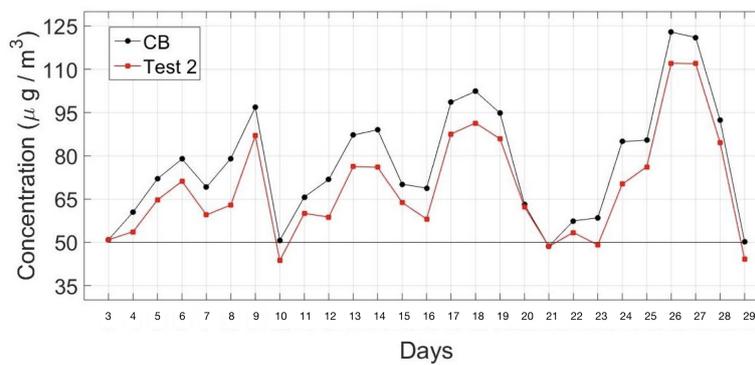
(**b**)

(**c**)

Figure 6. Particulate matter (PM_{10}) concentration before (CB) and after the actions for Test 1 (**a**), Test 2 (**b**) and Test Max (**c**).

Figure 7 presents, for each day, the measures application resulting from Test 1 (Figure 7a) and 2 (Figure 7b). It is possible to see that Test 2 had an obvious higher variability in the activation of the measures and, in days 9, 20 and 21 few or no measures were applied, allowing the final policy cost to

decrease. In Test 1, the 3-day choice constraint was clearly recognizable in the pattern. This Figure also confirms that the constraint inhibits the possible temporary deactivation of the measures seen in Test 2 for day 9, delays the deactivation of measures for day 20 and the subsequent reactivation two days later.

(a)

(b)

Figure 7. Resulting measure application for Test 1 (**a**) and Test 2 (**b**) for each day.

Table 3 presents, for the different tests performed, the number of exceedances with respect to the 50 μg/m^3 threshold, the measure application costs, and the monthly mean PM_{10} concentrations.

Table 3. Results Comparison.

Test	Exceedances	Cost	PM_{10}
Base Case	26	0	77.5
Test 1	24	268	69.0
Test 2	23	253	69.0
Test Max	21	351	67.3

The best result with respect to air quality (minimum number of exceedances and particulate matter concentration) was obviously obtained at the maximum cost for the maximum application scenario. This also established that with the current pool of measures the IAM could reduce the maximum 5 exceedance days for the current case study; still, building a IAM that helped to reach this 5-day reduction at the minimum cost can be extremely helpful in order to reach the 35 exceedance days limit required by the legislation.

The differences between Test 1 and 2 showed how an improvement in the dynamic capability of the control system (daily IAM run instead of 3 days' run) could improve the air quality and reduce the cost of the strategies.

As can be observed by mapping the reduction in exceedance days as in Figure 8, all the tests managed to achieve reductions, with a maximum of 10 days reduction for some cells located North of Brescia. It is important to notice how, for Test 1 and Test Max, where the actions applied were kept for several days, there are reductions reaching areas further from the city with respect to Test 2 where the actions are redefined everyday. These representation aids the comprehension of the results

previously presented in Table 3 and shows how, for example, Test 2 obtains higher reductions in the cells of interest (Zone 1) with respect to Test 1. Finally, 1 day reductions located in sparse cells outside the domain are due to computational approximations.
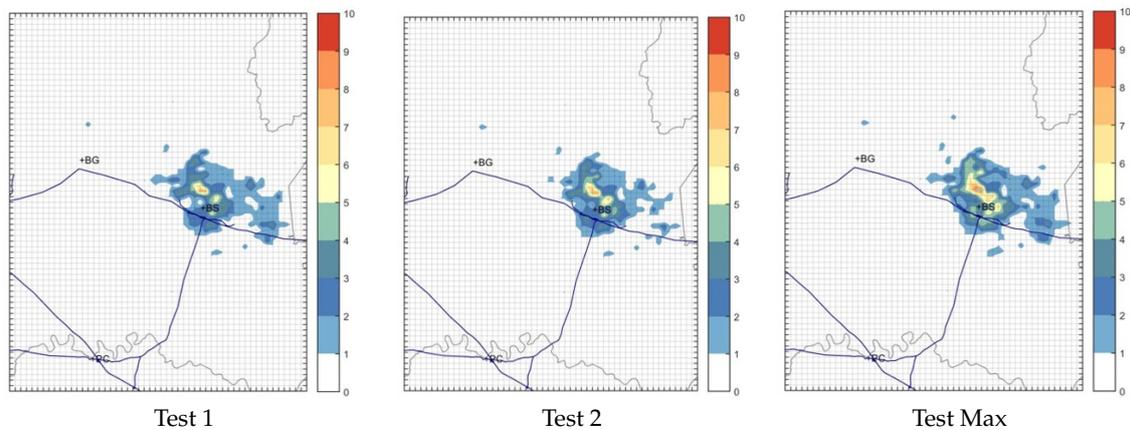

Figure 8. Map of exceeded days reduction.

5. Conclusions

The objective of this work was to implement and test a short term integrated assessment model to aid decision makers in the definition of short term plans (STPs) to reduce peak particulate matter concentration and the number of exceedance days with respect to thresholds values defined in the legislation.

In literature, many different long term decision support systems can be found. These systems tend to focus on the reduction of mean pollutant concentration values for wide temporal windows (usually annual) considering a steady state system. These IAMs are not able to handle daily variations in emissions and concentrations as a short term IAM, instead, should do. Furthermore, uncontrolled variables as weather conditions must be included in the latter problem as they have huge impacts on the daily variations of particulate matter concentration.

The IAM described in this paper is composed of a deterministic model coupled with an optimal interpolation algorithm to feed a nonlinear receding horizon controller able to select the optimal sets of short term emission abatement actions. The IAM, tested on a case-study for the month of January 2011 over the city of Brescia, managed to obtain cost-efficient strategies resulting in a reduction of 2 and 3 days of exceedance, depending on the configuration. This result should be seen in the light of a 5 days potential reduction obtained with the maximum application of all the actions considered in the problem.

A number of considerations arise from the case-study results:

- Running the IAM every day increases the computational burden and leaves little notification time for a real world application, but it allows to obtain better results with respect to occasional IAM runs for wider time windows. Further studies should be done in order to determine the best forecast window and running frequency combination to enhance the controller performance.
- PM_{10} exceedances forecasting is a challenging problem. Even if the overall performances of the CAMx model are good (in particular in combination with the implemented optimal interpolation technique), little deviations with respect to the measured values can consistently affect the performances, in particular when values are close to the threshold.
- The actions applied in order to reduce particulate matter concentration only over the city of Brescia, also resulted in an air quality improvement for the surrounding areas.
- Further studies should be done in order to add variability to the cost index to take into account the disadvantages arising from last minute notification to the population. This also implies the need of a better model in order to predict further in time.

- Long term actions effects (such as those arising from regional plans) should be included in the problem allowing to evaluate the combined effects with the short term actions selected by the short term IAM.

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