# Continuous-discrete choices of control transitions and speed regulations in full-range adaptive cruise control

Varotto, Silvia; Farah, Haneen; Toledo, Tomer; van Arem, Bart; Hoogendoorn, Serge

**Publication date**
2018

**Document Version**
Final published version

**Published in**
Transportation Research Board Conference Proceedings 2018

**CONTINUOUS-DISCRETE CHOICES OF CONTROL TRANSITIONS AND SPEED REGULATIONS IN FULL-RANGE ADAPTIVE CRUISE CONTROL**

**Silvia F. Varotto** (corresponding author)
Department of Transport and Planning
Faculty of Civil Engineering and Geosciences
Delft University of Technology
Stevinweg 1, P.O. Box 5048, 2600 GA Delft, The Netherlands
Tel: +31 (0)15 2789575, Fax: +31 (0)15 2783179, Email: s.f.varotto@tudelft.nl

**Haneen Farah**
Department of Transport and Planning
Faculty of Civil Engineering and Geosciences
Delft University of Technology
Stevinweg 1, P.O. Box 5048, 2600 GA Delft, The Netherlands
Tel: +31 (0)15 2783401, Fax: +31 (0)15 2787956, Email: h.farah@tudelft.nl

**Tomer Toledo**
Transportation Research Institute
Faculty of Civil and Environmental Engineering
Technion - Israel Institute of Technology
711 Rabin Building, 32000 Haifa, Israel
Tel: +972 4 8293080, Fax: +972 4 8295708, Email: toledo@technion.ac.il

**Bart van Arem**
Department of Transport and Planning
Faculty of Civil Engineering and Geosciences
Delft University of Technology
Stevinweg 1, P.O. Box 5048, 2600 GA Delft, The Netherlands
Tel: +31 (0)15 2786342, Fax: +31 (0)15 2783179, Email: b.vanarem@tudelft.nl

**Serge 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, The Netherlands
Tel: +31 (0)15 2785475, Fax: +31 (0)15 2783179, Email: s.p.hoogendoorn@tudelft.nl

**PAPER NUMBER 18-03199**

Extended abstract: 1719 words, 1 figure, 2 tables

Submission date: November, 15th 2017

## 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.

## INTRODUCTION

Driving assistance systems such as Adaptive Cruise Control (ACC) and automated vehicles can contribute to mitigate traffic 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 have been gradually introduced into the market, such as in the case of Adaptive Cruise Control (ACC). The ACC assists drivers in maintaining a desired speed and time headway, therefore influencing substantially the performance of the driving task. On-road studies have shown potential safety benefits of ACC systems that are inactive at low speeds when they are activated (*2-5*). In certain traffic situations, drivers may prefer to disengage ACC and resume manual control (*6*). These transitions between automation and manual driving are called *control transitions* (*7*) and may influence considerably traffic flow efficiency (*8*) and safety (*9*). Recently, *full-range* ACC systems that can operate in dense traffic have been introduced into the market. These ACC systems are more likely to be active in dense traffic conditions and have a positive impact on traffic flow efficiency (*10*).

Despite the influence of control transitions on driving behavior, most car-following and lane-changing models currently used to evaluate the impact of ACC do not describe these transitions and therefore could result in misleading predictions. A few mathematical models (*11-13*) have proposed deterministic decision rules for transferring control, which do not account for variability between and within drivers in the decision-making process. Recently, we identified the main factors influencing drivers' choice to resume manual control in a mixed logit model (*14*). Drivers are likely to deactivate full-range ACC when approaching a slower leader and to overrule the system by pressing the gas pedal a few seconds after it has been activated. However, this study did not quantify explicitly the range in which the ACC system operation is acceptable and ignored the possibility of adapting the ACC system settings to regulate the longitudinal control task.

This research aims to develop a continuous-discrete choice modelling framework describing the underlying decision-making process of drivers with ACC. This paper focuses on control transitions and ACC speed regulations which are not related to lane changes (within a time window of 10 seconds before and 10 seconds after the action). The following research hypotheses are tested using empirical data:

1. Control transition and target speed regulation choices with full-range ACC are related to the driver behavior characteristics (speed, distance headway and relative speed) which inform risk feeling and task difficulty evaluations in driver control theories (*15*);
2. The range in which ACC system operation is considered acceptable differs significantly between drivers and is influenced significantly by driver characteristics;
3. The ACC target speed regulation choices are related to driver characteristics and to the difference between the current ACC target speed and the actual speed.

In this framework, we hypothesize that drivers choose to resume manual control or to regulate the ACC target speed (binary logit and regression models) if the perceived level of risk feeling and task difficulty falls outside the range considered acceptable to maintain the system active (ordinal probit model). The model was estimated using a dataset collected in an on-road experiment in which twenty-three participants drove a research vehicle equipped with full-range ACC on a 35.5-km freeway in Munich during peak hours.

The results reveal that the perceived level of risk feeling and task difficulty is higher when time headways are shorter, when approaching a slower leader and when expecting vehicles cutting in. Everything else being equal, some drivers have a larger acceptable range with ACC and choose smaller ACC target speed regulations. The model can be implemented into a microscopic simulation to assess the effects of ACC on traffic flow accounting for control transitions and target speed regulations.

## METHODOLOGY

Based on previous studies (*14-16*), we propose two levels of decision-making describing changes in both discrete and continuous variables in transitions to manual control with ACC (Figure 1): risk feeling and task difficulty evaluation (discrete choice model), and ACC system state and ACC target speed regulation choice (continuous-discrete choice model). At the highest level, the driver evaluates whether the *perceived level* of risk feeling and task difficulty (RFTD) falls within the *range* which is considered *acceptable* to maintain the ACC active and the current ACC target speed. If the perceived RFTD level falls outside the acceptable range, the driver will choose to resume manual control or to regulate the ACC target speed maintaining the system active. The magnitude of the ACC target speed regulation is chosen simultaneously to the system state.

The unobservable RFTD is modelled as a latent variable with a mean value which is a function of the driver behavior characteristics. The RFTD evaluation is formulated as an ordered probit model with random thresholds *(17)* that represent the minimum and the maximum risk acceptable. These thresholds are influenced by driver characteristics and by unobserved preferences which affect all choices made by individual drivers over time (driver-specific error term). Drivers who consider the risk feeling higher than the maximum value acceptable choose to deactivate the ACC (transition to *Inactive*) or maintain the system active and decrease the target speed. This decision is formulated as a binary logit model and is influenced by the functionalities of the ACC system, environmental conditions, and unobserved driver-specific characteristics. The ACC target speed decrement is formulated as a regression model in which the magnitude of the decrement is determined by driver behavior characteristics, the functioning of the system, and unobserved driver-specific characteristics. Since ACC target speed decrements are observed only when drivers choose to decrease the ACC target speed, a selectivity correction term is included into the regression equation to correct for the system state selectivity bias (*18*). If the actual RFTD level falls within the acceptable range, the ACC remains active and the target speed is not regulated. Drivers who consider the risk lower than the minimum value acceptable choose to overrule the system by pressing the gas pedal (transition to *Active and accelerate*) or to maintain the system active and increase the target speed. The ACC system state choice in low risk situations and the ACC target speed increment are formulated similarly to the decisions in high risk situations.

The parameters of the ACC system state choices and of the ACC target speed regulations are estimated simultaneously with full information maximum likelihood methods (*19*). The probability of deactivating the ACC is given by the product of the probability of the actual level of RFTD being higher than the maximum value acceptable and the conditional probability of transferring to *Inactive.* The probability of decreasing the ACC target speed and selecting a certain target speed decrement is given by the product of the probability of the actual level of RFTD being higher than the maximum value acceptable, the conditional probability of decreasing the target speed, and the conditional probability density function of the target speed decrement. The probability of overruling the ACC system by pressing the gas pedal and the probability of increasing the ACC target speed and selecting a certain target speed increment are calculated similarly.

The model is estimated using the software PythonBiogeme (*20*). The dataset comprises 23,568 1-s observations in which the ACC system is active and a leader is detected by the radar (120 m range). We assume that only one decision 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 (21).

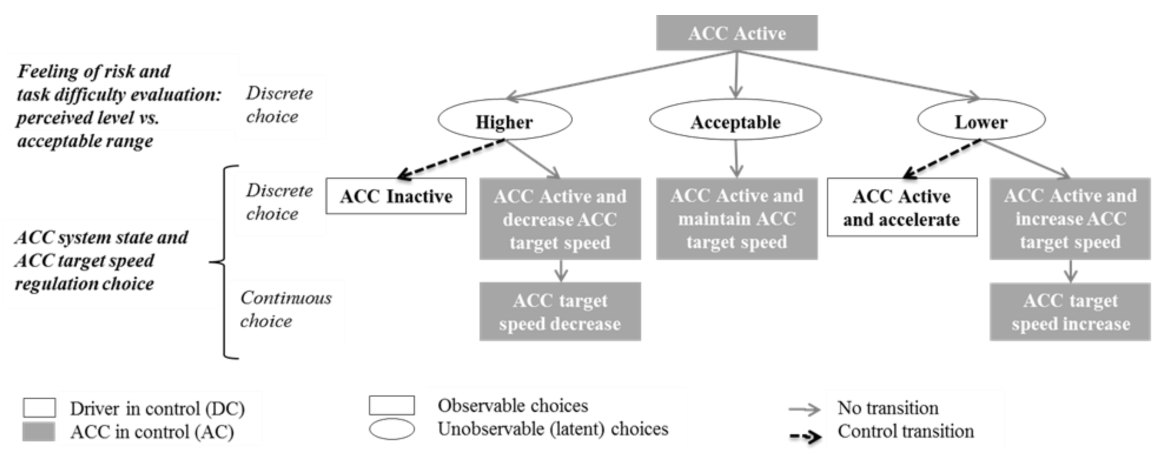


**FIGURE 1 Model framework for driver behavior in control transitions between ACC and manual driving.**

## FINDINGS

Estimation results (Tables 1-2) show that the model framework proposed contributed to explain the choice of resuming manual control and regulating the target speed significantly. The risk feeling and task difficulty are considered high when driving at short time headways, when approaching a considerably slower vehicle, and when expecting vehicles cutting in. Interestingly, patient and careful drivers (MDSI (*22*)) showed a smaller acceptable range with the ACC active. When the risk feeling is considered higher than the maximum value acceptable, drivers are more likely to deactivate the ACC in proximity to on-ramps and before exiting the freeway. Drivers select a larger ACC target speed decrement when the ACC target speed is higher than the current speed. When the risk feeling is considered lower than the minimum value acceptable, drivers are more likely to overrule the system by pressing the gas pedal a few seconds after the system has been activated. Drivers inexperienced with ADAS prefer smaller ACC target speed increments. Drivers who have a larger acceptable range with ACC active are less likely to resume manual control and choose smaller target speed regulations.

## CONCLUSION

Control transitions to *Inactive* (deactivations) and ACC target speed decrements occurred most often in high risk feeling and task difficulty situations (short time headways, slower leader, and cut-ins expected), while control transitions to *Active and accelerate* (overruling actions by pressing the gas pedal) and target speed increments in low risk feeling and task difficulty situations (large time headways and faster leader). Control transitions and ACC target speed regulations can be interpreted as an attempt to decrease or increase the complexity of a traffic situation.

These findings shed light on the decision-making of drivers with ACC and have important implications for developing new driving assistance systems which can adapt their settings based on different traffic situations and driver characteristics to prevent control transitions while guaranteeing safety and comfort. Moreover, the framework proposed can be directly implemented into a microscopic traffic flow simulation to analyze the impact of ACC on traffic safety and traffic flow efficiency at different penetration rates accounting for drivers' interventions.

In this study, the sample of participants was limited (twenty-three) and was not representative of the driver population in terms of gender, age, employment status and experience with ADAS. Moreover, the findings are influenced by the characteristics of the ACC system and cannot be directly generalized to other types of driving assistance systems. The key implication of this study is that, to describe driver interaction with ACC, we need a conceptual framework that connects driver behavior characteristics, driver characteristics, ACC system settings, and environmental factors. Future research will focus on the development of the model framework describing mathematically the impact of control transitions on the longitudinal control task in a car-following model. The final model can be implemented into a microscopic traffic flow simulation to assess the effect of control transitions in ACC on traffic flow efficiency and safety.

**TABLE 1 Statistics of the continuous-discrete choice model**

| *Statistics* | |
|---|---|
| Number of parameters associated with explanatory variables | 22 |
| Number of constants | 8 |
| Number of drivers | 23 |
| Number of observations | 23,568 |
| Constant log likelihood $\mathcal{L}(c)$ | -3496 |
| Final log likelihood $\mathcal{L}(\hat{\beta})$ | -3158 |

**TABLE 2 Estimation results of the continuous-discrete choice model ([1] variable centered on the mean value between drivers; ** p-value>0.10, * 0.05<p-value<0.10)**

| *Variable* | *Description* | *Parameters* | *Estimate* | *T-test* | |
|---|---|---|---|---|---|
| *Risk feeling and task difficulty evaluation* | | | | | |
| *THW30* | Time headway (front bumper to rear bumper) in s when the speed is higher than 30 km/h | $\lambda_{THW30}$ | -0.0607 | -3.01 | |
| *RelSpeed* | Relative speed (i.e., leader speed – subject vehicle speed) in km/h | $\lambda_{RelSpeed}$ | -0.0299 | -10.98 | |
| *RelAcc* | Relative acceleration (i.e., leader acceleration – subject vehicle acceleration) in m/s$^2$ | $\lambda_{RelAcc}$ | -0.291 | -6.59 | |
| *AntCutIn3* | Number of vehicles that will cut in in the following three seconds | $\lambda_{AntCutIn3}$ | 0.452 | 5.65 | |
| - | Constant lowest acceptable risk with ACC active | $\mu^{L}$ | 0.485 | 13.04 | |
| - | Constant highest acceptable risk with ACC active | $\mu^{H}$ | 0.654 | 15.85 | |
| *TimeAct* | Time after the ACC has been activated in s | $\tau^{L}_{TimeAct}$ | 0.0849 | 11.12 | |
| *TimeAct* | Time after the ACC has been activated in s | $\tau^{H}_{TimeAct}$ | 0.0546 | 6.22 | |
| *PatCar* | Score on the driving-style factor 'Patient and careful'[1] (MDSI (*22*)) | $\tau^{L,H}_{PatCar}$ | -0.0849 | -3.68 | |
| $\vartheta_n$ | Individual specific error term | $\gamma^{L,H}$ | 0.0347 | 3.26 | |
| *ACC system state choice* | | | | | |
| - | Alternative specific constant | $\alpha^{AAc}$ | 0.257 | 0.70 | ** |
| - | Alternative specific constant | $\alpha^{I}$ | -1.59 | -4.55 | |
| *TimeAct* | Time after the ACC has been activated in s | $\beta^{AAc}_{TimeAct}$ | -0.569 | -6.24 | |
| *DiffTarSpeed* | Difference between the target speed set in the ACC and the speed of the subject vehicle in km/h | $\beta^{I}_{DiffTarSpeed}$ | -0.0161 | -1.69 | * |
| *DiffTarSpeed* | Difference between the target speed set in the ACC and the speed of the subject vehicle in km/h | $\beta^{AAc}_{DiffTarSpeed}$ | 0.0375 | 4.99 | |
| *Acc* | Acceleration of the subject vehicle in m/s$^2$ | $\beta^{AAc}_{Acc}$ | -2.00 | -4.07 | |
| *RelAcc* | Relative acceleration (i.e., leader acceleration – subject vehicle acceleration) in m/s$^2$ | $\beta^{I}_{RelAcc}$ | -1.16 | -3.14 | |
| *OnRamp* | Binary variable equal to 1 when the drivers are in the mainline close to an on-ramp, or between two ramps closer than 600 m (*23*) | $\beta^{I}_{OnRamp}$ | 1.34 | 3.23 | |
| *Exit* | Binary variable equal to 1 when the distance to the closest exit is shorter than 1600 m (first exit sign) | $\beta^{I}_{Exit}$ | 3.41 | 4.77 | |
| $\vartheta_n$ | Individual specific error term | $\gamma^{AAc,I}$ | -0.825 | -3.84 | |
| *ACC target speed regulation choice* | | | | | |
| - | Mean ACC target speed increase | $\eta^{TS+}$ | 2.82 | 20.18 | |
| - | Mean ACC target speed decrease | $\eta^{TS-}$ | 1.91 | 8.24 | |
| *DiffTarSpeed* | Difference between the target speed set in the ACC and the speed of the subject vehicle in km/h | $\xi^{TS-}_{DiffTarSpeed}$ | 0.0230 | 4.49 | |
| *RelSpeed* | Relative speed (i.e., leader speed – subject vehicle speed) in km/h | $\xi^{TS-}_{RelSpeed}$ | -0.0295 | -2.35 | |
| *NoviceADAS* | Binary variable equal to 1 when the driver is inexperienced with ADAS | $\xi^{TS+}_{NoviceADAS}$ | -0.549 | -4.05 | |
| $C^{TS+}$ | Selectivity correction term in low risk situations | $\varphi^{TS+}$ | 0.480 | 4.07 | |
| $C^{TS-}$ | Selectivity correction term in high risk situations | $\varphi^{TS-}$ | 0.0346 | 0.17 | ** |
| $\vartheta_n$ | Individual specific error term | $\gamma^{TS}$ | -0.437 | -4.81 | |
| $\upsilon_n^{TS+}(t)$ | Observation specific error term | $\omega^{TS+}$ | 0.679 | 19.00 | |
| $\upsilon_n^{TS-}(t)$ | Observation specific error term | $\omega^{TS-}$ | 1.08 | 15.40 | |

## 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,* Vol. 2422, 2014, pp. 113-120.
[2] Alkim, T. P., G. Bootsma, and S. P. Hoogendoorn. Field Operational Test "The Assisted Driver". *IEEE Intelligent Vehicles Sysmposium*, Istanbul, 2007. pp. 1198 - 1203.
[3] Gorter, M. Adaptive Cruise Control in Practice: a Field Study and Questionnaire into its influence on Driver, Traffic Flows and Safety. *Department of Transport and Planning, MSc thesis*, Delft University of Technology, 2015.
[4] Automotive Collision Avoidance System Field Operational Test Report: Methodology and Results. U.S. Department of Transportation, National Highway Safety Administration, 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. 2012.
[6] 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. *IEEE Intelligent Vehicles Symposium*, Eindhoven, 2008.
[7] Lu, Z., R. Happee, C. D. D. Cabrall, M. Kyriakidis, and J. C. F. de Winter. Human factors of transitions in automated driving: A general framework and literature survey. *Transportation Research Part F: Traffic Psychology and Behaviour,* Vol. 43, 2016, pp. 183-198.
[8] 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,* Vol. 2489, 2015, pp. 105-114.
[9] 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, The Netherlands, 2015.
[10] 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 Transportation Systems,* Vol. 14, No. 4, 2010, pp. 197-208.
[11] van Arem, B., A. P. de Vos, and M. J. W. A. Vanderschuren. The microscopic traffic simulation model MIXIC 1.3. TNO Inro, Delft, 1997.
[12] 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,* Vol. 2129, 2009, pp. 145-151.
[13] Xiao, L., M. Wang, and B. van Arem. Realistic car-following models for microscopic simulation of adaptive and cooperative adaptive cruise control vehicles. *Transportation Research Record: Journal of the Transportation Research Board,* Vol. 2623, 2017.
[14] Varotto, S., H. Farah, T. Toledo, B. van Arem, and S. Hoogendoorn. Resuming manual control or not? Modelling choices of control transitions in full-range adaptive cruise control. *Transportation Research Record: Journal of the Transportation Research Board,* Vol. 2622, 2017, pp. 38-47.
[15] Fuller, R. Driver Control Theory: From Task Difficulty Homeostasis to Risk Allostasis In *Handbook of Traffic Psychology*, Elsevier, 2011. pp. 13 -26.
[16] 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.
[17] Greene, W. H., and D. A. Hensher. Ordered choices and heterogeneity in attribute processing. *Journal of Transport Economics and Policy,* Vol. 44, No. 3, 2010, pp. 331-364.
[18] Train, K. Continuous/Discrete Models. In *Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand*, MIT Press, Cambridge, 1986.
[19] Greene, W. H. *Econometric Analysis*. 2012.
[20] Bierlaire, M. PythonBiogeme: a short introduction. *Biogeme*, Transport and Mobility Laboratory, School of Architecture, Civil and Environmental Engineering, Ecole Polytechnique Fédérale de Lausanne, Lausanne, 2016.
[21] Toledo, T. Integrated Driving Behavior Modeling. *Civil and Environmental Engineering, PhD thesis*, Massachusetts Institute of Technology, Boston, 2003.

[22] Taubman-Ben-Ari, O., and D. Yehiel. Driving styles and their associations with personality and motivation. *Accident Analysis and Prevention,* Vol. 45, 2012, pp. 416-422.
[23] FGSV, *Richtlinie für die Anlage von Autobahnen (RAA)*, 2008.