ICAPS Summer School 2018: Sequential Optimization for Traffic Signal Control

Scott Sanner

QTM slides courtesy of Iain Guilliard (ANU) and Surtrac slides courtesy of Steve Smith (CMU)
Optimal Traffic Signal Control

• Motivation

• Existing Approaches
  – Practice
  – Theory

• New approaches
  – QTM MILP optimization
  – Surtrac Scheduling

• Frontiers: connected and autonomous vehicles
Motivation
More Motivation
Traffic Impacts Everyone

- **Not a problem I have to motivate**
  - Economically, impact of better control is in billions of $$$ for large cities!

- **Real & unsolved problem**
  - Multidimensional state (integer / continuous)
  - Multidimensional concurrent actions
  - Stochastic
  - Building a high fidelity model is difficult
  - Optimizing it is just as hard
Theory vs. Practice

• **Theory**
  – Idealized
  – Models major phenomena
  – Good analytical techniques

  ![Flow Density Relationship](image)

  **Need a stronger connection!**

• **Practice**
  – Control is rule-based
    • No models or optimization
  – Manually tuned
Practice: It’s worse than you thought

• Billions of $$$ in legacy infrastructure

• Systems are safety verified
  – Difficult and expensive to replace
  – Figure out where to fit in for lowest cost

• Hardware/software limited, e.g., 1970’s era:
  – PDP-11 assembly on PDP-11 simulators!
  – 300 baud rate of infrastructure communication
  – Day divided into four time periods
    • Morning rush, mid-day, evening rush, other
    • Software allows four plan variations per period
Massive Opportunity for Change

• Not only is existing technology rooted in 70’s era
  – But methodologies are often pre-70’s

  – Data collection via human surveys

  – Flow modeling makes strong assumptions
    • Static Nash equilibrium (Wardrop and Whitehead, 1952)

  – Predictions often not validated against flow data
    • Gravity model!

• But now we collect and store masses of data!
And we have tons of data!
Vision: Optimized Traffic Control

• Use predictive traffic model
  – Models traffic well based on existing theory
  – Ideally model parameters are learned from data

• Optimize future signals to maximize traffic flow (i.e., replan every 5 seconds wr.t. current state/model)
  – Use the online learned model for prediction
  – Use a MILP to optimally solve for signal changes
But first...

- We need to understand traffic flow modeling
- And existing methods for signal control
  - In practice
  - In theory
- What’s wrong with existing work?
  - We’ll see...
Traffic Control: In Practice
Signalized Control Timeline

- **Late 1920’s**: Timed Control, Some Sensing
- **1952**: Analog Control (Denver)
- **1960**: Digital Control (Toronto), IBM Mainframe, Some Sensing, Coord. Plans
- **Late 1970’s**: SCATS, SCOOT: Adaptive Control
- **2000+**: Regional Coordination, Metering, VSL, Priority
Terminology

• Signal, e.g.,
• Signal Group
• Phase
• Turns
  – Protected Turn
  – Filter Turn
    • unprotected
Phase Illustration in Commuter
Each intersection has one or more **phase plans**
- Each phase gets a **split** of the **cycle time**

Typically four plans per intersection
- Heavy inbound / outbound, balanced, & light

Now just choose a plan and cycle time for one intersection!
Delay vs. Optimal Cycle Times

- Use maximum best cycle time of any phase

Best cycle time \( \approx \max \text{ of best cycle times per phase} \)
Optimal Cycle Times vs. Flow

- **Light traffic**
  - Short cycle times
  - Minimize delay for individual cars

- **Heavy traffic**
  - Long cycle times
  - Maximize steady-state flow
Problems with Local Control

• Intersections are not independent
  – In-flow of cars $q_i$ is not uniformly distributed!

• Platoons
  – Cars tend to “clump” into platoons
    • Due to discharge from upstream queues
  – Best throughput with good platoon management
    • Careful timing needed
Multi-intersection Control

- Optimize phase offsets for platoon throughput:
Master/Slave Offset Control

- Fix timing offsets from critical intersections
  - Allows platoons to pass in dominant flow direction

Diagram:
- Critical intersection
- Offset Green = 25s
- Offset Green = 40s
- Offset Green = 30s
Multi-intersection Control in Practice

- **Split, Cycle, Offset Optimization (SCOOT, SCATS)**
  - Decide on synchronized intersections
  - Decide on intersection offsets
    - Based on dominant flow direction
  - Decide on phase splits
    - W.r.t. offset constraints
    - Rules to modulate splits by observed flow

- **Practical, but rule-based and very heuristic**
  - Room for data-driven modeling & optimization!
That was practice... let’s take a more theory driven approach
Fundamental Diagram of Traffic Flow

Flow \( q \): cars/s

Density \( k \): cars/m

Velocity \( v \): m/s

\[ q = kv \]

\[ v = q/k \]
Types of Models

• Macrosimulation
  – Model aggregate properties of traffic
  – Average flow, density, velocity of cells

• Microsimulation
  – Model individual cars
  – Typically cellular automata

• Nanosimulation
  – Model people (inside & outside of cars)
Human Factors in Microsimulation

• Microsimulation often involves driver choice:
  – Filter turns
  – Turns into flowing traffic
  – Lane merges
  – Lane changes

• Theories such as gap acceptance theory
  – Attempt to explain driver choices
  – e.g., gap size willing to accept on filter turn $\propto 1$/time

• See Ch. 3 of Traffic-Flow Theory, Henry Lieu
Microsimulation Turn Models

Two ways to model turns:

1. Turn probabilities at each intersection

2. Frequencies in origin-destination (OD) matrix (routes predetermined for each OD pair)

Which is better?

Car may go in loops for 1, more realistic to choose 2!
Microsimulation

• Nagle-Schreckenberg
  – Cellular Automata Model
    • nominally each cell is 7.5m in length

  – Simplest model that reproduces realistic traffic behavior

Image and description from: http://www.thp.uni-koeln.de/~as/Mypage/traffic.html
Car Following in Microsimulation

- Nagel-Schreckenberg
- 4 Rules
  - Acceleration:
    \[ v_i := \min(v_i + 1, v_{\text{max}}) \]
  - Safety Distance:
    \[ v_i := \min(v_i, d) \]
  - Randomization:
    \[ \text{prob} \ p: \ v_i := v_i - 1 \]
  - Driving:
    \[ x_i' = x_i + v_i \]

Image and description from: http://www.thp.uni-koeln.de/~as/Mypage/traffic.html
Car Following Microsimulation

- Continuous traffic flow example:
  - Upper plot is space/time diagram
  - Lower plot is actual traffic

High fidelity online simulation available at [http://www.traffic-simulation.de/](http://www.traffic-simulation.de/)
Microsimulation Software

- **Quadstone Paramics**
  - Largest market share, $$$
  - Industrial strength, fast simulator

- **Vissim**
  - Highly used, $$$
  - Can model a variety of path-based user behavior

- **SUMO**
  - Free
  - Can download maps directly from OpenStreetMap

You most likely won’t be able to test your traffic control tools in the real world, so microsimulation is the only way to test.
Microsimulator Example
An Even Better Microsimulator

Traffic Jam without Bottleneck

Experimental evidence for the physical mechanism of forming a jam

Yuki Sugiyama, Minoru Fukui, Macoto Kikuchi, Katsuya Hasebe, Akihiro Nakayama, Katsuhiro Nishinari, Shin-ichi Tadaki and Satoshi Yukawa

Movie 1

https://www.youtube.com/watch?v=Suugn-p5C1M
But microsimulation is difficult for real-time control

Ideally would like some form of closed-form macro-model

\[ K_d = 0.1 \text{ cars/m, } v_d = 15 \text{ m/s} \quad K_u = 0.05 \text{ cars/m, } v_u = 30 \text{ m/s} \quad K_d = 0.1 \text{ cars/m, } v_d = 15 \text{ m/s} \]
Shockwaves in Macro Models

- Low density traffic meets high density traffic…

- Shockwave (density wave) $u = -20\text{m/s}$
Calculation of Shockwave Speed

• Law of conservation of cars:
  – “Cars can neither be created nor destroyed”

• Traffic flows in/out of shockwave at rate:

\[
q_{\text{enter}} = k_u (v_u - u)
\]
\[
q_{\text{exit}} = k_d (v_d - u)
\]

\[
q_{\text{exit}} = q_{\text{exit}} \Rightarrow u = \frac{k_d v_d - k_u v_u}{k_d - k_u} = \frac{q_d - q_u}{k_d - k_u} = \frac{\Delta q}{\Delta k}
\]
Theory of Shockwaves

Determine shockwave speed $u$ from diagram:
Theory of Shockwaves

Determine shockwave speed $u$ from diagram:

$$u = \frac{q_d - q_u}{k_d - k_u} = \frac{\Delta q}{\Delta k}$$

$u < 0$ causes shockwave to propagate back
Theory of Shockwaves

Determine shockwave speed $u$ from diagram:

$$u = \frac{q_d - q_u}{k_d - k_u} = \frac{\Delta q}{\Delta k}$$

$u > 0$ dissipates shockwaves!
Cell Transmission Model (CTM)

- **CTM setup:**
  - **Variables:** flow rate, density
  - **Constants:** max capacity, peak and jam densities
  - Piecewise linear difference equation transition model
  - Recreates shockwave phenomena at macro-level!

CTM requires a lot of cells…

Is there a more high-level macrosimulation model?
Link-based Alternatives to CTM

- Link is a traffic queue vertically stacked at stopline
- Limitations [Gartner'02, Han et al'12]
  - Some versions poorly model delay
  - Single traffic boundary (single platoon)
QTM: A Non-homogeneous Time Mixed Integer LP Formulation for Traffic Signal Control

Iain Guilliard, Scott Sanner, Felipe Trevizan, Brian Williams
A New Queue-based Model (QTM)

• Each link is a FIFO queue of traffic
• If traffic signals known, flow is an LP!
• If make traffic signals binary decisions ➔ MILP!
QTM Example
QTM Example – Flow with fixed control
QTM Example – Queuing Behavior
QTM Example – Platoons
QTM Example – Turn Probabilities
QTM – Variables and Parameters
QTM - Dynamics

Link traffic state

free flow → congested

platoon

queue at light

QTM

CTM 3 cells

c1  c2  c3

CTM 9 cells

c1  c2  c3  c4  c5  c6  c7  c8  c9
Non-Homogenous Link Flow LP

- **Constraints**

  \[ \text{in}_j^n \leq Q_j^{IN} \]

  \[ q_{j,\text{in}}^n = \text{in}_j^n \Delta t^n + \sum_{i=1}^{Q} f_{i,j}^n \Delta t^n \]

  \[ \text{out}_j^n \leq Q_j^{OUT} \]

  \[ q_{j,\text{out}}^n = \text{out}_j^n \Delta t^n + \sum_{i=1}^{Q} f_{j,i}^n \Delta t^n \]

  \[ f_{j,i}^n = F_{j,i}^{\text{P},\text{OB}} \sum_{k=1}^{Q} f_{j,k}^n \]

  \[ q_{j,\text{out}}^n \leq q_j^{n-1} \]

  \[ q_j^n \leq Q_j^{\text{MAX}} \]

  \[ q_j^n = q_j^{n-1} - q_{j,\text{out}}^{n-1} + q_{j,\text{in}}^{n-\text{delay}} \]

  \[ q_{j,\text{in}}^{n-\text{delay}} + \sum_{k=n-\delta+2}^{n-1} q_{k,\text{in}}^k \leq Q_j^{\text{MAX}} - q_j^{n-1} \]

  \[ q_{j,\text{in}}^{n-\text{delay}} = (1 - \alpha)q_{j,\text{in}}^{n-\delta} + \alpha q_{j,\text{in}}^{n-\delta+1} \]

- **Maximize** \( \sum \text{outflows} \)
What to Optimize?

• Minimize delay, but how to define?

• Formally:

\[
\left( \sum_{n=1}^{N} \sum_{j=1}^{Q} (T_{\text{MAX}} - t^n + 1)q_{j,\text{out}}^n \right) + \sum_{n=1}^{N} \sum_{j=1}^{Q} (T_{\text{MAX}} - t^n + 1)in_j^n
\]
QTM with optimized control
Example: Delay Map, fixed vs optimized

Fixed

QTM Optimized
Extensions

• Globally Optimal Fixed-time Control
  – Simulate fixed adaptive controllers (e.g. SCATS)
  – Pre-compute optimal schedules for fixed controllers

• Light Rail Schedules
  – Nullify the impact of introducing light rail

• Uncontrolled intersections
  – Optimize via neighboring intersection signals
Globally Optimize Fixed-time Controllers

Constrain phase times to be same over all cycles – leads to best fixed-time controller!
Fixed Time Control – micro-simulation
Light Rail – Network 1
Light Rail – Delay Heat Map 3400 vph

Optimized

Fixed

$q_0$, $q_1$, $q_2$, $q_3$

$q_4$, $q_5$, $q_6$, $q_7$

$q_8$, $q_9$, $q_{10}$, $q_{11}$

$q_{12}$, $q_{13}$, $q_{14}$, $q_{15}$

$q_{16}$, $q_{17}$, $q_{18}$, $q_{19}$

$q_{20}$, $q_{21}$, $q_{22}$, $q_{23}$
Light Rail – Delay Heat Map 4300 vph

Optimized

Fixed
Uncontrolled Intersections
Future Work

• Close the loop
  – Use high fidelity microsimulator
  – Learn QTM parameters from data

• Compare QTM:
  – with CTM and LTM MILPS

Code on Github:

github.com/iainguilliard/QTM_Traffic_Model
Lecture Midpoint Goals Recap

1) To understand fundamentals of traffic signal control in theory and practice

2) To understand QTM approach for optimizing traffic signals using MILPs

3) To understand the Surtrac job-shop scheduling approach to traffic signal control

4) To understand frontiers of traffic signal control: connected and autonomous vehicles