



Constrained model predictive control for effective tonal noise attenuation in acoustic ducts

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Abstract

Active noise control (ANC) effectively reduces tonal noise in industrial ducts, particularly at low frequencies, which is crucial for maintaining a safe and compliant working environment. However, traditional algorithms, such as filtered-x least mean squares (FXLMS), struggle to handle well-known operational constraints, including actuator saturations. Conversely, model predictive control (MPC) effectively manages these constraints but encounters computational challenges, particularly in fast dynamic systems like ANC. This study presents an innovative MPC framework that explicitly addresses operational constraints while ensuring effective noise attenuation. Unlike conventional MPC applications, which treat primary noise as a disturbance in ANC, our framework utilizes primary path modeling to estimate future reference values, thereby enhancing control performance in this fast dynamic system. The methodology is validated through numerical experiments, utilizing identified primary and secondary path models in an active noise control test setup. Results demonstrate the proposed MPC framework's practical feasibility and significant performance advantages over traditional FXLMS methods, including improved noise attenuation and robust handling of operational constraints.

Keywords ANC · MPC · Constraint handling · Real-time system

1 Introduction

Tonal noise, characterized by its single-frequency nature, is commonly generated by rotating machinery such as fans, compressors, and turbines [1]. These sources produce noise that propagates through ducts and pipes, leading to significant challenges in industrial environments [2]. These challenges include health risks ranging from hearing loss to non-auditory

outcomes such as increased stress, fatigue, and reduced cognitive performance [3], as well as potential violations of occupational noise regulations [4]. Effective control of this noise is essential for maintaining safe, comfortable, and regulation-compliant work environments.

Active noise control (ANC) has emerged as an effective solution for mitigating tonal noise, particularly at low frequencies where traditional passive methods, such as barriers and absorbers, are less efficient [5, 6]. ANC systems employ electro-acoustic mechanisms to generate anti-noise signals that destructively interfere with unwanted sound waves, thereby reducing overall noise levels. Several studies [7–9] report that ANC systems exhibit optimal performance below approximately 600 Hz, where the acoustic wavelengths remain sufficiently long to preserve phase coherence and the plane-wave assumption is valid. This low-frequency regime enables effective anti-noise creation and spatial control, whereas performance typically degrades at higher frequencies due to spatial aliasing, sensor/actuator spacing limitations and increased diffuse field components.

In practical implementations, ANC systems often encounter operational constraints that can significantly impact perfor-

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mance. Common examples in ANC applications include voltage and current limitations of power amplifiers, displacement bounds of speaker diaphragms, pressure range limits of microphones, depolarization thresholds of piezoelectric actuators, and force limits of inertial drives [10]. Among these, actuator saturation is one of the most prevalent, occurring when the control signal exceeds predefined limits. Such saturation typically arises when system resources are insufficient to achieve the desired output or when doing so could lead to mechanical or electrical failure, as well as the introduction of nonlinearities into the system response [11, 12].

The filtered-x least mean squares (FXLMS) algorithm remains the most widely used method for ANC due to its simplicity and effectiveness in a broad range of scenarios [5, 13–15]. Although it achieves substantial noise reduction, its inability to explicitly manage system constraints poses significant challenges in real-world applications [16]. When actuator limitations are exceeded, the control signal can surpass acceptable limits, causing nonlinear distortions in anti-noise waves [17, 18] and potentially leading the algorithm to diverge from its optimal trajectory [19].

To mitigate these issues, researchers have developed various advanced adaptive algorithms. Linear approaches [20] primarily focus on adjusting control filter weights to regulate the control signal, preventing the power amplifier from reaching saturation. Although effective in specific cases, parameter tuning in these methods is neither straightforward nor consistently reliable across all frequency ranges [21], making practical implementation challenging. In contrast, nonlinear adaptive algorithms are designed to model the inherent nonlinearities of the secondary path [22], allowing for more effective mitigation of output distortions. However, this enhanced accuracy often comes at the cost of substantial computational effort, complicating real-time implementation in practical scenarios. These limitations highlight the need for control strategies that effectively handle constraints, ensuring robust and stable ANC performance.

In this context, model predictive control (MPC) emerges as a promising alternative due to its capacity to optimize control actions while explicitly considering system constraints [23]. MPC predicts future system behavior over a finite horizon and optimizes the control signals accordingly, making it particularly suitable for applications with strict operational requirements. Although the rapid dynamics and wide frequency range of acoustic systems present challenges for conventional MPC algorithms [24, 25], recent advances in digital processing and optimization techniques have made real-time MPC implementations increasingly feasible. Some studies have already demonstrated the effectiveness of MPC in ANC systems [10, 26–28].

An adaptive MPC using recursive least squares for noise control in an acoustic duct was introduced by [27], effectively eliminating the need for a state estimator. Their approach

demonstrated significant noise reduction across different scenarios but came at the cost of high computational demand. Building on this work, [28] proposed a feedback ANC algorithm designed to remain stable even under sudden changes in the secondary path. This algorithm employed a recursive least squares method to model both the secondary path and the primary noise using an autoregressive moving average model. The resulting strategy reduced computational complexity while effectively handling rapid variations in the secondary path, outperforming traditional LMS-based algorithms in terms of stability and adaptability. However, it is important to note that neither [27] nor [28] considered constraints in their models, highlighting a crucial gap in the literature.

The work of [10] explored the application of MPC for systems with fast dynamics. To alleviate computational costs, part of the algorithm was executed offline, and a specialized solver for quadratic programs was developed. The strategy was validated on an experimental setup with actuator limitations, demonstrating success in complex dynamic systems while respecting input constraints, but in the context of vibration control. Furthermore, [26] conducted the only study to date that explored MPC for active acoustic noise control in ducts under constrained conditions, benchmarking its performance against the FXLMS algorithm. Their numerical results revealed that MPC achieved faster convergence at very low frequencies and excelled in scenarios where control signal amplitude constraints were applied, effectively reducing noise while adhering to these limitations. However, its performance significantly deteriorated at frequencies above 140 Hz, highlighting a key limitation for broader applications.

Despite these advances, the application of MPC in ANC systems - particularly with explicit constraint handling - remains scarcely explored in the literature. This paper seeks to address this gap by developing and validating an innovative MPC-based control framework for active tonal noise control in acoustic ducts, specifically in the presence of plane waves. This study advances the understanding of MPC in fast dynamic systems with the following contributions:

1. **Novel Control Strategy:** Unlike standard methods, this approach treats the primary noise as the reference for the control signal rather than as a disturbance within the MPC framework. This strategy eliminates the need for an adaptive MPC, bypassing the requirement to estimate the combined plant and disturbance model.
2. **Primary Path Modeling:** Using primary path modeling to estimate future reference values over the prediction horizon enhances the controller's performance in managing the system's fast dynamics.
3. **Explicit Constraint Handling:** Presentation of an MPC algorithm that explicitly addresses operational constraints,

such as actuator saturation and rate of change limitations, while maintaining effective noise attenuation.

The methodology is validated through numerical experiments using identified primary and secondary path models in an active noise control test bench [29]. The results demonstrate the practical feasibility and performance advantages of the proposed control framework over traditional FXLMS methods.

The remainder of this paper is organized as follows: Section 2 describes the system setup used as a reference for this work. Section 3 presents the formulation of the MPC strategy, including handling operational constraints. Section 4 details the methodology, outlining the proposed framework and the procedures for validating the strategy. Section 5 provides a detailed discussion of the results from the numerical experiments. Finally, Section 6 concludes the paper by summarizing the main findings and suggesting directions for future research.

2 System description

The subject of this study is the numerical model of the experimental ANC bench. The setup consists of a tubular duct with a primary loudspeaker positioned at one end and an open termination at the other. The primary loudspeaker generates the tonal noise to be controlled, which propagates as plane waves from left to right through the duct. A reference microphone detects the incident noise waves and provides an input signal to the controller. Based on this input, the controller generates an anti-phase signal that is emitted by the control loudspeaker, aiming to destructively interfere with the primary noise. An error microphone, located further down the duct, captures the residual noise and sends an error signal back to the controller, closing the feedback loop.

The dynamics of this system are represented by mathematical models of the acoustic-electronic paths involved, as shown in Fig. 1. These paths are divided into two main components:

1. **Primary Path $P(z)$:** This path represents the propagation of the primary noise from its source to the error microphone. It includes the noise source, the medium through which the sound travels, and the physical environment of the duct.
2. **Secondary Path $S(z)$:** This path describes the trajectory of the anti-noise signal emitted by the control loudspeaker and its interaction with the primary noise at the error microphone. It encompasses the digital-to-analog (D/A) converter, reconstruction filter, amplifier, loudspeaker, the acoustic path from the loudspeaker to the error microphone, the microphone itself, preamplifier, anti-aliasing

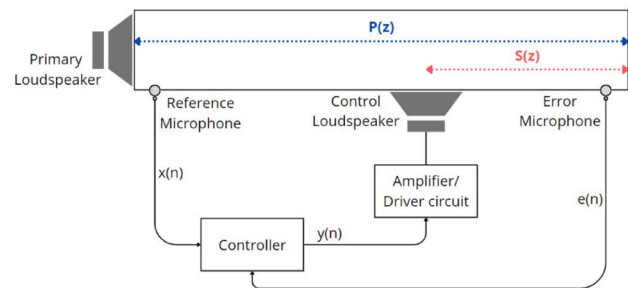


Fig. 1 Active Noise Control System

filter, and analog-to-digital (A/D) converter [30]. Proper modeling of the secondary path is crucial for effective ANC, as it determines how the anti-noise signal propagates and interferes with the original noise.

Accurate modeling of the primary and secondary paths is essential for effective noise cancellation. The state-space models for these paths, experimentally identified by [29] using an active noise control bench, are employed in this study. The system was excited with broadband white noise, with the primary path measured using only the noise loudspeaker and the secondary path using only the control loudspeaker. Microphone signals were recorded for 6 s, with half used for model identification and half for validation. Models were estimated using the prediction error minimization (PEM) method from MATLAB's system identification toolbox and evaluated via fit percentage. The resulting models accurately reproduced the measured acoustic responses, ensuring that the simulations presented in this work closely reflect the real experimental conditions.

3 MPC formulation

The mathematical formulation of MPC for ANC systems involves defining a state-space representation, constructing a cost function that balances performance and control effort, and incorporating constraints to ensure feasible and safe operation. Solving this optimization problem at each time step enables real-time adjustment of control actions, effectively mitigating unwanted noise and optimizing system performance. This work utilized the formulation of a constrained predictive control presented in [31], briefly described below.

The ANC system dynamics are modeled using discrete-time state-space equations:

$$\begin{aligned}\mathbf{x}(k+1) &= \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) \\ \mathbf{y}(k) &= \mathbf{C}\mathbf{x}(k)\end{aligned}\quad (1)$$

where $\mathbf{x}(k)$ represents the state vector at time step k , $\mathbf{u}(k)$ denotes the control input vector, and $\mathbf{y}(k)$ is the output vector. The matrices $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$ characterize the system dynamics and the relationships between states, inputs, and outputs.

The predicted control actions over a horizon of N steps and the corresponding future states resulting from the application of these control actions can be expressed as follows:

$$\tilde{\mathbf{u}}(k) = [u(k), u(k+1), \dots, u(k+N-1)]^T \quad (2)$$

$$\tilde{\mathbf{x}}(k) = [x(k+1), x(k+2), \dots, x(k+N)]^T \quad (3)$$

The states at any given sampling instant within the N -step-ahead prediction horizon can be determined based on the current states and the sequence of future control inputs. This relationship is expressed as:

$$x(k+1) = \Phi_i \cdot x(k) + \Psi_i \cdot \tilde{\mathbf{u}}(k) \quad (4)$$

where Φ_i and Ψ_i are the state transition and control influence matrices, respectively. These matrices are derived from the discrete-time model as follows:

$$\Phi_i := A^i \quad (5)$$

$$\Psi_i := [A^{i-1}B \dots AB \ B]^T \begin{bmatrix} \Pi_1^{(n_u, N)} \\ \Pi_2^{(n_u, N)} \\ \vdots \\ \Pi_i^{(n_u, N)} \end{bmatrix} \quad (6)$$

where n_u is the dimension of the control vector $\mathbf{u}$, and the matrix $\Pi_i^{(n_u, N)}$ is the selection matrix defined as:

$$\Pi_i^{(n_u, N)} = [0_{n_u \times n_u(i)} \ I_{n_u \times n_u} \ 0_{n_u \times n_u(N-i)}] \quad (7)$$

The output vector to be regulated can be expressed as any linear combination of the system states. Thus, the regulated output is defined as:

$$\mathbf{y}_r(k) := C_r \cdot \mathbf{x}(k) \quad (8)$$

where $C_r \in \mathbb{R}^{n_r \times n}$ defines the regulated output vector $\mathbf{y}_r$, where n is the number of system states and n_r is the number of regulated outputs. In cases where a reference is available on the whole state, it can be chosen to be the identity matrix.

The predictions are used in the optimization process using the following cost function:

$$J(\mathbf{u}|\mathbf{x}(k), \mathbf{y}_d(k), \mathbf{u}_d) = \sum_{i=1}^N \|\mathbf{y}_r(k+i) - \mathbf{y}_d(k+i)\|_{Q_y}^2 + \sum_{i=1}^N \|\Pi_i^{(n_u, N)}(\mathbf{u} - \mathbf{u}_d)\|_{Q_u}^2 \quad (9)$$

where N is the prediction horizon, $\mathbf{y}_r(k+i)$ is the predicted output at time $k+i$, $\mathbf{y}_d(k+i)$ is the desired output at time $k+i$, $\mathbf{u}_d$ represents the steady-state control input, Q_y and Q_u are weighting matrices that penalize tracking errors and control input variations.

This cost function penalizes the tracking error between the predicted and desired outputs, and the variations in control inputs. It can be expressed in the following standard quadratic form:

$$J(\mathbf{u}|\mathbf{x}(k), \mathbf{y}_d(k), \mathbf{u}_d) = \frac{1}{2} \tilde{\mathbf{u}}^T H \tilde{\mathbf{u}} + F^T \tilde{\mathbf{u}} \quad (10)$$

provided that the following definitions are used:

$$H := 2 \sum_{i=1}^N \left[\Psi_i^T C_r^T Q_y C_r \Psi_i + \left(\Pi_i^{(n_u, N)} \right)^T Q_u \left(\Pi_i^{(n_u, N)} \right) \right] \\ = F_1 \cdot x(k) + F_2 \cdot y_r(k) + F_3 \cdot u_d$$

$$F_1 := 2 \sum_{i=1}^N \Psi_i^T C_r^T Q_y C_r \Psi_i$$

$$F_2 := -2 \sum_{i=1}^N \Psi_i^T C_r^T Q_y \Pi_i^{(n_u, N)}$$

$$F_3 := 2 \sum_{i=1}^N \left(\Pi_i^{(n_u, N)} \right)^T Q_u \quad (11)$$

The optimization algorithm is designed to find the sequence of future control actions that minimize the cost function over a prediction horizon N . This process is crucial for achieving optimal control performance, as it ensures that the system operates within the specified constraints while minimizing the tracking error and control input variations.

Physical systems often require operational constraints to ensure both safety and efficiency, maintain effective noise reduction, and guarantee the longevity and optimal performance of the equipment. Three operational constraints were adopted in this work:

- **Acoustic Output Constraints:** This constraint imposes limits on the predicted acoustic pressure of the anti-noise signal as it arrives at the error microphone. The goal is to ensure that the cancelation sound generated by the system does not itself become excessively loud, which could be a safety or comfort concern for listener:

$$\mathbf{y}_{\min} \leq \mathbf{y}(k+i) \leq \mathbf{y}_{\max}, \quad i = 1, \dots, N \quad (12)$$

where $\mathbf{y}_{\min}$ and $\mathbf{y}_{\max}$ are the minimum and maximum allowable output values, respectively.

- **Actuator Input Signal Constraint:** This constraint imposes hard limits on the instantaneous amplitude of the signal sent from the controller to the actuator (e.g., the speaker). Its purpose is to respect the hardware's physical operational limits, preventing damage from excessive excursion and avoiding nonlinear distortion from amplifier clipping:

$$\mathbf{u}_{\min} \leq \mathbf{u}(k+i) \leq \mathbf{u}_{\max}, \quad i = 1, \dots, N \quad (13)$$

where $\mathbf{u}_{\min}$ and $\mathbf{u}_{\max}$ represent the minimum and maximum allowable values for control inputs, respectively.

- **Rate of Change Constraints:** To ensure a smooth control action and respect the physical limitations on actuator velocity, constraints are imposed on the control increment. This prevents excessive mechanical stress on the equipment and avoids exciting unmodeled high-frequency dynamics:

$$\delta_{\min} \leq \mathbf{u}(k+i) - \mathbf{u}(k+i-1) \leq \delta_{\max} \quad i = 1, \dots, N \quad (14)$$

where $\delta_{\min}$ and $\delta_{\max}$ are the minimum and maximum allowable changes in control inputs between consecutive time steps.

If restrictions of the form (12), (13), (14) are to be satisfied on the manipulated and controlled variables, the minimization of the cost is subject to the following linear constraints on $\mathbf{u}$

$$\mathbf{A}_{\text{ineq}} \mathbf{u} \leq \mathbf{G}_1 \mathbf{x}(k) + \mathbf{G}_2 \mathbf{u}(k-1) + \mathbf{G}_3 \quad (15)$$

where

$$\mathbf{A}_{\text{ineq}} = \begin{pmatrix} \mathbf{A}_{\text{ineq}}^{(1)} \\ \mathbf{A}_{\text{ineq}}^{(2)} \end{pmatrix}, \quad \mathbf{G}_1 = \begin{pmatrix} \mathbf{G}_1^{(1)} \\ \mathbb{O}_{(2Nn_u) \times n} \end{pmatrix}, \quad (16)$$

$$\mathbf{G}_2 = \begin{pmatrix} \mathbb{O}_{(2Nn_c) \times n_u} \\ \mathbf{G}_2^{(2)} \end{pmatrix}, \quad \mathbf{G}_3 = \begin{pmatrix} \mathbf{G}_3^{(1)} \\ \mathbf{G}_3^{(2)} \end{pmatrix}.$$

The intermediate matrices are defined by:

$$\mathbf{A}_{\text{ineq}}^{(1)} = [+C_c \Psi_1 \cdots +C_c \Psi_N -C_c \Psi_1 \cdots -C_c \Psi_N]^T$$

$$\mathbf{A}_{\text{ineq}}^{(2)} = \begin{bmatrix} +\mathbb{I} & \mathbb{O} & \mathbb{O} & \cdots & \mathbb{O} & \mathbb{O} \\ -\mathbb{I} & +\mathbb{I} & \mathbb{O} & \cdots & \mathbb{O} & \mathbb{O} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbb{O} & \mathbb{O} & \mathbb{O} & \cdots & -\mathbb{I} & +\mathbb{I} \\ -\mathbb{I} & \mathbb{O} & \mathbb{O} & \cdots & \mathbb{O} & \mathbb{O} \\ +\mathbb{I} & -\mathbb{I} & \mathbb{O} & \cdots & \mathbb{O} & \mathbb{O} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbb{O} & \mathbb{O} & \mathbb{O} & \cdots & +\mathbb{I} & -\mathbb{I} \end{bmatrix} \quad (17)$$

$$\mathbf{G}_1^{(1)} = [-C_c \Phi_1 \cdots -C_c \Phi_N + C_c \Phi_1 \cdots + C_c \Phi_N]^T$$

$$\mathbf{G}_2^{(2)} = [+ \mathbb{I} \mathbb{O} \cdots -\mathbb{I} \mathbb{O} \cdots \mathbb{O}]^T$$

$$\mathbf{G}_3^{(1)} = [+y_{\max} \cdots +y_{\max} -y_{\min} \cdots -y_{\min}]^T$$

$$\mathbf{G}_3^{(2)} = [+ \delta_{\max} \cdots + \delta_{\max} -\delta_{\min} \cdots -\delta_{\min}]^T$$

where $C_c \in \mathbb{R}^{n_c \times n}$ is the constraints output matrix, $\mathbb{I}$ represents the identity matrix and $\mathbb{O}$ represents the zero matrix.

Thus, the optimization task centers on quadratic programming at each sampling interval, benefiting from well-established numerical methods. The control strategy is executed using a receding horizon approach, where only the first computed control input $u(k)$ is implemented on the plant. This iterative process continues, with the optimization recalculated at each new sampling point based on updated measurements.

4 Methodology

Conventional MPC for ANC [10, 27, 32] is typically formulated as a disturbance rejection problem, where the objective is to maintain the system's output at a zero reference ($r(k)=0$). As illustrated in Fig. 2, the disturbance signal $d(k)$ is the result of the original noise source, $\xi(k)$, after it propagates through the primary path. To reject structured disturbances, this approach necessitates an augmented state-space representation that combines a dynamic model of the noise source (primary path) with the plant model (secondary path). The combined plant and disturbance model is unknown and must be estimated, making this an adaptive model-predictive control application that has received little attention [28]. The controller must then operate on this composite model.

The practical challenge of this formulation, however, lies in its sensitivity to the non-stationary nature of its components; both the disturbance characteristics (e.g., frequency shifts from a variable-speed fan) and the plant dynamics (e.g., acoustic path changes with temperature) are often time-varying. This characteristic increases both computational complexity and sensitivity to modeling errors.

In contrast, the framework proposed herein recasts the problem from disturbance rejection to reference tracking, thereby circumventing the need for an augmented model.

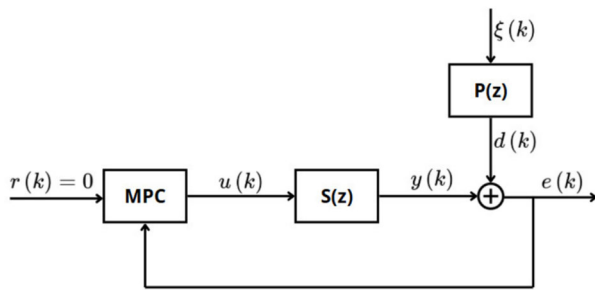


Fig. 2 Block diagram of a conventional disturbance rejection ANC system ($r(k) = 0$). The disturbance $d(k)$ is generated by the noise source $\xi(k)$ propagating through the primary path $P(z)$. The controller uses the error $e(k)$ to create an anti-noise $y(k)$ that cancels this disturbance

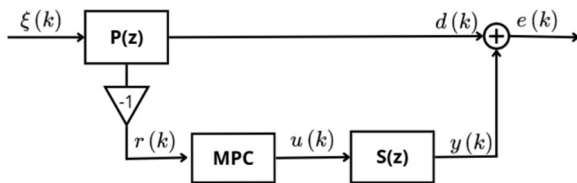


Fig. 3 The proposed reference-tracking MPC framework, where the reference is the inverted prediction of the primary noise, $r(k) = -\hat{d}(k)$, generated from the primary path model $\hat{P}(z)$

The primary noise is treated not as an internal disturbance to be rejected, but as an external trajectory to be canceled. A separate adaptive filter predicts the future noise trajectory, which is then inverted to serve as a time-varying reference for the controller, $r(k) = -\hat{d}(k)$, as shown in Fig. 3. The principal advantage of this decoupled architecture is that the MPC's internal predictive model is concerned solely with the secondary path dynamics. This simplification reduces the dimensionality of the online optimization problem, a critical benefit for real-time implementation. Furthermore, by isolating the disturbance model from the control loop, potential inaccuracies in the noise prediction do not propagate through the plant model, enhancing the overall robustness of the closed-loop system.

The estimated models [29] allow for predicting future values of the primary noise over the prediction horizon, considering the current value measured by the reference microphone. Moreover, the tonal noise source exhibits well-defined and stationary characteristics, such as a constant frequency and a nearly periodic waveform. These properties significantly reduce uncertainty in predicting future system responses, as the disturbance behavior can be accurately estimated N steps ahead from its current value. By incorporating this information into the MPC algorithm, the controller exhibits anticipative behavior, enabling it to leverage online estimations of potential future trajectories during system operation, thereby enhancing control performance. This capability is particularly advantageous in fast dynamic systems such as ANC in ducts. Without such predictions,

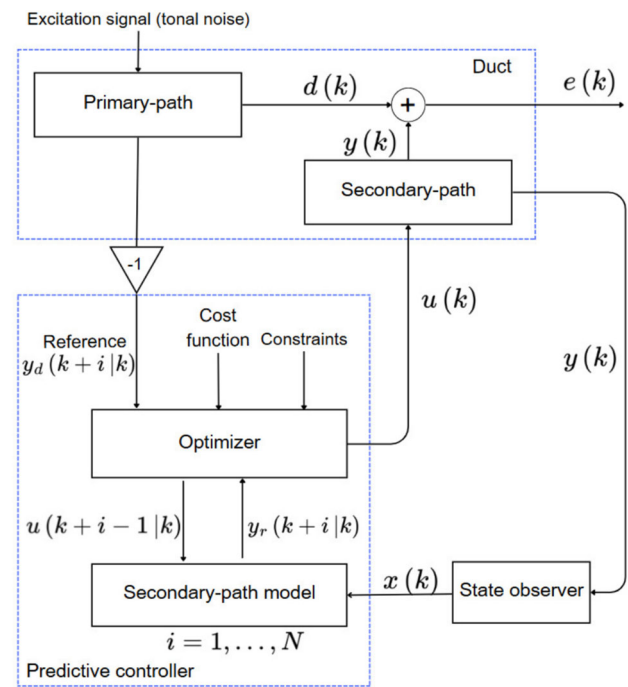


Fig. 4 Schematic of the proposed predictive control loop

however, the controller may struggle to keep pace with the rapid dynamics of the system, leading to delays in response.

The schematic of the predictive control loop implemented in this study is shown in Fig. 4. The control signal $u(k)$, generated by the controller, is applied to the plant through the control loudspeaker. To enable feedback, the controller relies on the estimated state vector $x(k)$ at each discrete-time step k . Since the system states are not directly measurable, they are estimated using a state observer based on the output signal of the secondary path, denoted by $y(k)$. The resulting residual noise, after the interaction between the primary noise and the anti-noise, is denoted by:

$$e(k) = d(k) + y(k) \quad (18)$$

Given the significant practical interest in reducing computational demand, it is essential to minimize unnecessary online operations. In this context, an implementation of MPC was adopted that distinguishes between offline calculations involving constant elements and online calculations that handle frequently changing elements. Specifically, the following offline procedure is required:

5 Results

This section details the simulation results for the proposed MPC-based active noise control (ANC) framework,

Algorithm 1 Implementation procedure of the MPC controller

- 1: **Offline initialization:**
- 2: Choose the prediction horizon N and the weighting matrices Q_y and Q_u .
- 3: Compute matrices H , F_1 , F_2 , F_3 according to (11).
- 4: Define the constraint based on physical and operational limits.
- 5: Compute matrices A_{ineq} , G_1 , G_2 , G_3 according to (16).
- 6: Configure and initialize the state observer.
- 7: **Online operation (at each sampling instant):**
- 8: Apply the control action computed in the previous iteration.
- 9: Measure the system output.
- 10: Estimate the system state using the observer.
- 11: Predict the reference trajectory over the prediction horizon.
- 12: Solve the Quadratic Programming (QP) problem under the given constraints.
- 13: Apply the first element of the optimal control sequence to the system.

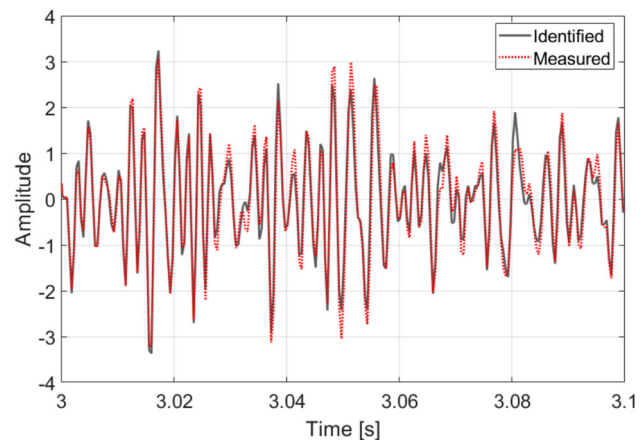
including a comparative analysis against established adaptive filtering methods. All simulations were performed in MATLAB R2023a and Simulink on a machine running Windows 10 Pro, equipped with an Intel Core i7-11700 CPU @ 2.50 GHz and 16 GB of RAM. To ensure the results are representative of a future experimental implementation, the models were executed in Simulink's Desktop Real-Time mode at a sampling frequency of 2.4 kHz, with all code running in a single thread. The predictive control law and the required QP solver, based on the work of [33], were implemented via a custom C-based S-function.

The system was excited by tonal disturbances with unit amplitude, ranging from 100 Hz to 600 Hz in 100 Hz increments. To thoroughly evaluate the controller's performance, its attenuation capabilities were assessed under both unconstrained and constrained operating conditions. The prediction horizon was also empirically determined, starting from a small value and increasing until performance saturated at $N = 40$, as larger horizons offered no further improvement.

The performance of the proposed MPC algorithm was benchmarked against two variants of the classical Filtered-x Least Mean Square (FXLMS) algorithm, which is the most widely adopted method in ANC literature. For the constrained case, the comparison was made against an FXLMS algorithm with a clipping saturation mechanism. This approach emulates a common physical limitation in control systems, such as actuator saturation or hardware output limits [12]. Furthermore, the recently developed minimum output variance filtered reference least mean square algorithm (MOV-FXLMS) [34] was implemented as an advanced benchmark for constrained control.

Table 1 Model identification quality (white-noise validation)

Model	Order	FIT (%)
Primary path $P(z)$	40	83.14
Secondary path (plant) $S(z)$	60	82.38
Secondary path (controller model) $\hat{S}(z)$	40	83.96

**Fig. 5** Model validation of the 40th-order secondary path using white-noise excitation: measured versus identified responses

5.1 Models identification

The primary and secondary acoustic paths were identified using white-noise excitation and least squares estimation, resulting in discrete-time state-space models. The primary path was represented by a 40th-order identified model as it provided the best trade-off between accuracy and computational cost. Similarly, the 40th-order model of the secondary path was selected for controller design, while a 60th-order model was used in the simulation to represent the physical plant, introducing a realistic model-plant mismatch.

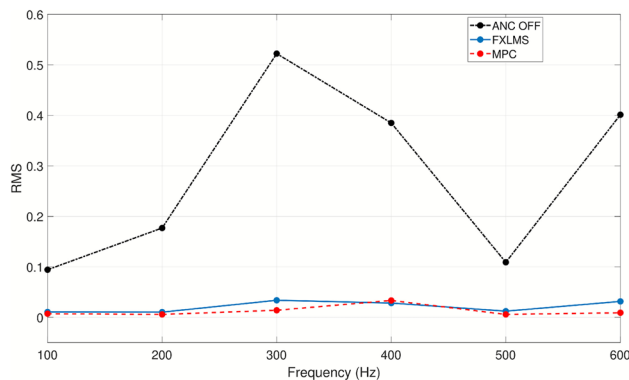
Table 1 summarizes the identification results, and Fig. 5 illustrates the fit between the identified and simulated responses of the 40th-order secondary path under white-noise excitation.

5.2 Unconstrained performance

For the unconstrained analysis, the controller was tuned for optimal performance. The weighting matrices, Q_y and Q_u , were determined through an iterative empirical process. The objective was to maximize noise attenuation by increasing Q_y to prioritize error minimization, while Q_u was set to the minimum value required to ensure closed-loop stability and prevent divergence. The final selected values of $Q_y = 100$ and $Q_u = 1$ achieved the highest attenuation while maintaining a stable and robust response across all tested frequencies.

Table 2 FXLMS step size (μ) values used for each frequency

Frequency (Hz)	Step size (μ)
100	0.0100
200	0.0010
300	0.0010
400	0.0001
500	0.0001
600	0.0010

**Fig. 6** RMS of the residual noise signal $e(k)$

For the benchmark FXLMS algorithm, the step size, μ , was individually tuned for each disturbance frequency to maximize attenuation while ensuring convergence, as summarized in Table 2. The adaptive filter length was set to 70 taps, and the leaky factor was fixed at unity.

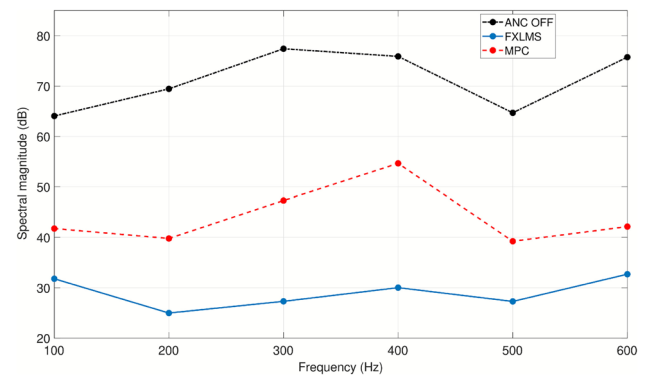
To simulate the unconstrained condition, the minimum and maximum allowable values for (12), (13), and (14) were effectively set to infinity in the MPC formulation. The efficiency of the ANC system was evaluated using two criteria: spectral magnitude (SR), and the root-mean-square (RMS), given by (19).

$$\text{RMS} = \sqrt{\frac{1}{n} \sum_{i=1}^N e(i)^2} \quad (19)$$

where n is the total number of samples and $e(i)$ is the value of the i -th sample.

Figures 6 and 7 present the performance of both control strategies across the evaluated frequencies. Figure 6 displays the RMS values of the residual noise signal, while Fig. 7 shows the spectral magnitude in decibels (dB). From these results, it is evident that both the classical FXLMS algorithm and the proposed MPC approach successfully attenuated the tonal noise at all tested frequencies.

While the analysis of the RMS values indicated a comparable reduction in the overall energy of the residual noise, the frequency-domain results reveal that the FXLMS algorithm

**Fig. 7** Spectral magnitude in decibels of the residual noise signal $e(k)$

achieved slightly greater attenuation at the target frequencies. This behavior can be attributed to two main factors. Firstly, the logarithmic nature of the decibel scale can amplify small differences in absolute amplitude. Secondly, this outcome also reflects the intrinsic characteristics of each control strategy. FXLMS is designed to minimize the instantaneous mean square error, a strategy that excels at suppressing a dominant tonal component. Conversely, MPC optimizes the predicted system response over a future horizon, balancing noise reduction against control energy based on its internal model.

Additionally, the performance of the MPC is highly dependent on the accuracy of the internal plant model. In this study, a deliberate model-plant mismatch was introduced by using a 40th-order model for the controller ($\hat{S}(z)$) and a different, 60th-order model for the simulated duct ($S(z)$). This discrepancy inherently limits the MPC's maximum achievable attenuation, as its predictions are based on imperfect system dynamics.

Figures 8 and 9 present a detailed analysis for the 300 Hz signal. The power spectrum in Fig. 8 confirms the slightly deeper attenuation of the FXLMS at the target frequency. However, the time-domain response in Fig. 9 reveals one of MPC's key advantages: faster convergence. Its predictive nature allows the controller to anticipate future states and generate optimal control actions that accelerate the transient response without overshoot.

This makes MPC particularly advantageous in scenarios where rapid adaptation is required, such as in response to time-varying noise or when constraints are active. From a practical standpoint, for disturbances that are steady over long periods (e.g., fixed-speed motors), the superior steady-state tonal attenuation of FXLMS may be preferable. However, in scenarios with changing operating conditions (e.g., variable-speed engines), the faster convergence of MPC may be an advantage, enabling effective noise suppression even as the disturbance evolves.

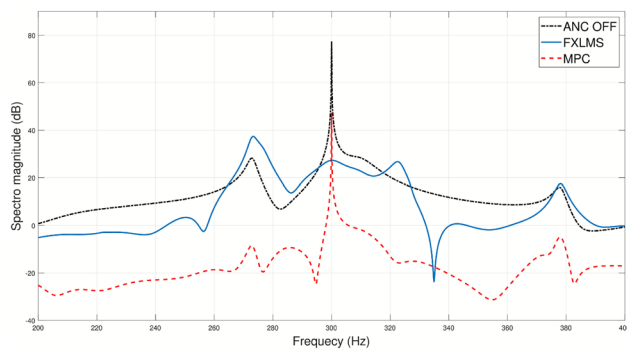


Fig. 8 Power spectrum of the residual noise at 300 Hz

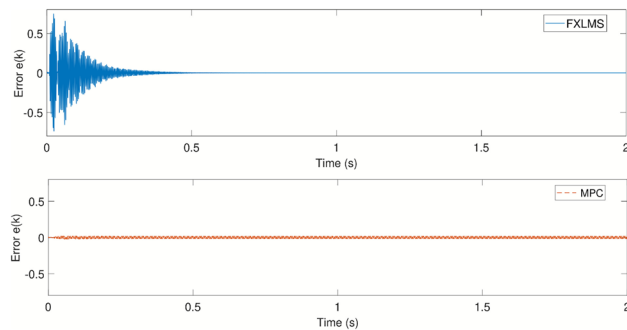


Fig. 9 Residual noise in the time domain at 300 Hz

5.3 Constrained performance

To validate the central premise of this study—that MPC provides a feasible and effective solution for ANC under operational constraints—the proposed framework was evaluated under three representative types of limitations:

1. **Output Constraint - $y(k)$:** Ensures that the acoustic anti-noise at the error microphone does not exceed a specified level.
2. **Control Input Constraint - $u(k)$:** Imposes hard limits on the actuator input signal to prevent physical damage (e.g., over-exursion) and nonlinear distortion due to amplifier saturation.
3. **Input Slew-Rate Constraint - $\Delta u(k)$:** Restricts the rate of change of the control signal to respect actuator dynamics and ensure smooth, physically achievable control actions.

The specific constraint values adopted in this analysis were selected to demonstrate the controller's behavior under bounded conditions rather than to match the physical limits of a particular experimental setup. Although the actuators used in practice may allow a wide dynamic range, industrial ANC applications frequently impose tighter operational bounds. Therefore, the chosen limits serve as illustrative examples, emphasizing the practical relevance of constrained MPC in

real-world ANC systems. For comparative analysis, a representative output constraint of $y(k) \in [-0.4, 0.4]$ V was applied to all controllers.

Each algorithm was then configured to account for this limitation. For the MPC, the input weighting matrix was increased to $Q_u = 10$ to more strongly penalize aggressive control actions, enabling the solver to systematically find an optimal solution that respects the imposed bounds. The standard FXLMS algorithm retained its nominal parameters, but its output was passed through a saturation block to emulate hard clipping, a common practical workaround. The MOV-FXLMS algorithm was tuned empirically to maintain the control signal within the same limits. This iterative tuning process, characteristic of adaptive methods, yielded $\mu_1 = 0.0004$ and $\rho^2 = 0.08$. Such reliance on manual parameter adjustment to satisfy constraints underscores a practical limitation of adaptive algorithms when compared to the systematic and explicit approach inherent to MPC.

The resulting control signals under the imposed constraint $-0.4 \leq y(k) \leq 0.4$ are shown in Fig. 10. As observed, the standard FXLMS algorithm cannot proactively enforce the constraint; its control signal is simply clipped whenever the predefined limits are exceeded. This uncontrolled saturation not only degrades performance but may also compromise system stability. In contrast, both the MOV-FXLMS and the proposed MPC maintain their control signals strictly within the feasible region. While the MOV-FXLMS achieves this adaptively by modulating its step size, the MPC enforces it deterministically by embedding the constraint directly into the optimization problem. This allows MPC to anticipate and plan control actions that respect the limits without requiring empirical or reactive adjustments.

The negative impact of clipping on attenuation performance is confirmed by the residual error signals as shown in Fig. 11. The saturated output of the standard FXLMS introduces distortion into the anti-noise signal, compromising its ability to cancel the tonal disturbance. Consequently, the residual error waveform becomes visibly distorted and deviates from the ideal sinusoidal shape. In contrast, both the proposed MPC and the MOV-FXLMS maintain effective attenuation, yielding a clean, low-amplitude sinusoidal residual signal. This demonstrates that systematic constraint handling preserves not only the attenuation level but also the fidelity of the cancelation, avoiding the distortion typically induced by hard clipping.

The control effort required to maintain the acoustic output within the imposed constraint is shown in Fig. 12. When the output constraint on $y(k)$ becomes active, the behavior of the control signal $u(k)$ differs markedly among the algorithms. In the case of the standard FXLMS, the controller has no internal knowledge of the constraint; it continues to increase its output in an attempt to further attenuate the residual error. However, since the constraint acts externally through the saturation

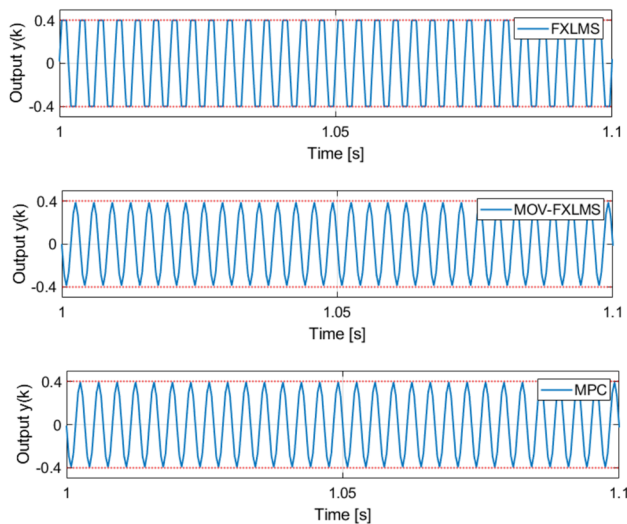


Fig. 10 Output signal $y(k)$ for the FXLMS, MOV-FXLMS, and MPC controllers under an constraint of ± 0.4 V (red dashed lines). The standard FXLMS exhibits clipping, whereas both MOV-FXLMS and MPC successfully respect the bounds

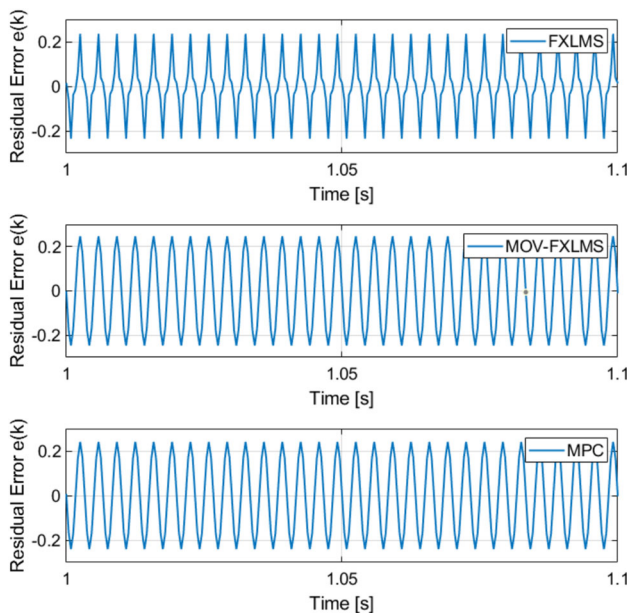


Fig. 11 Residual error signal $e(k)$ for the three controllers under the ± 0.4 V input constraint. The standard FXLMS performance is degraded due to clipping, while MPC and MOV-FXLMS maintain effective attenuation and signal fidelity

block, the effective control action is clipped, and the adaptive algorithm interprets this as a degradation in performance. As a result, the controller diverges, producing large oscillations and instability in $u(k)$.

In contrast, both the MOV-FXLMS and the proposed MPC exhibit stable and well-behaved control actions. The MOV-FXLMS achieves this by adaptively reducing its step size when the output approaches the constraint limit, while

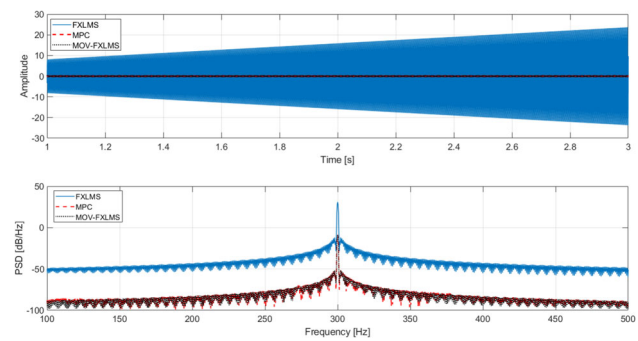


Fig. 12 Control signal $u(k)$ under output constraint ± 0.4 V: **a** time-domain response and **b** power spectral density. The standard FXLMS exhibits divergence due to its inability to account for the saturation, whereas MOV-FXLMS and MPC maintain bounded and energy-efficient control actions

the MPC enforces the constraint directly in its optimization problem, anticipating and regulating $u(k)$ accordingly. As a consequence, both algorithms maintain bounded, smooth control signals without excessive energy expenditure. This behavior is confirmed by the energy density plots, where the MPC and MOV-FXLMS show significantly lower total control energy compared to the divergent FXLMS case. These results demonstrate the inherent advantage of predictive control and constraint-aware adaptation in preventing overdriving and maintaining stable performance even under stringent output limits.

To further illustrate the versatility of the proposed MPC framework, Fig. 13 shows the controller behavior under two distinct constraint types applied separately: the input amplitude constraint $u(k)$ (top) and the input slew rate constraint $\Delta u(k)$ (bottom), both evaluated at 300 Hz. In both cases, the MPC successfully enforces the specified limits throughout the simulation, ensuring smooth and feasible control actions without compromising attenuation performance. In contrast, neither the FXLMS nor the MOV-FXLMS algorithms are capable of adapting to these restrictions, as their formulations lack mechanisms to account for control input or rate constraints.

Similar behavior was observed across all other tested frequencies, with the MPC consistently maintaining compliance with both input and rate constraints while preserving stable and effective noise attenuation. This demonstrates the robustness and general applicability of the proposed predictive control strategy for real-world ANC implementations.

5.4 Computational efficiency of MPC

A primary challenge in applying MPC to ANC systems is managing the computational cost, especially given the high sampling rates required for acoustic control. The execution time of online optimization algorithms can be uncertain;

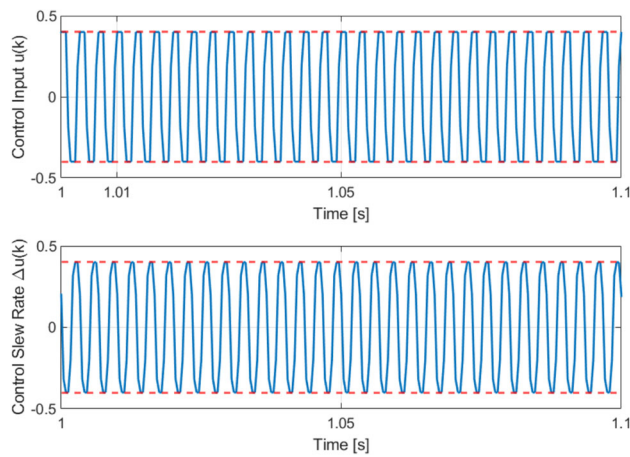


Fig. 13 MPC control signal under separate constraint conditions at 300 Hz: (top) control input $u(k)$ and (bottom) input slew rate $\Delta u(k)$ limited to ± 0.4 V/sample. In both cases, the MPC strictly respects the limits while maintaining smooth control actions

while some methods have better theoretical complexity, the practical efficiency often depends on the specific problem instance [10]. To evaluate the feasibility of the proposed controller, its execution time was therefore rigorously monitored during simulation. This was achieved using the Simulink *Execution Time* block, supplemented by C-level instrumentation within the S-Function to precisely measure the QP solver's performance.

Figure 14 presents the mean execution time per control cycle for each algorithm, simulated at a 2.4 kHz sampling rate, under $-0.4 \leq y(k) \leq 0.4$. As expected, the FXLMS and MOV-FXLMS algorithms exhibit negligible computational load, with average execution times under 10^{-5} s. In contrast, the MPC controller's demand is higher due to the online optimization; yet, its execution time remains well below the sampling period, confirming its real-time feasibility.

To further investigate solver performance, Table 3 summarizes the statistics collected from the QLD solver used in the MPC S-function. Specifically, it achieved a mean execution time of 1.2×10^{-4} s, corresponding to approximately 30% of the available sampling interval (416 μ s). This indicates that the solver converges reliably within the allotted time, even when constraints become active. These results confirm that real-time predictive control for ANC is computationally viable when using an efficient QP solver within the proposed reference-tracking framework.

Although only the output constraint $y(k)$ was enforced in this test, the solver statistics show that constraints were active in approximately 7% of the optimization calls. This occurs because the MPC enforces bounds across the entire prediction horizon, meaning that multiple future steps may simultaneously reach the constraint limits. The solver efficiently detects and manages these active constraints without

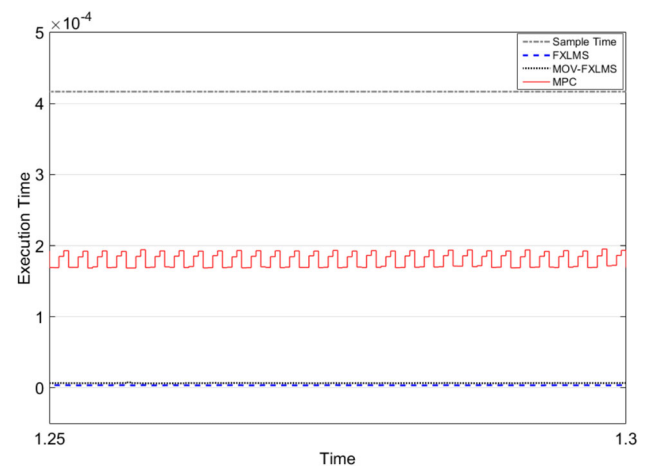


Fig. 14 Average computational time per control iteration for the FXLMS, MOV-FXLMS, and MPC controllers. The MPC requires additional computation due to the online QP solution but remains feasible for real-time implementation at 2.4 kHz

Table 3 QLD solver statistics for constrained MPC (2.4 kHz sampling rate) at 300 Hz and 600 Hz

Metric	300 Hz	600 Hz
Total QP calls	24,001	48,002
Mean exec. time [s]	1.20×10^{-4}	1.965×10^{-4}
<i>Active constraints distribution</i>		
0 active	93.2%	91.6%
1–6 active	4.4%	1.6%
> 6 active	2.4%	6.8%

compromising timing requirements, reinforcing its suitability for real-time acoustic control applications.

To assess the effect of operating frequency on solver performance, a similar analysis was conducted at 600 Hz. In this case, the mean solver execution time increased to 1.96×10^{-4} s, and the percentage of active constraints rose to approximately 8.4%. This behavior is consistent with the expected increase in computational demand at higher frequencies. As frequency increases, the system requires higher sampling rates, which proportionally reduces the available computation time within each control period. This well-known limitation of MPC in fast dynamic systems, combined with the fact that active noise control is inherently more effective at lower frequencies, justifies the frequency range adopted in this study.

6 Conclusion

This study proposed a model predictive control (MPC) framework specifically designed for active noise control (ANC) systems operating under practical constraints. Unlike

conventional adaptive algorithms, the MPC formulation explicitly incorporates limits on control input, acoustic output, and signal variation directly into its optimization process, an essential feature for real-world ANC applications, where actuator capabilities and safety requirements must be strictly observed.

Simulation results demonstrated that the proposed MPC approach consistently attenuates tonal disturbances while rigorously adhering to all predefined constraints. Comparative analysis with classical FXLMS with clipping and the advanced MOV-FXLMS algorithm highlighted MPC's superior flexibility in constraint handling. While MOV-FXLMS indirectly manages control effort through adaptive step size adjustment (e.g., via parameter ρ^2), MPC enables direct and intuitive constraint specification on physical quantities such as the acoustic pressure at the error sensor $y(k)$, which is often the primary performance target in ANC systems.

Furthermore, MPC uniquely supports the simultaneous enforcement of multiple constraint types, such as input amplitude, output level, and slew rate, within a unified predictive optimization framework. This capability enhances its applicability to complex operational scenarios that traditional algorithms cannot explicitly handle. Computational analysis confirmed the feasibility of real-time implementation, with the QP solver consistently converging well within the sampling interval.

Future work will focus on the experimental validation of the proposed control structure and on extending the comparison to alternative MPC formulations for active noise control, including disturbance rejection schemes. Additional research will address the extension of the proposed approach to multi-tonal and broadband noise scenarios. These investigations will require the assessment of real-time QP solvers and the development of tailored optimization strategies to handle the increased computational complexity while preserving real-time feasibility.

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Materials Availability Not applicable.

Code Availability Not applicable.

Declarations

Conflict of interest The authors declare no conflict of interest.

Ethics approval and consent to participate Not applicable.

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