Model predictive control of arterial traffic networks: A positive system approach

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Short summary

This paper proposes a model predictive control approach to alleviate traffic congestion in urban arterials within a positive systems framework. The prediction model is based on a cumulative store-and-forward formulation, representing arterial network dynamics through cumulative link inflows and outflows. A piecewise affine outflow function is adopted, with switching conditions determined solely by current and predicted cumulative flows, ensuring the active mode is independent of the optimization variables. The network-wide traffic signal control problem, including all constraints, is formulated as an optimization problem with a linear objective function maximizing cumulative arterial outflow, with green times as control variables. Numerical results indicate that the proposed method reduces average travel time by 39.3% compared to fixed-time control and decreases mean solver computation time by 42 seconds per cycle compared to a quadratic objective formulation, confirming real-time applicability on the Nicholson arterial in Melbourne, Australia.
Keywords: Positive Systems, Cumulative Store-and-Forward Model, Switching Model Predictive Control

1 Introduction

Traffic congestion in urban networks has become a significant challenge, primarily due to inefficient use of infrastructure and network capacity, leading to extended delays, reduced efficiency, and increased air pollution. To address these challenges, several Traffic Signal Control (TSC) methods have been developed Papageorgiou et al. (2003), classified into fixed-time Webster (1958) and traffic-responsive approaches. Fixed-time methods determine signal timing based on historical data and do not adapt to real-time traffic variations, whereas traffic-responsive methods dynamically compute green times based on real-time traffic conditions.

Among traffic-responsive strategies, Store-and-Forward Model (SFM)-based methods, initially developed by Gazis et al. (1963), have shown strong performance in oversaturated conditions while also mitigating measurement inaccuracies Aboudolas et al. (2009, 2010). In particular, several extensions have been proposed, including probabilistic constraints to reduce spillback risk Stoilova & Stoilov (2023), decentralized formulations based on various SFM dynamics Pedroso & Batista (2021); Pedroso et al. (2024), and data-driven and feedback-based approaches combining Kalman filtering, LQR, and learning-based control Pedroso et al. (2024); Liu et al. (2022).

However, most existing SFM-based approaches Aboudolas et al. (2009, 2010); Pedroso & Batista (2021); Pedroso et al. (2024) rely on a simplified representation in which the model time step equals the signal cycle time. To address these limitations and improve real-time applicability, rolling-horizon MPC frameworks have been introduced, including nonlinear outflow models to better capture intra-cycle dynamics Aboudolas et al. (2010). In this context, while MPC is effective for handling input and output constraints Qin & Badgwell (2003), and linear programming-based formulations are more tractable than conventional quadratic MPC Zhang et al. (2016, 2020), the resulting nonlinear outflow leads to non-convex and nonlinear optimization problems that are computationally intractable for large-scale networks. More recently, linear time-varying formulations have been proposed, where outflows correspond to vehicles discharged during the effective green time, together with mappings to equivalent LTI representations Najafabadi & Haeri (2025).

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Therefore, a key challenge in SFM-based MPC for traffic networks is the computational tractability of the resulting optimization problem. Since cumulative inflow and outflow of network links are inherently nonnegative, traffic network dynamics can be naturally cast as a positive system Farina & Rinaldi (2011), where stability can be established using linear copositive Lyapunov functions rather than quadratic ones Rantzer (2015). This structure enables the MPC problem to be reformulated as an optimization problem with linear objective function Zhang et al. (2016), which is more scalable for network-wide traffic signal control. Furthermore, MPC frameworks for positive systems with disturbances Zhang et al. (2015) show that this structure facilitates robust stability analysis Colombino & Smith (2016) and controller synthesis Shen & Lam (2016), making it particularly well suited for receding-horizon control of arterial traffic networks.
This paper develops a switching MPC framework for arterial traffic networks that explicitly accounts for queue spillback while improving computational tractability through a positive systems formulation of traffic dynamics. The proposed MPC incorporates cycle length constraints, minimum and maximum green time constraints for each phase, and a fixed, predefined phase sequence. The contributions of this paper are as follows:

- We propose a cumulative SFM-based MPC formulation using cumulative link inflows and outflows, yielding a positive-system representation with non-negative state evolution.
- The proposed traffic signal control method is based on a piecewise affine outflow model of network links that captures limited storage capacity and queue spillback effects. The switching mode sequence is driven exclusively by current and predicted traffic states rather than optimization variables, ensuring that the active mode is determined independently of the control inputs.
- The positive-system structure enables the MPC problem to be reformulated as a constrained maximization problem with a linear objective function that maximizes network cumulative outflow, improving computational efficiency compared to conventional quadratic optimization frameworks.

The remainder of this paper is organized as follows. Section 2 presents the cumulative store-and-forward model and its positive-system formulation, then develops the switching MPC framework, including the piecewise affine outflow model and the linear objective function-based optimization problem. Section 3 describes the simulation setup and presents the results for the Nicholson arterial in Melbourne. Section 4 concludes the paper.

2 Methodology

The optimal TSC method proposed in this paper is based on the cumulative SFM model of traffic networks. This section explains the cumulative formulation, in which cumulative refers to the total accumulated count over time from the beginning of the control period. The goal is to reformulate the system dynamics as a positive system, a class of dynamical systems formally characterized as follows.

Definition 1 (Farina & Rinaldi (2011)**)** *The state space realization of a discrete-time LTI system* $(\mathcal{A}, \mathcal{B}, \mathcal{C}, \mathcal{D})$*, governed by*

$$\begin{aligned} x(k+1) &= \mathcal{A}x(k) + \mathcal{B}u(k), \\ y(k) &= \mathcal{C}x(k) + \mathcal{D}u(k), \end{aligned} \tag{1}$$

is called internally positive *if and only if* $\mathcal{A} \geq 0$*,* $\mathcal{B} \geq 0$*,* $\mathcal{C} \geq 0$*, and* $\mathcal{D} \geq 0$*, i.e., all system matrices are elementwise nonnegative. Equivalently, the system* (1) *is positive if and only if for every nonnegative initial state* $x(0) \geq 0$ *and every nonnegative input* $u(k) \geq 0$*, the state* $x(k)$ *and output* $y(k)$ *remain nonnegative for all* $k \geq 0$*.*

Cumulative Store-and-Forward model

The urban traffic network is modeled as a directed graph $\mathcal{G} = (\mathcal{J}, \mathcal{Z})$, where the nodes $j \in \mathcal{J} = \{1, 2, \ldots, J\}$ represent the signalized intersections and the edges $z \in \mathcal{Z} \subseteq \mathcal{J} \times \mathcal{J} = \{1, 2, \ldots, Z\}$ represent the links of the network. The tail and head of an edge z are denoted as τ_z and σ_z, respectively, i.e., $z = (\tau_z, \sigma_z)$. For link z, the set of downstream links is $\mathcal{Z}^+(z) := z' \in \mathcal{Z} : \tau_{z'} = \sigma_z$.

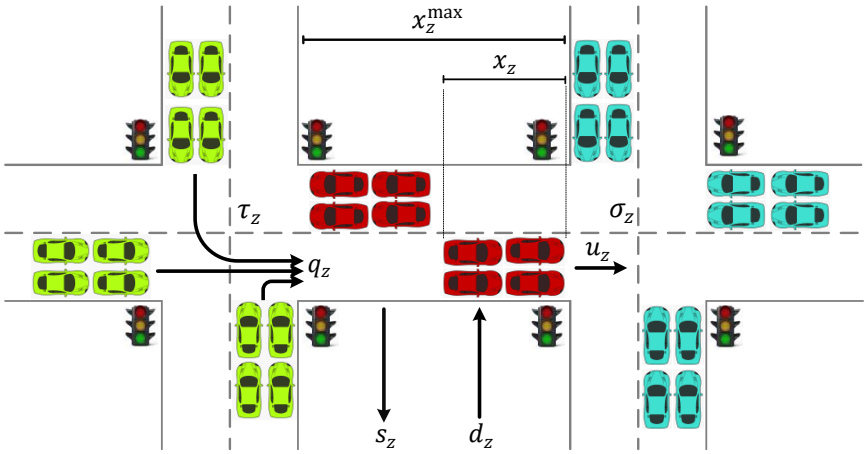


Figure 1: An urban road link connecting two intersections

For any signalized intersection j, we denote incoming links $\mathcal{I}_j$ and outgoing links $\mathcal{O}_j$. The signal control policy at intersection j, with lost time L_j and cycle time C_j, is based on phases belonging to set Φ_j. The saturation flow S_z of link z, and the turning rates $t_{w,z}$, where $w \in \mathcal{I}_j$ and $z \in \mathcal{O}_j$, are assumed to be known and constant for the control paradigm. The green time of phase i at intersection j, denoted by $g_{j,i}$, must satisfy the following constraint

$$g_{j,i}^{\min} \leq g_{j,i} \leq g_{j,i}^{\max}, \quad i \in \Phi_j \tag{2}$$

where $g_{j,i}^{\min}$, $g_{j,i}^{\max} \in \mathbb{R}$ are, respectively, the minimum and maximum acceptable green times for phase i. The green times of all phases at intersection j should satisfy the constraints

$$\sum_{i \in \Phi_j} g_{j,i} + L_j = C_j, \quad \forall j \in \mathcal{J}. \tag{3}$$

We now consider link z, connecting two intersections τ_z and σ_z, such that $z \in \mathcal{O}_{\tau_z}$ and $z \in \mathcal{I}_{\sigma_z}$. As shown in Figure 1, $d_z(k)$ and $u_z(k)$ denote the external inflow demand and outflow of link z at discrete time index $k \in \mathbb{N}$. The total inflow to link z at time step k is given by $q_z(k) = \sum_{w \in \mathcal{I}_{\tau_z}} t_{w,z}\, u_w(k)$, where $t_{w,z}$, with $w \in \mathcal{I}_{\tau_z}$, denotes the turning rate from link w to link z at junction τ_z. The exit flow from link z is modeled as $s_z(k) = t_{z,0}\, q_z(k)$, where $t_{z,0}$ is the constant exit rate from link z. Hence, substituting $q_z(k)$ into $s_z(k)$ gives $s_z(k) = t_{z,0} \sum_{w \in \mathcal{I}_{\tau_z}} t_{w,z}\, u_w(k)$. The dynamics of the cumulative inflow of link z at time step $k+1$, $n_z^{\text{in}}(k+1)$, can be modeled as

$$n_z^{\text{in}}(k+1) = n_z^{\text{in}}(k) + T_{\text{s}} \left((1 - t_{z,0}) \sum_{w \in \mathcal{I}_{\tau_z}} t_{w,z} u_w(k) \right) + T_{\text{s}} d_z(k), \tag{4}$$

which can be rewritten, after algebraic manipulation, in compact form including the cumulative inflows of all links as

$$N^{\text{in}}(k+1) = A N^{\text{in}}(k) + B_{\mathcal{U}}^{\text{in}} U(k) + T_{\text{s}} D^{\text{in}}(k), \tag{5}$$

where $N^{\text{in}} = \text{col}\left((n_z^{\text{in}})_{z \in \mathcal{Z}}\right)$, $U = \text{col}\left((u_z)_{z \in \mathcal{Z}}\right)$, $D^{\text{in}} = \text{col}\left((d_z)_{z \in \mathcal{Z}}\right)$, $A = \mathbf{I}_Z$, and $B_{\mathcal{U}}^{\text{in}} = T_{\text{s}}\big((\mathbf{I}_Z - \text{diag}(\mathbf{t_0}))\, \mathbf{T} \big)$, where $\mathbf{T}$ is computed as

$$[\mathbf{T}]_{zw} := \begin{cases} t_{w,z}, & w \in \mathcal{I}_{\tau_z}, \\ 0, & w \notin \mathcal{I}_{\tau_z}, \end{cases} \quad z, w \in \mathcal{Z}. \tag{6}$$

Furthermore, the dynamics of the cumulative outflow of link z at time step $k+1$, $n_z^{\text{out}}(k+1)$, can be modeled by the equation

$$n_z^{\text{out}}(k+1) = n_z^{\text{out}}(k) + T_{\text{s}} u_z(k), \tag{7}$$

where $u_z(k)$, the outflow of link z, is formulated as follows:

$$u_z(k) = \begin{cases} 0, & \text{if any } x_{z'}(k) \geq c_g x_{z'}^{\max},\ z' \in \mathcal{Z}^+(z) \\ \dfrac{x_z(k)}{T_{\text{s}}}, & \text{else if } \dfrac{x_z(k)}{T_{\text{s}}} < \dfrac{G_z^{\min} S_z}{C_{\sigma_z}} \\ \dfrac{G_z(k) S_z}{C_{\sigma_z}}, & \text{else} \end{cases} \tag{8}$$

where $x_z(k) = n_z^{\text{in}}(k) - n_z^{\text{out}}(k)$ is the number of vehicles in link z, and C_{σ_z} indicates the cycle time of the downstream intersection σ_z. The total green time of link z, $G_z(k)$, is computed as $G_z(k) = \sum_{i \in \mathcal{V}_z} g_{j,i}(k)$, where $\mathcal{V}_z$ is the set of phases that give link z the right of way. The parameter c_{g} should be tuned to adjust the sensitivity of gating. Using (8), we can model queue spillback in the downstream link of link z. If the downstream link $z' \in \mathcal{Z}^+(z)$ is at full capacity, it may prevent vehicles from moving forward from link z. This blockage propagates upstream, restricting outflow in preceding links and potentially causing congestion across multiple links.
Following the same procedure as for the inflow case, the cumulative outflow dynamics can be written, after algebraic manipulation, in compact form as follows:

$$N^{\text{out}}(k+1) = AN^{\text{out}}(k) + B_{\mathcal{U}}^{\text{out}} U(k), \tag{9}$$

where $N^{\text{out}} = \text{col}\left((n_z^{\text{out}})_{z \in \mathcal{Z}}\right)$ and $B_{\mathcal{U}}^{\text{out}} = T_{\text{s}} \mathbf{I}_Z$. Having the cumulative inflow and outflow of all network links, the augmented compact form of the traffic dynamics can be defined as the centralized multiple-output state and multiple-input control vectors as

$$N(k+1) = \mathcal{A}\, N(k) + \mathcal{B}_{\mathcal{U}}\, U(k) + D(k), \tag{10}$$

where the augmented state vector and matrices are defined as $N(k) = \left[\, N^{\text{in}}(k)^\top \quad N^{\text{out}}(k)^\top \,\right]^\top$, $\mathcal{B}_{\mathcal{U}} = \left[(B_{\mathcal{U}}^{\text{in}})^\top \quad (B_{\mathcal{U}}^{\text{out}})^\top\right]^\top$, $D(k) = \left[D^{\text{in}}(k)^\top \quad \mathbf{0}^\top\right]^\top$, and $\mathcal{A} = \begin{bmatrix} A & \mathbf{0} \\ \mathbf{0} & A \end{bmatrix}$. Since all elements of the system matrices in (10) are nonnegative, and for every nonnegative initial state $N(0) \geq 0$ and every nonnegative input $U(k) \geq 0$ the state $N(k)$ remains nonnegative for all $k \geq 0$, the cumulative SFM model is a positive system according to Definition 1.

Model Predictive Control

The primary objective of the proposed predictive TSC method is to maximize network outflow while accounting for the cumulative system dynamics described in (10) and the green time constraints defined in (2) and (3). To this end, the following objective function is proposed:

$$J(k) = \sum_{\tau=1}^{N_p} q^\top N^{\text{out}}(k+\tau \mid k), \tag{11}$$

where $\tau \in \{1, \ldots, N_p\}$ denotes the prediction step index, N_p is the prediction horizon, and the weighting vector is given by $q = \text{col}\left(\frac{1}{x_z^{\max}}\right)_{z \in \mathcal{Z}}$.
In the proposed MPC framework, the prediction problem is complicated by the piecewise affine nature of the outflow function $u_z(k)$ in (8). Specifically, the active subsystem at time step k is determined by the current state $x_z(k)$ and the downstream occupancy $x_{z'}(k)$, where $z' \in \mathcal{Z}^+(z)$. However, the subsystems activated at future prediction steps $\{k+1, \ldots, k+N_p\}$ depend on the applied control sequence $\{\mathbf{g}(k), \ldots, \mathbf{g}(k+N_u-1)\}$, which are the decision variables of the predictive TSC method, where N_u denotes the control horizon, and $\mathbf{g}(k) = \text{col}\left((g_{j,i}(k))_{i \in \Phi_j, j \in \mathcal{J}}\right)$ is the green time vector at time step k. Only the initial active subsystem $M(k)$, determined by the current state, is known a priori. In general, a sequence of subsystems $\mathcal{M} = \{M(k), M(k+1), \ldots, M(k+N_p)\}$ is activated over the prediction horizon, resulting in up to 3^{N_p-1} possible mode sequences, since $u_z(k)$ admits three modes. To address this, the sequence $\mathcal{M}$ is incorporated as an additional decision variable in the optimization problem.

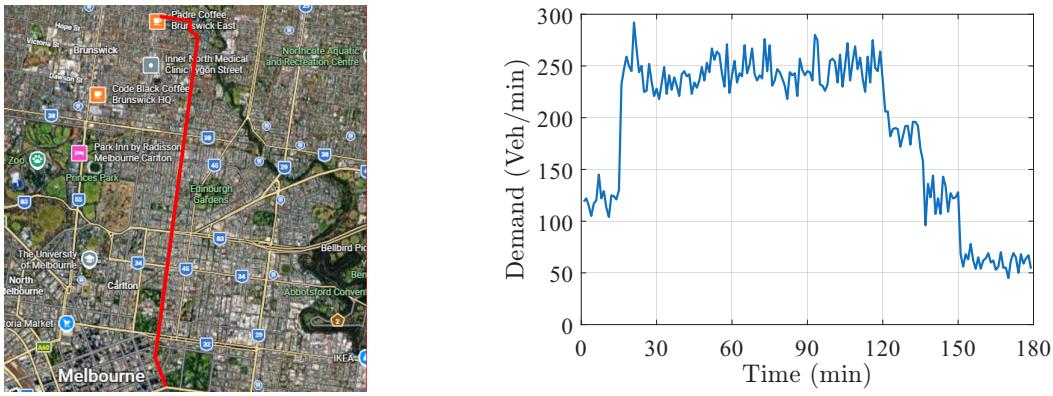
$$\{\mathbf{g}^*(k), \ldots, \mathbf{g}^*(k+N_u-1)\} = \arg\left(\underset{\mathbf{g}(k),\, \mathcal{M}}{\text{maximize}} \sum_{\tau=1}^{N_p} q^\top N^{\text{out}}(k+\tau|k)\right) \tag{12}$$

$$\begin{aligned} \text{subject to} \quad & \text{Cumulative Store-and-Forward dynamics (10)} \\ & \text{Green time constraints (2) and (3)} \\ & N^{\text{in}}(0) \text{ and } N^{\text{out}}(0) \text{ given.} \end{aligned}$$

In the studied problem, predictions of external traffic demands $D(k)$ are assumed to be available over the prediction horizon $\tau \in \{1, \ldots, N_p\}$. In practice, however, such predictions are highly uncertain; therefore, the green times computed by solving (12) should not be applied in an open-loop manner. Instead, they should be implemented in a receding horizon fashion to mitigate the effects of demand uncertainty.

3 Results and discussion

The simulations are carried out in the AIMSUN microsimulation environment. To evaluate the proposed MPC approach, the Nicholson arterial in Melbourne, comprising 28 signalized intersections and 100 phases, is considered. The upper and lower bounds for the green time duration are set to $g^{\min} = 10$ s and $g^{\max} = 100$ s. Furthermore, the cycle times of the intersections are set to $C = 120$ s. The prediction horizon N_p is set to 10 cycle times and the control horizon N_u is set to 5 cycle times. For the sake of brevity, we exclude detailed information on lost times L_j, saturation flows S_z, and turning rates $t_{w,z}$. The parameter c_g is set to 0.85, and the sampling time T_s is chosen as $5s$. Five simulation replications are conducted using different random seeds. The optimization problem 12 is solved by the Interior Point Optimizer (IPOPT) provided by the CasADi library Andersson et al. (2019). In the following, we compare the performance of the proposed MPC with that of a fixed time controller. For each control strategy, the evaluation metrics, including total travel time, total number of stops, and average speed, are computed for comparison.



(a) Nicholson Arterial

(b) Trapezoidal demand profile

Figure 2: Test case network: (a) map of Nicholson arterial; (b) Trapezoidal demand profile

Table 1 presents a comparison of the proposed MPC and fixed time control across three performance metrics. The proposed MPC reduces total travel time by 39.3%, increases the average network speed by 18.5%, and decreases the total number of stops by 16.7% compared to fixed time control. These results collectively demonstrate the effectiveness of the proposed positive systems based MPC in improving network wide traffic performance by preventing congestion, reducing travel time, and minimizing unnecessary stops across the Nicholson arterial network.

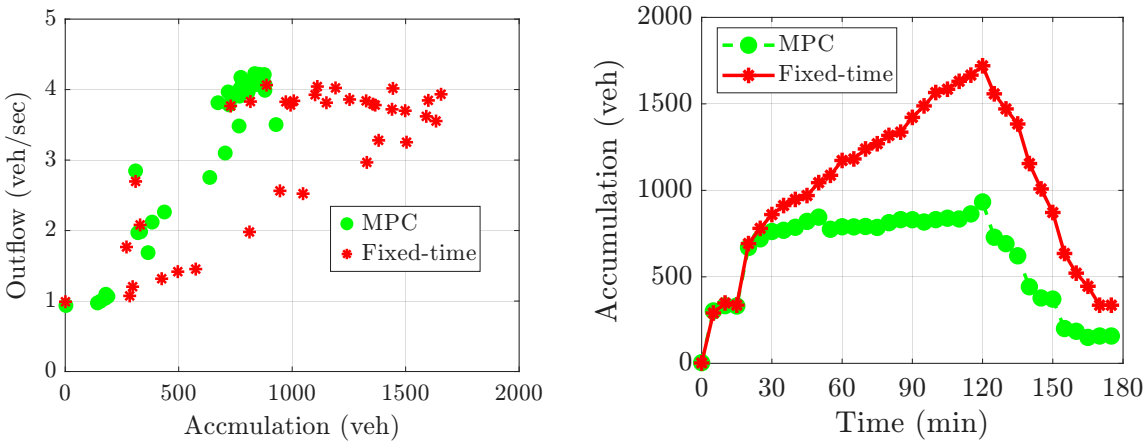
Table 1: Performance comparison of MPC and fixed-time control

Metric	**MPC**	**Fixed Control**
Total Travel Time (h)	1928	3174
Speed (km/h)	17.34	14.63
Total Number of Stops	90×10^3	108×10^3

Figure 3a depicts the outflow MFD for the MPC and fixed-time TSC methods, with data points computed every 5 minutes. The MPC method achieves higher peak outflow at lower accumulation compared to fixed-time control, operating near the critical accumulation of approximately 900 vehicles. In contrast, fixed-time control fails to prevent the network from entering the congested regime, where outflow decreases significantly due to spillback propagation across network links, with accumulation growing beyond 1700 vehicles.

The total number of vehicles in the network for the MPC and fixed-time TSC methods is shown in Figure 3b. Under fixed-time control, the total number of vehicles increases significantly, as this method is incapable of reducing or preventing queue spillback, which reduces network outflow and drives the network into congestion. In contrast, the proposed MPC stabilizes the network by maintaining accumulation below 1000 vehicles and subsequently discharging the network after $t = 120$ min as inflow demand decreases, demonstrating the effectiveness of the positive systems-based formulation in preventing gridlock.

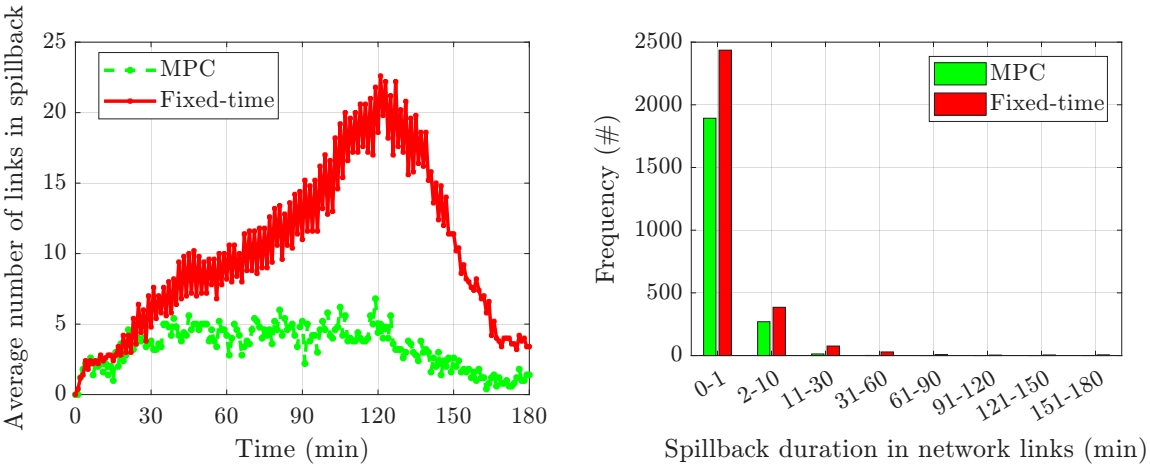
The results in Figure 4a demonstrate the superior performance of the proposed MPC, which



(a) MFD

(b) Total number of vehicles in the network

Figure 3: (a) MFD and (b) total number of vehicles. MPC maintains the network in the uncongested region of the MFD with accumulation below 1000 vehicles, successfully discharging the network after t = 120 min. MPC achieves higher peak outflow at lower accumulation compared to fixed-time control. Fixed-time control fails to prevent congestion, allowing accumulation to grow beyond 1700 vehicles, resulting in reduced outflow.



(a) Average number of links in spillback measured every minute

(b) Frequency of spillback duration in network links

Figure 4: (a) Average number of links in spillback: MPC keeps spillback around 5 links, while fixed-time show progressive spillback growth reaching over 20 links. (b) Spillback duration frequency: MPC limits spillback to short durations (0-10 min), whereas fixed-time exhibit extended spillback events lasting up to 60 minutes.

significantly reduces the number of network links experiencing spillback. Here, spillback is defined as the condition in which the number of vehicles in a link exceeds 80% of its maximum storage capacity. The proposed MPC method keeps the average number of links in spillback around 5 links throughout the simulation, whereas fixed-time control shows progressive spillback growth reaching over 20 links, indicating the network is pushed deep into the congested regime.

Furthermore, the impact of the two TSC methods on the frequency of spillback duration in network links is examined and presented in Figure 4b. We consider eight different ranges of spillback duration. As depicted in Figure 4b, the proposed MPC clearly reduces both the duration and frequency of spillback in network links. The MPC method limits spillback predominantly to short durations of 0–10 minutes, whereas fixed-time control exhibits extended spillback events lasting up to 60 minutes and beyond, with significantly higher frequency across all longer duration ranges.

Table 2 compares the computational performance of the quadratic MPC approach proposed by Aboudolas et al. (2009) with the proposed linear formulation. The results show a substantial reduction in solver time when using the linear objective function. Specifically, the proposed method

Table 2: Computational performance of linear and quadratic objective functions

Method	Objective	Mean (s)	Std (s)	Max (s)
Quadratic MPC Aboudolas et al. (2009)	$\sum x^\top Qx$	42.9610	0.8763	45.1410
Proposed (Linear)	$\sum q^\top N^{\text{out}}$	0.9447	0.5604	2.2325

achieves a mean computation time of 0.94 seconds, compared to 42.96 seconds for the quadratic formulation, representing a significant improvement in efficiency. In addition, the linear approach exhibits lower variability, with a smaller standard deviation and a much lower maximum computation time. These results highlight the computational advantage of the proposed method, making it more suitable for real-time traffic signal control applications.

4 Conclusions

This paper proposes a switching MPC framework for arterial traffic signal control, formulated within a positive systems framework using cumulative SFM dynamics. The key feature of the method is the piecewise affine outflow model, whose switching conditions are driven exclusively by the current and predicted traffic states rather than the optimization variables. This structure enables the MPC problem to be reformulated as a constrained maximization problem with a linear objective function, significantly improving computational tractability compared with conventional quadratic MPC formulations.

The proposed method was evaluated on the Nicholson arterial in Melbourne using the AIMSUN microsimulation environment. The results show that the MPC consistently outperforms fixed-time control across all performance measures, maintaining the network near critical accumulation levels and successfully recovering from congestion as demand decreases. In contrast, fixed-time control drives the network into a congested regime with reduced outflow. The proposed MPC also effectively mitigates queue spillback, reducing both its spatial extent and duration compared to fixed-time control. In addition, the linear formulation significantly reduces computational complexity relative to quadratic MPC, enabling real-time implementation.

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