Resuming manual control or not? Modeling choices of control transitions in full-range adaptive cruise control

Varotto, Silvia F.; Farah, Haneen; Toledo, Tomer; Van Arem, Bart; Hoogendoorn, Serge P.

DOI
10.3141/2622-04

Publication date
2017

Document Version
Final published version

Published in
Transportation Research Record

Resuming Manual Control or Not?

Modeling Choices of Control Transitions in Full-Range Adaptive Cruise Control

Silvia F. Varotto, Haneen Farah, Tomer Toledo,
Bart van Arem, and Serge P. Hoogendoorn

Automated vehicles and driving assistance systems such as adaptive cruise control (ACC) are expected to reduce traffic congestion, accidents, and levels of emissions. Field operational tests have found that drivers may prefer to deactivate ACC in dense traffic flow conditions and before changing lanes. Despite the potential effects of these control transitions on traffic flow efficiency and safety, most mathematical models evaluating the impact of ACC do not adequately represent that process. This research aimed to identify the main factors influencing drivers' choice to resume manual control. A mixed logit model that predicted the choice to deactivate the system or overrule it by pressing the gas pedal was estimated. The data set was collected in an on-road experiment in which 23 participants drove a research vehicle equipped with full-range ACC on a 35.5-km freeway in Munich, Germany, during peak hours. The results reveal that drivers were more likely to deactivate the ACC and resume manual control when approaching a slower leader, when expecting vehicles cutting in, when driving above the ACC target speed, and before exiting the freeway. Drivers were more likely to overrule the ACC system by pressing the gas pedal a few seconds after the system had been activated and when the vehicle decelerated. Everything else being equal, some drivers had higher probabilities to resume manual control. This study concludes that a novel conceptual framework linking ACC system settings, driver behavior characteristics, driver characteristics, and environmental factors is needed to model driver behavior in control transitions between ACC and manual driving.

Automated vehicles and driving assistance systems can contribute to reduce congestion, accidents, and levels of emissions. Automated vehicles may increase roadway capacity, improve traffic flow stability, and speed up the outflow from a queue (*1*). The functionalities of automated systems are gradually introduced into the market, such as in the case of adaptive cruise control (ACC). The ACC is designed to maintain a desired speed and time headway, therefore influencing substantially the performance of the driving task. The impact of ACC systems on driving behavior has been extensively analyzed since the 1990s, primarily in driving simulator experiments. Field operational tests have shown potential safety benefits of ACC systems that are inactive at low speeds when they are activated: drivers maintain larger time headways (*2–5*), follow the leader twice as long as in manual driving (*4*), and prepare lane changes in advance to refrain from interactions with slower vehicles (*2*). A possible explanation for these behavioral adaptations is that, when the ACC is active, drivers do not manually control the vehicle (*1*).

These findings, however, might be biased by the circumstances in which the system is engaged (e.g., medium-high speeds, medium-light traffic, and noncritical conditions). In certain traffic situations, drivers may prefer to deactivate the system and resume manual control, or the system deactivates because of its functioning limitations. These transitions between automation and manual driving are called control transitions (*6*) and may have a significant impact on traffic flow efficiency (*7*) and safety (*8*). The characteristics of the ACC, the road, the traffic flow, and the drivers affect the initiation of these transitions (*9*). Field operational tests have shown that dense traffic conditions (*4, 10*) and maneuvers such as lane changing may influence drivers' decision to disengage ACC systems that are inactive at low speeds. Recently, these functioning limitations have been overcome by the introduction of full-range ACC systems that can operate in stop-and-go conditions. Full-range ACC has been shown to positively affect traffic flow efficiency (*11*). To quantify this effect at varying penetration rates, mathematical models of manually driven and automated vehicles should be developed and implemented into microscopic traffic simulation models. However, most current car-following and lane-changing models do not account for these control transitions. A few microscopic traffic flow models (*12, 13*) have implemented deterministic decision rules for transferring control between ACC and manual driving, ignoring heterogeneity between and within drivers in the decision-making process. Thus the impacts on traffic flow predicted by these models could be misleading.

This research explores the factors that influence transitions from full-range ACC to manual control. A mixed logit model for this transition choice is estimated using a data set collected in a controlled on-road experiment. The paper is structured as follows. The next section discusses potential reasons for control transitions and limitations of existing models for these transitions. This section is followed by a description of the controlled on-road experiment. Next, the model specification and the estimation results are presented. The last section discusses the main factors influencing transitions to manual control and directions for future research.

S. F. Varotto, H. Farah, B. van Arem, and S. P. Hoogendoorn, Department of Transport and Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Stevinweg 1, P.O. Box 5048, 2600 GA Delft, Netherlands. T. Toledo, Transportation Research Institute, Faculty of Civil and Environmental Engineering, Technion–Israel Institute of Technology, 711 Rabin Building, 32000 Haifa, Israel. Corresponding author: S. F. Varotto, s.f.varotto@tudelft.nl.

Transportation Research Record: Journal of the Transportation Research Board, No. 2622, 2017, pp. 38–47.
http://dx.doi.org/10.3141/2622-04

LITERATURE REVIEW

This section reviews available behavioral theories and models for control transitions between ACC and manual driving, on the basis of on-road studies in real traffic [for a review of data collection methods, refer to Carsten et al. (*14*)]. Notably, transitions of control between ACC and manual driving in safety-critical situations and automation failures have also been investigated in driving simulator experiments with a high degree of controllability [for a review, refer to Varotto et al. (*7*)].

Control transitions can be initiated by the driver voluntarily or by the automated system because of its own functioning limitations. Lu and de Winter proposed a classification of transitions of control based on who (driver or automation) initiates the transition and who is in control afterward (*6*). Therefore, transitions are defined as driver initiated driver in control (DIDC) when drivers deactivate the system, driver initiated automation in control (DIAC) when drivers activate it, and automation initiated driver in control (AIDC) when the system disengages because of its functioning limitations. The circumstances in which these transitions occur appear to be strongly related to the characteristics of the driver support system. Several field operational tests (*2, 4, 10, 15*) have investigated driving behavior with ACC systems that are inactive at speeds below 30 km/h and have limited decelerations capabilities. DIAC transitions may occur for comfort reasons (*16, 17*) in noncritical and nondense traffic situations [e.g., after entering the freeway (*2*)]. DIDC transitions by braking have been primarily related to safety indicators such as time to collision. Xiong and Boyle classified events in which ACC decelerates automatically into near-crash, conflict, and low-risk cases on the basis of time to collision and distance headway rate (*15*). They found that drivers were more likely to resume control by braking in near-crashes (56%) and conflicts (42%), compared with low-risk situations (7%). However, drivers can also resume manual control in situations that ACC is able to manage when the response of the system does not match their expectations (*18*). Viti et al. found that most ACC deactivations occurred in noncritical situations; in their study, 65% to 70% of the deactivations were initiated by braking lightly, 20% to 25% without braking, and only 5% to 10% by braking hard (*10*). They concluded that drivers transfer to manual control to maintain a constant speed in medium-dense traffic conditions. Other studies (*16, 17*) proposed that further reasons to initiate DIDC transitions include preparation for changing lanes, anticipation of vehicles merging into the lane, and avoiding overtaking slower vehicles on the left lanes. AIDC transitions occur when the system fails (e.g., the sensors malfunction) or when the required control exceeds the system limits (e.g., hard braking is needed).

However, control transitions with full-range ACC systems might be initiated in different situations. In a controlled on-road experiment, Pereira et al. found that DIDC transitions occurred when the vehicle exited the freeway (51% of the deactivations), approached a moving vehicle (13%), and changed lane (13%), and when the leader changed lanes or a vehicle cut in (22%) (*19*). They also suggested that DIDC transitions by pressing the gas pedal can be seen as a compensation strategy to increase the complexity of a situation considered to be too simple. This study did not find significant learning effects related to control transition behavior over the duration of the experiment.

To date, few microscopic traffic flow models have accounted for the possibility of control transitions between ACC and manual driving. Van Arem et al. developed a microscopic traffic simulation model (MIXIC) in which drivers activated and deactivated the ACC (*12*). DIDC is initiated when the situation requires hard braking, when the vehicle approaches a considerably slower leader, and when changing lanes. DIAC is initiated when the current acceleration is in the range -0.5 to 0.5 m/s^2 and when the current distance headway allows synchronizing the speed with a deceleration equal to -1 m/s^2. On the basis of this model and empirical findings by Viti et al. (*10*), Pauwelussen and Feenstra (*16*), and Pauwelussen and Minderhoud (*17*), Klunder et al. (*13*) proposed a microscopic traffic simulation model (ITS Modeler) in which DIDC is initiated when the absolute value of the difference between the desired acceleration and the ACC acceleration is larger than 3.5 m/s^2 and the relative speed between the leader on the left lane and the subject vehicle is larger than 3.0 m/s. AIDC transitions occur when the desired speed or acceleration is outside the range supported by the system (30 to 160 km/h and -3 to $+3$ m/s^2). Drivers are assumed to activate the system (DIAC) after it has been inactive for at least 5 s and when both the speed and the acceleration are within the ranges of 36 to 160 km/h and 0 to 3 m/s^2. The main limitation of these models is that the decision rules are deterministic: heterogeneity between and within drivers in the decision-making process is ignored.

Xiong and Boyle estimated a logistic regression model to predict the probability that drivers would brake to initiate a DIDC transition as they closed in on a leader (*15*). They included variables that describe the situation and characteristics of the driver in their model. They found that drivers are more likely to intervene in nonhighway environments, at lower speeds, and with short gap settings. In addition, middle-aged drivers are more likely to resume manual control than young drivers. However, this model only handles transitions in a narrowly defined set of situations.

In summary, to date, limited efforts have been made to study and model control transitions in a way that would be suitable for implementation in microscopic traffic simulation models. This paper presents a mixed logit model predicting the probability of DIDC transitions, both deactivation (by braking or using the on–off button) and overruling (by pressing the gas pedal) of the ACC system.

DATA COLLECTION

A controlled on-road experiment was conducted using a BMW 5 Series research vehicle equipped with a standard version of full-range ACC. The experiment took place on the section of the A99 freeway in Munich, Germany, shown in Figure 1. The experiment consisted of a single 46-km-long drive using different freeway facilities (basic sections, on- and off-ramps) in varying traffic densities. In light traffic conditions, speed limits were not enforced in most of the main line. In medium-dense traffic conditions, a variable speed limit system recommended a certain speed (120, 100, 80, 60, or 40 km/h) based on real traffic information. The freeway sections were mostly separated six lanes. The test route was preset in the navigation system. Participants were instructed to try the ACC system and select their preferred gap setting in the first freeway segment. In the other 35.5 km of the route, they were asked to drive as they would do in real life, regulating the desired speed setting at any time and using the ACC system as they thought it was appropriate.

ACC System Specifications

The ACC system used in the experiment controls the speed in the range between 0 and 210 km/h and the time headway at speeds above 30 km/h. Drivers can select one of the following desired time

(a) (b)

FIGURE 1 A99 in Munich: (*a*) map (*20*) and (*b*) picture of the test route.

headways: 1.0, 1.4, 1.8, and 2.2 s. The ACC supports an acceleration range between -3 m/s^2 and $+3$ m/s^2, and the response sensitivity cannot be customized with respect to acceleration characteristics. When the radar (120-m range) does not detect any leader, the system maintains the desired speed as a conventional cruise control system. Figure 2 shows the three system states (inactive, active, and active and accelerate) and the transitions between them. When the system is inactive, it can be activated by pressing the on–off button, the desired speed setting switch, or the resume button. When the system is active, it can be deactivated by pressing the on–off button or by braking (to inactive) and temporarily overruled by pressing the gas pedal (to active and accelerate). When the gas pedal is released, the system transfers back to active.

Participants and Data Collection

Twenty-three participants (15 males, 8 females) were recruited from BMW employees who were not involved in the development of the system. Their age ranged between 25 and 51 years old (M = 31.57, SD = 6.73), and their driving experience between 3 and 33 years (M = 13.04, SD = 7.16). Six participants had no experience with ACC, nine were used to driving with ACC less than once a month, and eight more often than once a month. Participants received written instructions on the general scope of the research, the ACC system specifications, and the potential safety risks. Notably, the precise aim of the experiment (i.e., investigating driving behavior in control transitions) was not disclosed and a written informed consent was signed.

The experiment was conducted during morning and evening peak hours (7 to 9 a.m., 4 to 6 p.m., 6 to 8 p.m.) from June 29 to July 9, 2015. Participants were assigned to one of the above-mentioned time slots and drove between 45 and 90 min depending on the traffic conditions. The instrumented vehicle recorded the ACC system settings and state, GPS position, speed, acceleration, leader distance headway (from radar), and leader speed and acceleration (from radar). The data were synchronized and recorded at a frequency of 50 Hz (e.g., speed and acceleration of the subject vehicle), 15 Hz (e.g., distance headway), and 1 Hz (GPS position).

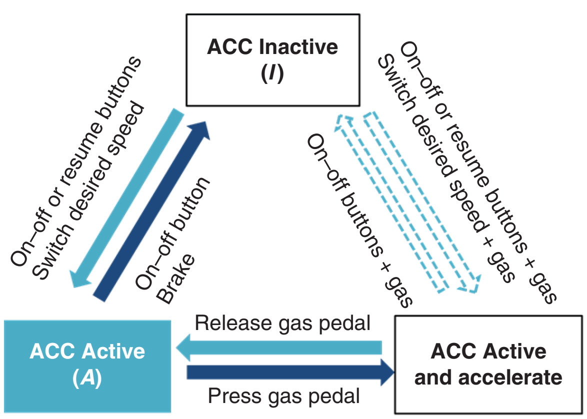

FIGURE 2 ACC system specifications [white boxes = system states in which drivers are in control; light-blue box = states in which ACC is in control; solid arrows = driver-initiated control transitions between ACC system states; dashed arrows = state transitions; light-blue solid arrows = driver-initiated automation in control transitions (DIAC); and dark-blue solid arrows = driver-initiated driver in control transitions].

DATA ANALYSIS

The data collected on the 35.5 km of the experiment for the 23 drivers were analyzed to understand the conditions in which control transitions occurred most often. This paper focuses on control transitions in cases that did not involve lane changes (within a time window of 10 s before and 10 s after the transition). The data were reduced to 1-Hz resolution, which resulted in 31,165 observations.

Overall, the ACC system was active in 83.8% of the observations, active and accelerate in 3.4%, and inactive in 12.8%. A leader was detected by the radar (120-m range) in 89.6% of the observations. In this paper, 23,568 1-s observations are analyzed in which the ACC system is active and a leader is detected. Of these, the number of observations for each driver ranges from 334 to 1,936 (M = 1,025, SD = 467). Fifty-five observations (0.23%) were immediately followed by a DIDC transition to inactive (deactivations), 106 (0.45%) by a DIDC transition to active and accelerate (overruling), and 23,407 (99.3%) by no transitions. Transitions initiated by the system are not analyzed. Drivers transferred to inactive from zero to seven times (M = 2.39, SD = 1.83) and to active and accelerate from zero to 26 times (M = 4.61, SD = 5.88).

Figure 3, to explore the circumstances in which the control transitions were initiated, compares the empirical cumulative distribution functions (CDFs) of the driver behavior characteristics when no transitions occurred, when the system was deactivated, and when it was overruled. Table 1 presents the mean and the standard deviations of these variables and the results of two-sample Kolmogorov–Smirnov tests on the similarity of the distributions between the three groups. Figure 3*a* shows that most transitions were initiated a few seconds after the ACC had been activated. Notably, 48.1% of the transitions to active and accelerate occurred up to 7 s after the activation. The distributions of time after last activation differed significantly between the three groups. Figure 3*b* indicates that most transitions were initiated at speeds between 80 and 130 km/h and, within this interval, transitions to active and accelerate were more frequent at higher speeds. The distributions of speed differed significantly between the three groups. Figure 3*c* shows that 76.1% of the transitions to active and accelerate occurred when the vehicle decelerated. Figure 3*d* illustrates that 86.3% of the deactivations

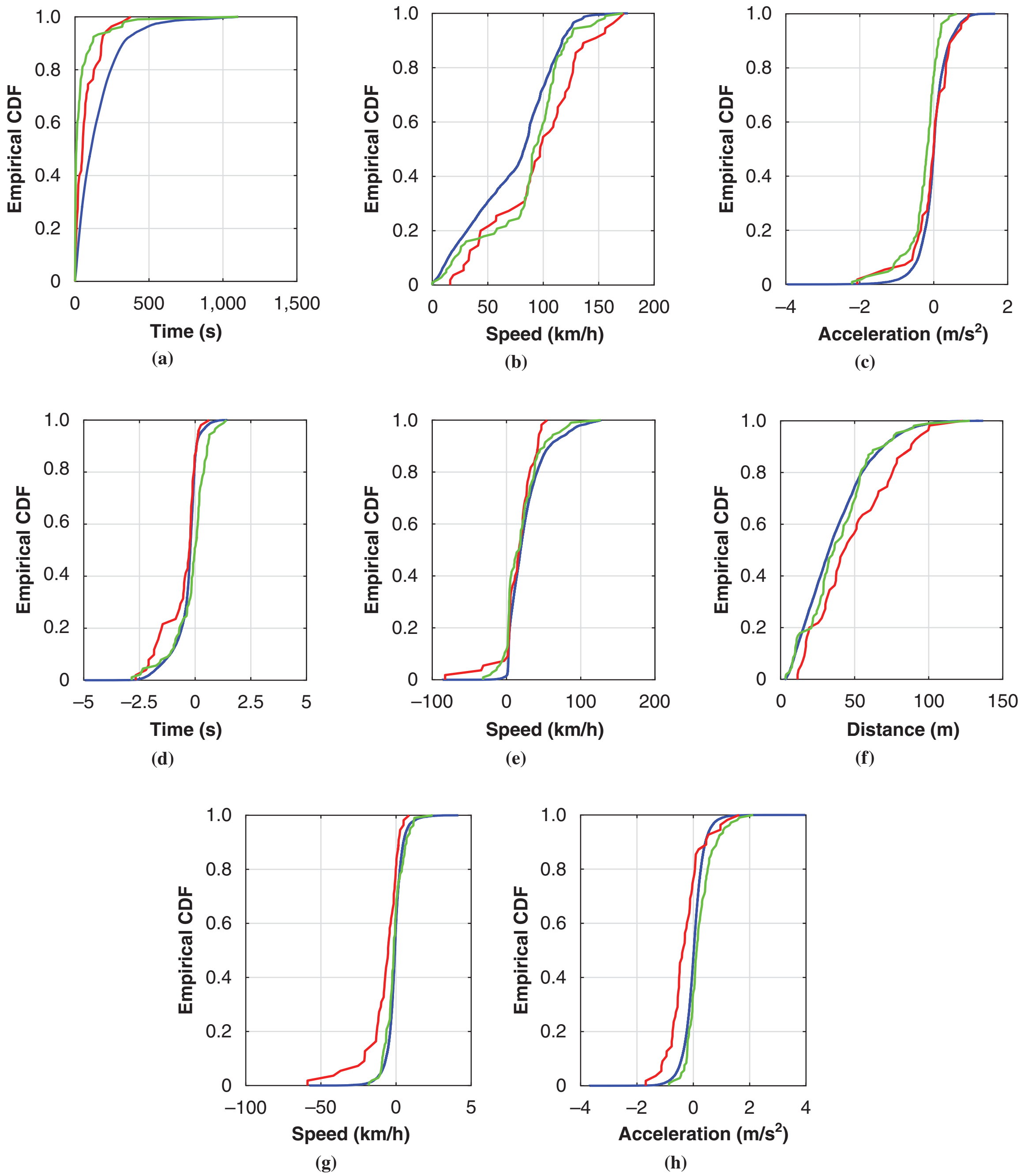

FIGURE 3 Empirical cumulative distribution functions of driver behaviors when system is maintained active (blue) and when transitions to inactive (red) and to active and accelerate (green) are initiated. Variables plotted are (*a*) time after last activation, (*b*) speed, (*c*) acceleration, (*d*) target time headway – time headway, (*e*) target speed – speed, (*f*) distance headway, (*g*) relative speed, and (*h*) relative acceleration.

TABLE 1 Statistics on Driver Behavior When System Is Maintained as Active and When Control Transitions Are Initiated to Inactive and to Active and Accelerate

		Mean and Standard Deviation			Two-Sample Kolmogorov–Smirnov Test: *p*-Value		
Variable	Description	*A*	*I*	AAc	*A* versus *I*	*A* versus AAc	*I* versus AAc
Time after last activation	Time after ACC has been activated (s)	152 (155)	76.0 (83.2)	50.3 (128)	4.73×10^{-5}	9.04×10^{-27}	8.64×10^{-5}
Speed	Speed of subject vehicle (km/h)	72.8 (37.9)	94.8 (40.9)	86.5 (36.9)	.00112	4.91×10^{-5}	.0486
Acceleration	Acceleration of subject vehicle (m/s^2)	−0.00254 (0.390)	−0.0491 (0.549)	−0.272 (0.462)	.432 (*)	2.01×10^{-10}	.00320
Target time headway – time headway	Difference between target time headway set in ACC and time headway (front bumper to rear bumper) (s)	−0.364 (0.561)	−0.574 (0.758)	−0.160 (0.780)	.192 (*)	1.79×10^{-11}	.000110
Target speed – speed	Difference between target speed set in ACC and subject vehicle speed (km/h)	25.6 (25.0)	16.2 (22.2)	20.2 (24.9)	.239 (*)	.00655	.464(*)
Distance headway	Distance headway (front bumper to rear bumper) (m)	36.7 (22.9)	49.8 (27.5)	39.1 (23.1)	.00935	.147(*)	.0335
Relative speed	Difference between leader speed and subject vehicle speed (km/h)	−0.810 (5.72)	−7.84 (11.8)	−1.04 (6.33)	2.86×10^{-8}	.0902(*)	.000230
Relative acceleration	Difference between leader acceleration and subject vehicle acceleration (m/s^2)	0.0142 (0.376)	−0.287 (0.609)	0.225 (0.479)	1.20×10^{-8}	.00113	7.67×10^{-9}

NOTE: *A* = active; *I* = transitioning to inactive; AAc = transitioning to active and accelerate.
* = *p*-value > .05.

occurred when the actual time headway was larger than the one set in the ACC. Figure 3*e* shows that 7.3% of the deactivations and 11.3% of the overruling actions occurred when the speed was higher than the target speed set in the ACC. Figure 3*f* suggests that, on average, deactivations were associated with larger distance headways. Figure 3*g* shows that 80.0% of the deactivations and 65.1% of the overruling actions occurred when the speed of the subject was higher than the speed of the leader. The distributions of relative speed differed significantly between transitions to inactive and the other two groups. Figure 3*h* indicates that 76.4% of the deactivations happened when the subject vehicle accelerated more than the leader. The distributions of relative acceleration differed significantly between the three groups. In addition, cut-in maneuvers were detected comparing the distance headway from radar to the distance headway calculated using the speed and the acceleration of the subject vehicle and the leader in the previous observation. When this difference was larger than 7 m, it was assumed that the distance headway reduction was caused by a new vehicle cutting in. The authors conclude that the driver behavior characteristics of the subject vehicle and the leader may influence significantly the choice to resume manual control.

Freeway sections of increased lane changing, merging, and weaving were associated with more frequent control transitions (Table 2). Deactivations occurred more often when drivers were on the freeway main line close to an on-ramp and in the segment between the first exit sign and the exit (1,600 m). Drivers overruled the system more often in proximity to on-ramps and between ramps placed at a distance shorter than 600 m, which might cause disturbances to traffic flow (*21*). Significant differences in transferring control were also associated with drivers with different characteristics (Table 3).

TABLE 2 Statistics on Road Sections When System Is Maintained as Active and When Control Transitions Are Initiated to Inactive and to Active and Accelerate

		Observation (percentage per group)		
Variable	Description	*A*	*I*	AAc
On-ramp	Freeway main line close to an on-ramp	3,608 (15.4)	16 (29.1)	26 (24.5)
Off-ramp	Freeway main line close to an off-ramp	274 (1.2)	3 (5.5)	1 (0.9)
Between ramp	Freeway main line between ramps closer than 600 m	987 (4.2)	3 (5.5)	10 (9.4)
Exit	Freeway main line between first exit sign and exit (1,600 m)	1,934 (8.3)	11 (20.0)	3 (2.8)
Total		23,407 (100)	55 (100)	106 (100)

TABLE 3 Statistics on Driver Characteristics When System Is Maintained Active and When Control Transitions Are Initiated to Inactive and to Active and Accelerate

	Observation (percentage per group)			Chi-Square Test		
Variable	*A*	*I*	AAc	df	χ	*p*-Value
Gender				2	9.49	.009
Male ($n = 15$)	15,707 (67.1)	36 (65.5)	86 (81.1)			
Female ($n = 8$)	7,700 (32.9)	19 (34.5)	20 (18.9)			
Driving experience				2	14.4	.0007
3–12 years ($n = 16$)	16,347 (71.6)	38 (76.0)	86 (88.7)			
13–33 years ($n = 7$)	6,493 (28.4)	12 (24.0)	11 (11.3)			
Experience with ADAS				4	14.9	.005
Inexperienced ($n = 6$)	6,246 (26.7)	10 (18.2)	15 (14.2)			
Medium experienced ($n = 9$)	7,905 (33.8)	22 (40.0)	51 (48.1)			
Experienced ($n = 8$)	9,256 (39.5)	23 (41.8)	40 (37.7)			

Females and drivers with 13 to 33 years of driving experience (31 to 50 years old) overruled the system less often. Drivers inexperienced with advanced driver assistance systems (ADAS) transferred control less often and drivers with medium experience with ADAS resumed control more often.

CHOICE MODEL FOR TRANSITIONS TO MANUAL CONTROL

A discrete choice model was developed for the decision to maintain the system active, to transfer to inactive (by pressing the brake pedal or the on–off button), or to transfer to active and accelerate (by pressing the gas pedal). Since these transitions are intentionally initiated by the drivers, it was assumed that only one transition may occur within a 1-s interval, a value similar to the mean reaction time between the detection of a stimulus and the application of the response available in literature (*22*). The choices are modeled for this time interval and are associated with the driver behavior characteristics registered at the beginning of the interval. Repeated observations of multiple time intervals (panel data) are available for each driver. To predict the probabilities of transition choices capturing this panel dimension, a mixed logit model was estimated introducing a driver-specific error term ϑ_n assumed to be normally distributed over the sample (*22*). This driver-specific error term captures unobserved preferences that affect all choices made by the individual driver over time (i.e., the alternative specific constants differ between drivers). Below, the final specification is presented, selected on the basis of statistical significance. The utility functions for remaining active (A), transitioning to inactive (I), and transitioning to active and accelerate (AAc) for driver n at time t are given by Equations 1 to 3:

$$U_n^A(t) = 0 + \varepsilon_n^A(t) \tag{1}$$

$$\begin{aligned} U_n^I(t) = {} & \alpha^I + \beta_{\text{TimeAct}}^I \cdot \log(\text{TimeAct}(t)) + \beta_{\text{Speed}} \cdot \text{Speed}(t) \\ & + \beta_{\text{LowTarSpeed}} \cdot \text{LowTarSpeed}(t) + \beta_{\text{THW30}}^I \cdot \text{THW30}(t) \\ & + \beta_{\text{RelSpeed}}^I \cdot \text{RelSpeed}(t) + \beta_{\text{RelAcc}}^I \cdot \text{RelAcc}(t) \\ & + \beta_{\text{AntCutIn3}}^I \cdot \text{AntCutIn3}(t) + \beta_{\text{OnRamp}} \cdot \text{OnRamp}(t) \\ & + \beta_{\text{exit}}^I \cdot \text{Exit}(t) + \gamma \cdot \vartheta_n + \varepsilon_n^I(t) \end{aligned} \tag{2}$$

$$\begin{aligned} U_n^{\text{AAc}}(t) = {} & \alpha^{\text{AAc}} + \beta_{\text{TimeAct}}^{\text{AAc}} \cdot \log(\text{TimeAct}(t)) + \beta_{\text{speed}} \cdot \text{Speed}(t) \\ & + \beta_{\text{LowTarSpeed}} \cdot \text{LowTarSpeed}(t) + \beta_{\text{Acc}-}^{\text{AAc}} \cdot \text{AccNeg}(t) \\ & + \beta_{\text{Acc}+}^{\text{AAc}} \cdot \text{AccPos}(t) + \beta_{\text{RelSpeed}}^{\text{AAc}} \cdot \text{RelSpeed}(t) + \beta_{\text{CutIn}}^{\text{AAc}} \\ & \cdot \text{CutIn}(t) + \beta_{\text{OnRamp}} \cdot \text{OnRamp}(t) + \beta_{\text{Female}}^{\text{AAc}} \cdot \text{Female}_n \\ & + \beta_{\text{ExpDriv}}^{\text{AAc}} \cdot \text{ExpDriving}_n + \gamma \cdot \vartheta_n + \varepsilon_n^{\text{AAc}}(t) \end{aligned} \tag{3}$$

where

α^I and α^{AAc} = alternative specific constants,
β^I and β^{AAc} = vectors of parameters associated with explanatory variables listed in Table 4,
γ = parameter associated with individual-specific error term $\vartheta_n \sim N(0,1)$, and
$\varepsilon_n^A(t)$, $\varepsilon_n^I(t)$, and $\varepsilon_n^{\text{AAc}}(t)$ = independent and identically distributed Gumbel error terms.

The model was estimated using the software PythonBiogeme (*23*). The log likelihood values, the goodness-of-fit indicators, and the estimation results are presented in Table 4. Most parameters associated with the explanatory variables in the utility functions are statistically significant at the 95% confidence level. The variables associated with transition-specific parameters had a significantly different impact on transitions to inactive and to active and accelerate. Both alternative specific constants are negative and large in magnitude, indicating that drivers are more likely to keep the system active than to transfer to manual control. Everything else being equal, drivers are more likely to overrule than to deactivate the system. The probability that drivers would resume manual control is highest in the first few seconds after the system has been activated. The logarithmic transformation is consistent with the empirical distribution function of time presented in Figure 3*a* and resulted in a significantly better fit than a linear specification. This effect is stronger for overruling than for deactivating the system. Analyzing the driver behavior characteristics of the subject vehicle, one notes that drivers are more likely to resume manual control at higher speeds. In addition, they are more likely to intervene when their speed is higher than the target speed set in the ACC and this probability increases for larger differences. Speeds lower than the target speed had nonsignificant effects on transitions. Drivers are more likely to overrule the system when the ACC acceleration is low. The time headway and the target time headway set in the ACC did not influence significantly the choice to overrule

TABLE 4 Statistics and Estimation Results of Mixed Logit Model

Variable	Description	Parameters	Estimate	*T*-Test
—	Alternative specific constant	α^{I}	−6.56	−11.3
—	Alternative specific constant	α^{AAc}	−3.01	−5.73
TimeAct	Time after ACC has been activated (s)	$\beta^{I}_{TimeAct}$	−0.198	−1.96
TimeAct	Time after ACC has been activated (s)	$\beta^{AAc}_{TimeAct}$	−0.740	−10.7
Speed	Speed of subject vehicle (km/h)	β_{Speed}	0.00705	2.79
LowTarSpeed	Difference between target speed set in ACC and speed of subject vehicle when the former is relatively lower (km/h)	$\beta_{TarSpeed-}$	−0.0290	−1.90*
AccNeg	Acceleration of subject vehicle (m/s^2) when this value is negative	β^{AAc}_{Acc-}	−1.52	−5.79
AccPos	Acceleration of subject vehicle (m/s^2) when this value is positive	β^{AAc}_{Acc+}	−3.71	−3.63
THW30	Time headway (front bumper to rear bumper) (s) when speed is higher than 30 km/h	β^{I}_{THW30}	−0.357	−1.84*
RelSpeed	Relative speed (leader speed − subject vehicle speed) (km/h)	$\beta^{I}_{RelSpeed}$	−0.106	−6.96
RelSpeed	Relative speed (leader speed − subject vehicle speed) (km/h)	$\beta^{AAc}_{RelSpeed}$	0.0574	3.82
RelAcc	Relative acceleration (leader acceleration − subject vehicle acceleration) (m/s^2)	β^{I}_{RelAcc}	−1.40	−5.69
AntCutIn3	Number of vehicles that will cut in during the following three seconds	$\beta^{I}_{AntCutIn3}$	1.77	6.96
CutIn	Dummy variable equal to 1 when a vehicle cuts in front of the subject	β^{AAc}_{CutIn}	1.91	3.68
OnRamp	Dummy variable equal to 1 when drivers are in main line close to an on-ramp or between two ramps closer than 600 m (*20*)	β_{OnRamp}	0.541	2.91
Exit	Dummy variable equal to 1 when distance to closest exit is less than 1,600 m (first exit sign)	β^{I}_{Exit}	1.93	5.15
Female	Dummy variable denoting female drivers	β^{AAc}_{Female}	−0.985	−2.56
ExpDriving	Years of driving experience	$\beta^{AAc}_{ExpDriv}$	−0.0456	−1.87*
ϑ_n	Individual specific error term	γ	0.857	4.23

NOTE: — = not applicable. Number of parameters K associated with explanatory variables = 17; number of alternative specific constants = 2; number of drivers = 23; number of observations = 23,568; constant log likelihood $\mathcal{L}(c) = -1{,}067$; final log likelihood $\mathcal{L}(\beta) = -818$; adjusted likelihood ratio index (rho-bar-squared) is $\bar{\rho}^2 = 1 - (\mathcal{L}(\hat{\beta}) - K)/\mathcal{L}(c) = 0.217$.
* = .05 < p-value < .10.

the system. Drivers are more likely to deactivate when the time headway is short for speeds higher than 30 km/h. The time headway at speeds lower than 30 km/h, the target time headway set in the ACC, and the ACC acceleration did not have a significant effect on deactivations. The driver behavior characteristics of the leader have a different effect on overruling and deactivating. Drivers are more likely to deactivate when they are faster (negative relative speed) and accelerate more (negative relative acceleration) than the leader and to overrule when they are slower (positive relative speed). Relative accelerations had a nonsignificant effect on choices to overrule. Drivers are more likely to deactivate the system when they expect that a vehicle will cut in during the next 3 s (proactive behavior) and to overrule after a vehicle has cut in (reactive behavior). This specification was selected on the basis of statistical significance, assuming that drivers are able to anticipate traffic conditions up to 3 s downstream (without any error in their predictions) and can be influenced by events that occurred in the previous 10 s.

Road locations influenced significantly the choices to transfer control. Drivers are more likely to deactivate the system close to on-ramps, between two ramps (closer than 600 m), and before exiting the freeway. The latter is consistent with previous findings (*19*). Drivers are more likely to overrule close to on-ramps and between two ramps. Proximity to exits did not influence significantly the decision to overrule the system. Proximity to off-ramps had a nonsignificant effect on transitions.

Notably, driver characteristics have a significant effect on transition choices. Female drivers and experienced drivers are less likely to overrule the system. However, these driver characteristics did not influence deactivations significantly. In addition, experience with ADAS did not affect significantly the transition choices. It was assumed that the driver-specific error terms for overruling and deactivating the ACC are equal because these terms were strongly correlated (r = .908), suggesting that drivers who deactivate more frequently also overrule more frequently. The effects of these terms on the transitions were nonsignificantly different, meaning that the variability between drivers in deactivating and overruling is similar (i.e., the alternative specific constants have equal variance).

To illustrate the impact of changes in the explanatory variables on the choice probabilities, the choice probability ratio was calculated between a baseline observation and observations in which only one variable was changed while all the other variables were kept fixed. In the baseline observation (choice probability ratio equal to 1), the driver was assumed to be a male with 13 years of driving experience. The actual speed was assumed to be equal to 89.3 km/h and lower than the target speed, the acceleration −0.195 m/s^2, the time headway 1.79 s, the relative speed −3.37 km/h, and the relative acceleration 0.0648 m/s^2. In addition, it was assumed that the ACC system had been activated for 59 s and the observation was not influenced by ramps, exits, or cut-in maneuvers. These values were chosen on the basis of the average conditions of the observed control transitions. The results are shown in Figure 4 (ratio variables) and Table 5 (ordinal and nominal variables). All results are consistent with previous discussions. Comparing the plots in Figure 4 reveals that the time after activation, the acceleration (negative), the difference between target speed and actual speed (negative), and the driver-specific error term (positive) have a stronger impact on the

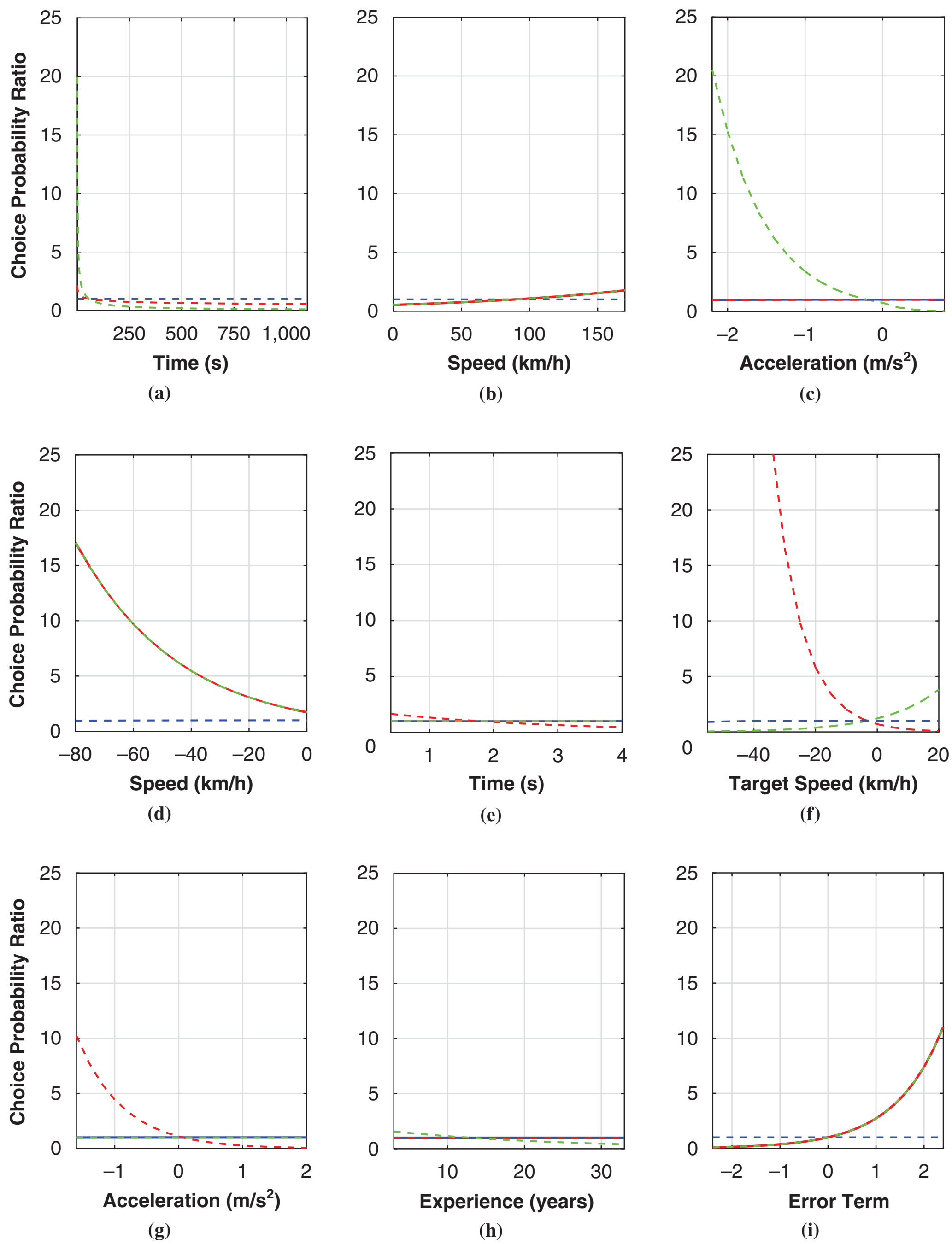

FIGURE 4 Effect of explanatory variables and driver-specific error term on choice probability ratio of keeping ACC active (blue), transferring to inactive (red), and transferring to active and accelerate (green). Variables plotted are (*a*) time after last activation, (*b*) speed, (*c*) acceleration, (*d*) target speed – speed, (*e*) time headway, (*f*) relative speed, (*g*) relative acceleration, (*h*) driver experience, and (*i*) driver-specific error term γ.

TABLE 5 Effect of Explanatory Variables (Ordinal and Nominal) on Choice Probability Ratio (Probability Predicted Divided by Probability Baseline Observation) of Keeping ACC Active, Transferring to Inactive, and Transferring to Active and Accelerate

Variable	*A*	*I*	AAc
CutIn	0.9909	0.9909	6.687
$AntCutIn_3 = 1$	0.9977	5.838	0.9977
$AntCutIn_3 = 2$	0.9846	33.71	0.9846
$AntCutIn_3 = 3$	0.9142	183.1	0.9142
OnRamp	0.9985	1.715	1.715
Exit	0.9972	6.884	0.9972
Female	1.001	1.001	0.3737

decision of overruling the system. The difference between target speed and actual speed (negative), the relative speed (negative), the relative acceleration (negative), and the driver-specific error term (positive) are the variables that influence most the decision of deactivating the system. In Table 5, note that the probability of deactivations is strongly influenced by the number of vehicles that are expected to cut in over the next 3 s.

DISCUSSION AND CONCLUSIONS

The aim of this paper was to identify the factors that influence drivers' decision to initiate a control transition between ACC and manual driving, which may have a significant impact on traffic flow efficiency (*7*) and safety. To gain empirical insight into the decision-making process, the authors estimated a mixed logit model with panel data collected in an on-road study. In this model, it was found that drivers are more likely to deactivate the system when approaching a slower leader, when driving above the ACC target speed, and when expecting vehicles cutting in over the following 3 s. Drivers are more likely to overrule the ACC by pressing the gas pedal a few seconds after the system has been activated, when the vehicle decelerates, and when driving above the ACC target speed.

The study concludes that drivers deactivate the system when the speed and acceleration of the leader are lower than their (unobservable) desired speed and acceleration. This condition happens when the leader is slower than the subject vehicle and the ACC system automatically decreases the speed to synchronize [similar to findings in Xiong and Boyle (*15*) and Pereira et al. (*19*)]. The desired speed and acceleration might be influenced by environmental conditions that cause disturbances to traffic flow, such as proximity to ramps and exits. In addition, drivers deactivate to anticipate cut-ins in the following few seconds, questioning whether the system will be able to handle a potential safety-critical situation. Drivers press the gas pedal when the ACC acceleration is lower than their desired acceleration, which is influenced by the functioning of the system (e.g., how long the system has been active) and by environmental conditions (e.g., proximity to ramps). In general, drivers transfer to manual control more often when driving above the ACC target speed (which has been reached by pressing the gas pedal in the previous observations), meaning that the target speed does not correspond to the desired speed anymore. Notably, some drivers (positive driver-specific error term) are more likely to deactivate and to overrule the system than others. Further research is needed to determine the origin of this effect, which may be linked to personality traits and driving styles.

The generalizability of the results presented is subject to certain limitations. For instance, the participants were not a sample representative of the driver population in relation to age, gender, employment status, and experience with ADAS. Because it was limited to 23 participants who drove the test route only once, this study gained little insight into the factors explaining heterogeneity between drivers. Moreover, the results presented are related to the characteristics of the ACC system tested and cannot be generalized to other technologies. Finally, the effects of the average traffic conditions (mean speed and flow from point-based loop detectors) and of the variable speed limits were not accounted for in the choice model, assuming that data at the individual vehicle level (driver behavior characteristics of the subject vehicle and of the direct leader) are more informative predictors of the decision-making process.

The key implication of this study is that, to assess the effects of ACC on traffic flow including control transitions, a conceptual framework is needed that links ACC system settings, driver behavior characteristics, driver characteristics, and environmental factors. Future research will focus on the mathematical formulation of this novel framework and on the model calibration using the data set available. The final model can be implemented into a microscopic simulation to assess the effects of control transitions on traffic flow.

ACKNOWLEDGMENTS

Silvia Varotto, Haneen Farah, Bart van Arem, and Serge Hoogendoorn conducted this research in the project HFAuto–Human Factors of Automated Driving. Tomer Toledo was funded by the Israeli Ministry of National Infrastructure, Energy, and Water Resources. The authors thank Klaus Bogenberger at Universität der Bundeswehr in Munich for his appreciated contribution in the design and setup of the experiment and Werner Huber, Pei-Shih (Dennis) Huang, and Martin Friedl of the BMW group in Munich for their valuable technical support in instrumenting the research vehicle and collecting the data.

REFERENCES

1. Hoogendoorn, R., B. van Arem, and S. Hoogendoorn. Automated Driving, Traffic Flow Efficiency, and Human Factors: Literature Review. *Transportation Research Record: Journal of the Transportation Research Board,* No. 2422, 2014, pp. 113–120. https://doi.org/10.3141/2422-13.
2. Alkim, T. P., G. Bootsma, and S. P. Hoogendoorn. Field Operational Test "The Assisted Driver." In *Proceedings of the IEEE Intelligent Vehicles Symposium,* Institute of Electrical and Electronics Engineers, Piscataway, N.J., 2007, pp. 1198–1203. https://doi.org/10.1109/IVS.2007.4290281.
3. Gorter, M. *Adaptive Cruise Control in Practice: A Field Study and Questionnaire into Its Influence on Driver, Traffic Flows, and Safety.* MSc thesis. Delft University of Technology, Netherlands, 2015.
4. Ervin, R. D. *Automotive Collision Avoidance System Field Operational Test Report: Methodology and Results.* U.S. Department of Transportation, NHTSA, 2005.
5. Malta, L., M. Ljung Aust, F. Faber, B. Met, G. Saint Pierre, M. Benmimoun, and R. Schafer. *EuroFOT Final Results: Impacts on Traffic Safety.* Ford Research and Advanced Engineering Europe, Aachen, Germany, 2012.
6. Lu, Z., and J. C. F. de Winter. A Review and Framework of Control Authority Transitions in Highly Automated Driving. In *Proceedings of the 6th International Conference on Applied Human Factors and Ergonomics,* Elsevier, New York, 2015.

7. Varotto, S. F., R. G. Hoogendoorn, B. van Arem, and S. P. Hoogendoorn. Empirical Longitudinal Driving Behavior in Authority Transitions Between Adaptive Cruise Control and Manual Driving. *Transportation Research Record: Journal of the Transportation Research Board,* No. 2489, 2015, pp. 105–114. https://doi.org/10.3141/2489-12.
8. Vlakveld, W., L. Vissers, K. Hulleman, and N. Van Nes. *An Empirical Exploration of the Impact of Control Transitions on Situation Awareness for Potential Hazards.* SWOV Institute for Road Safety Research, The Hague, Netherlands, 2015.
9. Varotto, S. F., R. G. Hoogendoorn, B. van Arem, and S. P. Hoogendoorn. Human Factors of Automated Driving: Predicting the Effects of Authority Transitions on Traffic Flow Efficiency. Presented at 2nd TRAIL Internal Congress, Delft, Netherlands, 2014.
10. Viti, F., S. P. Hoogendoorn, T. P. Alkim, and G. Bootsma. Driving Behavior Interaction with ACC: Results from a Field Operational Test in the Netherlands. In *Proceedings of the IEEE Intelligent Vehicles Symposium,* Institute of Electrical and Electronics Engineers, Piscataway, N.J., 2008, pp. 745–750. https://doi.org/10.1109/IVS.2008.4621199.
11. van Driel, C., and B. van Arem. The Impact of a Congestion Assistant on Traffic Flow Efficiency and Safety in Congested Traffic Caused by a Lane Drop. *Journal of Intelligent Transport Systems,* Vol. 14, No. 4, 2010, pp. 197–208. https://doi.org/10.1080/15472450.2010.516226.
12. van Arem, B., A. P. de Vos, and M. J. W. A. Vanderschuren. *The Microscopic Traffic Simulation Model MIXIC 1.3.* TNO Inro, Delft, Netherlands, 1997.
13. Klunder, G., M. Li, and M. Minderhoud. Traffic Flow Impacts of Adaptive Cruise Control Deactivation and (Re)Activation with Cooperative Driver Behavior. *Transportation Research Record: Journal of the Transportation Research Board,* No. 2129, 2009, pp. 145–151. https://doi.org/10.3141/2129-17.
14. Carsten, O., K. Kircher, and S. Jamson. Vehicle-Based Studies of Driving in the Real World: The Hard Truth? *Accident Analysis and Prevention,* Vol. 58, 2013, pp. 162–174. https://doi.org/10.1016/j.aap.2013.06.006.
15. Xiong, H., and L. N. Boyle. Drivers' Adaptation to Adaptive Cruise Control: Examination of Automatic and Manual Braking. *IEEE Transactions on Intelligent Transportation Systems,* Vol. 13, No. 3, 2012, pp. 1468–1473. https://doi.org/10.1109/TITS.2012.2192730.
16. Pauwelussen, J., and P. J. Feenstra. Driver Behavior Analysis During ACC Activation and Deactivation in a Real Traffic Environment. *IEEE Transactions on Intelligent Transportation Systems,* Vol. 11, No. 2, 2010, pp. 329–338. https://doi.org/10.1109/TITS.2010.2043099.
17. Pauwelussen, J., and M. Minderhoud. The Effects of Deactivation and (Re)Activation of ACC on Driver Behaviour Analyzed in Real Traffic. In *Proceedings of the IEEE Intelligent Vehicles Symposium,* Institute of Electrical and Electronics Engineers, Piscataway, N.J., 2008, pp. 257–262. https://doi.org/10.1109/IVS.2008.4621309.
18. Zheng, P., and M. McDonald. Manual Vs. Adaptive Cruise Control—Can Driver's Expectation Be Matched? *Transportation Research Part C: Emerging Technologies,* Vol. 13, No. 5–6, 2005, pp. 421–431. https://doi.org/10.1016/j.trc.2005.05.001.
19. Pereira, M., M. Beggiato, and T. Petzoldt. Use of Adaptive Cruise Control Functions on Motorways and Urban Roads: Changes over Time in an On-Road Study. *Applied Ergonomics,* Vol. 50, 2015, pp. 105–112. https://doi.org/10.1016/j.apergo.2015.03.002.
20. Google Maps. Test Route on A99 in Munich (48.1567429 N, 11.6926232 E). Accessed July 24, 2016.
21. FGSV. *Richtlinien für die Anlage von Autobahnen.* FGSV Publishing House, Cologne, Germany, 2008.
22. Toledo, T. *Integrated Driving Behavior Modeling.* PhD thesis. Massachusetts Institute of Technology, Cambridge, 2003.
23. Bierlaire, M. *PythonBiogeme: A Short Introduction.* Report TRANSP-OR 160706, Series on Biogeme. Transport and Mobility Laboratory, School of Architecture, Civil and Environmental Engineering, Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland, 2016.

The Standing Committee on Traffic Flow Theory and Characteristics peer-reviewed this paper.