Unified Route Choice Framework and Empirical Study in Urban Traffic Control Environment

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Motivation

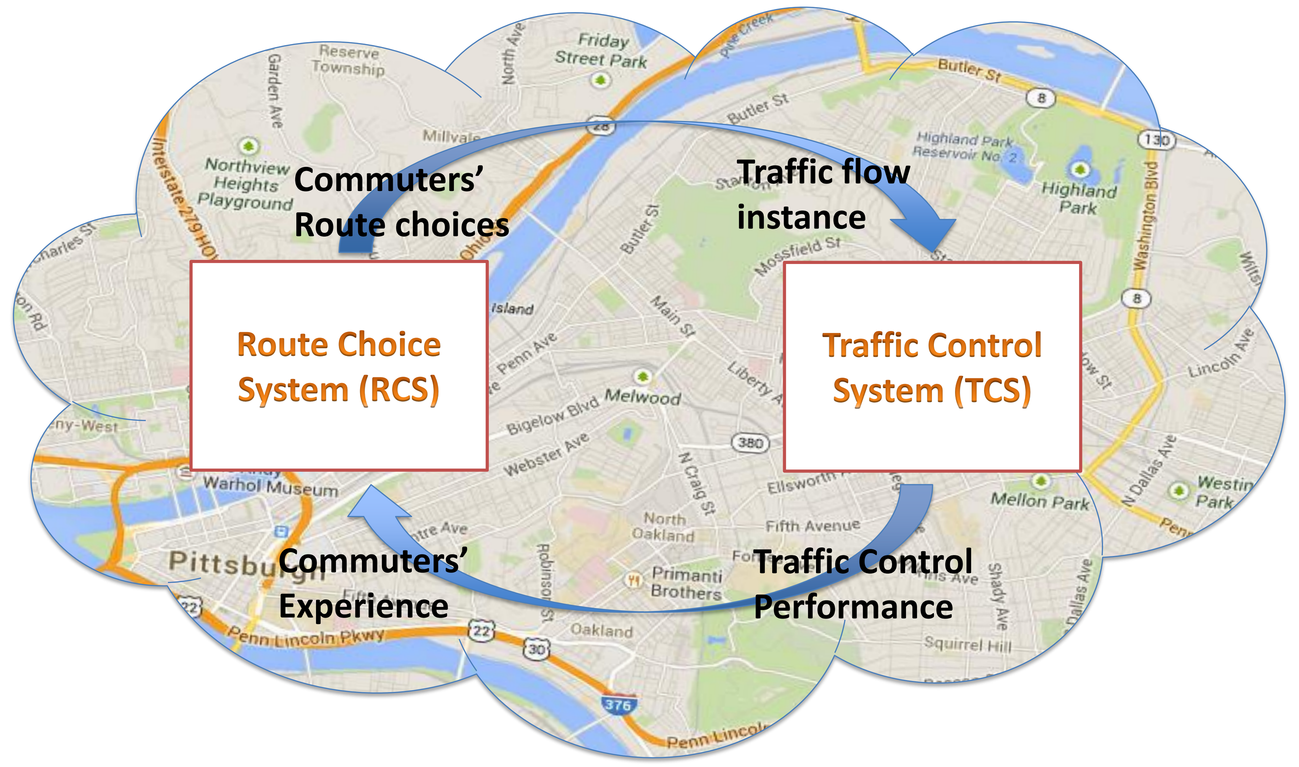
- Route choice system (RCS) and traffic control system (TCS) : Two major approaches to mitigating urban congestion
- Little attempt has been made to understand their performance and difference in real-world urban traffic control environment

Our Work

- Realize a unified framework for route choice models
- Implement existing route choice models and hybrid models
- Evaluate route choice models on real-world traffic control systems, under microscopic traffic simulation environment
- Study their subtle difference in approaching an equilibrium, and performing under fixed-time and adaptive traffic control

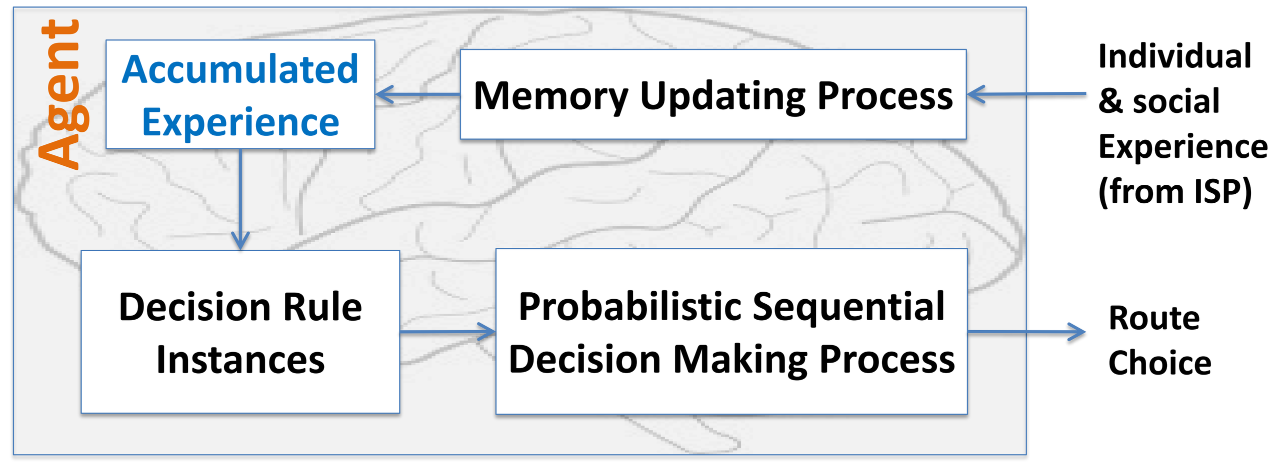
Problem Definition

- Day-to-day commuting problem in an urban road network
  - All commuters choose a route, based on existing experience
  - The routes (as traffic flows) are then executed in the context of TCS
  - The results of TCS become new experience for RCS
- Objective: to reach an (system optimal) equilibrium
  - Focus on studying difference in route choice strategies
  - Evaluate the role of the optimization capability of TCS as well



Route Choice Framework

- **Goal:** Specification/analysis of (pure and) hybrid route choice models
  - Provide a way to investigate properties of RC components and identify subtle differences between them
  - Accumulate and build more effective and stable RC models
- Assumes a simple ISP and a set of **agents**
  - Focus on realistic, decentralized user behavior



Agent: Memory Updating Process

– Assume accumulated experience is captured as a set of quantifiable features (called memory elements)

– Each feature value is updated on each iteration to reflect experience gained (using an associated update procedure)

– Updating of memory table proceeds sequentially (row by row) to allow specification and use of composite features

Memory	Initialization	Updating Process
$\widetilde{tt}$	$\widehat{tt}$	$R_{EMA}(\widetilde{tt},\widehat{tt}\mid\alpha=0.5)$
$\widetilde{\mathbf{TT}}$	$\widehat{\mathbf{TT}}$	$R^{vec}_{EMA}(\widetilde{\mathbf{TT}},\widehat{\mathbf{TT}}\mid\alpha=0.01)$
		$R^{index}_{EMA}(\widetilde{\mathbf{TT}},\widehat{tt},\widehat{k}\mid\alpha=0.5)$
$\widetilde{\mathbf{FF}}$	$\widehat{\mathbf{FF}}$	$R^{sum}_{NORM}(R^{vec}_{EMA}(\widetilde{\mathbf{FF}},\widehat{\mathbf{FF}}\mid\alpha=0.5))$
		$R^{sum}_{NORM}(R^{vec}_{EMA}(\widetilde{\mathbf{FF}},R_{CI}(\widehat{k})\mid\alpha=0.01))$
$\widetilde{\mathbf{F}}_{LRI}$	$\widehat{\mathbf{FF}}$	$R^{sum}_{NORM}(R_{LRI}(\widetilde{\mathbf{F}}_{LRI},\widetilde{\mathbf{TT}},\widehat{k}\mid\beta=0.01))$
$\widetilde{\mathbf{D}}$	$R_{RF}(\widehat{\mathbf{FF}})$ ($\theta=0.05$)	$R^{vec}_{EMA}(\widetilde{\mathbf{D}},R_{RF}(\widehat{\mathbf{FF}})\mid\alpha=0.01)$
		$R^{min}_{NORM}(\widetilde{\mathbf{D}}+R^{sum}_{NORM}(R_{BI}(\widetilde{\mathbf{TT}},\widehat{tt})))$

Agent: Decision Rule Instances

– Decision rules provide the building blocks for route generation

– Each returns either a route or a *can't decide* decision, based on current updated values of relevant features (memory elements)

(R1): $R^{\varepsilon}_{IN}(\widetilde{\mathbf{TT}})$	*ε-inertia*	(R5): $R_P(\widetilde{\mathbf{F}}_{LRI})$	*Proportional*
(R2): $R^{\delta}_{IN}(\widetilde{\mathbf{TT}})$	*δ-inertia*	(R6): $R_{MNL}(-\theta\cdot\widetilde{\mathbf{D}})$	*Multinomial logit*
(R3): R^{A}_{IN}	*inertia*	(R7): $R_{RM}(\widetilde{\mathbf{TT}},\widetilde{tt})$	*Regret matching*
(R4): $R_B(\widetilde{\mathbf{TT}})$	*Best-move*	(R8): $R_{ER}(\widetilde{\mathbf{TT}},\widetilde{\mathbf{FF}})$	*Exploration-replication*

Agent: Probabilistic Sequential Decision Making Process

– Decision rules are configured (using sequential execution) to define specific route choice models

– Basic form: sequence of < *Decision-Rule(i), Prob* $_{activation}$*(i)* > pairs

– If Decision-*Rule(i)* is not activated or returns *can't decide*, then execute Decision-*Rule (i+1)*

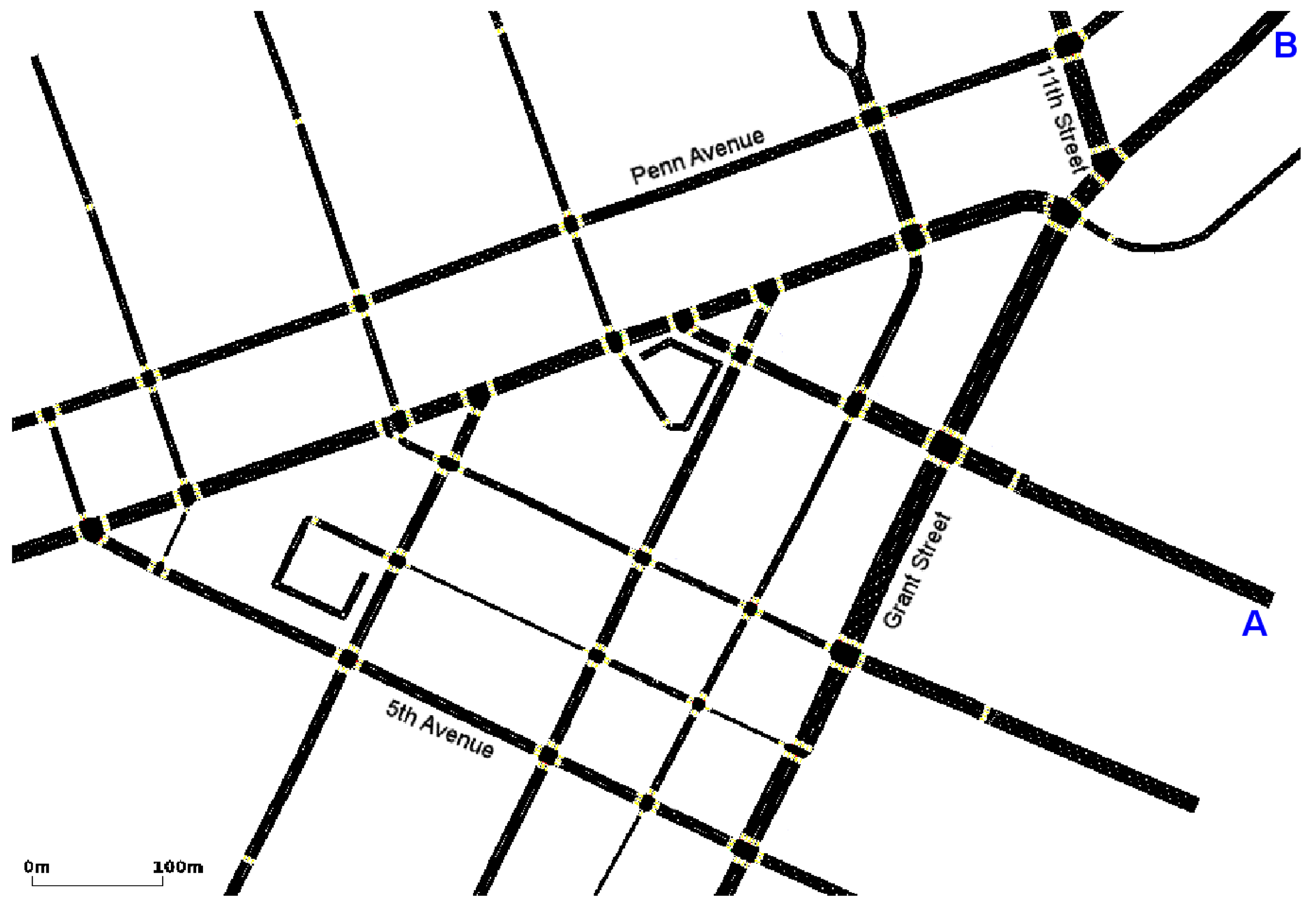
– Examples:

> Exploration Replication Policy (ERP) [12]:
> - (ERP): [(R3, .97) (R8, 1)]
>
> Agent-Based Model of [19]:
> - (ABM): [(R1,1) (R2, 1) (R6, 1)]
>
> A Hybrid ABM Model:
> - (ABM-BI): [(R3, .75) (R1,1) (R2, 1) (R4, .5) (R6, 1)]

– Supports specification of both fast-and-frugal heuristics and sophisticated RC models

Simulation Setup

- Real-world road network with grid-like character



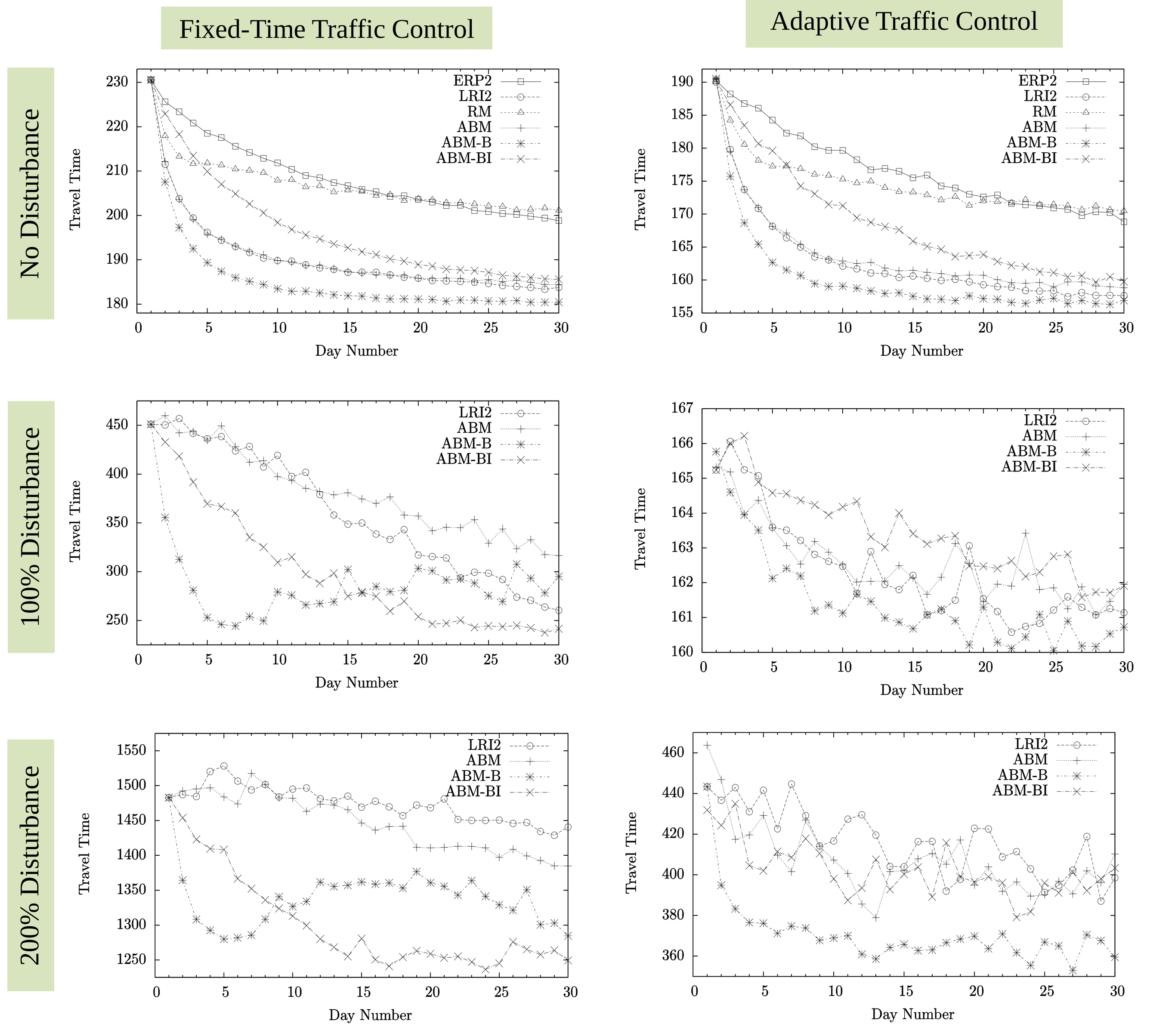
- Real-world traffic control systems (TCS)

  (1) "**Fixed-Time**": SYNCHRO-generated coordinated signal timings
  - ➢Cycle times, splits and offsets, provided by the City of Pittsburgh

  (2) "**Adaptive**": Scalable URban TRAffic Control (SURTRAC) system
  - ➢A decentralized TCS currently controlling 18 intersections in Pittsburgh
  - ➢Has reduced the average travel time through the pilot site by over 25%
- Microscopic simulation to capture complexity of urban traffic control

Results

- Reach an Equilibrium (No disturbance)
  – The adaptive RCS reduced average travel time by 21.7%, and the adaptive TCS produced a further reduction 13.4%
- Fixed-Time vs. Adaptive Traffic Control
  – Adaptive TCS: Real-time traffic adaptation leads to flexible capacity control and reducing the risk of congestion
  – Fixed-time TCS: The loss of effectiveness as dynamic flow changes might be seen as modeling an *aging* problem that is observed in the real world
- Observations on Decision Components
  – R4 (*best response*) can help for reaching to near optimal, R3 (*inertia*) can help for maintaining stable in congested cases
  – LRI2 and ABM variants make better decisions by updating choice probabilities rather than directly based on the cost array



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