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Mobility Impacts of Autonomous Vehicle Systems

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***Abstract*— Automated vehicle (AV) technologies are rapidly maturing, and time line for their wider deployment is currently uncertain. Despite uncertainty these technologies are expected to bring about numerous societal benefits, such as enhanced traffic safety, improved mobility and reduced fuel emissions. In this paper, we propose a novel bottom-up approach to model various SAE levels on VISSIM in a two lane highway environment featuring an on-ramp. Our results indicate that mobility in SAE level 1 always exceeds that of SAE level 0, because the former has a consistently higher acceleration for given conditions. SAE level 2 provides more lateral stability and therefore less implied accidents than level 1 or 0 due to lower lateral deviations. For level 3, key consideration is to model the transition between human and system control. In SAE level 4 we model the operation of autonomous vehicles in Operational Design Domain (ODD) and transition to minimal risk conditions outside ODD. SAE level 5 overcomes impact of these transitions and hence has a better mobility than lower SAE levels. The models can help policymakers to understand the impact of autonomous vehicles on mobility and guide them in making critical policy decisions.**

Keywords SAE level, Advanced Driver Assistance Systems, Autonomous Driving, Autonomous Vehicles

I. INTRODUCTION

Autonomous vehicles (AVs) are a rapidly advancing technology that will revolutionize numerous aspects of driving. Although an exact time line for their deployment is unknown, the introduction of AVs to consumer markets is projected to occur to an overwhelming extent by the 2050s [1]. In response to the increasing reality of an AV future, the National Highway Traffic Safety Administration (NHTSA) released the Federal Policy on Automated Vehicles in 2016 [2]. This policy includes guidelines for AV manufacturing and regulation. It also adopted the Society of Automotive Engineers (SAE) levels of automation [3]. These levels range from level 0 (no automation to levels 5 (full automation) [4].

A. Literature Review

In the past, modeling of numerous aspects of advanced driver assistance systems (ADAS) has been conducted, which has improved AV-related technology knowledge. As early as 2001, research was completed to evaluate the potential minimum spacing between autonomous vehicles [5]. In 2007, the placement of ultrasonic sensors in a variety of positions during automatic parking was modeled to develop recommendations for sensor location [6]. [7] proposed a multi-objective vehicular adaptive cruise control system. The system provided significant benefits in terms of fuel efficiency and tracking capability and performed satisfactory driver desired car following behavior. With respect to autonomous lane changing, an algorithm based on the recognition of surrounding features such as vehicle speed and distance was implemented in 2011 [8].The simulation results proved environmental recognition-based lane changing to be feasible. In 2017, Automatic Emergency Braking System (AEBS) based on the Nonlinear Model Predictive Algorithm, termed the Advanced Emergency Braking System, was modeled [9]. The modeling indicated the proposed AEBS system had higher performance than existing variants. Machine learning methodologies have opened new directions for modeling driver behavior. Multiple learning-based approaches have been employed to model car-following behavior using real world data to emulate human driving behavior [10] – [12].

B. Contributions

In spite of significant work on AVs, work on SAE modeling is very limited. We propose a novel bottom-up approach to explain the mobility impacts of various SAE levels on road networks. The bottom-up approach attempts to explain the proposed impacts of AVs by modeling autonomous functionalities which define each SAE levels.The decisions made during the modeling process were predicated upon past research in AV modeling. Level 0, representing exclusive human driving behavior was modeled with the Intelligent Driver Model (IDM) [13]. IDM quantitatively replicates the macroscopic and microscopic dynamics of human driving behavior in a straightforward manner [14]. Additionally, ACC, or level 1 automation, was modeled with enhanced IDM. IDM can be conservative under certain situations where braking reactions are needed [14]. Enhanced IDM on the other hand is less conservative and serves as a more realistic alternative. At level 2, we add lane-keeping assist functionality. This feature is modeled using a third order autoregressive time series [15]. Complete automation at level 3 is accomplished by automating the lane changing functionality. Minimizing Overall Braking Induced by Lane Changes (MOBIL) algorithm is used to model automated lane changing. MOBIL was employed because it has been proven through past simulations that it can model lane changing through employing the computations already completed in the IDM car following model and hence results in mathematical consistency [16]. As a result, AV lane changing can be modeled with minimal additional calculations, reducing

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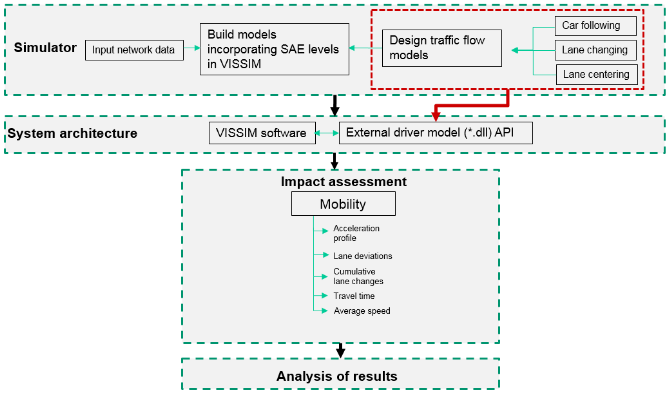

Fig. 1. Framework for modeling of SAE levels

computational complexity. Level 4 is modeled by designing automated control system for operational design. Complete automation architecture is applied for level 5.

We introduce stochasticity to a class of deterministic traffic flow models. The deterministic driving models though a fair representation of the human driving behavior fail to account for the heterogeneity in the driving behavior.

In summary, the main contributions of this work include:

1) To the best of our knowledge this is the first work to study the modeling of each SAE level.
2) The modeling of the SAE level is done using a bottom-up approach.
3) The modeling explores the impacts of SAE levels on traditional as well as non- traditional measures.

II. METHODOLOGY

SAE levels were modeled using a bottom-up approach using current models as the base. These SAE models were integrated with VISSIM using an external driver model API. The simulation data was used to analyze and interpret the impact of the different SAE levels on mobility measures like the acceleration profile, speed profile, lane deviations and lane changes. Figure 1 provides a visual description of the framework.

A. SAE Level Description

The NHTSA has adopted six levels of automated driving systems which range from complete human driver control to full vehicle autonomy. The longitudinal and the lateral control progressively gets transferred from the human to the system from level 0 to level 5. The monitoring of the environment is by the human, in level 1, and 2. On the other hand, for levels 3, 4 and 5, the automated system of the vehicle monitors the driving environment. The system fall backs on the human from level 0 to level 3 but in level 4 and 5 the system is responsible to keep the controls under unexpected circumstances. [4]

B. Traffic flow models and related components

In this section we will discuss the various models employed to model the human and the corresponding automated driving-related function.

1) Car-following models:

a) Human control: To model human car-following behavior, a stochastic variation of intelligent driver model (IDM) was employed. As preliminaries, we will introduce the IDM and then present the extensions to the model. IDM considers acceleration to be a continuous function, which is affected by numerous factors. These are the space headway between the vehicle and its leading vehicle, the desired velocity, the current velocity, and the velocity difference of the vehicle from the leading vehicle. The SAE 0 acceleration function is defined by:

$$a_{SAE_0}(a_{IDM}, \epsilon_0) = a_{IDM} + \epsilon_0 \tag{1}$$

where, a_{SAE_0} is SAE 0 acceleration and a_{IDM} is IDM acceleration. ϵ_0 is an error term added to the deterministic IDM acceleration to model a stochastic SAE 0 acceleration. ϵ_0 follows a normal distribution with mean as 0 and variance as $\sigma^2_{SAE_0}$ which is non−zero and and is uncorrelated with a_{IDM}. The IDM acceleration is given by:

$$a_{IDM}(s, v, \Delta v) = a\left[1 - (\frac{v}{v_0})^\delta - (\frac{s^*}{s})^2\right] \tag{2}$$

where, s is the headway between the leading vehicle and the follower, v is the current velocity of the vehicle, δ is the free acceleration component, Δv is the velocity differential between the leader and the follower,v_0 is the desired speed of the vehicle, s^* is the desired space headway. The function for s^* is given by:

$$s^*(v, \Delta v) = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}} \tag{3}$$

where, s_0 is the minimum headway space, T is the desired time headway, b is the maximum desired deceleration.

IDM, to account for heterogeneity, is made stochastic by modeling parameters a, b and T, to follow log-normal distribution [**?**]. For each vehicle the parameters are drawn from the below set of distributions.

$$\log(a) \sim \mathcal{N}(\mu_a, \sigma_a^2) \tag{4}$$

$$\log(b) \sim \mathcal{N}(\mu_b, \sigma_b^2) \tag{5}$$

$$\log(T) \sim \mathcal{N}(\mu_T, \sigma_T^2) \tag{6}$$

The value/mean value of a , b, T, δ, s_0 used in the paper are taken from [13]. $\epsilon_0 \sim \mathcal{N}(0, 0.3)$ and coefficients of variation of a , b, T is assumed to be 20%.

b) Autonomous control: Autonomous car-following behavior is modeled using Enhanced IDM model which simulates ACC feature [13]. This model is an extension of the IDM. However, the Enhanced IDM model is based on the following assumptions; the ACC acceleration is higher than that of IDM and the ACC acceleration is continuous. Below is the formulation for the ACC acceleration.

$$a_{CAH}(s, c, v_l, a_l) = \begin{cases} \frac{v^2 a_l}{v_l^2 - 2s\bar{a}_l}, \text{if } v_l(v - v_l) \leq 2s\bar{a}_l \\ \bar{a}_l - \frac{(v-v_l)^2 \Theta(v-v_l)}{2s}, \text{otherwise} \end{cases} \tag{7}$$

$$a_{acc} = a_{IDM}(1-c)+c[a_{CAH}+b\tanh\left(\frac{a_{IDM}-a_{CAH}}{b}\right)] \quad (8)$$

Where, a_{CAH} is the constant-acceleration heuristic (CAH) acceleration, v_l is the velocity of the leading vehicle, a_l is the acceleration of the leading vehicle, $\bar{a}_l$is the effective acceleration = min (a_l,a).

Θ is the heaviside step function which takes the value of 1 if v - v_l $>$ 0 and 0 otherwise. c is the coolness factor which ranges between 0 to 1. a_{ACC} is always higher than a_{IDM} and the acceleration profile of cars modeled after the Enhanced IDM have a more relaxed response to discontinuous headways which results in improved mobility.

$$a_{SAE_1}(a_{ACC}, \epsilon_1) = a_{ACC} + \epsilon_1 \quad (9)$$

$$\sigma^2_{SAE_1} = \sigma^2_{SAE_0}/k \quad (10)$$

where, ϵ_1 follows a normal distribution with mean as μ = 0 and variance as $\sigma^2_{SAE_1}$ which is non$-$zero and and is uncorrelated with a_{IDM}. Here we assume that $\sigma^2_{SAE_1}$ is lower than $\sigma^2_{SAE_0}$ by a factor of k where k is $>$ 1. In our model k = 10.

2) Lane-centering models:

a) Human control: Human control: The lateral position of vehicles under human control, is modeled as an autoregressive time series model [15]. In the time series model, Y_t is the lane position of the car at time t. Y_t = 0 when the vehicle is in the center of the driving lane, $Y_t \leq 0$ corresponds to when the vehicle is left of the center lane, and $Y_t \geq 0$ corresponds to when the vehicle is on the right of the center lane. In a third-order time series, the vehicles lateral position depends on the weighted average of the previous three time steps plus a signed error term. Therefore, the formulation for the lateral position for time step t is as below

$$Y_t = \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_3 Y_{t-3} + |e_t| I_t \quad (11)$$

$$\log\left(\frac{p_t}{1-p_t}\right) = \gamma_0 + \gamma_1 Y_{t-1} \quad (12)$$

Where, Y_t, Y_{t-1} and Y_{t-2} are the lateral positions of the vehicle at time $t-1, t-2$ and $t-3$ respectively, e_t is the error term, which follows a normal distribution, and I_t is 1 or -1 depending upon the value of p_t which is assumed to have a functional form following the logistic model given in equation 12. Dawson et. al [15] calibrated this model which is used in our paper. Δy is the difference between the current lateral position and the future lateral position.

The lateral position is given as an input to VISSIM as an angle instead of the position itself as the API is designed is such a manner. Below is the transformation of the future lateral position to an angle (in radians).

$$\theta_{SAE} = d_{SAE}\theta \quad (13)$$

$$\frac{\Delta y}{\Delta x} = \theta \quad (14)$$

$$\Delta x = vt \quad (15)$$

where, Δy is the difference between the future lateral position and the current lateral position, Δx is the difference between the future longitudinal position and the current longitudinal position , t is the time-step of analysis which is 0.1 seconds. The angle θ therefore, can be approximated as the ratio of Δy with respect to Δx. d_{SAE} is the deviation factor for a particular SAE level ranging from 0 to 1. The lower the value of the deviation factor, lower is the tendency for deviation of the car from the centerline of the lane. Under human control d is assumed to be 1.

b) Autonomous control: Deviation factor for autonomous lane centering is assumed to be 0.5 since AVs can sense smaller deviations and correct themselves.

3) Lane-changing models:

a) Human control: The lane changing model used is MOBIL, a rule-based lane changing model is used as the base model to simulate the added autonomous feature along with probabilistic extensions [16]. MOBIL considers two criteria for lane change; 1) safety criterion, where the vehicle behind the vehicle which changes lanes will not require to brake more than a safe level of deceleration and 2) incentive criterion, where the vehicle changes lane only if the below condition holds

$$a'_c - a_c + p(a'_n - a_n + a'_o - a_o) \geq \Delta a_{thr} \quad (16)$$

$$a_n \geq -b_{safe} \quad (17)$$

where, c is the vehicle considering to change lane, n is upstream vehicle on the target lane, o is the upstream vehicle on the present lane, a_c is the acceleration of vehicle c on the current lane, a'_c is the acceleration of vehicle c on the target lane, a_o is the acceleration of vehicle o before lane change by vehicle c, a'_o is the acceleration of vehicle o after lane change by vehicle c, a_n is the acceleration of vehicle n before lane change by vehicle c and a'_n is acceleration of vehicle n after lane change by vehicle c, p is the politeness factor, ranging between 0 to 1 [16]. Δa_{thr} is a threshold to be crossed by the weighted sum of acceleration of the vehicle and the affected neighbors. This results in reduced adverse impact on the neighborhood vehicles' movement. For humans we have assumed the Δa_{thr} to be 3.2 ft/s^2. We used a politeness factor of 0.5 which is a more realistic value for the parameter.

b) Autonomous control: For autonomous lane changing we assume that the Δa_{thr} = 0.32ft/s^2, which is lower than the Δa_{thr} for humans as AVs will be able to identify more minute mobility-enhancing opportunities.

C. Mapping of SAE Levels to Driver Models and Driving Features

Below we map the SAE levels to driver models/features comprised of car-following, lane-changing and lane-keeping functions. Simulations were done using VISSIM and employing the External Driver Model (EDM) Dynamic-link library (DLL) to replace the default driving behavior by a fully user-defined driving behavior.

1) SAE Level 0: SAE Level 0is modeled using a stochastic extension of IDM as the car following model. The lane centering is modeled using the third order autoregressive time series with human control parameters. The lane changing model uses the MOBIL algorithm with acceleration threshold parameter for humans.

2) SAE Level 1: SAE level 1 is modeled by introducing automated acceleration and deceleration by means of Adaptive Cruise Control (ACC) in the vehicle. ACC is modeled in the paper using a model which employs a stochastic version of the Enhanced IDM model [13].

3) SAE Level 2: Level 2 automation involves automating both steering and acceleration/deceleration under certain conditions. The paper models Level 2 by means of ACC and lane-keeping assist. The lane centering feature is modeled using a third-order autoregressive time series model with parameters for autonomous control [15].

4) SAE Level 3: Level 3 automation translates to fully autonomous behavior in certain conditions. Control is given back to the driver when pre-specified conditions for automation are not met. In our study this level is modeled by assuming that a vehicle is fully autonomous in a highway environment only. If the vehicle exits these conditions, the control is given back to the driver. while in a fully autonomous state the car-following, lane-centering as well as lane changing features are automated. While modeling the different SAE levels one of the key features for the levels until SAE 3 automation is the need for transition of control between the system and human. We have used the data from a recent study to model the reaction time of the drivers during transition of control [17].

5) SAE Level 4: Level 4 automation implies that the vehicle is completely autonomous while operating within its operational design domain (ODD) [3]. The vehicle will transition to a low-risk operating mode for example lowering its desired speed when outside the ODD which we will define as the Minimal Risk Conditions Desired Speed (MRCDS). In this paper we assume ODD as any roadway with clear lane marking. The vehicle enters a minimal risk operating condition when the lane markings are not clearly visible. We study the impact on traffic while the vehicles travel both inside and outside the ODD.

6) SAE Level 5: Level 5 automation is the highest level of automation among the various SAE levels. This level of automation involves the vehicles having control under all type of conditions.

III. Numerical results and insights

The network, as illustrated in Figure 2 designed for the simulations is a 1.5 mile straight two-lane highway with a single-lane on-ramp joining the highway at 0.3 mile. Traffic from on-ramps into the highway are typical scenarios for traffic congestion and bottlenecks and hence this particular network was chosen to analyze the performance of different SAE levels in such a network. The traffic is composed of cars which are of length 12 ft and width 4.5 ft. We have chosen a homogeneous traffic to be able to analyze the effects of the various SAE levels on the traffic. Also the simulations for each SAE level vehicles was run separately assuming 100% penetration of the particular SAE level vehicle. The traffic flow on the highway is assumed to be 800 veh/hr/lane and the traffic flow on the on-ramp is 300veh/hr/lane. The speed distribution of the vehicles is 50mph to 80mph.

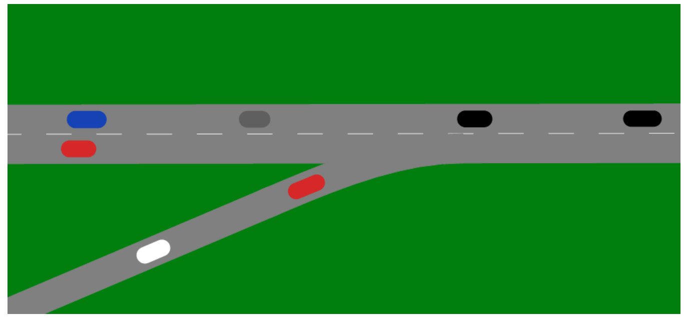

Fig. 2. Illustration of a highway segment with an on-ramp

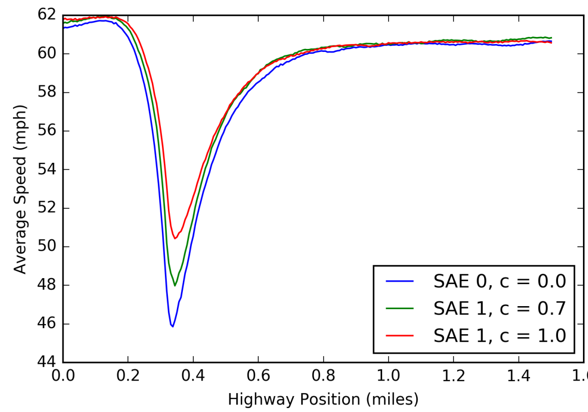

Fig. 3. Speed profiles of SAE 0 and SAE 1 vehicles (with different coolness factors)

Figure 3 plots the speed profile of SAE 1 vehicles on the highway for different levels of coolness factor c and compares them with the speed profile of SAE 0 vehicles. From the enhanced IDM formulation we know that, as coolness factor c increases the braking response to discontinuous headways reduces. At 0.3 mile there is an on-ramp because of which the vehicles on the highway as well as the ones on the on-ramp end up experiencing non-continuous headways as their predecessor change on account of the merging activity. The vehicles experience deceleration as they approach the point of entry where the on-ramp merges with the highway. It is observed that the maximum deceleration of the through vehicles is at the point at which the on-ramp merges with the highway. SAE 1 vehicles with higher c are able to negotiate this segment of the road with higher effectiveness without having to brake as much as SAE 0 and SAE 1 vehicles with

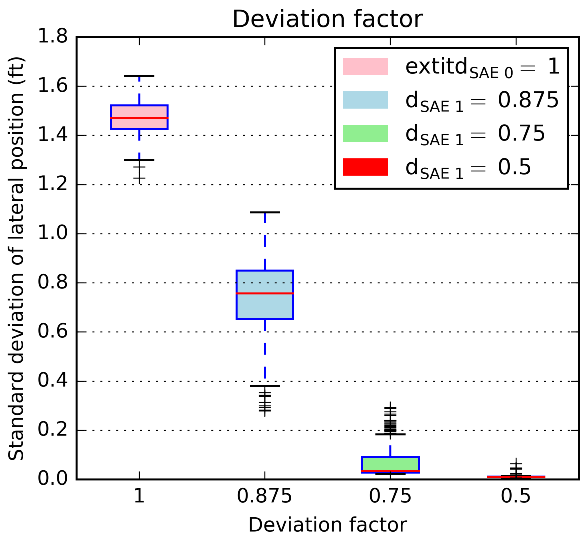

Fig. 4. Box pot of the standard deviation of lateral position of SAE 1 and SAE 2 for different deviation factors

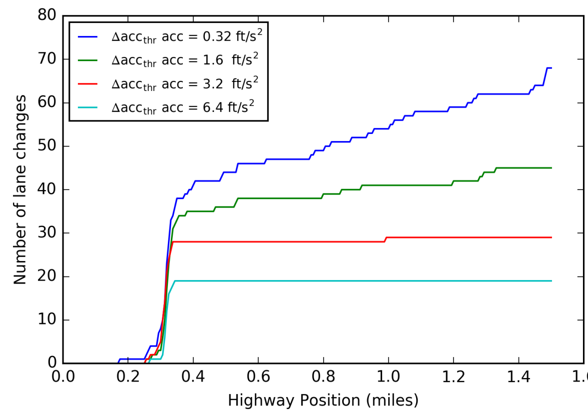

Fig. 5. Total number of lane changes for different levels of threshold accelerations for SAE 3 vehicles

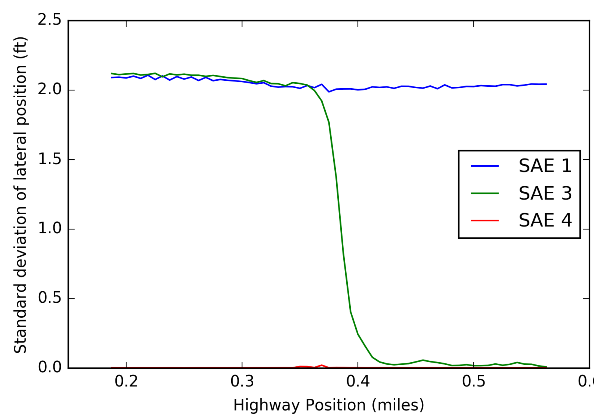

Fig. 6. Change in lateral deviation with shift in control from human to autonomous

lower c. We can see this from Figure 3 that as the value of c increases the minimum speed that the vehicles decelerate to increases and hence results in higher mobility. Once the vehicles cross the merging section they start picking up speed after the merging operation is completed to match the desired speed on the highway. The minimum speed of SAE level 1 vehicles with $c = 1$ is 50.5 mph whereas the minimum speed of SAE level 1 vehicles with $c = 0$ is 46 mph. The speed profile across the highway section shows that the SAE level 1 vehicles with higher c travel faster than the SAE level 0 vehicles at all points on the network. Hence we conclude that SAE level 1 vehicles under autonomous longitudinal control experience higher mobility as compared to SAE 0 level vehicles under human control.

Figure 4 compares the standard deviation of the lateral position of SAE 2 vehicles across the entire stretch of the segment with different levels of deviation factors. The fist box plot in the figure from the left is the standard deviation under human control. As we go towards the right with decreasing deviation factor we observe the mean value of the deviations reduce and the spread of the range also narrows down.Therefore SAE 2 vehicles travel much closer to centerline as compared to SAE 1 vehicles.

Figure 5 shows the impact on lane changes as the acceleration threshold in the MOBIL algorithm is changed. The number of lane changes decrease as the acceleration threshold Δa_{thr} increases. An increase in Δa_{thr}, especially in semi-congested traffic situations can result in reduced mobility. To quantify the change in mobility depending on change in Δa_{thr} is part of our future work.

SAE level 3 is characterized by the option of transferring control between human and the system. In our model we have assumed that SAE level 3 the vehicles are completely autonomous on highways and not otherwise. In our particular network, the vehicles that enter the highway from the on-ramp are initially under human control as they enter. The control is then transferred to the system based on reaction time from previous studies [17], [18]. We have assumed that both the time taken for taking control from the autonomous system and giving control to the autonomous system follow log-normal distributions. In figure 6 we have plotted the standard deviation in lateral position for SAE 1, SAE 3 and SAE 4 vehicles. We can see that for SAE level 3 vehicles as cumulative number of vehicles in autonomous control increase the standard deviation of the lateral position gradually reduces and converges to that of SAE level 4 vehicles.

SAE 4 level vehicles are completely autonomous in ODD and operate at minimal risk conditions outside ODD. In our study we assume that SAE 4 level vehicles' ODD is any roadway with clear lane markings. In our study we assume that the highway has unclear lane markings from 1 mile to 1.2 mile segment on the highway. As SAE level 4 vehicles enter this segment they reduce speed to satisfy minimal risk condition. We look at the impact on SAE 4 level vehicle

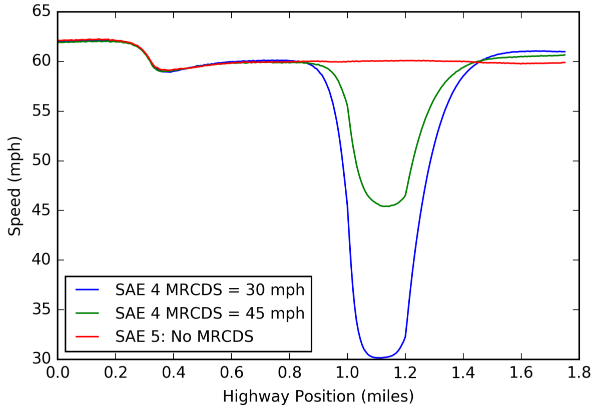

Fig. 7. speed profiles for different minimal risk speeds in unclear lane markings area

mobility depending on the minimal risk condition desired speed (MRCDS) they need to acquire. Figure 7 shows the speed profile of SAE 4 level vehicles for various minimal risk condition speed levels as compared to SAE 5 level vehicles. We observe that the speed profiles monotonically fall as defined minimal risk speed for SAE 4 level vehicle decreases outside the Operational Design Domain decreases.

IV. Conclusion

This paper makes a significant contribution in the modeling of SAE levels. The analysis was conducted with a bottom-up modeling approach. Level 0 was modeled with the IDM car following model. Level 1, featuring adaptive cruise control, was modeled with the Enhanced IDM Model. Data from simulations of level 1 exhibited a significant improvement in mobility over that of level 0. Level 2, featuring automated lane centering and ACC, was modeled with the Enhanced IDM Model and a third-order autoregressive time series model for lane centering. Level 2s performance indicated it provided or far more stable mobility than levels 1 and 0, which would result in less accidents. Level 3 represented the synthesis of level 2s automated features with automated lane changing enabled by modeling with MOBIL. The automated lane changing prompted a higher rate of lane changes than lower levels, providing for more efficient traffic movement. We observe that for SAE level 4 there can be a negative impact on the traffic flow due to transition to minimal risk condition under poor lane markings. SAE level 5 is able to overcome these traffic disruptions and oscillations and has a smoother velocity and acceleration profile. We conclude that AVs can have significant benefits on safety and mobility.

This work will be an asset for practitioners, policymakers, OEMs and researchers to perform capacity analysis, highway design, mobility analysis as the autonomous future becomes a reality. Our model can be used as a platform to integrate new ADAS features and evaluate their impact on traffic.

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