

Driver behavior classification for stop-n-go traffic via machine learning based driver model

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ABSTRACT

Modeling driver behavior in car-following scenarios is crucial for traffic simulation and the development of intelligent transportation systems. In dense urban environments, particularly in stop-and-go traffic, capturing the nuances of individual driving styles is essential for realistic predictions. This paper addresses the limitations of the well-established Optimal Velocity Model (OVM) that fails to identify the driver's behavior and yields physically unrealistic parameters. A new driver model is developed via collecting detailed vehicle motion data from stop-and-go urban traffic using image processing. We introduce a speed policy-based driver model via the fitting of a universal differential equation to the data. Then, the identified policy is approximated by a simple, piecewise smooth function with a small number of physically interpretable parameters. These parameters and the driver reaction times are identified from the traffic data with excellent consistency. Using the principal component analysis, driving behaviors are characterized. Finally, numerical simulations of vehicle strings confirm that the proposed model is more applicable and robust for simulating stop-and-go traffic than the traditional OVM.

KEYWORDS

Driver models; Data-driven model identification; Driver behavior identification

1. Introduction

Nowadays, public road transportation systems have become an integral part of everyday life. People living in urban and suburban areas need road transportation daily; therefore, its efficiency and safety affect the basic standard of living. The categorization of the drivers of the participating vehicles is essential. In intelligent transportation systems, detecting undesirable behavior (aggressiveness, inattention, drowsiness, or driving under the influence) is required to better predict the traffic flow and/or warn adjacent (human-driven or autonomous) vehicles. This challenge is more crucial in today's mixed-traffic environment, where human-driven vehicles interact with vehicles equipped with advanced driver-assistance systems (ADAS) and different levels of automation. (Gouribhatla and Pulugurtha (2022); Negash and Yang (2023))

The significant role of driver behavior in road accidents is indisputable. Based on studies (Maycock, 1995) and (Horne and Reynier, 1995), 10-20% of road accidents are caused by drowsiness, which is especially critical on monotonous roads, typically on highways. In heavy urban traffic environments, driver distraction is the main contributing factor. According to (David L Strayer, 2006), distraction due to cell phone usage has as profound an impact as driving under the influence of alcohol. Since then, the wide availability of smartphones and modern in-vehicle systems has created a significant cognitive load for drivers, see Almutalib et al. (2022). Namely, driver distraction may be rooted in many factors. The main way to characterize this is through the

Perception-Brake Reaction Time (PRT), which is decomposed by Green (2000) into mental processing time, movement time, and device response times. The perception is influenced by the sensation, perception, and response selection processes. Olson (2006) similarly presents the PRT as a combination of detection, identification, decision, and response. Both studies agree that identifying a single PRT value is impossible due to environmental, social, cultural, and physiological factors. Thus, the complex nature of the PRT may indicate the driver’s state but is also influenced by many environmental factors.

Based on the Fatality Analysis Reporting System (FARS) data (AAA Foundation, 2009), 55.7% of accidents in the United States between 2003 and 2007 have had an aggressive trait as a contributing factor in the accident. By far, the most significant factor was speeding in these cases. Law enforcement has tools to enforce the speed limit. These tools can potentially decrease accidents on road sections that are sensitive to accidents due to excessive speed. Based on previous studies, fixed and mobile speed cameras or average speed monitoring could decrease accident rates; see, for example, Andy Jones (2008); Borsati et al. (2019); Hess (2004). However, law enforcement lacks reliable tools to identify drivers who exhibit behavioral patterns that endanger traffic. Unlike speeding, aggressiveness, inattention, or driving under the influence are difficult to quantify. This task is further complicated by many internal and external factors. Sociodemographic attributes like age, gender, or cultural norms influence behavioral group distinctions. Shinar et al. (2001) shows the issue’s complexity and that age and experience are reliable indicators of accident involvement. The study finds that male drivers reported fewer errors and more violations than females. These findings are also supported by Özkan et al. (2006). In Nordfjærn et al. (2011), wide cross-cultural attitudes are shown towards the risks in traffic. McCarty and Kim (2024) also presents the significant influence of driver demographics on accident rates. Due to this heterogeneous and complex nature, several studies have taken a data-driven approach rather than first-principle-based driver behavior modeling.

Machine learning techniques such as support vector machines, hidden Markov models, and artificial neural networks are used by Aoude et al. (2012); Colombaroni and Fusco (2014); Ying et al. (2021); Yuksel and Atmaca (2021). Murphey et al. (2009) and Higgs and Abbas (2015) analyze the direct measurement of kinematic information to identify different driver behaviors. In this paper, the identification of driver behavior is approached through fitting microscopic traffic models on individual drivers in a heavy urban traffic environment. The main goal of this study is to find a driver model with physically interpretable parameters, which forms the basis of driver behavior identification.

Some studies calibrate driver models based on isolated measurements. In Brockfeld et al. (2005) and Ranjitkar et al. (2004), GPS-equipped vehicle platoons are investigated on test tracks. In Punzo and Simonelli (2005), a vehicle platoon including four test drivers is used to collect trajectory data in real traffic.

In Kesting and Treiber (2008), headway data is acquired in traffic by a single vehicle equipped with a radar sensor. The work of Schorr et al. (2017) utilizes the calibration of a car-following model and conducts a parameter analysis. Their work is based on known GPS recordings of 18 drivers on road segments. Other studies (Kurtc, 2020) calibrate driver models based on publicly available datasets such as the NGSIM (U.S. Department of Transportation Federal Highway Administration, 2016) or HighD (Krajewski et al., 2018) datasets. However, the NGSIM dataset has a sampling frequency of 10 Hz, which resolution is insufficient for our goals. Also, the dataset requires pre-processing and filtering in order to extract derivatives of the data. Another issue is the outdated vehicle fleet and social environment. Since 2005, electric vehicles, hybrids, and vehicles with Advanced Driver-Assistance Systems (ADAS) like Adaptive Cruise Control (ACC) have had a significant presence. Furthermore, driver behavior has evolved, most notably with smartphones causing different types of distraction. The HighD dataset is much more up-to-date, but the highway-centric focus of the data collection does not align with our aims to investigate heavy urban traffic environments.

Thus, stop-n-go traffic data are collected through image processing described in Section 2. In Section 3, we incorporate the reaction time in the Optimal Velocity Model (OVM) and distinguish the time delays of the states with respect to their sources. The fitting of this model is carried



Figure 1. One frame from a recorded video made in Budapest, Hungary. The red rectangle highlights the area of interest.

out in Sections 4 and 5, where we highlight the inconsistency of the identified driver model parameters. Then, in Section 6, based on the findings in Section 5, we introduce a speed policy-based driver model in two stages. First, a universal differential equation is trained to capture and understand the structure of the speed policy function. Then, it is substituted with a simplified and interpretable piecewise linear velocity function with the desired structure. Simulations are used in Section 7 to verify the model’s applicability to describe traffic flow in an urban environment and evaluate the model’s performance compared to the OVM. In Section 8, we use Principal Component Analysis and Gaussian Mixture Models to classify the drivers into different behavior groups. Our results are concluded in Section 9.

2. Data collection

To analyze drivers’ behaviors in urban traffic scenarios, traffic data was collected via image processing of videos captured from tall buildings; see the example frame in Fig. 1. The video recordings are focused on a straight road section with heavy urban traffic, where drivers must stop and start repeatedly on a straight road. In the video recordings, the traffic flow of multiple lanes is captured with Canon EOS 7D in 1920×1080 resolution with 30 FPS, see Fig. 1. The videos were evaluated using a custom script developed for this purpose. The first step of the algorithm is the selection of the lane of interest (red rectangle in Fig. 1). Then, the background is separated from the vehicles by averaging the frames, and the individual vehicles are identified. Then, these vehicles are tracked in time, with their positions and velocities stored. The algorithm also corrects for the perspective distortion and provides processed data after filtering. The algorithm relies on classical image processing methods, i.e., it does not use machine learning-based vehicle recognition. Therefore, the data collection is robust, given that the weather conditions are favorable Yoneda et al. (2019). The flowchart of the algorithm is shown in Fig. 2.

The algorithm also collects the length of the vehicles in order to calculate the headways. In Fig. 3, the positional data is shown for an example stop-n-go scenario that will serve as a test case in the following sections. The figure shows multiple phenomena that are worth observing. The first is the stopping and starting waves propagating backward in the traffic flow with a speed of approximately 3-4 m/s. Furthermore, the drivers do not behave uniformly: each individual chooses a significantly different headway (both when following and stopping) for this urban scenario. We recorded four hours of footage at two locations in Budapest, Hungary.

The main limitation of our image processing is the strict weather requirements. The algorithm works when there is a scattered light (cloudy day) condition. In strong directional sunlight, the shadows of vehicles will interfere with adjacent vehicles. Similarly, the reflections on the road surface have the same effect in rainy conditions. Another limitation is the small area of interest since the camera’s view angle limits the observed area. It is also important to note that the collected data is limited to one social environment and several locations. Considering the limitations, we manually chose scenarios where at least one complete stopping and starting was captured in the recorded section. Overall, we deal with 47 trajectories measured with a 30 Hz

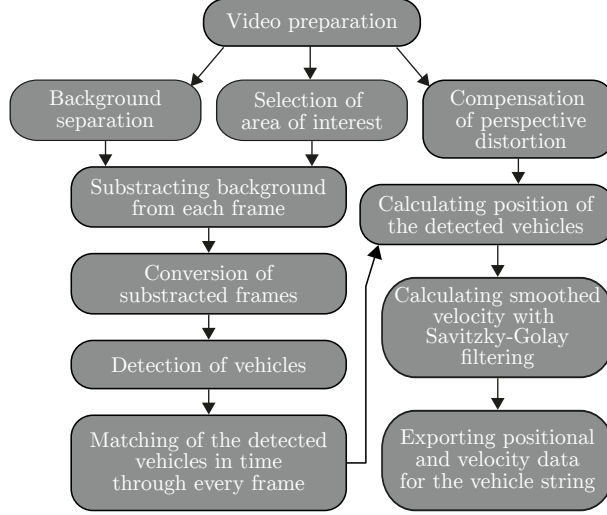


Figure 2. Flowchart of the vehicle detection algorithm.

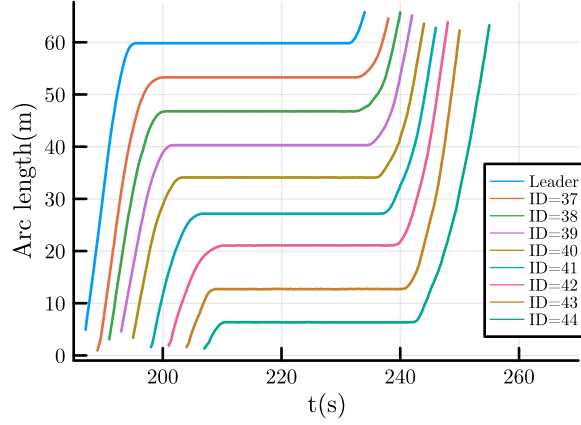


Figure 3. Test example: vehicle positions along the lane (arc length coordinate) in a stop-n-go scenario.

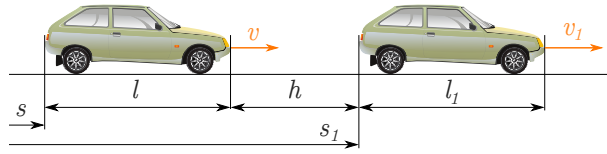


Figure 4. Car-following scenario with the leader and the follower vehicles.

sampling frequency across 8 vehicle platoons. The development of a more reliable data collection method is out of the scope of our study, although drone measurements, machine learning based image processing, diversified measurements, etc. can overcome the limitations.

3. Optimal Velocity Model with reaction time

To investigate the car-following behavior of drivers, we choose the Optimal Velocity Model (OVM) as our baseline model. OVM is widely used (see Bando et al. (1995), Bando et al. (1998), Orosz et al. (2004), Orosz et al. (2010)) when traffic flow is modeled on the microscopic level, i.e., when the interactions between individual vehicles are considered. Our choice is mainly motivated by the model's physically interpretable parametrization, which is beneficial for analyzing the

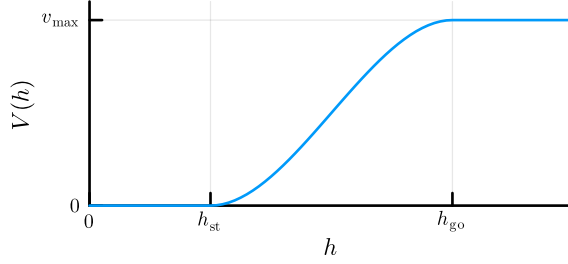


Figure 5. Graph of the cubic range policy function (2).

drivers. While other widely used models exist, such as the first-order Gipps' model (Gipps (1981)), Newell's model (Newell (2002)), or the second-order Intelligent Driver Model (IDM) (Treiber et al. (2000)), the OVM structure allows for a clear separation of driver intent into headway maintenance and velocity matching. As discussed by Orosz and Molnar (2025), the IDM can be considered an alternative parametrization regarding the linear stability analysis of the car-following problem, namely, its key parameters playing similar roles to those in the OVM.

Our work primarily relies on the formation of stop-n-go waves resulting from bistability in the nonlinear system. As established in the literature, a time-delayed nonlinear model like the OVM or the IDM is sufficient to reproduce this phenomenon without needing to invoke more complex model structures (see. Molnar and Orosz (2024)).

The model used in this work is a variant of the OVM: the Full Velocity Difference Model (FVDM) (Jiang et al., 2001). The FVDM incorporates a velocity headway, which is the difference between the velocities of the controlled and the lead vehicles, analogously to the headway. Figure 4 shows platoon vehicles comprised of two members: the arc length s gives the position of the following vehicle along its lane, from which the headway $h = s_1 - s - l$ can be calculated, where s_1 denotes the position of the lead vehicle and l denotes the length of the vehicle. In the simplest case, i.e., when road grade, air drag, rolling resistance, and drivetrain dynamics are neglected, the evolution of the headway h and the speed v of the following vehicle can be described by

$$\begin{aligned}\dot{h}(t) &= v_1(t) - v(t), \\ \dot{v}(t) &= \alpha(V(h(t)) - v(t)) + \beta\dot{h}(t),\end{aligned}\tag{1}$$

where the dot refers to differentiation with respect to time t , v_1 is the velocity of the lead vehicle, α and β are feedback gains, which are positive in general, and $V(h)$ denotes the range policy function (illustrated in Fig. 5). In this study, the cubic range policy function (Ersal et al., 2020) is used, which has the form of

$$V(h) = \begin{cases} 0, & \text{for } h \leq h_{\text{st}} \\ v_{\text{max}} \frac{(3h_{\text{go}} - h_{\text{st}} - 2h)(h - h_{\text{st}})^2}{(h_{\text{go}} - h_{\text{st}})^3}, & \text{for } h_{\text{st}} < h \leq h_{\text{go}}, \\ v_{\text{max}}, & \text{for } h_{\text{go}} < h, \end{cases}\tag{2}$$

where h_{st} refers to the minimal headway distance below which the driver stops, while above h_{go} the driver drives with the maximal speed v_{max} . These parameters, together with the feedback gains α and β , determine the stability (Hajdu et al., 2020) of the traffic flow.

As shown in Sykora et al. (2020), the plant and string stability of the car-following problem is also strongly influenced by the time delay of the system. In car-following situations, the time delay originates from the reaction time of the drivers. Namely, drivers process the information, decide about the required action, and act. Then, the engine delivers the required torque, and only then does the vehicle accelerate. All of this requires time, which is captured by this time

delay. Although the stability analysis is far beyond the scope of our paper and is only relevant in different traffic scenarios, to characterize the drivers' behavior, the reaction time has to be identified together with the gains α and β . Rewriting (1) with the consideration of the time delays (based on Ge and Orosz (2016)) leads to:

$$\begin{aligned}\dot{s}(t) &= v(t), \\ \dot{v}(t) &= \alpha(V(s_1(t - \tau_1) - s(t - \tau) - l) - v(t - \tau)) \\ &\quad + \beta(v_1(t - \tau_1) - v(t - \tau)).\end{aligned}\tag{3}$$

The model (3) has two delays based on the source of the measured state. The delay τ corresponds to the driver perceiving its position and velocity, while the time delay τ_1 corresponds to perceiving the leader vehicle's position and velocity. The justification for this decision is that drivers have more accurate and reliable information about their states and can even predict their own behavior as they know their intentions. On the other hand, they have to estimate the states of the leader vehicle and have less information about the other driver's intentions. Therefore, one can safely assume that $\tau < \tau_1$, and this assumption is confirmed in later sections when these models are fitted on the data collected from the traffic. We note, as it was mentioned in Section 1, the Perception-Brake Reaction Time is a result of a very complex process, which is simplified by these time delay values. However, we found that separating the time delays is an efficient compromise to gain valuable insight into the underlying process.

At this point of our study, it has to be noted that identifying time delays via measurement data is a challenging task since gradient-based optimization still has open questions for delay systems. Although some studies already have promising results in the field (see Ji and Orosz (2024)), here, we substitute the effect of time delays within the model by means of additional first-order differential equations that are often used to consider time lag in different models. Taylor expansions were used to approximate the delayed terms in Insperger (2015); Mastinu et al. (2023), which provides a finite state space approximation of the original delay system. The first-degree Taylor expansion of the delayed term with respect to the delay simplifies exactly to the time lag representation for the car-following problem with a single time delay in Orosz and Molnar (2025). This approach captured an essential part of the car-following dynamics and gave basic stability criteria for the vehicle string. Assuming that a similar approach (as in Xu et al. (2021)) may be suitable for a system with multiple delays, we approximate $x(t - \tau)$ with $\bar{x}(t)$ via

$$\dot{\bar{x}}(t) = \frac{1}{T} (x(t) - \bar{x}(t)),\tag{4}$$

where the settling time T determines how directly the signal $\bar{x}(t)$ is able to track the variation of $x(t)$. In this sense, applying time lag instead of time delay can be imagined as a rudimentary approximation ($T \propto \tau$) of the delay system. This implementation also acts as a filtering on signal $x(t)$. This could be beneficial in modeling as humans tend to react to short-term trends instead of rapid changes.

We note that this substitution is a significant methodological simplification, transforming the delay differential equation (DDE) of model (3) into a system of ordinary differential equations (ODEs). Mathematically, this reduces the infinite-dimensional state space of the DDE to a finite-dimensional one. While this makes the model computationally efficient for standard gradient-based optimization, there is the potential risk of oversimplifying the driver's true response behavior. Later, we check the validity of this simplification by examining whether this approach yields physically plausible and consistent parameters. As will be demonstrated, this approximation proves to be a practical and effective trade-off for modeling the observed traffic phenomena.

Hence, the delayed OVM in (3) can be rephrased by means of (4) as

$$\begin{aligned}
\dot{s} &= v, \\
\dot{v} &= \alpha(V(\bar{s}_1 - \bar{s} - l) - \bar{v}) + \beta(\bar{v}_1 - \bar{v}), \\
\dot{\bar{s}} &= (s - \bar{s})/T, \\
\dot{\bar{v}} &= (v - \bar{v})/T, \\
\dot{\bar{s}}_1 &= (s_1 - \bar{s}_1)/T_1, \\
\dot{\bar{v}}_1 &= (v_1 - \bar{v}_1)/T_1,
\end{aligned} \tag{5}$$

where we dropped the notation (t) of the time dependence to shorten the formulas and improve readability. The input of this system is the leader's path coordinate s_1 and speed $v_1 = \dot{s}_1$. The time lags T and T_1 characterize the reaction times related to own and leader's states, respectively. Through gradient-based optimization, the parameters (h_{st} , h_{go} and v_{max}) of the range policy function, the gains (α and β) of the OVM model, and the time lags (T and T_1) can be fitted simultaneously.

4. Fitting and optimization

The following sections describe an optimization algorithm for identifying system parameters of different car-following models. The optimization is carried out with a gradient descent-based algorithm, starting from an arbitrarily chosen initial parameter set. Then, the parameters are substituted into the model, which is numerically integrated, with the simulated states recorded at the measurement times. The numerical integration and gradient-descent-based optimization is done in the Julia SciML ecosystem, with the `DiffEqFlux.jl` package. Next, the measured traffic data and the model-based numerically simulated solution are compared via the cost function

$$C(\mathbf{p}) = \frac{1}{n} \sum_{i=0}^n \sigma \left(s_i^{\text{ref}} - s_i^{\text{sol}}(\mathbf{p}) \right)^2 + \vartheta \left(v_i^{\text{ref}} - v_i^{\text{sol}}(\mathbf{p}) \right)^2, \tag{6}$$

where s_i^{ref} refers to the measured path coordinate of the vehicle at the i th measurement time, where n refers to the last data point of the measurement series. Similarly, s_i^{sol} denotes the simulated solution at the same time instant. The current solution of the investigated system is formulated with the actual parameter $\mathbf{p}$, which is the subject of the optimization. In the second term of the cost function, v_i^{ref} and v_i^{sol} refer to measured and simulated speeds, respectively. The coefficients σ and ϑ are the hyperparameters of the optimization, helping to find the balance between optimizing for the positional and speed data. In this study, these values are manually set to $\sigma = 1.0 \text{ m}^{-2}$ and $\vartheta = 0.2 \text{ s}^2\text{m}^{-2}$.

To find these values, a preliminary sensitivity analysis was conducted on the test example presented in Fig. 3. As evaluation metrics we use the Mean Squared Error for the positional ($\text{MSE}_s = \frac{1}{n} \sum_{i=0}^n (s_i^{\text{ref}} - s_i^{\text{sol}}(\mathbf{p}))^2$) and speed ($\text{MSE}_v = \frac{1}{n} \sum_{i=0}^n (v_i^{\text{ref}} - v_i^{\text{sol}}(\mathbf{p}))^2$) data separately. Parameter $\sigma = 1.0 \text{ m}^{-2}$ is fixed while ϑ is varied from 0 to 1. The evolution of the Mean Squared Errors are shown in Fig. 6. If the speed error term is omitted ($\vartheta = 0$), the optimizer produces accurate positional trajectories but with poorly fitted, often noisy or oscillating, speed profiles. All these results in a large MSE_v value. Conversely, heavily weighting the speed term could lead to drift in the positional data. The chosen values of the hyperparameters are a robust trade-off that results in a good qualitative and quantitative fit for both position and speed for our dataset. The parameter setup $\sigma = 1.0 \text{ m}^{-2}$ and $\vartheta = 0.2 \text{ s}^2\text{m}^{-2}$ produces the lowest speed error, and apart from $\vartheta = 0$, this is the best fit for the positional data. Note that the optimal ratio of the weights may be data-dependent, and for different traffic scenarios or data sources, a recalibration might be necessary to ensure reliable model identification.

We take the gradient as $\text{grad} C(\mathbf{p}) = \frac{\partial C(\mathbf{p})}{\partial \mathbf{p}}$ with automatic differentiation and modifying

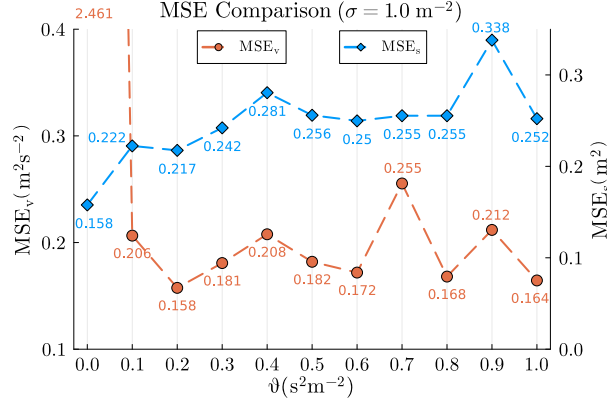


Figure 6. Mean Squared Error for the positional and speed data for different weighting in (6).

the values of $\mathbf{p}$ according to the gradient and the step size to minimize the cost function. The optimization happens in two stages motivated by Rackauckas et al. (2020). First, the ADAM optimizer (Kingma and Ba, 2014) is used with a learning rate $\eta = 0.001$ until 80 iterations. In the second stage of the optimization, $C(\mathbf{p})$ is minimized via the L-BFGS (Liu and Nocedal, 1989) method, with an initial stepnorm of 0.01, until 80 iterations.

5. Application of the OVM in urban traffic

In this section, we identify the parameters of the OVM model using the measurement data of Section 2 and the optimization algorithm of Section 4.

5.1. Fitting the OVM with time delays

As mentioned, gradient-based optimization is challenging for the driver's time delay. However, it is possible to use gradient-based optimization for other parameters while we set different but fixed delay values in the model. Namely, we iterate through a set of time delays, fitting the parameters of the equations (3) for each iteration, and then choose the result that produces the minimal $C(\mathbf{p})$. First, the time delays are set equal, i.e., $\tau_1 = \tau$, which reduces the optimization to the case when the delays are equal, and then the set of potential time delays $\tau \in \{0.1, 0.2, \dots, 2.0\}$ s is defined. For each fixed delay value, the parameters α , β , h_{st} , h_{go} and v_{max} are fitted with the above described gradient-based optimizers, where the necessary gradients are obtained via automatic differentiation. In each case, the initial system parameters were $\alpha = 1 \text{ s}^{-1}$, $\beta = 1 \text{ s}^{-1}$, $h_{st} = 4 \text{ m}$, $h_{go} = 35 \text{ m}$ and $v_{max} = 50 \text{ km/h}$.

The fitting is done for each vehicle trajectory. The results of the fittings are shown in Tab. 1 for the stop-n-go scenario of Fig. 3, where along with the identified parameters, the mean squared errors (MSE) produced by cost function (6) are also provided. In Fig. 7, position and speed are shown for the best (driver ID=37) and worst (driver ID=44) fittings. The leader data (input) of each vehicle is plotted by blue curves, and the measured time signals of the follower by orange. The fitted time signals with the optimal parameters are shown in green. To highlight the importance of time delay, simulated signals with different (non-optimal) time delays are also presented in purple and brown. As observed, time delays have a relevant effect on how the simulations fit the reference data. Significant discrepancies occur in the speed signals for large (but realistic) time delay values.

Nevertheless, the model fits well in the given time window with the optimized parameters, even for the highest MSE value. If the model can describe the system's behavior well, it is expected to have a physically interpretable distribution of the parameters. Figures 8 and 9 show the histograms of the parameters obtained by fitting to each measured trajectory. These figures

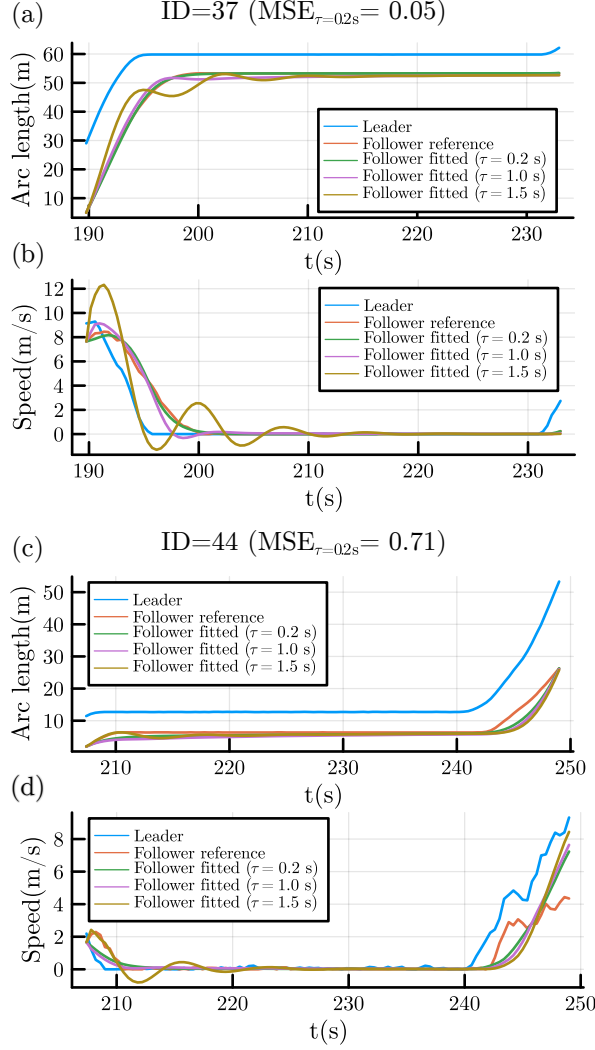


Figure 7. OVM fitted to the test data of Fig. 3. Reference and simulated positional and speed signals of best (ID=37) and worst (ID=44) fitting drivers.

ID	τ (s)	α (1/s)	β (1/s)	h_{st} (m)	h_{go} (m)	v_{max} (km/h)	MSE
-	-	-	-	-	-	-	-
37	0.2	0.11	0.52	6.4	35.5	48.6	0.05
38	0.1	2.78	0.00	6.0	32.2	52.2	0.34
39	0.1	0.57	0.58	6.0	31.9	50.5	0.28
40	0.1	1.20	0.40	5.7	33.9	50.7	0.19
41	0.2	0.33	4.38	6.7	13.1	52.4	0.14
42	0.1	1.08	1.01	5.4	35.5	49.4	0.27
43	0.1	0.50	0.11	8.0	35.1	49.8	0.66
44	0.1	0.16	0.61	5.2	35.8	48.6	0.71

Table 1. Time delayed OVM parameter values obtained for the test data of Fig. 3 through delay iteration.

highlight whether the OVM can consistently and realistically describe the drivers' behavior in urban traffic.

In Fig. 8(a), the distribution of α is close to zero for most cases, while there are many instances where the value is negative, which is physically impossible. This is also true for β in panel (b), even though its distribution is more realistic than the distribution of α , but negative values still appear. In most cases, the identified time delays in panel (c) are in the range of 0.1 – 0.15 s, which

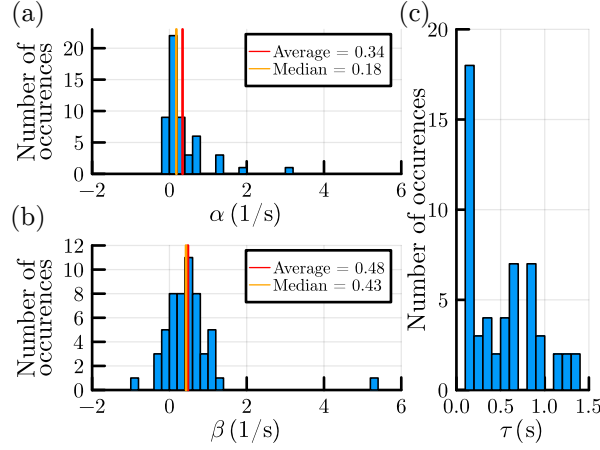


Figure 8. Histograms of the parameters α , β and τ after fitting (3) to the measurement data.

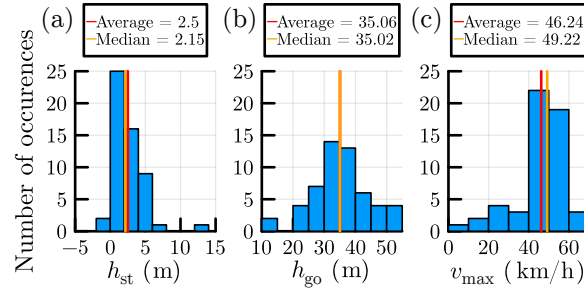


Figure 9. Histogram of the range policy function parameters for (3) fitted for the measurement data.

ID	T	T_1	α	β	h_{st}	h_{go}	v_{max}	MSE
-	(s)	(s)	(1/s)	(1/s)	(m)	(m)	(km/h)	-
37	0.31	0.98	-0.03	0.62	7.0	35.0	50.0	0.04
38	0.33	0.16	0.05	0.97	5.0	34.4	50.3	0.15
39	0.46	0.24	0.84	0.16	5.9	34.5	50.3	0.33
40	0.39	0.23	0.92	0.15	5.5	34.4	50.3	0.28
41	0.16	0.12	0.03	0.55	5.7	32.9	50.8	0.28
42	0.33	0.45	1.35	0.47	5.6	35.1	50.1	0.45
43	1.18	1.06	0.07	0.78	8.7	34.8	50.2	0.19
44	0.83	2.50	0.43	1.39	7.2	34.7	50.3	0.52

Table 2. Obtained parameter values for OVM with first order dynamic system based time lag.

is below the average human reaction time that is cc. 0.2 s even for simple control tasks (Insperger and Milton, 2021). Moreover, the time delay in our system also accounts for the actuation delay due to the vehicle's dynamics; hence, the identified time delay values are unrealistic.

5.2. Fitting the OVM with time lags

This section considers the model (5), where the delayed signals in the model are substituted with the signals filtered and shifted by (4). This way, the automatic differentiation can be applied to $C(\mathbf{p})$ for each parameter of (5). This eliminates the need to iteratively re-fit the parameters for each delay value τ ; therefore, all system parameters can be fitted simultaneously, significantly speeding up the fitting process.

The fitted parameters are given in Tab. 2 for our test data shown in Fig. 3. We also show

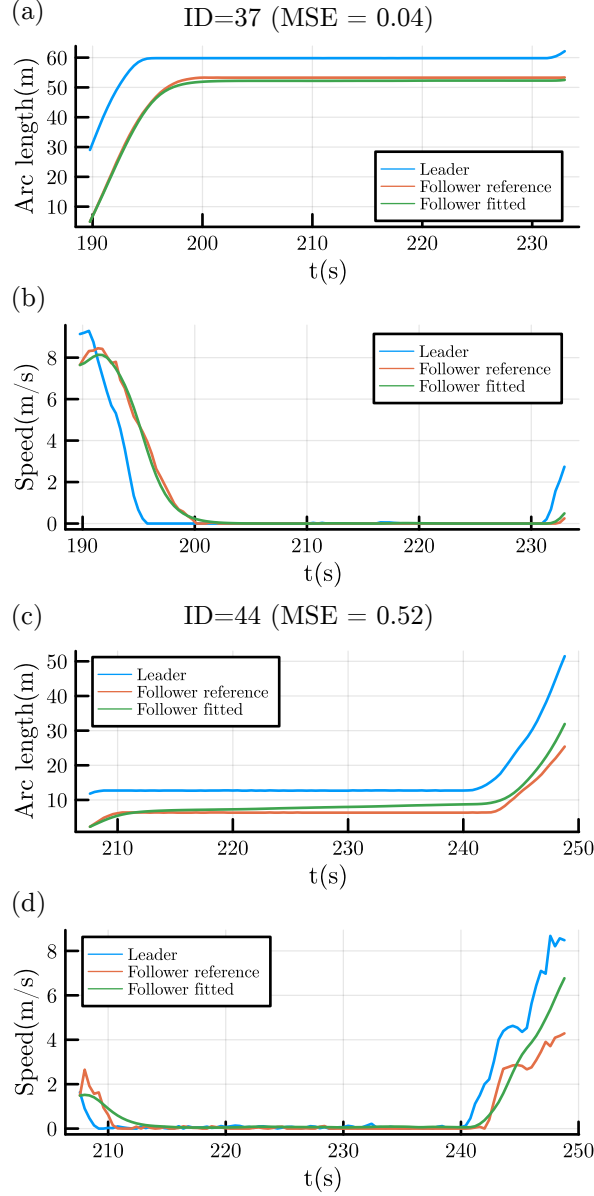


Figure 10. Solutions of (5) for the best (ID=37) and worst (ID=44) fitting drivers of the test example shown in Fig. 3.

the fitted trajectories in Fig. 10 for the driver models producing the best (ID=37) and worst (ID=44) fitting results in regards to MSE. Similarly to the delay iteration approach in Fig. 7, both position and speed signals agree with the measured data.

Figure 11 shows the histogram of parameters α , β , T , and T_1 fitted for all measurements, along with their average and median values. The histograms for the parameters of the range policy function are presented in Fig. 12.

Figure 11(a) shows that the parameter α is distributed around an almost zero mean or median, with almost half of the samples being negative. Meanwhile, the parameter β in panel (b) has one order of magnitude larger values, with almost all samples being positive. This suggests that the drivers are trying to match the velocity of the leading vehicle rather than keeping an optimal distance for a given velocity. This confirms the results of the previous subsection, but here, the distribution supports our observation more clearly.

Figures 12(c)-(d) show that the average and median of the time lag T_1 are larger than those of T . This confirms that the drivers consider their vehicle states more directly than the states of the lead vehicle. Based on Fig. 12, the parameters h_{go} and v_{max} of the range policy function

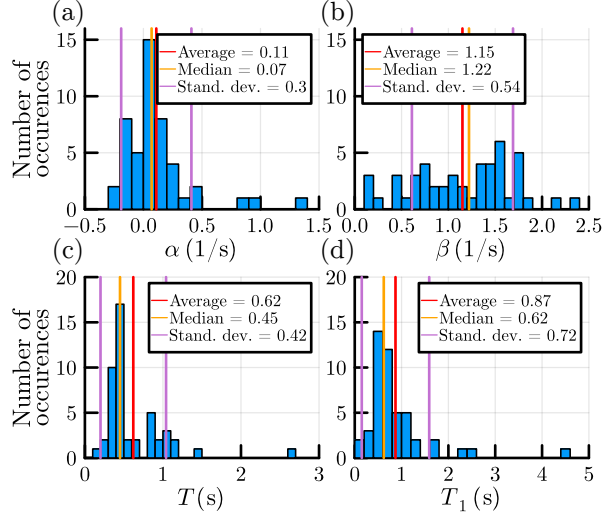


Figure 11. Histogram of the parameters α , β , T and T_1 on histograms in case of fitting (5) on the measurement data.

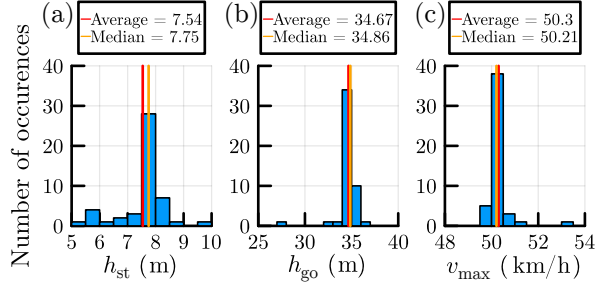


Figure 12. Histogram of the cubic range policy function in case of fitting (5) on the measurement data.

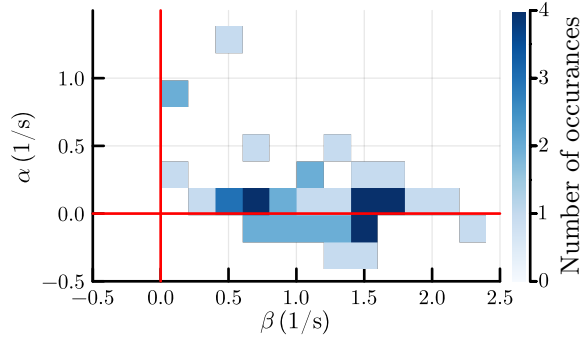


Figure 13. Density plot of the gains α and β of the OVM.

are similar to Fig. 9. However, it is important to note that due to the α values being small, the squared error $C(\mathbf{p})$ is not sensitive to the parameters of the velocity policy function V ; therefore, the results for h_{st} , h_{go} and v_{max} are unreliable.

To highlight that β dominates over α in our measurement data, the joint frequency histogram of α and β is shown in Fig. 13. Except for a few outliers, most values are around $\alpha = 0 \text{ s}^{-1}$ while fitted β values significantly differ from 0. This suggests that in the stop-n-go scenario, drivers match their speed to the vehicles in front of them. However, setting $\alpha = 0$, eliminating the term corresponding to the headway, removes all the limitations with respect to the maximal acceleration and deceleration that characterize the vehicle performance and driver behavior. Therefore, in the

following sections, we construct a speed policy-based driver model that better describes driver behavior in heavy urban traffic.

It is important to contextualize our results with previous studies. Many studies mentioned in the introduction have successfully applied the OVM to investigate different traffic scenarios. Those works often focus on characterizing the average behavior of drivers over much longer time windows. In such contexts, the OVM is very effective at capturing the long-term dynamics of the traffic. In contrast, our study addresses a different problem: We want to identify individual driver behavior by having information about the trajectories captured by a roadside camera in heavy urban traffic within a short time window. Our data is characterized by the rapid accelerations and decelerations of one stop-n-go maneuver of each driver. When forced to fit these highly dynamic and quick events, the OVM’s structure struggles to reconcile the driver behavior with a single, consistent set of physically interpretable parameters, leading to the unrealistic reaction times and inconsistent gains we identified. Therefore, our critique is not a general refutation of the OVM’s usability but a specific assessment of its limitations for the real-time behavior classification task, which is the aim of our research.

6. Data-driven driver model construction for heavy urban traffic

When first principle-based mathematical models of dynamic systems show disagreement with practical observations, the concept of scientific machine learning can be used to explore the unmodeled parts of the real system. Therefore, this section identifies the drivers’ urban traffic control strategy using data-driven methods.

6.1. Universal differential equations

Universal differential equations (UDE) are created by including parametric universal approximators (such as neural networks) within the rate function of the differential equation to learn the behavior of complex systems. In the general form, universal differential equations can be expressed as

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, t) + \mathbf{U}(\mathbf{x}, t), \quad (7)$$

where $\mathbf{x}$ is the vector of the state variables, $\mathbf{f}(\mathbf{x}, t)$ is the known part of the system, and $\mathbf{U}(\mathbf{x}, t)$ is the universal approximator that is introduced in order to learn the unknown part of the system. It is important to note that having the known part $\mathbf{f}$ in the UDEs is unnecessary. However, in our case, the goal is to encode all our prior knowledge about the system and only replace the unknown parts, i.e., the driver’s control strategy, with a universal approximator. By using (7) and automatic differentiation, we can fit the phase portrait of the system, meaning that the trained system will be able to handle different initial conditions within the trained phase space and extrapolate over the trained time domain.

6.2. Identification of driver dynamics by means of universal differential equations

Universal differential equations are used to explore the driver’s dynamics in urban traffic. To do this, we rely on the time lag-based system description, as shown before. This way, the same gradient descent-based optimization can be used but for an extended parameter set. Based on the experiences gathered in Section 5, the drivers in heavy urban traffic try to drive with a speed-matching strategy instead of utilizing the range policy function. In order to investigate this behavior in more detail, let us introduce the speed policy function $W_{NN}(\Delta v)$ that is going to be

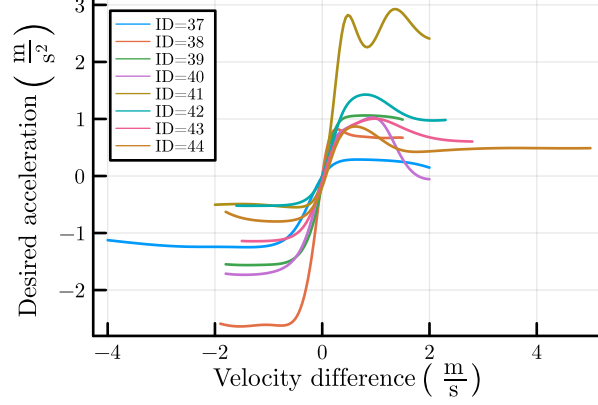


Figure 14. Visulation of the universal approximator fitted on the measurement data of Fig. 3.

identified with the help of fitting the universal differential equation:

$$\begin{aligned}
 \dot{s} &= v, \\
 \dot{v} &= W_{\text{NN}}(\bar{v}_1 - \bar{v}), \\
 \dot{\bar{v}} &= (v - \bar{v})/T, \\
 \dot{\bar{v}}_1 &= (v_1 - \bar{v}_1)/T_1,
 \end{aligned} \tag{8}$$

which is based on (5) considering $\alpha = 0$ and the unknown speed policy W_{NN} .

The speed policy W_{NN} is optimized by introducing the universal approximator mapping from $\mathbb{R} \rightarrow \mathbb{R}$. The applied universal approximation has an input layer ($\mathbb{R} \mapsto \mathbb{R}^5$), two hidden layers with 5 neurons ($\mathbb{R}^5 \mapsto \mathbb{R}^5$) and an output layer ($\mathbb{R}^5 \mapsto \mathbb{R}$). The nonlinearity applied to each layer is the radial basis activation function e^{-x^2} , and each layer consists of weights and biases, totaling 81 parameters. These parameters and T and T_1 are trained simultaneously and tuned for each driver individually.

Figure 14 shows the speed policy estimated via the neural network W_{NN} for each vehicle of our test examples presented in Fig. 3. The range of the velocity difference corresponds to the values that occurred in the measurement data. As can be seen, the identified velocity policies of the different drivers have very similar shapes. Saturations can be clearly identified at different limiting values for positive and negative velocity differences, respectively. The intermediate segments strictly monotonically increase for each driver. Since each curve exhibits a qualitatively similar shape, it is possible to define a theoretical speed policy function with a low number of parameters. Thus, we introduce the piecewise smooth speed-policy function as

$$W_{\text{SMDM}}(\Delta v) = \begin{cases} a_{\min}, & \text{for } \Delta v \leq v_{\text{st}}, \\ \frac{a_{\min}}{v_{\text{st}}} \Delta v, & \text{for } v_{\text{st}} < \Delta v \leq 0, \\ \frac{a_{\max}}{v_{\text{go}}} \Delta v, & \text{for } 0 < \Delta v \leq v_{\text{go}}, \\ a_{\max}, & \text{for } v_{\text{go}} < \Delta v, \end{cases} \tag{9}$$

which is plotted in Fig. 15. The defined function is capable of describing asymmetric acceleration-breaking policies with different slopes for the positive and negative velocity differences, modeling that drivers may choose different accelerations for the accelerating and braking maneuvers. Hence, our speed policy is characterized by four parameters: maximal deceleration $a_{\min}$ and acceleration $a_{\max}$, and the corresponding velocity limits v_{st} and v_{go} . This way, we can use the speed policy (9) in (8) instead of the neural network to construct a model that we call the speed-matching driver model (SMDM).

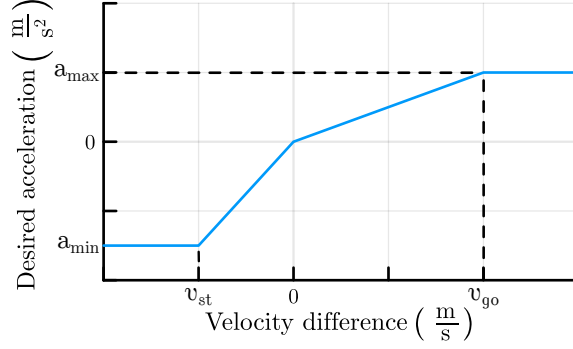


Figure 15. The piecewise smooth speed policy function characterized by four parameters.

ID	T (s)	T_1 (s)	$a_{\min}$ (1/s)	$a_{\max}$ (1/s)	v_{st} (m)	v_{go} (m)	MSE	OVM MSE
-	-	-	-	-	-	-	-	-
37	0.22	1.27	-2.27	1.20	-2.82	2.83	0.06	0.04
38	0.47	0.73	-2.58	1.51	-1.33	1.05	0.18	0.15
39	0.19	0.41	-2.22	1.25	-2.05	1.43	0.11	0.33
40	0.60	1.22	-2.44	1.67	-1.49	1.29	0.03	0.28
41	0.48	1.05	-1.33	2.18	-2.67	1.63	0.15	0.28
42	0.48	1.28	-1.83	1.81	-2.26	1.29	0.21	0.45
43	1.25	1.07	-2.12	1.18	-1.99	1.72	0.11	0.19
44	0.70	0.69	-2.20	0.60	-1.92	0.89	0.33	0.52

Table 3. Identified parameter values of the SMDM for the reference trajectories in Fig. 3. The last column is the mean squared error for the OVM fittings from Tab. 2.

We fit the SMDM on the measurements with the method presented in Section 4 to assess the consistency of the fitted parameters. In Tab. 3, the identified values are shown for the reference trajectories shown in Fig. 3. In the table, we also present the MSE both for the SMDM and the OVM fits. As can be seen, lower errors correspond to the SMDM in most cases, confirming the model’s capability to capture the trajectory evolution in our measured stop-n-go traffic. Figure 16 shows the frequency histograms of the fitted parameters of the speed policy function for all measured trajectories. The distributions are realistic, meaning all the parameters are in a physically meaningful range. The values of $a_{\max}$ and $a_{\min}$ are related to the vehicle’s acceleration and braking capabilities and the driver’s comfort tolerance. A tighter distribution for $a_{\max}$ is captured compared to the braking $a_{\min}$. Inspecting the distribution of v_{st} , it can be said that there may be more cautious drivers (smaller value for v_{st}) and drivers who are more comfortable with larger speed differences. Nevertheless, the identified parameters are in a well-bounded region. Based on the histogram of v_{go} , most drivers take advantage of their vehicle’s full comfortable accelerating capability if the speed difference reaches 1.1 – 2.3 m/s.

The frequency histograms of the time lags T and T_1 are shown in Fig. 17. The distributions are much more consistent than in the case of the OVM (cf. Fig. 9), indicating that the speed policy-based model is more suitable for modeling the drivers’ behavior in heavy urban traffic.

7. Model performance evaluation for traffic simulation

We now temporarily shift our focus from fitting individual trajectories to evaluating how these models perform in a predictive simulation of a vehicle platoon. This section should be viewed as an exploratory analysis to understand the SMDM’s potential to be used for traffic simulations. It was shown that the universal approximator in Fig. 14 has been significantly simplified with the piecewise smooth speed policy function shown in Fig. 15. This simplification results in a

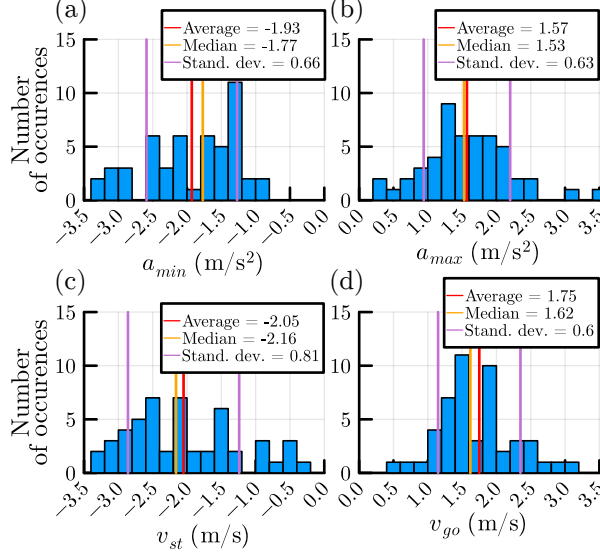


Figure 16. Histogram of the piecewise smooth speed policy function parameters.

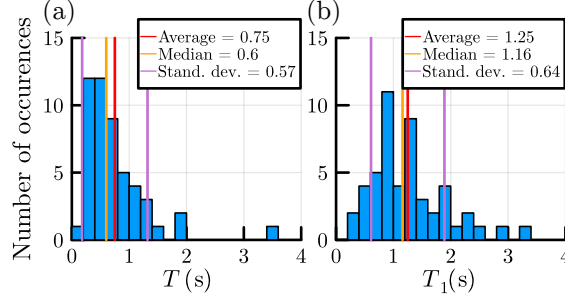


Figure 17. Histogram of the time lags T and T_1 of the speed matching driver model (SMDM).

consistent parameter distribution after the fittings. However, this does not imply automatically that our driver model is suitable for describing and predicting vehicle trajectories in urban traffic. This section aims to investigate how the error propagates at a platoon level and to understand how the qualitative dynamics manifest at a macroscopic level in the vehicle string.

While the Mean Squared Error (MSE) presented in Tab. 3 provides an evaluation metric for individual fittings, it does not capture how model inaccuracies propagate in a vehicle platoon. We introduce a second evaluation metric, the vehicle string headway error derived from traffic flow simulations, to perform a more comprehensive comparison. The individual parameters identified from the measurement data are used to simulate the vehicle string. In this simulation, only the lead vehicle's trajectory is used as an input from the measurements. Each subsequent vehicle follows the simulated trajectory of the one ahead, meaning that all following vehicles in the string rely on the simulated trajectories of the vehicle ahead of it. This causes the models' errors to propagate and accumulate, and the vehicle string headway error serves to quantify this effect.

Let us introduce the vehicle string headway error

$$\Theta = \frac{1}{k} \sum_{j=1}^k \frac{1}{n} \sum_{i=0}^n \left(\left(s_i^{\text{ref}_j} - s_i^{\text{ref}_{j+1}} \right) - \left(s_i^{\text{sol}_j} - s_i^{\text{sol}_{j+1}} \right) \right)^2, \quad (10)$$

where the notations are in accordance with (6) and j denotes the j th vehicle and $k + 1$ is the number of vehicles in the string. The vehicle string headway error compares the relative distances of the vehicles instead of calculating the position error of a vehicle relative to the reference trajectory. The latter solution might introduce a bias drift due to accumulating the errors of the

Scenario ID	OVM string error (m ²)	SMDM string error (m ²)
-		
1	10802.51	21.26
2	63.84	13.71
3	66.06	10.67
4	16.10	20.44
5	3.76	3.69
6	115.42	135.53
7	54.96	16.12
8	108.01	3.42

Table 4. Vehicle string error (10) calculated for the OVM and the SMDM model in different traffic scenarios.

simulated lead vehicle trajectories.

The calculated vehicle string errors are presented in Tab. 4 both for the OVM and SMDM models for all 8 different vehicle platoons. The SMDM model outperforms the OVM model in most cases, except scenarios 4 and 6, where the OVM model performs slightly better than the SMDM model. Figure 18 presents the simulated and measured trajectories for three different cases: scenario 4, where OVM performs better; scenario 5, where the two models perform similarly; and scenario 8, where the SMDM performs better. We present the measured trajectories of the leading and following vehicles by thick orange and thin gray curves, respectively. The simulated trajectories are denoted with the thin colored curves. In optimal case, the simulated trajectories (colored curves) are in perfect overlap with the measured trajectories (thin gray curves). The peculiarity of the time lag implementation in (8) is that the simulation can be done just for the time period covered by the leader of the vehicle string. Namely, $\bar{v}_1$ can be calculated for a time instant when v_1 is also known. Hence, the simulated trajectories in the blue transparent area are made by linearly extrapolating the lead vehicles' speeds, and, based on that, predicting the motion of the rest of the vehicles within the platoon.

In Fig. 18(a), scenario 4 is presented for both driver models. The string error is higher for the SMDM model, however, the OVM introduces oscillating motion into the trajectories, especially for vehicles at the end of the string. Figure 18(b) shows scenario 5, which was used as the reference scenario throughout this paper (see Fig. 3). In this case, both models provide approximately the same low value for the string error (see Tab. 4). Nevertheless, the trajectories show a different picture. Again, the OVM model produces small amplitude oscillations, while the SMDM model maintains a consistent headway even in the predicted sections of the trajectories. Finally, Fig. 18(c) presents scenario 8, where the SMDM clearly outperforms the OVM. The main reason behind the weak performance of the OVM is that the trajectory of the third vehicle (yellow curve) is poorly captured. Meanwhile, the SMDM is able to reproduce even the behavior of the last vehicle quite well.

Overall, the proposed speed-matching driver model outperforms the optimal velocity model in urban environments in terms of string error and individual driver accuracy. Moreover, it captures the qualitative behavior of the drivers better. The SMDM is more robust and is better suited to model the phenomenon of stop-n-go wave propagation.

Its simplicity and small number of parameters also make the SMDM a suitable candidate for classifying different driver behaviors.

8. Driver behavior classification based on the speed matching driver model

In this section, the drivers are clustered into multiple driving behavior groups based on the results of Section 6.2. For this purpose, first, the parameters are analyzed to determine whether their histograms satisfy the main assumptions of the model. Namely, the time lags T and T_1 are separated by the source of information, and the speed policy function is asymmetric. Then, the significant parameters are highlighted via *Principal Component Analysis* (PCA), and the drivers

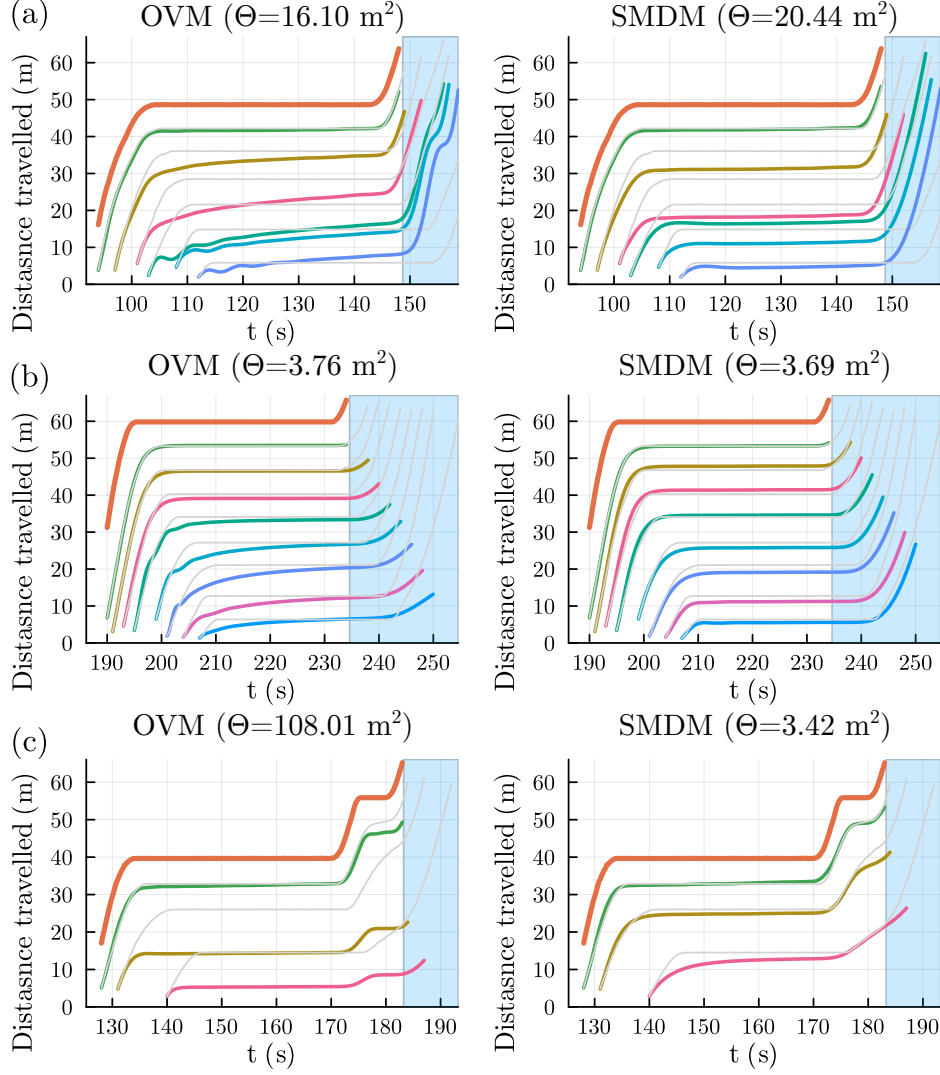


Figure 18. Simulated trajectories (thin color lines) of a vehicle string using the OVM and SMDM with the identified parameters. The reference measurement data is shown in gray.

are grouped in a new parameter space.

The drivers are expected to have a smaller time lag corresponding to their own speed v than the lead vehicle's speed v_1 . Figure 19(a) shows each measurement subject's identified time lag values. Apart from one obvious outlier, the model performs according to the assumption: the time lag corresponding to the self-state is smaller than the time lag corresponding to the lead vehicle states.

We expect an asymmetry in the speed policy. Drivers are strictly constrained when braking since they try to avoid collisions with the corresponding lead vehicles. In contrast, the key factors during acceleration are passenger comfort, time effectiveness, and/or vehicle capabilities, which do not have dire consequences like a poorly executed breaking maneuver. Figure 19(b) shows the acceleration and deceleration intensities, where they are defined as the slopes of the speed-policy function: $a_{\max}/v_{\text{go}}$ and $a_{\min}/v_{\text{st}}$, respectively. Figure 19(b) confirms these slopes significantly differ in most cases. Moreover, the values strongly vary among drivers. This disparity supports the assumption that the speed policy function (9) is asymmetric.

Next, we use Principal Component Analysis to find the parameter combinations best describing the different driver behaviors. The aim is to capture the parameter combinations that best describe the variance in the dataset. Then, we use only these combinations to cluster the drivers into groups corresponding to different behaviors. First, we apply the PCA to the dataset, obtain-

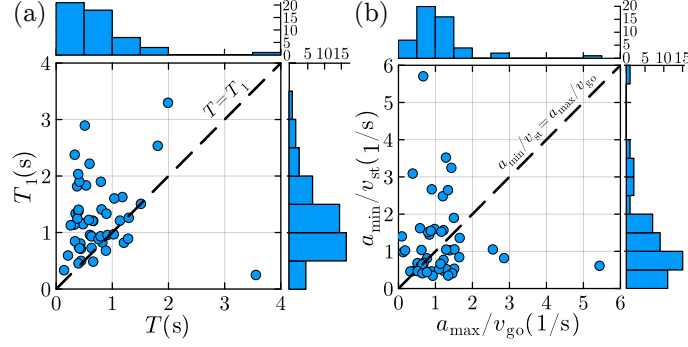


Figure 19. (a) Time lags distribution of the drivers with marginal distributions (b) Deceleration and acceleration intensities with marginal distributions.

Table 5. Result of the PCA based on the dataset created in Section 6.2. Principal component vectors are normalized to unit vectors. Dominant components are highlighted for each PC.

	PC1	PC2	PC3	PC4	PC5	PC6
$a_{\min}$	0.16	0.52	0.18	0.32	0.42	0.63
$a_{\max}$	-0.10	0.23	0.64	0.35	0.14	-0.62
v_{st}	-0.16	-0.72	0.40	-0.06	0.48	0.24
v_{go}	0.03	-0.07	-0.61	0.32	0.62	-0.35
T	0.96	-0.12	0.13	-0.17	0.07	-0.14
T_1	0.15	-0.36	-0.05	0.80	-0.42	0.15
Cumulative variance	40 %	64 %	79 %	90 %	96 %	100 %

ing the principal components presented in Table 5. The first principal component is dominated by the time lag T , while the second principal component is mainly influenced by the parameters v_{st} and $a_{\min}$. Similarly, we obtain v_{go} and $a_{\max}$ as dominant components for the third principal component. The most dominant part of the fourth principal component is the time lag T_1 . The first four principal components describe 90% of the variance of the dataset.

These results suggest, that the pairs v_{st} and $a_{\min}$, and v_{go} and $a_{\max}$ are highly correlated. When these parameters are pairwise combined to the slopes $a_{\max}/v_{\text{go}}$ and $a_{\min}/v_{\text{st}}$ of the speed-policy function W_{SMDM} , the number of relevant parameters are reduced from 6 to 4. Of course, some information about the drivers is lost. However, we gain a more compact insight into the driver behavior. This is confirmed when applying the PCA to this reduced dataset (see Table 6), as now even two principal components (PCs) explain 88% of the parameter variance, while in the previous representation, we needed four for a similar result. Now, the first PC is dominated by the deceleration intensity ($a_{\min}/v_{\text{st}}$), while the second PC is mainly related to the time lag T .

Next, the drivers are classified by fitting a *Gaussian mixture model* (GMM) (see Friedman et al. (2009) and Bishop (2006)) to the first two PCs. Figure 20(a) shows the driver parameters in the space of the first two PCs, and confidence ellipses corresponding to the three clusters determined by the GMM. Each driver is assigned to their most probable cluster, represented by the different colors. The optimal cluster number was found as the *elbow* in panel (b) at three, where the slope of the sum of squares-within (SSW) function suddenly changes (see Friedman

Table 6. Results of the PCA for the dataset reduced by the introduction of the acceleration and deceleration intensities. Principal component vectors are normalized.

	PC1	PC2	PC3	PC4
$a_{\min}/v_{\text{st}}$	-0.97	-0.08	0.07	-0.21
$a_{\max}/v_{\text{go}}$	0.06	0.22	0.97	-0.04
T	0.15	-0.94	0.19	-0.26
T_1	-0.17	-0.27	0.11	0.94
Cumulative variance	67 %	88 %	97 %	100 %

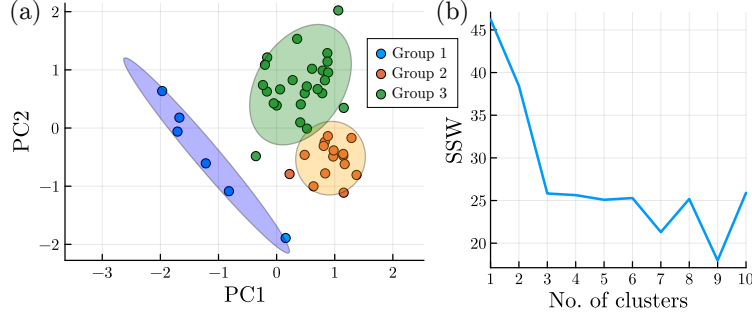


Figure 20. (a) Drivers visualized in the space of the first two principal components with soft clustering. (b) The sum of squares within clusters value for different numbers of clusters.

et al. (2009)).

Based on our investigation, the additional variance explained by PC3 and PC4 does not bring any meaningful insight into the data analysis. Therefore, their presentation is omitted.

The deceleration intensity $a_{\min}/v_{\text{st}}$ and the time lag T dominate PC1 and PC2, respectively. Figure 21 shows the drivers in the plane of T and $a_{\min}/v_{\text{st}}$ to demonstrate that drivers are indeed differentiated based on these parameters. Moreover, Fig. 21 suggests that the driver behaviors are clearly separable. We can separate the drivers of Group 1 (blue dots) from the rest based on the deceleration intensity ($a_{\min}/v_{\text{st}}$), see the horizontal dashed line at $a_{\min}/v_{\text{st}} = 2 \text{ s}^{-1}$. Note that only a few drivers are mixed around the horizontal dashed line. The rest of the drivers can be further divided into Groups 2 (orange dots) and 3 (green dots) according to the time lag value (T); see the vertical dashed line at $T = 0.5 \text{ s}$.

Assigning driving behavior (e.g., aggressive, distracted, focused, etc.) to the groups is challenging, and labeled data is required to validate that our clustering is meaningful. However, based on the physical interpretation of the parameters, we can hypothesize about the kinematic patterns observed for each group. Group 1 (blue dots) in Fig. 21 is characterized by larger deceleration intensity and low time lag. This pattern could be interpreted as a more assertive or aggressive driving style. Group 2 (orange dots) exhibits moderate ($0 - 2 \text{ s}^{-1}$) deceleration intensity and short time lag ($< 0.5 \text{ s}$) suggesting a more attentive and smooth pattern. Group 3 (green dots) is situated in the same deceleration range, but shows a longer time lag ($> 0.5 \text{ s}$). This may suggest a less attentive or more cautious driving behavior. We emphasize that this classification is phenomenological, which groups drivers based on observed kinematic patterns rather than their definitive psychological or physiological attributes. For instance, a long reaction time, which places a driver into Group 3, could stem from multiple reasons: distraction, being overly cautious, the driver intentionally leaving a large gap for comfort, fatigue, etc. While the causes may differ, the resulting behavior may similarly affect the traffic dynamics. Therefore, from the perspective of traffic flow modeling, these drivers can be considered a single behavioral class due to their comparable impact on the vehicle string. Note that a strict analysis would need to consider the drivers' reaction to the other lanes, former vehicles in the string, traffic light, and other confounding factors.

9. Conclusion

The main objectives of this paper are to compare driver models in heavy urban traffic and to differentiate among driver behaviors in stop-n-go scenarios. The corresponding data was collected via video recordings in heavy urban traffic at multiple locations, where the drivers continuously engaged in stop-n-go maneuvers. First, the Optimal Velocity Model with time delay was fitted on the measurement data using a cubic range policy function and delay iteration. Second, to improve the efficiency of the fitting, we replaced the time delays with time lags. The applicability of this concept was evaluated by examining the distribution of the fitted parameters. It was found that

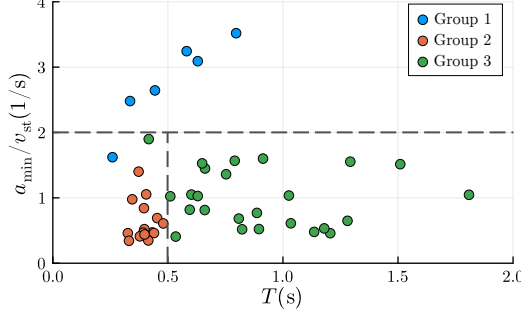


Figure 21. Drivers visualized in the time lag (T) and deceleration intensity ($a_{\min}/v_{st}$) space with the coloring of the clustering results as in Fig.20(a).

the distributions of the parameters were unrealistic and, in many cases, contrary to our physical sense.

Discovering that drivers practically do not rely on the headway when choosing their speed in stop-n-go traffic, a driver model was introduced that uses only the speed difference between the leader and the follower. We constructed and fitted a universal speed policy-based driver model described by a neural network with 81 parameters. Then, this was reduced into a computationally tractable piecewise smooth model with 6 parameters, referred to as the speed-matching driver model (SMDM). In the case of the SMDM, the fitted parameter distributions were consistent: both the parameters corresponding to the time lags and the speed policy were within a physically interpretable range. The identified SMDM model confirmed the disparity between the time lags corresponding to the self-state and the leader-state and the asymmetry of the speed policy for breaking and accelerating.

We used the identified driver parameters in simulations, which demonstrated the SMDM’s applicability for reproducing the stop-n-go wave propagation observed in the data. However, it is crucial to note that the study’s main objective is the identification and classification of driver behavior in dense, stop-n-go conditions rather than the development of a universal traffic simulation tool. The SMDM’s formulation, which omits a headway-dependent part in favor of a speed-matching strategy, makes it unsuitable for sparse traffic scenarios.

A promising direction for future work would be the development of a hybrid or switching driver model. Furthermore, the analysis excludes external influences such as adjacent lane traffic or driver reactions to traffic signals. Integrating these elements represents another direction for extending the model’s capabilities. We propose that the model should be applied to predict the macroscopic and statistical behavior of the traffic and the behavior of individual drivers in dense traffic scenarios.

The data analysis was conducted using the parameters of the SMDM via principal component analysis (PCA) and Gaussian mixture clustering. We found two key parameters to differentiate among driver behaviors: the deceleration intensity and the time lag corresponding to the self-state. Based on these parameters, three different groups of drivers were hypothesized: assertive/aggressive, attentive/focused, and distracted/cautious. It is crucial to contextualize this classification. Our model identifies distinct kinematic signatures from trajectory data, but these signatures are likely manifestations of deeper driver characteristics. As discussed in the introduction, sociodemographic and environmental factors play a key role in the classification of drivers. Thus, validation of this classification requires labeled data, and it is the subject of future work. Due to traffic safety considerations, we aim to collect labeled data in a simulated driving environment with subjects of known state. An additional benefit of a simulation environment is the possibility to vary the environmental factors such as weather, traffic lights, crosswalks, etc.

We also acknowledge that our dataset is limited to a specific urban environment and a small number of participants. Consequently, the results of our work should not be considered statistically generalizable to a broader population. The primary contribution of this work lies in the development of a robust modeling and identification framework that successfully extracts

physically meaningful behavioral parameters from real-world data. Future work should focus on applying this framework to larger, more diverse datasets to validate or refine the generalizability of the behavioral clusters identified here.

Beyond the immediate goal of classifying driver behavior, the proposed Speed-Matching Driver Model (SMDM) has the potential for several practical applications in intelligent transportation systems. We see benefits in autonomous vehicle integration by providing external information on the traffic participants on a microscopic and macroscopic level. We also see potential in V2I applications, like adaptive traffic signaling for increased traffic flow or custom-tailored warnings for increased traffic safety.

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Appendix

Table 7.: Nomenclature of variables used in the document.

Variable	Description	Unit
t	Time	s
i	Iteration variable for time instants	-
n	Number of data points	-
j	Iteration variable for vehicles	-
k	Number of vehicles	-
<i>Kinematic variables</i>		
s	Positional coordinate of the following vehicle	m
v	Speed of the following vehicle	m/s
s_1	Positional coordinate of the lead vehicle	m
v_1	Speed of the lead vehicle	m/s
l	Length of the following vehicle	m
h	Headway distance ($s_1 - s - l$)	m
<i>Optimal Velocity Model (OVM) Parameters</i>		
$V(h)$	Optimal velocity function (range policy)	m/s
h_{st}	Minimal headway distance for stopping	m
h_{go}	Headway distance for reaching v_{max}	m
v_{max}	Maximum desired speed	m/s, km/h
α	OVM feedback gain on the headway term	s^{-1}

Continued on next page

Table 7 – continued from previous page

Variable	Description	Unit
β	OVM feedback gain on the velocity difference term	s^{-1}
<i>Time Delay and Lag Parameters</i>		
τ	Time delay for driver's own states	s
τ_1	Time delay for leader vehicle's states	s
T	Time lag for own states (first-order filter)	s
T_1	Time lag for leader's states (first-order filter)	s
<i>Speed-Matching Driver Model (SMDM) Parameters</i>		
W_{SMDM}	Piecewise smooth speed policy function	m/s^2
a_{max}	Maximum acceleration parameter	m/s^2
a_{min}	Maximum deceleration parameter (negative value)	m/s^2
v_{st}	Velocity difference threshold for deceleration	m/s
v_{go}	Velocity difference threshold for acceleration	m/s
<i>Derived Parameters for Analysis</i>		
$a_{\text{min}}/v_{\text{st}}$	Deceleration intensity	s^{-1}
$a_{\text{max}}/v_{\text{go}}$	Acceleration intensity	s^{-1}
<i>Optimization</i>		
$\mathbf{p}$	Parameter vector for optimization	N/A
$C(\mathbf{p})$	Cost function for parameter fitting	Dimensionless
s_i^{ref}	Measured path coordinate for optimization	m
v_i^{ref}	Measured speed for optimization	m/s
s_i^{sol}	Simulated path for optimization	m
v_i^{sol}	Simulated speed for optimization	m/s
σ	Weight for position error in cost function	m^{-2}
ν	Weight for speed error in cost function	$s^2 m^{-2}$
<i>Error Metrics</i>		
MSE_s	Mean Squared Error for the positional data	m^2
MSE_v	Mean Squared Error for the speed data	m^2/s^2
MSE	Mean Squared Error produced by $C(\mathbf{p})$	Dimensionless
Θ	Vehicle string headway error	m^2
<i>Machine Learning Model Parameters</i>		
Δv	Velocity difference (argument of W_{SMDM})	m/s
W_{NN}	Neural network based speed policy function	m/s^2
$U(x, t)$	Universal approximator in a UDE	Varies