Center for <u>T</u>eaching <u>O</u>ld <u>M</u>odels <u>Ne</u>w <u>T</u>ricks (TOMNET)

A USDOT Tier 1 University Transportation Center

PROJECT PROPOSAL: 2021-22

Title: Drivers' attitudes toward rerouting: Impacts on network congestion

Principal Investigator: Jorge A. Laval, Professor, School of Civil & Environmental Engineering, Georgia Institute of Technology

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1. Introduction/Problem Statement

In urban transportation networks, traffic congestion can be caused by different unexpected events. An unexpected event is defined as any change of traffic state or traffic information not known by all drivers. Unexpected events that would cause congestion includes incidents, road work, traffic restrictions, etc. As a result, local congestion may spread to other places, and may lead to gridlock across the whole city if drivers stick to their routes under the new conditions. This project will explore the hypotheses that a machine learning framework can be set up to provide alternative routes for such users to minimize the probability of gridlock.

2. Project Objectives

The proposed study plans to answer the following questions:

(1) What factors can influence the bifurcation phenomena in MFD? We will focus on traffic signal settings and driver's rerouting behaviors.
(2a) What machine learning (ML) approaches can be more efficient for rerouting drivers under near gridlock conditions?
(2b) If we use reinforcement learning (RL) to do the adoption, how to choose the agent, observation and reward in each step?
(3) How does the rerouting decision influence the bifurcation phenomena in macroscopic fundamental diagram (MFD).

3. Proposed Methodology and Data

In the literature, gridlock has been described as bifurcations of the macroscopic fundamental diagram, MFD. The MFD gives the relationship between average flow and average density in the network (Herman and Prigogine, 1979; Mahmassani et al., 1984; Mahmassani et al., 1987;

Williams et al., 1987; Mahmassani and Peeta, 1993; Williams et al., 1995; Geroliminis and Daganzo, 2008). bifurcation takes place when the MFD curve collapses to zero flow at densities lower than the jam density (Daganzo et al., 2011; Mahmassani et al., 2013). They pointed out that the instability of equilibrium patterns in congested regime is the main reason, and driver's random turning is an influential factor. This project will adopt this approach to evaluate the performance of the proposed framework. this framework based on deep reinforcement learning (DRL), which has been applied in decision problems across many fields (Mnih et al., 2013, 2015). In that case, DRL can be regarded as a useful tool to instruct drivers to do rerouting behavior under different congestion problems. However, recent findings (Laval and Zhou, 2019) reveal that current DRL unable to learn due to the vanishing gradient caused by the congested network property. The finding is surprising, but the conclusion was drawn upon the assumption of full driver adaptation, which requires all drivers to adaptively reroute. In this project, our target is to find whether rerouting under different congestion could remission the bifurcation phenomenon and increase the capacity flow.

The proposed methodology will use a microscopic network simulation model together with a reinforcement learning framework for driver's adoption of rerouting. It includes agent definition, reward and observation designing. Details of the methodology are described in the work plan below.

4. Work Plan (Project Tasks)

The tasks are described as follows.

Task 1: Literature review

This task will keep going throughout the life of the project due to the constant developments in machine learning; keeping the methods up-to-date on the literature is especially important.

Task 2: Determine and design the machine learning method

There are four main types of machine learning methods that will be analyzed for suitability for this project: Supervised learning, Un-supervised learning, Semi-supervised learning and Reinforcement learning. The characteristics of each type are:

1. **Supervised learning:** All data are 'labeled' and tell the machine the corresponding value, which is used in machine learning to determine errors in output.
2. **Un-supervised learning:** All the data are 'unlabeled', and the machine classifies the data itself by looking for features.
3. **Semi-supervised learning:** Only few data are 'labeled', and computer learn from these labeled data to find corresponding features and do the classification.
4. **Reinforcement learning:** The computer learns in each iteraction with the designed environment to maximize the expected benefit.

After choosing the machine learning method, we need to determine the parameters in reinforcement learning:

- What is the agent in reinforcement learning
- What is the observation for agent in each episode

- How to design the reward function

Task 3. Design the simulation in SUMO

We will built a idealized network in a microscopic traffic simulator, SUMO (Krajzewicz et al., 2012). For designing the network, we need to determine the following items:

1. The basic setting of network including nodes, lanes, etc.
2. The traffic signal assignment.
3. Traffic flow definition.
4. The location of the loop detectors.

Since we need a complete MFD, we need to reach to jam density in the end. There are two methods:

- Defined fixed traffic flow before the simulation program running;
- Keep insert new vehicle until each lane get to the jam density during simulation program.

These two methods are different and may get different results. The first one is more corresponding to real life. However, it is hard to find a satisfied value.

Task 4. Analyze the simulation data

We will analyze the convergence of learning results to find out if the design of reinforcement learning is successful. After the parameters of reinforcement learning are set appropriately, we will get the relationship between network arrival rate and density and the relationship between trip completion and density. Then we will compare the results under fixed rerouting probabilities and the results under DRL model.

Task 5: Prepare paper

In first year, we will to produce a paper to explain how the rerouting adoption influence bifurcation in MFD.

5. Project Schedule

	Task Name	Month											
		1	2	3	4	5	6	7	8	9	10	11	12
1	Literature review												
2	Determine and design the machine learning method												
3	Design the simulation in SUMO												
4	Analyze the data												
5	Prepare paper												

6. Relevance to the Center Theme/Mission

TOMNET's mission is to advance data and methods to reflect the role of attitudes, perceptions, values, and preferences in travel behavior models. The proposed project combines rerouting behavior and deep reinforcement learning (DRL) to find an proficient framework to minimize gridlock.

7. Anticipated Outcomes and Deliverables

In terms of the results, this study will give an explanation about the relationship between rerouting behavior and the bifurcation phenomenon in MFDs, which will provide insights into how to best combat severe congestion on urban networks. The outcome of the project will be a journal paper and a final report.

8. Research Team and Management Plan

Principal Investigator ***Jorge A. Laval*** is an internationally-known traffic flow theory scholar, who has specialized in traffic flow theory, simulation of traffic flow models, and queueing theory in transportation. He will be responsible for the overall direction of the project, and will be directly engaged with its ongoing progress. In addition, ***one PhD student*** will be responsible for the day-to-day execution of substantive project tasks.

The project team will meet weekly for in-depth reports on progress and tactical planning. All members are local, so communication will be straightforward, of course including online video meetings and email.

9. Technology Transfer Plan

To disseminate the work among practitioners, we expect to present the study at the annual research exposition hosted by the Georgia Department of Transportation, and/or in other locations as opportunities are made available. In addition, the project team will seek out an opportunity to present a webinar regarding the research results, to disseminate to practitioners who may be unable to travel to conferences at which we present the work.

10. Workforce Development and Outreach Plan

The project will employ a PhD student what will become familiar with advanced traffic simulation tools in combination with machine learning models. Accordingly, this project will collaterally contribute to the professional development of the PhD student.

11. References

Buisson, C., Ladier, C., 2009. Exploring the impact of homogeneity of traffic measurements on the existence of macroscopic fundamental diagrams. Transportation Research Record: Journal of the Transportation Research Board, No. 2124, 127–136.

Daganzo, C.F., 1996. The nature of freeway gridlock and how to prevent it. Proceedings of the 13th International Symposium on Transportation and Traffic Theory, Elsevier Science Publishing, 629-646.

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Geroliminis, N. Sun, J., 2011. Hysteresis Phenomena of a Macroscopic Fundamental Diagram in Freeway Networks. Proceedings of the 10th International Symposium on Transportation and Traffic Theory, Elsevier Science Publishing, 213–228.

Herman, R., Prigogine, I., 1979. A two-fluid approach to town traffic. Science 204, 1979, 148-151.

Knoop, V., Van Lint, J.W.C., Hoogendoorn, S., 2012. Routing Strategies based on the Macroscopic Fundamental Diagram. Transportation Research Record: Journal of the Transportation Research Board, Transportation Research Board of the National Academies, Washington, D.C. (in press).

Krajzewicz, D., Erdmann, J., Behrisch, M., Bieker, L., 2012. Recent development and applications of SUMO - Simulation of Urban MObility. International Journal On Advances in Systems and Measurements 5, 128–138. URL: http://elib.dlr.de/8048

Laval, J.A., Zhou, H., 2019. Large-scale traffic signal control using machine learning: some traffic flow considerations. arXiv preprint arXiv:1908.02673

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Mahmassani, H.S., Williams, J.C., Herman, R., 1987. Performance of urban traffic networks. Proceedings of the 10th International Symposium on Transportation and Traffic Theory, Elsevier Science Publishing, 1-20.

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Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., Riedmiller, M., 2013. Playing atari with deep reinforcement learning. arXiv preprint arXiv:1312.5602.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G., et al., 2015. Human-level control through deep reinforcement learning. Nature

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Williams, J.C., Mahmassani, H.S., Herman, R., 1995. Sampling strategies for two-fluid model parameter estimation in urban networks. Transportation Research Part A 29 (3), 229-244.
Zheng, N., Rérat, G., & Geroliminis, N. (2016). Time-dependent area-based pricing for multimodal systems with heterogeneous users in an agent-based environment. Transportation Research Part C: Emerging Technologies, 62 , 133–148.

12.Qualifications of Investigators (One-page CV per Investigator)

Appears after the budget page.

13.Budget Including Non-Federal Matching Funds

This project is funded by TOMNET, and the budget form is attached below.

CATEGORY	Budgeted Amount	Match	Explanatory Notes; Identify Source of Matching Funds
Faculty Salaries	$19,280	$57,408	Academic-year salary
Other Staff Salaries			
Student Salaries	$28,800		12 months
Fringe Benefits	$7,840	$18,198	32.6% for faculty; 5.4% for students
Total Salaries & Benefits	$55,920	$75,606	
Student Tuition Remission	$18,684		
Operating Services and Supplies	$3,000		Open access fees (partial)
Domestic Travel	$2,000		TRB conference
Total Direct Costs	$79,604	$75,606	
F&A (Indirect) Costs	$35,212	$4,400	57.8 % of MTDC
TOTAL COSTS	$114,815	$80,006	

BIOGRAPHICAL SKETCH

NAME: Laval, Jorge

POSITION TITLE & INSTITUTION: Full Professor, Georgia Institute of Technology

(a) PROFESSIONAL PREPARATION -(see PAPPG Chapter II.C.2.f.(a))

INSTITUTION	LOCATION	MAJOR / AREA OF STUDY	DEGREE (if applicable)	YEAR YYYY
Universidad Católica de Chile	Santiago, RM	Transportation	BCE	1995
University of California at Berkeley	Berkeley, CA	Transportation	MCE	2001
University of California at Berkeley	Berkeley, CA	CEE	PHD	2004

(b) APPOINTMENTS -(see PAPPG Chapter II.C.2.f.(b))

2020 - present Full Professor, Georgia Institute of Technology, Atlanta, GA

2012 - 2020 Associate Professor, Georgia Institute of Technology, Atlanta, GA 2006

- 2012 Assistant Professor, Georgia Institute of Technology, Atlanta, GA 2005 -

2006 Postdoctoral Researcher, University of Lyon, Lyon

2004 - 2005 Postdoctoral researcher, California PATH, University of California, Berkeley, CA 1996

- 2000 Planning engineer, Ministry of Public Works, Santiago

(c) PRODUCTS -(see PAPPG Chapter II.C.2.f.(c))

Products Most Closely Related to the Proposed Project

1. Li T, Chen D, Zhou H, Xie Y, Laval J. Fundamental diagrams of commercial adaptive cruise control: Worldwide experimental evidence. Transportation Research Part C: Emerging Technologies. 2022; 134:103458-103458.
2. Li T, Chen D, Zhou H, Laval J, Xie Y. Car-following behavior characteristics of adaptive cruise control vehicles based on empirical experiments. Transportation research part B: methodological. 2021; 147.
3. Zhou H, Laval J, Zhou A, Wang Y, Wu W, Qing Z, Peeta S. Review of Learning-based Longitudinal Motion Planning for Autonomous Vehicles: Implications on Traffic Congestion. Transportation Research Board 100th Annual MeetingTransportation Research Board. 2021; (TRBAM-21-04248).
4. Abbink D, Hao P, Laval J, Shalev-Shwartz S, Wu C, Yang T, Hamdar S, Chen D, Xie Y, Li X, others. Artificial Intelligence for Automated Vehicle Control and Traffic Operations: Challenges and Opportunities. ; c2020.
5. Xu T, Laval J. Statistical inference for two-regime stochastic car-following models. Transportation Research Part B: Methodological. 2020; 134.

Other Significant Products, Whether or Not Related to the Proposed Project

1. Aghamohammadi R, Laval J. Dynamic traffic assignment using the macroscopic fundamental diagram: A review of vehicular and pedestrian flow models. Transportation Research Part B: Methodological. 2020; 137.

2. Delpiano R, Herrera J, Laval J, Coeymans J. A two-dimensional car-following model for two-dimensional traffic flow problems. Transportation Research Part C: Emerging Technologies. 2020; 114.
3. Xu T, Laval J. Driver reactions to uphill grades: inference from a stochastic car-followingmodel. Transportation research record. 2020; 2674(11).
4. Xu T, Laval J. Analysis of a two-regime stochastic car-following model: Explaining capacity drop and oscillation instabilities. Transportation Research Record. 2019; 2673(10).
5. Laval J, Toth C, Zhou Y. A parsimonious model for the formation of oscillations in car-following models. Transportation Research Part B: Methodological. 2014; 70:228-238.

(d) SYNERGISTIC ACTIVITIES -(see PAPPG Chapter II.C.2.f.(d))

1. Subcommittee Chair: Traffic flow webinars subcommittee of the Traffic Flow Theory andCharacteristics Committee (AHB45) of the Transportation Research Board
2. Committee Member: Transportation Research Board Traffic Flow Theory and Characteristics
3. Editorial Advisory Board Member, RTS (Recherche-Transports-Sécurité, French refereed journal)
4. Advisory Board Member: Ingeniería de Transporte (Chilean refereed journal)
5. Editorial Advisory Board Member, Transportation Research Part B: Methodological

Grant Deliverables and Reporting Requirements for UTC Grants (November 2022)

Exhibit F

UTC Project Information	
Project Title	Drivers' attitude towards rerouting: Impacts on network congestion
University	Georgia Institute of Technology
Principal Investigator	Jorge A. Laval
PI Contact Information	jorge.laval@ce.gatech.edu, 404-894-2360
Funding Source(s) and Amounts Provided (by each agency or organization)	
Total Project Cost	$114,815
Agency ID or Contract Number	
Start and End Dates	Aug. 1, 2021 - July 31, 2022
Brief Description of Research Project	Combine microscopic network simulation models and machine learning models to change drivers routing behavior to minimize congestion
Describe Implementation of Research Outcomes (or why not implemented) Place Any Photos Here	Field implementation is out of scope.
Impacts/Benefits of Implementation (actual, not anticipated)	
Web Links • Reports • Project Website	