Smoothing Traffic with Connected and Automated Vehicles via Trajectory Control

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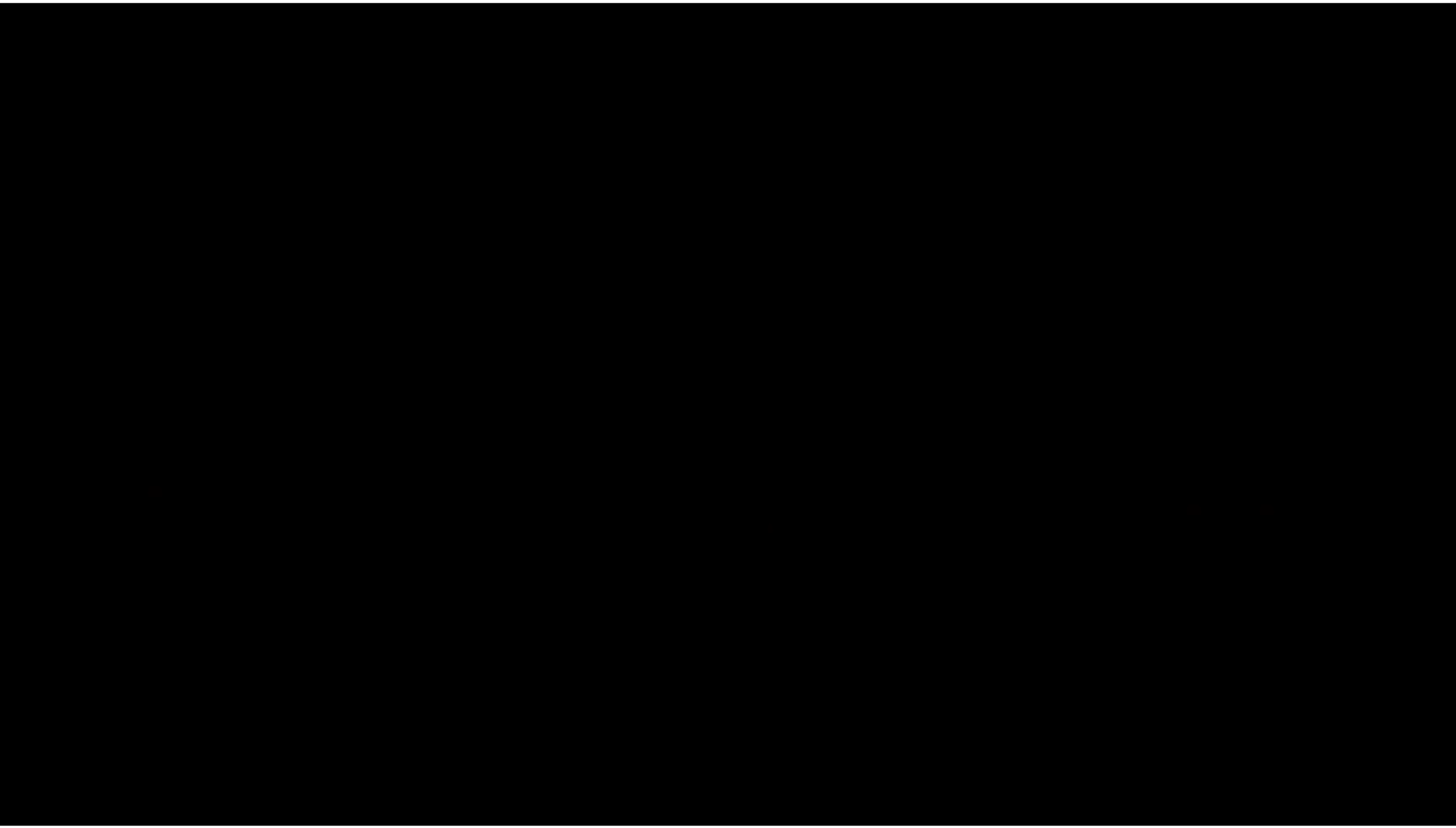
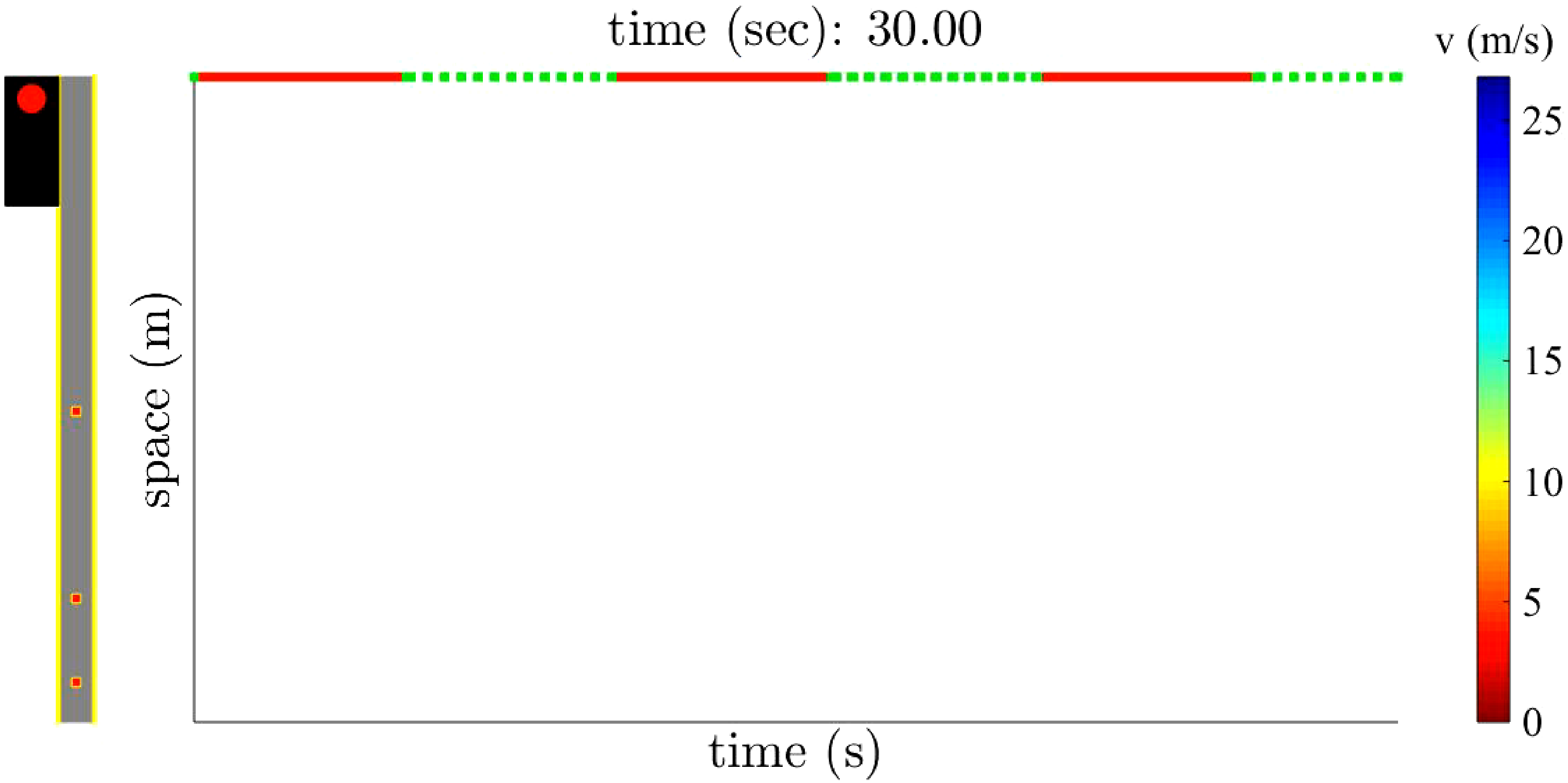
USF UNIVERSITY OF SOUTH FLORIDA

Stop-and-Go Traffic – Freeway



Stop-and-Go Traffic – Arterial

- Stop-and-go waves



Impacts of Stop-and-Go Traffic

- Traffic congestion in US
  - 42 hours of delay per car commuter
  - Costs $960 per auto commuter

Tampa: 11th most congested cities
http://mobility.tamu.edu/ums/report/

Impacts of Stop-and-Go Traffic

- Fuel consumption & emissions in US
  - 70% petroleum fuel consumption
  - 30% greenhouse gas emission
  - Congestion wastes 3.1 billion gallons of fuel /year

Impacts of Stop-and-Go Traffic

- Traffic safety in US
  - 2,200,000 injuries
  - 33,000 fatalities

Why Stop-and-Go

- Humans – Imperfect drivers
  - "In the distant future it will be only outlaws driving cars… can't have a person driving a two-ton death machine" – Elon Musk at 2015 Nvidia's Annual Developers Conference

Why Stop-and-Go

- Limitations of human drivers
  - Disconnected
  - Uncooperative
  - Unpredictable
  - Slow
  - Erroneous
  - …

Connected Vehicles

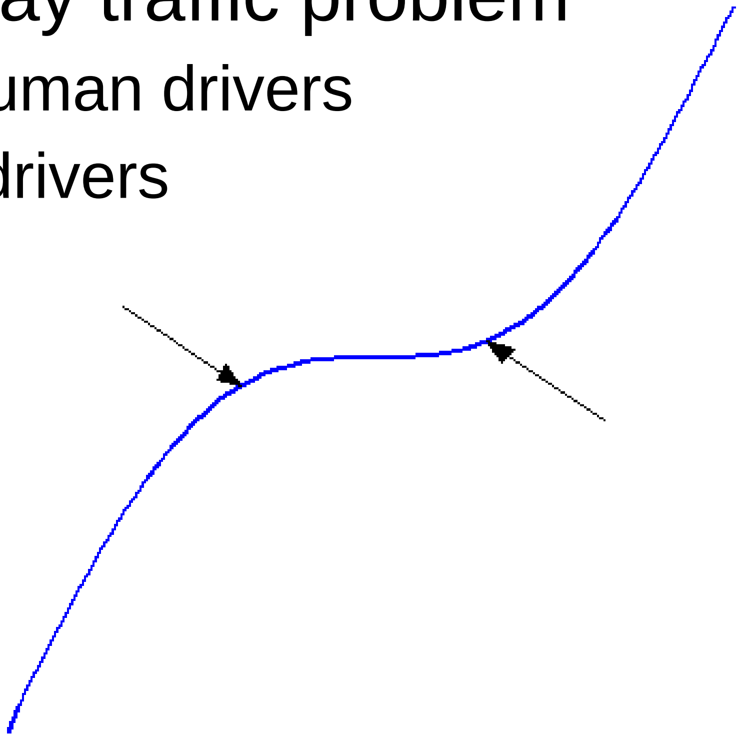
- Vehicle connection = Information sharing

Automated Vehicles

- Human drivers → Robot drivers

Cure: Connection + Automation

- Connected automated vehicles (CAVs)
- Enable trajectory-level vehicle control and coordination
- The fundamental highway traffic problem
  - Past – accommodating human drivers
  - Future - designing robot drivers

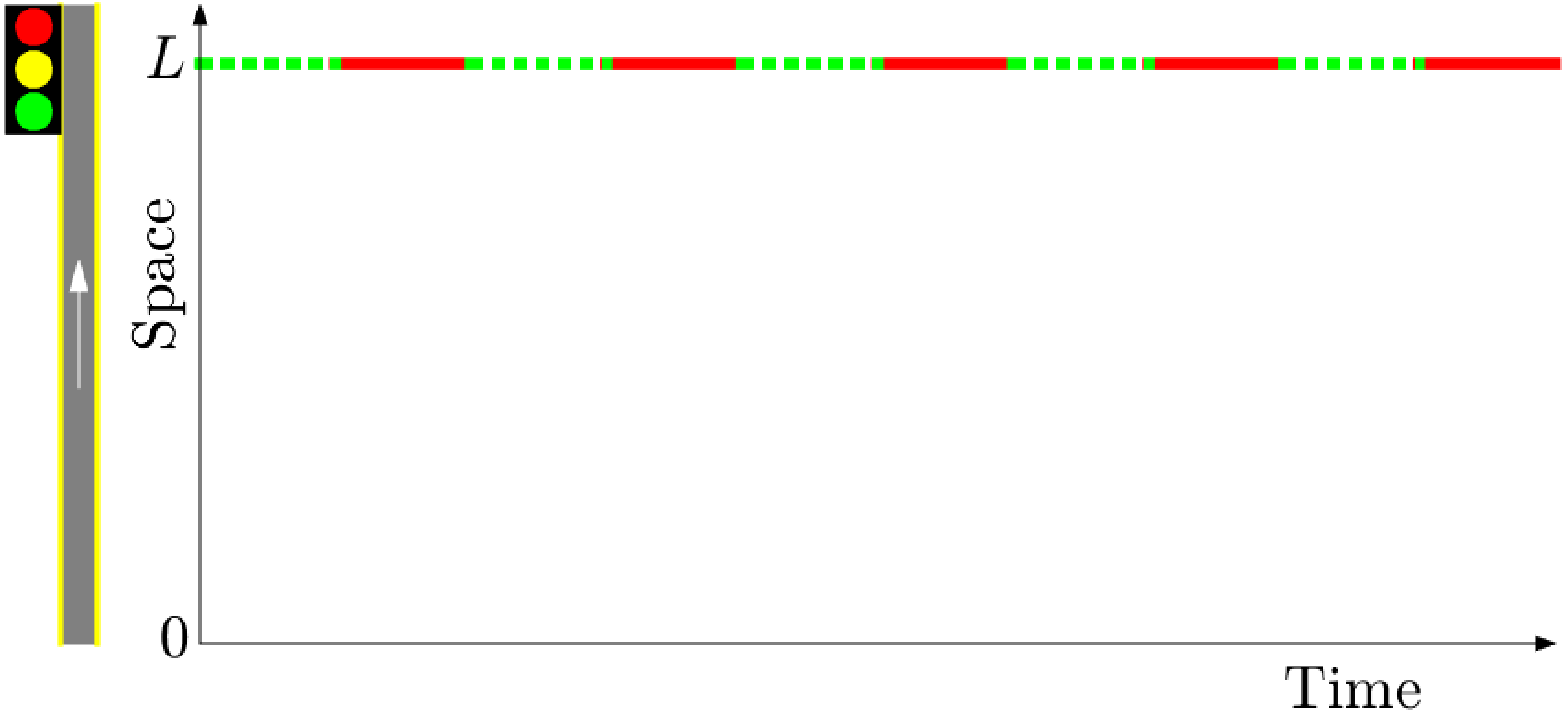


Objectives of This Study

- Efficient and parsimonious algorithm to smooth a stream of CAVs along a road
- Applicable to various road facilities

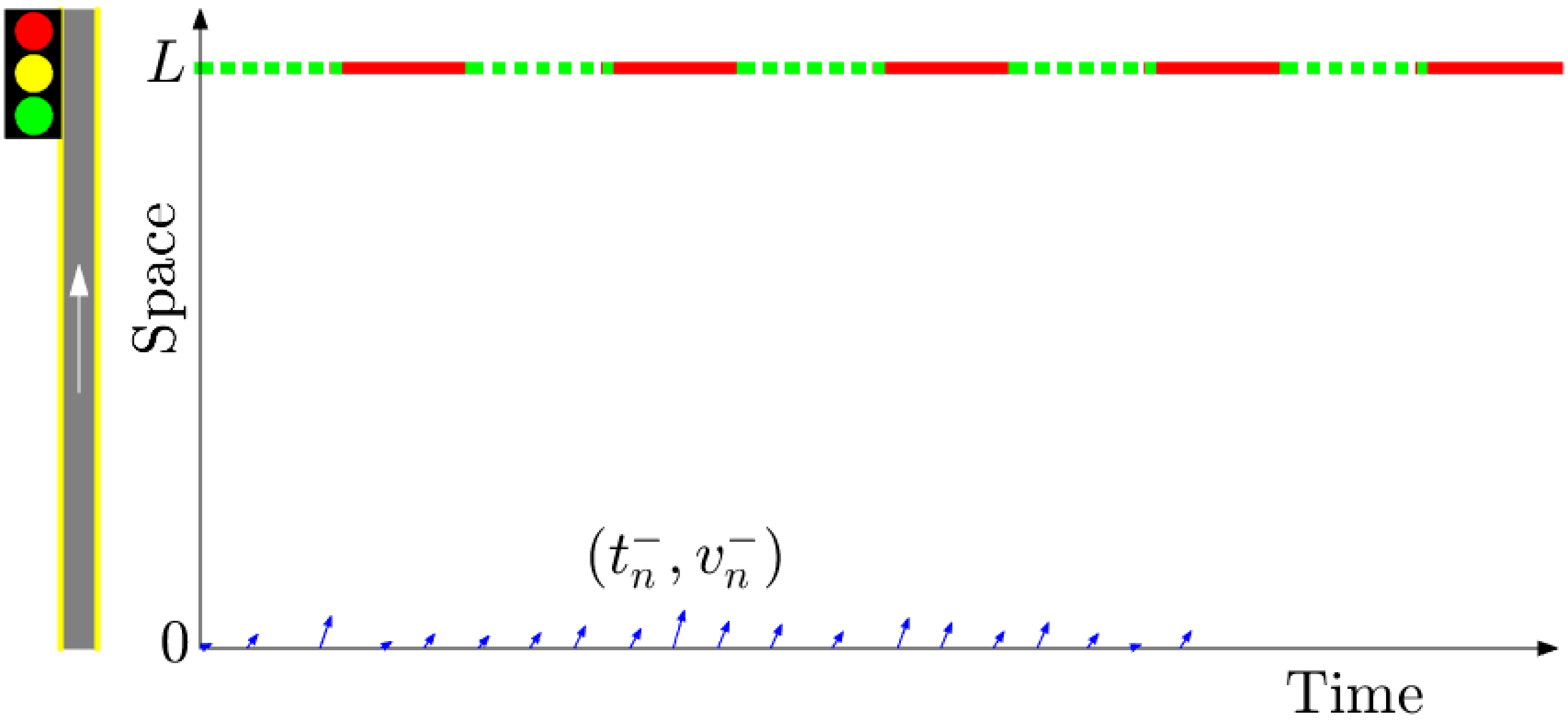
Infrastructure

- Single lane highway segment $[0, L]$
- Fixed signal timing $G, R, G, \ldots$ at location L



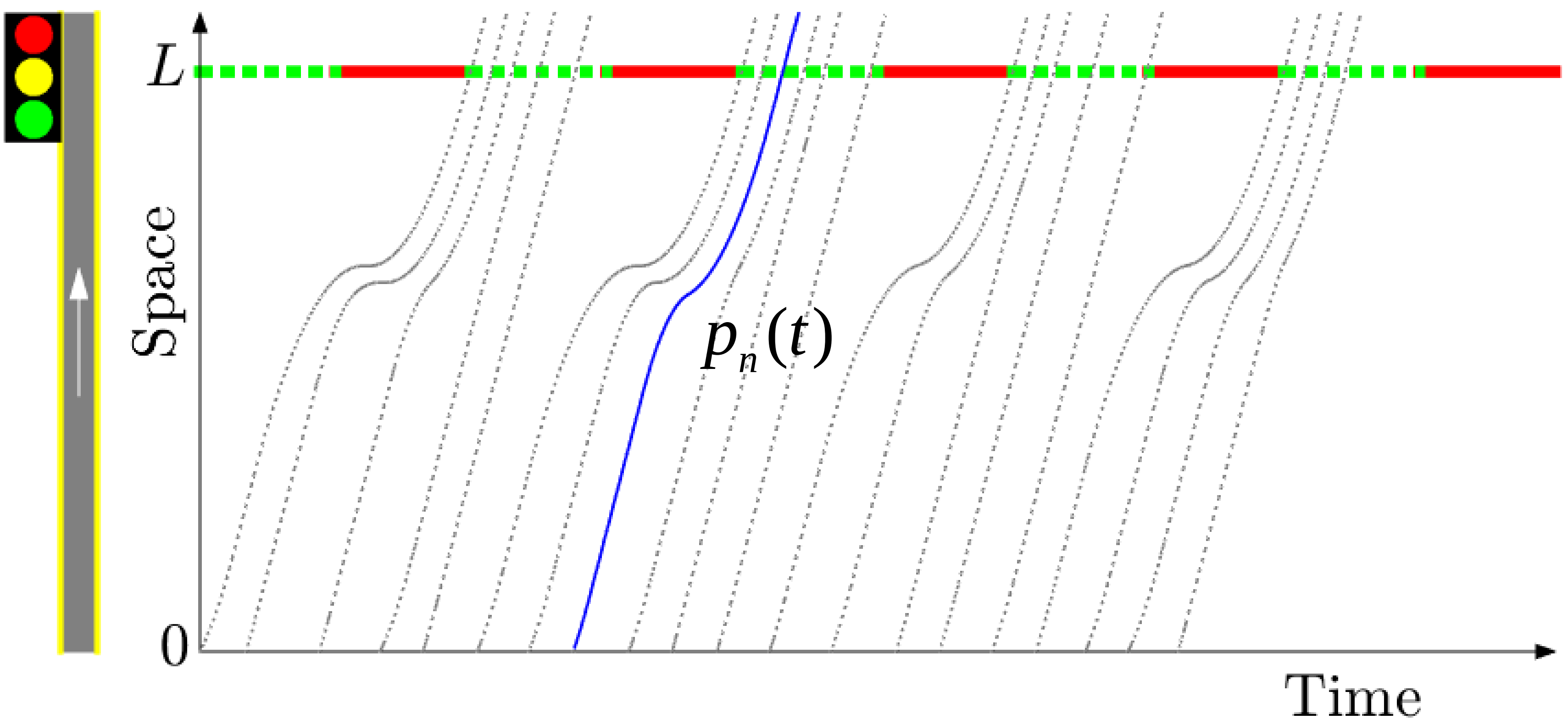
Entry Boundary Condition

- Indexed by $n = 1, 2, \dots, N$
- Entry time t_n^-, speed v_n^-, known a priori



Physical Bounds

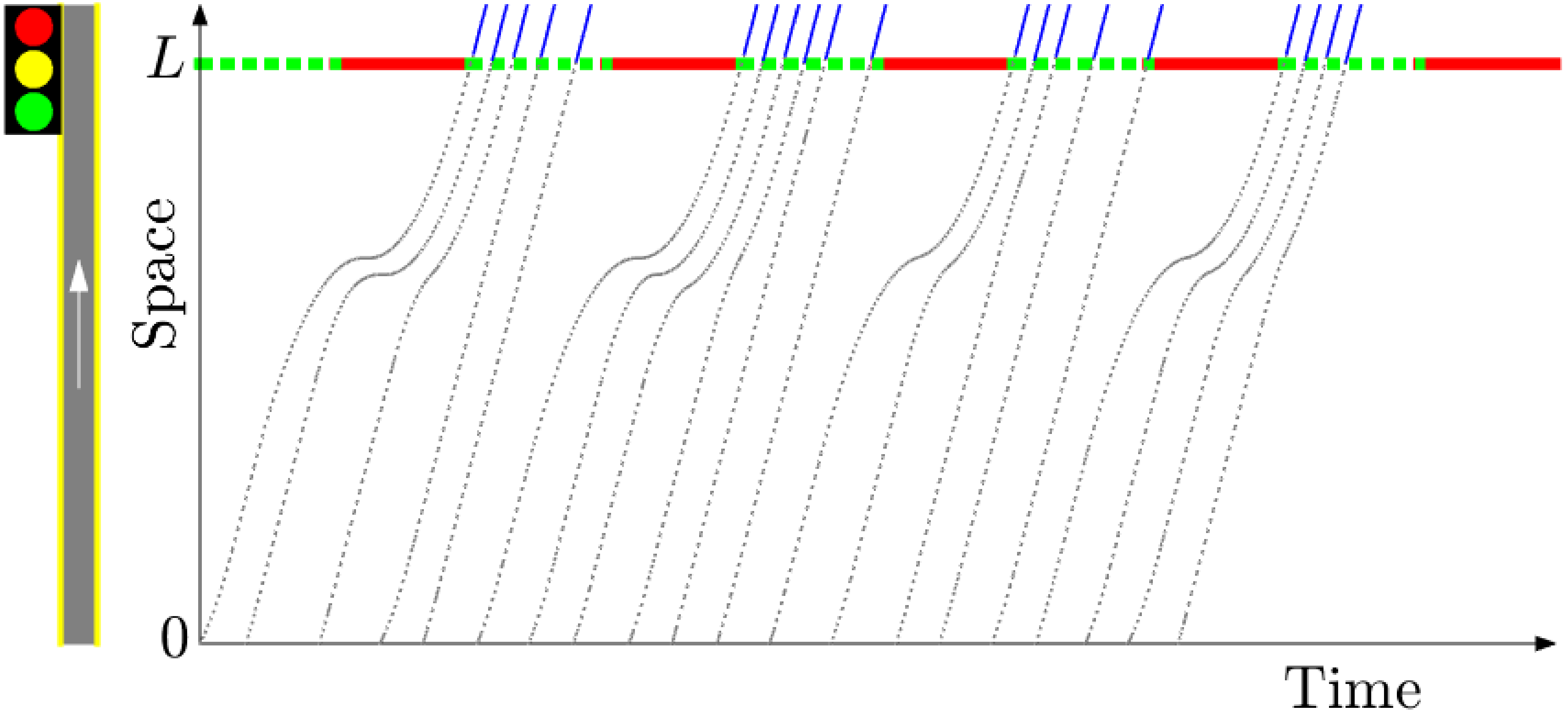
- Trajectory $p_n(t)$
- Speed $\dot{p}_n(t) \in [0, \bar{v}]$, acc. $\ddot{p}_n(t) \in [\underline{a}, \bar{a}]$



Exit Boundary Constraint

- Exit during green time:

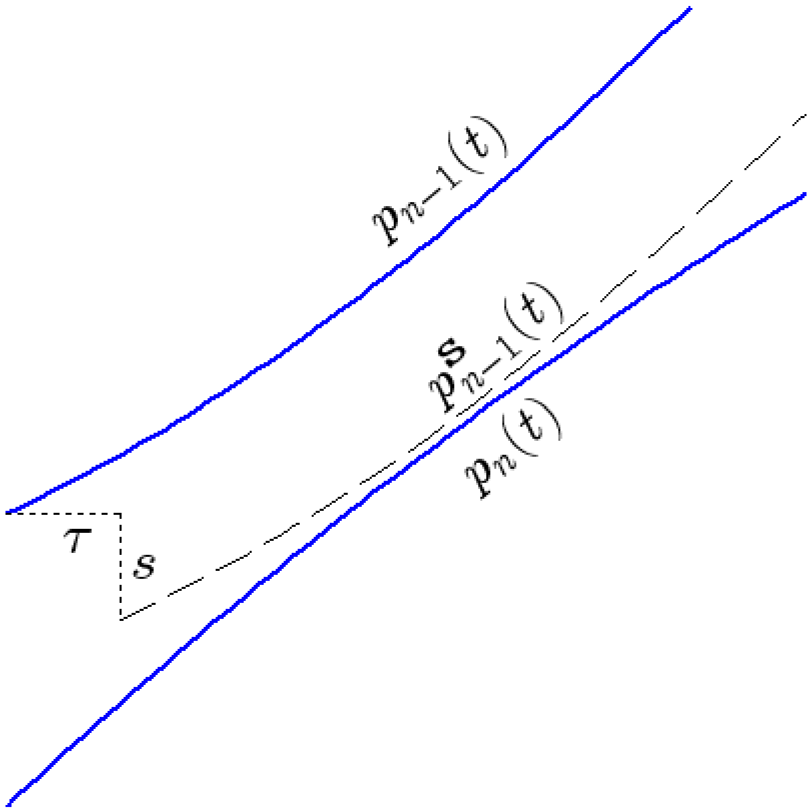
$$\mathrm{mod}(p_n^{-1}(L), G + R) \le G$$



Vehicle Following Safety

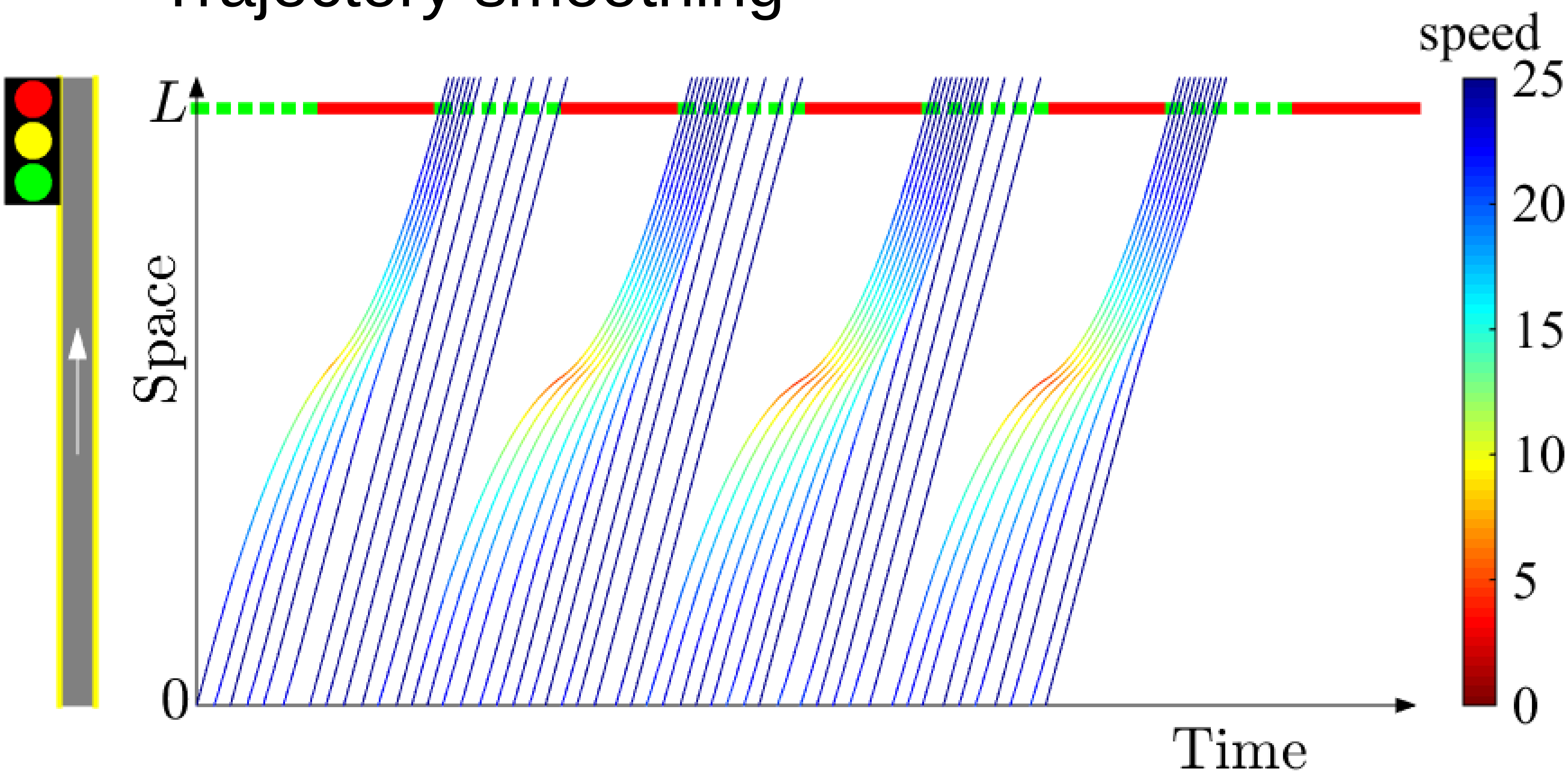
- Two consecutive vehicles *n*-1 and *n*
- Shadow trajectory $p_{n-1}^{S}(t) = p_{n-1}(t+\tau) - s$
- Reaction time τ
- Safety spacing *s*
- *Safety constraint:*

  $p_n(t) \le p_{n-1}^{s}(t)$



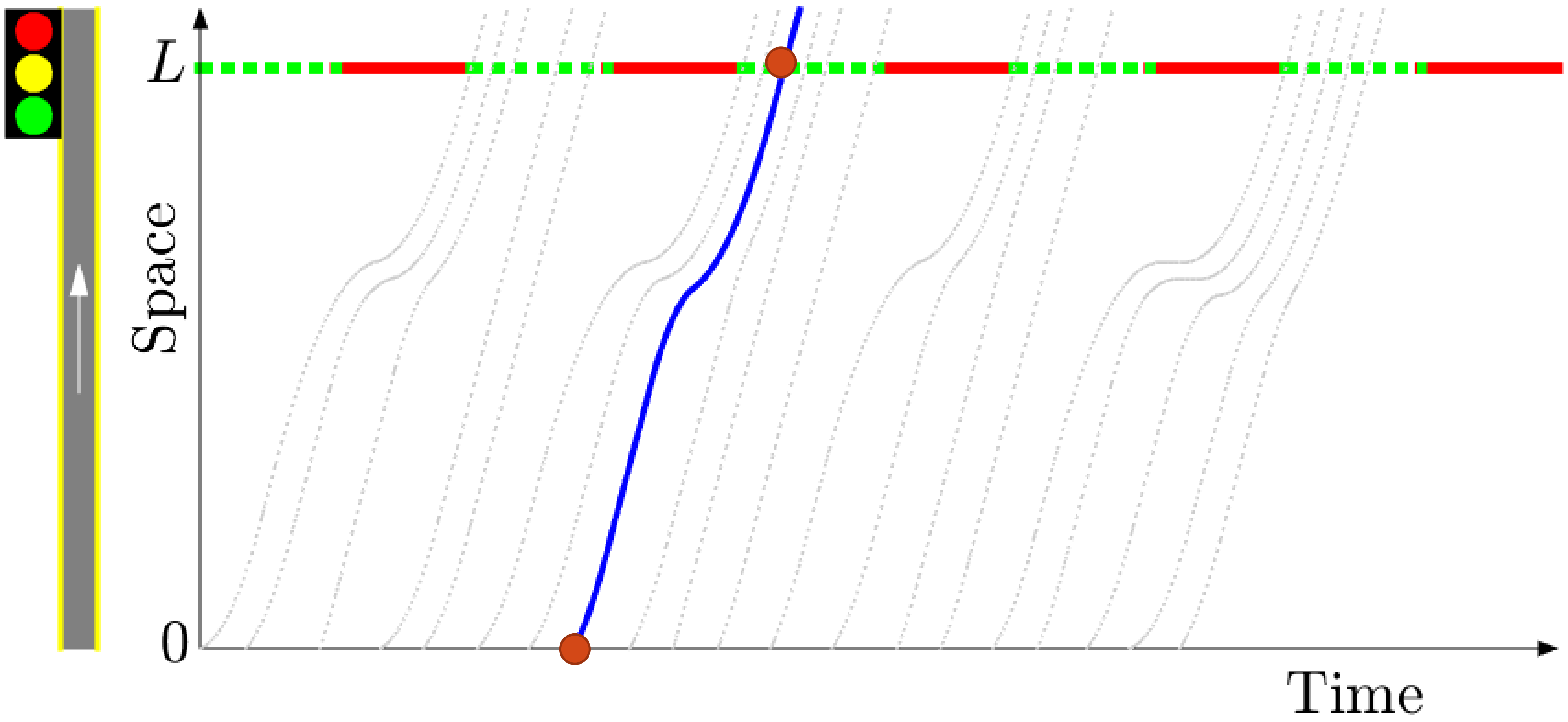
Research Question

- Design CAV trajectories to optimize MOEs
  - Travel time, fuel consumption, safety
- Trajectory smoothing



Travel Time MOE

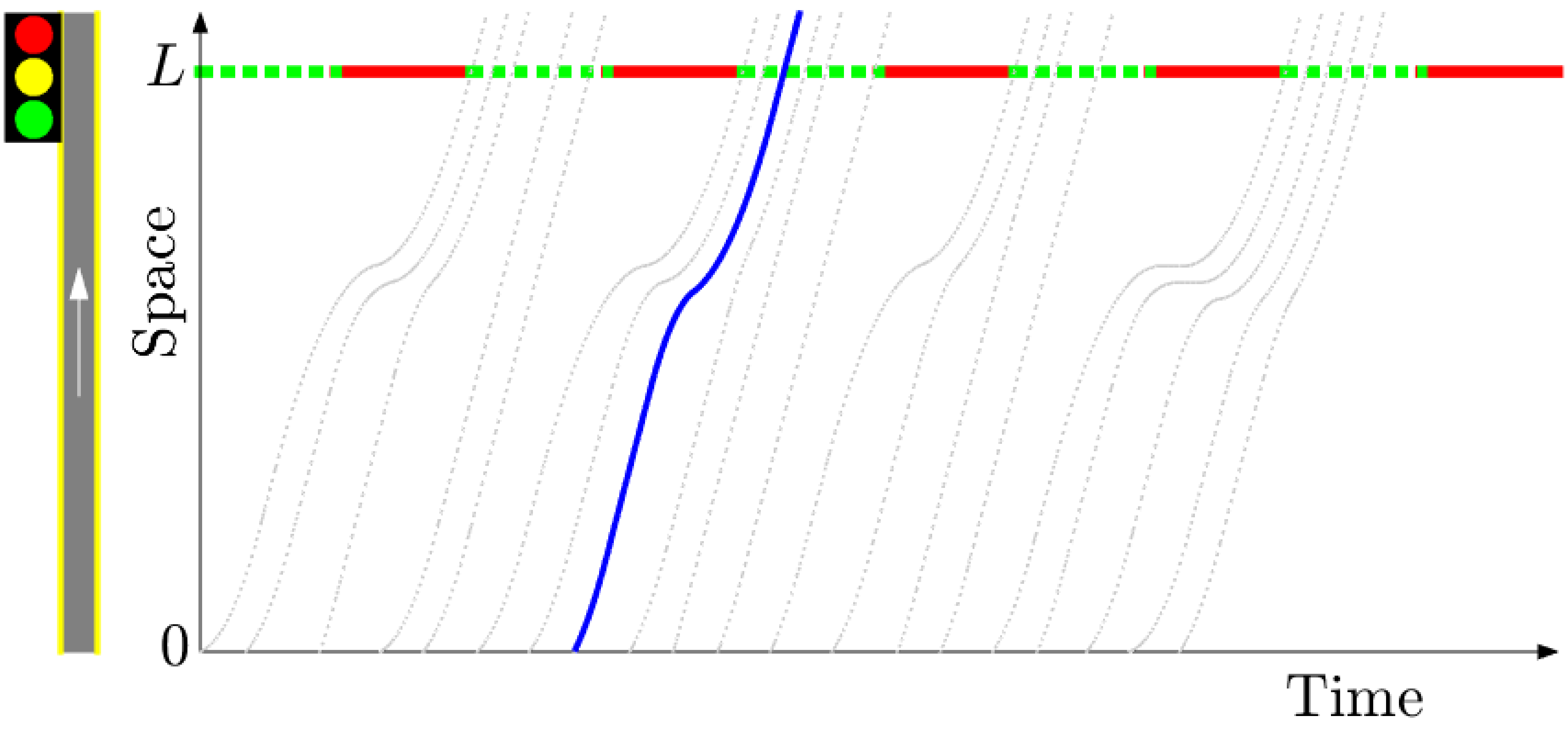
$$T := \sum_{n \in \mathcal{N}} \left(p_n^{-1}(L) - t_n^{-} \right) / N,$$



Fuel Consumption MOE

- E.g., VT-micro, CMEM, MOVES

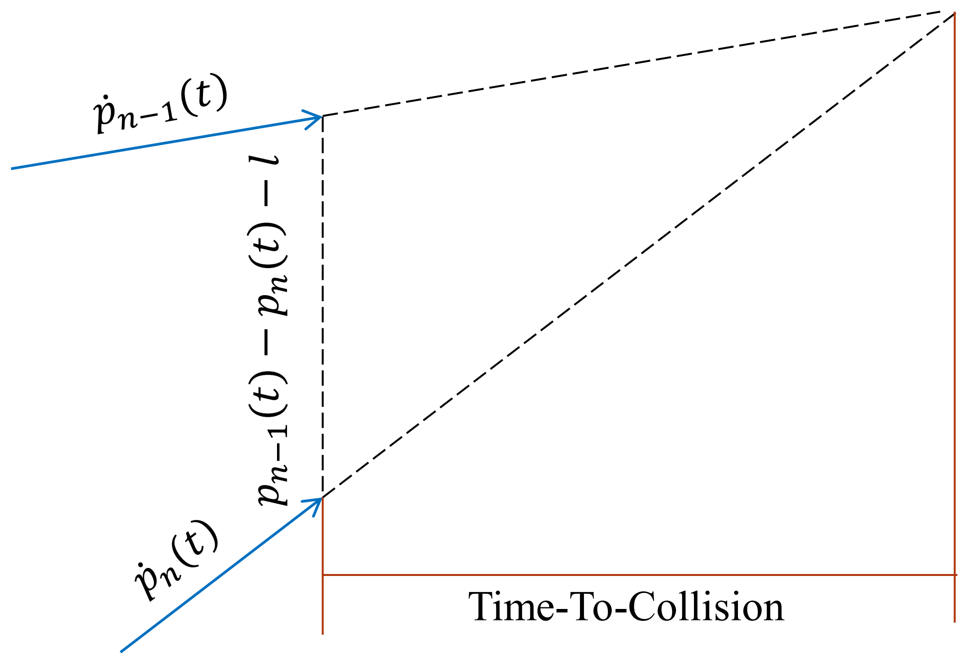
$$E := \sum_{n=1}^{N} \int_{t_n^-}^{p_n^{-1}(L)} e\big(p_n(t), \dot{p}_n(t), \ddot{p}_n(t)\big)\, dt \,/\, N$$



Safety MOE

- Surrogate measure – Inverse Time-To-Collision (iTTC)

$$S := \sum_{n=1}^{N} \int_{t_n^-}^{p_{n-1}^{-1}(L)} H\left(h^{\text{iTTC}} - \frac{\dot{p}_n(t) - \dot{p}_{n-1}(t)}{p_{n-1}(t) - p_n(t) - l} \right) dt \,/\, N$$



Trajectory Optimization (TO)

$$\min_{\{p_n(t)\}} \quad M(\{p_n(t)\}) := \alpha T + \underbrace{\beta E + \gamma S}$$

Infinite dimension

High nonlinearity

subject to

$p_n(t_n^-) = 0;$
$\dot{p}_n(t_n^-) = v_n^-,$ $\forall n$ (entry)

$0 \leq \dot{p}_{n(t)} \leq \bar{v};$
$\underline{a} \leq \ddot{p}_{n(t)} \leq \bar{a},$ $\forall n, t$ (kinematics)

Differential equations

Non-convexity

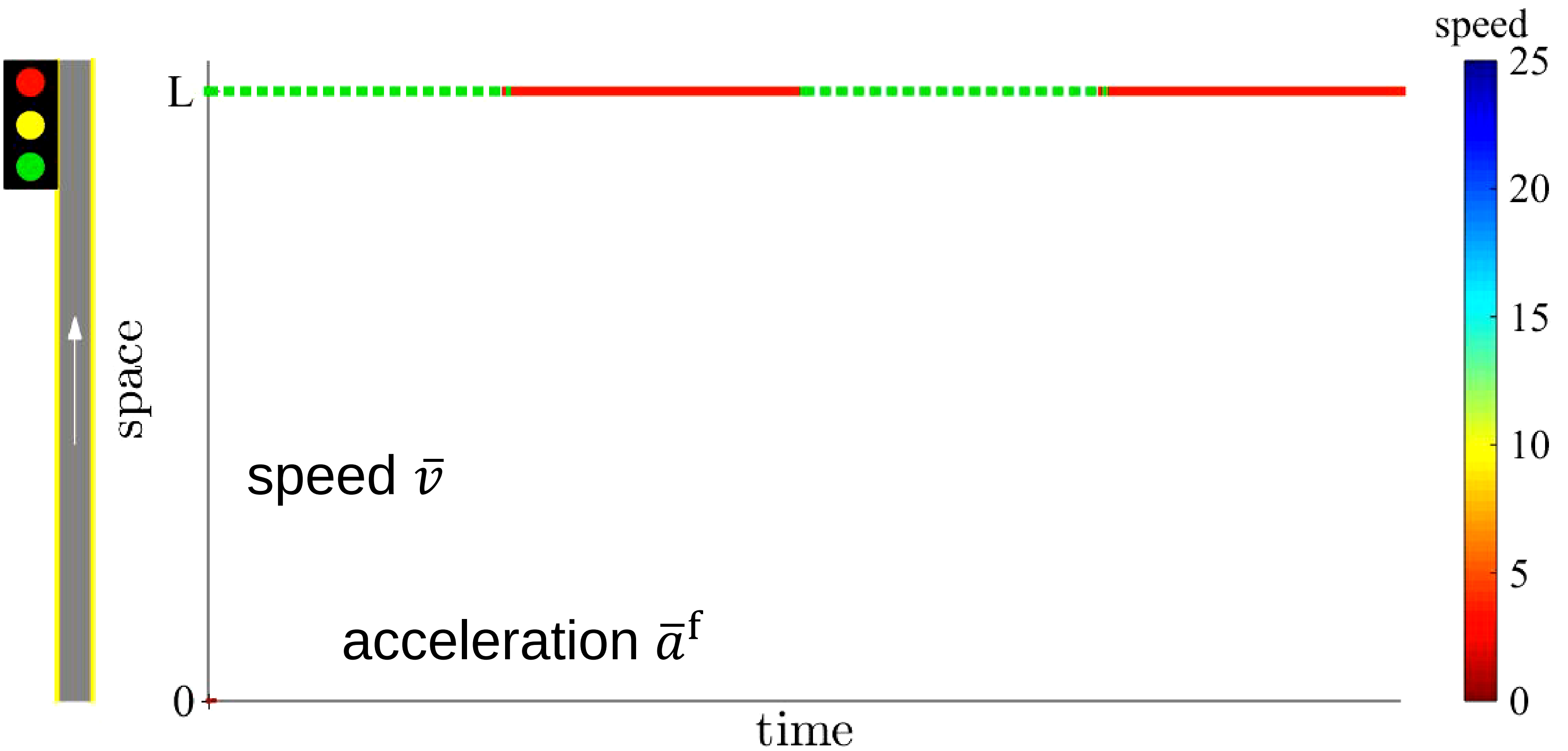
$\mathrm{mod}(p_n^{-1}(L), G + R) \leq G$, $\forall n$ (exit)

Vehicle interactions

$p_n(t) \leq p_{n-1}(t + \tau) - s, \forall n \neq 1$ (safety)

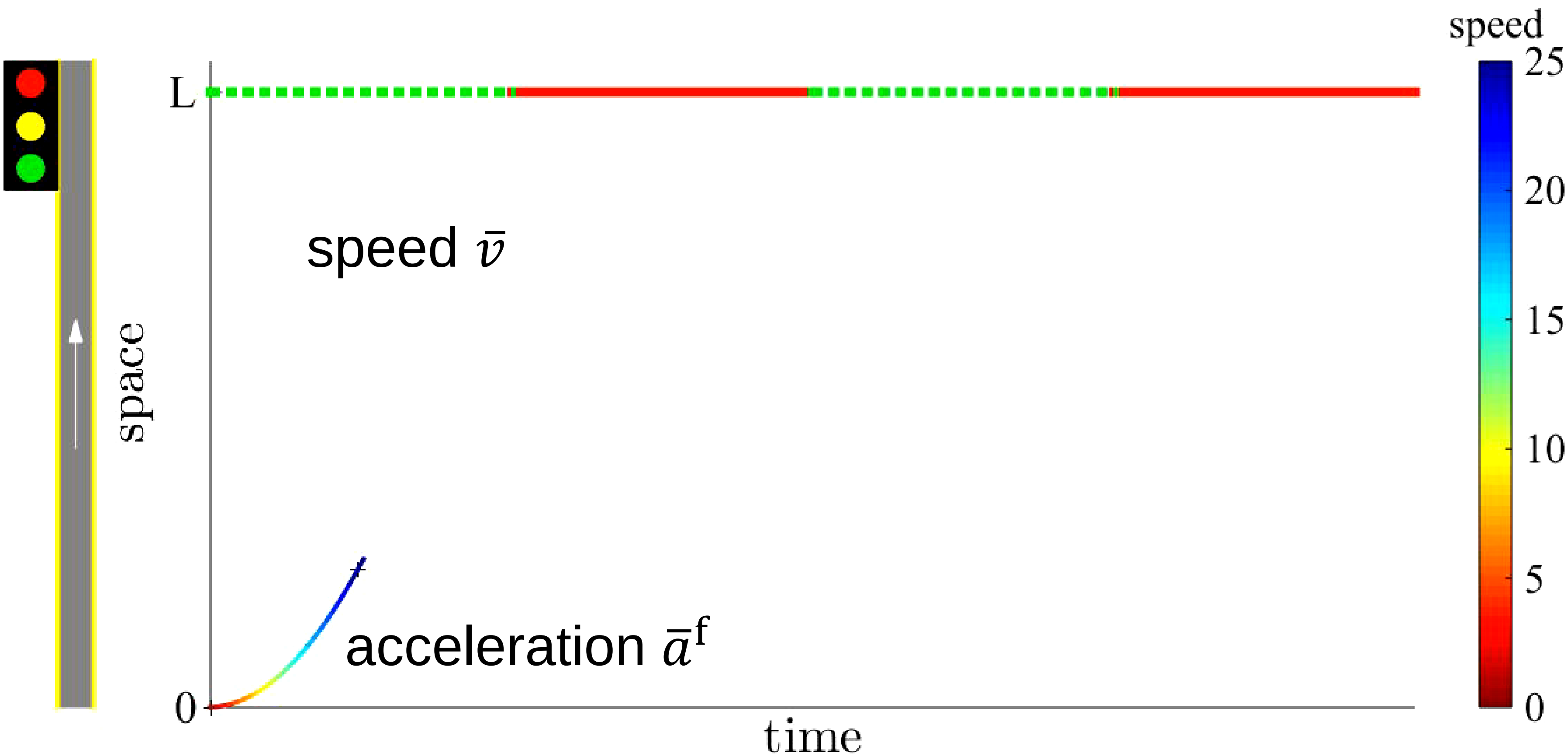
Forward Shooting Process (n = 1)

- Accelerate with rate $\bar{a}^{\mathrm{f}}$ up to speed $\bar{v}$
- 1st variable: forward acc. $\bar{a}^{\mathrm{f}} \in [0, \bar{a}]$



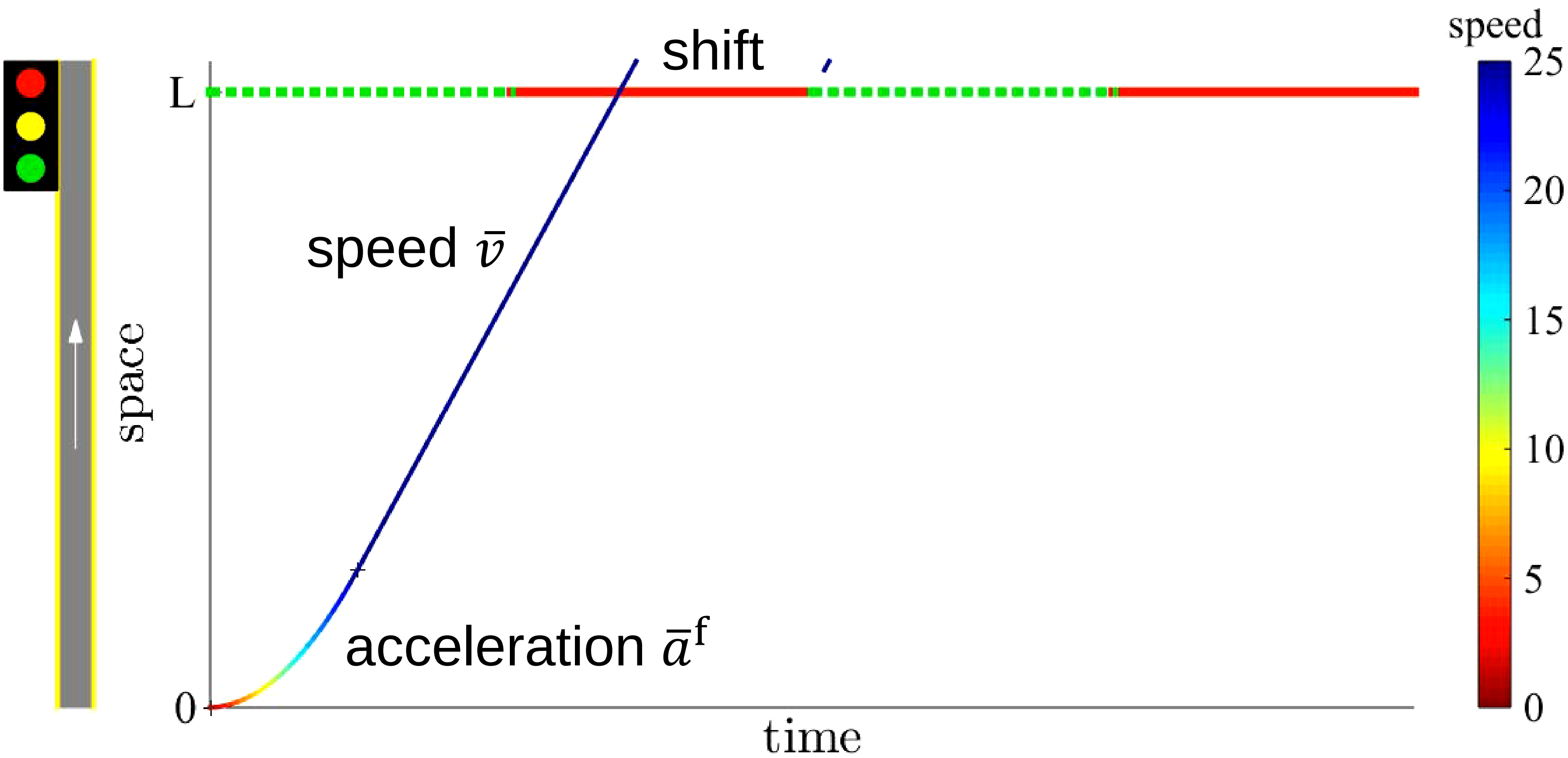
Forward Shooting Process (n = 1)

- Then maintain speed $\bar{v}$ all the way
- Hit the red light?



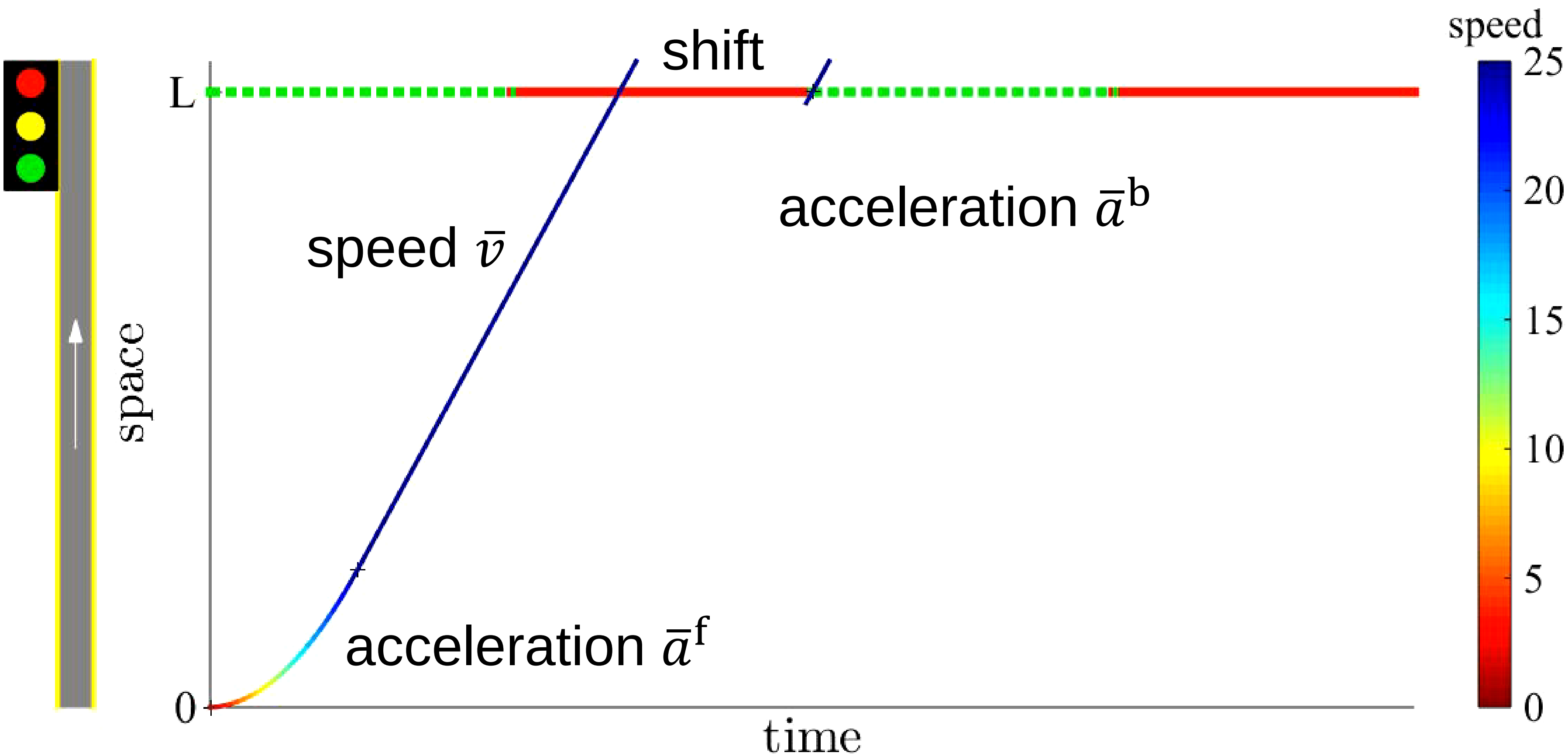
Backward Shooting Process (n = 1)

- Shift the section above location L rightwards to the next green phase



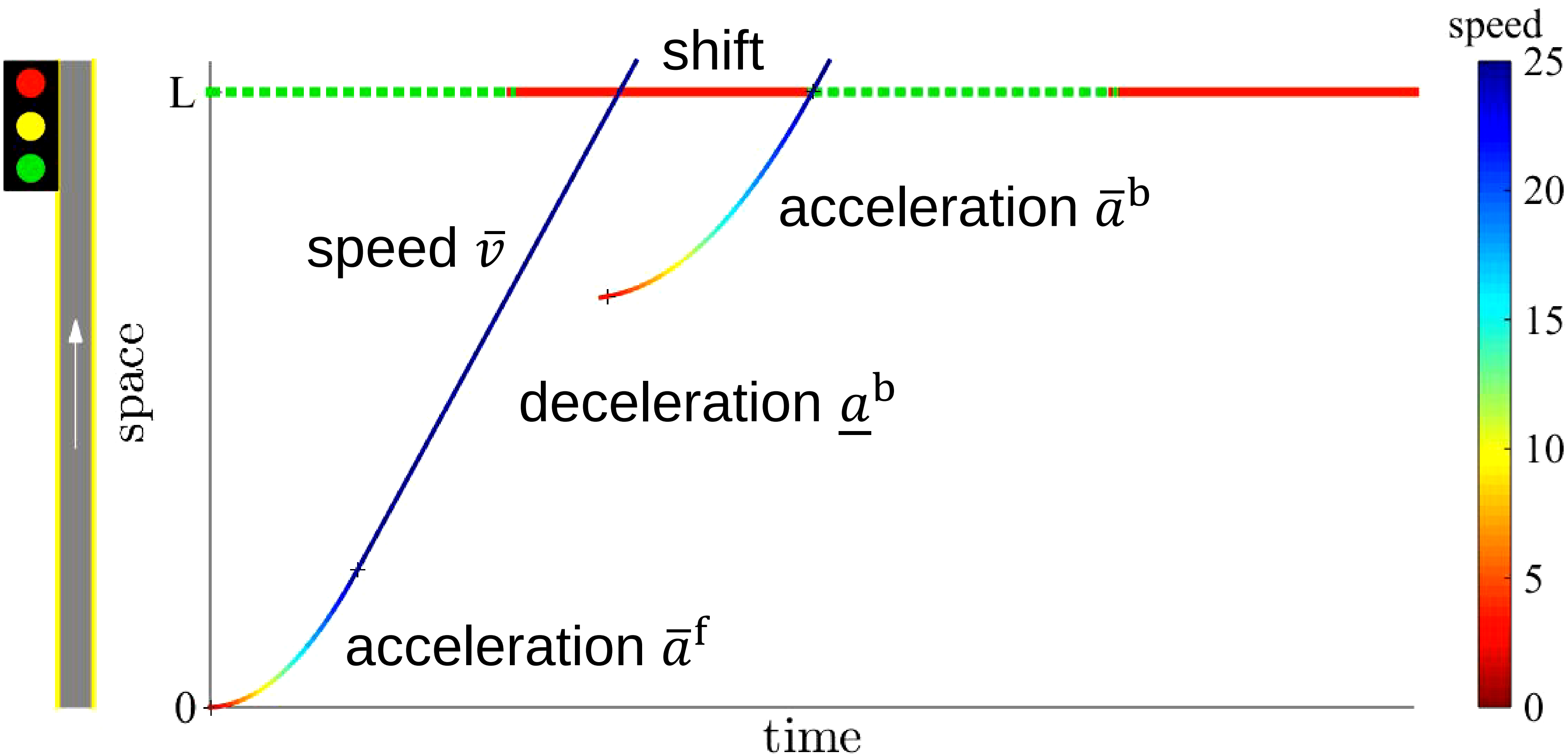
Backward Shooting Process (n = 1)

- Back up with acceleration $\bar{a}^{\mathrm{b}}$ down
- 2nd variable: backward acc. $\bar{a}^{\mathrm{b}} \in [0, \bar{a}]$



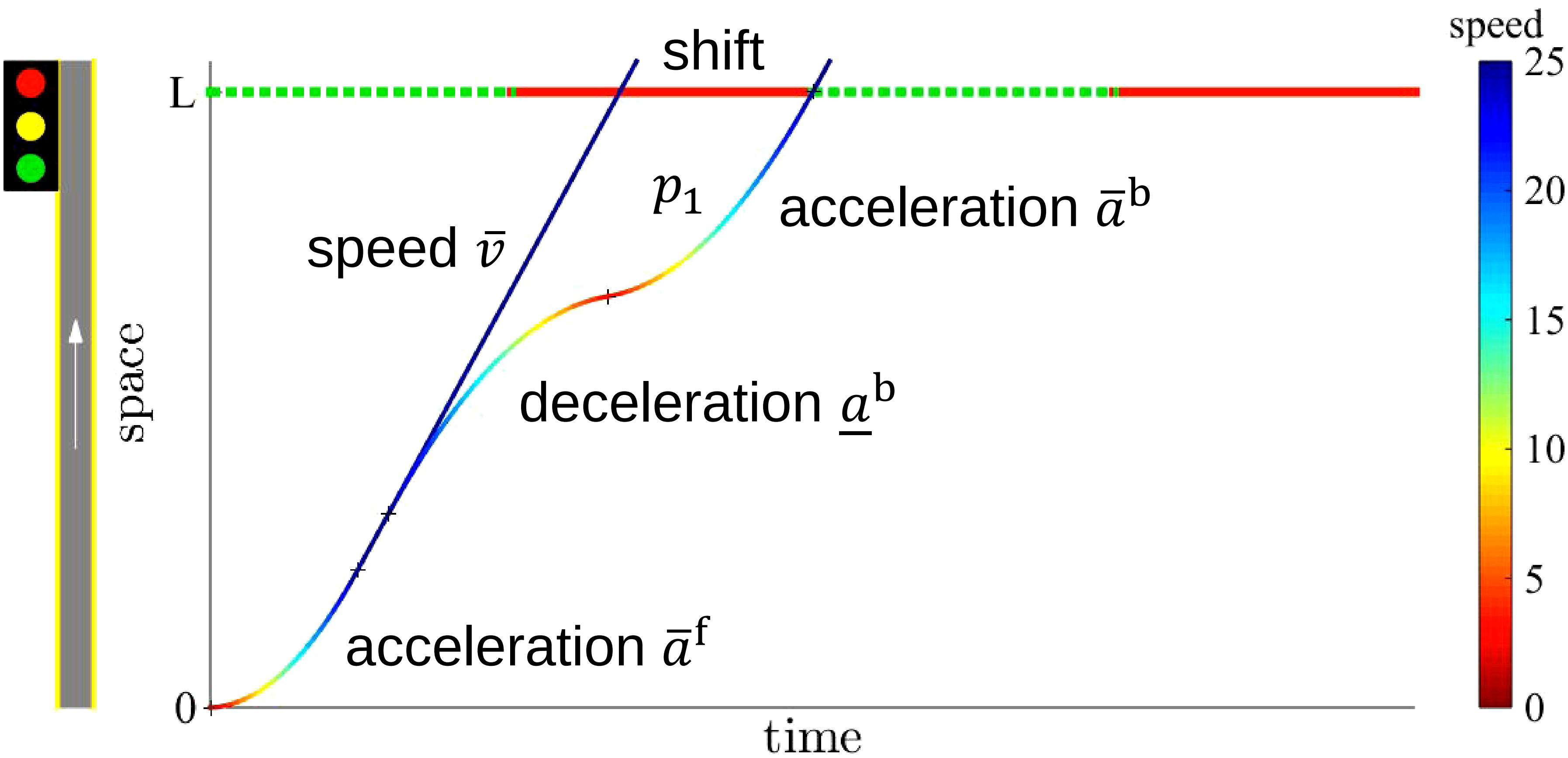
Backward Shooting Process (n = 1)

- Merge with deceleration $\underline{a}^{\mathrm{b}}$
- 3rd variable: backward dec. $\underline{a}^{\mathrm{b}} \in [0, \bar{a}]$



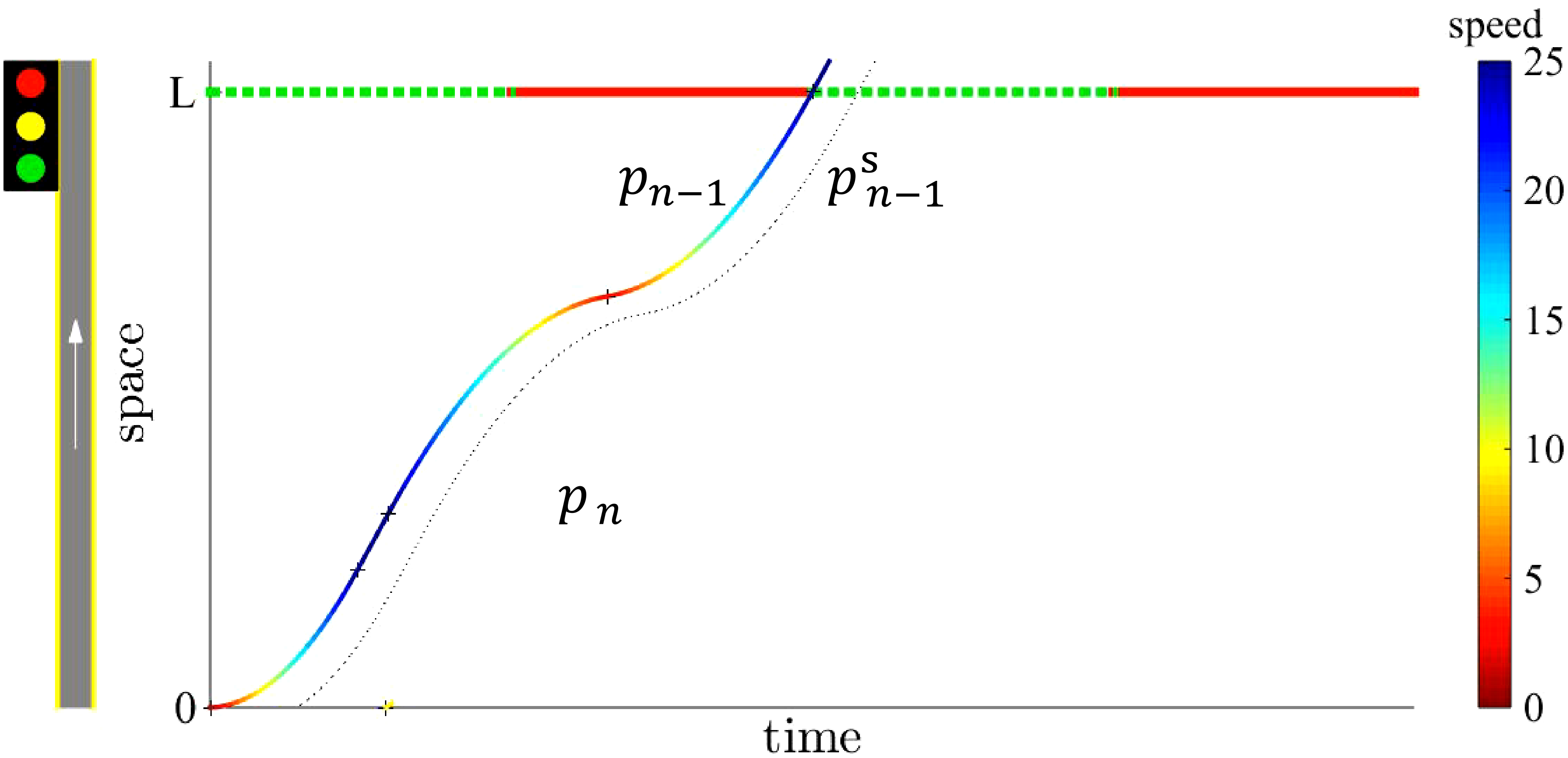
Backward Shooting Process (n = 1)

- Merge the forward and backward trajectories
- Obtain a feasible trajectory p_1



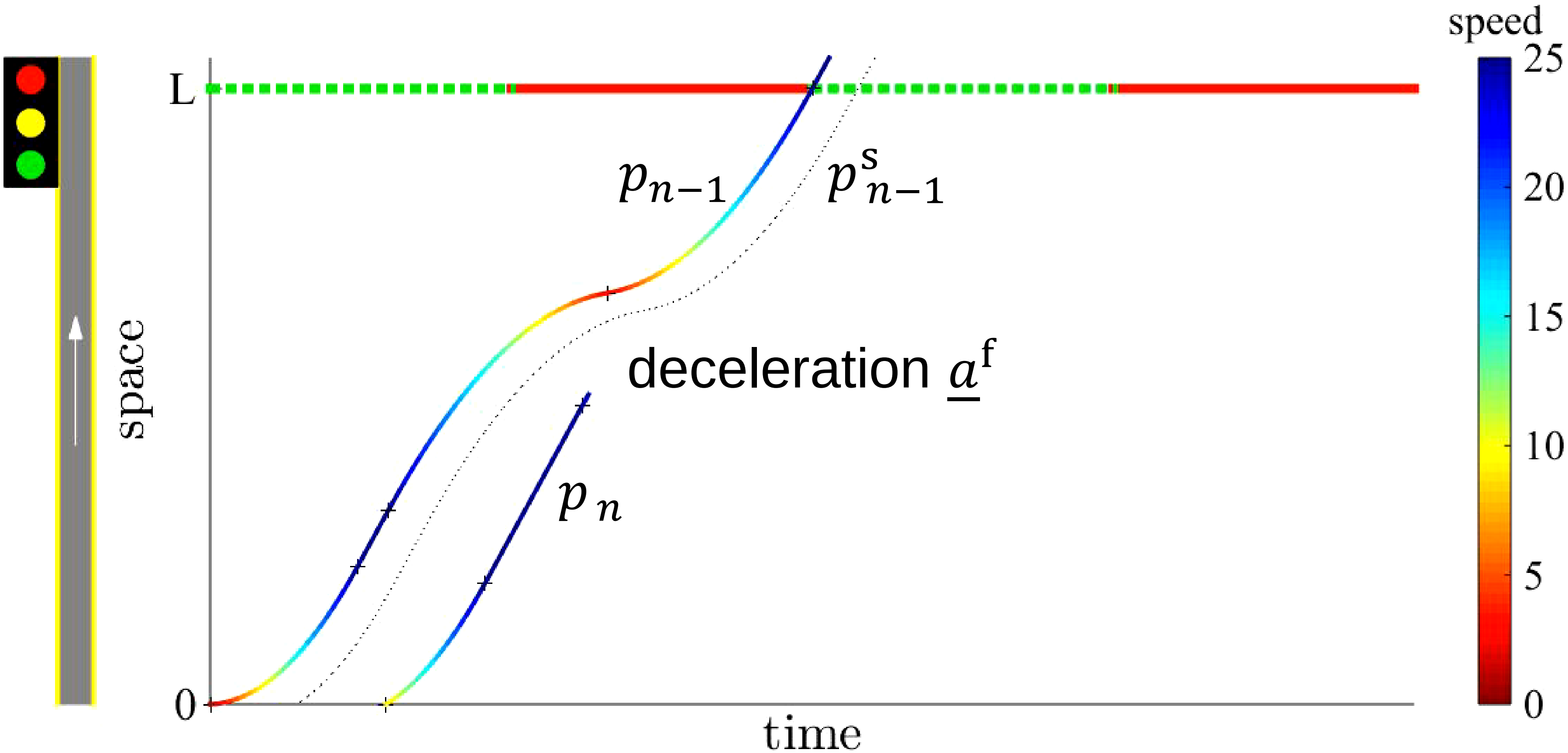
Forward Shooting Process (*n* > 1)

- The same till blocked by p^s_{n-1} (p_{n-1}'s shadow)
- Pause at a proper place



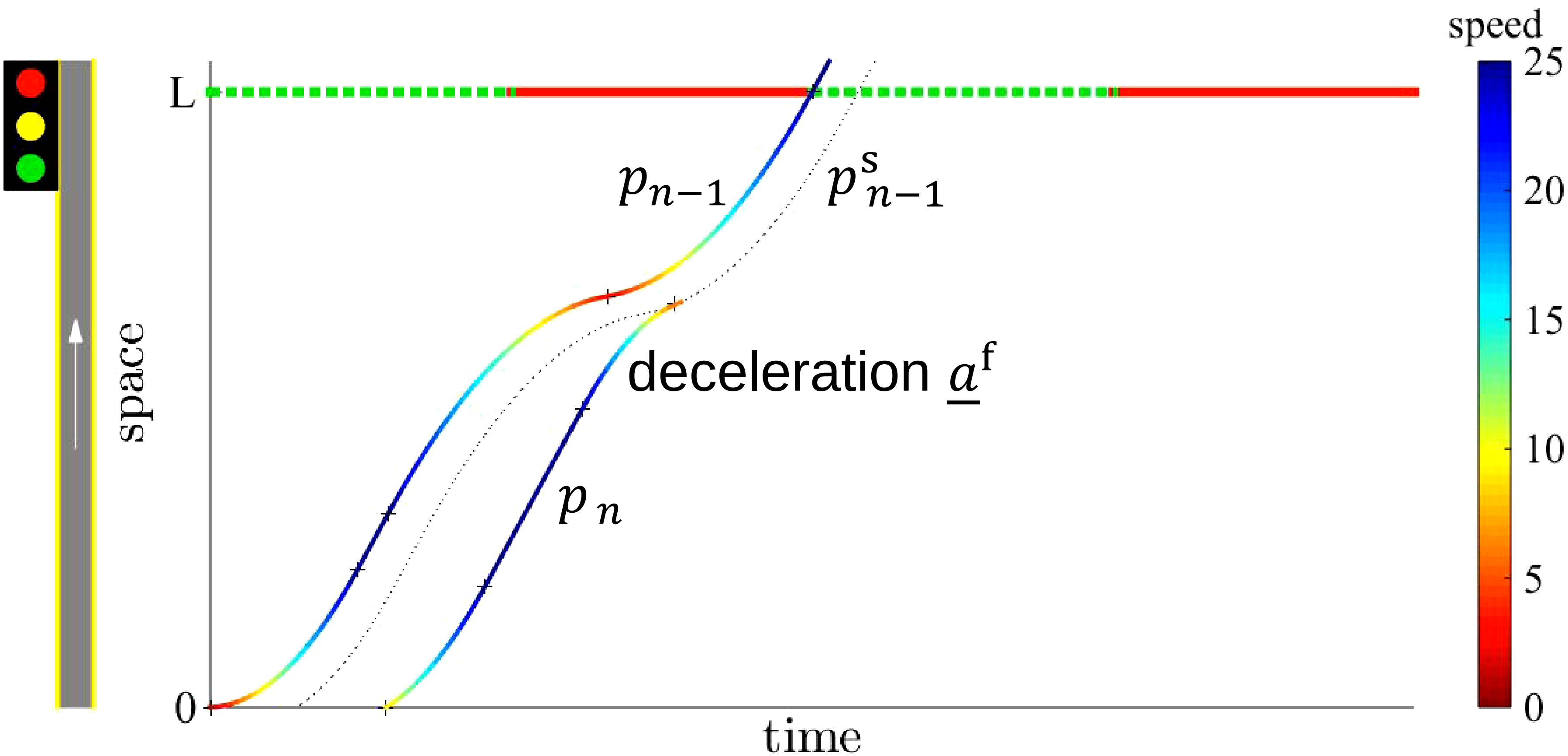
Forward Shooting Process ($n > 1$)

- Merge into p^s_{n-1} with deceleration $\underline{a}^{\mathrm{f}}$
- 4th variable: forward dec. $\underline{a}^{\mathrm{f}} \in [0, \underline{a}]$



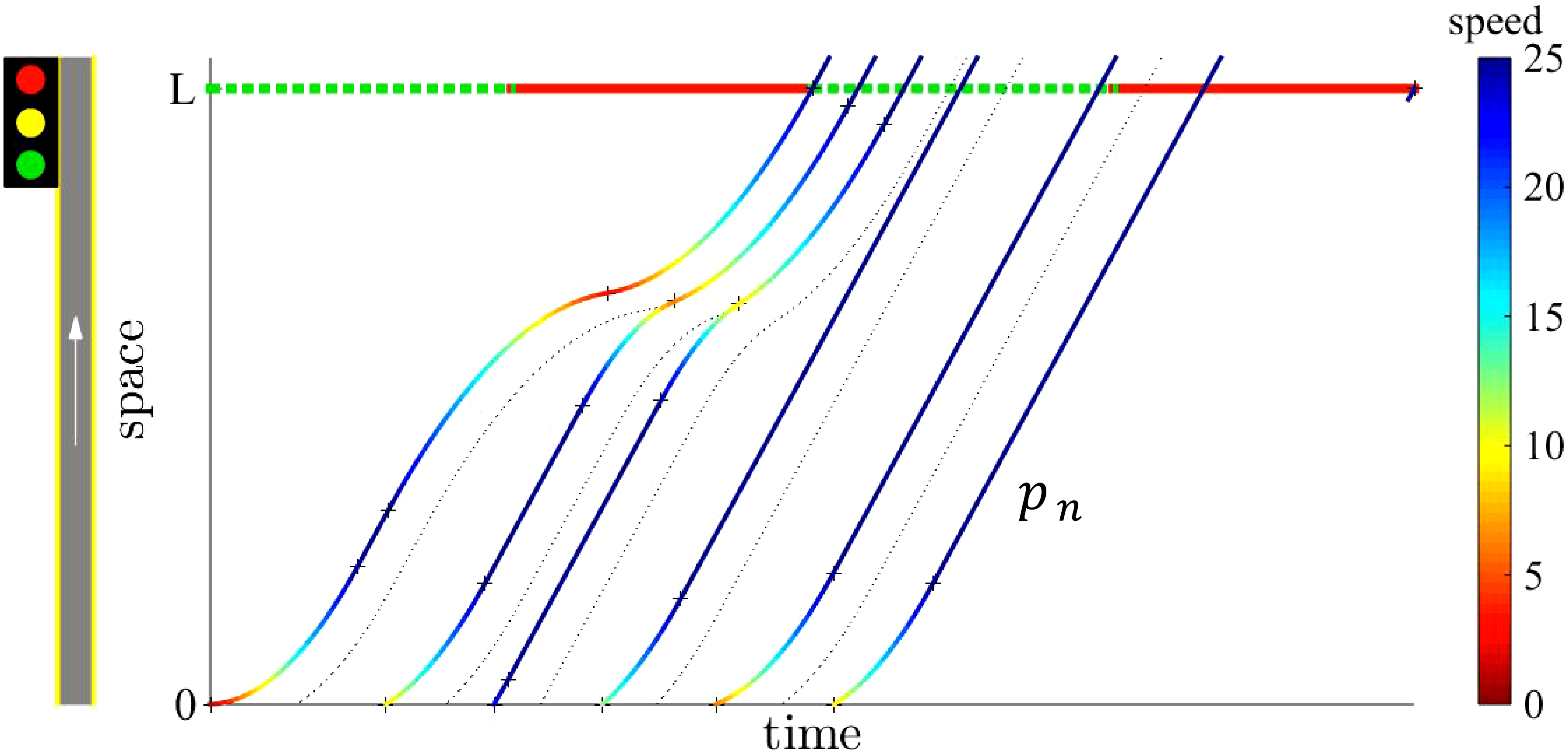
Forward Shooting Process (n > 1)

- Then exactly follow p^s_{n-1}



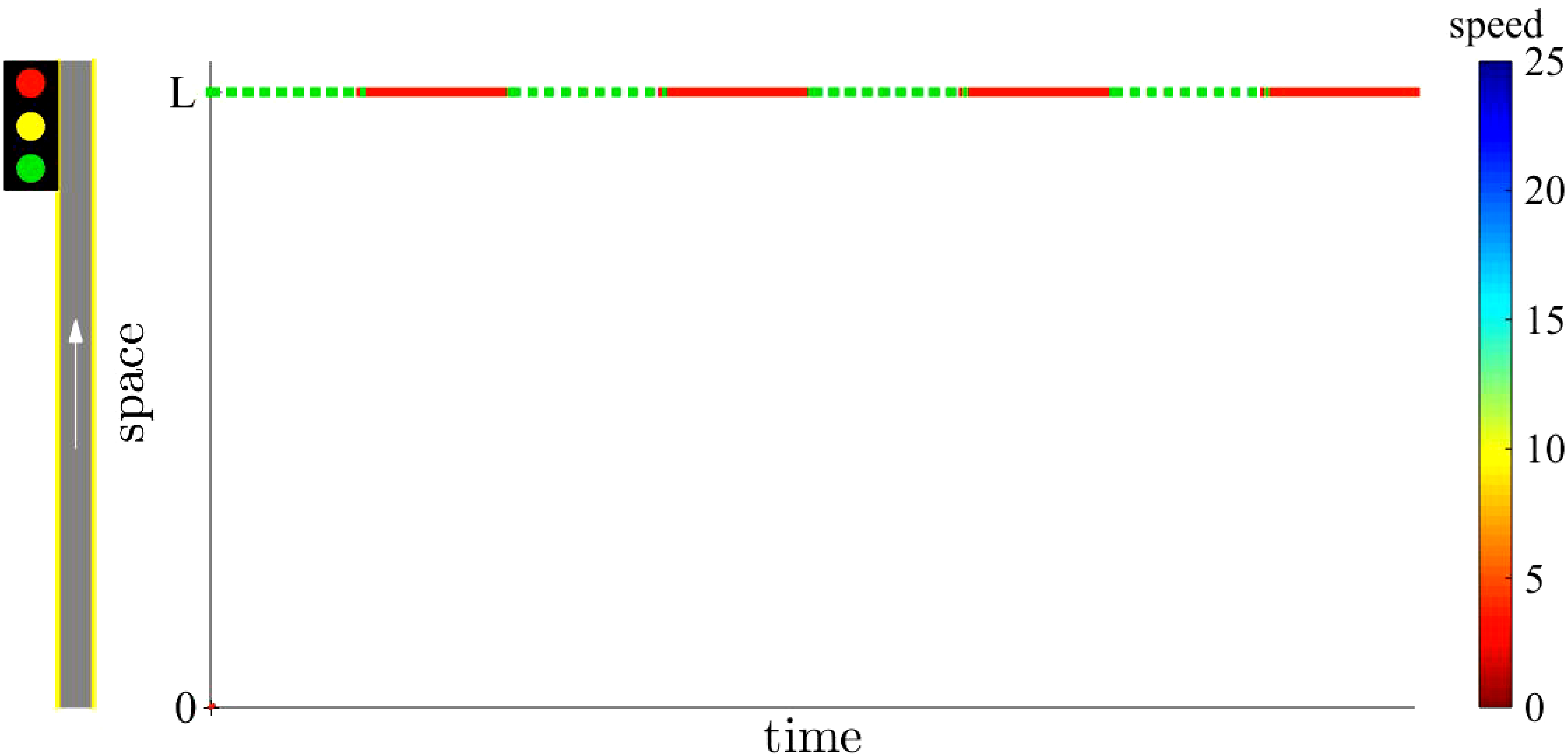
Backward Shooting Process (n > 1)

- The same as that for n = 1

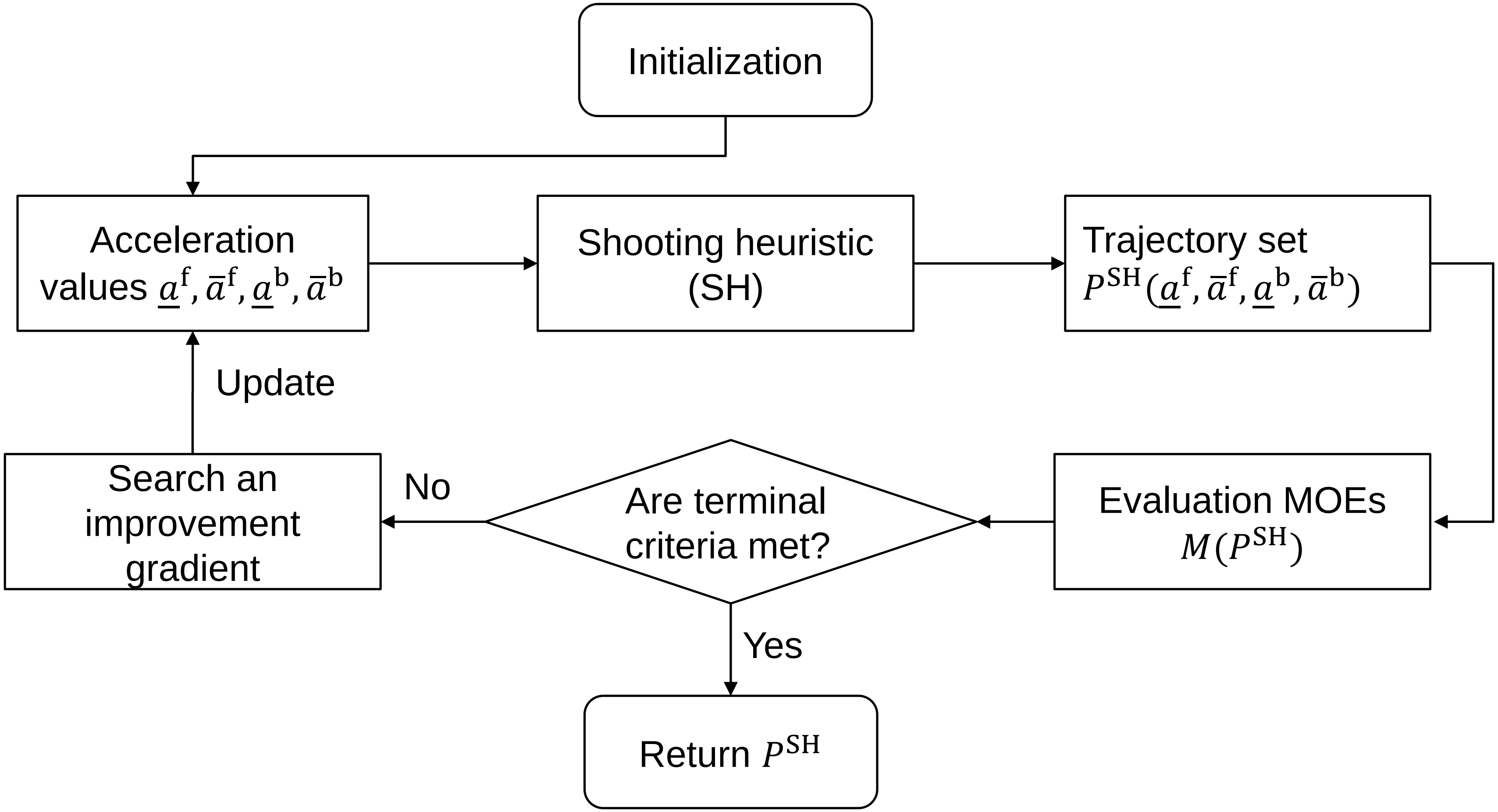


Shooting Heuristic (SH) Outcome

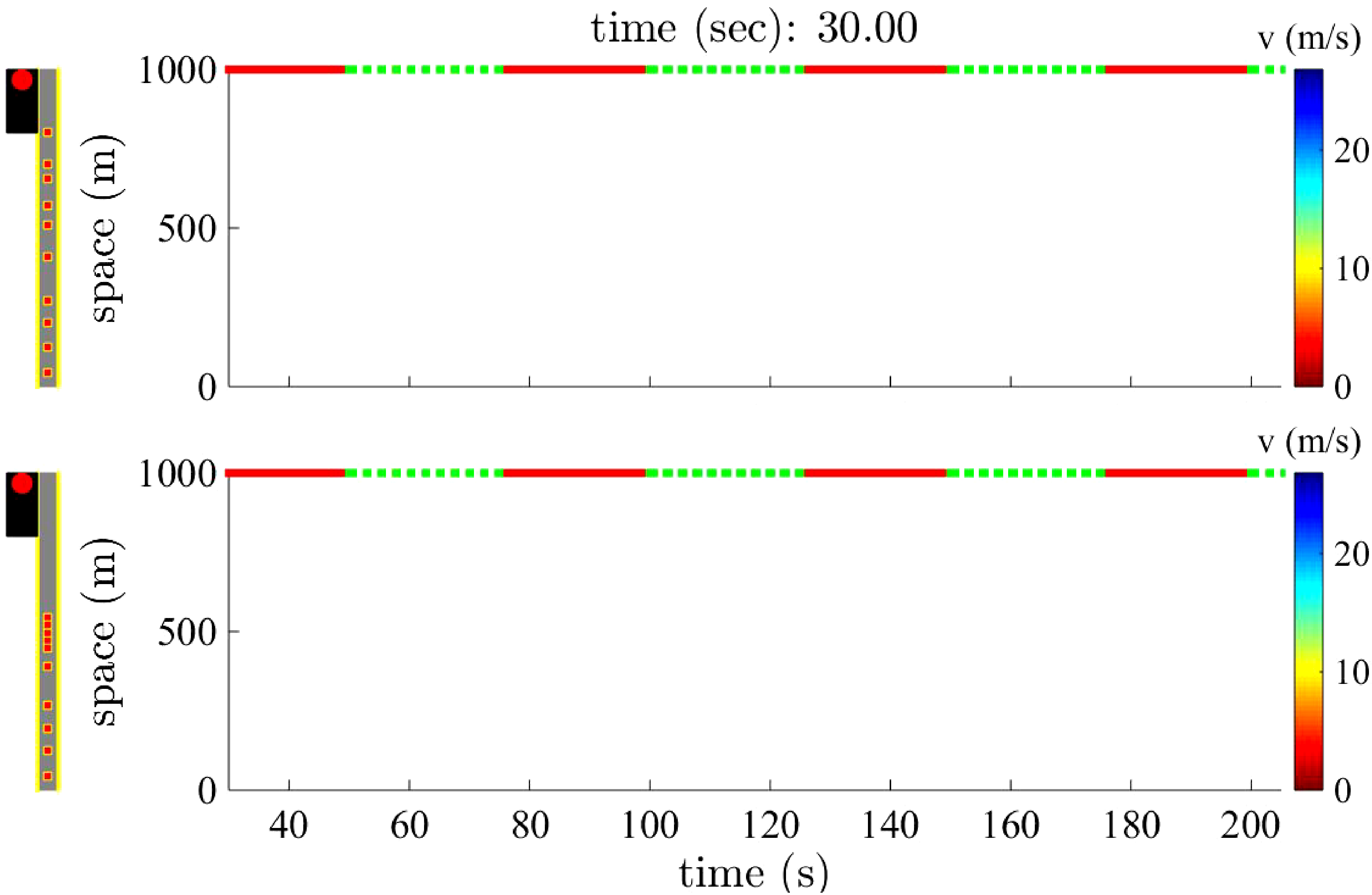
- A *small* number of *analytical* sections
- *four* variables: $\bar{a}^{\mathrm{f}}, \bar{a}^{\mathrm{b}} \in [0, \bar{a}], \underline{a}^{\mathrm{f}}, \underline{a}^{\mathrm{b}} \in [0, \underline{a}]$



Gradient – Based Algorithm



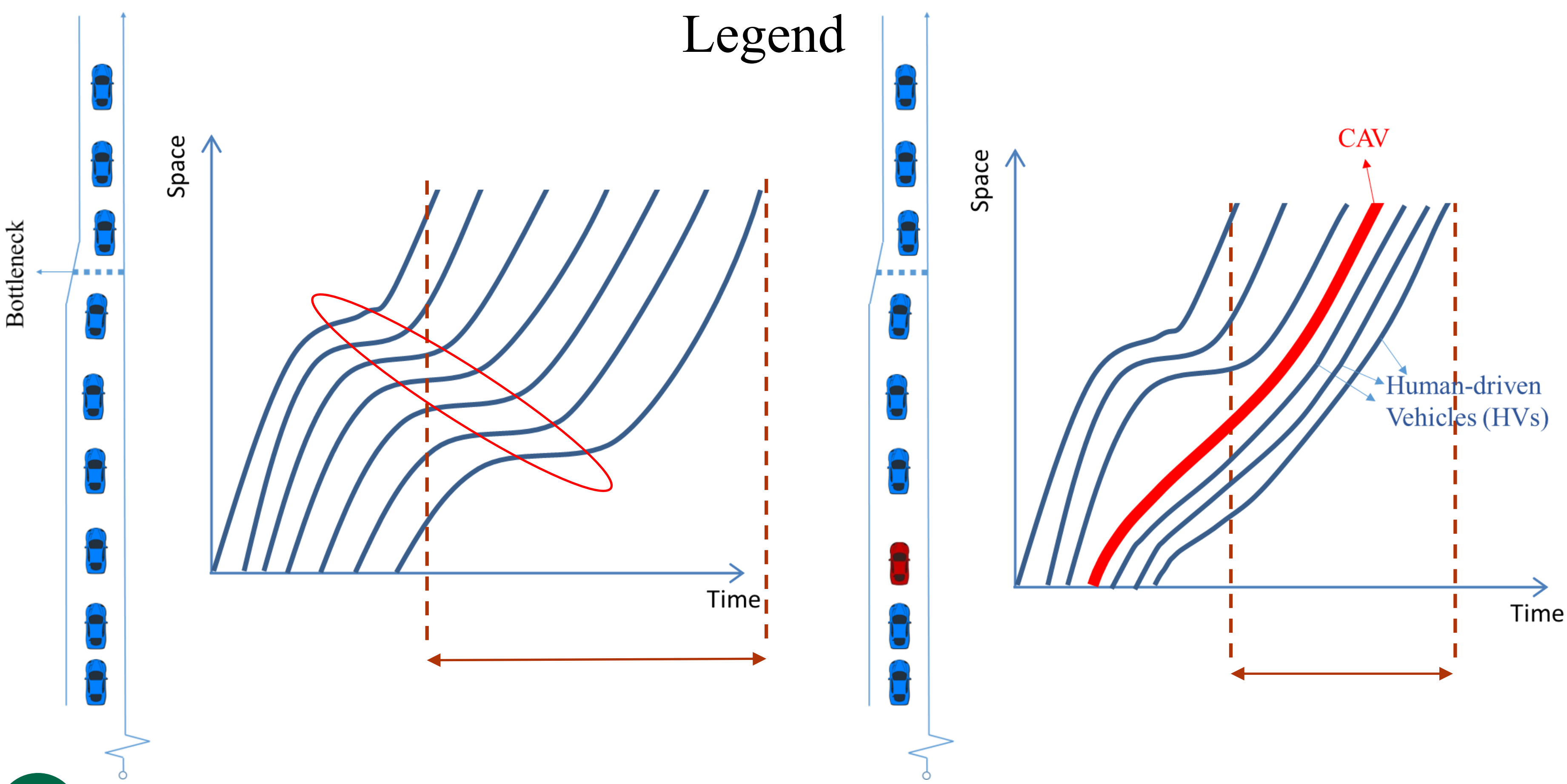
Benchmark (Top) vs. SH (Bottom)



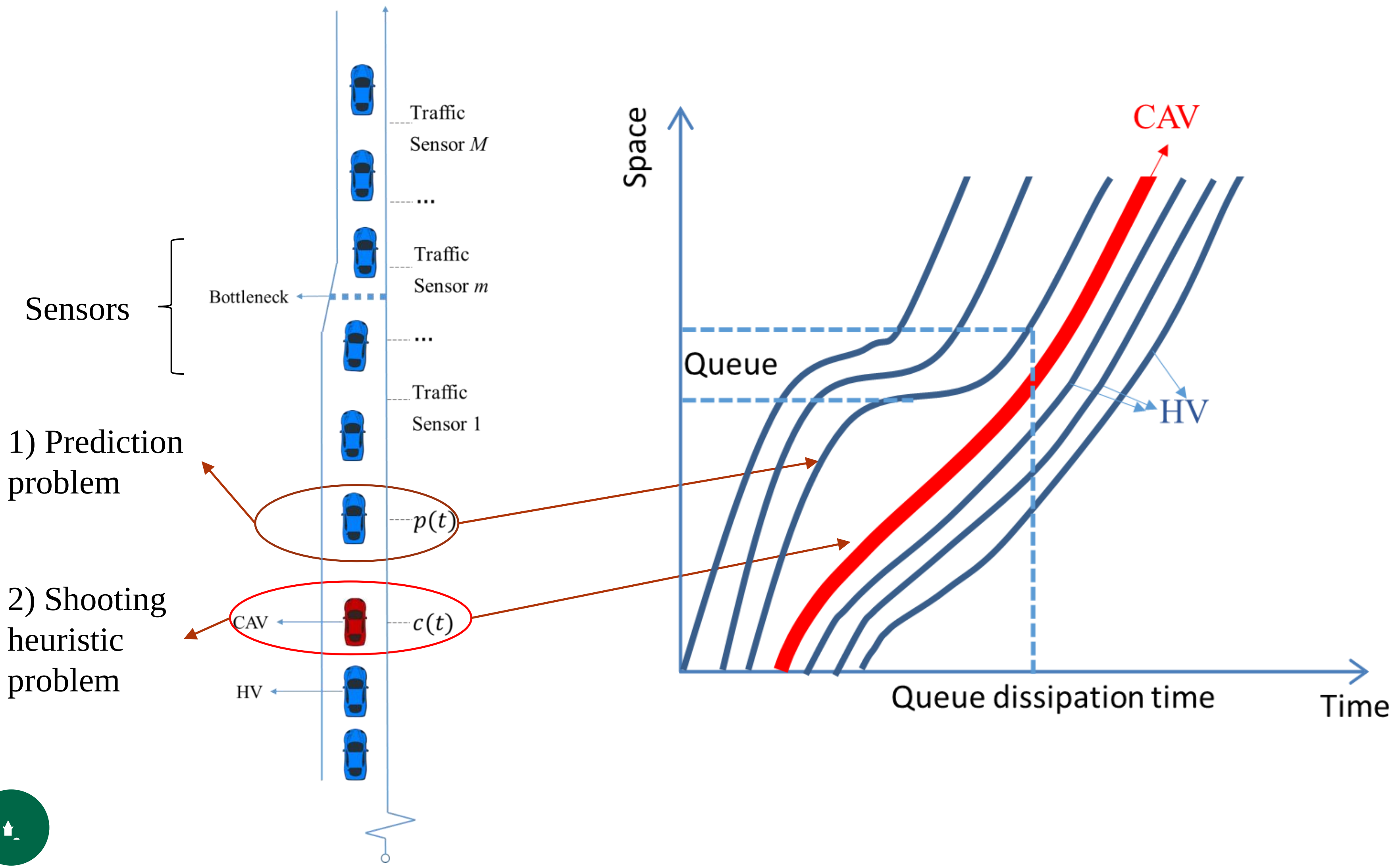
Benchmark vs. SH

C(s)	L(m)	f^s	ΔT	ΔE	ΔS	ΔM	Solution Time
60	1500	0.9	35.22%	32.78%	66.36%	41.23%	12.14
60	1500	1.5	34.23%	33.86%	66.43%	40.00%	9.44
60	2500	0.9	41.86%	46.96%	77.79%	50.78%	9.63
60	2500	1.5	41.72%	48.07%	80.21%	51.01%	13.05
80	1500	0.9	40.11%	32.06%	62.94%	43.07%	9.16
80	1500	1.5	38.73%	40.10%	62.26%	44.28%	12.26
80	2500	0.9	32.29%	45.91%	74.00%	43.22%	8.89
80	2500	1.5	29.59%	37.96%	46.49%	34.20%	7.29
Average			36.72%	39.71%	67.06%	43.47%	10.2

Speed Harmonization in Mixed Traffic

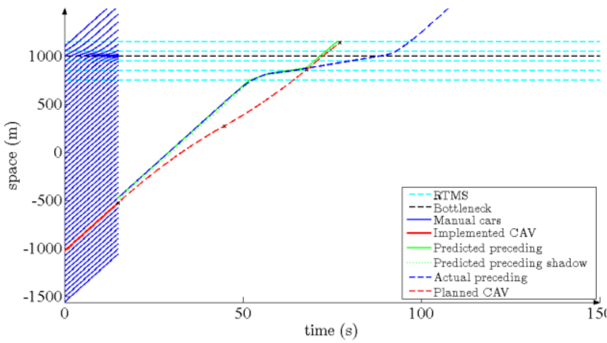


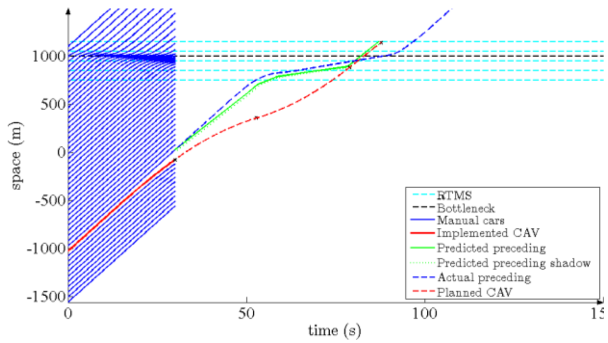
Speed Harmonization in Mixed Traffic

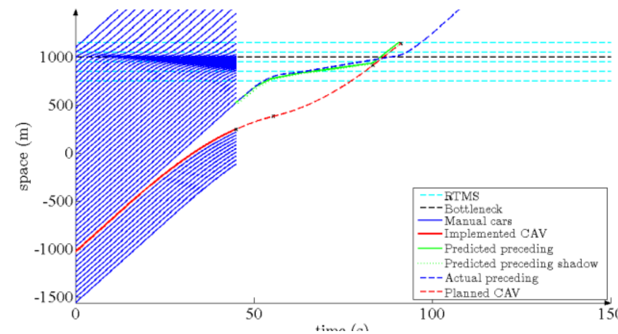


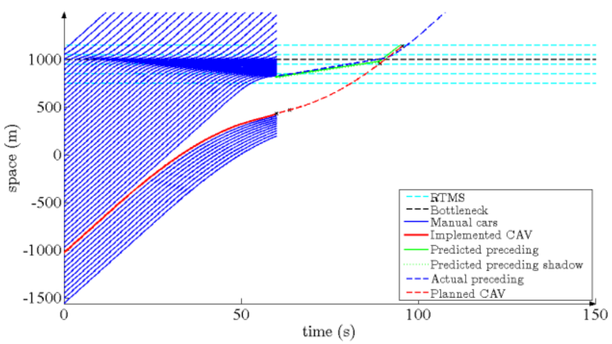
Speed Harmonization in Mixed Traffic

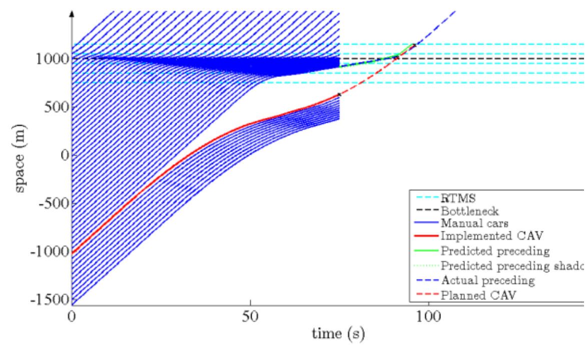
- Numerical example results:

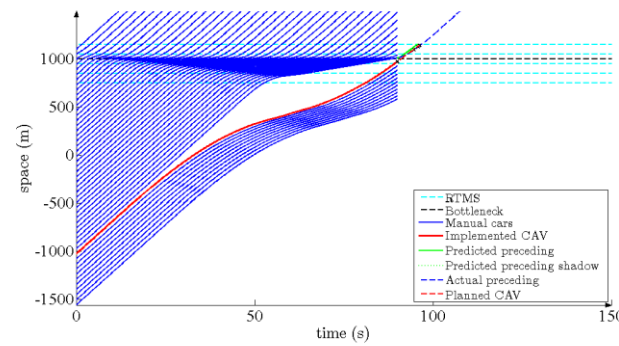






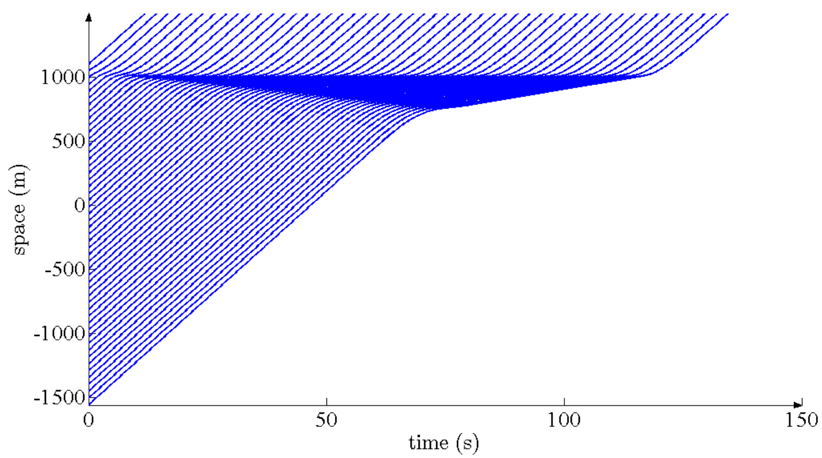


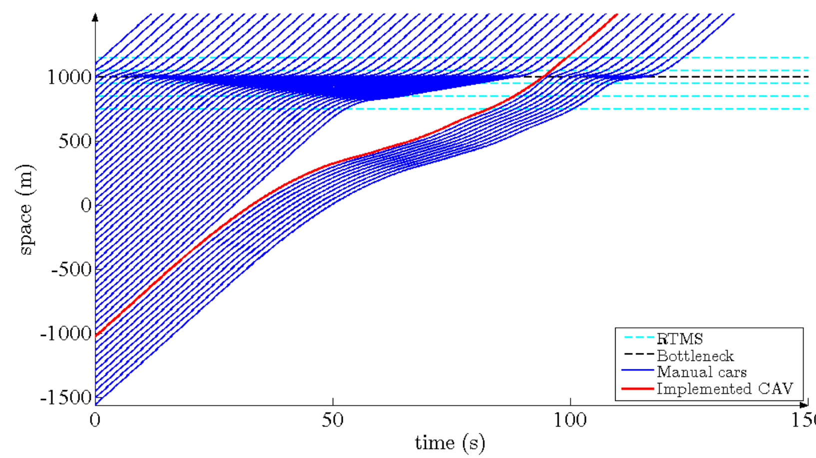




Speed Harmonization in Mixed Traffic

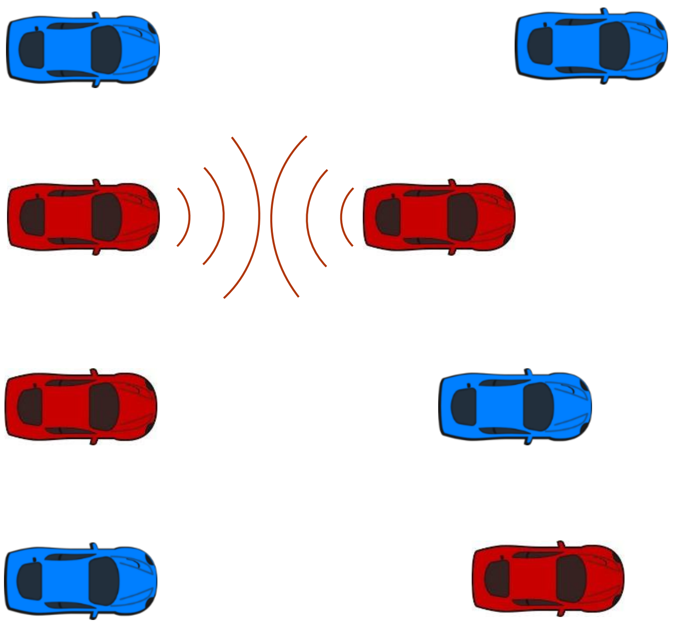
- Numerical example results:
  - 12.9% improvement in throughput
  - 12.6% improvement in fuel consumption and emissions

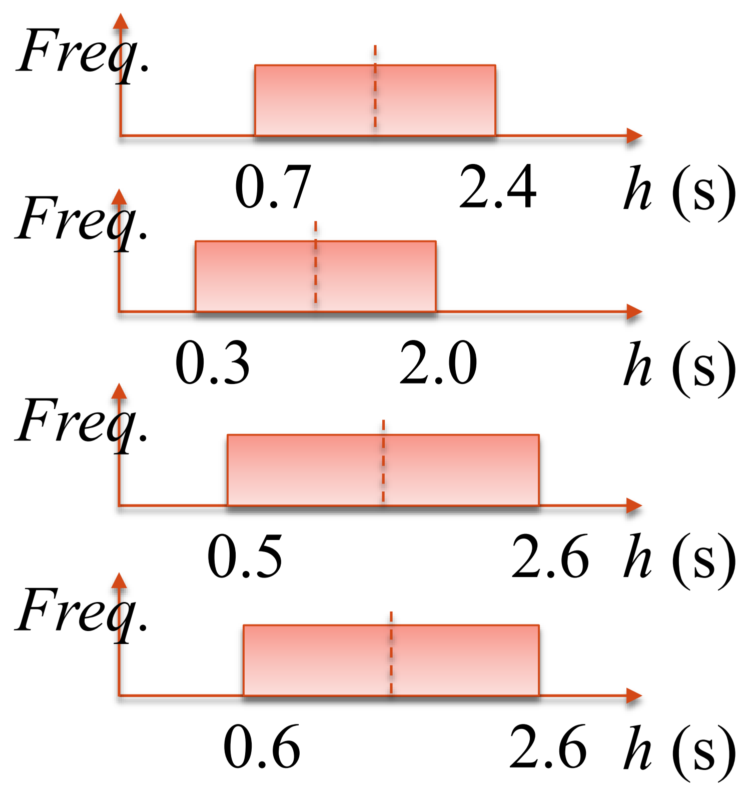




Headways in Mixed Traffic

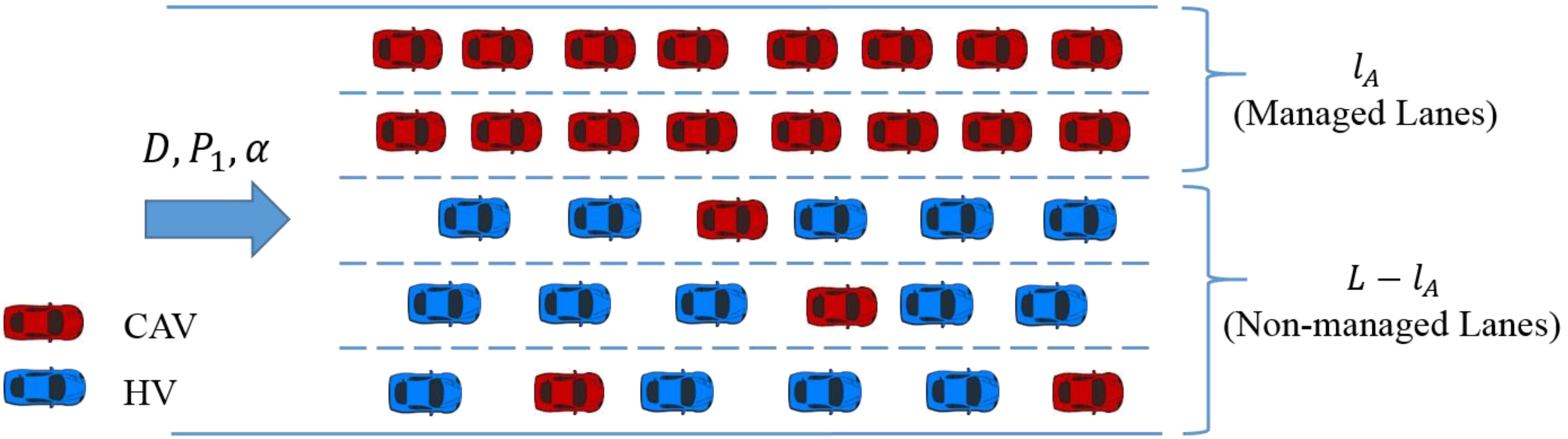
- Stochasticity
  - HV
  - CAV





AV Platooning Lane Management

D: mixed traffic demand



Ongoing Research

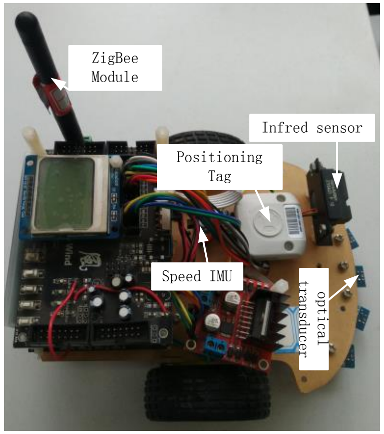
- Field Tests

FHWA Turner Fairbank Testbed

Chang’an University Test Track, China

Reduced Scale (SVIL) Platform

Reduced Scale Model



Intelligent vehicles

Driving simulator

Traffic simulator

- Integration of hardware, communications, sensors, human and computer simulation
- Expandable modules, controlled environment
- Low cost (<100K for the whole platform), no safety concern, customizable
- Ideal for testing new CACC and AV trajectory control algorithms
- Behaviors need to be calibrated to be consistent with the full scale counterparts

AV Sharing

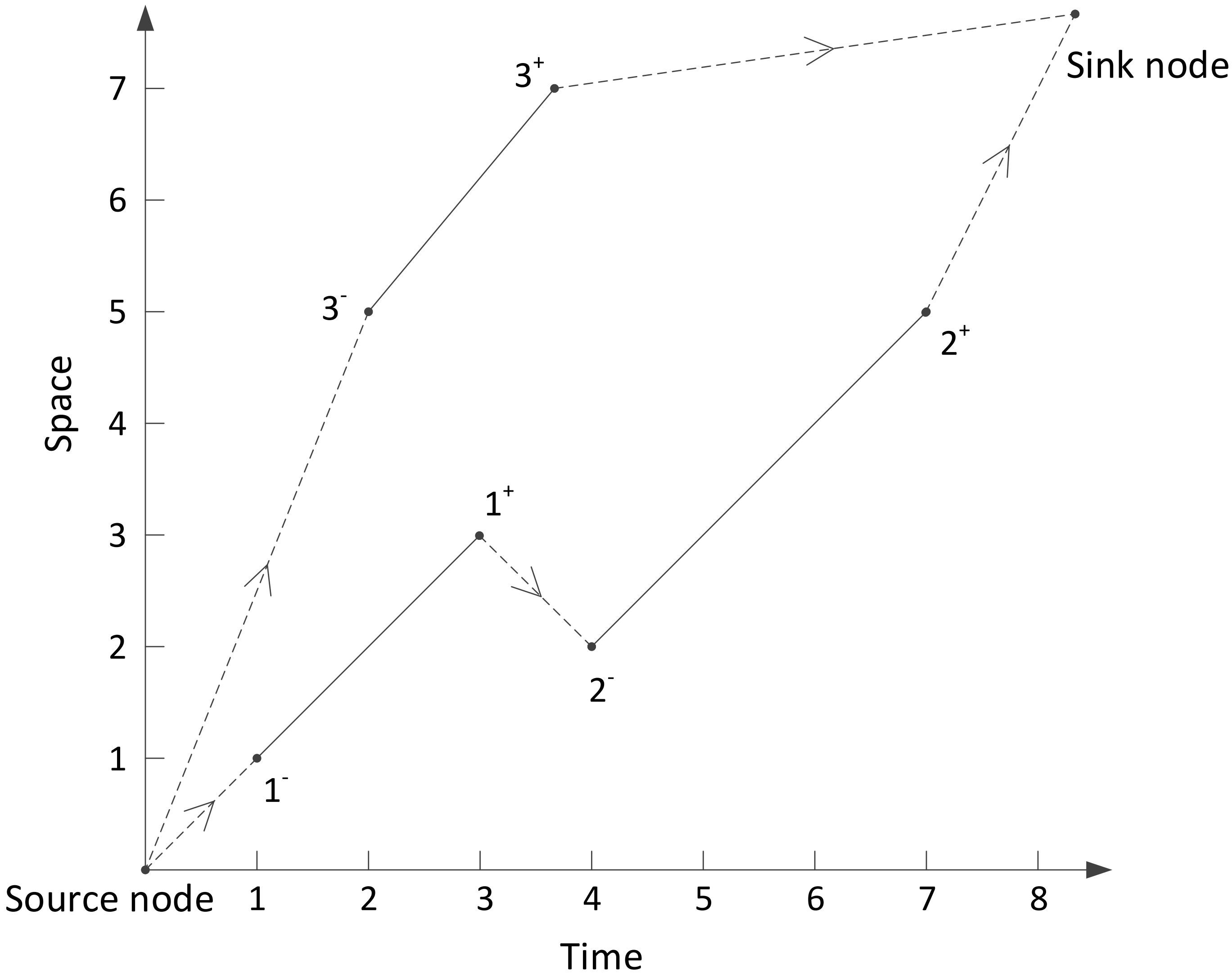
- Uber's Vision

Driverless Car

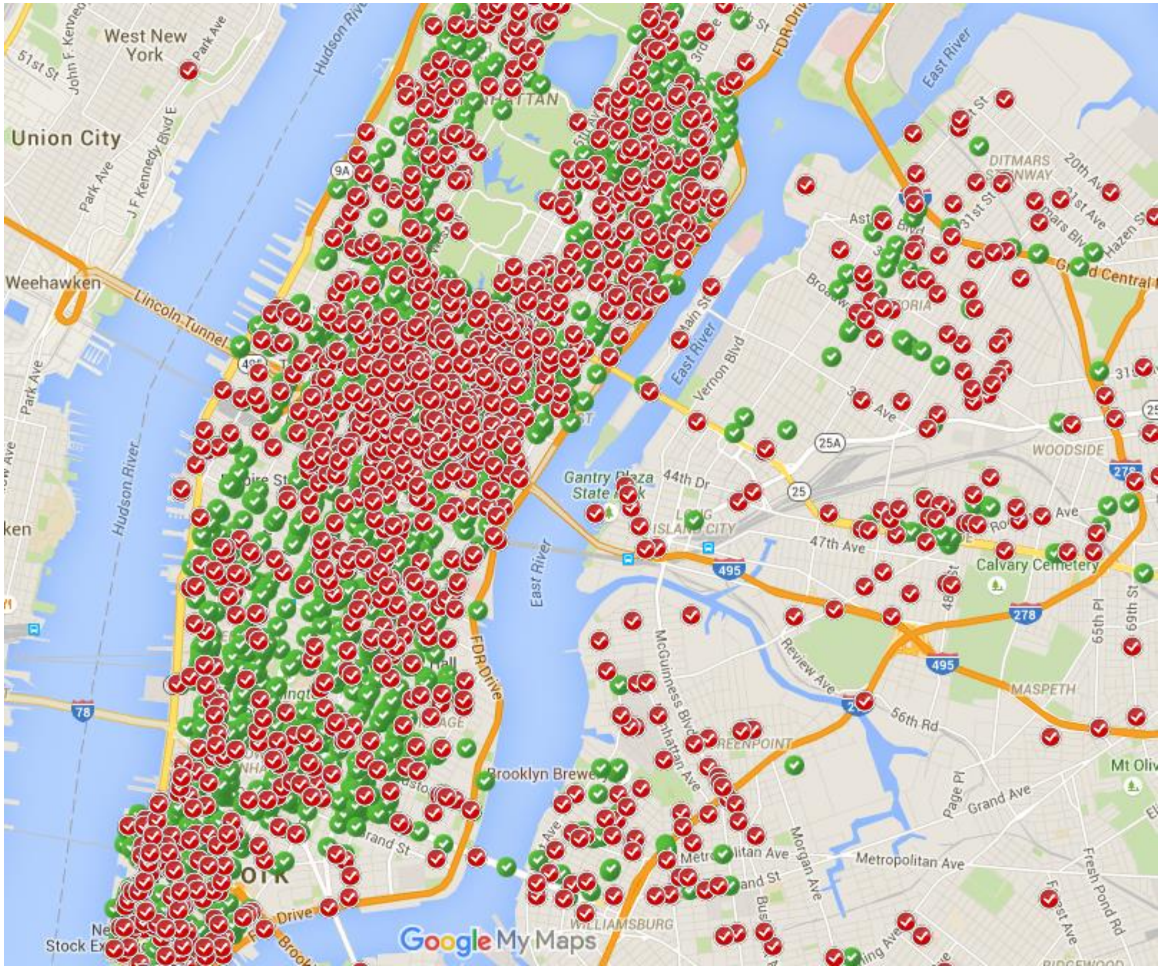
+

Shared Car

Network AV Sharing Optimization



Test Data

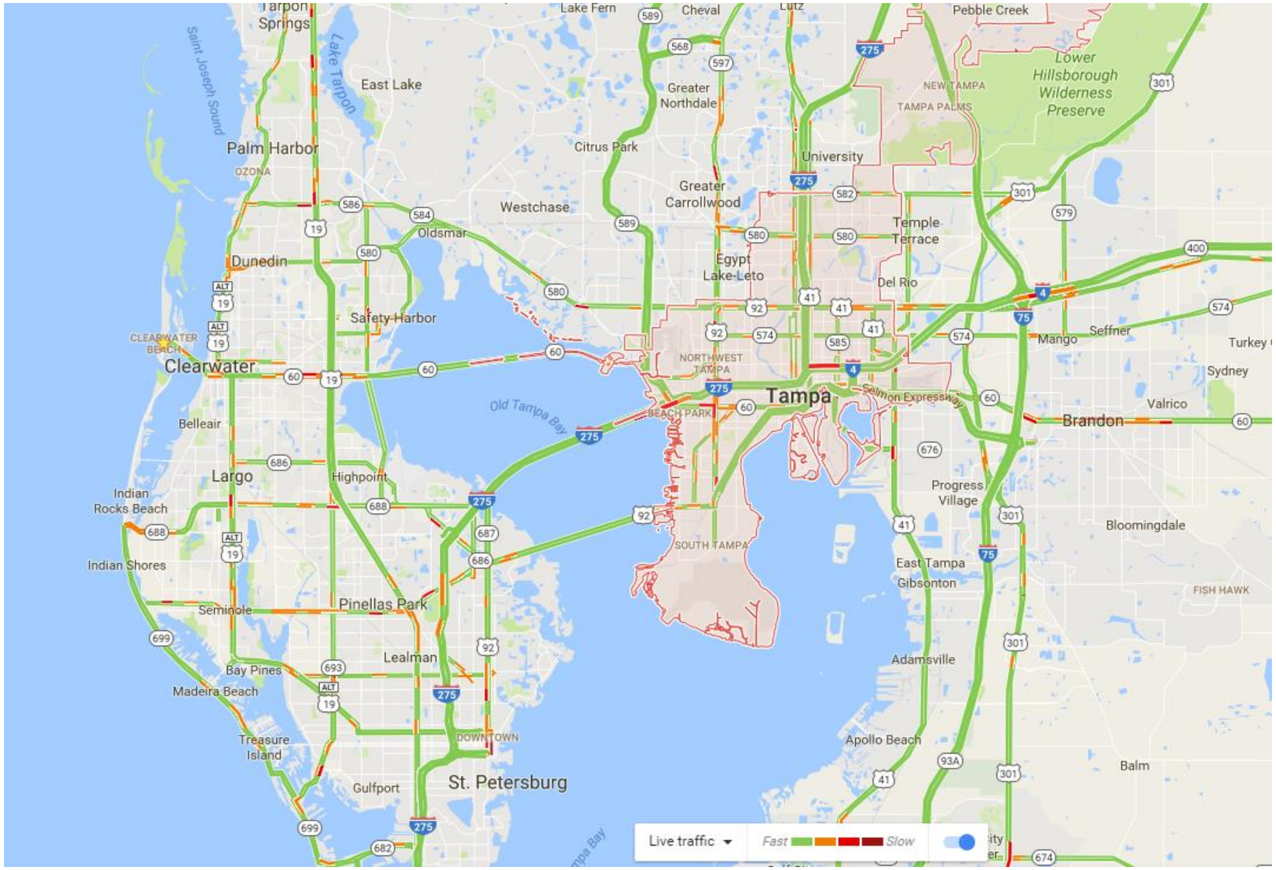


Results

Scenario	VUR			VMT (miles)			VMT Ratio		
1% of Daily Demand									
θ	μ=5	μ=15	μ=100	μ=5	μ=15	μ=100	μ=5	μ=15	μ=100
0	3.80	12.56	12.56	11013	12983	12998	0.97	1.14	1.15
5	1.79	2.35	2.36	11095	12493	12525	0.98	1.10	1.10
10	1.44	1.61	1.61	11199	11973	11973	0.99	1.06	1.06
20	1.08	1.08	1.08	11326	11396	11396	1.00	1.00	1.00
30	1.00	1.00	1.00	11343	11343	11343	1.00	1.00	1.00
2% of Daily Demand									
θ	μ=5	μ=15	μ=100	μ=5	μ=15	μ=100	μ=5	μ=15	μ=100
0	4.03	13.90	13.90	21974	25706	25722	0.97	1.14	1.14
5	1.81	2.39	2.39	22147	24912	24943	0.98	1.10	1.10
10	1.44	1.60	1.61	22335	23778.34	23809.73	0.99	1.05	1.05
20	1.08	1.09	1.09	22597	22735	22735	1.00	1.00	1.00
30	1.00	1.00	1.00	22631	22631	22631	1.00	1.00	1.00

Discussion of AI

- Similarity between transportation networks and images allows adaptation



Discussion of AI

- Traffic flow physics (car following behavior,) can expedite training of data-driven models

Discussion

- Learning based optimization for trajectory (or traffic) control

AlphaGo

Thank you

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Ma, J., Li, X., Zhou, F., Hu, J. and Park, B. "Parsimonious shooting heuristic for trajectory design of connected automated traffic part II: Optimization framework." *Transportation Research Part B*, in press. [http://dx.doi.org/10.13140/RG.2.1.1721.1924]
Zhou, F., Li, X. and Ma, J. "Parsimonious shooting heuristic for trajectory design of connected automated traffic part I: Theoretical analysis with generalized time geography." *Transportation Research Part B*, in press. [http://arxiv.org/abs/1511.04810]
Li, X., Ghiasi, A. and Xu, Z. "A piecewise trajectory optimization model for connected automated vehicles: Exact optimization algorithm and queue propagation analysis" Transportation Science, submitted.
Ma., J., Li, X. and Zhou, F., "Designing Optimal Autonomous Vehicle Sharing and Reservation Systems: A Linear Programming Approach", *Transportation Research Part C*, under review.
*Ghiasi, A., Hussain, O. and Li, X. "Freeway Lane Management Approach In Mixed Traffic Environment with Connected Autonomous Vehicles." Submitted. https://arxiv.org/abs/1609.02946

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