# Highway On-Ramp Merging for Mixed Traffic: Recent Advances and Future Trends

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***Abstract*—Due to the ability to support a wide range of applications and to involve infrastructure elements, connected and automated vehicles (CAVs) technology has played an important role in the development of cooperative intelligent transport systems. Thus, with the available sensing system, CAVs can perceive the surrounding environment. Indeed, due to the involvement of CAVs, communication of vehicles to other related devices using vehicle-to-everything (V2X) communication plays critical roles. This paper summarizes the research and development trends when proposing driving models, with a particular attention to highway on-ramp merging scenarios. The challenges and future research directions are also presented.**

***Index Terms*—Connected and automated vehicles (CAVs), vehicle-to-everything (V2X) communication, highway on-ramp merging, lane-changing, gap-acceptance, car-following.**

## I. Introduction

The registration of accidents and the mortality rate associated with transport systems, is a frightening reality that requires mitigating measures to overcome these occurrences. The significant increase in traffic accidents in recent years is due to the high number of vehicles in circulation, the negligence practiced by drivers and the poor conditions of public roads [Milakis et al., 2017]. According to figures from the World Health Organization, about 1.35 million crash-related fatalities occurred in 2018, the latest year for which data is available [Organization et al., 2018].

An alarming factor in these records is the impact that human behavior has in these events, with a record of about 90% in responsibility for road accidents. Factors such as fatigue, distraction, alcohol and other substances, as well as irresponsibility in certain actions taken during the driving activity, make the human being the biggest threat to the safety and efficiency in road driving [Bener et al., 2017].

Investigating the characteristics and circumstances of vehicle accidents has been the subject of intensive studies in the transportation community. Through exploratory analysis to investigate the scenarios involved in crashes, on-ramp merging areas are among the most critical parts of highways that got increased attention. In the highway on-ramp merging area, the traffic in the main lane is disarranged because of the vehicles merging in the acceleration lane, this can lead traffic to turn into chaos and therefore, it is an accident-prone area [Rong et al., 2009].

It is crucial to think about solutions in order to reduce continuous conflicts on-ramp. Many studies in cooperative intelligent transport systems (C-ITS) are taking place, which may become a key factor for such kind of improvements. C-ITS can be considered as the integration of computational, communication and control technologies, allowing the connection between vehicles and between vehicles and infrastructure [Dar et al., 2010].

C-ITS enables a wide range of advanced driver assistance systems (ADAS) and automated driver (AD) functions. The complexity and the type of assistance provided make it possible to classify vehicles into different levels of automation [Warrendale, 2016]. To this end, the Society of Automotive Engineers (SAE) has developed classifications, taking into account the role of the driver and the vehicle in the driving task. SAE organizes autonomy in six different levels (Figure 1) ranging from SAE 0 (without automation) to SAE 5 (total automation), this last level is also known as future connected and autonomous vehicles (CAVs).

| LEVEL | NAME | DESCRIPTION |
|---|---|---|
| | | **These are driver support features** |
| 0 | No automation | • Automatic emergency braking<br>• Blind spot warning<br>• Lane departure warning |
| 1 | Task assistance | • Lane centering<br>OR<br>• Adaptive cruise control |
| 2 | Portal automation | • Lane centering<br>AND<br>• Adaptive cruise control |
| | | **These are automated driving features** |
| 3 | Highly automated | • Traffic jam chauffeur |
| 4 | Fully automated | • Local driverless taxi<br>• Pedals/steering wheel may or may not be installed |
| 5 | Autonomous | • Same as level 4, but feature can drive everywhere in all conditions |

Fig. 1. System automation level descriptions [international, 2016].

CAVs present multiple opportunities to deal with the negative aspects of conventional non-autonomous vehicles. These vehicles have the ability to anticipate and avoid possible collisions, to move around using more efficient routes to reach their destination, using up-to-date traffic reports, identifying available parking lots nearest to them and minimizing emissions. Thus, the necessity for CAVs has become universal. Even though there are a lot of vehicles with some kind of automation, it is hard to imagine a scenario with vehicles on road 100% automated. Taking this into account, research has been done with the aim of optimizing transportation

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efficiency for both conventional and hybrid systems that take into consideration whether vehicles have ADAS and AD functionalities or not. With this in mind, many models that allow for the vehicle-to-vehicle (V2V) and vehicle-to-everything (V2X) communications have been proposed which in turn allows cooperation between vehicles.

This paper presents a literature review of the state-of-the-art of the improvements that have been made on driving models and the methodologies employed when proposing such models. In particular, this work focuses on on-ramp merging models and the need for proposing new frameworks that include mixed traffic characteristics and how those models integrate V2X communication. The remaining of this paper is structured as follows: Section II presents an overview of the main driving behavior models formulations and the proposed model from the literature are summarized. Section III covers the literature related to on-ramp merging behavior models and highlight the ones that considered V2X communications in their approaches. Section IV provides a summary of the main characteristics of the most common used methodologies. The more relevant challenges and open issues are analyzed in Section V followed by the conclusions in Section VI.

## II. Driving Behavior Models

Understanding real-life driving patterns during highway merging and exiting can become a basis for the design of future CAV that will enable mixed traffic scenarios. Innovative approaches based on C-ITS which integrate driving behavior models have emerged during the last decades. As stated on previous studies [Panwai and Dia, 2005, Zhao et al., 2019], most of those driving behavior models are usually built upon one of the three scenarios presented in this section: car-following, lane-changing and gap-acceptance. Thus, this section presents the studies that have been proposed during the last decade. The following works were obtained by running a search procedure including the logical condition: *"car-following model OR lane-changing model OR gap-acceptance model" AND "driver behavior" AND "Highway"* in the well-known database of peer-reviewed literature *Scopus*. Among the papers found, the ones that proposed a driver behavior model on the last 10 years were choosen to be presented.

### A. Car-following model

Car-following models describe the processes by which drivers follow each other in the traffic stream [Brackstone and McDonald, 1999]. The car-following model can be considered as one of the closest to human driver behavior's in reality, this is due to the fact that car-following models capture many factors and variables involved in observed traffic behavior. Some authors classify the car following models depending on the variables and characteristics involved. Commonly, car-following models can be divided into Gazis-Herman-Rothery models [Gazis et al., 1961], psycho-physical or action-point models [Wiedemann, 1974, Wiedemann and Reiter, 1992], and collision-avoidance models [Gipps, 1981, Treiber et al., 2000].

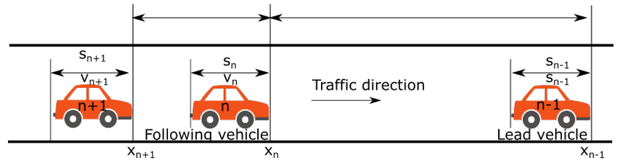


Fig. 2. A basic scenario of the car-following behavior and the relationship with the model's variables

In order to describe the formulation of car-following models, the one proposed by Gipps [1981], which is widely used, particularly in microscopic traffic simulation, is presented. The model is briefly illustrated in Figure 2 and described as follows:

$$
\begin{aligned}
v_n(t+T) \leq b_n T + (b_n^2 T^2 - b_n \{2[x_{n-1}(t) - \\
s_{n-1} - x_n(t)] - v_n(t)T - \frac{[v_{n-1}(t)]^2}{\hat{b}}\})^{\frac{1}{2}},
\end{aligned}
\tag{1}
$$

where $v_n(t+T)$ is the maximum speed of the $n$-th vehicle with respect to the leading vehicle at the time $t+T$, $v_{n-1}$ is the speed of $(n-1)$-th vehicle, $T$ is the driver reaction time, $x_n(t)$ is the position of the following vehicle at time $t$, $x_{n-1}(t)$ is the position of the leading vehicle at the time $t$, $s_{n-1}$ is the length of the following vehicle which in turn include the stationary stoppage allowance, and $b_n$ and $\hat{b}$ are the deceleration (or breaking) rate of the following and leading vehicle. This model has become popular due to the ease of calibrating its parameters. Thus, it is commonly employed for modeling drivers' behavior for situations involving either a pair of vehicles or platoons.

Table I summarizes different studies that have been proposed employing car-following characteristics. Notice that in most of the studies, the authors proposed the models based on driving simulators or observed data from well-known data sets. In order to propose prediction models, such as the one proposed by Khodayari et al. [2011a] and Angkititrakul et al. [2011], the available data is usually divided into two subsets, the first is known as the testing and training data-set and the second is used to validate the performance of the trained model. Features such as lateral position, velocity, acceleration and time are extracted from the available data-sets. In particular, the NGSIM data set is widely used to train and test the models. The NGSIM data set contains detailed vehicle information provided by the Federal Highway Administration. On the other hand, some studies, such as [Huang et al., 2018], propose car-following models for individual drivers to personalize headway control. In that case, the method to build those models is to collect information from clean and real car-following data from pre-selected drivers on real road scenarios.

There are also some approaches that take a generalization of previous car-following models and build a new one taking into account new assumptions. An example of this kind of approach is the one proposed by Yang et al. [2013] which proposed a bi-directional looking formula for Gipps' model. The validation of such models is made by extending the

TABLE I
SUMMARIZE OF CAR-FOLLOWING MODELS

| Papers | Methodology | Environment |
|---|---|---|
| Khodayari et al. [2011a] | Locally Linear Neuro-Fuzzy Model | US-101 NGSIM |
| Khodayari et al. [2011b] | Soft Computing Approaches | Generated Scenario |
| Angkititrakul et al. [2011] | Gaussian Mixture Model | Real Road Driving Test |
| Talebpour et al. [2011] | Prospect Theory | I-80 NGSIM |
| Yang et al. [2013] | Bi-directional Looking Model | Generated Scenario |
| Horiguchi and Oguchi [2014] | Concave Flow-Density (Q-K) Curve | Generated Scenario |
| Ngoduy [2015] | Time-Continuous Model | Generated Scenario |
| He et al. [2015] | *k*-Nearest Neighbour | US-101 NGSIM |
| Peng et al. [2016] | Taylor Series Expansion | Generated Scenario |
| Salehinia et al. [2016] | Auto Regressive Moving Average Model -ARMAX | US-101 NGSIM |
| Hao et al. [2016] | Fuzzy Logic | US-101 NGSIM |
| Sun et al. [2018a] | Taylor Series Expansion | Generated Scenario |
| Ou and Tang [2018] | Euler Method | Generated Scenario |
| Zhai and Wu [2018] | Sensitivity Analysis | Generated Scenario |
| Kim et al. [2018] | Markov Chain Model | The 100-car Naturalistic Driving Study |
| Wang et al. [2018a] | Linear Analysis Method | Generated Scenario |
| Messaoudi [2018] | Game Theory Model | Generated Scenario |
| Huang et al. [2018] | Empirical Analysis | Real Road Driving Test |
| Kuang et al. [2019] | Linear Stability Analysis | Generated Scenario |
| Ngoduy et al. [2019] | Langevin Equations | US-101 NGSIM |
| Cao [2020] | Mean Memory Evolution Model | Generated Scenario |
| Jiao et al. [2020] | Grey Rational Analysis Method | Generated Scenario |
| Fadhloun and Rakha [2020] | Empirical Analysis | The 100-car Naturalistic Driving Study |
| Wang et al. [2020] | Support Vector Machine | Real Road Driving Test |
| Chang et al. [2020] | Fundamental Diagram Analysis | Generated Scenario |
| Zhou et al. [2020] | Markov-Decision Process | Data collected in Huzhou City and Xi'an City in China |

linear stability analysis to the model setting up mathematical and numerical analysis scenarios. The linear stability analysis is a popular strategy in traffic flow literature to derive the conditions influencing the stability of the proposed models.

### *B. Lane-changing model*

Lane-changing models try to replicate the behavior of drivers moving from the existing lane to a target lane. This behavior has an impact on the traffic flow since lane-changing influences the congestion at bottlenecks. Thus, many lane-changing models have been proposed due to the need of improving the current transportation systems' capacity and safety. Throughout previous literature reviews on driver decision models, the lane-changing models have been classified as either collision prevention models or automation models [Moridpour et al., 2010].

Throughout the literature, it is evident that many studies have proposed lane-changing decision models based on the Gipps [1986] lane-changing model which in turn was developed based on the author's car-following model. This model includes a hierarchy of considerations that determine the necessity and desirability of lane changes. In the context of Gipss' model, the target lane is the one in which the vehicle intends to move and the model evaluates whether it is necessary to make such a lane change. The proposed model is based in pre-determined rules, *i.e.*, in which lane the driver will move into according to prioritized rules and can be summarized as follows:

$$b_n = \left[2 - \frac{D - x_n(t)}{10 v_n}\right] b_{LC}\theta, \quad (2)$$

where $\theta$ is a safety margin parameter also known as a "driver aggressivity parameter", $b_{LC}$ is the average deceleration a following vehicle is willing to accept, and $D$ is the location of the target lane change. Figure 3 illustrates a scenario where the following vehicle considers lane change to the left. The previous equation is a modified version of the original formula proposed by Gipps [Gipps, 1986, Hidas, 2002]. In sum, for the lane change model, the maximum safe speed in Equation 1 is limited by the following vehicle's desired speed and maximum deceleration. The lane change is most likely to happen when a "sufficient" gap exists, and it is safe to take it.

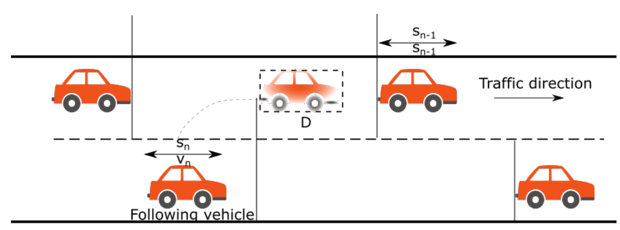


Fig. 3. A basic scenario of the lane-changing behavior

Table II summarizes the works that have proposed models that analyzes driver behavior characteristics during the execution of the lane change. One can note that some of the studies, the proposed models are based on empirical analysis, such as the one proposed by Schmidt et al. [2014], this is done by carrying out experimental analysis so a mathematical model describing the captured behavior can be proposed afterwards. With this kind of approach, a detailed exploration of some

TABLE II
SUMMARIZE OF LANE-CHANGING MODELS

| Papers | Methodology | Environment |
|---|---|---|
| Xu et al. [2011a] | Dynamic Parameter Model | Driving Simulator |
| Xu et al. [2011b] | Hidden Markov Model | Generated Simulation |
| Bham [2011] | Integer Value Method | The Baltimore-Washington Parkway I-95 data-set |
| Schakel et al. [2012] | Relaxation and Synchronization Method | Data collected in the Netherlands - A20 freeway |
| Schmidt et al. [2014] | Empirical Analysis | Driving Simulator |
| Tehrani et al. [2015] | Two-Segments Model | Generated Scenario |
| Julian and Damerow [2015] | Risk Theory | Generated Scenario |
| Backfrieder et al. [2016] | Empirical Analysis | Generated Scenario |
| Cao et al. [2016] | Probability Model | Data collected in Australia (Melbourne) |
| Do et al. [2017] | $dx/dv$ Graph Method | Data collected in Japan (Aichi) - Isewangan Expressway |
| Zhou et al. [2017] | Empirical Analysis | Real Road Driving Test |
| Park et al. [2019] | Hidden Markov Model | Real Road Driving Test |
| Gu et al. [2019] | Random Forest Model | US-101 and I-80 NGSIM |
| Tang et al. [2019] | Fuzzy C-means and Artificial Neural Network | Driving Simulator |
| Liu et al. [2019] | $dx/dv$ Graph Method | Real Road Driving Test |
| Li et al. [2020] | Quantitative Method | I-80 NGSIM |
| Jin et al. [2020] | Gauss Mixture Hidden Markov Model | US-101 and I-80 NGSIM |
| Liu et al. [2020] | Non-Linear Polynomial Regression and Hidden Markov Model | Driving Simulator |
| Bae et al. [2020] | Recurrent Neural Network | Generated Scenario |

parameters is provided so a better analytically understanding can be done, which in turn, lead to a mathematical model proposition. In which case, analysis of a driving simulator may be carried out. Driving simulator setup, highway design and reference tasks vary depending on the experimental conditions that are being evaluated. In particular, driving simulator STISIM Drive 100w is widely known for such experiments. The driver simulator consists of a BMW 350i with automatic transmission and a 135-degree field of view for the projection. Driving scenarios can be created in a precise and reproducible manner for each participant, which allows for investigating the behavior of different populations in various conditions.

Moreover, some methodologies such as the $dx/dv$ graph model proposed in [Do et al., 2017, Liu et al., 2019], are based on intuitive decisions once the driver behavior is recorded/extracted in highway scenarios. Particularly, the $dx/dv$ graph model aims to select the suitable lane change behavior, for a given scenario, using active and passive information derived from the distance and related velocity graph.

### C. Gap-acceptance model

When proposing gap-acceptance models, the definition of gap is related to the elapsed time between approaches of successive vehicles in the opposing flow from a specific reference point in a traffic stream. The intention of developing gap-acceptance models is to predict drivers' decisions that attempt maneuvers such as intersection, entering a roundabout or changing lanes. In the literature, the minimum gap that a driver is usually willing to accept is known as the critical gap. The most clear and referenced definition of such is the one given by The Highway Capacity Manual (HCM 2000): "the minimum time interval between the front bumpers of two successive vehicles in the major traffic stream that will allow the entry of one minor-street vehicle" [Manual, 2000]. Understanding such driver behavior is of great important for developing countermeasures that help to maintain time-gaps of systems such as Adaptive Cruise Control. Thus, many studies have attempted to model gap-acceptance behavior.

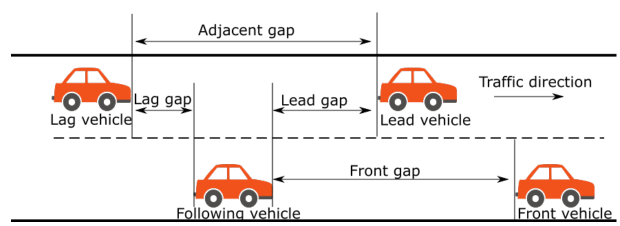


Fig. 4. Definition of the lag and lead gap with respect to the following vehicle

As for the case of gap-acceptance models, the first models were formulated assuming that the critical gap follows a Exponential, Log-Normal and Normal probability distribution functions, respectively [Herman and Weiss, 1961, Drew et al., 1967, Miller, 1971]. A generalized form of the expression for the critical gap model is the one introduced by Ahmed et al. [1996], Ahmed [1999] given below:

$$\ln\left(G_{nt}^{gd,cr}\right) = \beta^{g^T} X_{nt}^{gd} + \alpha^g v_n + \epsilon_{nt}^{gd}, \tag{3}$$

where $g \in \{lead, lag\}$, $d \in \{right, left\}$, $G_{nt}^{gd,cr}$ is the critical gap $cr$ measure for gap $g$ in the direction of change $d$ perceived by vehicle $n$ at the time $t$, $X_{nt}^{gd}$ is the vector of explanatory variables used to characterize the mean of the critical gap $G_{nt}^{gd,cr}$, $\beta^{g^T}$ is the corresponding vector of parameters, $\epsilon_{nt}^{gd} \sim N(0, \sigma_g^2)$ is a random term following the Log-Normal assumption and $\alpha^g v_n$ is the parameter of the driver-specific random term $v_n$. The gap acceptance model assumes that the driver must accept both the lead gap and the lag gap to find the total adjacent gap acceptable as illustrated in Figure 4.

Table III summarizes the works that have proposed models that analyzes gap-acceptance driver behavior characteristics. It

TABLE III
SUMMARIZE OF GAP-ACCEPTANCE MODELS

| Papers | Methodology | Environment |
|---|---|---|
| Zohdy and Rakha [2012] | Agent-based Model | Data collected in Christiansburg (US-460), Virginia - US. |
| Gazzarri et al. [2012] | Non-Linear Empirical Regression Model | Data collected in Northern Tuscany - Italy |
| Fatema and Hassan [2013] | Probabilistic Design | Ottawa Highway 417 |
| Hassein et al. [2017] | Logistic Regression Technique | Real Road Driving test |
| Mafi et al. [2018] | Data Mining Models | Generated Scenario |
| Das et al. [2020] | Multivariate Adaptive Regression Splines | SHRP2 NDS |

is observed that the use of probabilistic techniques has been used to analyze lane-changing gap-acceptance behavior. This fact may be due to the non parametric techniques' advantages over the traditional parametric techniques in investigating driver behavior.

## III. ON-RAMP MERGING BEHAVIOR MODELS

In this section the works that have approached driver behaviors on on-ramp merging scenarios on the last 10 years are presented. As mentioned before in Section I, on-ramp merging points are a critical part of an expressway because the vehicles willing to merge should interpret the scenario in order to merge safely. Thus, there are many variables that may influence the merging decision, such as, lateral movement which refer to the lane-changing that vehicles that are already in the main-lane execute so the merging vehicles can merge, gap selection and the acceleration/deceleration that the merging vehicle makes before entering in the highway. In fact, to better illustrate the on-ramp merging behavior, the merging process is commonly modeled taking into account the gap selection and the merging vehicle acceleration models. For modeling the gap selection many models are based on the formulation presented in Section II-C, regarding the acceleration model, the formulation proposed by Gazis et al. [1961] have been widely used as a basis for different acceleration models. The model is given by:

$$a_n(t) = \alpha \frac{v_n(t)^\beta}{\Delta x_n(t-T_n)^\gamma} \Delta v_n^{front}(t-T_n) \qquad (4)$$

where $a_n(t)$ is the acceleration applied by driver $n$ at time $t$, $v_n^{front}(t-T_n)$ is the lead or front vehicle speed minus the following vehicle speed at time $(t-T_n)$, $\Delta x_n(t-T_n)$ denotes the space headway at time $(t-T_n)$, $T_n$ is the reaction time for driver $n$ and $\alpha, \beta$ and $\gamma$ are model parameters. However, merging behavior is not limited to the gap acceptance and/or acceleration models. A typical scenario of on-ramp merging behavior is illustrated in Figure 5.

In the last ten years some studies have proposed strategies for modeling on-ramp merging driving behaviors. In [Marczak et al., 2013], the authors proposed a conceptual framework for describing merging behaviors. The proposed framework was based on accepted and rejected gap theory. The strategy was tested using two data-sets collected in two different sites, one in the Netherlands and one in France. The length of the road was 283 m and 210 m, respectively. The video camera employed for collecting the data recorded a video with a frame rate of 10 to 30 images per second and during a period of time of about 30 to 60 min. The collected data was not continuous in time since the authors focused on periods where the amount of traffic was relatively high so the merging behavior could be studied. There is no evidence of whether the vehicles present on the road during the data collection were CAVs or not. The authors analysed different factors as the relation between the gaps and the location of the merge and merging speed. Based on the gaps, the authors identified the most contributing variables for building up a stochastic model based on Principal Component Analysis. Authors did not test the proposed model using simulators, instead they presented a comparative analyses of both scenarios.

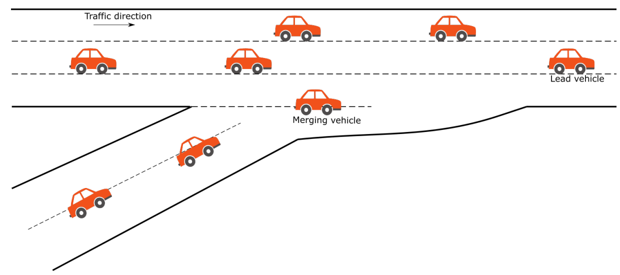


Fig. 5. A basic scenario of the on-ramp merging behavior

In [Guzmán et al., 2015], authors proposed a probabilistic cellular automata model that considered the on-ramp merging scenario. The model was built upon assumptions for traffic flow that represent drivers' reactions under different circumstances. Moreover, the model takes into account the right lane preference and the right lane overtaking restriction which are mechanisms used in Mexican and European freeways. The model does not differentiate whether the vehicles on the road are CAVs or not, however, two type of cars are considered: passenger cars and trucks. The simulation of the proposed model was carried out on an open two-lanes system with one lane on-ramp and three phases were considered on the simulations: jammed, synchronized and free flow.

Dong et al. [2017] presented an extended 1-to-1 probabilistic graphical model that handle multi-merging vehicles with respect to a host vehicle that is on the main lane. The task of the probabilistic graphical model is to generate an intention estimation with maximum probability, given observed information, so that the cause-effect relationship among previous states and intention can be understood. The 1-to-1 model considers one host vehicle which is a human-driven vehicle and the merging vehicle which is an autonomous vehicle. The model is extended by duplicating and applied to each merging vehicle in the ramp. The focus of the proposed model is to predict the intention of the merging vehicle given observed speeds and time-to-arrival. The model was tested using ramp data from the US-101 and I-80 highways in the Next Generation Simulation (NGSIM) project data set [Kovvali et al., 2007]. The merging groups are to exemplify and train the model. The data sets are taken from merging ramp regions which are about 600 meters long. Later, the same authors extended the previous model by considering an auxiliary lane which follows the on-ramp, instead of using a fixed merging point for all merging vehicles [Dong et al., 2018]. The goal of the proposed methodology was to predict whether or not the merging vehicle intends to yield to the host car, and then safely react to it.

In [Jin et al., 2017], authors proposed a gap metering method for adjusting the gap distribution of the mainline traffic. The authors' idea was to develop such method as a new Active Traffic Management strategy to be added to the existing Intelligent Transportation System toolboxes for freeway merge control. The proposed method is to use traffic signs to guide or regulate mainline through-lane vehicles to yield gaps before merging areas. Thus, authors modeled the driver behavior under gap metering by adjusting the standstill distance in Wiedenmann's car-following model. The experimental design was based on the simulation results of the I-894 and I-35 corridor data sets from the cities of Milwaukee and Austin in US, respectively. The authors divided the simulation in two steps: during the first step a study on the system parameters was conducted based on the results of the I-894 corridor, and in the second step they compared the ramp metering method based on the I-5 corridor data. The study did not analyse whether the vehicles had AD/ADAS functionalities.

Wang and Chan [2017] proposed a Long Short-Term Memory (LSTM) architecture to model the environment between a merging behavior and other surrounding vehicles in an on-ramp scenario. In the model, an internal state representation from LSTM at each time step is fed into a Deep Q-network for action selection. The vehicle action is composed of the acceleration and lateral steering angle taken by the merging vehicle. The LSTM model was trained on a simulated scenario of a section of the NGSIM data set, the US interstate Highway I-80 however, the study did not present any verification nor validation of the proposed methodology. Authors claimed that the proposed model has the potential to be applied to autonomous driving scenarios however during the training stage the model does not differentiate between autonomous and non-autonomous vehicles.

Sun et al. [2018b] investigated the impact that multi-rejected gaps have on merging behavior, thus, they proposed a logistic regression model that take into account multi-rejected gaps at on-ramp merging scenarios. The proposed model was tested using field data from the US-101 NGSIM and Hongxu on-ramp data-sets. The experimental analysis focused on the relationship between multi-rejected gaps and accepted gaps at the acceleration lane during the on-ramp merging behavior. Moreover, the authors applied a non-parametric method of survival analysis in order to get a probability distribution of merging with respect to critical gaps. Even though the authors claimed that autonomous vehicles can benefit from the model, the work did not consider autonomous vehicles characteristics in the proposed model.

Wang et al. [2017] presented a model based on Support Vector Machine (SVM) to predict different lane-changing behaviors at the on-ramp. The proposed SVM model was adopted to predict free and non-free lane changing and successful and non-successful lane changing behaviors. The SVM model introduced several penalty parameters in order to improve the prediction accuracy of the merging behavior. Thus, the authors proposed a grid search method for parameter optimization, so the optimal penalty parameters combination could be found. The model was trained and tested using two on-ramp bottlenecks located on Yan'an Expressway in Shanghai. Authors suggested that the proposed method could be used for real-time driver assistant system on CAVs, however, during the study the authors did not contemplate such characteristics.

Huang and Sun [2019] proposed a cooperative ramp merging model that consider human-operated vehicles and CAVs. The authors used in-parallel simulation in order to predict the vehicles states up until they reach the merge point and check whether ramp vehicles can merge at that point so an optimal merge sequence can be found and therefore, the systems at a merge point are minimized. Thus, a bi-level optimization model was proposed. The upper level aims at finding the optimal merge sequence, and the lower level problem consists in optimizing the vehicles trajectories during a single merge maneuver. The model considers scenarios in which cooperative and non-cooperative merging may apply and include a restriction ensuring that cooperative vehicles can only be controlled once. The model was validated in a simulated scenario the authors generated. In simulations, the ramp merging behavior employed a deterministic binary choice model. The model assumes merging decisions are made with safety and courtesy considerations.

Li et al. [2019] investigated the existence of heterogeneity among merging position selection behaviors. While doing the study the authors also analysed different driving styles and attitudes during the merging process. The authors proposed a driver behavior model based on the merging position. They assumed that merging drivers would choose the desired merging position after they chose the accepted gap. The authors presented a model that is composed of a finite mixture of linear regression models. The model was built using data-set provided by the Federal Highway Administration's Next Simulation project which was collected on a segment of southbound U.S. Highway 101 (Hollywood Freeway) in Los Angeles, CA. The parameters of the finite mixture of linear regression were estimated using Latent GOLD 5.0 which uses expectation-maximization and Newton-Raphson algorithms. The authors

TABLE IV
SUMMARIZE OF THE RECENT WORKS PROPOSING ON-RAMP MERGING MODELS

| Papers | Methodology | Environment |
|---|---|---|
| Marczak et al. [2013] | Principal Component Analysis | Data collected in the Netherlands (Bodegraven) and in France (Grenoble) |
| Guzmán et al. [2015] | Cellular Automata Model | Generated Scenario |
| Dong et al. [2017, 2018] | Probabilistic Graphical Model | US-101 and I-80 NGSIM |
| Jin et al. [2017] | Gap Metering Control Method | US I-894 and I-35 VISSIM |
| Wang and Chan [2017] | Long Short-Term Memory | US I-80 NGSIM |
| Sun et al. [2018b] | Logistic Regression Analysis | US-101 NGSIM and Hongxu |
| Wang et al. [2017] | Support Vector Machine Models | HongXu and HongJing |
| Huang and Sun [2019] | Bi-level Optimization Model | Generated Scenario |
| Li et al. [2019] | Finite Mixture of Linear Regression Models | US-101 NGSIM |
| Li and Dai [2019] | Speed Merging Control Method | Generated Scenario |
| Okuda et al. [2019] | Logistic Regression Model | Driving Simulator |
| Schester and Ortiz [2019] | Game Theory Model | Generated Scenario and US I-80 NGSIM |
| Kang and Rakha [2020] | Game Theory Model | US-101 NGSIM |

suggested the collection of more data so the proposed model can be used to recognize different driving styles which in turn facilitate the development of autonomous driving systems.

Li and Dai [2019] proposed an on-ramp merging control method for highway entering. They propose that, by using co-operative vehicle infrastructure system, the on-ramp merging vehicles receives advisory speed according to traffic condition in the ramp area. The idea is that ramp vehicles start to move from the location of a light sign at zero time and then enter the control area or guidance ramp. The intention behind the merging control is to make sure that the traffic flow on the main lane is not affected by the merging vehicles from the ramp. The authors then modeled the merging process in ramp areas taking into account a gap acceptance criterion. The model is validated on a simulation environment developed by using AnyLogic simulation software. For analysis purposes the authors conducted simulations with and without the proposed merging method. Even though, the authors may consider information from the cooperative vehicle infrastructure system, the work does not take into consideration any form of communication between the vehicles.

Okuda et al. [2019] investigated the achievement of a consensus among automated cars that are merging from the ramp into the highway. The authors proposed a logistic regression model for the driver's acceptance for the merging car merging to the main-lane. The driving behavior was observed using a driver simulator and the prediction performance of the proposed model was analysed with a cross-validation method. However, the prediction accuracy of the overall model was not quantitatively discussed. Moreover, a merging behavior control method of the car on the merging lane was proposed. The proposed control method considered two stages: the first stage consists in realizing a fast consensus with the cars on the main lane by optimizing the speed and; the second stage consists in finalizing the merging task after making consensus in the first stage. By doing so, the control method enables an automated vehicle to merge at a highway junction.

Schester and Ortiz [2019] proposed a model for the interaction of two vehicles: the merging vehicle and the vehicle positioned in the main-lane. The model is grounded in non-cooperative game theory. Authors assumed that the merging car is the automated vehicle and knows direction information of the lane vehicle's actions but not the contrary, that means that the vehicle on the main lane does not have information regarding the merging one. Moreover, the study considered only the interaction between two vehicles. The objective of the model is to capture essential actions that an automated driving vehicle must take to merge into traffic without causing a collision. Moreover, authors presented variations of multi-agent Q-learning approach within a simulator to study on-ramp merging. To validate and analyse the performance of the proposed model the authors used the NGSIM simulator.

More recently, [Kang and Rakha, 2020] proposed a game theoretical model for merging behaviors. The model is based on lane-changing decisions between two decision-makers: the one who wants to make a lane-change and the one who allows or not the lane change. The model was calibrated and evaluated using NGSIM vehicle trajectory data set. For calibration and validation purposes the authors used 685 and 819 observations, respectively. The study used a total of 1504 observations extracted from NGSIM data. Moreover, for demonstrating the performance of the proposed game model, a microscopic simulation model based on an agent-based method was developed on MATLAB so that a comparison between the simulation and NGSIM data could be provided.

It is clear the effort put by that the research community into modeling on-ramp merging behavior. The main goal behind the proposed models found in the literature is to develop avoiding collision systems that can be adopted by driving assistance models for adaptive cruise control. By doing that, prevention models as well as automation models can be further considered. Table IV summarizes the insights from the works reviewed in this section. In particular, we want to highlight whether the authors validate the proposed model using well-known data-sets, data extracted from different real scenarios or simulated scenarios.

## A. V2X Communications

Several studies have attempted to include autonomous vehicles' characteristics. CAVs present multiple opportunities to deal with the negative aspects of conventional non-autonomous vehicles. Cooperation between vehicles is based on V2X communication which is intended for the exchange of information between a vehicle and any element of the transport system such as other vehicles, pedestrians, internet gateways and equipment of the road infrastructure as traffic lights and signals. Reliable V2X communications is the critical component of connected vehicle technology applications. One of the great challenges is the development of V2X communication protocols, which would be able to support a variety of different use-cases, scenarios and autonomy levels.

Among the advantages of communication between vehicles, one can highlight the following ideas: (*i*) collisions can decrease dramatically when vehicles are warned of dangerous situations in advance; (*ii*) mobility can be optimized when drivers, public transport users and traffic controllers have access to up-to-date, accurate and comprehensive information on traffic conditions and; (*iii*) the environmental impact can be reduced if the decisions made by drivers are the result of advanced information about routes avoiding unnecessary stops, acceleration and or deceleration, thus, optimizing fuel consumption [Dey et al., 2016].

On this matter, recent studies have considered the inclusion of V2X characteristics when modeling driver behaviors. Wang et al. [2018b] proposed a protocol for the highway on-ramp merging system and made some assumptions while modeling the system. The proposed system takes advantage of V2X communications assuming that all vehicles in the study were CAVs with the ability to communicate between each other and with the infrastructure. The proposed protocol was designed to arrange vehicles with a predefined sequence, so they can cooperate with each other before merging. Authors tested the proposed system by using the microscopic traffic simulator VISSIM, in particular, authors built the simulation based on the on-ramp from University of California, Riverside County campus area.

Recently, [Nassef et al., 2020] proposed a coordination model based on reinforcement learning for a scenario where a vehicle is merging into a carriageway between two vehicles. The NGSIM data-set was used for training, testing and validating the proposed model. The proposed model was compared against state-of-the-art machine learning prediction algorithms in order to provide some insights of the expected accuracy. Moreover, to facilitate the lane merge coordination, a V2X gateway was responsible for forwarding messages to connected vehicles.

Although studies have focused on ramp merging using V2X [Wang et al., 2018b, Nassef et al., 2020], minimum effort has been made for analysing the effect of mixed traffic on the highway for developing a driver behavior model using real world traffic data. Furthermore, those works are based on deterministic traffic data input. When dealing with deterministic information strong assumptions are made, for example, it is assumed that precise information about the vehicles is known (*i.e.*, positions, speeds, accelerations, etc.), it is expected that all actors are able to share information with each other and that no lane change maneuver is conducted. However, it is crucial to build the models using real driver data and assess them from statistical and behavioral standpoints.

Reliable V2X communications is the critical component of connected vehicle technology applications. One of the great challenges is the development of V2X communication protocols, which would be able to support a variety of different use-cases, scenarios and autonomy levels.

# IV. Methodologies and Techniques

In order to give a succinct outlook of the main principles and ideas involved with the most commonly-used methodologies for modeling the decision-making characteristics of modelling drivers behavior at ramp area, we briefly summarize the main aspects of the most used methodologies from the works analysed before. All in all, machine learning techniques have been well adopted to predict human-driven vehicles' trajectory and/or infer driving intention when interacting with other traffic.

## A. Machine Learning

Machine Learning algorithms are characterized by adjusting the parameters of a model by optimizing a criterion that indicates its performance against the data presented. Each machine learning problem can be precisely defined as the problem of improving some measure of performance $P$ when executing some task $T$, through some type of training experience $E$. Once the three components $\langle T, P, E\rangle$ have been specified fully, the learning problem is well defined [Mitchell, 2017].

When considering a machine learning problem it is useful to treat them from different perspectives: ($i$) Machine learning as optimization, in that case, the learning algorithm is often itself an optimization algorithm; ($ii$) Machine learning as probabilistic inference, in fact, the two primary principles for deriving learning algorithms are the probabilistic principles of Maximum Likelihood Estimation (in which the learner seeks the hypothesis that makes the observed training data most probable), and Maximum a Posteriori Probability estimation (in which the learner seeks the most probable hypothesis, given the training data plus a prior probability distribution over simple hypothesis); ($iii$) Machine learning as parametric programming, in that case, learning algorithms are choosing parameter values that define a function or a computer program written in a programming language which is defined by their hypothesis space and; ($iv$) Machine learning as evolutionary search, note that some forms of learning do not admit an easy formulation as an optimization or probabilistic inference problem, instead, the notion of "increasingly successful organism" may itself change over time, as the environment of the organism and its set of competitors evolve as well.

### B. Game Theory

The main objective of Theory of Games is to analyse situations where the result of the action of individuals, group of individuals, or institutions, depends substantially on the actions of the others involved. In other words, it deals with situations where no individual can conveniently make a decision without taking into account the possible decisions of others.

For a situation be considered as a game, it would have to present the existence of conflict and interdependence between the decisions of the participants. This is the most abstract characterization we can make of a game. However, on a more concrete level, we can identify two types of game: $(i)$ the non-cooperative game, when its organic conditions do not allow the formation of coalitions that can determine the outcome of the game and; $(ii)$ the cooperative game, when the very organic conditions of the game allow the possibility of the participants to act through coalitions.

### C. Logistic Regression Models

Logistic Regression is an approach to learning functions of the form $f : X \to Y$, or $P(X \mid Y)$ in the case where $Y$ is discrete-valued and $X = \langle X_1 \ldots X_n \rangle$ is any vector containing discrete or continuous variables. Logistic Regression assumes a parametric form for the distribution $P(X \mid Y)$, that directly estimates its parameters from the training data.

Interestingly, the parametric form of $P(X \mid Y)$ used by Logistic Regression is precisely the form implied by the assumptions of a Gaussian Naive Bayes (GNB) classifier. Therefore, we can view Logistic Regression as a closely related alternative to GNB, though the two can produce different results in many cases. All in all, Logistic Regression is a function approximation algorithm that uses training data to directly estimate $P(X \mid Y)$, in contrast to Naive Bayes. In this sense, Logistic Regression is often referred to as a discriminative classifier because we can view the distribution $P(X \mid Y)$ as directly discriminating the value of the target value $Y$ for any given instance $X$ [Mitchell, 2005].

## V. Summary and Future Research Directions

Highway on-ramp merging is a complex situation which drivers face on the daily basis. As an important part of highways, ramp area often becomes a sensitive point leading to traffic efficiency dropping and collisions where vehicles merge in and exit off the main lane. In this scenario, it is expected that human drivers use their judgements as well as analysis of other drivers' behavior to decide when and where it is appropriate to merge into traffic. Therefore, understanding real-life driving patterns can become a basis for the design of future CAVs for highway merging and exiting, what will enable mixed traffic scenarios. Even though, there exists a lot of research in the area of CAVs and many simulation studies have been proposed, one particular question that arises is: "how to enable CAVs to merge and exit the flow of human-driven vehicles on the highway given the existing technologies/protocols available?".

Communications are needed for the vehicles to be able to exchange information such as its position in real time with each other. To the best of our knowledge, V2X communications are promising when talking about reducing traffic accidents and easing congestion by enabling vehicles to give a rapid response for changes in their mutual environment. Thus, another question is related to the infrastructure and the actual environment as it is with tons of data from vehicle and infrastructure: "how can CAV handle interventions from human-driven traffic merging/exiting highway with the assistance V2X-enabled traffic-camera system?". This is likely to understand the data which needs to be communicated from infrastructure to CAV to enable safe driving. Formulate requirements for maximum uncertainties in parameters estimation achieved by camera-based system (e.g. speed and acceleration) as well as for overall latency from the moment of retrieving these parameters until they should be communicated to CAV.

Finally, most of the research in this field in general, were conducted with data collected. While the structure of those models is general enough to be applied for traffic in urban arterials, some factors that affect lane changing behavior in urban streets may not be present in freeway traffic. It is hard to collect plenty of real-world data to increase the data diversity since it is expensive. Therefore, a novel approach is required to sufficiently train and evaluate the intention of the drivers.

## VI. Conclusions

The present work displays the studies that have been proposed methods for modeling driving behaviors during the last 10 years. Particularly, the study focused on the efforts related to coordinating CAVs for improving traffic flow on specific transportation segments such as the highway on-ramp merging. Advanced Driver Assistance Systems have assumed an enormous importance in the process of adapting conventional vehicles to new levels of automation, contributing to the smoothing of safety over the last years. Thus, it is noticeable the need for studying how the wireless communications network is adapted to transport systems, since the existence of a solid communications network is the pillar of such infrastructures. In this regard, existing communication technology, such as vehicle-to-everything (V2X), showed notable potentialities, which can benefit safety, emissions, comfort in traffic and a key point such as reducing congestion. Although the research efforts studied to date have tried to enhance the understanding of coordination of CAVs, some open issues to be addressed were found.

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