Minimax Theory and its Applications
Volume 11 (2026), No. 4s, 780 to 791

Robust Predictive Control of Networked Systems under Bounded Communication Delays

Dr. Chethan B. K.[1], Dr. G. Rajamani[2], Dr. Mohammad Taj[3], Dr. K. Jayachitra[4], Seethaladevi S[5], Dr. T. Ramaswamy[6]

[1]Associate Professor, Department of Computer Science and Engineering, JSS Technical Institutions Campus, University of Mysore Campus, Mysuru – 570006, Karnataka, India, Email: chethanbk@jssstuniv.in,
ORCID ID: 0000-0003-4236-4454
[2]Assistant Professor, Department of Commerce with Accounting and Finance, Sri Ramakrishna College of Arts and Science, Coimbatore, Email: rajamani@srcas.ac.in, ORCID ID: 0000-0001-5418-7518
[3]Department of Electronics and Communication Engineering, Aditya University, Surampalem, Andhra Pradesh – 533437, Email: tajmd@adityauniversity.in, ORCID ID: 0000-0003-0772-5736
[4]Department of Physics, New Prince Shri Bhavani College of Engineering and Technology, Email: kjayachitra2011@gmail.com, ORCID ID: 0000-0002-9330-6484
[5]Assistant Professor, Department of Mathematics, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, Email: seethaladevi@maher.ac.in, ORCID ID: 0009-0004-5071-4754
[6]Associate Professor, Department of Electronics and Communication Engineering, Sreenidhi Institute of Science and Technology, Hyderabad, Email: ramaswamy.t@sreenidhi.edu.in, orcid id: https://orcid.org/0009-0005-1514-5389

Abstract
Networked control systems (NCSs) are increasingly used in motion-control and cyber-physical applications in which sensing, computation, and actuation are connected through digital communication channels. Although networking provides flexibility and enables remote computation, communication delays create a mismatch between the plant's physical state and the state available to the controller. When combined with bounded disturbances, this mismatch can cause a conventional model predictive controller (MPC) to optimize a trajectory that is feasible for its delayed model but infeasible for the actual plant. This paper develops a low-complexity robust MPC formulation for linear networked systems subject to bounded communication delays and additive disturbances. The proposed approach does not augment the plant with a sequence of delay-dependent states. Instead, the delayed measurement is propagated through the original plant model to reconstruct the current state, while the resulting reconstruction error is analytically bounded using the maximum communication delay and disturbance magnitude. The uncertainty is subsequently propagated across the prediction horizon and introduced into the MPC problem through stage-dependent constraint tightening. Consequently, the online controller remains a standard quadratic program with the original plant dimension, while communication uncertainty is incorporated through an offline-computed uncertainty sequence. A constrained position-velocity model is used to evaluate the method under a maximum communication delay of five sampling periods and bounded disturbances. The robust controller reduces position RMSE from 0.9723 to 0.3174 and accumulated absolute error from 13.2166 to 3.6708 while reducing the accumulated position constraint violation from 8.3093 to zero. The results demonstrate that explicitly separating nominal prediction from delay-induced uncertainty can provide a practical compromise between robustness, constraint protection and computational simplicity.

Keywords: Networked Control Systems, Predictive Control, Time Delay, Robust Control, Constraint Tightening, State Prediction, Disturbance Boundedness, Quadratic Programming.

1. Introduction

The integration of communication networks into feedback control loops has fundamentally changed modern control applications. Instead of direct point-to-point connections between sensors, controllers and actuators, NCSs transmit measurements and control commands through shared digital communication infrastructures. This architecture supports distributed automation, remote motion control, mobile robotics, industrial automation, and cyber-physical systems by enabling sensing and computational resources to be geographically separated and shared among multiple devices. However, communication introduces effects that are generally absent from conventional local feedback loops, including transmission delay, packet loss, sampling irregularity, quantization and limited bandwidth. Among these, network-induced delay is particularly significant because the controller may

make decisions using information describing a previous physical state rather than the plant's current state. Its effects on control performance and stability have therefore motivated extensive research on delay compensation and delay-dependent stability (Zhang et al., 2001).

A substantial body of research has addressed this challenge through delay-dependent models, augmented-state representations, robust MPC, distributed estimation, event-triggered controland min-max formulations. Early studies established that communication characteristics should be incorporated into controller design rather than treated solely as implementation details (Tipsuwan & Chow, 2003; Hespanha et al., 2007). Model-based approaches demonstrated that known plant dynamics can predict system evolution between communication updates, reducing dependence on continuous measurements (Montestruque & Antsaklis, 2003). More explicit delay-aware MPC formulations have considered bounded arbitrary delays through augmented state-space models and Lyapunov-based conditions (Tang & Ding, 2012), while offline synthesis methods have addressed bounded deterministic delays affecting both sensor-to-controller and controller-to-actuator links (Tang et al., 2015).

The robustness problem is closely related to MPC under bounded uncertainty. Robust MPC commonly employs invariant sets, min-max optimization, feedback policies, or tube-based approaches to maintain acceptable behavior under disturbances (Scokaert & Mayne, 1998; Mayne et al., 2005). However, explicitly representing network-induced delay together with disturbance uncertainty can increase computational complexity. Robust distributed MPC may employ augmented models and LMI-based optimization for delay uncertainty (Zhang et al., 2014), while other methods combine delay prediction, moving-horizon estimation, and distributed robust MPC with a more elaborate controller structure (Razavinasab et al., 2018). Recent studies further investigate this trade-off through event-triggered robust MPC and prediction-consistent tube MPC for nonlinear networked systems with delays and packet losses (Ghorbani et al., 2021; Beger & Hirche, 2024).

The present study therefore investigates a mathematically transparent alternative for systems with bounded communication delay, bounded disturbances, a reasonably accurate plant model, and a preference for standard QP-based MPC. The proposed approach separates network uncertainty from nominal MPC dynamics. The controller propagates the most recently received state using known plant dynamics and previously applied inputs to reconstruct the current state. The mismatch between the reconstructed state and the actual state is represented as a finite disturbance convolution and converted, using the known delay and disturbance bounds, into an offline-computed norm bound. This uncertainty is then propagated across the prediction horizon to obtain horizon-dependent margins for tightening nominal state constraints. The online optimization consequently retains the conventional quadratic-program structure without increasing the plant-state dimension. The main contribution is therefore the specific integration of state reconstruction and analytical delay-dependent uncertainty propagation into a compact robust NCS-MPC formulation.

2. Related Work and Research Position

MPC is naturally suited to constrained control because its optimization explicitly incorporates physical limits on both system states and control inputs. Conventional MPC assumes that the current state is available when optimization begins, after which the plant model predicts future behavior. In networked systems, this assumption is violated when measurements experience transmission delay. Networked-control research has therefore developed several compensation strategies, including prediction-based control, augmented-state representations and delay-dependent stability analysis. Early studies established the relationship between communication delay and closed-loop performance, while subsequent research increasingly addressed the preservation of constraint satisfaction under uncertain communication conditions (Zhang et al., 2001; Tipsuwan & Chow, 2003).

One important direction is model-based prediction. When the plant dynamics and previously applied inputs are known, a delayed measurement can be propagated forward to estimate the current state. Montestruque and Antsaklis (2003) demonstrated how plant-model knowledge can reduce dependence on continuous network updates. This principle has subsequently supported predictive networked-control approaches in which predicted states or control sequences maintain useful system information during intervals without newly received measurements.

A second direction incorporates communication delay directly into an augmented state representation. Tang and Ding (2012) addressed bounded arbitrary delays using an augmented state-space model and Lyapunov-based stability analysis. Tang et al. (2015) later developed an offline MPC synthesis approach for bounded deterministic delays affecting both communication directions. These formulations give an explicit description of communication history and become relevant when there is a need to model several delay elements with a high degree of accuracy.

Another well-established method of dealing with uncertainty is Robust MPC. While min-max MPC considers worst-case disturbance sequences, tube MPC decouples the system dynamics from the bounded error tube around it (Scokaert & Mayne, 1998; Langson et al., 2004). Mayne et al. (2005) introduced the concept of a robust MPC

formulation for linear systems with constraints and bounded disturbance inputs. This is why bounded uncertainty margins were considered in the current paper instead of considering the optimization over all disturbance sequences. But the uncertainty in the current work was only due to delay in state measurement and disturbances in the plant.

Networked robust MPC techniques have been further developed into distributed, nonlinear and event-triggered formulations in recent years. In this regard, Zhang et al. (2014) used augmented polytopic uncertainty and LMI optimization for uncertain networked systems with delays, whereas Razavinasab et al. (2018) applied distributed prediction, moving-horizon estimation and robust distributed MPC. Further, Mao et al. (2020) examined semi-feedback min-max MPC for nonlinear networked systems with delays and disturbances. Additionally, event-triggered methods have been proposed in the context of delays and packet losses (Yang et al., 2018; Ghorbani et al., 2021).

Such works serve to confirm that the area of delay-aware robust MPC has reached a certain maturity level. Hence, there should be no attempt at novelty in the areas of prediction, delay compensation, tubes, and constraint tightening. Rather, a concise mathematical framework is created that will transform bounded communication delay and bounded disturbances into an uncertainty bound on the state based on the finite horizon in such a way that preserves the initial dimension of the state and the original QP form.

Table 1. Comparison of representative networked MPC approaches

Approach	**Delay handling**	**Robustness mechanism**	**Online optimization**	**Model growth with delay**
Tang & Ding (2012)	Augmented model	Lyapunov-based delay analysis	Delay-dependent MPC	Yes
Tang et al. (2015)	Augmented model	Offline synthesis	Reduced online burden	Yes
Razavinasab et al. (2018)	Prediction + estimation	Robust distributed MPC	Distributed optimization	System dependent
Mao et al. (2020)	Prediction	Semi-feedback min-max MPC	Min-max	Potentially high
Ghorbani et al. (2021)	Delay-aware	Robust/event-triggered MPC	Convex/LMI based	System dependent
Beger & Hirche (2024)	Prediction-consistent	Tube MPC	Tube-based QP	Network-dependent
Proposed	State prediction	Offline error bound + tightening	Standard QP	No direct growth

This formulation can thus be understood to be complementary in nature rather than a panacea for all the other methods that are included in Table 1. In case any of the factors such as packet loss, actuator side delays, non-linearity and high uncertainty in the network become prevalent in the particular application area, then a more complete approach would have to be taken. The benefit that we are looking for is structural simplicity.

3. Mathematical Model and Proposed Methodology

3.1 Networked Plant Model

Consider a discrete-time linear plant represented by Eq. (1)

$$x_{k+1} = Ax_k + Bu_k + Ew_k \quad (1)$$

where $x_k \in \mathbb{R}^n$is the physical state, $w_k \in \mathbb{R}^n$is a bounded disturbance,$u_k \in \mathbb{R}^m$ is the control input and$A$, B and $E$are system matrices. The disturbance is assumed to satisfy Eq. (2)

$$\| w_k \|_\infty \leq \bar{w} \quad (2)$$

The application considered here is a position-velocity motion-control problem in Eq. (3)

$$x_k = \begin{bmatrix} p_k \\ v_k \end{bmatrix} \quad (3)$$

where $p_k$denotes position and $v_k$denotes velocity. With a sampling interval of $T_s = 0.1$s, the adopted model is in Eq. (4)

$$A = \begin{bmatrix} 1 & 0.1 \\ 0 & 1 \end{bmatrix},\ B = \begin{bmatrix} 0.005 \\ 0.1 \end{bmatrix},\ E = I_2 \quad (4)$$

The above model can be likened to a double integrator sampled motion control system, where the control input is acceleration. Even though simple, it shows the basic principle involved in networked motion control: the velocity integral gives position; hence, any delay in the estimation of the velocity will cause an increase in position error. The model can consequently represent the local dynamics of a servo axis, mobile platform, positioning stage, or other motion subsystem after linearization around an operating condition.

The reference position is $p_r = 1.0$m. These constraints are deliberately incorporated into the control problem because the main purpose of the proposed robustness mechanism is not merely to reduce tracking error, but to prevent communication uncertainty from pushing the physical state outside the admissible region.

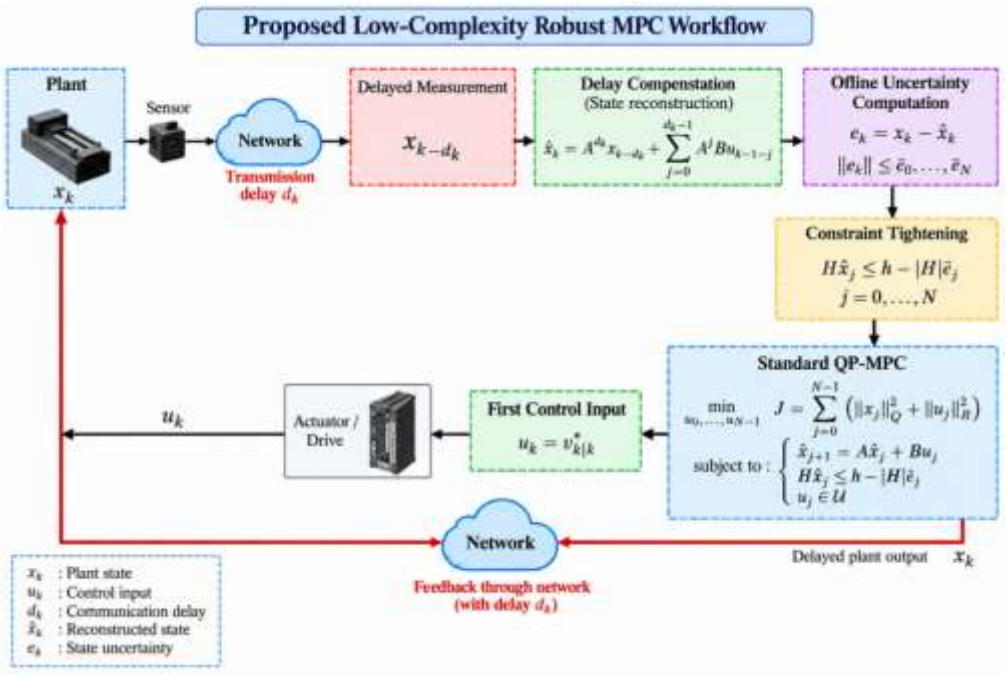


Figure 1. Proposed methodology flow

Fig. 1 shows that the network is assumed to introduce a bounded sensor-to-controller delay d_k, expressed in sampling periods, is shown in Eq. (5)

$$0 \le d_k \le d_{\max} \quad (5)$$

The maximum delay used in the main simulation is $d_{\max} = 5$, corresponding to a physical delay of 0.5s. This assumption does not require the delay to be constant, the controller can receive measurements with different delays if the actual delay remains inside the known bound.

3.2 Delay Compensation Through Model-Based State Reconstruction

At time k, the controller receives the delayed measurement x_{k-d_k}. If this measurement were used directly as the MPC initial condition, the optimizer would be predicting from a state that belongs to an earlier time instant. Instead, the proposed controller propagates the delayed measurement using the plant dynamics and the control actions that were applied during the intervening samples. The reconstructed state is in Eq. (6)

$$\hat{x}_k = A^{d_k} x_{k-d_k} + \sum_{j=1}^{d_k} A^{j-1} B u_{k-j} \quad (6)$$

This equation is central to the proposed model because it allows the communication delay to be handled without changing the dimension of the plant state. The first term propagates the received state forward by $d_k$are considered a sampling interval, whereas the summation takes into account the control actions that have been performed at those sampling intervals. In case the model is correct and there are no disturbances, then the reconstruction will yield the exact current state of the system. Thus, the function of the network delay is not necessarily to induce a state error but, instead, the error results from disturbances that may have occurred in the plant.This is an essential difference from a modeling standpoint. In an augmented-state formulation, one explicitly models the delayed states or inputs such that all possible delay cases can be described by the dynamic model. On the other hand, the method proposed here uses the plant model itself for prediction and treats the rest of the uncertainty as additive error. As a result, the controller is based on the physical meaning of the original system without increasing state dimension with respect to $d_{\max}$.

3.3 Mathematical Characterization of the Reconstruction Error

Recursive substitution of the plant equation into the reconstruction equation yields Eq. (7).

$$x_k = A^{d_k} x_{k-d_k} + \sum_{j=1}^{d_k} A^{j-1} B u_{k-j} + \sum_{\ell=0}^{d_k-1} A^{\ell} E w_{k-1-\ell} \qquad (7)$$

Consequently, in Eq. (8)

$$e_k = x_k - \hat{x}_k = \sum_{\ell=0}^{d_k-1} A^{\ell} E w_{k-1-\ell} \qquad (8)$$

This equation represents the primary connection between communication delay and robust MPC in terms of mathematics. The reconstruction error is the finite convolution of previous disturbances, and the number of disturbance terms is defined explicitly by the communication delay. Therefore, when the delay is larger, the uncertainty set is likely to become larger.Using the induced infinity norm and the disturbance bound in Eq. (9)

$$\| e_k \|_\infty \leq \sum_{\ell=0}^{d_k-1} \| A^{\ell} E \|_\infty \| w_{k-1-\ell} \|_\infty \qquad (9)$$

which yields Eq. (10)

$$\| e_k \|_\infty \leq \bar{w} \sum_{\ell=0}^{d_k-1} \| A^{\ell} E \|_\infty \qquad (10)$$

Since $d_k \leq d_{\max}$, an offline upper bound can be calculated as in Eq. (11)

$$\boxed{\epsilon_0 = \bar{w} \sum_{\ell=0}^{d_{\max}-1} \| A^{\ell} E \|_\infty} \qquad (11)$$

and therefore in Eq. (12)

$$x_k \in \hat{x}_k \oplus \mathcal{B}_\infty(\epsilon_0) \qquad (12)$$

$\mathcal{B}_\infty(\epsilon_0)$denotes an infinity-norm uncertainty box. This approach proves to be especially helpful since it reduces the problem of an uncertain communication to a certain geometric figure.For the adopted model, $\bar{w} = 0.01$and $d_{\max} = 5$, giving$\epsilon_0 = 0.0600$ .The value is not a tuning parameter selected arbitrarily. It follows directly from the plant matrices, disturbance bound and maximum communication delay. This is an important aspect of the proposed formulation because the robustness margin can be recalculated whenever the communication specification or disturbance estimate changes.

3.4 Horizon-Dependent Uncertainty Propagation

The initial uncertainty bound does not remain constant over the prediction horizon. Even if no additional measurement delay occurs, the uncertainty already present in the current state is propagated by the system dynamics. At the same time, new disturbances enter the plant. Therefore, a robust MPC formulation should distinguish uncertainty at the current prediction point from uncertainty at future prediction stages.

For the prediction step i, the proposed uncertainty radius in Eq. (13)

$$\boxed{\epsilon_i = \| A^i \|_\infty \epsilon_0 + \bar{w} \sum_{\ell=0}^{i-1} \| A^{\ell} E \|_\infty} \qquad (13)$$

with $\epsilon_0$given above. The first term represents propagation of the uncertainty already contained in the reconstructed state, while the second represents the accumulated effect of disturbances introduced during the prediction interval.

The above equation is a core mathematical component of the suggested model. In place of choosing a single safety margin value for all phases, the uncertainty is clearly linked with system dynamics. The sequence will thus demonstrate the plant's impact on state uncertainty during prediction. In the numerical case, the uncertainty will start from$\epsilon_0 = 0.0600$at the current prediction point to$\epsilon_{10} = 0.2650$at the end of the ten-step horizon. If a remote controller is regulating the position of a moving system, the uncertainty associated with a delayed velocity measurement may initially be modest but can produce increasingly significant position uncertainty over the prediction horizon. The controller therefore needs to become progressively more conservative when predicting states farther into the future. The proposed $\epsilon_i$sequence provides exactly this mechanism without requiring the optimizer to consider explicit disturbance scenarios.

3.5 Robust Constraint Tightening

The uncertainty bounds are incorporated into the MPC problem through constraint tightening. Let $z_{k+i|k}$represent the nominal predicted state. The physical state is represented as Eq. (14)

$$x_{k+i} = z_{k+i|k} + \delta_{k+i} \quad (14)$$

where

$$\| \delta_{k+i} \|_\infty \leq \epsilon_i \quad (15)$$

To ensure that the actual state remains within the original physical limits, the nominal state is restricted,that shows in Eq. (16)

$$\boxed{x_{\min} + \epsilon_i \leq z_{k+i|k} \leq x_{\max} - \epsilon_i} \quad (16)$$

The logic is direct. If the nominal position is at least $\epsilon_i$away from the physical boundary, then an error of magnitude up to $\epsilon_i$cannot push the actual state beyond that boundary. The same reasoning applies to velocity. Hence, the constraint-tightening operation transforms the uncertainty bound into a robust feasibility condition.

This construction also explains why the proposed controller does not simply increase the input penalty when communication deteriorates. Increasing Rmay discourage aggressive actuation, but it does not explicitly establish a geometric relationship between state uncertainty and state constraints. In contrast, the proposed tightening mechanism directly modifies the feasible state region according to the calculated uncertainty. The robustness therefore acts where the communication uncertainty enters the problem.

3.6 MPC Optimization Problem

With the reconstructed state and uncertainty margins available, the controller solves the following finite-horizon optimization problem in Eq. (17)

$$\min_{\{v_{k+i|k}\}} J \quad (17)$$

where

$$J = \sum_{i=0}^{N-1} \left[\| z_{k+i|k} - r_{k+i} \|_Q^2 + \| v_{k+i|k} \|_R^2 \right] + \| z_{k+N|k} - r_{k+N} \|_P^2 \quad (18)$$

The nominal dynamics are shown in Eq. (19)

$$z_{k+i+1|k} = A z_{k+i|k} + B v_{k+i|k} \quad (19)$$

With$z_{k|k} = \hat{x}_k$.

The state constraints are shown in Eq. (20)

$$x_{\min} + \epsilon_i \leq z_{k+i|k} \leq x_{\max} - \epsilon_i \quad (20)$$

and the control constraints are in Eq. (21)

$$u_{\min} \leq v_{k+i|k} \leq u_{\max} \quad (21)$$

The weighting matrices are in Eq. (22)

$$Q = \begin{bmatrix} 10 & 0 \\ 0 & 1 \end{bmatrix},\ R = 0.1,\ P = Q \qquad (22)$$

The prediction horizon is $N = 10$. The important computational property is that the optimizer itself remains a conventional quadratic program. The network-related calculations consist of state reconstruction and evaluation of precomputed uncertainty margins. Thus, the communication delay affects the initial condition and constraint bounds without requiring the QP to optimize over delayed-state trajectories or explicit disturbance policies. This is the intended low-complexity feature of the proposed controller.

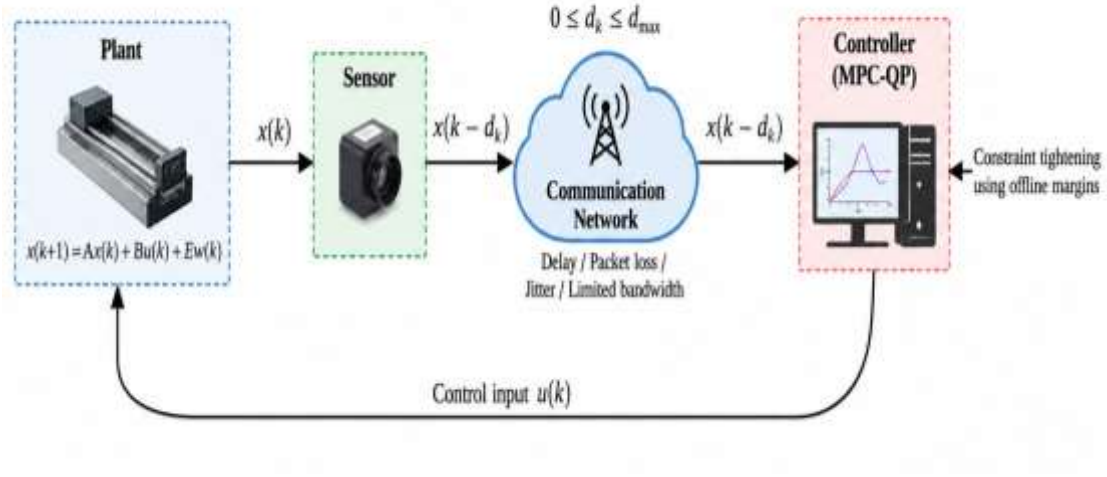


Figure 2. Networked control architecture

Table 2. Simulation configuration

Parameter	**Value**
Sampling time	0.1 s
Prediction horizon	10
Simulation duration	15 s
Maximum communication delay	5 samples
Maximum physical delay	0.5 s
Disturbance bound	0.01
Position constraint	$[-, 22]$
Velocity constraint	$[-, 33]$
Control constraint	$[-, 11]$
Position weight	10
Velocity weight	1
Input weight	0.1
Reference position	1.0 m
Initial state	$[0, 0]^T$

4. Simulation Results and Analysis

The proposed controller was evaluated over a 15 s simulation using the parameters in Table 2. The maximum communication delay was five samples, corresponding to 0.5 s, while the additive disturbance was bounded by 0.01in the infinity norm. A conventional MPC controller using the delayed state without the proposed uncertainty compensation was used as the comparison case. Both controllers used the same plant model, prediction horizon, state and input constraints, weighting matrices, referenceand initial state. The comparison therefore focuses on the effect of the proposed delay reconstruction and uncertainty-aware constraint tightening rather than differences in nominal MPC tuning.

4.1 Tracking Performance

The position response is shown in Figure 3. The proposed controller reaches the desired position while maintaining a substantially closer trajectory to the reference than the conventional delayed-state MPC. The improvement is not produced by simply increasing the control effort. Instead, the robust controller modifies the feasible prediction region before the optimization is solved, preventing the optimizer from selecting nominal trajectories that rely excessively on an uncertain state estimate.

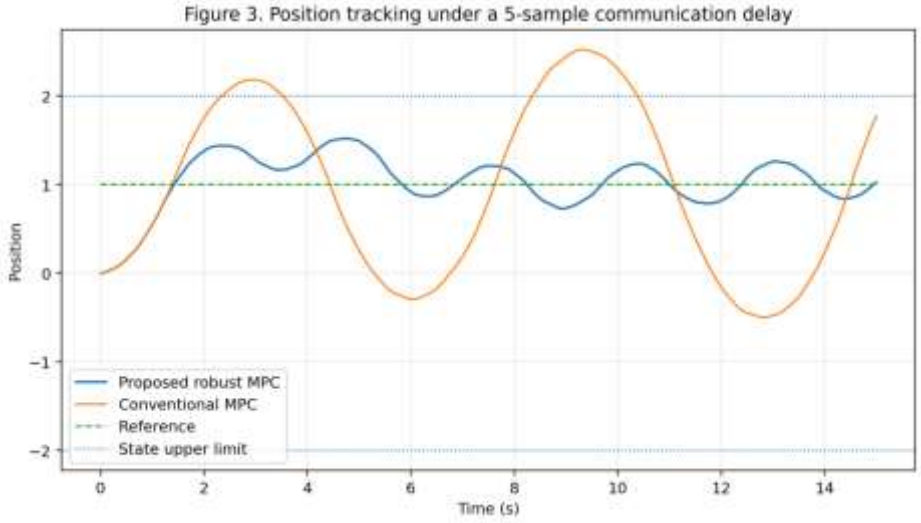


Figure 3. Position tracking under five-sample maximum communication delay

In the case of the proposed controller, the RMSE is 0.3174, while in the case of conventional MPC, it equals 0.9723; the integrated absolute error drops from 13.2166 to 3.6708, which is a decrease of approximately 72.2%. As both controllers utilize identical models and objectives, the improvement is related to the explicit incorporation of the communication uncertainty into the process of state reconstruction and constraint handling. For example, conventional MPC can consider a delayed measurement as the actual state of the plant and take corresponding actions that can be wrong or too aggressive and then fix them. Meanwhile, the proposed controller takes into account the bounded uncertainty in the process of state reconstruction and tightens physical constraints. The uncertainty bound also depends on the horizon – in the case of the chosen five-sample delay, the uncertainty bound grows as the prediction proceeds.

4.2 Constraint Satisfaction

Constraint protection is one of the clearest differences between the two controllers. The conventional MPC produced an accumulated position violation magnitude of 8.3093 during the simulation, whereas the proposed controller produced zero accumulated position violation. The maximum absolute position reached 2.6112 for conventional MPC, exceeding the specified physical limit of 2, while the proposed controller reached a maximum absolute position of 1.5179.The result follows directly from the constraint-tightening mechanism. Conventional MPC imposes in Eq. (23)

$$-2 \leq z_{k+i|k} \leq 2 \qquad (23)$$

on the nominal trajectory implicitly if the nominal prediction represents the physical state accurately. Under communication delay and disturbances, this assumption is not guaranteed. The proposed controller instead imposes in Eq. (24)

$$-2 + \epsilon_i \leq z_{k+i|k} \leq 2 - \epsilon_i \qquad (24)$$

Consequently, the nominal trajectory is deliberately prevented from approaching the physical boundary by an amount related to the uncertainty at each stage. The resulting behavior is therefore not an accidental improvement caused by reduced actuation, it follows from the mathematical relationship between the error bound and the tightened feasible set.

4.3 Control Effort

The control-energy measure was calculated as in Eq. (25)

$$E_u = \sum_k u_k^2 \qquad (25)$$

The proposed controller achieved a slightly lower accumulated control energy of 14.2814 compared with 14.6324 for conventional MPC. Thus, improved tracking and constraint protection were not obtained through substantially higher control effort. Instead, state reconstruction and uncertainty-aware feasibility improved control timing, reducing unnecessary corrective actions caused by delayed and inconsistent state information.

Table 3. Main simulation results

Metric	**Conventional MPC**	**Proposed robust MPC**
Position RMSE	0.9723	0.3174
IAE	13.2166	3.6708
Control energy	14.6324	14.2814
Accumulated position violation	8.3093	0.0000
Average QP time	1.8707 ms	1.6429 ms
Maximum position magnitude	2.6112	1.5179

4.4 Computational Performance

An important objective of the proposed formulation is to introduce robustness without significantly increasing online optimization complexity. The measured average QP solution time was 1.6429 ms for the proposed controller, compared with 1.8707 ms for conventional MPC. These values are implementation-dependent and should not be treated as hardware-independent measures. More importantly, the proposed formulation preserves the same MPC state dimension as the maximum delay increases, because delay-dependent uncertainty is computed offline rather than represented through additional delayed state variables in the online optimization.

As illustrated in Figure 4, computational performance has been obtained when the assumed maximum delay is varied. The model keeps the same MPC state dimension even as $d_{\max}$ the assumed maximum delay increases, since the offline computation of the MPC uncertainty is affected, not the introduction of delayed states.

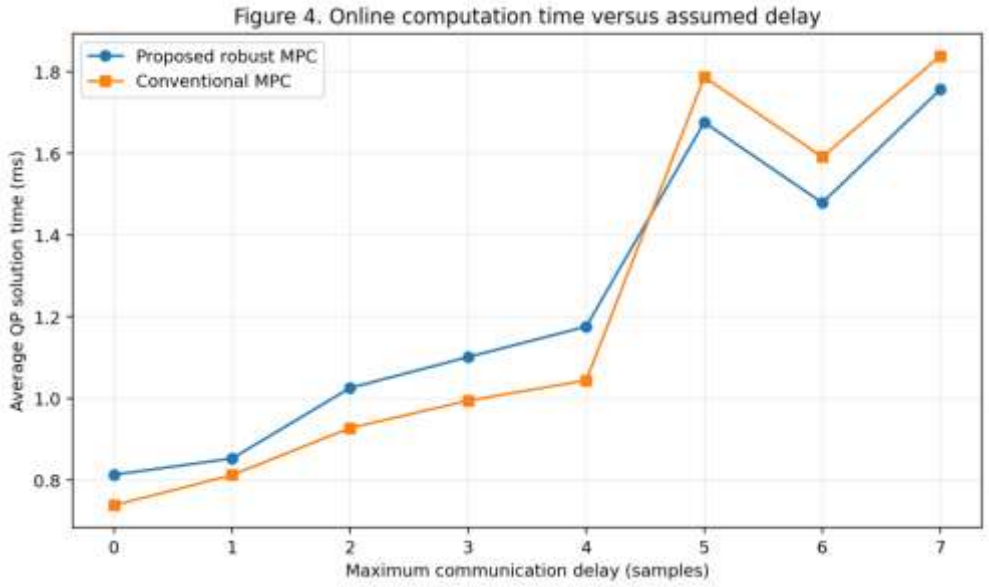


Figure 4. Computational behavior with varying assumed maximum delay

What makes the present approach different from augmented state methods is that the number of delayed states could increase in relation to the maximum possible delay. While the present approach does not exclude delay-dependent state reconstruction in the controller, it does make this procedure somewhat different from that in the case of augmented state formulation, as it involves matrix multiplication and addition and does not involve increased dimensions of the optimization vector.

5. Discussion

These numerical results show three inter-related benefits of the proposed mathematics. Firstly, state reconstruction improves the discrepancy arising due to the use of the outdated measurement in place of the current measurement. Secondly, this reconstruction error is no longer treated as such but is explicitly turned into an uncertainty bound. Thirdly, this uncertainty bound is carried along the prediction horizon and is used to alter the feasible nominal state domain. The mathematics offers an interpretable link between communication quality and conservatism of the controller. When the maximum delay $d_{\max}$is increased, the initial uncertainty bound Eq. (26)

$$\epsilon_0 = \bar{w} \sum_{\ell=0}^{d_{\max}-1} \| A^{\ell} E \|_{\infty} \quad (26)$$

Typically, the uncertainty margin expands as more disturbances are added due to the increase in prediction horizon length. As a result, the feasible set that is contracted will get smaller; hence, the controller design will become more conservative under unfavorable communication. On the other hand, an improvement in either of these parameters without changing the controller design decreases the uncertainty margin.

It offers an application-specific interface for relating communications and control constraints. A designer for the network can specify a constraint on the upper limit of delay, which can be mathematically expressed in terms of a state uncertainty margin by the controller designer. The margin in turn decides the amount of physical operating space available to the optimizer of the MPC scheme.

This methodology entails a certain trade-off due to the fact that the norm-based bound is generally conservative. The infinite norm considers each element of the state vector under the worst-case independent bounds and does not utilize correlation between position and velocity uncertainties. Furthermore, the computation involves the maximum possible delay for communication rather than an instantaneous delay if it is less than the former. This conservatism is intentional in order to keep an online controller simple.

The proposed method is not meant to be a total solution for all situations involving the control of a networked system. Situations in which there are packet losses, significant levels of out-of-order measurement signals, delayed actuators, or stochastically distributed delays that do not have any deterministic upper bound will need additional work. Nonlinear systems might also need linearization or prediction techniques.In the case of the double integrator application, the physical significance is clear: position is obtained from the integration of velocity, and therefore, any delay in velocity data would cause growing uncertainty about the position, given that the system continues evolving without measurements.

The absence of accumulated position violation is indicative of the importance of including constraint protection within the delay compensation approach. Furthermore, parameters like uncertainty bounds can be computed offline, with the online controller taking care of the state estimation, QP solving, and control input application (Tang et al., 2015). The numerical results confirm this conclusion: RMSE goes from 0.9723 to 0.3174, IAE from 13.2166 to 3.6708, and there is no more accumulated position violation, while the control energy varies little.

6. Conclusion

The paper has proposed a novel low-complexity robust MPC scheme for linear networked control systems with bounded delays and disturbances. The key feature here is the avoidance of augmentation of the physical plant with delay-dependent states and the decomposition of state prediction and uncertainty representation into two separate parts. Delayed measurements are passed through the existing physical model using the control sequence obtained up to the moment to estimate the current state. The difference between the estimated and real state is computed as a finite convolution of disturbances and represented in terms of the induced norm.

The generated uncertainty will be propagated over the prediction horizon via the dynamics of the system along with the bound on the disturbance magnitude to obtain the set $\bar{e}_0, \ldots, \bar{e}_N$. This is achieved via stage-dependent constraint tightening without increasing the dimension of the state space in the quadratic program format. Consequently, the dimension of the online state space will not grow with the maximum communication delay. The primary innovation lies in combining the prediction aspect with constraint tightening for delay awareness.

In the case of a maximum delay of five sampling instants and under the disturbance constraint provided, the RMSE for position using the suggested control scheme was 0.3174, whereas that for traditional MPC was 0.9723. The value of IAE was reduced from 13.2166 to 3.6708 and the position error sum went down from 8.3093 to zero. Maximum position was reduced from 2.6112 to 1.51.

The scheme has its drawbacks, such as the conservative nature of the worst-case bounds based on norms, the lack of consideration for the time delays of the actuators, losses of packets, non-linear system dynamics and the stochastic nature of the network. The next step is to incorporate delay-dependent margins, time delays of actuators, packet loss prediction, uncertainty sets and non-linear models. On the whole, the approach offers a reasonable compromise between standard MPC and robust networked MPC.

References

1. Beger, S., & Hirche, S. (2024). A robust model predictive control method for networked control systems. *Proceedings of the 2024 IEEE 63rd Conference on Decision and Control*, 6896–6903. https://doi.org/10.1109/CDC56724.2024.10886340

2. Ghorbani, S., Safavi, A. A., & Naghavi, S. V. (2021). Event-triggered robust model predictive control for Lipschitz nonlinear networked control systems subject to communication delays. *Transactions of the Institute of Measurement and Control, 43*(5). https://doi.org/10.1177/0142331220969058

3. Goulart, P. J., Kerrigan, E. C., & Maciejowski, J. M. (2006). Optimization over state feedback policies for robust control with constraints. *Automatica, 42*(4), 523–533. https://doi.org/10.1016/j.automatica.2005.08.023

4. Hespanha, J. P., Naghshtabrizi, P., & Xu, Y. (2007). A survey of recent results in networked control systems. *Proceedings of the IEEE, 95*(1), 138–162. https://doi.org/10.1109/JPROC.2006.887288

5. Langson, W., Chryssochoos, I., Raković, S. V., & Mayne, D. Q. (2004). Robust model predictive control using tubes. *Automatica, 40*(1), 125–133.

6. Mao, Y., Liu, S., & Liu, J. (2020). Robust economic model predictive control of nonlinear networked control systems with communication delays. *International Journal of Adaptive Control and Signal Processing, 34*(5), 614–637. https://doi.org/10.1002/acs.3103

7. Mayne, D. Q., Rawlings, J. B., Rao, C. V., & Scokaert, P. O. M. (2000). Constrained model predictive control: Stability and optimality. *Automatica, 36*(6), 789–814. https://doi.org/10.1016/S0005-1098(99)00214-9

8. Mayne, D. Q., Seron, M. M., & Raković, S. V. (2005). Robust model predictive control of constrained linear systems with bounded disturbances. *Automatica, 41*(2), 219–224. https://doi.org/10.1016/j.automatica.2004.08.019

9. Montestruque, L. A., & Antsaklis, P. J. (2003). On the model-based control of networked systems. *Automatica, 39*(10), 1837–1843. https://doi.org/10.1016/S0005-1098(03)00186-9

10. Razavinasab, Z., Farsangi, M. M., & Barkhordari, M. (2018). Robust output feedback distributed model predictive control of networked systems with communication delays in the presence of disturbance. *ISA Transactions, 80*, 12–21. https://doi.org/10.1016/j.isatra.2018.07.003

11. Scokaert, P. O. M., & Mayne, D. Q. (1998). Min-max feedback model predictive control for constrained linear systems. *IEEE Transactions on Automatic Control, 43*(8), 1136–1142. https://doi.org/10.1109/9.704989

12. Tang, X.-M., & Ding, B.-C. (2012). Design of networked control systems with bounded arbitrary time delays. *International Journal of Automation and Computing, 9*(2), 182–190. https://doi.org/10.1007/s11633-012-0632-6

13. Tang, X., Qu, H., Wang, P., & Zhao, M. (2015). Constrained off-line synthesis approach of model predictive control for networked control systems with network-induced delays. *ISA Transactions, 55*, 135–144. https://doi.org/10.1016/j.isatra.2014.11.007

14. Megat Sufian. (2026). Hybrid Solar–RF Energy Harvesting Architecture for Self-Sustaining Wireless Sensor Networks. *Journal of Wireless Sensor Networks and IoT*, *3*(2), 36-41.

15. Walsh, G. C., Ye, H., & Bushnell, L. G. (2002). Stability analysis of networked control systems. *IEEE Transactions on Control Systems Technology, 10*(3), 438–446. https://doi.org/10.1109/87.998034

16. Yang, H., Guo, X., Dai, L., & Xia, Y. (2018). Event-triggered predictive control for networked control systems with network-induced delays and packet dropouts. *International Journal of Robust and Nonlinear Control, 28*, 1350–1365. https://doi.org/10.1002/rnc.3958

17. Zhang, W., Branicky, M. S., & Phillips, S. M. (2001). Stability of networked control systems. *IEEE Control Systems Magazine, 21*(1), 84–99. https://doi.org/10.1109/37.898794

18. Zhang, Y., Wang, X., Ge, X., & Wang, J. (2014). Robust distributed model predictive control for uncertain networked control systems. *IET Control Theory & Applications, 8*, 1843–1851. https://doi.org/10.1049/iet-cta.2014.0311

19. Zhou, Y., Ma, Y., Cen, J., Ma, X., & Peng, X. (2024). Tube-based model predictive control for linear systems with bounded disturbances and input delay. *ISA Transactions, 150*, 56–66. https://doi.org/10.1016/j.isatra.2024.04.030