Microsimulation of Energy and Flow Effects from Optimal Automated Driving in Mixed Traffic

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Abstract—This paper studies the energy and traffic impact of a proposed Cooperative and Anticipative Cruise Controller in a PTV VISSIM microsimulation environment. We dissect our controller into two parts: 1. the anticipative mode, more immediately beneficial when automated vehicle fleet penetration is low, and 2. the connected mode, beneficial in coordinated platooning scenarios and high automated vehicle penetrations appropriate for autonomous vehicle specific applications. Horizon and terminal constraints handle safety considerations, and vehicle constraints for acceleration capabilities are implicitly understood through the use of powertrain maps. Real traffic scenarios are then modeled using time headway distributions from traffic data. To study impact over a range of demands, we vary input vehicle volume from low to high and then vary CAV penetration from low to high. When examining all-human driving scenarios, network capacity failed to meet demand in high-volume scenarios, such as rush-hour traffic. We further find that with automated vehicles introduced, network capacity was improved to support the high-volume scenarios. Finally, we find that our vehicles perform at a 10%-20% higher fuel efficiency over human drivers. Due to secondary effects of smoothing traffic flow, fuel benefits also apply to human-driven vehicles that interact with automated ones. Such simulated humans were found to drive up to 10% more fuel-efficiently than they did in the baseline all-human scenario.

Index Terms—PTV VISSIM, traffic simulation, autonomous vehicles, adaptive cruise control, energy efficiency, fuel economy, model predictive control.

I. INTRODUCTION

With ever-growing demand in the transportation and energy sector, annual costs of said systems can continue to rise. The period of 1970-2011 saw 68% increased activity in the U.S. transportation sector [1]. Further, a significant portion of total energy consumption in the U.S. is attributed to transportation - 28% of total energy consumption in 2018 [2]. In an effort to combat said effects, improving fuel economies of vehicles can offset energy costs for the immediate future.

In response to concerns over energy use and safety on the roadways, Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC) vehicles have been proposed for car-following and platooning - such as those depicted in Figure 1. Here, ACC vehicles decide their velocity based on traffic information from sensory data, whereas CACC vehicles additionally utilize information broadcast from each other to make more informed decisions over traditional cruise controllers, which simply track a desired velocity as specified by the user. From this, a 40% reduction in traffic collisions due to automated vehicles on roadways was estimated in [3].

Unfortunately, currently available commercial automated systems have been shown to be string unstable, leading to inefficient road utilization and propagation of traffic disturbances [4]. Various solutions exist to specifically address issues of string instability, [5] proposes a sliding-mode robust controller, while [6] proposes a collective lateral and longitudinal robust model predictive controller (MPC) with gain-scheduling.

Some literature on car-following and platooning has conducted fuel economy studies with drive cycle data imposing traffic conditions. However, various standard drive cycles have been shown to overestimate fuel economies of vehicles for similar intensities of traffic conditions in studies using real driving data [8]. In contrast, [9] show that current microsimulation software is capable of producing fuel estimations that approximately match those generated from real data. Furthermore, it can also be shown that ACC and CACC vehicles can smooth traffic and prevent disturbances from growing. So, imposing fixed drive cycles present artificial conditions: fixed drive cycles impose the same traffic disturbances, despite changes in fleet behavior, and may not represent the full impact of automation. A microsimulation approach can realize traffic conditions in an organic manner - particularly given that the parameters used produce simulation data similar to real data. By replicating real-world traffic conditions in a microsimulation, a study can then predict traffic impact due...
to changes in control algorithms used \[10\].

Microsimulation software such as Paramics and PTV VISSIM have been used to model vehicle interactions. VISSIM employs a psycho-physical driver model for human driving, stochastic distributions of vehicle flux into a network and preferred acceleration-deceleration behavior, altered driving behavior to account for road-grade and controlled intersections, and easy real-world modeling \[11\]. It has been shown that VISSIM simulation results are sensitive to simulation parameters, but only small changes to parameters are needed to replicate human driving well - it is sufficient to alter headway parameters alone \[12\]–\[14\]. From this, microsimulation software can be used to well-realize traffic dynamics and thus predict benefits of a control strategy. Fuel economy improvement has already been shown for traffic controllers handling ramp access and intersections \[15\]–\[17\]. VISSIM was also used in \[18\] to evaluate safety improvements from a variable speed limit controller.

In contrast to these prior infrastructure and policy-related studies, this paper leverages VISSIM microsimulations to study the impact of optimal anticipative cruise control among heterogeneous fleets of human and automated passenger vehicles. The control algorithm itself builds on the one the authors proposed in \[19\] with the new addition of chance constraints and time headway tracking to improve unconnected performance. Compared to drive cycle studies like \[19\]–\[21\], the use of microsimulation software enables more realistic performance assessment as mentioned previously. While experiments like \[4\], \[22\], \[23\] have the advantage of using real vehicles, they typically involve isolated strings of fewer than 10 of them. The microsimulation platform proposed here complements, but does not replace, experiments in favor of larger-scale evaluation.

First, the optimal control formulation of the anticipative cruise control algorithm is proposed in Section \[II\] which focuses on minimizing acceleration of the vehicle for secondary benefits in traffic smoothness and fuel economy. Traffic compactness is considered through the use of headway tracking terms in the objective, and further handled as a trade-off between vehicle safety and gap as a probabilistic constraint. Then, the setup for a VISSIM environment is depicted and simulation parameters are carefully justified in Section \[III\] where real-scenario conditions are replicated. The fuel economies of strings of vehicles are then evaluated, and benefits to traffic flow and discussion of its effects to fuel economy for both human and automated vehicles are finalized in Section \[IV\].

II. OPTIMAL CONTROL FORMULATION

An overview of the optimal control control formulation through model predictive control (MPC) is given as follows \[24\]. A linear set of discrete equations replicate the simulation model used in VISSIM, a quadratic objective is proposed to smooth acceleration experienced by the ego vehicle and maintain a reference time headway from the preceding vehicle, and constraints are formulated to set vehicle capabilities and incur safe driving. The optimal control problem is converted to a quadratic program (QP) and resolved at each timestep to realize closed-loop control. Further details, such as an optimal terminal constraint derivation based on particle kinematics, can be found in \[19\].

A. Modeling

We consider the 1D dynamics of a given MPC-controlled vehicle (ego) to be a set of Euler integration method equations between commanded acceleration and position - chosen to match the simulation method VISSIM employs.

As depicted in Figure \[I\] let \(s, v, a\) be the absolute position, velocity, and realized acceleration of the ego, and let \(u\) be the commanded acceleration of the ego. We additionally employ space headway modified with ego position, \(s\), output tracking from reference time headway \(T_H\), as well as ego acceleration tracking. Then, observe the output state-space given in Equation (1).

\[
\begin{bmatrix}
  s \\
  v \\
  a
\end{bmatrix}_{i+1} =
\begin{bmatrix}
  1 & \Delta t & 0.25\Delta t^2 \\
  0 & 1 & 0.5\Delta t \\
  0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
  s \\
  v \\
  a
\end{bmatrix}_i
+ \begin{bmatrix}
  0.25\Delta t^2 \\
  0.5\Delta t \\
  1
\end{bmatrix} u_i
\]

\[
\begin{bmatrix}
  \dot{s} \\
  \dot{a}
\end{bmatrix}_i =
\begin{bmatrix}
  1 & T_H & 0 \\
  0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
  s \\
  v \\
  a
\end{bmatrix}_i
\]

Here, subscript \(d\) denotes the discrete version of the control matrix, and \(\Delta t\) is the MPC discretization step size.

B. Objective

With the purpose of boosting fuel economy of the ego vehicle, a cost function may choose to directly penalize fuel consumption. This poses challenges when solving optimization routines online, however, due to the highly nonlinear nature of such a computation. So, the optimizing routines can occasionally fail to converge to a suitable optimality tolerance, fail to generate a feasible solution, or suffer large, inconsistent runtimes. In a vehicle driving application, these qualities can compromise safety and effectiveness.

With these considerations, a quadratic cost function can be chosen to reliably generate efficient, fast solutions when paired with a linear model. To promote velocity smoothing and eco-driving, as well as promote traffic compactness and safe driving, we choose cost function \(J\) to penalize ego acceleration and ego deviation from the time headway - using weights \(q_a\) and \(q_d\), respectively.

\[
J = q_d[\dot{s}(N) - s_r(N) + d_r]^2 + q_a a^2(N) + \sum_{i=0}^{N-1} \left[ q_d[\dot{s}(i) - s_r(i) + d_r]^2 + q_a a^2(i) + u^2(i) \right]
\]

(2)

Here, \(N\) is the optimization horizon length, index \(i\) corresponds to a respective optimization stage, \(d_r\) is an additional reference gap to track, and \(s_r\) is the preceding vehicle (PV) position, as further detailed in Section II-C.
Clearly, this cost function does not directly minimize fuel consumption. However, large accelerations correlate with large fuel consumption rates, so the above objective aids in reducing fuel consumption in a computationally efficient quadratic manner. Acceleration minimization also directly attenuates speed disturbances, thus bringing about secondary traffic smoothing benefits. This result is further shown in Section IV-B.

C. Prediction

To generate a trajectory of \( s_r \), we consider two cases: connected driving, and unconnected driving.

In connected driving, the preceding automated vehicle broadcasts its planned intentions as generated from its own optimization routine. Here, the future positions of the PV are solely considered in the optimization routine.

Likewise, in the unconnected case, anticipation of future positions of the PV is handled through the use of a prediction model. For this paper, a simple constant acceleration model was assumed, where acceleration of the PV is propagated forward until velocity saturation at \( v_{\text{min}} \) or \( v_{\text{max}} \). Here, we consider the recursive equation as given by Equation (3).

\[
s_r(i + 1) = s_r(i) + v_r(i)\Delta t + \frac{1}{2} a_r(0)\Delta t^2
\]

Other solutions for prediction exist, such as constant velocity modeling, game theoretic modeling, Markov modeling, etc. At first, a constant velocity model was evaluated, but slightly worse performance in fuel economy was observed. More importantly, a much higher risk for collisions and worse traffic compactness were also found.

D. Constraint Handling

1) Vehicle Capabilities: Take that, at a given current wheel speed of the ego, a limit on the torque at the wheel exists due to the powertrain. It then follows that a map of acceleration of the vehicle can be derived as a function of vehicle speed. To generate a map, we evaluate the responding vehicle acceleration from a set of applied engine torques through the powertrain and account for losses at the wheel due to friction and aerodynamic drag. With this, an assumption of constant road-grade was made. Figure 2 depicts such a map, whereas colored regions depict feasible operating space for the powertrain.

Max vehicle acceleration for a passenger car is then approximated as a convex pair of linear constraints - shown in Figure 2. Then, considering minimum and maximum velocities of the vehicle due to the road laws, the convex constraint equations follow.

\[
- m_1 v(i) + u(i) \leq b_1 \quad (4a)
\]

\[
- m_2 v(i) + u(i) \leq b_2 \quad (4b)
\]

\[
v(i) - \epsilon_1(i) \leq - v_{\text{min}} \quad (4c)
\]

\[
v(i) - \epsilon_2(i) \leq v_{\text{max}} \quad (4d)
\]

Here, \( m \) and \( b \) are the slope and intercept of the linear acceleration constraints, and \( \epsilon \) is a slack variable, formulated to softly constrain to improve reliability of finding solutions in otherwise infeasible driving routines. To do so, \( \epsilon \) is a decision variable included as a linear affine term in the cost function with a significant penalty - e.g. the new cost function becomes the following.

\[
J' = J + \sum_{i=0}^{N} q_r \epsilon(i) \quad (5)
\]

Here, \( q_r \gg q_\alpha \), and the overbar represents a vector of variables [24].

2) Safety: As mentioned in Section II-C, anticipation of the future gap positions of the PV is handled through the use of a prediction model in the case of an unconnected vehicle. This prediction is used to formulate in-horizon and terminal constraints, whereas it is modified through both: 1. A minimum allowable gap, and 2. A probabilistic constraint on PV position.

The following gives the safety constraint.

\[
s(i) - \epsilon_3(i) \leq s_\alpha(i, \alpha) - d_m \quad (6)
\]

Here, \( d_m \) denotes the minimum allowed following distance, and the safe position \( s_\alpha(i, \alpha) \) is the point that the PV will lie ahead of with probability \( \alpha \) at stage \( i \). In other words, the realized PV position results in a following distance of at least \( d_m \) relative to the planned ego position with probability \( \alpha \).

The following probabilistic derivation gives \( s_\alpha(i, \alpha) \). The first step in this process is to derive the distribution of the PV’s position over time. The second step uses this distribution to obtain \( s_\alpha(i, \alpha) \).

In the first step, we continue to use the constant-acceleration assumption of Section II-C but introduce stochasticity in the acceleration estimate. The dynamics of the stochastic state vector \( X_r = [s_r \ v_r \ A_r]^{\top} \) are modeled as a classic double integrator with state transition matrix \( A_r \), such that \( X_r(k + 1) = AX_r(k) \). The PV position \( S_r \) and velocity \( V_r \) are assumed to be measured with negligible variance at the current time, leaving \( X_r = [s_r \ v_r \ A_r]^{\top} \). After assuming normally distributed acceleration, i.e. \( A_r \sim N(\alpha, \sigma_A^2) \), the initial PV state separates into deterministic and stochastic.

![Fig. 2. Constraints of the ego with regards to acceleration capabilities at a given speed and maximum and minimum speed imposed. Colored contours indicate steady-state gear for a given velocity-acceleration pair.](image-url)
components, where the random acceleration error \( \hat{A}_r \sim \mathcal{N}(0, \sigma_A^2) \).

\[
X_r(0) = \begin{bmatrix} s_r \\ v_r \\ a_r \\ 0 \end{bmatrix}^T + \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}^T
\] (7)

Then, the model propagates forward to step \( i \). At this point, \( X_r \) is represented as a combination of its deterministic and stochastic parts \( \pi(i) \) and \( \hat{X}(i) \), respectively. Notice that since the expectation of acceleration error \( E\hat{A}_r = 0 \), \( \hat{X}(i) \) is entirely zero-mean and the position element of \( \pi(i) \) is the expected position that Section II-C provides.

\[
X_r(i) = A^i \begin{bmatrix} s_r \\ v_r \\ a_r \\ 0 \end{bmatrix}^T + A^i \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}^T = \pi(i) + \hat{X}(i)
\] (8)

The covariance \( \Lambda(i) \) of \( X_r(i) \) is still needed to characterize \( S_r(i) \). Noticing that \( \hat{X}(i) \sim \mathcal{N}(0, \Lambda(i)) \) and applying aforementioned assumptions yields the following formula.

\[
\Lambda(i) = A^i A_0 (A^i)^T, \quad A_0 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}
\] (9)

In summary, \( S_r(i) = s_r + \hat{S}_r(i) \) with \( \hat{S}_r(i) \sim \mathcal{N}(0, \sigma_s^2(i)) \) and the variance \( \sigma_s^2(i) \) is extracted from the upper-left corner of \( \Lambda(i) \).

Finally, the cumulative distribution function \( F_{\hat{S}_r(i)} \) of the position error \( \hat{S}_r \) is inverted to yield \( s_\alpha(i, \alpha) \) such that \( P(S_r > s_\alpha) = \alpha \). To make use of the zero-mean \( \hat{S}_r(i) \), let the distance error \( d_\alpha = s_\alpha - s_r \) so that \( S_r(i) > s_\alpha(i) \) and \( \hat{S}_r(i) > d_\alpha \) are equivalent events. The argument \( i \) is omitted in Equations (10) and (11) for compactness.

\[
\alpha = P(S_r > s_\alpha) = P(S_r > d_\alpha) = 1 - F_{\hat{S}_r}(d_\alpha)
\] (10a)

\[
\alpha = 1 - P(S_r \leq d_\alpha) = 1 - F_{\hat{S}_r}(-d_\alpha)
\] (10b)

Considering the symmetry of the zero-mean normal distribution, where \( F_{\hat{S}_r}(d_\alpha) = 1 - F_{\hat{S}_r}(-d_\alpha) \), the following applies.

\[
\alpha = 1 - (1 - F_{\hat{S}_r}(-d_\alpha)) = F_{\hat{S}_r}(-d_\alpha)
\] (11a)

\[
d_\alpha = -F_{\hat{S}_r}^{-1}(\alpha) = s_\alpha(\alpha) = s_r - F_{\hat{S}_r}^{-1}(\alpha)
\] (11b)

Thus, \( s_\alpha(i, \alpha) \) is obtained as needed. The same fundamental approach can also be applied to different probability models, e.g., Gaussian Mixture Models [25], by replacing the cumulative density function.

In horizon, a safety probability is then chosen - here, we choose a linearly-decreasing \( \alpha(i) \in [0.99, 0.50] \), emphasizing safe driving early in the horizon. Later in the horizon, we argue it is affordable to reduce \( \alpha \) in favor of improved traffic compactness and, because of the feedback nature of MPC, safe-driving is still achieved [26].

This is further illustrated in Figure 3, which depicts the inverse cumulative distribution function of \( \hat{S}_r \) with respect to time and probability. As shown by the dashed line, the increasing uncertainty in PV position forward in time causes large \( \alpha \) values later in the horizon to drastically increases the required safe gap, which reduce traffic compactness from the autonomous vehicles.

\[F_{\hat{S}_r}(\alpha) = 0.99, 0.50, \alpha \in [0.99, 0.50] \]

Fig. 3. Safety on PV position, \( s_\alpha \), with the results of the linearly decreasing function \( \alpha(i) \in [0.99, 0.50] \), where \( \alpha = 0.50 \) for time beyond 10 s. Additionally shown is a constant function \( \alpha(i) = 0.90 \).

### Table I

| Connected and Anticipative Algorithm Properties | Unconnected | Connected |
|-----------------------------------------------|-------------|-----------|
| Property                                      |        | Description       |
| \( N_a \)                                    | 16 s    | 17 s          | Horizon length |
| \( q_a \)                                    | 2050    | 4000         | Acceleration weight |
| \( T_H \)                                    | 1.8 s   | 0.0 s         | Time headway   |
| \( d_r \)                                    | 2 m     | 6 m          | Distance reference |
| \( d_m \)                                    | 2 m     | 2 m          | Minimum distance |

#### E. MPC Tuning

The list of control parameters used in simulation is given in Table I. To tune the parameters, VISSIM simulations at 2000 veh/hour/lane were used, as the most demanding traffic scenarios were found under this vehicle flux. This process was done iteratively as follows: 1. Modify \( T_H \) to approximately match human drivers and support traffic flow, 2. Modify \( q_a \) and \( N \) to achieve max fuel performance of the fleet of vehicles while meeting optimization time requirements, and 3) Repeat from 1 as necessary to observe benefit in fuel economy. Additionally, \( d_m \) was fixed to a low value to promote traffic compactness and approximately match stand-still following distances of human drivers when coming to rest behind another vehicle.

It was found that acceleration weighting can be increased considerably in low traffic intensities, which might be exploited to further improve energy efficiency. Instead of using a single set of weights over all traffic demands, more advanced approaches, such as weight scheduling, could modify MPC parameters based on observed local traffic demands. This study uses constant weighting, leaving weight scheduling for future research.

#### F. Quadratic Program Solution and Memory Usage

To solve for solutions to the quadratic program as created from MPC, the dual simplex method was interfaced in C++
III. SIMULATION ENVIRONMENT

A microsimulation approach to modeling traffic conditions has the advantage of producing more organic simulations than those in which fixed drive cycles are imposed as traffic from leading vehicles. As such, VISSIM is adopted to model traffic in a realistic manner by modeling human time headways from highway data. Furthermore, considerations to isolate the traffic effects due to the optimal controller are made, so: travel times are normalized among simulations, and only flat road is considered. It should be noted that separate optimal controllers and planners can further improve fuel economy over human drivers with these effects considered [28]. In addition, simulations are run with a timestep of 100 ms [11], while MPC is discretized with a timestep of 1000 ms and run every simulation timestep.

A. Driver Model Programming

1) Wiedemann Model: VISSIM bases their driving model on the Wiedemann (WIE) model for human car-following behavior. In addition, two variations exist: WIE74, suitable for urban and arterial driving, and WIE99, suitable for highway and interstate driving [14], [29].

The model takes on 4 distinct phases: 1. free-flow, 2. approaching, 3. following, and 4. braking [30]. At steady state car-following conditions, it exhibits limit cycle behavior on the velocity-acceleration phase space, naturally modeling the acceleration oscillation humans tend to exhibit when driving.

To model these phases and transitions from each phase in the WIE model calculations, the WIE99 model has parameters \( CC_0, CC_1, CC_2, ..., CC_9 \). The physically-intuitive parameters of static following distance, time headway, and following oscillation are set by \( CC_0, CC_1, \) and \( CC_2 \), respectively, while other model parameters include: following thresholds, acceleration during following oscillation, etc. Figure 4 depicts the calculated desired following distances employed by WIE vehicles [13].

Guidelines suggest caution when changing VISSIM parameters from the default settings, which are sufficient to use with modifications only to adjusted headway parameters [13], [31]. As such, the default parameters are used in all VISSIM simulations except for desired time headway, which is replaced with stochastic distributions as found in [32]. This was done because initial testing of high-traffic scenarios showed the resulting time headways of WIE drivers was overly aggressive compared to real car-following-car data [32]. Inaccurate results in time headway are especially significant when examining traffic flow with the addition of CAVs, as further detailed in Section IV-A. Furthermore, [2] calibrate VISSIM by affecting time headway, then show that the fuel economy numbers generated by VISSIM are realistic as compared to real traffic data.

2) User-Defined Behavior: To alter driving behavior for vehicles within the network, a separate process is executed in parallel to VISSIM. To accomplish this, a Dynamically-Linked Library (DLL) is attached to VISSIM on startup of a simulation. The DLL has the advantage that its memory is abstracted from VISSIM memory, so computations from both programs can be run with a controlled exchange of data.

On each simulation step, VISSIM checks that a certain vehicle in the network should be externally controlled, and then the calls to and from the DLL are as follows: 1. Ego information such as vehicle ID, velocity, and acceleration are passed to the DLL, as well as preceding vehicle information such as velocity and gap, and 2. Ego commands from the solution of the QP, such as desired acceleration, are retrieved from the DLL and used in dynamic computation at the end of the simulation step. Similar routines are defined for the creation and destruction of a vehicle as it enters and leaves the network, respectively.

Hence, a parallel computing scheme for all vehicles in the network can be defined. Figure 5 illustrates the computing architecture of such a programmed VISSIM simulation.
B. Real-Scenario Modeling

The goal in creating a VISSIM environment is to reproduce realistic traffic conditions, so that analysis of controller impact on the fleet can then be made [10]. Additionally, for all simulation results in this study, it was verified no vehicle collisions occurred.

1) Transient Considerations: We first consider that simulations have two sources of unwanted transient effects: 1. Those due to the time period before the network is filled with vehicles, and 2. Those due to the boundary effects in the road network, where once a vehicle leaves the network, those behind it shift to a free-flow driving mode.

For simulation results discussed in this paper, we only consider simulation time after the first vehicle has left the network, and we define the control volume as the center of the network to 2 times the max look-ahead distance of vehicles on both ends of the network [11], [33].

2) Physical Location Basis: To isolate car-following effects in a realistic scenario, these simulations use the speed limit and 3.65 km length of a real South Carolina road segment between entry and exit ramps. A desired velocity distribution as recommended in [11] is used, and road grade is neglected.

3) Travel Time Management: It was observed that, due to velocity smoothing effects and dissipation of jams from the autonomous vehicles, average vehicle travel times were improved. To isolate energy saved by the vehicles due to smooth driving, the average travel time of vehicles in the network was normalized, effectively minimizing differences in kinetic action between simulations.

To this end, the desired velocity of CAVs was tuned such that the average travel times of vehicles in the fleet matched to a tolerance of ±2% of the all-WIE scenario with the same input vehicle flux. These results are illustrated in Figure 6.

To feasibly achieve this result outside of a simulation environment, more advanced approaches could be taken by including a pacing algorithm, such as the analytical high-level planners introduced in [34], [35]. An estimator could also be introduced to learn the nearby traffic volume to dynamically choose desired velocity.

4) Vehicle Capabilities: To set realistic capabilities of the powertrains of simulated vehicles, consider the nonlinear max acceleration vs. velocity curves as given by the contour regions in Figure 2. We take the max acceleration vs velocity curve from a model of a Ford Escape and then impose in VISSIM. Here, only a single powertrain is imposed in VISSIM, as passenger vehicles rarely exert their maximum powertrain capabilities.

5) Delay Considerations: To consider delay due to communication and computation of the systems, first we observe ~10 ms delay from combined optimization building and solving routines. Then, we assume ~40 ms of delay for DSRC communication algorithms, which are received 86% of the time and can be sent twice to improve reliability [50]. Then, observe the probability of at least one message to reach the designated vehicle under line-of-sight conditions as \( P(A \cup B) = P(A) + P(B) - P(A \cap B) = 0.98 \). Thus, we consider broadcast communication information to lag one simulation timestep behind.

IV. SIMULATION RESULTS

To consider a wide range of traffic conditions that can occur throughout a year or even peak to off-peak hours of a given day, discrete scenarios are run by varying the input volume per hour of vehicles, or input flux, in the network. This is done along the interval [500, 750, ..., 2000] veh/hour/lane, which is selected up to the network capacity for the WIE vehicles. For each input flux considered, CAV penetration is then varied along the interval [0, 10, ..., 100]% of the total fleet composition.

A. Effects on Traffic Flow

It is important to note that any control algorithm that influences traffic should first examine the road capacity it supports. Reductions in road capacity inhibit travel times and the ability for travellers to reach their destination, effectively lowering the efficiency of the network.

From this, an effective metric in VISSIM to examine road capacity over a discrete grid of simulations is the supported flux of vehicles. This is measured as the total number of vehicles that can be populated in simulation for a given
simulation hour. It then follows that if the supported flux of the network is lower than the input flux for a given simulation, then the road capacity has been effectively reduced. This occurs due to jams in the network, which lead to insufficient space at the vehicle source to inject vehicles, and so fewer vehicles are introduced than what is desired.

Figure 7 shows the results for the supported flux of vehicles in the network at various input flux and CAV penetrations. Observing the highest input flux case slightly over capacity of the network, the supported vehicle volume per hour is limited in the all-human case by \( \sim 2\% \). This trend extends until 30% CAV penetration, in which the supported flux in the network improves to match the input flux. Here, with the presence of CAVs in the network, the road capacity was improved.

It should be noted that this result improves on the results observed in other automated driving applications. Our earlier work in [19] chose to assume worst-case braking of the PV for safe prediction. This resulted in a significant loss in road capacity until scenarios with majority CAVs. To address traffic compactness and safety issues explicitly, we introduced the chance constraint approach (Section II-D2).

Additionally, we choose to examine the average space headway of individual drivers at 2000 veh/hour - shown in Figure 8. Notably, due to the reduced headway of CAVs with communication benefits, the CAVs are able to achieve better average headway than the WIE drivers with at least 30% penetration. Thus, a bimodal distribution in the CAVs forms due to anticipative and connected modes - until the 100% CAV case. It can be observed that the 100% CAV case creates a unimodal distribution due to increases in the average headway despite all-connected driving. This is due to the combination of the uniform desired speed of the CAVs with the penalty on acceleration in the cost function: they drive under steady conditions once populated in the network and do not attempt to catch their PV despite having safe driving space to do so. In other words, the connected vehicles operate with a commanded headway as demanded by the traffic conditions, and are not operating at the limits of the road capacity of the network.

### B. Effects on Fuel Economy

From the traffic flow of the network at all vehicle fluxes and CAV penetrations, fuel economy results for feasible road conditions can be generated.

First, consider the fleet-wide average fuel efficiency as compared to the all-WIE case at each respective input flux, as depicted in Figure 9. Interestingly, at 1250 veh/hour, the fuel trend is approximately the same as those discussed and found from our earlier work in [19], which was limited to a string of 8 vehicles, and traffic demand was simulated with a fixed drive cycle in front of the string. However, this result highlights the benefit of the microsimulation approach detailed in this paper: fuel and traffic capacity results at various traffic demands are more apparent, and more traffic demands can be imposed. At increasing vehicle fluxes, the fuel benefits become more pronounced, where up to \( \sim 28\% \) fuel efficiency can be seen at max flux for the network if all vehicles are CAVs. At low vehicle fluxes, smaller benefits of \( \sim 10\% \) fuel efficiency...
are seen with the introduction of CAVs, largely due to the sparse nature of vehicle interactions.

Then, consider the separation of fuel economies between WIE and CAV, as shown in Figure 10. Here, histograms of the fuel economies of individual vehicles are stacked. There are two general observations to be made here: 1. Fuel economy of individual CAVs at all penetrations is typically much better than that of the WIE vehicles, and 2. Benefits to the fuel economy of WIE vehicles are observed with increasing numbers of CAVs. From this, the WIE vehicles receive secondary benefits to drive with higher fuel efficiency with the presence of CAVs in the fleet. Examining the WIE fuel economies in Figure 10 at the highest traffic demand and 70% CAV penetration, the WIE drivers receive up to 10% average improvement in fuel economy.

Table II summarizes fuel economy improvements of the CAVs over WIE drivers at various traffic demands, like those depicted in Figure 10. This result was consistent across all penetrations of CAVs.

### C. Effects on Driving Behavior

Clearly, fuel benefits observed are significant. To further study and explain some phenomena as to why they occurred, we can first examine traffic smoothing effects through dissipation of shockwaves.

Figure 11 depicts a series of cell density plots at 2000 veh/hour. Here, the density of vehicles measured within a discrete set of cells of the road network are plotted as colored regions over position and time. At 0% CAV penetration, an observed behavior are shockwaves in the network, shown as high density regions propagating backwards through the

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**Fig. 9.** Percentage improvement in the average fleet fuel economy in the network as compared to the all-WIE scenario. Color visualizes height of each bar.

**Fig. 10.** Histograms of fuel economy of vehicles in the network at various CAV penetrations and 2000 veh/hour.
network over time. Though, stabilizing effects are observed with the introduction of CAVs. Here, traffic is smoothed and the shockwaves are dissipated - as seen with 30% CAVs. Further, penetrations of 70% and 100% CAVs depict uniform platoons of vehicles moving forward through the network over time.

The vehicle control proposed here depicts secondary benefits of smoothing traffic. From this, reducing shockwave effects in the network created less stop-and-go behavior, and so less acceleration is experienced by vehicles. Therefore, fuel consumption is reduced for involved vehicles.

In further support of this argument, we can choose to examine the velocity behavior of vehicles in the network. Figure 12 depicts a scatter plot of all measured velocities, as well as the average velocity of all vehicles at each instance in time, for 2000 veh/hour. To again observe traffic smoothing, as CAV penetration increases, the velocities become more tightly packed to the average velocity profile. In addition, in this particular case, full stops that occurred for some vehicles no longer occur with increasing CAV penetration. With reductions in acceleration of vehicles and the variance in velocity, the fuel economies improved.

V. CONCLUSION AND FUTURE WORK

This paper studied the energy and traffic impact of a connected and anticipative car-following controller using PTV VISSIM. In doing so, realistic VISSIM simulations were set up by utilizing time headways from real traffic data in a high-density highway scenario and imposing realistic acceleration capabilities of vehicles, and delays in the control algorithm due to computation and communication were considered.

The proposed MPC algorithm utilized a cost function that tracks desired headway and minimizes acceleration, and constraints are handled to model passenger vehicle capabilities, as well as enforce safety considerations through the use of chance constraints. A trade-off between traffic compactness and safety was balanced through the use of said chance constraints, which showed that traffic compactness was not compromised through the introduction of automated vehicles; with market penetrations of at least 30% automated vehicles equipped with connectivity, road capacity was significantly improved. Further, a prediction model of constant acceleration is assumed for the preceding vehicle when anticipating trajectories in human vehicles.

It was found that the controller was effective in producing fuel-efficient results. We found that our vehicles performed at a 10% fuel efficiency over human drivers at low volume, and performed at a 20% fuel efficiency over human drivers at high volume - while improving in capacity of the road over the all-human driver scenario. Secondary effects were seen in that traffic was smoothed to dissipate shockwaves, and so human driver fuel economy was additionally improved. Overall, up to 30% fuel benefits in the entire fleet were observed in all-automated scenarios.

This paper highlights a framework that can be used to evaluate impact of autonomous vehicles, where method depicted here can be applied to more sophisticated scenarios deserving
of separate papers. In general, multi-lane controllers can be explored, whereas high fidelity VISSIM simulations of arterial and highway environments can be studied. Finally, nonlinear algorithms to further optimize fuel economy can be introduced.

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