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RESEARCH ARTICLE

A Model Predictive Control Methodology to Integrate Short and Long Term Air Quality Objectives

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ABSTRACT This study introduces and evaluates a methodology to define optimal integrated short and long-term air pollution control measures, to support policy formulation by Local Authorities. The approach utilized in this methodology is based on a receding horizon strategy. In this approach, an autoregressive model provides the dynamic characteristics of air quality within a designated time period. The model is established using daily observed data on pollutant concentration, meteorological variables, and estimated emission data in the study area. The model is the core of a model predictive control based on the solution, at each time step, of the resulting optimization problem. The effectiveness of the overall control has been assessed in the context of controlling NO_2 concentrations within the city of Milan. The outcomes of the study demonstrate that this control system can serve as a valuable tool to assist Local Authorities in making informed decisions regarding appropriate air quality management strategies.

INDEX TERMS Complex systems, control application, genetic algorithms (GAs), optimization, modelling, simulation.

I. INTRODUCTION

In recent years, the heightened of nitrogen dioxide (NO_2) concentrations has gained increasing prominence as a significant environmental concern, primarily due to its well-established adverse effects on human health, spanning from pulmonary to cardiovascular diseases [1], [2]. In fact, exposure to nitrogen dioxide can cause coughing, wheezing, and reduced lung function, especially in vulnerable populations like children, the elderly, and individuals with pre-existing respiratory conditions [1]. Moreover, long-term exposure to NO2 is linked to the development and exacerbation of respiratory diseases like asthma and can increase susceptibility to respiratory infections [3], [4]. Finally, as an indirect effect, nitrogen dioxide contributes to the formation of fine particulate matter and ground-level ozone, which are associated with respiratory and cardiovascular issues [5]. Strategies to address nitrogen dioxide (NO2) pollution encompass a range of approaches spanning policy, promotion of clean transportation, improved urban planning, technological innovation, and public awareness/behavioral changes initiatives. Unfortunately, the complex nonlinear phenomena governing the formation and accumulation of NO_2 in the atmosphere make the evaluation of the effects of emission reductions needed from national/regional/local authorities to take decision a really challenging task [6]. For this reason, the scientific community has started developing a series of tool based on the integration of control theory, identification and optimization to support the definition of suitable air quality management plan [7], [8], [9]. In this work, a methodology based on model predictive control [10] for the control of NO_2 concentrations is presented and applied to the Milan metropolitan area (Italy).

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A. RELATED WORKS

Numerous studies have been undertaken to develop suitable tools for assessing the impact of emission control strategies, with the aim of supporting regional, national, and local authorities in addressing this issue ([11], [12], [13], [14],

[15]). Based on the implemented solution/methodology these tools can be divided in:

- Monitoring instruments, enabling policy makers to assess the current concentration levels within a specified area. They encompass tolls for managing measured data [16], [17] and modeling systems capable of integrating their outputs with virtually any accessible measurement data [7], [18], [19];
- Forecasting tools, providing pollutant predicted concentrations within a specified area over a defined predictive time-frame. These tools comprehend (i) models based on data (data-driven) [20], capable of providing information about the pollutant concentrations at monitoring station locations, (ii) deterministic grid models [21], [22] or (iii) models employing a combined method [23];
- Management/Planning solutions, enabling the definition of air quality control measures in the designated area [24], [25] through cost-effectiveness and/or multi-objective methodologies [26], [27], [28].

In the context of this study, a novel methodology is introduced for delineating both short-term (up to several days) and long-term (1 year) emission control strategies to mitigate nitrogen oxide (NO_2) levels. While existing literature typically addresses this problem in the long-term, assuming a steady-state atmosphere conditions [26], [29], [30], [31], the presented approach grapples with the system's nonlinearity and dynamics affecting the decisions. In fact, unlike these solutions, this approach is based on the identification of a data-driven model able to reproduce both short term (few days) and long term (up to a year) pollutant dynamics and follows a model predictive control approach (MPC). MPC is widely used on control system community in particular for industrial and robotic application [32], [33], while only limited study has been performed for air quality management and/or climate change control [9], [34]. Moreover, in order to take into account both short and long term dynamic, a hierarchical model predictive control problem has been formulated [10], where the control law computed for the short term dynamic is used as a constraints for the long term control problem. Thus, to the extend knowledge of the authors, the main innovative aspects of the research relates to (i) the formalization and solution of a hierarchical model predictive control for a real-world system far from the "standard" industrial and robotic application; (ii) the use of a data-driven model approach to approximate the real, strongly nonlinear, system starting from measured and estimated data. The methodology's efficacy is evaluated in Milan, the capital of the Lombardia region in northern Italy, to control the usually elevated levels of nitrogen oxide (NO_2) concentrations acting on nitrogen oxides (NO_x) emissions.

II. METHODOLOGY

The problems is approached developing the two steps methodology presented in Figure 1:

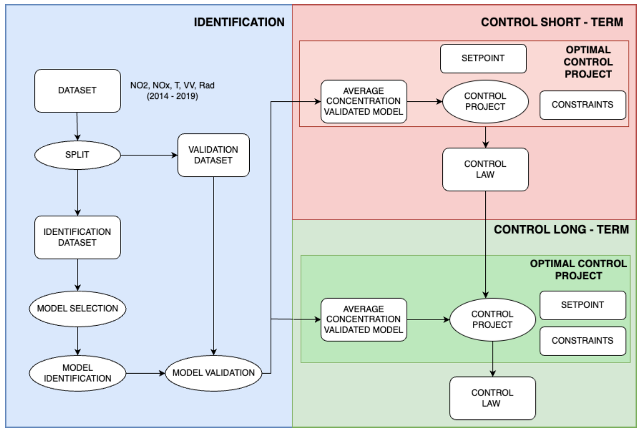

FIGURE 1. Methodology scheme.

- identification phase, where a data-driven relationship among nitrogen dioxide (NO_2) concentrations, meteorological variables and nitrogen oxide (NO_x) emissions has been recognized and confirmed for the designated region in order to calculate the daily average concentration;
- control definition phase, where an optimal control problem is formalized and solved. The control aims at (i) minimizing the the occurrence of short-term critical events, specifically reducing the number of days when the NO_2 average daily concentration exceeds the world health organization (WHO) limit threshold of $25\mu g/m^3$ and, (ii) ensuring that the annual average concentration of NO_2 remains below the specified limit threshold of $10\mu g/m^3$.

A. MODEL IDENTIFICATION PHASE

The initial stage of the methodology involves establishing a model for air quality management linking the daily NO_2 average concentrations with NO_x emissions and meteorological variables, including wind speed, temperature and solar radiation. As suggested in [9] the computation of the the daily average concentration is performed using a relatively simple ARX structure (Eq. (1)):

$$\begin{aligned} NO2^{av}(i+1) &= f(NO2^{av}(i), \ldots, NO2^{av}(N_{i-NO2^{av}}), \\ &\qquad NOx(i+1), \ldots, NOx(i+1-N_{NOx}), \\ &\qquad T(i), \ldots, T(i-N_T), WS(i), \ldots, \\ &\qquad WS(i-N_{WS}), RF(i), \ldots, RF(i-N_{RF})) \\ &= \sum_{i}^{N_{NO2}} a(i) \cdot NO2^{av}(i) \\ &\quad + \sum_{i}^{N_{NOx}} b(i) \cdot NOx(i+1) + \sum_{i}^{N_T} c(i) \cdot T(i) \\ &\quad + \sum_{i}^{N_{WS}} d(i) \cdot WS(i) + \sum_{i}^{N_{RF}} e(i) \cdot RF(i) \qquad (1) \end{aligned}$$

where:

- $NO2(i)^{av}$ $[\mu g/m^3]$ being the NO_2 concentration at day i.
- $NOx(i)$ $[ton/day]$ representing nitrogen oxide emissions NO_x on day i.
- $T(i)$ $[\circ C]$ representing the mean temperature in the area on day i.
- $WS(i)$ $[m/s]$ representing the mean wind speed in the area on day i.
- $RF(i)$ $[mm/day]$ representing the daily rainfall in the area on day i.
- N_{NO2} representing the order of the autoregressive part.
- $N_{NOx}, N_T, N_{WS}, N_{RF}$ representing the exogenous inputs' order.
- a, b, c, d, e being the coefficients of the autoregressive part and exogenous inputs.

To account for the physical behavior of the phenomena being investigated, a constrained optimization problem is formulated for the purpose of identification, with the objective of minimizing the mean squared error in simulations. This approach is chosen to restrict the gradient between the model's output and the controllable variable (emission levels) to be positive, to guarantee a reduction in concentration when emissions are decreased through control measures. Since the model will be used to control the annual average of NO_2 concentration, thus over a fairly long time frame, the interest lies in the behaviour of the model in simulation. Because of the simulation errors being minimised, the resulting optimization problem becomes non-linear. Consequently, genetic algorithms are employed in this phase for the solution of the problem, in order to mitigate the risk of ending up in local minima.

B. CONTROL PHASE

The control phase adopts a two-step model predictive control (MPC) approach, leveraging the model identified in (II.A) to offer insights into the dynamics of the chosen air quality pollutant over the horizon. MPC is founded on the concept of iteratively optimizing control inputs by predicting the system's future states over a predetermined finite time horizon. At every time step, a problem is solved through an optimization, taking into account the system's dynamics, the constraints, and the selected objectives [10]. The optimization problem for MPC can be mathematically expressed as follows:

$$\min J = \sum_{k=0}^{N-1} l(x(k), u(k)) + \phi(x(N)) \tag{2}$$

$$\text{s.t. } x(k+1) = f(x(k), u(k)) \quad k = 0, \ldots, N-1 \tag{3}$$

$$x(0) = x_0 \tag{4}$$

where:

- J represents the cost function to be minimized over the prediction horizon $[0, N]$.
- N is the prediction horizon, determining the finite time span over which future states are predicted and control inputs optimized.

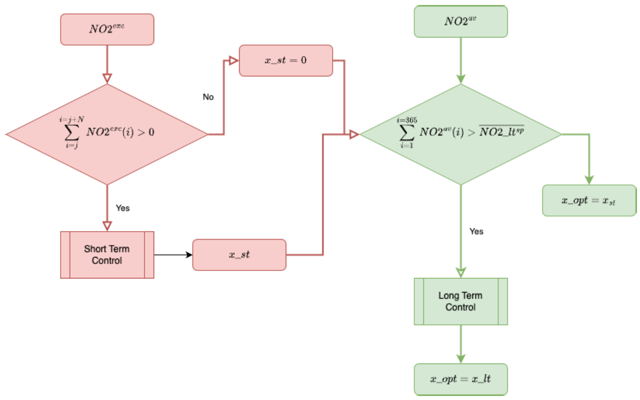

FIGURE 2. Diagram showing how the control is performed.

- $x(k)$ denotes the system state at time step k.
- $u(k)$ represents the control input at time step k.
- $l(x(k), u(k))$ represents the stage cost at time step k, capturing the immediate cost associated with the system state and control input at that time.
- $\phi(x(N))$ is the terminal cost, representing the cost associated with the predicted system state at the end of the horizon.
- $f(x(k), u(k))$ represents the system dynamics that describe how the state evolves over time.
- $x(0) = x_0$ is the initial condition of the system.

MPC proves particularly advantageous when addressing intricate, non-linear systems with imposed constraints.

In this context, the control law is compute first solving the short term control for a forecasting timeframe of N days, (within the range j until $j+N-1$) and then a long term control for a longer predictive horizon of up to the end of the year solving the two following optimization problems (Figure 2), respectively:

1) SHORT-TERM CONTROL

$$\min \sum_{i=j}^{j+N-1} NO2^{exc}(i) \tag{5}$$

$$\text{s.t. } NO2^{exc}(i) = h(NO2^{av}(i)) \tag{6}$$

$$NO2^{av}(i+1) = f(\cdot, NOx^{av}(i+1), \ldots, NOx^{av}(i+1-n_{NOx})),$$

$$i = j \ldots j+N-1 \tag{7}$$

$$NOx(i) = u\_st(i) \cdot \overline{NOx}(i) \quad i = j \ldots j+N-1 \tag{8}$$

$$NO2^{av}(i) \geq 0 \quad i = j \ldots j+N-1 \tag{9}$$

$$1 \leq u\_st(i) \leq LB_{st} \tag{10}$$

where:

- $u\_st(i)$ representing the control variables for the short term problem. It represents the total percentage reduction of NO_x emissions for the short term; $u\_st(i) = 1$ when the pollutant emission reduction is null on the $i-th$ day, 0 when it's equal to 100%.

- N is the receding horizon for the short term (15 days).
- $NO2^{exc}(i)$ being the number of NO_2 daily concentration exceeding; it represents the Boolean (equal to 1 when exceeding occurs, 0 otherwise).
- h is the identified function that find occurrence or not of a surplus (average daily concentration $> 25\ \mu g/m^3$ at day i) on the basis of the average daily concentration.
- $NO2^{av}(i)$ being the average NO_2 daily concentration (at day i).
- $\overline{NOx}$ representing the NO_x emissions in the baseline scenario (without any reduction implemented).
- $f(\cdot, NOx^{max}(i+1), \ldots NOx^{max}(i+1-n_{NOx^{max}}))$, $f(\cdot, NOx^{av}(i+1), \ldots NOx^{av}(i+1-n_{NOx^{av}}))$ being the models determined in the Section II-A and representing the system dynamics.
- LB_{st} being the selected lower bound for the decision variables in the given problem.

2) LONG-TERM CONTROL

$$\min \left[\left(\frac{1}{365} \cdot \sum_{i=1}^{365} \left(NO2^{av}(i)\right)\right) - \overline{NO2\_lt^{sp}(i)^2}\right] \quad (11)$$

$$\begin{aligned}
\text{s.t. } & NO2^{av}(i+1) = f(\cdot, NOx^{av}(i+1), \ldots, \\
& NOx^{av}(i+1-N_{NOx})), \\
& i = 1, \ldots, 365 && (12)\\
& NOx(i) = u_lt(i) \cdot \overline{NOx}(i), \quad i = 1, \ldots, 365 && (13)\\
& NO2^{av}(i) \geq 0 \quad i = 1, \ldots, 365 && (14)\\
& u_st(i) \leq u_lt(i) && (15)\\
& 1 \leq u_lt(i) \leq LB_{lt} && (16)
\end{aligned}$$

where:

- $u\_lt(i)$ representing the control variables for the short term problem. It represents the total percentage reduction of NO_x emissions for the short term; $u\_st(i)$=1 when the pollutant emission reduction is null on the $i-th$ day, 0 when it's equal to 100%;
- h is the identified function that find occurrence or not of a surplus (average daily concentration $> 25\ \mu g/m^3$ at day i) on the basis of the average daily concentration;
- $NO2^{av}$ being the average NO_2 daily concentration (on day i);
- $\overline{NO2\_lt^{sp}(i)}$ representing the NO_2 concentration set-point for the long term (according to the WHO guidelines equal to 10 $\mu g/m^3$);
- $\overline{NOx}$ being the NO_x emissions in the base case (no reduction applied);
- $f(\cdot, NOx^{max}(i+1), \ldots NOx^{max}(i+1-n_{NOx^{max}}))$, $f(\cdot, NOx^{av}(i+1), \ldots NOx^{av}(i+1-n_{NOx^{av}}))$ being the models identified in Section II-A.
- LB_{lt} being the selected lower bound for the decision variables in the given problem.

The objective functions (5) and (11) are designed to minimize the number of days with average nitrogen dioxide concentration surpassing the WHO limit and to keep its yearly mean concentration as near as possible to the set-point, respectively. This set-point may potentially vary for different periods of the year. Equations (6), (7), and (12) illustrate the system dynamics identified in Section II-A, whereas constraints (8) and (13) delineate the pollutant emissions subsequent to the implementation of the control actions $u\_st(i)$ and $u\_lt(i)$. Equations (9) and (14) constraint the average daily values of nitrogen dioxide concentrations not to be negative. (15) binds the second control problem (long term) to the short one by applying percentage reductions that are greater than or equal to those defined in the short-term control. Finally, constraints (10), (16) define the upper and lower bounds of the control actions for the problem.

As (5) and (11) define a problem with a non-linear objective function, a solver based on genetic algorithms has been employed to compute the solution for each interval from j to $j+N-1$.

C. GENETIC ALGORITHMS

Genetic algorithms are a class of meta-heuristic algorithms that simulate the evolution of a population of tentative solutions based on principles inspired by natural selection and genetics [35], [36], [37]. Typically, these algorithms consist of the following components:

- Population. A finite population of individuals represents potential solutions to a given problem.
- Fitness Function. A fitness function evaluates the quality of each solution and provides guidance on which individuals are most suitable for reproduction. In a classic optimization problem this is the objective function.
- Genetic Operators. These operators transform the current population into the next generation. They include:
  - Selection operator: akin to natural selection, involves identifying the most high-performing individual, namely, the most promising solutions.
  - Crossover operator: it combines the genetics of top-performing individuals to create hybrid solutions which then become integrated into the subsequent populations.
  - Mutation operator: new individuals are introduced by making small, random modifications to current solutions.
- Termination Criterion: the process of generating the new population is reiterated until one or more predefined stop conditions are met. Some of the most frequently encountered criteria include:
  - Reaching a predefined iteration number.
  - Failing to achieve consistent improvement in the solution over a specified number of iterations.
  - The exceeding of a predefined time limit.

The critical aspect of using genetic algorithms lies in defining an appropriate fitness function that accurately evaluates the quality of the evolved sets of solutions. The algorithm can be divided into several phases, as can be seen in Figure 3:

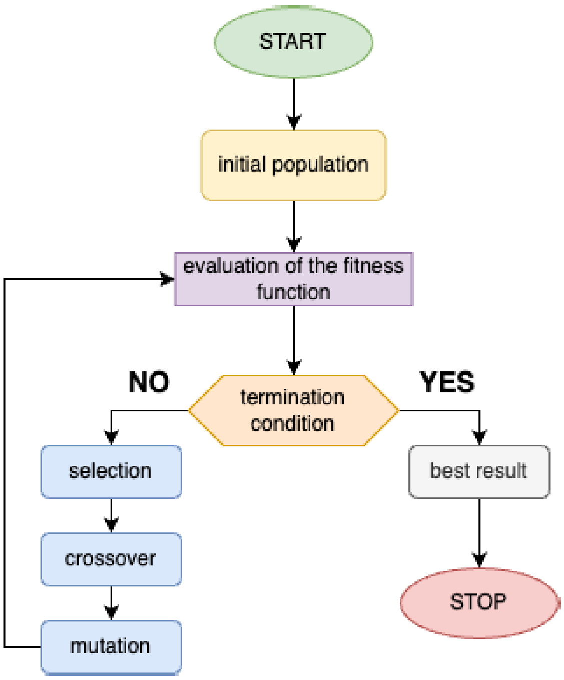

FIGURE 3. Flow chart of a genetic algorithm.

- Population Initialization: initially, a population of individuals is created entirely at random. This population then iteratively evolves until an optimal solution is found.
- New Population Generation: during this stage, the initial population undergoes evolution through the three operations mentioned: selection, crossover, and mutation.
- Termination Test: the process of generating a new population continues until one or more of the predefined stop criteria are satisfied, such as reaching a fixed iteration limit, achieving no significant improvement, or surpassing a specified time constraint.

III. APPLICATION AND RESULTS

The proposed methodology has been implemented for effectively addressing air quality management, specifically focusing on NO_2 levels, in the Milan agglomeration, located in Lombardia, Italy.

The Milan agglomeration encompasses the entire local jurisdiction, spanning a territory of 182 square kilometers and accommodating a population of 1,357,944 residents. Milan is recognized for having one of the poorest air quality records in Europe, primarily due to the extensive presence of road transportation and road and railway infrastructure, which contribute significantly to pollutant emissions within the municipality. Additionally, emissions from heating and industrial combustion also play a role. The WHO proposed a limit of 10 $\mu g/m^3$ as the maximum allowable annual average concentration of NO_2 to safeguard public health, while regarding the average daily limits, the legal threshold is set at 25 $\mu g/m^3$, which should not be surpassed more than 3 or 4 occurrences in a year (99th percentile). Moreover, the objective is to strike a balance between achieving air quality standards and minimizing the potential social disruptions caused by stringent emission reduction actions.

A. MODEL IDENTIFICATION PHASE

During the initial phase of the methodology, an autoregressive model has been identified using a dataset spanning from January 2014 to September 2020. This dataset encompassed: (i) daily average concentrations of NO_2 over Milan area, computed starting from the data monitored in ARPA Lombardia stations; (ii) daily NO_2 emission values derived from the annual emission database provided by INEMAR, distributed across various macrosectors/activities (i.e. industry, domestic heating, road transport) [38]; and (iii) meteorological data collected from 21 monitoring stations situated in the municipality of Milan and its surrounding areas. More in details, the concentrations and meteorological variables are calculated as the averages derived from data collected at all monitoring stations within the Milan municipality. Additionally, emissions are computed as the sum across the entire area of Milan.

As stated in Section II-A, in order to maintain the cause-effect relationship between emission and concentrations, the model identification has been carried out solving an optimization problem with a positive relationship between emissions and concentrations as a constraint by means of genetic algorithms using tuples from 2014 to 2018. The model validation (and the tests on the definition of the different control laws) have been performed with the 2019 data. In order to select the best model structure, a wide range of tests has been performed, varying the autoregressive and exogenous part orders. The resulting best performing model over the validation dataset has order 3 for autoregressive part and 2 for the exogenous input (Eq. (17)):

$$\begin{aligned}NO2^{av}(i+1) = f\big(&NO2^{av}(i), NO2^{av}(i-1),\\ &NO2^{av}(i-2), NOx(i+1), NOx(i),\\ &T(i), T(i-1), WS(i), WS(i-1),\\ &RF(i), RF(i-1)\big)\\ = \ &0.045 \cdot NO2^{av}(i)\\ &+ 0.069 \cdot NO2^{av}(i-1)\\ &+ 0.18 \cdot NO2^{av}(i-2)\\ &+ 0.65 \cdot NOx(i+1) + 0.23 \cdot NOx(i)\\ &+ -0.20 \cdot T(i) - 0.63 \cdot T(i-1)\\ &+ -0.049 \cdot WS(i) + 0.04 \cdot WS(i-1)\\ &+ 0.009 \cdot RF(i) + 0.01 \cdot RF(i-1) \quad (17)\end{aligned}$$

Table 1 shows the performance of the selected model in terms of:

- Normalized Mean Error:

$$NME = \frac{\sum_{k=1}^{N_v} NO2_k - \overline{NO2}_k}{\sum_{k=1}^{N_v} \overline{NO2}_k}$$

TABLE 1. Performance of the ARX model for the computation of the average daily concentration on the validation years.

	Simulation 2014-2018	Simulation 2019
NME	-0.0153	0.0227
NMAE	0.1636	0.1977
Corr	0.7754	0.7596

- Normalized Mean Absolute Error:

$$NMAE = \frac{\sum_{k=1}^{N_v} |NO2_k - \overline{NO2}_k|}{\sum_{k=1}^{N_v} \overline{NO2}_k}$$

- Correlation Coefficient:

$$Corr = \frac{\sum_{k=1}^{N_v}(NO2_k - \mu_{NO2})(\overline{NO2}_k - \mu_{\overline{NO2}})}{\sqrt{\sum_{k=1}^{N_v}(NO2_k - \mu_{NO2})^2} \cdot \sqrt{\sum_{k=1}^{N_v}(\overline{NO2}_k - \mu_{\overline{NO2}})^2}}$$

Here, N_v represents the number of tuples in the validation dataset, $NO2_k$ and $\overline{NO2}_k$ denote the computed and measured NO_2 daily mean concentrations on day k of the validation dataset (for the years 2019 and 2020, respectively). Furthermore, μ_{NO2} and $\mu_{\overline{NO2}}$ represent their averages over the validation dataset.

We can see that all the calculated statistical indexes allow us to assume that the model captures the trend of the average daily NO_2 concentrations over time quite accurately (Table 1). Notice that the models leads to the results of the average daily concentration for the long and short term control definition. As the model is intended for control definition over a relatively extensive period (ideally, the entire year), its performance is assessed by computing the output in a simulation scenario. In this simulation, only the initial value of NO_2 concentrations is assumed to be known.

B. CONTROL PHASE

The control objective is to determine the percentage of actions to be applied in the short and long terms to reduce the level of nitrogen dioxide concentrations. Coherently with the methodology presented in Section A, the integrated control system is based on the definition of two control laws with different time horizons:

- Short-term horizon: the control objective is to limit any possible excess of the average daily NO_2 concentration (25 $\mu g/m^3$) over a short-term time horizon of 15 days;
- Long-term horizon: the control has the objective of ensuring that the annual average NO_2 concentration must be below the European legal limit close to 10 $\mu g/m^3$, in order to do not *overcontrol* the system, causing unnecessary impacts on the population.

The overall control system first tests if in the next 15 days at least one exceedance will occur and eventually start defining the control law in order to limit its number. The impact of the defined control law on both exceedances and yearly average will be computed, applying the control for a control horizon of 5 days. If the yearly average is higher than 10 $\mu g/m^3$, the long-term control will be applied. The choice of first applying the short-term control problem instead of the long-term one (provided that their conditions of application are verified) was dictated by the immediate and priority need of avoiding surpluses of nitrogen dioxide in the near future in order to avoid serious consequences on public health and on the environment, so it is essential to reduce concentrations in order to guarantee a healthier environment in the short term. Optimal long-term control, on the other hand, remains crucial to maintain an annual average of NO_2 below the established threshold, thus ensuring sustainable air quality over time. In summary, this strategy integrates the immediate needs of public health and the long-term needs of environmental sustainability, ensuring that the goal of reducing pollution is effectively addressed in both time frames.

TABLE 2. Configuration of genetic algorithm for the control phase.

Feature	Value
Population	500
Crossover Function	Scattered
Crossover Fraction	0.8
Mutation Function	Gaussian

1) CONTROL VARIABLES

In this application, the control variables have been expressed as the daily percentage reduction $u(i)$ that the local authority could implement to decrease the $NOx(i)$ emissions on the $i-th$ day.

2) TEST DEFINITION

In order to evaluate the impact of the integration between short and long term control, three different test cases are performed and compared:

- Case 1: the *full* methodology (integration of short and long as presented in Section II) is applied.
- Case 2: only the short term control is applied.
- Case 3: only the long term control is applied.

Each of the case studies was compared with the uncontrolled cases. Moreover, 3 values of lower bound for u have been considered: 0.75 (maximum reduction of 25% with respect to the uncontrolled case); 0.5 (maximum reduction of 50% with respect to the uncontrolled case); 0.25 (maximum reduction of 75% with respect to the uncontrolled case); while the upper bound is always set equal to 1 (when no emission reduction is applied).

The configuration of the genetic algortihm (Table 2) has been selected after a series of test on the more challenging (for the algorithm) case, i.e. full methodology (short+long control), with lower bound equal to 0.25.

3) RESULTS

Table 3 compares the results obtained from the different computed optimisations with each other and with the uncontrolled case.

TABLE 3. Comparison of the annual average and the number of exceeding cases between the different implemented cases).

Test	LB	Average Concentration [μg/m^3]	Exceedances	Mean control action [%]
Base	-	43.097	358	-
Short+Long	0.75	29.25	219	0.76
	0.50	16.17	76	0.52
	0.25	10	10	0.43
Only Short	0.75	32.71	244	0.82
	0.50	24.59	139	0.67
	0.25	20.32	64	0.59
Only Long	0.75	29.81	222	0.77
	0.50	16.89	90	0.54
	0.25	10	14	0.4266

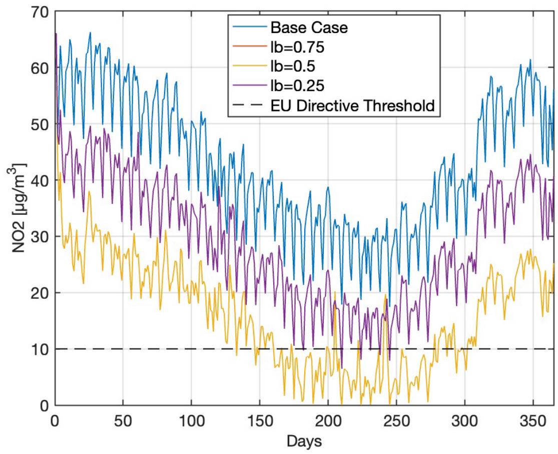

FIGURE 4. Average NO_2 concentration for the controlled and uncontrolled cases.

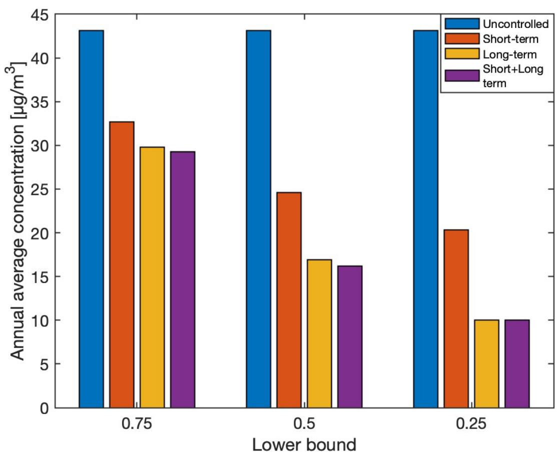

FIGURE 5. Comparison of the annual average concentration for the controlled and uncontrolled cases.

It clearly shows that the annual average concentration in the uncontrolled case has a value very close to 43.1 $\mu g/m^3$ while when the hybrid control is performed, the control law is able to lower the values of the nitrogen dioxide concentrations to a value of 29.26 $\mu g/m^3$, 16.18 $\mu g/m^3$ and 10 $\mu g/m^3$ respectively for the 3 different lower bounds

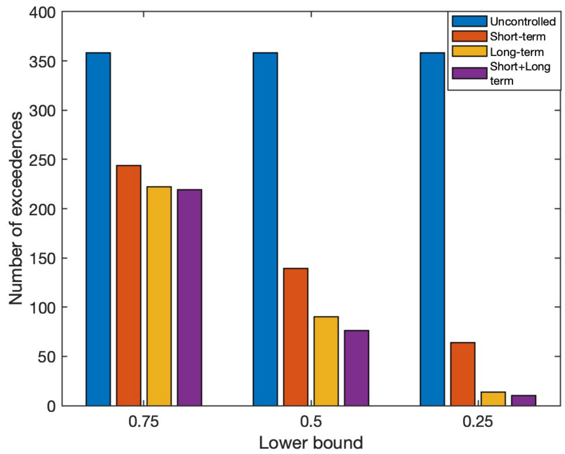

FIGURE 6. Comparison of the exceeding for the controlled and uncontrolled cases.

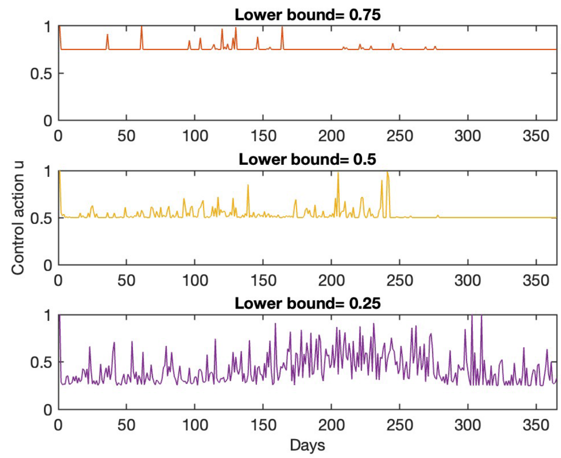

FIGURE 7. Emission reduction percentage applied for the short and long term control of the different lower bounds tested.

applied in the tests (0.75, 0.5 and 0.25). The control is capable of decreasing the concentration of nitrogen dioxide in the atmosphere in all performed cases, reaching the predefined set point when reducing concentrations by 75% (remembering that this case is hardly applicable in real life). As far as the number of daily excesses is concerned, the control once again demonstrates that it is possible to reduce the number of days with pollutant concentration above the threshold by a percentage equal to 60%, 80% and 97% in the three cases mentioned above. Concerning the short and long term separate control, as shown in Table 3, they are also able to reduce the annual average concentration and the number of exceeding but by a smaller percentage when compared with the hybrid one. The trend in the control action takes on the lowest value, i.e. with maximum reductions, almost always in the colder months and slightly higher values in the central months, denoting a slight reduction in applied actions, while in the changing seasons it takes on more variable values from one day to the next.

Figure 4 shows how in the winter months there is a more aggressive action, while in the summer months the action is reduced by around 3-4% compared to the cold months. Despite this, it is important to emphasise that the controllers further reduce the value of the NO_2 concentrations. Furthermore, Figure 5 and 6 show how the number of exceeding in the controlled case are reduced by the policies' application reduction and the resulting annual average concentration for the differente perfomend tests, respectively. Moreover, Figure 7 plots the percentage reduction applied, showing that, in particular in the last part of the year, a strong control action need to be performed to stay as close as possible to WHO standards.

IV. CONCLUSION

This work introduces and applies a receding horizon, data-driven control approach. The methodology is structured into two distinct phases: (i) the identification of a model that characterizes the daily average nitrogen dioxide concentrations and (ii) the development and implementation of control strategies. The implementation of the model enable the identification of optimal action percentage to be taken in the short and long term if certain threshold limits are exceeded in order to reduce the concentrations of the pollutant under study. The approach involves forecasting air quality, initially in the short term and then in the long term, to ensure that both daily and yearly average nitrogen dioxide concentrations remain below the legally established thresholds.

The implementation of this approach utilized short and long term control algorithms employing a receding horizon technique. The algorithm anticipates the emission reduction percentage to be applied over the next fifteen days from a predefined set of options. The model was applied across the entire Milan metropolitan area for the entirety of 2019, and genetic algorithms were employed to optimize the selection of actions.

The control algorithms are developed and compared for managing NO_2 concentrations. In all tested scenarios, the system successfully lowered the annual average concentration and the number of daily exceedances in the year. However, in order to get closer to the WHO threshold guidance, a big effort needs to be done, lowering the level of NO_x emissions up to 75%.

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