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Kalman filter–based Traffic Control for Urban Air Quality Management

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Abstract. Urban air pollution is addressed using a Kalman filter–based constrained MPC framework that regulates AQI under uncertainty. The proposed approach models traffic-induced emissions and background effects in a discrete-time setting and uses state estimation for predictive control. Simulation results demonstrate effective pollution mitigation through reduced AQI peaks and shorter high-pollution episodes compared to an uncontrolled case.

1. Introduction

Urban air pollution is a major challenge in modern cities due to rapid urbanization, increased vehicle ownership, and dense traffic networks. Traffic-related emissions are a dominant source of urban pollutants such as particulate matter ($PM_{2.5}$) and nitrogen dioxide (NO_2), which are directly reflected in regulatory indicators such as the Air Quality Index (AQI). Persistent exceedance of acceptable AQI levels poses serious risks to public health and urban livability, motivating traffic management strategies that explicitly account for environmental impacts [4].

The Air Quality Index (AQI) is a standardized indicator that aggregates major pollutant concentrations and serves as a practical output for feedback-based air quality control.

Keywords: Smart city, Air Quality Index (AQI), Adaptive traffic control, Kalman filter, Model predictive control.

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From a control perspective, AQI reflects the dynamics of pollution driven by traffic emissions, atmospheric processes, and disturbances. While recent sensing technologies enable real-time monitoring, most traffic control strategies address air quality indirectly, and existing model-based approaches are limited by noisy AQI measurements and assumptions of full-state availability. ***The objective of this paper is to develop an estimator-based traffic control framework that directly regulates AQI under uncertainty using real-time measurements, while explicitly accounting for operational constraints on traffic interventions.*** To achieve this objective, this paper proposes an AQI-based adaptive traffic control framework that integrates Kalman filter–based state estimation with constrained model predictive control using a control-oriented pollution dynamics model. ***The novelty of the proposed approach lies in treating AQI as the control-relevant feedback variable, separating fast traffic-induced and slow background pollution dynamics within a reduced-order state-space model, and integrating state estimation with constrained MPC to enable real-time AQI regulation under uncertainty.*** [3] Simulation results demonstrate significant reductions in AQI peaks and high-pollution episodes compared to an uncontrolled scenario. In this work, AQI is treated as a linearized and aggregated indicator around an operating range of interest [5].

2. Problem Formulation and State Estimation

Urban air pollution evolves dynamically due to pollutant accumulation and dispersion, with traffic-related activities being a major controllable source through their impact on vehicular emissions. From an engineering perspective, traffic management influences air quality indirectly via traffic regulation, emission generation, and pollutant accumulation processes.

2.1. Physical Interpretation of Pollution Dynamics

The proposed model is a control-oriented abstraction capturing the dominant temporal behavior of urban air pollution. It separates fast traffic-related emission dynamics from slower background accumulation, with traffic regulation influencing air quality indirectly through emissions. This reduced-order linear representation balances predictive accuracy with real-time implementability. Figure 1 illustrates the closed-loop structure of the proposed framework, in which traffic regulation influences air quality indirectly through emission reduction. Pollution dynamics are estimated from noisy AQI measurements using a Kalman filter, and the resulting state estimates are employed by a constrained MPC to compute environmentally aware traffic control actions. The model is control-oriented, balancing physical interpretability with real-time implementability rather than detailed atmospheric simulation.

FIGURE 1. Conceptual flowchart illustrating how traffic activity influences AQI dynamics through emissions

2.2. Traffic Control and Emission Modeling

Let $u_k \in [0, 1]$ denote a normalized traffic demand reduction level applied at time step k, representing the intensity of traffic management measures such as inflow regulation or demand control at the boundary of an urban area. These actions influence the effective traffic flow and, consequently, the emission rate of traffic-related pollutants. Following standard control-oriented emission modeling assumptions, the effective emission rate e_k is approximated by

$$e_k = e_0 - \gamma u_k, \tag{1}$$

where e_0 denotes the nominal emission level in the absence of control, and $\gamma > 0$ represents the emission reduction efficiency associated with traffic regulation.

2.3. Pollution Dynamics and Measurement Model

The temporal evolution of pollutant concentration is governed by accumulation and dispersion mechanisms and is influenced by both traffic-related emissions and external meteorological conditions. The pollution dynamics are modeled by the discrete-time state-space equations

$$x_{k+1} = Ax_k + B_e e_k + Ed_k + w_k, \tag{2}$$

$$y_k = Cx_k + v_k, \tag{3}$$

where $x_k \in \mathbb{R}^n$ denotes the pollution state vector, comprising a traffic-related component and a slower background component capturing persistence effects. The output y_k represents the Air Quality Index (AQI). The term d_k accounts for structured exogenous disturbances such as meteorological conditions, while w_k and v_k denote zero-mean Gaussian process and measurement noise with covariance matrices Q and R, respectively.

Substituting (1) into (2) yields the compact control-oriented form

$$x_{k+1} = Ax_k + Bu_k + Ed_k + w_k, \tag{4}$$

where $B := -B_e\gamma$ captures the aggregated effect of traffic regulation on emission generation and pollutant accumulation. This reduced-order formulation preserves physical interpretability while remaining suitable for real-time predictive control. A Kalman filter is employed to estimate the pollution state from noisy AQI measurements. The estimator reconstructs the combined effect of traffic-induced emissions and atmospheric dispersion, providing state estimates for the predictive controller.

3. Stability and Feasibility Discussion

This section provides a qualitative theoretical justification for the closed-loop behavior of the proposed Kalman filter–based constrained MPC framework.

3.1. Nominal stability

For the nominal disturbance-free system

$$x_{k+1} = Ax_k + Bu_k,$$

and a stabilizable pair (A, B), the unconstrained linear–quadratic regulator yields a stabilizing feedback law. In the presence of constraints, standard MPC results ensure nominal closed-loop stability when appropriate terminal costs and invariant terminal sets are employed. These conditions also guarantee recursive feasibility of the optimization problem [5].

3.2. Boundedness under disturbances

In the presence of bounded disturbances and stochastic noise, asymptotic convergence to the equilibrium cannot be guaranteed. Instead, the relevant property is practical stability: the closed-loop state remains bounded and converges to a disturbance-dependent neighborhood of the reference. Under the assumptions that (A, B) is stabilizable and (A, C) is detectable, the estimator-based MPC ensures bounded state and input trajectories while regulating AQI around the desired level within the available control authority [5].

3.3. Recursive feasibility

Hard constraints on the control input and its rate of change are enforced explicitly in the MPC formulation. When reference tracking becomes temporarily infeasible due to strong disturbances, the optimization yields the best admissible mitigation action while maintaining feasibility. This behavior is consistent with standard results on constrained MPC and is confirmed by the simulation results. Overall, the proposed framework aligns with established stability and feasibility properties of constrained MPC with state estimation, providing a sound qualitative theoretical basis for the observed closed-loop performance [3, 6].

3.4. Observability and Justification of Kalman Filtering

To ensure meaningful state estimation, observability of the pair (A, C) is verified. Although the pollution state includes fast traffic-related and slowly varying background components, the AQI measurement captures contributions from both states, and their distinct dynamics enable separation over time. The observability rank condition is satisfied for the parameters used, justifying the use of Kalman filtering for state estimation.

The Kalman filter is employed to estimate the pollution state resulting from the combined effects of traffic-induced emissions and atmospheric dispersion, while traffic control actions enter the estimator indirectly through their impact on emission rates. Due to the noisy nature of AQI measurements and unmodeled environmental variability, reliable estimation of the underlying pollution state is required prior to control action. A discrete Kalman filter is therefore employed to estimate the system state from the dynamic model and noisy measurements [1, 2]. The Kalman filter operates recursively through a prediction step,

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_{k-1} + Ed_{k-1}, \tag{5}$$

$$P_{k|k-1} = AP_{k-1|k-1}A^\top + Q, \tag{6}$$

followed by a measurement update step,

$$K_k = P_{k|k-1}C^\top \left(CP_{k|k-1}C^\top + R\right)^{-1}, \tag{7}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(y_k - C\hat{x}_{k|k-1}\right), \tag{8}$$

$$P_{k|k} = (I - K_kC)P_{k|k-1}, \tag{9}$$

where $\hat{x}_{k|k}$ and $P_{k|k}$ denote the state estimate and its associated estimation error covariance, respectively. The resulting state estimates provide the basis for short-term AQI prediction and the constrained predictive traffic control strategy developed in the next section.

4. AQI-Based Traffic Control Strategy

4.1. Control Objective

Following the standard separation principle, the Kalman filter is employed to estimate and predict the pollution state, while the control actions are determined through an optimization-based control framework. The control objective is to regulate traffic-related emissions such that the predicted air quality remains close to an acceptable reference level, while avoiding excessive or abrupt traffic interventions. Let $\widehat{\mathrm{AQI}}_{k+i|k}$ denote the i-step-ahead AQI prediction obtained from the state-space model and the Kalman filter. The control problem is formulated as a finite-horizon quadratic optimization problem:

$$\min_{\{u_{k+i}\}} J = \sum_{i=0}^{N-1} \left(\left\| \widehat{\mathrm{AQI}}_{k+i|k} - \mathrm{AQI}_{\mathrm{ref}} \right\|_2^2 + \|\Delta u_{k+i}\|_\lambda^2 + \|u_{k+i}\|_\rho^2 \right), \tag{10}$$

where N denotes the prediction horizon, $\mathrm{AQI}_{\mathrm{ref}}$ is the desired AQI reference level, and $\Delta u_{k+i} = u_{k+i} - u_{k+i-1}$. The weighted norms are defined as

$$\|x\|_\lambda^2 := x^T \lambda x, \qquad \|x\|_\rho^2 := x^T \rho x,$$

with $\lambda > 0$ and $\rho > 0$ denoting weighting parameters. The resulting optimization problem is a finite-horizon convex quadratic program. Since u_k represents the level of traffic regulation, it is subject to constraints on its magnitude and rate of change,

$$0 \leq u_k \leq u_{\max}, \qquad |\Delta u_k| \leq \Delta u_{\max}. \tag{11}$$

5. Numerical Results

In this section, the performance of the proposed AQI-based traffic control framework is evaluated through numerical simulations. The objective is to assess the controller's ability to mitigate air pollution under realistic disturbances and operational constraints.

5.1. Simulation Setup

The system matrices are selected to form a reduced-order, control-oriented model capturing fast traffic-related and slow background pollution dynamics, rather than a site-specific predictor. Simulations are conducted with a sampling time of 60 s over a 300-minute horizon, using an MPC prediction horizon of $N = 20$ and an AQI reference of $\mathrm{AQI}_{\mathrm{ref}} = 70$ from an initial level of 120. Traffic control intensity is constrained to $0 \leq u_k \leq 1$ with a rate limit $|\Delta u_k| \leq 0.15$. The quadratic cost penalizes AQI tracking error, control effort, and input variation. Meteorological disturbances are modeled as exogenous inputs, AQI measurements are filtered via a Kalman filter, and robustness to parameter uncertainty is assessed through sensitivity analysis.

5.2. AQI Regulation Performance

Figure 2 compares the AQI evolution under the proposed control strategy with an uncontrolled scenario. In the absence of control, adverse meteorological conditions lead to pronounced pollution peaks, with AQI values exceeding 200. In contrast, the controlled system exhibits significantly attenuated peaks and a substantially lower average AQI level.

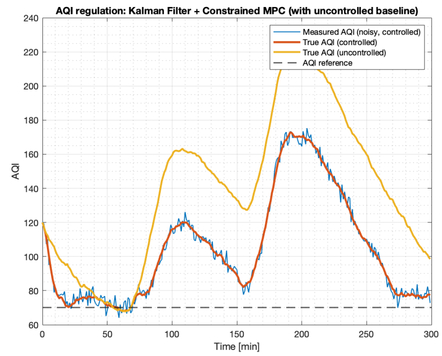

FIGURE 2. AQI regulation using the proposed Kalman filter–based constrained MPC

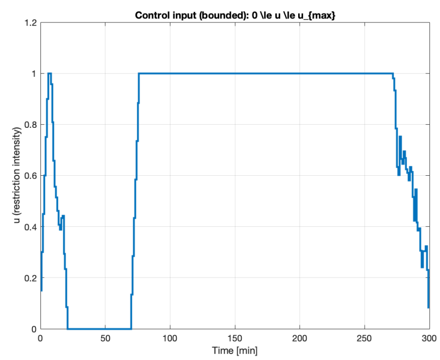

FIGURE 3. Control input generated by the MPC, remaining within magnitude and rate limits and increasing only during severe disturbance periods.

Although the reference level of $\mathrm{AQI}_{\mathrm{ref}} = 70$ is not always fully achievable due to strong exogenous disturbances and limited control authority, the proposed controller effectively mitigates pollution by reducing both the magnitude and duration of high-AQI episodes. In particular, during severe disturbance intervals, the controller prevents further deterioration and accelerates recovery once meteorological conditions improve. The close agreement between the noisy AQI measurements and the estimated true AQI demonstrates the effectiveness of the Kalman filter in providing reliable state estimates for predictive control. Figure 3 shows that the control input strictly satisfies magnitude and rate constraints throughout the simulation. The control intensity increases during high pollution periods and is gradually relaxed as air quality improves, ensuring smooth and realistic traffic interventions. These results confirm that the proposed Kalman filter–based constrained MPC effectively mitigates pollution under uncertainty while respecting operational limits.

6. Conclusion

Urban air pollution is modeled as a discrete-time system driven by traffic-induced emissions, background effects, and meteorological disturbances. A Kalman filter is used to estimate the pollution state from noisy AQI measurements and support constrained predictive traffic control. Simulation results show that, despite limited control authority and adverse conditions, the proposed approach effectively mitigates pollution by reducing AQI peaks and shortening high-pollution episodes. The resulting control actions remain bounded and smooth, indicating practical implementability. Overall, the framework provides a systematic tool for urban air quality management under uncertainty.

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