Review of Microscopic Lane-Changing Models and Future Research Opportunities

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***Abstract*—Driver behaviors, particularly lane-changing behaviors, have an important effect on the safety and throughput of the roadway-vehicle-based transportation system. Lane-changing models are a vital component of various microscopic traffic simulation tools, which are extensively used and playing an increasingly important role in Intelligent Transportation Systems studies. The authors conducted a detailed review and systematic comparison of existing microscopic lane-changing models that are related to roadway traffic simulation to provide a better understanding of respective properties, including strengths and weaknesses of the lane-changing models, and to identify potential for model improvement using existing and emerging data collection technologies. Many models have been developed in the last few decades to capture the uncertainty in lane change modeling; however, lane-changing behavior in the real world is very complex due to driver distraction (e.g., texting and cellphone or smartphone use) and environmental (e.g., pavement and lighting conditions) and geometric (e.g., horizontal and vertical curves) factors of the roadway, which have not been adequately considered in existing models. Therefore, large and detailed microscopic vehicle trajectory data sets are needed to develop new lane changing models that address these issues, and to calibrate and validate lane-changing models for representing the real world reliably. Possible measures to improve the accuracy and reliability of lane-changing models are also discussed in this paper.**

***Index Terms*—Driver behavior, lane-changing models.**

I. Introduction

DRIVER behavior highly affects the safety and throughput of the roadway-vehicle-based transportation system. In order to improve the current transportation system's capacity and safety, while providing the base for its future successor, a clear understanding of driver behavior is of paramount importance. Driving tasks are conducted depending upon two fundamental considerations: keeping a desired speed or distance and staying in a lane for either downstream turning or passing maneuvers [1]; the latter is usually described mathematically by lane-changing models. Lane-changing maneuvers consist of three critical driving behaviors: 1) lower-level control such as steering and acceleration, 2) monitoring which indicates awareness to maintain a situation, and 3) the decision to change lanes [2].

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Driving behavior during lane-changing maneuvers has a momentous effect on traffic flow phenomena. Several recent experiments have concluded that the development of congestion at bottlenecks due to lane drops is mainly attributed to lane-changing maneuvers [3]–[6]. In addition, when a vehicle moves from the existing lane to the target lane, such lane-changing maneuvers act as moving obstructions that reduce the capacity and safety of the freeway [6], [7]. Furthermore, inappropriate lane changes are responsible for one tenth of all accidents [8]. Developing strategies for collision avoidance during lane changes requires a thorough understanding of drivers' behavior during this driving task [9].

Several factors make modeling lane changes at the microscopic level a complicated problem: 1) the asymmetric behavior of lane changes; 2) the variance of gap acceptance behavior under different traffic conditions; 3) the minimum gaps that depend on the speed of the subject vehicle and the speeds of vehicles in the target lane; and 4) the assumption of heterogeneous vehicles resulting in high lane-changing rates [10]–[16].

Microscopic traffic simulators can be used to create virtual scenarios in which the lane-changing model is an essential component for replicating real-world traffic conditions. Microscopic traffic simulation, which utilizes car-following and lane-changing models to represent each driver's maneuvering behaviors in traffic, has been applied in intelligent transportation systems studies [17]–[20] as a cost-effective alternative to field tests. Several microscopic traffic simulation models that incorporated lane-changing models have been developed in the last decade. However, few details about these lane-changing models have been published [21]. Considering the accuracy of microscopic traffic simulation models is highly dependent on the lane-changing model, it is very important to ensure that lane-changing models are clearly understood, appropriately designed, and carefully calibrated.

On the other hand, many macroscopic lane-changing models have been studied to understand various traffic flow characteristics, such as the exchange rate of flows between lanes [22]–[25], density oscillation and instability of traffic flow [26], [27], and the degree of first-in-first-out violation among vehicles [28]. As a special lane-changing area, the weaving area and its level of service has been also studied since the publication of the Highway Capacity Manual [29].

Lane-changing behavior greatly increases the level of difficulty of the model specification to capture real life scenarios and the calibration process for large number of parameters [30]. To reduce the complexity of modeling lane changes, several hybrid (micro-/macroscopic) lane-changing models have been proposed [6], [31]. In [31], a new variable called lane-changing

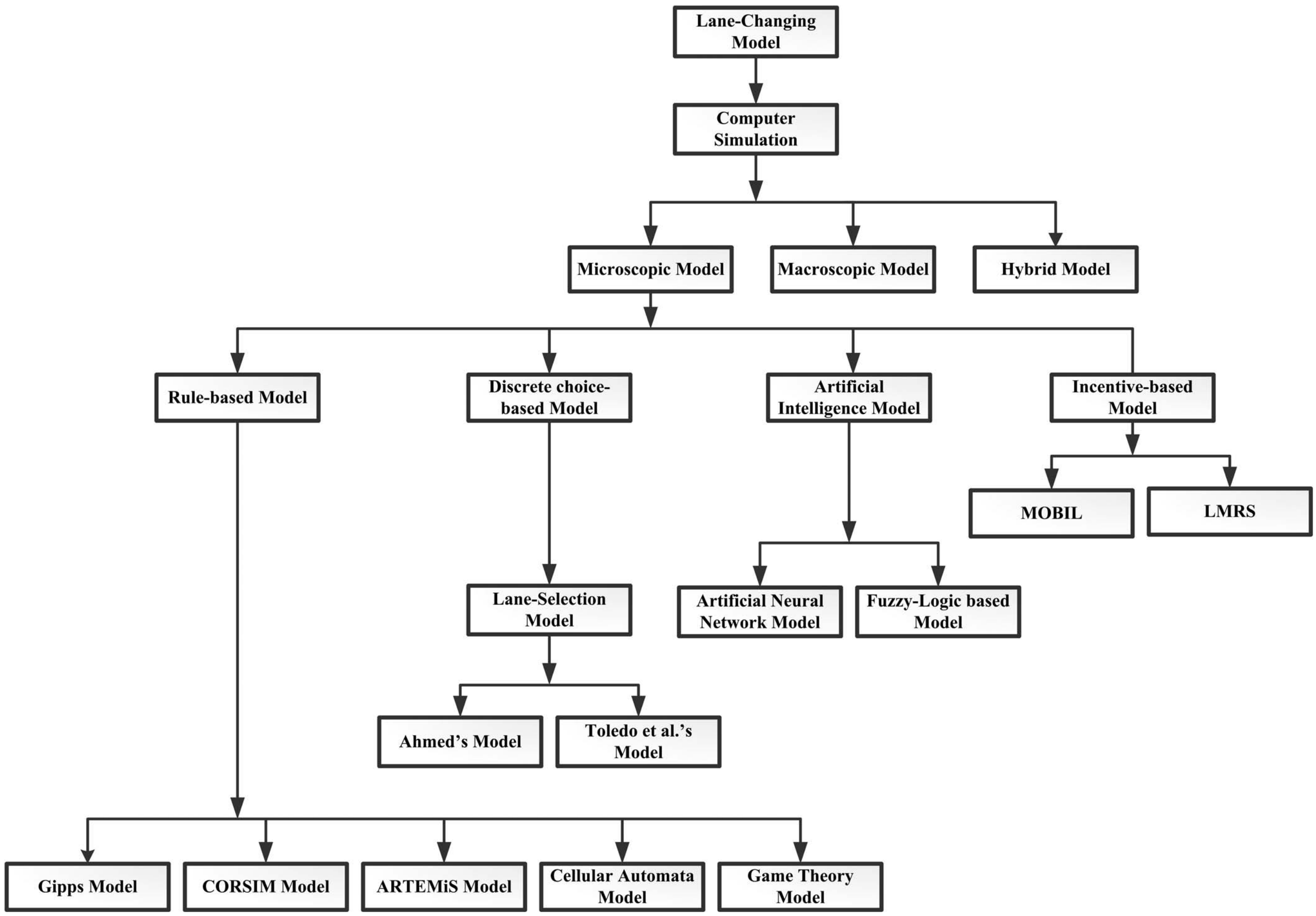

Fig. 1. Classification of lane-changing models.

intensity is introduced, which is the ratio of vehicle lane-changing time to the total travel time of a roadway section. Other variables, such as traffic density, travel speed, and flow rate, at any time and any section of the roadway are also included in this model. An intensity–density relation is hypothesized and incorporated into the Greenshield's fundamental diagram [32]. This improved fundamental diagram is used to study the lane-changing impact on overall traffic flow.

Recently, a few literature reviews [1], [33] on driver decision models have been conducted to classify lane-changing models. Different from our paper, these reviews either do not cover any incentive-based models or do not include any comparative analysis between different types of lane-changing models. In addition, in our paper, critical factors and vehicle trajectory data needs for future model development have been identified, given the limitations of existing lane-changing models and advancements in data collection technologies.

The key aspects of this study involve classifying and reviewing the existing microscopic lane-changing models for computer simulation, as well as systematically comparing the reviewed models. Furthermore, potential for future model improvement using existing and emerging data collection technologies is identified. First, a detailed review and comparison of existing lane-changing models is conducted to provide a better understanding of the state-of-the-art lane-changing research. Based upon the review and comparison, modeling challenges that could be addressed to improve the accuracy and reliability of lane-changing models are presented and discussed.

II. Classification of Lane-Changing Models

With the technological advancements for reliable traffic data collection, the lane-changing modeling has received increasing attention since the early 1980s [34]. The applications of lane-changing models can be broadly classified into two groups: adaptive cruise control and computer simulation. Lane-changing models for adaptive cruise control are mainly focused on developing driving assistance models, which can be further classified into collision avoidance models and automation models. Collision avoidance models are for controlling drivers' lane-changing maneuvers and assisting them with completing lane changes safely. Automation models are for adjusting the steering wheel angle of vehicles automatically to perform safe lane-changing maneuvers [35]–[42]. The main focus of this paper is to review and compare microscopic lane-changing models for computer simulation (see Fig. 1). Since the 1980s, many lane-changing models have been developed for microsimulators to replicate driver decisions at the microscopic level. These lane-changing models are categorized into four groups: rule-based model, discrete-choice-based model, artificial intelligence model, and incentive-based model. In the next four sections, the four types of microscopic lane-changing models are discussed in detail. Theoretical comparisons of these lane-changing models are presented in Section VII.

III. Rule-Based Models

A. Gipps Model

Gipps' model describes the lane-changing decisions and the execution of lane changes on freeways and urban streets [43] as the result of three factors: lane-changing possibility, necessity for changing lanes, and lane-changing desirability. It incorporates the difference between the wish to change lanes and the execution of lane changes that was first introduced by Sparmann [44]. Gipps' model includes several factors, such as the existence of safety gap, locations of permanent obstructions, intent of turning movement, presence of heavy vehicles, and speed advantage. It also considers several lane-changing reasons: avoiding permanent obstructions, avoiding special-purpose lanes such as transit lanes, turning at downstream intersections, avoiding a heavy vehicle's influence, and gaining speed advantage. In this model, a driver's behavior falls into three zones, which are separated by the distance of the driver to the intended turn. When the intended turn is away from her/his position, it has no impact on the driver's latent lane-changing plan. When the intended turn is in a zone that is the middle of the way, the driver ignores the speed advantage opportunity. When the intended turn is close enough, the driver chooses either the appropriate or adjacent lane, as maintaining or gaining speed is not important. The boundaries of the three zones, which do not depend on the driver's behavior patterns over time, are deterministic in nature. The structure of Gipps' lane-changing model is based on his car-following model, which applies some restrictions on the braking rate by drivers [45]. His car-following model ensures that the follower driver selects his/her speed to bring the vehicle to a safe stop in case of a sudden stop. In Gipps' lane-changing model, the deceleration of the subject vehicle is used to evaluate the feasibility to change lanes. A special braking rate is assigned to the subject vehicle, so that the maximum deceleration can be achieved to complete a successful lane-changing maneuver. If the required deceleration for a lane-changing maneuver is not within the acceptance range, then this lane-changing maneuver is determined as infeasible. According to Gipps' lane-changing model, the subject vehicle driver can alter the braking rate parameter depending on the urgency of the lane-changing maneuver.

Gipps' model summarizes the lane-changing process as a decision tree with a series of fixed conditions typically encountered on urban arterial, and the final output of this rule-based triggered event is a binary choice (i.e., change/not change). Any new or special lane-changing reasons can be added or replaced because of its flexible structure. However, the variability in individual driver behavior is not incorporated in this model, particularly the different interaction strategies among the surrounding vehicles and the subject vehicle under various traffic conditions. For example, under congested traffic conditions, either the lag vehicle gives permission to the subject vehicle to change lane, or the subject vehicle forces its way into the target lane. Although the Gipps model is used in several microscopic traffic simulation tools, it is based upon some tactically simplified assumptions and does not include any framework for model validation based on microscopic driver behavior and traffic data.

B. CORSIM Model

Halati *et al.* developed a lane-changing model that was implemented in CORridor SIMulation (CORSIM), in which lane changes are classified as mandatory lane changing (MLC), discretionary lane changing (DLC), and random lane changing (RLC) [46]. MLC occurs when drivers merge onto a freeway or move to the target lane to make an intended turn or avoid obstructions (e.g., lane blockage and lane drop) in a lane. DLC is applied when lane changes are required for speed advantage. For instance, a driver may want to pass a slow-moving vehicle by changing to the left lane. RLC is applied when there is no apparent reason. RLC may or may not result in an advantage for the subject vehicle over its current position. In CORSIM, a certain percentage (the default value is 1%) of drivers are randomly selected to perform RLC. In this model, motivation, advantage, and urgency are considered as the three major factors behind a lane-changing decision. The motivation to change lanes depends upon either the lead vehicle speed or the lead headway threshold. The advantage factor captures the benefits of driving in the target lane. The urgency of lane changing depends upon the number of lanes to change and the distance required to execute a complete lane-changing maneuver. In CORSIM, lane-changing maneuvers (i.e., MLC, DLC, or RLC) depend on the availability of acceptable lead and lag gaps in the target lane. An acceptable lead gap is modeled utilizing the deceleration required by the subject vehicle for avoiding collision with its lead vehicle in the target lane. According to this model, the required deceleration for the subject vehicle is computed, assuming the deceleration of the lead vehicle in the target lane is maximized. This computed deceleration of the subject vehicle is compared with an acceptable deceleration, which is also called the acceptable lane-changing risk. If the required deceleration is less than the acceptable risk, the lead gap is accepted and the subject vehicle initiates a lane change into the target lane.

Lane-changing algorithms used in the FREeway SIMulator (FRESIM) and NETwork SIMulator (NETSIM) are similar. The only difference lies in measuring gaps between the subject vehicle and the lead/lag vehicles in the target lane. NETSIM measures the gaps in terms of time differences, and the gaps in FRESIM are a function of time headways and speed differences. Only the FRESIM DLC procedure is described here. It is based on the car-following model developed by the University of Pittsburgh, Pittsburgh, PA, USA [47], [48]. The FRESIM model assumes that the follow vehicle tries to keep a suitable gap between itself and the lead vehicle. A lane change occurs, when the follow vehicle cannot maintain the required space headway. In addition, in the FRESIM model, an "intolerable" speed is calculated using the desired free-flow speed. The subject vehicle is eligible for a lane change, if its current speed is less than the free-flow speed. The subject vehicle driver performs a lane-changing maneuver, if her/his current speed is less than the intolerable speed.

In the FRESIM DLC procedure, lane-changing benefits are referred to as "Advantage." Advantage is modeled through either the "lead factor" or "putative factor." The disadvantage of staying in the current lane is represented by the lead factor. On the other hand, the putative factor represents the benefits of executing lane changes. Theoretically, a subject vehicle driver could select any one of the adjacent lanes (left/right) as the target lane for performing lane changes. Thus, the advantage is calculated for both adjacent lanes through the putative factor. Based on the larger putative factor, the target lane is chosen from the adjacent lanes (left/right). The putative factor can be also determined as the lead factor using the putative lead headway in the adjacent lane. The overall advantage for DLC is represented by the difference between the putative factor and the lead factor. It is then compared with a threshold value of 0.4 [48]. If the overall advantage is greater than the threshold value, a lane change occurs. So far, only the FRESIM DLC model has been discussed. The RLC and MLC are also incorporated in FRESIM. More detailed information on these lane-changing models could be found in [48].

Additionally, after the subject vehicle moves into the target lane, a "shadow vehicle" in CORSIM is generated in the current lane in place of the subject vehicle for a while to avoid rapid speed changes of its follower. Another nice feature of CORSIM is the flexibility of taking user-provided parameters. As all drivers in CORSIM are assumed to have similar gap acceptance behavior, it does not consider the variability in gap acceptance behavior.

C. ARTEMiS Model

ARTEMiS, which is an abbreviation for Analysis of Road Traffic and Evaluation by Micro-Simulation, is a microscopic traffic simulation model developed by Hidas [49]. Previously named Simulation of Intelligent TRAnsport Systems (SITRAS), this model describes lane-changing maneuvers based upon the courtesy of the lag vehicle in the destination lane [50]–[53]. In this model, a lane change is triggered by required downstream turning movements, lane drops, lane blockages, lane use restrictions, speed advantages, or queue advantages. MLC occurs in the case of downstream turning movements, lane drops, and lane blockages, and DLC happens in the early and middle distance zones. The boundaries of different zones are defined in the same way as Gipps' model [43]. Hidas modeled each vehicle as a driver-vehicle object (DVO), using an autonomous agent technique to describe drivers' interactions involved in a complex decision-making process [53]. DVOs can act as giving way, slowing down, or not giving way, based on road congestion conditions, individual driver characteristics, and the perception of a DVO in terms of whether another DVO is trying to move into its lane or not. According to this model, lane-changing reasons are evaluated, and the results are classified as "essential," "desirable," or "unnecessary," based on which a target lane is chosen.

In ARTEMiS, gap acceptance model selection depends on lane-changing modes. Two lane-changing modes are proposed according to traffic conditions and the necessity of changing lanes: normal lane changing and courtesy/forced lane changing. A normal lane change occurs when a sufficient gap is available in the target lane. This lane-changing mode is based on the Hidas car-following model and can be expressed as: 1) acceptable deceleration (or acceleration) is required for the subject vehicle to follow the lead vehicle in the target lane [52], and 2) acceptable deceleration is required for the lag vehicle in the target lane, so that the subject vehicle can safely serve as its lead vehicle.

For the courtesy/forced lane-changing mode, the subject vehicle sends a "courtesy" signal to the vehicles in the target lane. Starting from the first lag vehicle, the required deceleration is calculated using the aforementioned Hidas car-following model to allow the subject vehicle to safely merge. Based on the calculated decelerations, a follow vehicle in the target lane can be found, and the new lead vehicle (to the subject vehicle) is the one right in front of the follower. A sufficient gap is created for the subject vehicle by applying the Hidas car-following algorithm to the new lead vehicle, the subject vehicle, and the new lag vehicle, so that the subject vehicle can change lane to the target lane.

Later, Hidas categorized lane-changing maneuvers into three classes: free, forced, and cooperative [49]. Lane-changing feasibility is checked using acceptable gaps (lead/lag). The lead and lag gaps are calculated, based on the statuses of the vehicles involved, before lane change happens. A free lane-changing maneuver is feasible, if both lead and lag gaps are greater than the desired critical gaps. If the previous condition is not satisfied, a lane change is considered "essential" and the feasibility of cooperative (courtesy) or forced lane change needs to be checked. The cooperative lane change depends on the willingness of the lag driver and the feasibility of the lane-changing maneuver. If a lag vehicle selects a certain maximum speed decrease, it indicates the willingness, which is a function of a vehicle's aggressiveness parameter and the urgency of lane change. The lag gap at the end of deceleration can be calculated by setting the deceleration period. This represents the smallest gap between the subject vehicle and the lag vehicle after changing lanes. A cooperative lane change is feasible, if the lag gap at the end of deceleration is larger than the minimum acceptable lag gap. The forced lane change is similar to the cooperative lane change. The difference lies only in that the maximum speed decrease and deceleration are assumed by the subject vehicle as average values.

Hidas validated the lane-changing model using vehicle trajectory data collected from the Sydney central business district in Australia [49]. A total of four hours of video recording was collected from a road section where lane-changing or merging maneuvers occurred. Hidas found ambiguity between forced and cooperative lane changes by only using the trajectories from the video data. He concluded that an empirical method could be designed to collect lane-changing data. One disadvantage of this model is that the given lane-changing reason set is incomplete. Lane-changing reasons, such as giving way to a merging vehicle and avoiding heavy vehicle influence, were not considered. Another downside of this model is that there is no framework for calibrating model parameters. In addition, ARTEMiS is unable to resolve the conflict when a driver desires to move in one direction (left/right) for an intended turning movement and, at the same time, another direction to get speed advantage. Moreover, cooperative and forced lane changes were considered separately in this model [49]. However, only the lag vehicle has the ability to initiate a cooperative lane change.

D. Cellular Automata Model

In the generic multilane cellular automata model, it is assumed that a vehicle changes to another lane if the following set of conditions is satisfied [54]:

Condition 1: $\text{gap}_n(t) < \min(V_n(t) + 1, V_{\max})$
Condition 2: $\text{gap}_{n,o}(t) > \min(V_n(t) + 1, V_{\max})$
Condition 3: $\text{gap}_{n,ob}(t) > V_{\max}$

where

$\text{gap}_n(t)$	number of empty cells ahead in the same lane;
$\text{gap}_{n,o}(t)$	number of empty cells ahead in the other lane;
$\text{gap}_{n,ob}(t)$	number of empty cells backward in the other lane;
$V_n(t)$	speed of vehicle n at time t;
$V_{\max}$	maximum speed of vehicles allowed.

The first two inequalities or conditions aforementioned check the current and target lanes for favorable speed conditions. Then, the availability of sufficient space to perform the lane change is checked by the third condition. The lane change potential is expressed with certain probability, depending on the three condition checking results. Lane-changing conditions in this model are classified as either symmetric or asymmetric. Based on this model, Nagel *et al.* later proposed various additional lane-changing rules and described their characteristics in details [36].

E. Game Theory Model

The game theory model is based on the giveway behavior in a merging situation when a traffic conflict arises between through and merging vehicles, in which they try to influence each other. Kita modeled this situation based upon the game theory and specified the game type, the number of players, and the repetition of games [55]. He also considered the cooperative nature of the game.

First, two players are defined in the game theory lane-changing model: the merging vehicle and the through vehicle. Kita only considered two players because of the close interaction between them and neglected their interaction with the surrounding vehicles. Another key characteristic of the game theory model is the number of games to be repeated, which can be one of the following three cases: each through vehicle in a conflict area plays several games; each through vehicle plays one game in a conflict area; and each merging vehicle and all through vehicles having a possible conflict with it play one game together, known as a one-shot game.

It is assumed that the games are independent, and the strategies of each player (i.e., the payoff matrices) are known by the other player and noncooperative because both players have information of each other. These two players play two different strategies: "merge" and "pass" for the merging vehicle and "giveway" and "do not giveway" for the through vehicle. If the merging vehicle and the through vehicles are denoted by player 1 (X1) and player 2 (X2), respectively, the pure strategy of X1 $\mathbf{m}$ is

$$\mathbf{m} = \{1 : \text{merge}, 2 : \text{pass}\}.$$

and the strategy of X2 $\mathbf{n}$ is

$$\mathbf{n} = \{\text{I} : \text{giveway}, \text{II} : \text{do not giveway}\}.$$

$$\begin{array}{ccc} [\text{X1}] & \text{I} & \text{II} \\ 1 & p_{11} & p_{12} \\ 2 & p_{21} & p_{22} \end{array} \qquad \begin{array}{ccc} [\text{X2}] & \text{I} & \text{II} \\ 1 & q_{11} & q_{12} \\ 2 & q_{21} & q_{22} \end{array}$$

Fig. 2. Payoff matrices for each player.

A payoff matrix is developed for each player, as shown in Fig. 2, in which each element (i.e., p_{ij}, q_{ij}) expresses the combination of situations of each vehicle.

Whether a merging car merges or a through car gives way depends on the given situation with a certain probability. Both players use mixed strategies for this type of situation. For a mixed strategy game, a bimatrix provides at least one equilibrium solution [56]. Kita [57] modeled on-ramp merging behavior using a discrete choice model, and the probability of giving way is estimated based on this game theory model. In Kita's model, drivers compare the utilities of the current lane and the target lanes (left/right) and choose the target lane with a higher utility. In this case, the utilities perceived by the drivers captured the payoff of the players.

The maximum-likelihood method is used to estimate the merging probability of the merging vehicle and the giveway probability of the through vehicle. The estimated parameters of this model are reasonable, as suggested by the likelihood ratio (0.347) and the value of the corresponding correlation coefficient (0.7) [58], showing that the game theory model is capable of explaining the real-world merging and giveway behaviors. For congested traffic conditions, Pei and Xu developed another lane-changing model based on game theory for two types of lane-changing maneuvers [59]. Traffic information and experience were the basis of their model to describe lane-changing maneuvers. In their model, cooperative and forced lane changes were also defined. The values of time and safety were the main factors affecting driver behavior. When drivers are in safe situations, they will execute a lane-changing maneuver. The game theory model is largely limited to describing the merging–giveway behavior in freeway merging areas and cannot be easily extended to other lane-changing maneuvers.

IV. Discrete-Choice-Based Models

A. Ahmed's Model

Ahmed [14], [60] proposed a dynamic discrete choice model to capture the heterogeneity in driving characteristics across the driving population and considered explanatory variables that affect driver behaviors. He modeled lane-changing decisions as a three-stage process: whether or not to make a lane change, target lane choice, and acceptance of a gap that is sufficient to execute the lane-changing. In addition, he proposed three categories of lane-changing maneuvers: MLC, DLC, and forced merging (FM). MLC situations apply when a driver is forced to change the current lane. DLC occurs when the driver is unsatisfied with the driving situation in the current lane and wishes to gain some speed advantage [61]. FM occurs when a gap is not sufficient but is created by the driver to execute a lane-changing maneuver in heavily congested traffic conditions. According to Ahmed's lane-changing model classification, lane-changing behavior is either MLC or DLC, which prohibits considering any tradeoffs between them. The mathematical formulation of the discrete choice framework is shown in the following functions, which describe the probability that driver n performs MLC, DLC, or FM at time t as follows:

$$P_t(\mathrm{LC}|v_n) = \frac{1}{1+\exp\left(-X_n^{LC}(t)\beta^{LC} - \alpha^{LC} v_n\right)}$$
$$\mathrm{LC} = \mathrm{MLC}, \mathrm{DLC}, \mathrm{FM}$$

where

- $P_t(\mathrm{LC}|v_n)$ probability of executing MLC, DLC, or FM for driver n at time t;
- X_n^{LC} vector of explanatory variables affecting decision to lane changes;
- β^{LC} corresponding vector of parameters;
- v_n driver-specific random term;
- α^{LC} parameter of v_n.

In Ahmed's gap acceptance model, he defined the critical lead and lag gaps as the minimum acceptable gaps. In this model, a lane change is performed when the available lead and lag gaps in the target lane are greater than their critical gaps. The following equation represents the critical lead and lag gaps for lane-changing maneuvers of driver n at time t:

$$G_n^{\mathrm{cr,gap}j}(t) = \exp\left(X_n^{\mathrm{cr,gap}j}(t)\beta^{\mathrm{gap}j} + \alpha^{\mathrm{gap}j} v_n + \varepsilon_n^{\mathrm{gap}j}(t)\right)$$
$$\mathrm{gap}j = \mathrm{lead}, \mathrm{lag}$$

where

- $G_n^{\mathrm{cr,gap}j}(t)$ critical lead and lag gaps for driver n at time t;
- $X_n^{\mathrm{gap}j}(t)$ vector of explanatory variables affecting the critical gap j;
- $\beta^{\mathrm{gap}j}$ corresponding vector of parameters;
- v_n driver-specific random term;
- $\alpha^{\mathrm{gap}j}$ parameter of v_n;
- $\varepsilon_n^{\mathrm{gap}j}(t)$ $N(0, \sigma_{\varepsilon j}^2)$ is a random term.

The probability of accepting a gap during MLC, DLC, or FM for driver n at time t is given as follows:

$$\begin{aligned} &P_n(\text{gap acceptance}|v_n) \\ &= P_n(\text{lead gap acceptable}|v_n) P_n(\text{lag gap acceptable}|v_n) \\ &= P_n\left(G_n^{\mathrm{lead}}(t) > G_n^{\mathrm{cr,lead}}(t)|v_n\right) P_n\left(G_n^{\mathrm{lag}}(t) > G_n^{\mathrm{cr,lag}}(t)|v_n\right) \end{aligned}$$

where

- G_n^{lead}(t) probable lead gaps in the target lane;
- G_n^{lag}(t) probable lag gaps in the target lane.

Ahmed subsequently implemented his model in MIcroscopic Traffic SIMulator (MITSIM). It was developed primarily to assess advanced traffic management systems and advanced traveler information systems at the operational level. Although his lane-changing model was unable to capture the tradeoffs between MLC and DLC decision processes, it accurately described the differences between drivers' MLC, DLC, and FM decisions. For instance, in MITSIM, drivers are unable to overtake when mandatory considerations are active. Similar to the Gipps model, the existence of an MLC is determined based upon the distance of the subject vehicle to the downstream exit ramp. In addition, a dummy variable is introduced to capture the differences in acceptable gap values between a passenger car and a heavy vehicle when the heavy vehicle is the subject. Although this very coarse and simplistic method accounts for the differences in operational characteristics of these two vehicle types, the aforementioned models incorporate a rigid separation between MLC and DLC, which is unrealistic in real-life driving.

B. Toledo et al's Model

Toledo *et al.* developed a probabilistic lane-changing decision model to describe the tradeoffs between MLC and DLC [62]. The tradeoffs between MLC and DLC are captured by considering both types of lane changes in a single utility function. A discrete choice framework is employed to model drivers' tactical and operational lane-changing decisions. The model is calibrated using the maximum-likelihood estimation technique [63]. The lane-changing decision model consists of 1) the choice of the destination lane and 2) the decision for accepting a gap. Four groups of explanatory variables are considered in the model underlying lane-changing decisions: neighborhood variables (e.g., gaps and speeds), path plan variables (e.g., distance from the intended exit off-ramp), network knowledge and experience (e.g., avoiding the nearest lane next to the shoulder), and driving style and capabilities. In the target lane model, the set of target lane choices includes: 1) remaining in the current lane, 2) shifting to the right, and 3) shifting to the left adjacent lane. The target lane choice model, the probability of selecting a specific lane, and the critical gap model are similar to those in Ahmed's model. In this model, the decision of selecting the target gap is based on the target lane choice. The model assumes that the driver will change lane to the target lane based on the acceptance of the lead and lag gaps in the target lane and does not consider any other gaps. Toledo *et al.* defined the critical lead and lag gaps as the minimum acceptable gaps. When the available target lead and lag gaps are greater than their corresponding critical values, they will be accepted. A log-normal distribution is assumed for the critical gaps to ensure they are always positive.

According to this model, after selecting a target lane and finding gaps of sufficient sizes, the subject vehicle driver performs a sequence of accelerations and decelerations in order to move into the target lane [64]. Toledo *et al.* used a conditional probability to determine whether a lead/lag gap is acceptable or not.

In Toledo's model, the subject vehicle employs a three-stage acceleration behavior model to select the target gap. First, if the subject vehicle driver wishes to remain in the current lane, a stay-in-the-lane selection model applies. Second, if the driver accepts the available target gap and changes into an adjacent lane, an acceleration model applies for changing lane. Third, if the subject vehicle driver initially accelerates or decelerates for changing lane but later rejects the target gap, a target gap acceleration model applies.

This lane-changing model was implemented in MITSIM and tested using detailed vehicle trajectory data collected in Arlington, VA, USA. The purpose of the implementation was to estimate travel time, speed, and the distribution of traffic volumes across lanes. During the implementation, the MLC and DLC models were first separated and later integrated. The estimated values by MITSIM were then compared against the observed values. In the case of travel time and speed, both the separated and integrated scenarios resulted in differences between the observed and estimated values. The travel time differences of the separated and integrated scenarios were 3.20% and 9.50%, respectively. For speed, the corresponding values were −5.60% and −2.90%, respectively. However, the estimated and observed distributions of traffic volumes across lanes were similar for both the separated and integrated scenarios. The main weakness of this lane-changing model is the difficulty of determining the utility functions for various decision choices. Built upon this work, Choudhury *et al.* proposed a cooperative and forced gap acceptance model for congested traffic conditions [65].

V. Artificial Intelligence Models

A. Fuzzy-Logic-Based Models

Fuzzy-logic-based models consider the uncertainty of lane-changing maneuvers and take into account the natural or subjective perception of real variables [66]. The unique nature of fuzzy logic models is that they can translate nonlinear systems into IF-THEN rules [67]. Fuzzy-LOgic-based motorWay SIMulation (FLOWSIM) is a simulation model built upon fuzzy sets and systems [34], [68]–[70]. In this model, lane-changing maneuvers are based on two premises: changing to a slower lane and changing to a faster lane. Das and Bowles proposed a new microscopic simulation methodology based on fuzzy rules for implementation in the Autonomous Agent SIMulation Package (AASIM) software [71]. In this fuzzy-logic-based model, lane-changing maneuvers are classified as MLC and DLC. MLC fuzzy rules consider the distance to the next exit or merge point and the required number of lanes to change. DLC is a binary decision that is based on the driver's speed satisfaction [72], but it does not consider vehicle types in lane-changing decisions. Moridpour *et al.* also developed a lane-changing model using fuzzy logic, which is used to predict the lane-changing maneuver of heavy vehicles on freeways [73]. This model considers three types of lane-changing behavior: motivation of lane-changing, selection of the target lane, and execution of the lane-changing maneuver. Because of abstract fuzzy rules and membership functions, the recalibration and validation process for fuzzy-logic-based lane-changing models is fairly complex.

B. ANN Model

Artificial neural network (ANN) models process information using functional architecture and mathematical models that are similar to the neuron structure of the human brain. These models learn human behaviors from training and are capable of demonstrating those human behaviors in a new situation. In recent years, neural networks have been also used for modeling driver behavior in the transportation field [74]–[76]. For instance, Hunt and Lyons predicted drivers' lane-changing decisions using neural networks on dual carriageways [76]. Neural network models are completely data driven and require supervised training by field-collected traffic data before they can be used to predict driving behavior. Their dependence on the availability of field-collected traffic data is the main disadvantage of neural network models, although previous results show that they can accurately predict lane-changing behavior [77].

Dumbuya *et al.* developed neural driver agents (NDAs) for modeling lane-changing maneuvers [77]. A multilayer NDA model was designed and implemented. A back-propagation training algorithm was used to train the NDA model, which takes inputs such as current direction of the vehicle, current speed, distance from the vehicle, preferred speed, and current lane. The output of the model includes new direction and new speed. This NDA model learned lane-changing behavior from known situations using data collected from the Transport Research Laboratory (TRL) driving simulator. The authors then used the fitted NDA model to predict driver behavior for unseen situations. They demonstrated that NDA has the ability to properly model lane-changing maneuvers. Later, the NDA model was incorporated into the commercial NeuroSolutions software package developed by NeuroDimension, Gainesville, FL, USA.

During the study using the driving simulator, Dumbuya *et al.* recruited eight participants to "drive" on a simulated two-lane highway. At first, the participants were in lane 1. They changed to lane 2 to overtake a slow-moving vehicle and returned back to lane 1 as if they were on a real U.K. highway. For each completed simulation, a set of data was recorded. Using those data sets, they trained the NDA model. When the training process was completed, the trained model was used to simulate the vehicle trajectory. It was found that the simulated vehicle followed a realistic path around the lead slow-moving vehicle. This result shows that the changes in direction generated by the NDA model match those of real drivers, when executing an overtaking maneuver at a speed of 70 mi/h.

The reasonably close lane-changing behaviors of humans and NDA suggest that the NDA is a promising tool to replicate a wide range of lane-changing behaviors (e.g., aggressive, tired, alcohol-impaired, and learner drivers). However, the results also show that the NDA is unable to accurately model lane-changing trajectories when the travel speed is either low or high [78].

VI. Incentive-Based Models

A. MOBIL

The MOBIL lane-changing model is based on two criteria: incentive and safety. The incentive criterion measures the attractiveness of a given lane based on its utility, and the safety criterion measures the risk associated with lane changing (i.e., acceleration) [79], [80]. According to this model, the target lane is more attractive to the driver of the subject vehicle if the incentive criterion is met. A lane change takes place if the safety criterion is satisfied as well. The MOBIL rules are applied for simulation of multilane traffic in the intelligent driver model (IDM) [79]. In IDM, two types of passing rules are considered for lane changes: symmetric and asymmetric. The symmetric passing rules are based on safety and incentive criteria. They are applied when changing to the right lane is not strictly forbidden. When the deceleration (a') of the follow vehicle (F') in the target lane is equal to the IDM braking deceleration (a'_{IDM}), the safety criterion is satisfied. For a lane change to happen, the deceleration of the follow vehicle should also not exceed a certain limit b_{safe}, as shown below. Thus

$$a'(F') > -b_{\mathrm{safe}}.$$

The incentive criterion is determined by weighing the lane-changing advantage against imposed disadvantage to other vehicles. The increased acceleration (or reduced braking deceleration) is the measure of advantage to the subject vehicle before and after the potential lane change. The total decreased acceleration or increased braking deceleration is the measure of disadvantage to vehicles in the target lane. In this model, the lane-changing decision is also influenced by a politeness factor p. This politeness factor p will be further described later, and its value is typically less than 1.

The disadvantages of target-lane vehicles, the advantage of the subject vehicle, and politeness factor p all affect the lane-changing decision. Thus, typical strategic features of classical game theory have been incorporated in MOBIL [80]. It can describe different driving behaviors by varying the politeness factor (p), whereas other lane-changing models typically assume the politeness factor to be zero (0). In MOBIL, $p > 1$ is for an altruistic driving behavior; $0 < p < 0.5$ is for a realistic driving behavior; $p = 0$ is for a purely selfish driving behavior; and $p < 0$ is for a malicious driving behavior.

A special case of this model is given by $p = 1$ and a lane-changing acceleration threshold $a_{\mathrm{thr}} = 0$. For this special case, a lane-changing maneuver will take place whenever the sum of the advantage and disadvantage of all affected drivers is positive after the change. This explains the acronym for this model, which is MOBIL = Minimizing Overall Braking Decelerations Induced by Lane changes.

The asymmetric rules are applied in many European countries where changing to the right lane is prohibited, unless traffic is congested or the subject vehicle is forced to change to the right lane (i.e., on-ramp, off-ramp, and lane drop). A lane-usage bias rule is introduced to capture this asymmetric situation. This rule only represents operational lane-changing decisions. However, a lane-changing model should be able to describe both strategical and tactical aspects of lane-changing behaviors for mandatory lane changes and for congested traffic conditions.

B. LMRS

Schakel *et al.* proposed a Lane-changing Model with Relaxation and Synchronization (LMRS), based on drivers' desire to change lanes [81]. The desire is a combination of the route, speed, and keep-right incentives. A tradeoff is considered within the combination of incentives, with the route incentive being dominant. The following equation is a sample combination of incentives representing the desire to change from lane i to lane j:

$$d^{ij} = d_r^{ij} + \theta_v^{ij} * \left(d_s^{ij} + d_b^{ij}\right)$$

where

- d^{ij} combined desire to change lane from i to j;
- d_r^{ij} desire to follow a route;
- d_s^{ij} desire to gain speed;
- d_b^{ij} desire to keep right;
- θ_r^{ij} voluntary (discretionary) incentives.

The total desire determines drivers' lane-changing behaviors. The range of meaningful desire is from -1 to 1. Negative values represent that a lane change is not desired, and positive values mean the driver wants to change lane. Depending upon the desire value, Schakel *et al.* further classified lane changes as free lane changing (FLC), synchronized lane changing (SLC), and cooperative lane changing (CLC). Thus

$$0 < d_{\mathrm{free}} < d_{\mathrm{sync}} < d_{\mathrm{coop}} < 1.$$

Schakel *et al.* also considered a relaxation phenomenon in their model. As in the real world, drivers may accept small gaps for a large desire. For very small desire values, no lane changes will occur. For a relatively large desire, FLC will happen and no preparation is required. In case of SLC and CLC, the subject vehicle speed needs to be synchronized with the speeds of vehicles in the target lane for creating a gap. This behavior is also called synchronization.

The gap acceptance module in this model is similar to MOBIL. In addition, this model considers an applicable headway for gap acceptance. A gap is accepted if the accelerations of the subject vehicle and the new follower are larger than a safe deceleration threshold. According to this model, large decelerations and short headways can be accepted for a large desire, and the relaxation of headway values is exponential with relaxation time. The subject vehicle driver will synchronize her/his speed, if the lane-changing desire is above the synchronization threshold (d_{sync}). She/he will synchronize the speed with the target lane speed by applying a maximum deceleration, which is both comfortable and safe. A gap can be created, if an adjacent leader lane-changing desire is above cooperation threshold.

Schakel *et al.* used a modified version of IDM developed by Treiber and Helbing [79] to evaluate the proposed lane-changing model. They referred to this new simulation model as IDM+, based on which they calibrated and validated the LMRS model in both free-flow and congested traffic conditions. The main goal of their study was to accurately represent real-world observations at the lane level, such as the lane volume distribution, lane-specific speed, and progression of congestion. Their lane-changing model has a set of seven (7) parameters with physical and intuitive meanings. The full model, combining the LMRS and IDM+, has twenty (20) parameters. Schakel *et al.* tried to alleviate the calibration difficulties by considering the two flow scenarios (i.e., free flow and congested) separately. They calibrated and validated the model using data from a segment of A20 freeway near Rotterdam, Netherlands. This segment included a few on- and off-ramps and a lane drop. The data were collected utilizing loop detectors, which were closely spaced (300–500 m). Although realistic lane volume distributions and lane-specific speeds were generated for the free-flow condition, the model fitting result for the congestion condition was unclear. Furthermore, the generalization ability of their lane-changing model is unknown for scenarios with different levels of congestion and numbers of lanes.

VII. Theoretical Comparison of Lane-Changing Models

Based on the review of existing lane-changing models, rule-based and discrete-choice-based models appear to be the most popular ones. These models have been widely implemented in microscopic traffic simulators. Among them, rule-based lane-changing models are based on the perspective of drivers. For rule-based models, typically the subject vehicle's lane-changing reasons are evaluated first. If these reasons warrant a lane change, a target lane from the adjacent lane(s) is selected. A gap acceptance model fitted based on field data/simulation data is then used to determine whether the available gaps should be accepted.

Most discrete-choice-based lane-changing models are based on logit or probit models. For discrete-choice-based models, the lane-changing maneuver is usually modeled as either MLC or DLC, following three steps: 1) checking lane change necessity, 2) choice of target lane, and 3) gap acceptance. Each of these steps can be formulated as a probit or logit model. Depending on which step and the number of lanes, the subject driver may face a binary or multichoice decision. Similar to rule-based models, discrete choice model parameters and utility functions need to be calibrated using field collected data. In existing discrete-choice-based lane-changing models, the heterogeneities in drivers and vehicles (i.e., driver aggressiveness, driving skill level, and vehicle acceleration performance) have not been given adequate consideration. A major reason is that existing traffic data and data collection technologies cannot provide information that is detailed enough for developing and testing such models. Nevertheless, these characteristics are important for accurately describing real-world lane-changing behaviors, and relevant explanatory variables should be incorporated into the utility functions of future discrete-choice-based lane-changing models.

ANN lane-changing models are completely data driven and fundamentally different from the rule-based and discrete-choice-based models. Although researchers can specify some network parameters, such as numbers of input units, hidden neurons, and layers, they have very low control over the model structure (such as the utility functions in discrete-choice-based models). ANN models have to be trained and validated using field-collected microscopic traffic data before they can be used to predict any lane-changing behavior. The fitted ANN model parameters do not have practical meaning either and cannot be interpreted as those in discrete-choice-based models. Fuzzy-logic-based models describe lane-changing behaviors using fuzzy rules and membership functions. Compared with other models, a major advantage of them is that they can better incorporate human experience and reasoning into the development of lane-changing models. However, it is not an easy task to determine the fuzzy membership functions and rules. The calibration process of fuzzy-logic-based models is very difficult.

The idea behind the incentive-based models is intuitive and straightforward: drivers choose to change or not change lanes in order to maximize their benefits. It is similar to the utility function concept in discrete-choice-based models. However, there are multiple utility functions in a discrete-choice-based model, and the value of each utility function represents the utility (or "advantage") of a choice alternative. In incentive-based models, such as MOBIL, there is only one "advantage" value, which is compared against a threshold value for final decision making. An advantage of the incentive-based model LMRS is that it takes into account the driver's desire to follow a route into consideration. This may potentially generate more realistic lane-changing behaviors. For instance, through traffic, drivers on a multilane highway typically tend to stay away from the rightmost lane to avoid the interference of exiting and entering traffic. This model also has a flexible structure, and additional incentives may be easily integrated into it. The previous discussions provide a brief summary and theoretical comparison of the reviewed lane-changing models. A more detailed and systematic comparison of the four groups of models is presented in Table I.

VIII. Modeling Challenges and Future Research Opportunities

Based on the literature survey, a number of limitations of existing lane-changing models have been identified. The survey also reveals some challenges in terms of the data needs for calibrating and validating existing lane-changing models. These limitations and challenges are further described in the remaining of this section. In addition, recent advancements in sensor technologies have made it possible to collect very detailed and accurate traffic data. The potential impact of such data on developing new lane-changing models is discussed as well.

A. Limitations of Existing Models

To model a driver's lane-changing behavior, existing models only consider the characteristics (i.e., relative speed and positions) of the immediate lead and lag vehicles of the subject vehicle. However, the subject driver's lane-changing behavior and reaction depend on not only those immediate lead and lag vehicles but also the conditions of the broader traffic range. In addition, the conditions that trigger MLC or FM lane-changing behavior are specified using various zones, and the boundaries of which are selected arbitrarily and calibrated with ad-hoc procedures in a deterministic fashion in most of the cases. As a result, the heterogeneity characteristics of lane-changing behaviors of drivers are not adequately considered [1].

The lane-changing maneuvers follow a hierarchy of processes, with each process being a combination of several performances at different levels [82]. Existing lane-changing models deal only with the decision-making hierarchy of the

TABLE I
THEORETICAL COMPARISON OF LANE-CHANGING MODEL CATEGORIES

Microscopic Lane-Changing model			
Rule-based Model	**Discrete Choice-based Model**	**Artificial Intelligence Model**	**Incentive-based model**
Lane-Changing Decision			
Decide on decision tree with series of fixed condition	Utilize logit or probit model	Based on driver-vehicle status	Decide on lane-change desire (LMRS)
Reason for Lane-Changing			
Decide whether lane-changing applies or not through explanatory Variables (EV) EV: Maximum subject vehicle's safe speed and brake, front gap, subject vehicle driver's estimation of front vehicle driver's brake	Explanatory Variable for gained utilities are: MLC-Exit/merge distance, number of lane changes, DLC-Presence of heavy vehicle, front relative speed and deceleration	• Completely data driven and require supervised training • Fuzzy sets and systems EV: MLC-Exit/merge distance, number of lane changes, DLC-Left and right lane density, drivers' satisfaction	Measure level of lane-changing desire based on speed incentive, Route incentive, Keep right incentive
Target lane selection			
Decide on fixed lane-changing purpose or advantage for lane-changing EV: Acceptable lead and lag gaps, Critical gaps	At each stage, utilities for all alternatives are calculated in the lane-changing process EV: Target lead and lag gaps and relative speeds , subject vehicle speed, presence of heavy vehicle, tailgating, avoiding the rightmost-lane, distance to the exit off-ramp	Fuzzy rules, Drivers' recent speed history, and the level of congestion • Change lanes to left or right EV: Left-Motivation, opportunity, Right-Pressure, Gap satisfaction	Depend on level of lane-changing desire EV: Anticipation Speed, Maximum vehicle speed, Desired speed, Anticipation distance, Speed limit, Speed gain
Gap acceptance			
Gap acceptance parameters for are picked up from field/simulation data, and calculated using gap acceptance formulae	• Permission of lane change decides on the lead and lag gap acceptance • Gap acceptance EV: Target lead and lag relative speeds, distance between target lead and lag	Consider the safe headway to the front vehicle in the current lane • Find a gap in target lane EV: Front, lead and lag gaps and relative speeds. • Accept sufficient size gap EV: Target lead and lag speeds and gaps, exit/merge distance	Based on deceleration rate utilizing the car-following model • Find a gap in target lane EV: Front, lead and lag gaps and relative speeds • Accept sufficient size gap EV: Target lead and lag acceleration and time headway, deceleration threshold
Divers variability			
Does not consider driver's variability on gap acceptance	Does not consider invariant characteristics of drivers and their vehicles for a given driver over time and choice dimensions such as choice of target lane, gap acceptance	Attempt to capture drivers' variability with training data sets of driver behaviors.	Capture driver's variability using politeness factor (MOBIL) and accepted headway, deceleration, and level of desire (LMRS)
Advantages			
• Simplicity in modeling • Decision process in one simple stage, Small number of variables	• Decide on the basis of maximum gained utility • Probabilistic results instead of binary answers (yes/no)	Consider human's imprecise perception, require numerical data, calibrating using optimization algorithm	• Small number parameters • Take into account drivers variability
Disadvantages			
• Difficulties in calibrating the model parameters. • Use only primary variables • Binary answers (yes/no)	• Require to calculate probability functions to determine the utility of each choice	• Difficulties and complexity in fuzzy rules, membership functions • Require large amount of data	• Fit in congestion is unclear • MOBIL only considers operational process
Applications			
These models are utilized in microscopic traffic simulators and are applicable to capacity analysis.			

lane-changing maneuver and ignore the process of execution of that maneuver [43], [61]. They simply assume a straight line from the starting point of the current lane to the ending point of the target lane for a fixed lane-changing duration. This assumption is far from realistic lane-changing behavior. In real-life situation, traffic flow characteristics are highly affected by the execution process of a lane-changing maneuver. To improve the microscopic traffic simulation results, the execution process of a lane-changing maneuver must be considered.

Moreover, existing studies on lane-changing models estimate macroscopic traffic characteristics from the model outputs and compare them with field data for model evaluation. The measures of performance (MOPs) selected to evaluate those models are the 1) comparison of vehicles distribution between the end lane and the starting lane, 2) lane-specific speeds, 3) total number of complete lane changes by a vehicle, and 4) comparison of lane changes between "from" and "to" lanes. All the MOPs are macroscopic in nature [33], [83], [84]. To better evaluate the accuracy and reliability of lane-changing models, the lane-changing maneuver needs to be microscopically analyzed with estimated values and compared with the microscopic field data.

Another downside of the existing models is that they neglect the effect of the roadway geometry (e.g., horizontal, vertical, sag, and crest curves) and environmental conditions (e.g., pavement and lighting conditions) [43], [46], [60]. The execution of lane-changing maneuver in the real world depends on driver performance, which is greatly affected by such roadway geometry and environmental conditions. In addition, the accuracy of microscopic simulation packages heavily depends upon how well the existing models can replicate the real-life lane-changing behavior.

Last, but not least, drivers prepare a plan for each trip and then make corresponding decisions for navigation to create a trip schedule and path, respectively. Obviously, the trip schedules affect the desired speeds and travel lanes. Moreover, several researchers have pointed out that the path plan is a vital factor affecting the lane selection process [81], [62]. However, only few of the existing lane-changing models include these two factors [58], [81].

B. Requirement of Large Trajectory Data Set

To improve the accuracy of lane-changing models, large vehicle trajectory data sets are required at the individual (microscopic) level. Data such as speed, acceleration, lane changes, and the variables defining the relationship among the subject vehicle and other vehicles including relative speed, relative position, time, and space headways are required with high time resolution to estimate lane-changing model parameters.

The Next Generation SIMulation (NGSIM) program has produced a large amount of microscopic vehicle trajectory data for calibration and validation of lane-changing models [85]. A few models such as the discrete-choice-based models have used NGSIM data for model calibration and validation. However, the NGSIM data were developed by processing video images with time resolution every tenth of a second. Research discovered some unrealistic results such as overlapping vehicles by analyzing the NGSIM data [86]. Another downside of the NGSIM vehicle trajectory data set is that the length of the roadway section is less than one mile. Despite of the downsides of this data set, NGSIM database provides important vehicle trajectory data for calibration and validation of lane-changing models. Calibration of any lane-changing model parameters requires detailed trajectory data, including vehicle positions at discrete points in time, as well as other variables such as number of lane changes, speeds, accelerations, headways, and intravehicle gaps in traffic. These important data and the relationship between the subject vehicle and surrounding vehicles (lead/lag) can be generated from the NGSIM trajectory data.

Other than the NGSIM data, Daamen *et al.* [87] used a helicopter to collect vehicle trajectory data at two locations in Netherlands: one on A12 in the direction of Utrecht near Bodegraven and the other one on A2 near Vinkeveen. The same data collection technique was used by Hoogendoorn *et al.* in their study [88]. Daamen *et al.* collected the data at the microscopic level and used them for empirical analysis of merging behavior of lane-changing vehicle at a freeway on-ramp. The resolution of the monochrome images was at a rate of 15 images/s. The Vinkeveen data set was used for a qualitative check of the empirical findings from the Bodegraven data set. The length of the A12 roadway section was 3.11 m, and the data collection period was 35 min.

Knoop *et al.* [89] used microscopic vehicle trajectory data from A270 near Eindhoven, Netherlands, and M42 near Birmingham, U.K., for their study to quantify the number of lane changes. Both the A270 and M42 vehicle trajectory data sets were collected on freeways. Among them, the length of the A270 roadway section was 6500 m, and 55 cameras were mounted on roadside poles. There were some discrepancies in the collected trajectory data because of different heights of vehicles, camera overlaps, and the angle of view. Later on, a moving average filter was used to smooth the data set.

Although video detectors mounted on utility poles or helicopters have been used to collect vehicle trajectory data, it is costly to install them and to cover long segments of various characteristics. The video data postprocessing is challenging, and the quality of the processed data sometimes is not very good. However, new lane-changing models with different driving regimes often require data sets from long roadway sections that can accurately capture driving behaviors in different driving regimes. In addition, it is difficult to extract driver characteristic information from video data. Such data can be useful in developing lane-changing models. As a result, data sets collected via video detectors alone (e.g., NGSIM data) are not sufficient for developing high-fidelity models to accurately describe lane-changing behavior.

Another study focused on individual level driving behavior is Strategic Highway Research Program (SHRP) 2 Naturalistic Driving Study (NDS) [90]–[92]. In this research, video cameras are also used. Instead of mounting video cameras on fixed roadside objects as in NGSIM, multiple video cameras are installed inside a vehicle to collect driver characteristic data (e.g., driver's facial data, interactions with the dashboard, and other conditions in the vehicle) and the surrounding driving conditions (e.g., forward, rear, and right-side views). Other technologies are also utilized for vehicle location, speed information, and alcohol detection.

Recently, smartphones have been implemented to collect vehicle trajectory data. For instance, Google introduced smartphones powered by Android to collect real-time vehicle position and speed data using Google maps and navigation functions in the U.S. and many other countries [93]. If privacy and position accuracy (particularly lateral position) issues can be properly addressed, smartphones can effectively reduce the cost of vehicle trajectory data collection and produce data at the microscopic level under different traffic and geometric conditions. In addition, vehicle infrastructure integration (VII) technology (recently known as connected vehicles) that integrates vehicles and infrastructure via wireless communication interfaces has also shown great potential in collecting vehicle operational data, such as speed, acceleration/deceleration, and position.

A large trajectory data set would enable future research to model drivers' lane-changing behavior under different traffic and geometric conditions. Furthermore, the differences between drivers, as well as the differences in the behavior of the same driver, over time would be better captured with large microscopic data sets. The collection and compilation of a large trajectory data set for model development is often costly and time consuming, however.

C. New Model Development

New lane-changing models should focus on providing an enhanced capability for modeling drivers' lane-changing behavior. Most existing lane-changing models are unable to integrate multiple driving regimes. Thus, it is necessary to define the boundaries to determine when to activate each model for different driving regimes. In order to develop more sophisticated simulation tools, it is also important to take into account the interdependencies of the decisions a driver makes over time and under different traffic conditions.

Driver's reactions not only depend on the adjacent vehicles but also vary with the traffic conditions in a broader sense. Only a few existing lane-changing models attempt to better represent the real-world traffic conditions by combining the traditional lane selection model with the FM and courtesy yielding [65], [81]. In addition, it is important to model heavy-vehicle drivers' lane-changing decisions separately, considering the unique physical characteristics of heavy vehicles (e.g., length and size) and their operational characteristics (e.g., acceleration, deceleration, and maneuverability). To further improve the lane-changing modeling accuracy, acceleration/deceleration models should be developed for different vehicle types during lane-changing execution. These models will estimate the acceleration and deceleration behavior of drivers while changing lanes.

Distracted driving (e.g., texting, talking on the phone or to a passenger, eating, drinking, grooming, reading maps, setting a navigation system, checking emails, adjusting a radio, CD player, or MP3 player) diverts driver's attention away from performing the primary task of driving. Distracted driving due to the aforementioned activities significantly degrades driver performance and has become a major safety concern over the last two decades, particularly as the use of cell phones has enormously increased [94]. Texting is probably the most dangerous of these activities as it requires the manual, visual, and cognitive attention of the driver. A study shows that, when a driver is on a cell phone, the brain activity associated with driving drops to 37% [95]. According to the distracted driving data published on a website maintained by the U.S. Department of Transportation, in 2011, distracted driving killed 3313 compared to 3267 and injured 327 000 people compared to 416 000 injured and attributed to 18% of all injury crashes, in 2010 [94]. New lane-changing models should include the effect of driver distraction to improve the fidelity of microscopic traffic simulation packages.

Drivers' lane-changing behavior is not only affected by human performance but also by roadway geometric characteristics (e.g., horizontal, vertical, sag, and crest curves) and environmental factors (e.g., pavement and lighting conditions). Existing lane-changing models have not directly considered any of these geometric and environmental factors that have repercussions, either adversely or positively, on the driver behavior. Including additional factors in lane-changing models intuitively will lead to increased number of parameters and variables. However, this may not always be the case if these factors are considered from an integrated and systematic perspective. For instance, new and old factors can be systematically combined, so that some existing parameters and variables can be excluded, in addition to including new parameter and variables. Such an approach can at least minimize the total number of parameters and variables needed compared with the existing lane-changing models.

Extensive microscopic driver data in real-world driving situations, which include complete information of driver, vehicle, and surrounding conditions will be needed to develop new lane-changing models. Currently, although a lot of vehicle trajectory data have been generated in related studies primarily based on video detectors, the amount of data available for developing new lane-changing models is limited. Driving simulators are a cost-beneficial alternative for collecting driver-related data under varying situations (e.g., distractions, sharp roadway curves, crash-imminent braking, lane incursions, driver impairment, night driving and passing, which can later be verified with real-world data). Most traffic management centers (TMCs) monitor roadway sections with video cameras as their regular function. TMC collected video data could be also utilized as secondary data sources for validating lane-changing models, particularly at a macroscopic level. In the future, data collected through smartphones, connected vehicles, and SHRP 2 NDS may also be able to support the development and validation of new models and calibration and validation of existing models.

IX. Conclusion

The authors conducted an in-depth review of microscopic lane-changing models, an important component of driving behaviors, as they relate to roadway traffic simulation. Based upon the review, it has been concluded that existing models only consider variables of the immediate lead and lag vehicles of the subject vehicle to define lane-changing maneuvers. The subject vehicle driver's lane-changing behavior and reaction depend upon not only those immediate lead and lag vehicles but also the conditions of the broader traffic range, such as traffic density around lead and lag vehicles. One of the primary limitations of most existing lane-changing models is that they fail to capture drivers' path planning and anticipation capabilities over time. Moreover, existing lane-changing models deal only with decision-making hierarchy of lane-changing maneuvers and ignore the process of execution of lane-changing maneuvers. Furthermore, although lane-changing models are microscopic, existing evaluations of such models are based upon macroscopic MOPs. Lastly, existing models neglect the effect of roadway geometry and environmental conditions on lane-changing maneuvers, while a driver's performance is highly affected by those factors.

Currently, extensive microscopic traffic data are unavailable beyond the limited data from a few studies, such as NGSIM, to reliably model lane-changing behaviors. More detailed and reliable microscopic traffic data are necessary for calibrating and validating lane-changing models, which may be obtained through existing technologies such as global positioning systems and smartphones. The future implementation of connected vehicle technology may be also utilized to collect reliable microscopic traffic data that would permit the respective development and improvement of new and existing lane-changing models.

References

[1] T. Toledo, "Driving behavior: Models and challenges," *Transp. Rev.*, vol. 27, no. 1, pp. 65–84, Feb. 2007.

[2] D. D. Salvucci, "Modeling driver distraction from cognitive tasks," in *Proc. 24th Annu. Conf. Cognit. Sci. Soc.*, Hillsdale, NJ, USA, 2002, pp. 792–797.

[3] M. Cassidy and R. Bertini, "Some traffic features at freeway bottlenecks," *Transp. Res. Part B, Methodol.*, vol. 33, no. 1, pp. 25–42, Feb. 1999.

[4] R. L. Bertini and M. T. Leal, "Empirical study of traffic features at a freeway lane drop," Intell. Transp. Syst. Lab., Portland State Univ., Portland, OR, USA, Feb. 2004, Working Paper.

[5] Y. Hou, P. Edara, and C. Sun, "Modeling mandatory lane changing using Bayes classification and decision trees," presented at the Operations Traffic Management, Transportation Research Record, Washington, DC, USA, 2013, Session:497, Paper 13-1359.

[6] J. A. Laval and C. F. Daganzo, "Lane-changing in traffic streams," *Transp. Res. Part B, Methodol.*, vol. 40, no. 3, pp. 251–264, Apr. 2006.

[7] J. C. Muñoz and C. F. Daganzo, "Moving bottlenecks: A theory grounded on experimental observation," in *Proc. 15th Int. Symp. Transp. Traffic Theory*, M. A. P. Taylor, Ed., 2002, pp. 441–462.

[8] J. D. Chovan, L. Tijerina, G. Alexander, and D. L. Hendricks, "Examination of lane change crashes and potential IVHS countermeasures," Nat. Highway Traffic Safety Admin., U.S. Dept. Transp., Washington, DC, USA, Tech. Rep., 1994.

[9] H. Jula, E. B. Kosmatopoulos, and P. A. Ioannou, "Collision avoidance analysis for lane changing and merging," *IEEE Trans. Veh. Technol.*, vol. 49, no. 6, pp. 2295–2308, Nov. 2000.

[10] P. Fox and F. G. Lehman, "A digital simulation of car following and overtaking," *Highway Res. Rec.*, vol. 195, pp. 33–41, 1967.

[11] M. Levin, "Freeway lane-changing process: A microscopic approach (Abridgement)," *Transp. Res. Rec.*, vol. 596, pp. 30–32, 1976.

[12] C. F. Daganzo, "Estimation of gap acceptance parameters within and across the population from direct roadside observation," *Transp. Res. Part B, Methodol.*, vol. 15, no. 1, pp. 1–15, Feb. 1981.

[13] H. Mahmassani and Y. Sheffi, "Using gap sequences to estimate gap acceptance functions," *Transp. Res. Part B, Methodol.*, vol. 15, no. 3, pp. 143–148, Jun. 1981.

[14] K. I. Ahmed, M. E. Ben-Akiva, H. N. Koutsopoulos, and R. G. Mishalani, "Models of freeway lane changing and gap acceptance behavior," in *Proc. 13th Int. Symp. Theory Traffic Flow Transp.*, 1996, pp. 501–515.

[15] C. Hill, "Exploration of lane changing behavior on freeways," presented at the Operations Traffic Management, Transportation Research Record, Washington, DC, USA, 2013, Session:497, Paper 13-2199.

[16] D. Helbing, "Traffic and related self-driven many-particle systems," *Rev. Mod. Phys.*, vol. 73, no. 4, pp. 1067–1141, Dec. 2001.

[17] Y. Ma, M. Chowdhury, A. Sadek, and M. Jeihani, "Integration of vehicle infrastructure integration (VII) system and artificial intelligence (AI) for online travel time prediction," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 3, pp. 1369–1382, Sep. 2012.

[18] Y. Ma, R. Fries, M. Chowdhury, and I. Inamdar, "Evaluation of integrated allocation of intelligent transportation systems (ITS) technologies using stochastic incident generation and resolution modeling," *Simulation: Trans. Soc. Model. Simul. Int.*, vol. 88, no. 1, pp. 123–133, 2012.

[19] L. Li and F. Y. Wang, "The automated lane-changing model of intelligent vehicle highway systems," in *Proc. IEEE 5th Int. Conf. Proc. Intell. Transp. Syst.*, 2002, pp. 216–218.

[20] Y. Ma, M. Chowdhury, A. Sadek, and M. Jeihani, "Real-time highway traffic condition assessment framework using vehicle-infrastructure integration (VII) with artificial intelligence (AI)," *IEEE Trans. Intell. Transp. Syst.*, vol. 10, no. 4, pp. 615–627, Dec. 2009.

[21] P. Hidas, "Modelling lane-changing and merging in microscopic traffic simulation," *Transp. Res. Part C*, vol. 10, no. 5/6, pp. 351–371, Oct./Dec. 2002.

[22] P. G. Michalopoulos, D. E. Beskos, and Y. Yamauchi, "Multilane traffic flow dynamics: Some macroscopic considerations," *Transp. Res. Part B, Methodol.*, vol. 18, no. 4/5, pp. 377–395, Aug.–Oct. 1984.

[23] E. N. Holland and A. W. Woods, "A continuum model for the dispersion of traffic on two-lane roads," *Transp. Res. Part B, Methodol.*, vol. 31, no. 6, pp. 473–485, Nov. 1997.

[24] C. F. Daganzo, "A behavioral theory of multi-lane traffic flow. Part I: Long homogeneous freeway sections. II: Merges and the onset of congestion," *Transp. Res. Part B, Methodol.*, vol. 36, no. 2, pp. 131–158, Feb. 2002.

[25] B. Coifman, "Estimating density and lane inflow on a freeway segment," *Transp. Res. Part A*, vol. 37, no. 8, pp. 689–701, Oct. 2003.

[26] D. C. Gazis, R. Herman, and G. H. Weiss, "Density oscillations between lanes of a multilane highway," *Oper. Res.*, vol. 10, no. 5, pp. 658–667, Sep./Oct. 1962.

[27] P. K. Munjal and L. A. Pipes, "Propagation of on-ramp density waves on uniform unidirectional multilane freeways," *Transp. Res.*, vol. 5, no. 4, pp. 241–255, Nov. 1971.

[28] W. L. Jin, Y. Zhang, and L. Chu, "Measuring first-in-first-out violation among vehicles," in *Proc. Transp. Res. Board Annu. Meet.*, 2006, pp. 1–24.

[29] J. E. Leisch, "A new technique for design and analysis of weaving sections on freeways," *ITE J.*, vol. 49, no. 3, pp. 26–29, 1979.

[30] J. A. Laval and C. F. Daganzo, "Multi-lane hybrid traffic flow model: A theory on the impacts of lane-changing maneuvers," presented at the 84th Transportation Research Board's Annu. Meet., Washington, DC, USA, 2005.

[31] W.-L. Jin, "A kinematic wave theory of lane-changing traffic flow," *Transp. Res. Part B, Methodol.*, vol. 44, no. 8/9, pp. 1001–1021, Sep./Nov. 2010.

[32] B. D. Greenshields, "A study in highway capacity," in *Highway Res. Board Proc.*, 1935, vol. 14, pp. 448–477.

[33] S. Moridpour, M. Sarvi, and G. Rose, "Lane changing models: A critical review," *Transp. Lett. Int. J. Transp. Res.*, vol. 2, no. 3, pp. 157–173, Jul. 2010.

[34] M. Brackstone, M. McDonald, and J. Wu, "Lane-changing on the motorway: Factors affecting its occurrence, and their implications," in *Proc. 9th Int. Conf. Road Transp. Inf. Control*, London, U.K., 1998, pp. 160–164.

[35] J. Lygeros, D. N. Godbole, and S. Sastry, "Verified hybrid controllers for automated vehicles," *IEEE Trans. Autom. Control*, vol. 43, no. 4, pp. 522–539, Apr. 1998.

[36] K. Nagel, D. E. Wolf, P. Wagner, and P. Simon, "Two-lane traffic rules for cellular automata: A systematic approach," *Phys. Rev. E*, vol. 58, pp. 1425–1437, Aug. 1998.

[37] S. Maerivoet and B. de Moor, "Cellular automata models of road traffic," *Phys. Rep.*, vol. 419, no. 1, pp. 1–64, Nov. 2005.

[38] A. Eidehall, J. Pohl, F. Gustafsson, and J. Ekmark, "Toward autonomous collision avoidance by steering," *IEEE Trans. Intell. Transp. Syst.*, vol. 8, no. 1, pp. 84–94, Mar. 2007.

[39] D. D. Salvucci and H. M. Mandalia, "Lane-change detection using a computational driver model," *Human Factors Ergonom. Soc.*, vol. 49, no. 3, pp. 532–42, Jun. 2007.

[40] A. Doshi and M. Trivedi, "A comparative exploration of eye gaze and head motion cues for lane change intent prediction," in *Proc. IEEE Intell. Veh. Symp.*, Eindhoven, Netherlands, 2008, pp. 49–54.

[41] R. J. Kiefer and J. M. Hankey, "Lane change behavior with a side blind zone alert system," *Accid. Anal. Prev.*, vol. 40, no. 2, pp. 683–690, Mar. 2008.

[42] J. Li-Sheng, F. Wen-Ping, Z. Ying-Nan, Y. Shuang-Bin, and H. Hai-Jing, "Research on safety lane change model of driver assistant system on highway," in *Proc. IEEE Intell. Veh. Symp.*, Shaanxi, China, 2009, pp. 1051–1056.

[43] P. G. Gipps, "A model for the structure of lane-changing decisions," *Transp. Res. Part B, Methodol.*, vol. 20, no. 5, pp. 403–414, Oct. 1986.

[44] U. Sparmann, "Spurwechselvorgänge auf Zweispurigen BABRichtungsfahrbahnen. ForschungStraßenbau und Straßenverkehrstechnik," *Heft*, vol. 263, 1978.

[45] P. G. Gipps, "A behavioral car-following model for computer simulation," *Transp. Res. Part B, Methodol.*, vol. 15, no. 2, pp. 105–111, Oct. 1981.

[46] A. Halati, H. Lieu, and S. Walker, "CORSIM—Corridor traffic simulation model," in *Proc. Traffic Congest. Traffic Safety 21st Century Conf.*, 1997, pp. 570–576.

[47] *CORSIM Reference Manual Guide. Version 5.2*, ITT Industries, FHWA Off. Oper. Res., Dev. Technol., Fed. Highway Admin., Turner-Fairbank Highway Res. Center, McLean, VA, USA, 2004.

[48] P. Holm and D. Tomich, *Traffic Analysis Toolbox: Volume IV: Guidelines for Applying CORSIM Microsimulation Modeling Software*. Washington, DC, USA: U.S. Dept. Transp. Fed. Highway Admin., Jan. 2007. [Online]. Available: http://ops.fhwa.dot.gov/trafficanalysistools/tat_vol4/app_i.htm

[49] P. Hidas, "Modelling vehicle interactions in microscopic simulation of merging and weaving," *Transp. Res. Part C*, vol. 13, no. 1, pp. 37–62, Feb. 2005.
[50] P. Hidas and K. Behabahanizadeh, "Urban transport network simulation: An object-oriented approach," in *Proc. 4th Int. Conf. Comput. Urban Plann. Urban Manage.*, R. Wyatt and H. Hossein, Eds., Melbourne, VIC, Australia, 1995, vol. 2, pp. 229–243.
[51] P. Hidas and K. Behbahanizadeh, "Route guidance as an incident management tool in urban arterial networks," in *Proc. 3rd Int. Conf. ITS Australia*, Brisbane, Qld, Australia, 1997, [CD-ROM].
[52] P. Hidas and K. Behbahanizadeh, "SITRAS: A simulation model for ITS applications," in *Proc. 5th World Congr. Intell. Transp. Syst.*, Seoul, Korea, Oct. 1998, [CD-ROM].
[53] P. Hidas, "Modelling lane changing and merging in microscopic traffic simulation," *Transp. Res. Part C*, vol. 10, no. 5/6, pp. 351–371, Oct.–Dec. 2002.
[54] M. Rickert, K. Nagel, M. Schreckenberg, and A. Latour, "Two lane traffic simulations using cellular automata," *Phys. A*, vol. 231, no. 4, pp. 534–550, Oct. 1996.
[55] H. Kita, "A merging-give-way interaction model of cars in a merging section: A game theoretic analysis," *Transp. Res. Part A*, vol. 33, no. 3/4, pp. 305–312, Apr. 1999.
[56] R. J. Aumann, *Lectures on Game Theory*. Boulder, CO, USA: Westview Press Inc., 1989.
[57] H. Kita, "Effects of merging lane length on the merging behavior at expressway on-ramps," in *Transportation and Traffic Theory*, C. Daganzo, Ed. Amsterdam, The Netherlands: Elsevier, 1993, pp. 37–51.
[58] T. A. Domencich and D. McFadden, *Urban Travel Demand: A Behavioral Analysis*. Amsterdam, The Netherlands: North-Holland, 1989, Research Report on the Design of Merging Sections No. 1, No. 2, 1988, No. 3. (In Japanese), 1987.
[59] Y. Pei and H. Xu, "The control mechanism of lane-changing in jam condition," in *Proc. 6th World Congr. Intell. Control Autom.*, Dalian, China, 2006, pp. 8655–8658.
[60] K. I. Ahmed, "Modeling drivers' acceleration and lane-changing behavior," M.S. thesis, Dept. Civil Environ. Eng., Massachusetts Inst. Technol., Cambridge, MA, USA, Feb. 1999.
[61] Q. Yang and H. N. Koutsopoulos, "A microscopic traffic simulator for evaluation of dynamic traffic management systems," *Transp. Res. Part C*, vol. 4, no. 3, pp. 113–129, Jun. 1996.
[62] T. Toledo, "Integrated driving behavior models," Ph.D. dissertation, Dept. Civil Environ. Eng., Massachusetts Inst. Technol., Cambridge, MA, USA, Feb. 2002.
[63] T. Toledo, H. N. Koutsopoulos, and M. E. Ben-Akiva, "Modeling integrated lane-changing behavior," *Transp. Res. Rec.*, vol. 1857, pp. 30–38, 2003.
[64] T. Toledo, H. N. Koutsopoulos, and M. E. Ben-Akiva, "Integrated driving behavior modeling," *Transp. Res. Part C*, vol. 15, no. 2, pp. 96–112, Apr. 2007.
[65] C. F. Choudhury, M. E. Ben-Akiva, T. Toledo, G. Lee, and A. Rao, "Modeling cooperative lane-changing and forced merging behavior," in *Proc. 86th Transp. Res. Board Annu. Meet.*, Washington, DC, USA, 2007, [CD-ROM].
[66] X. Ma, "Toward an integrated car-following and lane-changing model based on neural-fuzzy approach," presented at the Proc. Helsinki Summer Workshop, 2004, CTR2004:13.
[67] J. M. Mendel, "Fuzzy logic systems for engineering: A tutorial," *Proc. IEEE*, vol. 83, no. 3, pp. 345–377, Mar. 1995.
[68] M. McDonald, J. Wu, and M. Brackstone, "Development of a fuzzy logic based microscopic motorway simulation mode," in *Proc. IEEE Conf. Intell. Transp. Syst.*, Boston, MA, USA, Nov. 1997, pp. 82–87.
[69] J. Wu, M. Brackstone, and M. McDonald, "Fuzzy sets and systems for a motorway microscopic simulation model," *Fuzzy Sets Syst.—Special Issue Fuzzy Sets Traffic Transport Systems*, vol. 116, no. 1, pp. 65–76, Nov. 2000.
[70] J. Wu, M. Brackstone, and M. McDonald, "The validation of a microscopic simulation model: A methodological case study," *Transp. Res. Part C*, vol. 11, no. 6, pp. 463–479, Dec. 2003.
[71] S. Das and B. A. Bowles, "Simulations of highway chaos using fuzzy logic," in *Proc., 18th Int. Conf. North Amer. Fuzzy Inf. Process. Soc.*, Jul. 1999, pp. 130–133.
[72] S. Das, B. A. Bowles, C. R. Houghland, S. J. Hunn, and Y. Zhang, "A fuzzy logic model of freeway driver behavior," in *Proc. Int. ICSC Congr. Comput. Intell. Methods Appl.*, New York, NY, USA, 1999, p. 5.
[73] S. Moridpour, M. Sarvi, G. Rose, and E. Mazlami, "Lane-changing decision models for heavy vehicles drivers," *J. Intell. Transp. Syst., Technol., Plann., Oper.*, vol. 16, no. 1, pp. 24–35, Jan. 2012.
[74] H. Yang, T. Akiyama, and T. Sasaki, "A neural network approach to the identification of real time origin destination flows from traffic counts," in *Proc. Int. Conf. Artif. Intell. Appl. Transp. Eng.*, San Buenaventura, CA, USA, 1992, pp. 253–269.
[75] M. S. Dougherty and M. Joint, "A behavioral model of driver route choice using neural networks," in *Proc. Int. Conf. Artif. Intell. Appl. Transp. Eng.*, San Buenaventura, CA, USA, 1992, pp. 91–110.
[76] J. G. Hunt and G. D. Lyons, "Modeling dual carriageway lane-changing using neural networks," *Transp. Res. Part C*, vol. 2, no. 4, pp. 231–245, Dec. 1994.
[77] A. Dumbuya, A. Booth, N. Reed, A. Kirkham, T. Philpott, J. Zhao, and R. Wood, "Complexity of traffic interactions: Improving behavioural intelligence in driving simulation scenarios," in *Complex Systems and Self-organization Modelling*. New York, NY, USA: Springer-Verlag, 2009, pp. 201–209.
[78] R. S. Tomar, S. Verma, and G. S. Tomar, "Prediction of lane change trajectories through neural network," in *Proc. IEEE Int. Conf. Comput. Intell. Commun. Netw.*, 2010, pp. 249–253.
[79] M. Treiber and D. Helbing, "Realistische Mikrosimulation von Straßenverkehr mit einem einfachen modell," in *Proc. 16th Symp. Simulationstechnik ASIM 2002 Rostock*, D. Tavangarian and R. Grützner, Eds., Sep. 2002, pp. 514–520.
[80] A. Kesting, M. Treiber, and D. Helbing, "General lane-changing model MOBIL for car-following models," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1999, pp. 86–94, 2007.
[81] W. J. Schakel, V. L. Knoop, and B. van Arem, "Integrated lane change model with relaxation and synchronization," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2316, pp. 47–57, 2012.
[82] R. J. Koppa, "Monograph of traffic flow theory," in *Human Factors*, N. H. Gartner, C. J. Messer, and A. K. Rathi, Eds. Washington, DC, USA: U.S. Dept. Transp. Fed. Highway Admin., 1997. [Online]. Available: http://www.tfhrc.gov/its/tft/tft/htm
[83] C. F. Choudhury, "Modeling lane-changing behavior in presence of exclusive lanes," M.S. thesis, Dept. Civil Environ. Eng., Massachusetts Inst. Technol., Cambridge, MA, USA, Feb. 2005.
[84] T. Tang, S. C. Wong, H. Huang, and P. Zhang, "Macroscopic modeling of lane-changing for two-lane traffic flow," *J. Adv. Transp.*, vol. 43, no. 3, pp. 245–273, Jul. 2009.
[85] NGSIM. Home of next generation simulation. Datasets, Aug. 2012. [Online]. Available: http://ngsimcommunity.org/index.php?option=com_docman&task=cat_view&gid=28&Itemid=34
[86] Center for Transportation studies. University of Virginia. Traffic Operations Laboratory, Aug. 2012. [Online]. Available: http://cts.virginia.edu/ngsimAnalyzer.htm
[87] W. Daamen, L. Loot, and S. Hoogendoorn, "Empirical analysis of merging behavior at a freeway on-ramp," in *Proc. Transp. Res. Board 89th Annu. Meet.*, Washington, DC, USA, 2010, pp. 108–118, [DVD-Rom].
[88] S. P. Hoogendoorn, H. J. van Zuylen, M. Schreuder, B. Gorte, and G. Vosselman, "Traffic data collection from aerial imagery," Delft Univ. Technol., Delft, The Netherlands, Res. Rept., 2003.
[89] V. L. Knoop, S. P. Hoogendoorn, S. Yasuhiro, and C. Buisson, "Quantifying the number of lane changes in traffic: Empirical analysis," in *Proc. 91th Annu. Meet. Transp. Res. Board*, Washington, DC, USA, Jan. 2012, pp. 22–26.
[90] R. J. Hanowski, R. L. Olson, J. S. Hickman, and A. Dingus, "The 100-car naturalistic driving study: A descriptive analysis of light vehicle heavy vehicle interactions from the light vehicle driver's perspective," Fed. Motor Carrier Safety Admin., U.S. Dept. Transp., Washington, DC, USA, FMCSA-RRR-06-004, Mar. 2006.
[91] SHRP 2-Strategic Highway Research Program. Naturalistic Driving Study, Dec. 2012. [Online]. Available: http://www.shrp2nds.us/index.html
[92] Driving Transportation with Technology, Virginia Tech Transportation Institute. Naturalistic Driving Research at VTTI, Dec. 2012. [Online]. Available: http://www.vtti.vt.edu/1Pagers%20for%20Website/Gen%20VTTI_Box/VTTI%20Naturalistic%20Driving%20Research
[93] Traffic Technology. News.Google provides traffic information for more USA cities, Aug. 2012. [Online]. Available: http://www.traffictechnologytoday.com/news.php?NewsID=41738
[94] The official US Government website of distracted driving, Aug. 2012. [Online]. Available: http://www.distraction.gov/content/get-the-facts/facts-and-statistics.html
[95] M. A. Just, T. A. Keller, and J. A. Cynkar, "A decrease in brain activation associated with driving when listening to someone speak," *Brain Res.*, vol. 1205, pp. 70–80, Apr. 2008.

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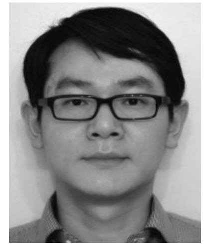

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