**Simulation Scenarios of Machine Learning Vehicle Platoon Agents to Support Safety Assurance, Infrastructure Interoperability and Policy Analysis for Autonomous Systems**

by

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# I. Problem Statement and its Setting

Due to the rising number of autonomous, decentralized and self-managed agents that individually react to the current infrastructure, the advancement of the transportation system in the coming years faces major challenges. Because infrastructure capacity has not kept pace with the needs of travel demand, traffic congestion continues to escalate. Participants such as electric and autonomous vehicles, travelers, and traffic management centers each can have diverse behaviors, and their interplaying interactions in large quantities within one mutual infrastructure system is still widely unknown and unexplored.

Though autonomous vehicles (AVs) hold the potential to decrease congestion (Anderson et al, 2014), the changes in vehicle-kilometer-traveled (VKT) due to the advent of AVs remain unclear, and some researchers even believe that VKT would in fact actually increase due to what is known as the ‘‘rebound effect’’ (Bagloee et al, 2016). Furthermore, connected vehicles and spectrum allocation are also influencing factors in AV deployment.Federal regulation of the spectrum used in vehicle communications may affect how automation proceeds. This decision has competitive implications for the automotive, electronics, and telecommunications industries, and subsequently may affect the availability of safety technologies and the path toward vehicle automation (Canis, 2020).

**Highway and road infrastructure** will also be greatly impacted by the **implications of AVs**.Deployment of fully autonomous vehicles will require not only a suite of new sensor and communications technologies, but also changes to the highway and road infrastructure on which those vehicles will operate. The current generation of AVs being tested today relies on clear pavement and road markings as well as legible signage to stay in their lanes and navigate through traffic. Major highways as well as side roads in urban and rural settings will need to accommodate AVs in addition to a large fleet of conventional vehicles with human drivers (Canis, 2020).

# A. Research Questions

Given the aforementioned problem space and using co-simulation, this thesis research poses and will seek to answer the following inquiries below, and use metrics for safety, network efficiency and asset management provided in section *IV. Research Methodology*:

1. In examining how adverse road conditions such as weather affect human driving behavior, using co-simulation, what type of behavior can be observed under similar conditions that affects the abilities of automated vehicles to **operate safely**, and what type of actionable data outcomes and decision support results can be produced for infrastructure owners and operators and information providers to plan accordingly?
2. What type of outcomes can the simulation provide that will support assessments of infrastructure such as the number of road-side equipment required per # of AVs as well as regulatory and technical issues that may inhibit nationwide vehicle platooning, and to support **infrastructure interoperability** readiness for AV testing and deployment?
3. What type of simulation output / outcomes can be observed to support exploratory scenario planning, and provide the associated performance measures outcomes to support **policy analysis** for automated vehicle adoption?

# B. Hypotheses

The initial set of hypotheses that this research seeks to affirm include the following:

* Machine learning-based vehicle platooning enhances road safety and reduces accidents: The coordinated nature of platooning allows vehicles to maintain safe distances, follow predetermined routes, and communicate with each other effectively.
* Machine learning-based vehicle platooning improves traffic flow and reduces congestion: By maintaining consistent speeds, minimizing unnecessary braking and acceleration, and optimizing traffic patterns, platooning can enhance the overall efficiency of traffic movement. This hypothesis suggests that autonomous vehicle platooning can lead to smoother traffic flow, reduce bottlenecks, and mitigate congestion, resulting in improved travel times and reduced delays for both platooning vehicles and other road users.
* Machine learning-based vehicle platooning reduces fuel consumption and carbon emissions: By optimizing the aerodynamics and maintaining consistent speeds within a platoon, vehicles can benefit from reduced wind resistance and improved fuel efficiency, resulting in a decrease in overall fuel consumption and carbon emissions compared to individual vehicles traveling independently.
* Machine learning-based vehicle platooning enhances adaptive and responsive coordination among vehicles: This hypothesis suggests that machine learning-based platooning systems can achieve better coordination, synchronization, and responsiveness, leading to improved traffic flow, reduced delays, and enhanced overall efficiency.
* Machine learning-based vehicle platooning improves traffic capacity and road infrastructure utilization: ​​By maintaining consistent speeds and minimizing following distances, platooning vehicles can occupy less space on the road, allowing for more vehicles to utilize existing roadways effectively. The hypothesis suggests that autonomous vehicle platooning can enhance road network efficiency, reduce the need for additional infrastructure construction, and make better use of available transportation resources.

# C. Definitions of Terms

**Agent** –

**Deep Reinforcement Learning** –

**Intelligent Transportation System (ITS)** – systems in which information and communication technologies are applied in the field of road transport, including infrastructure, vehicles and users, and in traffic management and mobility management, as well as for interfaces with other modes of transport.

# D. Assumptions / Delimitations and Limitations

# E. Significance of the Research

The U.S. Department of Transportation (U.S. DOT) Intelligent Transportation Systems Joint Program Office (ITS JPO) conducts technical and policy research to accelerate the safe, efficient, and equitable integration of automation into the transportation system. This thesis research aligns with, contributes to and supports the federal role in planning automation safety assurance, infrastructure interoperability, and policy analyses.

# II. Review of the Related Literature

The following selected research has been identified as significant and relevant in the areas of this thesis research regarding ITS, co-simulation and for the elements of the ITS scenario I will focus on.

# III. Data and Treatment of the Data

ITS DataHub will be the main source of data to use in my thesis research. It contains a wealth of open ITS research project datasets, associated documentation and data management tools. This resource will decrease the time from research to insight.

Datasets in the ITS Datahub contain a diverse range of information which includes, but is not limited to, connected vehicle messages, automated vehicle data, trajectories, field test data, sensor data, connected equipment data, weather data, and application messages. Large, continuously expanding, or immature data is stored in a “sandbox” data environment.

Graphical user interface, website

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*Figure 1. ITS DataHub website - data.transportation.gov*

For this thesis research, the initial datasets listed have been identified as relevant for building models and constructing the simulations:

* Road Weather Demonstration Data
* Tampa CV Pilot Basic Safety Message (BSM) Sample
* Intelligent Network Flow Optimization Prototype Infrastructure Traffic Sensor System Data Aggregator
* Test Data of Proof-of-Concept Vehicle Platooning Based on Cooperative Adaptive Cruise Control (CACC)
* Multi-Modal Intelligent Traffic Signal Systems Vehicle Trajectories for Roadside Equipment

The table below displays a sample of the data contained in the *Intelligent Network Flow Optimization Prototype Infrastructure Traffic Sensor System Data Aggregator* dataset:

|  |  |  |
| --- | --- | --- |
| Column Name | Description | Type |
| DZId | Zone ID | Plain Text |
| DSId | Detector Station Id. A detector station usually consists of multiple detection zones. | Plain Text |
| DateReceived | Date and time when the infrastructure traffic sensor data was received in UTC format. | Plain Text |
| IntervalLength | Length in seconds of the data collection interval | Number |
| Volume | Number of vehicles detected during the data collection interval | Number |
| Occupancy | Percent of time the detection zone or detector station was occupied during the data collection interval. | Number |
| AvgSpeed | Average speed of the detection zone or detector station across all lanes | Number |
| Queued | Queued state of the detection zone or detector station as compared to Queue Speed Threshold. | Plain Text |
| Congested | Congested state of detection zone or detector station as compared to Congestion Speed Threshold | Plain Text |

*Table 1. Partial Data in the Intelligent Network Flow Optimization Prototype Infrastructure Traffic Sensor System Data Aggregator Set*

**Treatment of the Data**

When using this data distributed by the US DOT and affiliated organizations, I will uphold the following responsibilities as outlined on the ITS DataHub website:

Where the contributed materials have been utilized to any extent to enable, verify, supplement or validate performance measurement, analysis, research or software development, to fully reference the contributing organization and the contributions of the individuals in all subsequent and related publications or public events, specifically:

1. In publications, reference the data contributor and the date accessed, data and/or data processing tools (by name and version number), and individual contributors
2. In presentations or other oral communication, by noting the data and/or data processing tool by name and version number and communicating the address of the website.

Additionally, I will accurately post and update within ITS DataHub website a description of the project utilizing the data and/or the data processing tools, including:

1. A description of the project, including a brief statement of the project goals.
2. A summary of the hypotheses and findings (when available) of the project.
3. Individuals directing and/or substantively participating in the project.
4. The name and version number of the data and/or data processing tools downloaded and utilized in the project.
5. The current state of the project (upcoming, underway, completed).
6. References to published materials (if any).

In the event that the data contains anomalies, errors or other questionable data elements, I will contact the data contributor referencing the specific data set by name and version number.

I will also refrain from duplication and dissemination of the data to third parties.

Publication of certain derived information such as location of residence, specific stores visited,

purpose of trips, etc. must be cleared with the data set originator prior to publication.

Additionally, alternative secondary data sources may be utilized in situations where the ITS DataHub does not have such required data for the research. The above-mentioned treatment of data shall also apply.

# IV. Research Methodology

To investigate the research questions, a suitable set of models and simulations representing intelligent transportation systems will be created and explored. Therefore, this section gives an overview of the chosen research methodology and section *A. Conceptual Framework* outlines the development approach for the intended interface.

Creating the models for the simulation will first consist of a scenario planning approach. Scenarios are narratives regarding the future that planners develop in order to consider and prepare for potential challenges and opportunities. Scenario planning assist transportation agencies in working with stakeholders and the public to establish a vision and implement a strategic plan for success in uncertain times. Scenarios that are designed well inspire critical thinking about issues and events that could significantly affect a region’s economy, environment, and quality of life (Twaddell et al, 2016).

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*Figure 2. U.S. DOT FHWA Six-Phase Scenario Planning*

In addition to using modeled forecasts based on historical trends or formulas, scenarios will use simulation and interactive 3D visualizations to illustrate complex data analysis in the form of holistic, plausible illustrations of future conditions. Scenario planning typically includes both qualitative and quantitative analyses to illustrate the tradeoffs between different futures and their relative impacts on different community goals.

**Performance Measures**

To validate the research hypothesis the following set of performance measures have been identified as desirable outputs:

**Safety** –Ultimately, safety is measured as the number of fatalities, injuries or property damage for vehicleoccupants and other road users. Other road users may include pedestrians, bicyclists, slow moving vehicles, construction workers and first respondents (Innamaa and Kuisma, 2018). Performance measures are:

* Number of crashes (distinguishing property damage, and crashes with injuries and fatalities), in total and per 100 million km or miles
* Number of conflicts encountered where time-to-collision (TTC) is less than a predetermined threshold / 100 million km or miles
* Circumnavigates areas with bad road conditions.

**Network Efficiency** – Network efficiency refers to lane, link and intersection capacity and throughput in a regional transport network. It also refers to travel time and travel time reliability (Innamaa and Kuisma, 2018). Performance measures are:

* Throughput, i.e.. number of vehicles per hour through a particular road section or intersection approach, normalized to number of lanes and proportion of green time (where relevant)
* Maximum road capacity (for a given road section)
* Peak period travel time along a route
* Road capacity at design speed (for a given road section)
* Number of V2X-messages sent via cellular communication
* Number of V2X-messages sent via ITS-G5 communication

**Asset Management** – Assets include physical and digital infrastructure of road transportation (Innamaa and Kuisma, 2018). Performance measures are:

* V2I infrastructure for automation
* Arrival time of the Inter and IntraVehicle messages via AdHoc networks
* Range of Road-Side Units at their defined location
* Number of V2X-messages received by vehicles

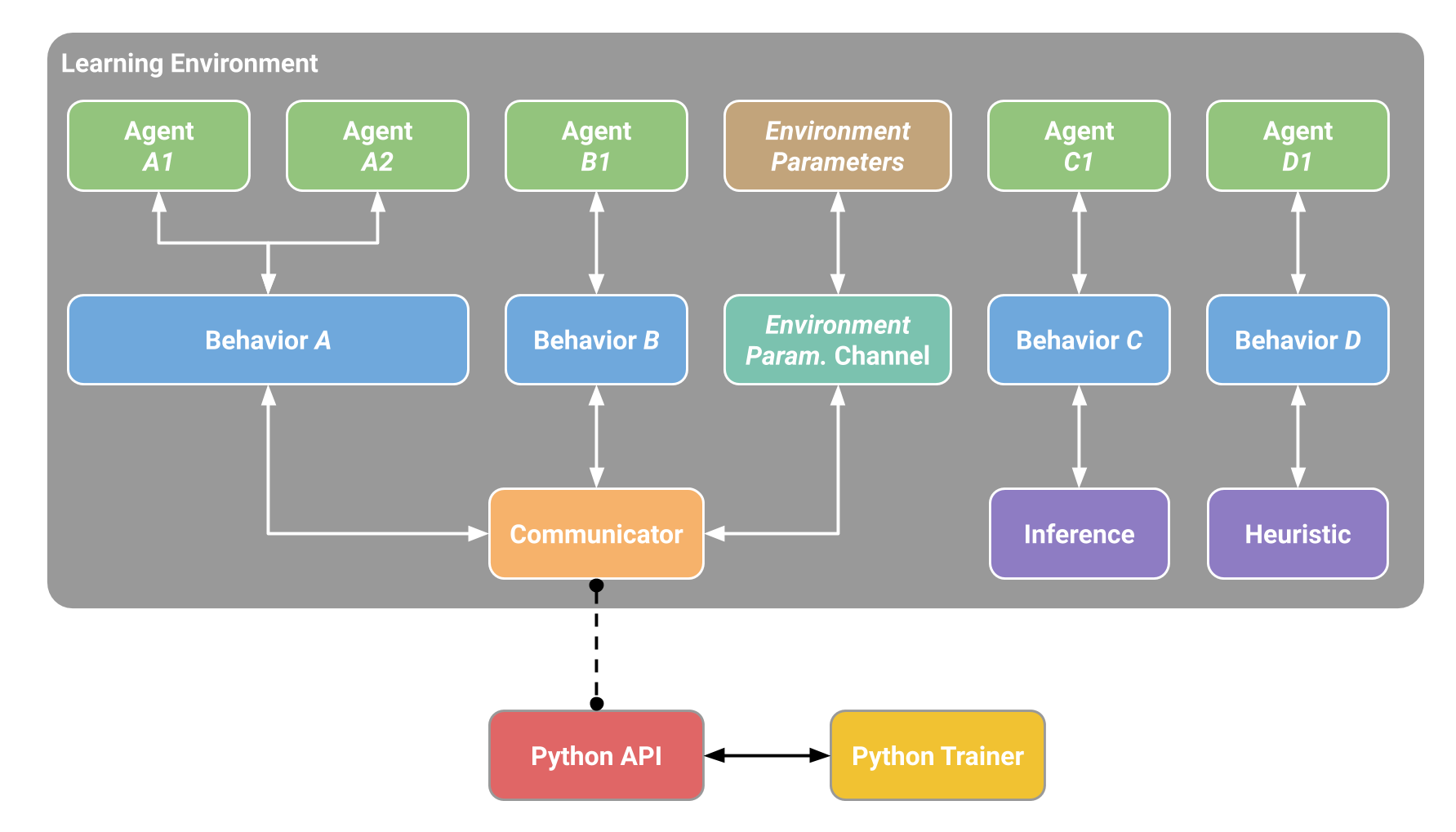
# A. Conceptual Framework

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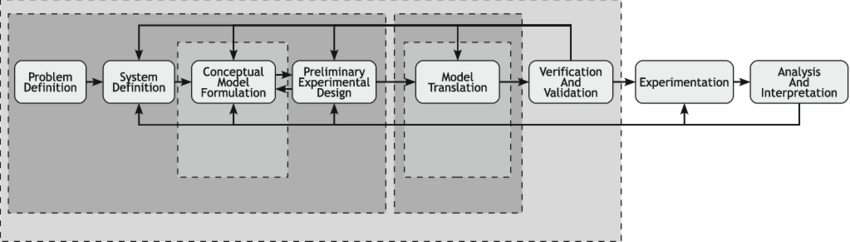
*Figure 3. Unity3D Engine Simulation Framework*

Components of the machine learning simulation environment are as follows:



# B. Research Design

With regard to modeling and simulation in systems engineering of ITS projects, the insight into current state-of-the-art research showed that many questions have already been answered. However, …



*Figure 4. Scenario Planning Simulation Process*

# D. Construction and Analysis of Scenarios

Below are datasets that are proposed to serve as the basis for scenario planning from which to construct models for the co-simulation:

**Scenario Construction and Analysis**

**1. Single Lane Platoon:** Simulate a single lane scenario where a lead vehicle moves along a straight road, and a group of following vehicles needs to maintain a specific distance and speed with respect to the lead vehicle. Train the following vehicles to adjust their speed and maintain a safe following distance.

**2. Multi-Lane Platoon:** Create a scenario with multiple lanes where vehicles need to coordinate and change lanes while maintaining the platoon formation. Train the vehicles to switch lanes appropriately, merge with other platoons, and avoid collisions with other vehicles.

**3. Dynamic Lead Vehicle:** Introduce a lead vehicle that dynamically changes its speed or path, requiring the following vehicles to adapt and maintain the platoon formation. This scenario can help train the following vehicles to respond to sudden changes in the lead vehicle's behavior.

**4. Communication and Coordination:** Implement a communication system between the platoon vehicles. Train the vehicles to exchange information about speed, acceleration, and potential obstacles to improve coordination within the platoon. This can involve creating a messaging system or using inter-agent communication within Unity ML-Agents.

**5. Sensor Limitations:** Simulate scenarios where vehicles have limited sensor range or accuracy. This can mimic real-world scenarios where sensor limitations affect perception. Train the vehicles to make decisions based on partial or noisy information, emphasizing the need for adaptive behavior and sensor fusion techniques.

**6. Environmental Challenges:** Introduce various environmental challenges such as adverse weather conditions, road obstacles, or traffic congestion. Train the platoon vehicles to handle these challenges and adjust their behavior accordingly, such as maintaining safe distances and adjusting speed during slippery road conditions.

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