

# **1 A Non-homogeneous Time Mixed Integer LP**

## **2 Formulation for Traffic Signal Control**

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## 1 ABSTRACT

2 We build on the body of work in mixed integer linear programming (MILP) approaches that at-  
3 tempt to jointly optimize traffic signal control over an *entire traffic network* (rather than focus on  
4 arterial routes) and specifically on improving the scalability of these methods for large urban traf-  
5 fic networks. Our primary insight in this work stems from the fact that MILP-based approaches to  
6 traffic control used in a receding horizon control manner (that replan at fixed time intervals) need to  
7 compute high fidelity control policies only for the early stages of the signal plan; therefore, coarser  
8 time steps can be employed to “see” over a long horizon to preemptively adapt to distant platoons  
9 and other predicted long-term changes in traffic flows. To this end, we contribute the queue trans-  
10 mission model (QTM) which blends elements of cell-based and link-based modeling approaches  
11 to enable a non-homogeneous MILP formulation of traffic signal control. We then experiment with  
12 this novel QTM-based MILP control in a range of networks demonstrating the improved scalabil-  
13 ity possible with non-homogeneous time steps in comparison to the best homogeneous time step.  
14 Our experiments also provide near-optimal traffic control policies for larger horizons and larger  
15 networks than shown in previous implementations of MILP-based traffic signal control.

16 Using 204 words up to here. Maximum is 250 words.

17 1

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<sup>1</sup>Make sure to follow instructions and author guide: <http://onlinepubs.trb.org/onlinepubs/AM/InfoForAuthors.pdf> <http://onlinepubs.trb.org/onlinepubs/am/2015/WritingForTheTRRecord.pdf>

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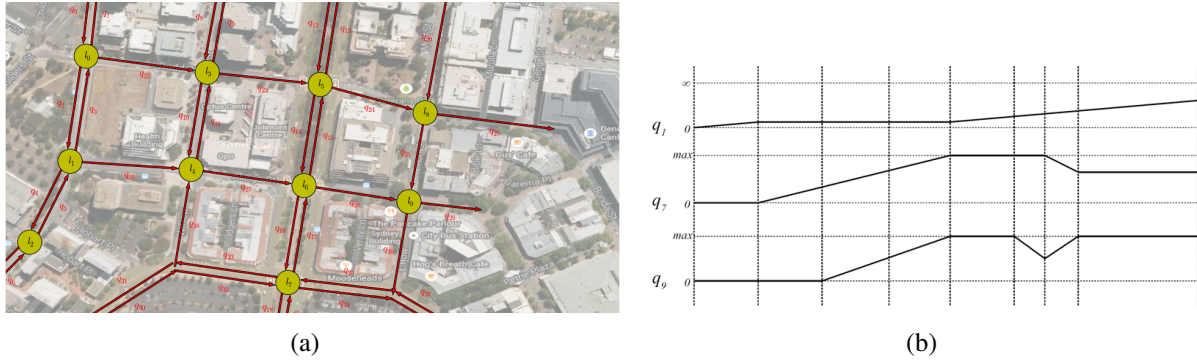
## 1 INTRODUCTION

2 As cities rapidly grow in population while urban traffic infrastructure often adapts at a slower pace,  
 3 it is critical to maximize capacity and throughput of existing road infrastructure through optimized  
 4 traffic signal control. Unfortunately, many large cities still use some degree of *fixed-time* control  
 5 (e.g., Toronto (1)) even if they also use *actuated* or *adaptive* control methods such as SCATS (2)  
 6 or SCOOT (3). However, there is further opportunity to improve traffic signal control even beyond  
 7 adaptive methods through the use of *optimized* controllers as evidenced in a variety of approaches  
 8 ranging from mixed integer (linear) programming (4, 5, 6, 7, 8, 9) to heuristic search (10, 11) to  
 9 scheduling (12) to reinforcement learning (1). While such optimized controllers hold the promise  
 10 of maximizing existing infrastructure capacity by finding more complex (and potentially closer to  
 11 optimal) jointly coordinated intersection policies than arterially-focused master-slave approaches  
 12 such as SCATS and SCOOT, such optimized methods are computationally demanding and either  
 13 (a) do not guarantee jointly optimal solutions over a large intersection network (often because they  
 14 only consider coordination of neighboring intersections or arterial routes) or (b) fail to scale to  
 15 large intersection networks simply for computational reasons (which is the case for many mixed  
 16 integer programming approaches).

17 In this work, we build on the body of work in mixed integer linear programming (MILP) ap-  
 18 proaches that attempt to jointly optimize traffic signal control over an *entire traffic network* (rather  
 19 than focus on arterial routes) and specifically on improving the scalability of these methods for  
 20 large urban traffic networks. In our investigation of existing approaches in this vein, namely exem-  
 21 plar methods in the spirit of (6, 8, 9) that use a (modified) cell transmission model (CTM) (13, 14)  
 22 for their underlying prediction of traffic flows, we remark that a major drawback is the CTM-  
 23 imposed requirement to choose a predetermined homogeneous (and often necessarily small) time  
 24 step for reasonable modeling fidelity. This need to model large number of CTM cells with a small  
 25 time step leads to MILPs that are exceedingly large and intractable to solve.

26 Our primary insight in this work stems from the fact that MILP-based approaches to traffic  
 27 control used in a receding horizon control manner (that replan at fixed time intervals) need to  
 28 compute high fidelity control policies only for the early stages of the signal plan; therefore, coarser  
 29 time steps can be employed to “see” over a long horizon to preemptively adapt to distant platoons  
 30 and other predicted long-term changes in traffic flows. This need for non-homogeneous control  
 31 in turn spawns the need for an additional innovation: we require a traffic flow model that permits  
 32 non-homogeneous time steps and properly models the travel time delay between lights. To this  
 33 end, we might consider CTM extensions such as the variable cell length CTM (15), stochastic  
 34 CTM extensions (16, 17), extensions for better modeling freeway-urban interactions (18) including  
 35 CTM hybrids with link-based models (19), asymmetric CTMs for better handling flow imbalances  
 36 in merging roads (20), the situational CTM for better modeling of boundary conditions (21), and  
 37 the lagged CTM for improved modeling of the flow density relation (22). However, despite the  
 38 widespread varieties of the CTM and the usage of the CTM (23) for a range of applications, there  
 39 seems to be no extension that permits non-homogeneous time steps as required in our novel MILP-  
 40 based control approach.

41 For this reason, as a major contribution of this work to enable our non-homogeneous  
 42 time MILP-based model of joint intersection control, we contribute the queue transmission model  
 43 (QTM) which blends elements of cell-based and link-based modeling approaches with the follow-  
 44 ing key benefits:



**FIGURE 1 (a) Example of how a real network is modeled using QTM. (b) Volume of traffic in different queues as a function of non-homogeneous discretized time.**

- unlike previous joint intersection control work (6, 8, 9), it is inherently intended for *non-homogeneous* time steps that can be used for control over large horizons,
- any length of roadway with no merges or diverges can be modeled as a single queue leading to compact models of large traffic networks thus maintaining relatively compact MILPs for large traffic networks (i.e., large numbers of cells are not required between intersections), and
- it accurately models fixed travel time delays critical to green wave coordination as in (4, 5, 7) through the use of a non-first order Markovian update model and combines this with the more global intersection signal optimization approach of (6, 8, 9).

In the remainder of this paper, we first formalize our novel QTM model of traffic flow with non-homogeneous time steps and show how to encode it as a linear program for simulating traffic. We proceed to allow the traffic signals to become discrete variables subject to a delay minimizing optimization objective and standard cycle and phase time constraints leading to our final MILP formulation of traffic signal control. We then experiment with this novel QTM-based MILP control in a range of networks demonstrating the improved scalability possible with non-homogeneous time steps in comparison to the best homogeneous time step. These experiments also provide near-optimal traffic control policies for larger horizons and larger networks than shown in previous implementations of MILP-based traffic signal control. <sup>2 3</sup>

## THE QUEUE TRANSMISSION MODEL

A Queue Transmission Model (QTM) is the tuple  $(\mathcal{Q}, \mathcal{L}, \vec{\Delta t}, \mathbf{I})$ , where  $\mathcal{Q}$  and  $\mathcal{L}$  are, respectively, the set of queues and lights;  $\vec{\Delta t}$  is a vector of size  $N$  representing the discretization of the simulation horizon  $[0, T]$  and the duration in seconds of the  $n$ -th time interval is denoted as  $\Delta t_n$ ; and  $\mathbf{I}$  is a

<sup>2</sup>We could really use some pictures in the Intro to refer to here and subsequently – both a traffic network divided into queues, and the concept of the piecewise linear evolution of traffic flow with **non-homogeneous** (dilated) time steps, something like I had provided in my early writeup. I think these help visually explain much of the context for the paper and its approach and are critical for reviewer understanding on a time budget for reading this They may only read the first 2-3 pages and then skim!

<sup>3</sup>A picture is worth a 1000 words but we only pay 250, hence a 4X ROI on pictures!

1 matrix  $|\mathcal{Q}| \times T$  in which  $I_{i,n}$  represents the flow of cars requesting to enter queue  $i$  from the outside  
 2 of the network at time  $n$ .

3 A **traffic light**  $\ell \in \mathcal{L}$  is defined as the tuple  $(\Psi_\ell^{\min}, \Psi_\ell^{\max}, \mathcal{P}_\ell, \vec{\Phi}_\ell^{\min}, \vec{\Phi}_\ell^{\max})$ , where:

- 4 •  $\mathcal{P}_\ell$  is the set of phases of  $\ell$ ;
- 5 •  $\Psi_\ell^{\min}$  ( $\Psi_\ell^{\max}$ ) is the minimum (maximum) allowed cycle time for  $\ell$ ; and
- 6 •  $\vec{\Phi}_\ell^{\min}$  ( $\vec{\Phi}_\ell^{\max}$ ) is a vector of size  $|\mathcal{P}_\ell|$  and  $\Phi_{\ell,k}^{\min}$  ( $\Phi_{\ell,k}^{\max}$ ) is the minimum (maximum) allowed  
 7 time for phase  $k \in \mathcal{P}_\ell$ .

8 A **queue**  $i \in \mathcal{Q}$  represents a segment of road that vehicles traverse at free flow speed; once  
 9 traversed, the vehicles are vertically stacked in a stop line queue. Formally, a queue  $i$  is defined by  
 10 the tuple  $(Q_i, T_i^{\text{prop}}, F_i^{\text{out}}, \vec{F}_i, \vec{P}r_i, \mathcal{Q}_i^P)$  where:

- 11 •  $Q_i$  is the maximum capacity of  $i$ ;
- 12 •  $T_i^{\text{prop}}$  is the time required to traverse  $i$  and reach the stop line;
- 13 •  $F_i^{\text{out}}$  represents the maximum traffic flow from  $i$  to the outside of the modeled network;
- 14 •  $\vec{F}_i$  and  $\vec{P}r_i$  are vectors of size  $|\mathcal{Q}|$  and their  $j$ -th entry (i.e.,  $F_{i,j}$  and  $\text{Pr}_{i,j}$ ) represent the  
 15 maximum flow from queue  $i$  to  $j$  and the turn probability from  $i$  to  $j$  ( $\sum_{j \in \mathcal{Q}} \text{Pr}_{i,j} = 1$ ),  
 16 respectively; and
- 17 •  $\mathcal{Q}_i^P$  denotes the set of traffic light phases controlling the outflow of queue  $i$ .

18 Differently than CTM (8, 13), QTM does not assume that  $\Delta t_n = T_i^{\text{prop}}$  for all  $n \in \{1, \dots, N\}$ ,  
 19 that is, the QTM can represent non-homogeneous time intervals. The only requirement over  $\Delta t_n$  is  
 20 that no traffic light maximum phase time is smaller than any  $\Delta t_n$  since phase changes occur only  
 21 between time intervals; formally,  $\Delta t_n \leq \min_{\ell \in \mathcal{L}, k \in \mathcal{P}_\ell} \Phi_{\ell,k}^{\max}$  for all  $n \in \{1, \dots, N\}$ .<sup>4</sup>

## 22 Traffic Flow Simulation with QTM

23 In this section, we present how to simulate traffic flow in a network using QTM and non-homogeneous  
 24 time intervals  $\Delta t$ . We assume for the remainder of this section that a *valid* control plan for  
 25 all traffic lights is fixed and given as parameter; formally, for all  $\ell \in \mathcal{L}$ ,  $k \in \mathcal{P}_\ell$ , and interval  
 26  $n \in \{1, \dots, N\}$ , the binary variable  $p_{\ell,k,n}$  is known a priori and indicates if phase  $k$  of light  $\ell$  is  
 27 active (i.e.,  $p_{\ell,k,n} = 1$ ) or not on interval  $n$ .

28 We represent the problem of finding the flow between queues as a Linear Program (LP)  
 29 over the following variables defined for all interval  $n \in \{1, \dots, N\}$  and queues  $i$  and  $j$ :

- 30 •  $q_{i,n} \in [0, Q_i]$ : traffic volume waiting in the stop line of queue  $i$  at the beginning of  
 31 interval  $n$ ;
- 32 •  $f_{i,n}^{\text{in}} \in [0, I_{i,n}]$ : inflow to the network via queue  $i$  during interval  $n$ ;

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<sup>4</sup>**To Iain:** Maybe bring forward a small network and any other figure that would help illustrate the model and comment about it.

- $f_{i,n}^{\text{out}} \in [0, F_i^{\text{out}}]$ : outflow from the network via queue  $i$  during interval  $n$ ; and
- $f_{i,j,n} \in [0, F_{i,j}]$ : flow from queue  $i$  into queue  $j$  during interval  $n$ .

The maximum traffic flow from queue  $i$  to queue  $j$  is enforced by constraints (C1) and (C2). (C1) ensures that only the fraction  $\text{Pr}_{i,j}$  of the total internal outflow of  $i$  goes to  $j$ , and (C2) forces the flow from  $i$  to  $j$  to be zero if all phases controlling  $i$  are inactive (i.e.,  $p_{\ell,k,n} = 0$  for all  $k \in \mathcal{Q}_i^P$ ). If more than one phase  $p_{\ell,k,n}$  is active, then (C2) is subsumed by the domain upper bound of  $f_{i,j,n}$ .

$$f_{i,j,n} \leq \text{Pr}_{i,j} \sum_{k=1}^{|\mathcal{Q}|} f_{i,k,n} \quad (\text{C1})$$

$$f_{i,j,n} \leq F_{i,j} \sum_{p_{\ell,k,n} \in \mathcal{Q}_i^P} p_{\ell,k,n} \quad (\text{C2})$$

To simplify the presentation of remainder of the LP, we define the helper variables  $q_{i,n}^{\text{in}}$  (C3),  $q_{i,n}^{\text{out}}$  (C4), and  $t_n$  (C5) to represent the volume of traffic to enter and leave queue  $i$  during interval  $n$ , and the time elapsed since the beginning of the simulation until the end of interval  $\Delta t_n$ .

$$q_{i,n}^{\text{in}} = \Delta t_n (f_{i,n}^{\text{in}} + \sum_{j=1}^{|\mathcal{Q}|} f_{j,i,n}) \quad (\text{C3})$$

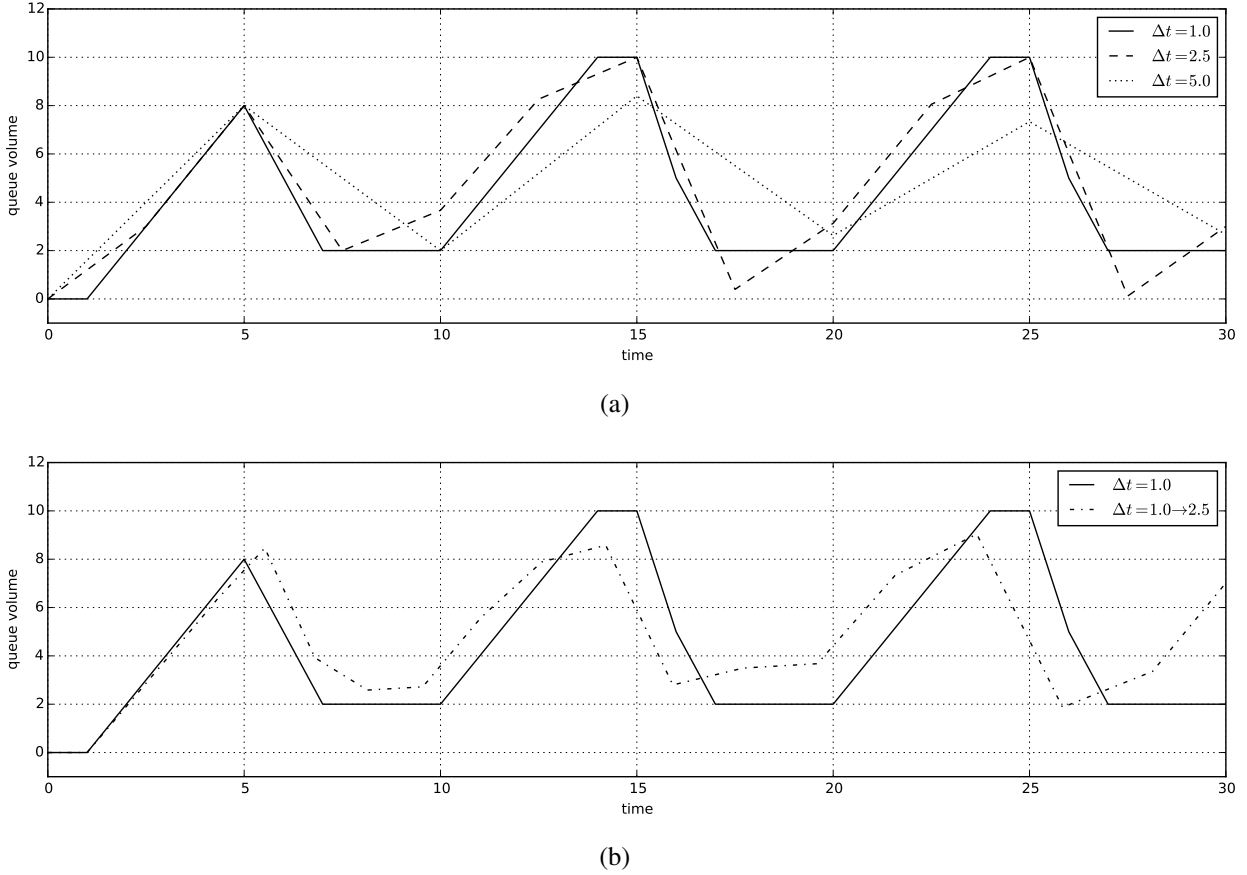
$$q_{i,n}^{\text{out}} = \Delta t_n (f_{i,n}^{\text{out}} + \sum_{j=1}^{|\mathcal{Q}|} f_{i,j,n}) \quad (\text{C4})$$

$$t_n = \sum_{x=1}^n \Delta t_x \quad (\text{C5})$$

In order to account for the misalignment of the different  $\Delta t$  and  $T_i^{\text{prop}}$ , we need to find the volume of traffic that entered queue  $i$  between two arbitrary points in time  $x$  and  $y$  ( $x \in [0, T]$ ,  $y \in [0, T]$ , and  $x < y$ ), i.e.,  $x$  and  $y$  might not coincide with any  $t_n$  for  $n \in \{1, \dots, N\}$ . This volume of traffic, denoted as  $V_i(x, y)$ , is obtained by integrating  $q_{i,n}^{\text{in}}$  over  $[x, y]$  and is defined in (1) where  $m$  and  $w$  are the index of the time intervals s.t.  $t_m \leq x < t_{m+1}$ , and  $t_w \leq y < t_{w+1}$ . Because the QTM dynamics is piecewise linear,  $q_{i,n}^{\text{in}}$  is a step function w.r.t. time and this integral reduces to the sum of  $q_{i,n}^{\text{in}}$  over the intervals contained in  $[x, y]$  and the appropriate fraction of  $q_{i,m}^{\text{in}}$  and  $q_{i,w}^{\text{in}}$  representing the misaligned beginning and end of  $[x, y]$ .

$$V_i(x, y) = (t_{m+1} - x) \frac{q_{i,m}^{\text{in}}}{\Delta t_m} + \left( \sum_{k=m+1}^{w-1} q_{i,k}^{\text{in}} \right) + (y - t_w) \frac{q_{i,w}^{\text{in}}}{\Delta t_w} \quad (1)$$

Using these helper variables, (C6) represents the flow conservation principle for queue  $i$  where  $V_i(t_{n-1} - T_i^{\text{prop}}, t_n - T_i^{\text{prop}})$  is the volume of cars that reached stop line during  $\Delta t_n$ . Since  $\Delta t$  and  $T_i^{\text{prop}}$  for all queues are known a priori, the indexes  $m$  and  $w$  used by  $V_i$  can be pre-computed in order to encode (1); moreover, (C6) represents a non-first order Markovian update because the update considers the previous  $w - m$  time steps. To insure that the total volume of



**FIGURE 2 (a) Convergence with increasing refinement of  $\Delta t$  from 5.0 down to 1.0. (c) Dilation of  $\Delta t$  from 1.0 to 2.5 compared to a fixed  $\Delta t$  of 1.0.**

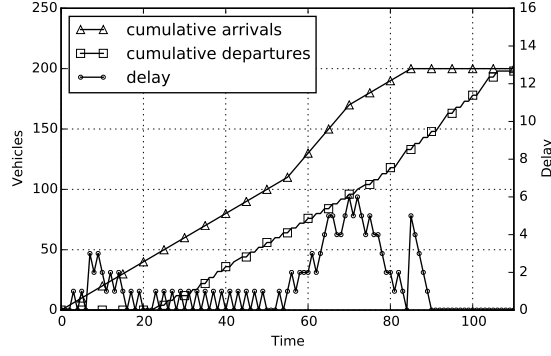
1 traffic traversing  $i$  (i.e.,  $V_i(t_n - T_i^{\text{prop}}, t_n)$ ) and waiting at the stop line does not exceed the capacity  
 2 of the queue, we apply (C7).

$$3 \quad q_{i,n} = q_{i,n-1} - q_{i,n-1}^{\text{out}} + V_i(t_{n-1} - T_i^{\text{prop}}, t_n - T_i^{\text{prop}}) \quad (\text{C6})$$

$$4 \quad V_i(t_n - T_i^{\text{prop}}, t_n) + q_{i,n} \leq Q_i \quad (\text{C7})$$

6 As with MILP formulations of CTM (e.g. Lin and Wang (8)), QTM is also susceptible to  
 7 *withholding traffic*, i.e., the optimizer might prevent cars from moving from  $i$  to  $j$  even though  
 8 the associated traffic phase is active and  $j$  is not full. We address this issue through our objective  
 9 function (O1) by maximizing the total outflow  $q_{i,n}^{\text{out}}$  (i.e., both internal and external outflow) of  $i$   
 10 plus the inflow  $f_{i,n}^{\text{in}}$  from the outside of the network to  $i$ . This quantity is weighted by the remaining  
 11 time until the end of the simulation horizon  $T$  to force the optimizer to allow as much traffic volume  
 12 as possible into the network and move traffic to the outside the network as soon as possible. (O1)  
 13 is analogous to minimizing delay in CTM models, e.g., (O1) is equivalent to the objective function  
 14 (O3) in Lin and Wang (8) for their parameters  $\alpha = \beta = 1$ .<sup>5</sup> **Figure 3 shows the delay experienced**  
 15 **by each vehicle travelling through a network, where delay is the horizontal difference at each point**  
 16 **between the cumulative departure and arrival curves, less the free flow travel time through the**

<sup>5</sup>To Iain: Add a paragraph linking the plots with the objective function.



**FIGURE 3** Cumulative arrival (blue) and departure (green) curves, and the resulting delay curve (red). The departure curve is maximized by the objective function, which has the same effect as minimizing the delay curve

network. The objective function tries to maximise the departure curve by pushing it up closer to the arrival curve, which also has the effect of minimising the horizontal distance, or delay.<sup>6</sup>

$$\max \sum_{n=1}^N \sum_{i=1}^{|Q|} (T - t_n + 1)(q_{i,n}^{\text{out}} + f_{i,n}^{\text{in}}) \quad (\text{O1})$$

The objective function (O1) and constraints (C1–C7) form the LP representing the dynamic, piecewise linear model of flow in a QTM network over time when a control plan  $p_{\ell,k,n}$  is given as an input parameter.

Figures 2(a) and 2(b) show the results of applying the LP formulation to a simple model with a fixed signal plan, using both homogeneous  $\Delta t$  and non-homogeneous  $\Delta t$ .

## TRAFFIC CONTROL WITH QTM AS AN MILP

In this section, we remove the assumption that a valid control plan for all traffic lights is given and extend the LP (O1, C1–C7) to an Mixed-Integer LP (MILP) that also computes the optimal control plan. Formally, for all  $\ell \in \mathcal{L}$ ,  $k \in \mathcal{P}_\ell$ , and interval  $n \in \{1, \dots, N\}$ , the phase activation parameter  $p_{\ell,k,n} \in \{0, 1\}$  becomes a free variable to be optimized. In order to obtain a valid control plan, we enforce that one phase of traffic light  $\ell$  is always active at any interval  $n$  (C8) and that phase changes happen sequentially (C9), i.e., if phase  $k$  was active during interval  $n - 1$  and has become inactive in interval  $n$ , then phase  $k + 1$  must be active in interval  $n$ . (C9) assumes that  $k + 1$  equals 1 if  $k = |\mathcal{P}_\ell|$ .

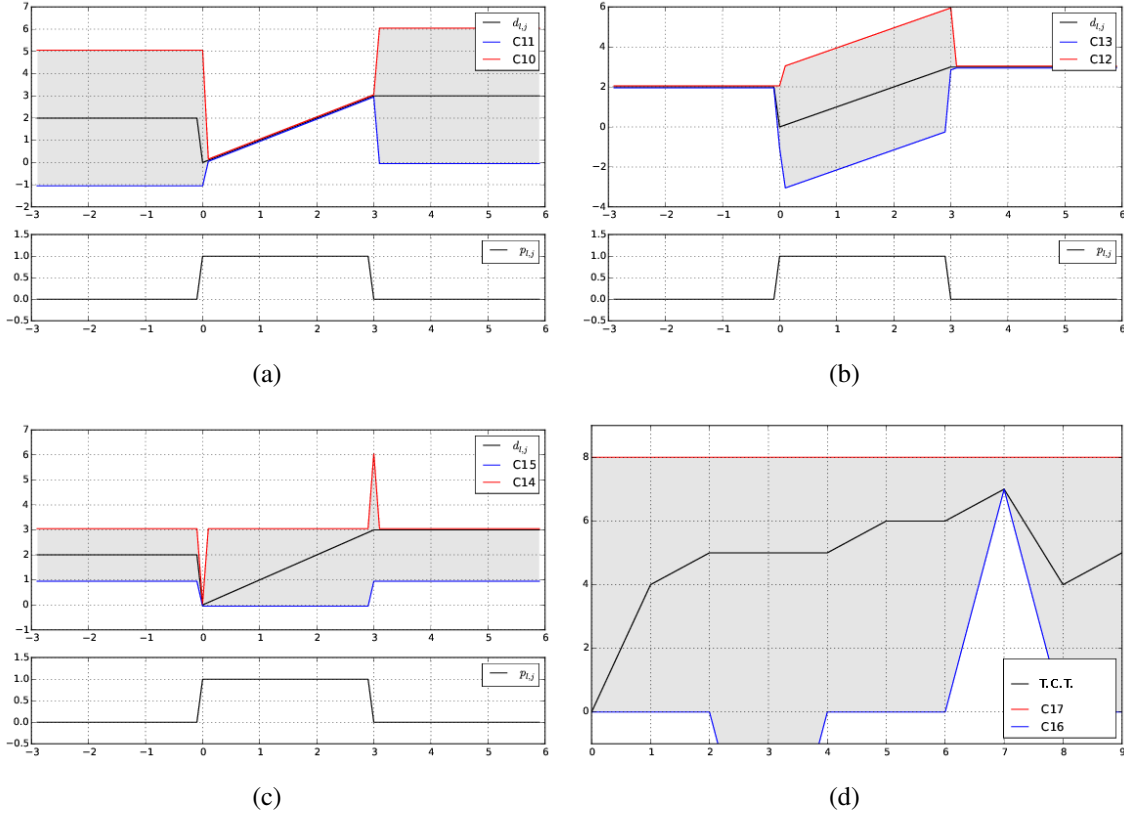
$$\sum_{k=1}^{|\mathcal{P}_\ell|} p_{\ell,k,n} = 1 \quad (\text{C8})$$

$$p_{\ell,k,n-1} \leq p_{\ell,k,n} + p_{\ell,k+1,n} \quad (\text{C9})$$

Next, we enforce the minimum and maximum phase durations (i.e.,  $\Phi_{\ell,k}^{\min}$  and  $\Phi_{\ell,k}^{\max}$ ) for each phase  $k \in \mathcal{P}_\ell$  of traffic light  $\ell$ . To encode these constraints, we use the helper variable

<sup>6</sup>Show diagrams with traffic predictions converging as time increment gets smaller. Validates that large time-steps are rough approximations while model behavior converges for small time steps.





**FIGURE 4** Visualization of constraints (C10–C17) for a traffic light  $\ell$  as a function of time. (a–c) present, pairwise, the constraints (C10–C15) for phase  $k$  ( $d_{\ell,k,n}$  as the black line) and the activation variable  $p_{\ell,k,n}$  in the attached plot. (d) presents the constraint for the cycle time of  $\ell$  (C16 and C17) where T.C.T. is the total cycle time and is defined as the left hand side of both constraints. For this example,  $\Phi_{\ell,k}^{\min} = 1$ ,  $\Phi_{\ell,k}^{\max} = 3$ ,  $\Psi_{\ell}^{\min} = 7$ , and  $\Psi_{\ell}^{\max} = 8$ .

1  $d_{\ell,k,n} \in [0, \Phi_{\ell,k}^{\max}]$  defined by constraints (C10–C14) that: (i) holds the elapsed time since the  
2 start of phase  $k$  when  $p_{\ell,k,n}$  is active (C10,C11); (ii) is constant and holds the duration of the last  
3 phase until the next activation when  $p_{\ell,k,n}$  is inactive (C12,C13); and (iii) is restarted when phase  $k$   
4 changes from inactive to active (C14). Notice that (C10–C14) employs the *big-M* method to turn  
5 the cases that should not be active into subsumed constraints based on the value of  $p_{\ell,k,n}$ . We  
6 use  $\Phi_{\ell,k}^{\max}$  as our large constant since  $d_{\ell,k,n} \leq \Phi_{\ell,k}^{\max}$  and  $\Delta t_n \leq \Phi_{\ell,k}^{\max}$  by assumption (Section 2.1).  
7 Similarly, constraint (C15) ensures the minimum phase time of  $k$  and is not enforced while  $k$  is  
8 still active. Figures 4(a) to 4(c) present an example of how (C10–C15) work together as a function  
9 of the time  $n$  for  $d_{\ell,k,n}$ ; the domain constraint  $0 \leq d_{\ell,k,n} \leq \Phi_{\ell,k}^{\max}$  for all  $n \in \{1, \dots, N\}$  is omitted

1 for clarity.

$$2 \quad d_{\ell,k,n} \leq d_{\ell,k,n-1} + \Delta t_{n-1} p_{\ell,k,n-1} + \Phi_{\ell,k}^{\max}(1 - p_{\ell,k,n-1}) \quad (\text{C10})$$

$$3 \quad d_{\ell,k,n} \geq d_{\ell,k,n-1} + \Delta t_{n-1} p_{\ell,k,n-1} - \Phi_{\ell,k}^{\max}(1 - p_{\ell,k,n-1}) \quad (\text{C11})$$

$$4 \quad d_{\ell,k,n} \leq d_{\ell,k,n-1} + \Phi_{\ell,k}^{\max} p_{\ell,k,n-1} \quad (\text{C12})$$

$$5 \quad d_{\ell,k,n} \geq d_{\ell,k,n-1} - \Phi_{\ell,k}^{\max} p_{\ell,k,n-1} \quad (\text{C13})$$

$$6 \quad d_{\ell,k,n} \leq \Phi_{\ell,k}^{\max}(1 - p_{\ell,k,n} + p_{\ell,k,n-1}) \quad (\text{C14})$$

$$7 \quad d_{\ell,k,n} \geq \Phi_{\ell,k}^{\min}(1 - p_{\ell,k,n}) \quad (\text{C15})$$

9 Lastly, we constrain the sum of all the phase durations for light  $\ell$  to be within the cycle  
10 time limits  $\Psi_{\ell}^{\min}$  (C16) and  $\Psi_{\ell}^{\max}$  (C17). In both (C16) and (C17), we use the duration of phase 1  
11 of  $\ell$  from the previous interval  $n - 1$  instead of the current interval  $n$  because (C14) forces  $d_{\ell,1,n}$  to  
12 be 0 at the beginning of each cycle; however, from the previous end of phase 1 until  $n - 1$ ,  $d_{\ell,1,n-1}$   
13 holds the correct elapse time of phase 1. Additionally, (C16) is enforced right after the end of the  
14 each cycle, i.e., when its first phase is changed from inactive to active. The value (C16) and (C17)  
15 over time for a traffic light  $\ell$  is illustrated in Figure 4(d).

$$16 \quad d_{\ell,1,n-1} + \sum_{k=2}^{|\mathcal{P}_{\ell}|} d_{\ell,k,n} \geq \Psi_{\ell}^{\min}(p_{k,1,n} - p_{k,1,n-1}) \quad (\text{C16})$$

$$17 \quad d_{\ell,1,n-1} + \sum_{k=2}^{|\mathcal{P}_{\ell}|} d_{\ell,k,n} \leq \Psi_{\ell}^{\max} \quad (\text{C17})$$

19 The MILP that encodes the problem of finding the optimal traffic control plan in a QTM network  
20 is defined by (O1, C1–C17).

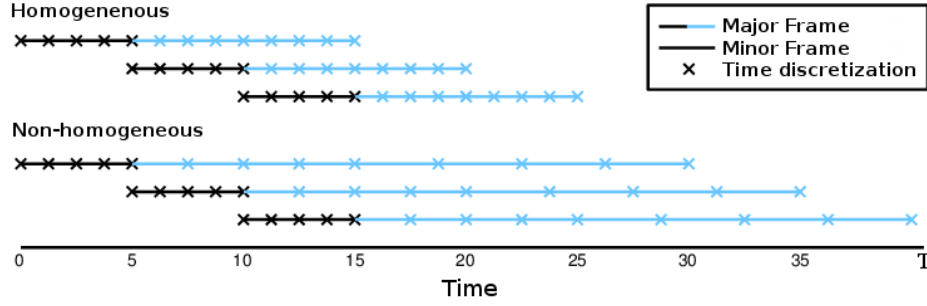
## 21 EMPIRICAL EVALUATION

22 In this section we compare the solutions for traffic networks modeled as a QTM using homoge-  
23 neous and non-homogeneous time intervals in two aspects: the quality of the solution and con-  
24 vergence to the **optimal solution**.<sup>7</sup> We compare the quality of solutions based on the total travel  
25 time and we also consider the third quartile and maximum of the observed delay distribution. Our  
26 hypotheses are: (i) the quality of the non-homogeneous solutions is at least as good as the homoge-  
27 neous ones when the number of time intervals  $N$  is fixed; and (ii) the non-homogeneous approach  
28 requires less time intervals (i.e., smaller  $N$ ) than the homogeneous approach to converge to the  
29 optimal solution. In the remainder of this section, we present the traffic networks considered in the  
30 experiments, our methodology, and the results.

### 31 Networks

32 We consider three networks of increasing complexity (Figure 6): an avenue crossed by three side  
33 streets; a 2-by-3 grid; and a 3-by-3 grid with a diagonal avenue. The queues receiving cars from  
34 outside of the network are marked in Figure 6 and we refer to them as input queues. The maximum  
35 capacity ( $Q_i$ ) is 60 cars for non-input queues and **infinity** for input queues to prevent interruption

<sup>7</sup>FWT: I don't think that optimal is the best word here since we arbitrarily fixed a value of  $\Delta t$ . Also, there is the technical problem that Gurobi might not have found the true optimal.



**FIGURE 5 Receding horizon control.** For this figure, the problem horizon  $T$  is 40s. The major frames are discretized in 12 time intervals ( $N = 12$ ) and they span 15s and 30s for homogeneous and non-homogeneous discretizations, respectively.

1 of the input demand due to spill back from the stop line. The traversal time of each queue  $i$  ( $T_i^{\text{prop}}$ )  
 2 is set at 9s (a distance of about 100m with a free flow speed of 50km/h). Flows are defined from  
 3 the head of each queue  $i$  into the tail of the next queue  $j$ ; there is no turning traffic ( $\text{Pr}_{i,j} = 1$ ),  
 4 and the maximum flow rate between queues,  $F_{i,j}$ , is set at 5 cars/s. All traffic lights have two  
 5 phases, north-south and east-west, and lights 2, 4 and 6 of network 3 have the additional northeast-  
 6 southwest phase to control the diagonal avenue. For networks 1 and 2,  $\Phi_{\ell,k}^{\min}$  is 1s,  $\Phi_{\ell,k}^{\max}$  is 3s,  $\Psi_{\ell}^{\min}$   
 7 is 2s, and  $\Psi_{\ell}^{\max}$  is 6s, for all traffic light  $\ell$  and phase  $k$ . For network 3,  $\Phi_{\ell,k}^{\min}$  is 1s and  $\Phi_{\ell,k}^{\max}$  is 6s  
 8 for all  $\ell$  and  $k$ ; and  $\Psi_{\ell}^{\min}$  is 2s and  $\Psi_{\ell}^{\max}$  is 12s for all lights  $\ell$  except for lights 2, 4 and 6 in which  
 9  $\Psi_{\ell}^{\min}$  is 3s and  $\Psi_{\ell}^{\max}$  is 18s.

## 10 Experimental Methodology

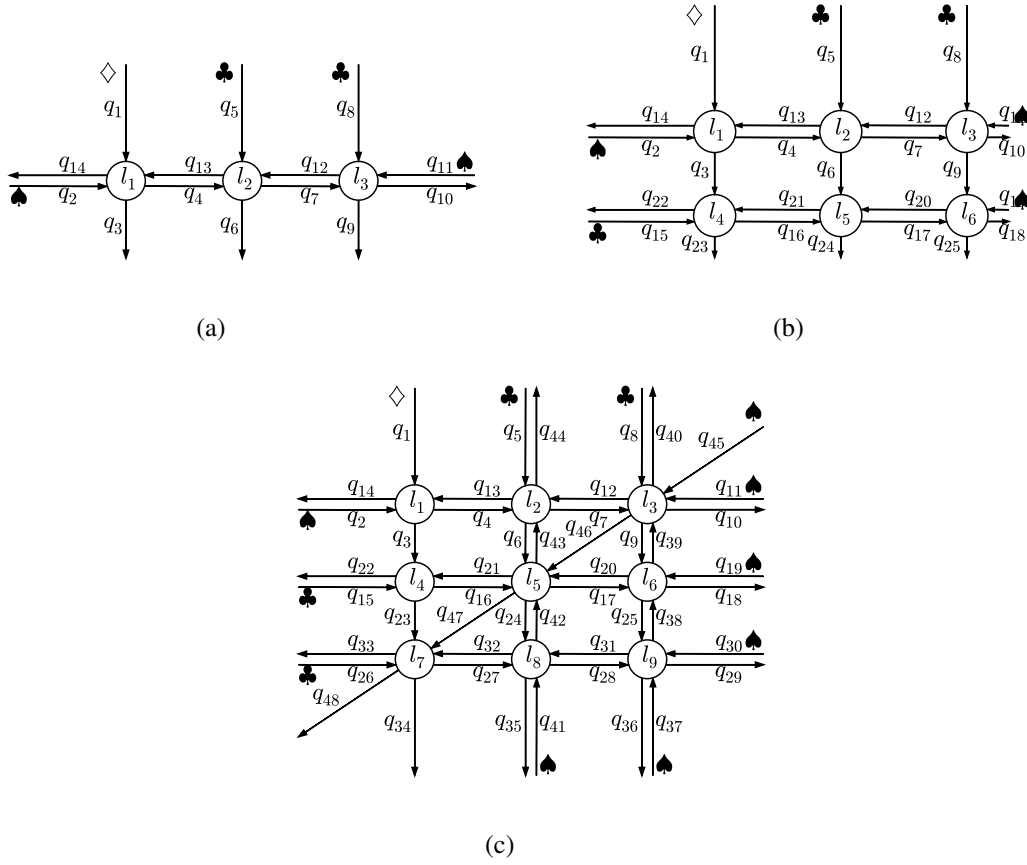
11 For each network, a constant background level traffic is injected in the network in the first 55s to  
 12 allow the solver to settle on a stable policy. Then a spike in demand is introduced in the queues  
 13 marked as ♠ (Figure 6) from time 55s to 70s to trigger a policy change. From time 70s to 85s,  
 14 the demand is returned to the background level, and then reduced to zero for all input queues. We  
 15 extend the problem horizon  $T$  until all cars have left the network. By clearing the network, we can  
 16 easily measure the total travel time for all the traffic as the area between the cumulative arrival and  
 17 departure curves measured at the boundaries of the network.<sup>8</sup> The background level for the input  
 18 queues are 1, 4 and 2 cars/s for queues marked as ♦, ♣ and ♠ (Figure 6), respectively; and during  
 19 the high demand period, the queues ♠ receive 4 cars/s.

20 For both homogeneous and non-homogeneous intervals, we use the MILP QTM formula-  
 21 tion (Section 3) in a receding horizon manner: a control plan is computed for a pre-defined horizon  
 22 (smaller than  $T$ ) and only a prefix of this plan is executed before generating a new control plan.  
 23 Figure 5 depicts our receding horizon approach and we refer to the planning horizon as a major  
 24 frame and its executable prefix as a minor frame. Notice that, while the plan for a minor frame is  
 25 being executed, we can start computing the solution for the next major frame **based on a forecast**  
 26 **model**.<sup>9</sup>

27 To perform a fair comparison between the homogeneous and non-homogeneous discretiza-  
 28 tions, we fix the size of all minor frames to 10s and force it to be discretized in homogeneous

<sup>8</sup>FWT: is this explanation of how to compute the total travel time still necessary?

<sup>9</sup>FWT: not sure if we should mention this.



**FIGURE 6** Networks used to evaluate the QTM performance. Queues marked as  $\diamond$ ,  $\clubsuit$ , and  $\spadesuit$  receive traffic from the outside of the network.

1 intervals of 0.25s. For the homogeneous experiments,  $\Delta t$  is kept at 0.25s throughout the major  
 2 frame; therefore, given  $N$ , the major frame size equals  $N/4$  seconds for the homogeneous ap-  
 3 proach. For the non-homogeneous experiments,  $\Delta t$  linearly increases from 0.25s at the end of  
 4 the minor frame to 1.0s at the end of the major frame; therefore, the major frame size used by  
 5 the non-homogeneous approach is  $10.375 + 0.625(N - 40)$  seconds for a given  $N > 40$ . Once  
 6 we have generated a series of minor frames, we concatenate them into a single plan and simulate  
 7 the flow through the network using the QTM LP formulation with a fixed (homogeneous)  $\Delta t$  of  
 8 0.25s.<sup>10</sup> We also compare both receding horizon approaches against the **optimal** solution obtained  
 9 by computing a single control plan for the entire control horizon (i.e.,  $[0, T]$ ) using a fixed  $\Delta t$  of  
 10 0.25s.

11 For all our experiments, we used Gurobi<sup>TM</sup> as MILP solver with 12 threads on a 3.1GHz  
 12 AMD Opteron<sup>TM</sup> 4334 processor with 12 cores. We limit MIP gap accuracy to 0.1% and the time  
 13 cutoff for solving a major frame to 3000s for the receding horizon approaches and unbounded for  
 14 the optimal plan. All our results are averaged over five runs to account for Gubori's stochastic  
 15 strategies.

<sup>10</sup>Do we need to justify why we use the QTM as the simulator over say a micro simulator?

## 1 Results

2 Figures 7(a), 7(c) and 7(e) show, for each network, the increase in the total travel time w.r.t. the  
 3 optimal solution as a function of  $N$ . As we hypothesized, the non-homogeneous discretization re-  
 4 quires less time intervals (i.e., smaller  $N$ ) to obtain a solution with the same total travel time. This  
 5 is important because the size of the MILP, including the number of binary variables, scales linearly  
 6 with  $N$ ; therefore, the non-homogeneous approach can scale up better than the homogeneous one  
 7 (e.g., Figure 7(e)). Also, for homogeneous and non-homogeneous discretizations, finding the opti-  
 8 mal solution of major frames with large  $N$  requires more time than our imposed 3000s time cutoff;  
 9 therefore, Gurobi returns a feasible control plan that is far from optimal. This effect can be seen in  
 10 Figure 7(e) for  $N > 120$ .

11 The distribution of the total delay observed by each car while traversing the network  
 12 is shown in Figures 7(b), 7(d) and 7(f). Each group of box plots represents a different value  
 13 of  $N$ : when the non-homogeneous  $\Delta t$  first converges to the optimum solution; when the homoge-  
 14 neous  $\Delta t$  first converges on the optimum solution; and the optimum solution itself. In all networks,  
 15 the quality of the solution obtained using non-homogeneous  $\Delta t$  is better or equal than using ho-  
 16 mogeneous  $\Delta t$  for fixed  $N$  in both the total travel time and *fairness*, i.e., smaller third quartile and  
 17 maximum delay.

18 Finally, Figure 8 shows the cumulative arrival and departure curves and the how delay  
 19 evolves over time for  $q_1$  of network 2. Figure 8(a) shows the comparison at the point where the  
 20 non-homogeneous  $\Delta t$  first converges and shows that with the longer major frame time of the  
 21 non-homogeneous  $\Delta t$ , the solver is able to find a coordinated signal policy along the avenue to  
 22 dissipate the extra traffic that arrives at the 55s point, while the homogeneous  $\Delta t$  with its shorter  
 23 major frame. Once the homogeneous  $\Delta t$  has converged in Figure 8(b), both solutions are close to  
 24 the optimum solution which is shown in Figure 8(c).<sup>11</sup>

## 25 CONCLUSION

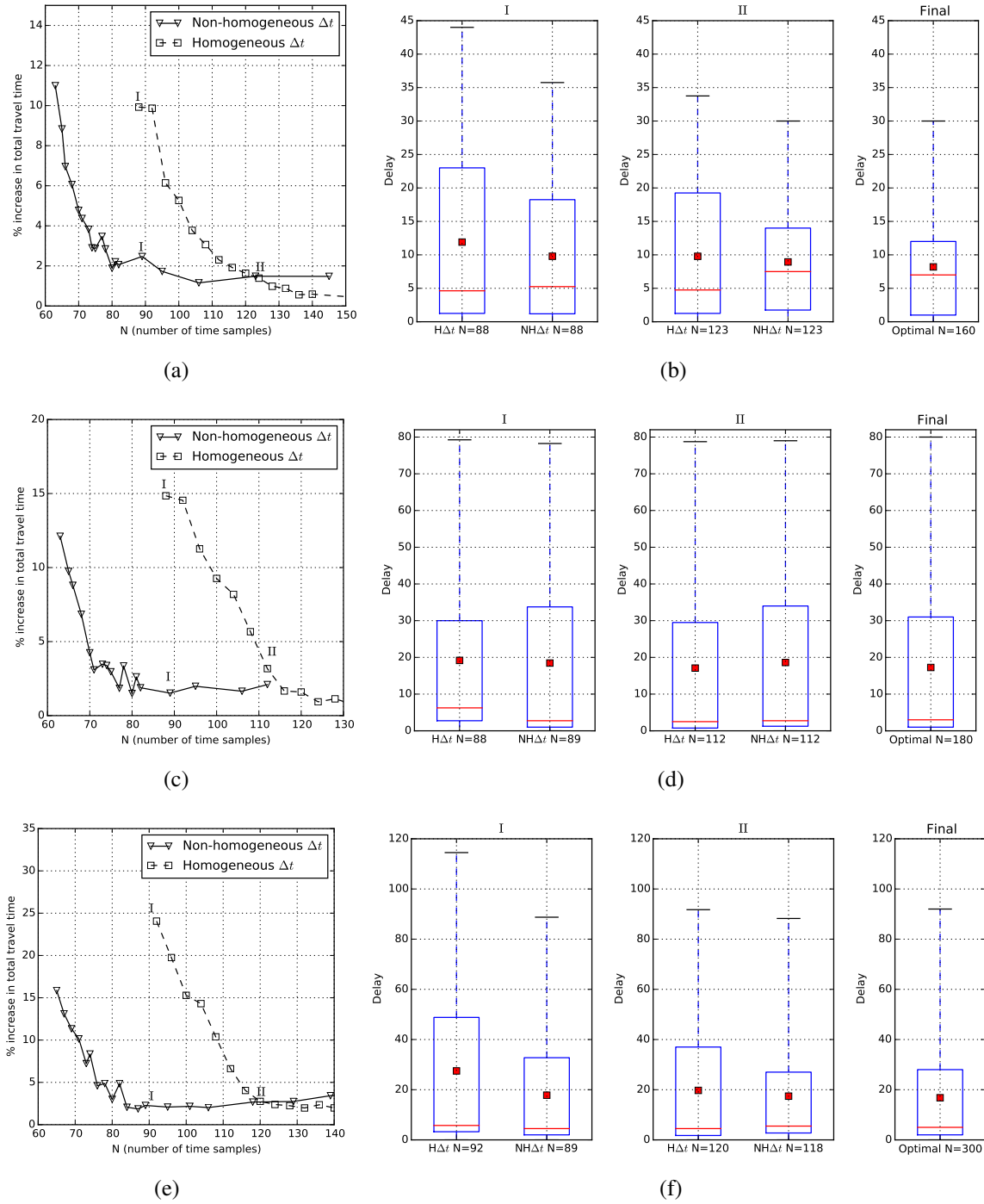
26 In this paper, we showed how to formulate a novel queue transmission model (QTM) model of  
 27 traffic flow with non-homogeneous time steps as a linear program. We then proceeded to allow the  
 28 traffic signals to become discrete variables subject to a delay minimizing optimization objective  
 29 and standard traffic signal constraints leading to a final MILP formulation of traffic signal control.  
 30 We experimented with this novel QTM-based MILP control in a range of networks and demon-  
 31 strated that by exploiting the non-homogeneous time steps supported by the QTM, we are able  
 32 to scale the model up to larger networks whilst maintaining the same quality of a homogeneous  
 33 solution using more binary variables. Altogether, this work represents a major step forward in the  
 34 scalability of MILP-based jointly optimized traffic signal control via the use of a non-homogeneous  
 35 traffic models and thus helps pave the way for fully optimized joint urban traffic signal controllers  
 36 as an improved successor technology to existing signal control methods.

## 37 ACKNOWLEDGMENT

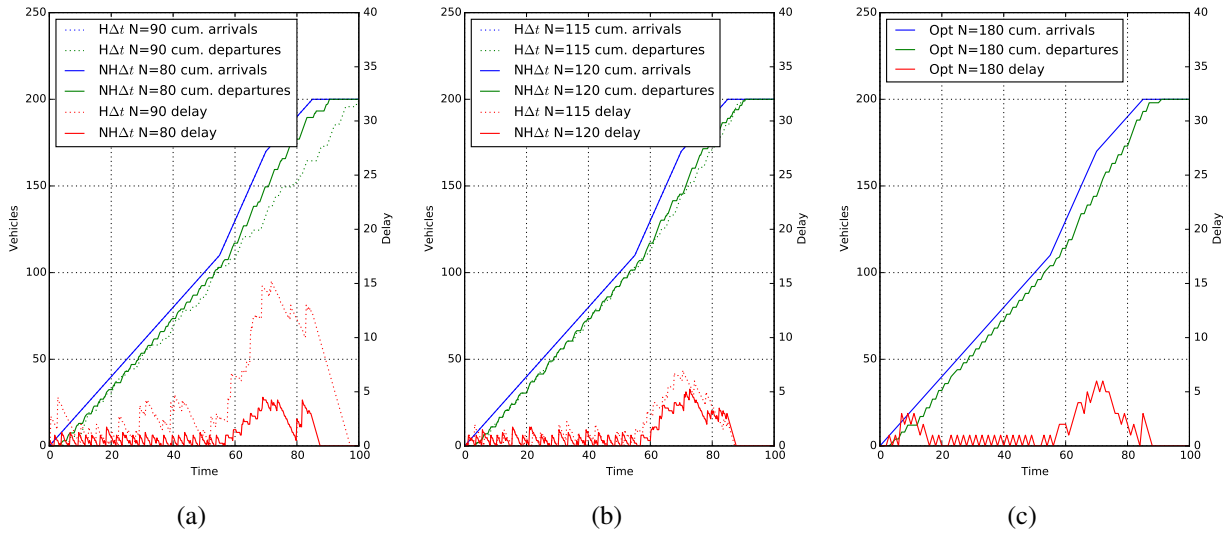
38 This work is part of the Advanced Data Analytics in Transport programme, and supported by Na-  
 39 tional ICT Australia (NICTA) and NSW Trade&Investment. NICTA is funded by the Australian  
 40 Government through the Department of Communications and the Australian Research Council  
 41 through the ICT Centre of Excellence Program. NICTA's role is to pursue potentially economi-

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<sup>11</sup>FWT: although Figure 8 is a nice illustration of how homogeneous and non-homogeneous differ, it is currently not backing up any of our claims.



**FIGURE 7** Increase in the total travel time w.r.t. the optimal solution as a function of  $N$  (Figures a, c, and e) and distribution of the total delay of each car for different values of  $N$  (Figures b, d, and f). For each row, the roman numeral on top of the box plots corresponds to point the travel time plot marked with the same numeral. The mean of the total delay is presented as a red square in box plots. Plots in the  $i$ -th row correspond to the results for the  $i$ -th network in Figure 6.



**FIGURE 8** Cumulative arrival and departure curves and delay for queue 1 in the 2-by-3 network (Figure 6(b)). The value of  $N$  in plots (a) and (b) corresponds, respectively, to the convergence point of the non-homogeneous and homogeneous approaches (Figure 7(c)). (c) presents the same curves for the **optimal** solution.

1 cally significant ICT related research for the Australian economy. NSW Trade&Investment is the  
2 business development agency for the State of New South Wales.

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