2017

Exploring Factors Contributing to Lane Changes during Left Turns on Quadruple Left-Turn Lanes at Signalized Intersections

Fulu Wei
Jilin Jianzhu University

Zhenyu Wang
University of South Florida, zwang9@cutr.usf.edu

Jian Lu
Tongji University

Special Issue Article

Advances in Mechanical Engineering

Advances in Mechanical Engineering
2017, Vol. 9(5) 1–9

DOI: 10.1177/1687814017700062
journals.sagepub.com/home/ade
SAGE

Exploring factors contributing to lane changes during left turns on quadruple left-turn lanes at signalized intersections

Fulu Wei[1], Zhenyu Wang[2] and Jian Lu[3]

Abstract
Quadruple left-turn lanes are employed gradually at some major intersections in Jilin, China. At these intersections, frequent lane changes during left turns of vehicles can lead to vastly disordered traffic operations. In this study, the factors contributing to lane changes during left turn behaviors at quadruple left-turn lane intersections were interpreted based on a field survey. In total, data on 192 green intervals and 550 individual lane-change behaviors were collected in Changchun, Jilin Province. A lane-changing rate model was established to predict the rate of lane changes during left turns. In addition, an interval selection model was built to estimate the probability of lane changes during left turn (from inside to outside only) for an individual vehicle using logistic regression. The two models provide insights to assess the traffic conditions of quadruple left-turn lane at intersections. The results of this study suggest that weaving distance, initial lane, traffic flow rate, and percentage of large vehicles significantly contribute to lane changes during left turn. Based on the identified factors, safety countermeasures to reduce lane changes during left turn behaviors are proposed.

Keywords
Quadruple left-turn lanes, lane-changing rate, lane-changing interval selection, traffic capacity, traffic safety

Date received: 4 August 2016; accepted: 22 February 2017

Academic Editor: Yongjun Shen

Introduction

Problem statement

In the past decade, vehicle ownership in China has increased rapidly with the fast growth of the economy. Traffic congestion, and its consequential traffic conflicts, energy consumption, and air pollution, has been a severe issue for transportation agencies, travelers, and residents in urban areas in China. To satisfy the growth in traffic demand, elevated expressways have been built widely in some metropolises. As the connector between an elevated expressway and a major surface arterial, a signalized intersection transfers high left-turn volume from the elevated expressway to the arterial. Quadruple left-turn lanes (QLLs) have been constructed gradually at these intersections to provide enough capacity for the left-turn movements from elevated expressways. The use of QLLs improves the efficiency for releasing left-turning vehicles in a traffic signal cycle; however, it also increases the difficulty of lane changing for left-turning vehicles whose initial lane is different from the target lane.

[1]School of Transportation Engineering, Jilin Jianzhu University, Changchun, China
[2]Center for Urban Transportation Research (CUTR), University of South Florida, Tampa, FL, USA
[3]School of Transportation Engineering, Tongji University, Shanghai, China

Corresponding author:
Zhenyu Wang, Center for Urban Transportation Research (CUTR), University of South Florida, Tampa, FL 33620, USA.
Email: zwang9@cutr.usf.edu

For example, as shown in Figure 1, a driver exits from an elevated expressway, and his or her target is to merge into the right-most (most outside) lane on the intersecting arterial. Due to the high traffic volume, the driver has few opportunities to stay in the right-most lane before entering the intersection (a common phenomenon in peak hours). Ideally, the driver makes a lane change after completing the left turn. In many Chinese arterials, however, raised green belts are a popular design to separate the right-most lane from other lanes. This design determines the space (weaving distance) that can be used for lane changing in the receiving approach. The shorter the weaving distance is, the less frequent lane-change opportunities are, especially during peak hours. In this situation, the driver may have to seek lane-change opportunities during the left turn within the intersection area. It should be noted that this issue is the same for drivers whose target lane is the left-most (inside) lane and the initial lane is on the right (outside).

Lane-changing behaviors of left-turning vehicles at intersections, either from inside to outside (I2O) or from outside to inside (O2I), are divided into two types in this study: (1) lane changes after left turn (LCAL), in which a lane change occurs after a left turn at the downstream weaving area of the intersection, starting at the lateral boundary of the exit crosswalk and ending at the nose of the green belt, as shown in Figure 1(a), and (2) lane changes during left turn (LCDL), in which a lane change occurs during a left turn within an intersection area, starting at the entry stop line and ending at the lateral boundary of the exit crosswalk, as shown in Figure 1(b).

LCDL is strongly discouraged, because it tends to cause serious conflicts between turning vehicles. Consequently, traffic congestion caused by LCDL can block intersections and even lead to traffic accidents. Thus, it is necessary to understand the mechanism of LCDL and contributing factors for developing effective safety countermeasure at QLL intersections.

Literature review

In the past several decades, lane changes have been widely studied, and the negative effects of lane changes on traffic efficiency and safety have been confirmed frequently.[1–6] At present, research on lane-changing focuses on both macroscopic and microscopic aspects. The macroscopic performance of traffic flow is affected by lane-changing behaviors.[7–10] Macroscopic lane-changing models were built to predict lane-changing rates and highway capacity and to probe the characteristics of lane-changing flow.[3,11,12] However, the special impact of large vehicles was not considered in these studies. Kinematic wave theory was introduced to describe traffic dynamics and lane-changing traffic flow.[13–15] However, the kinematic wave theory does not reflect the specific performance of individual lane-changing vehicles.

During the past three decades, many kinds of microscopic lane-changing models have been proposed to reflect the decision-making process of drivers of

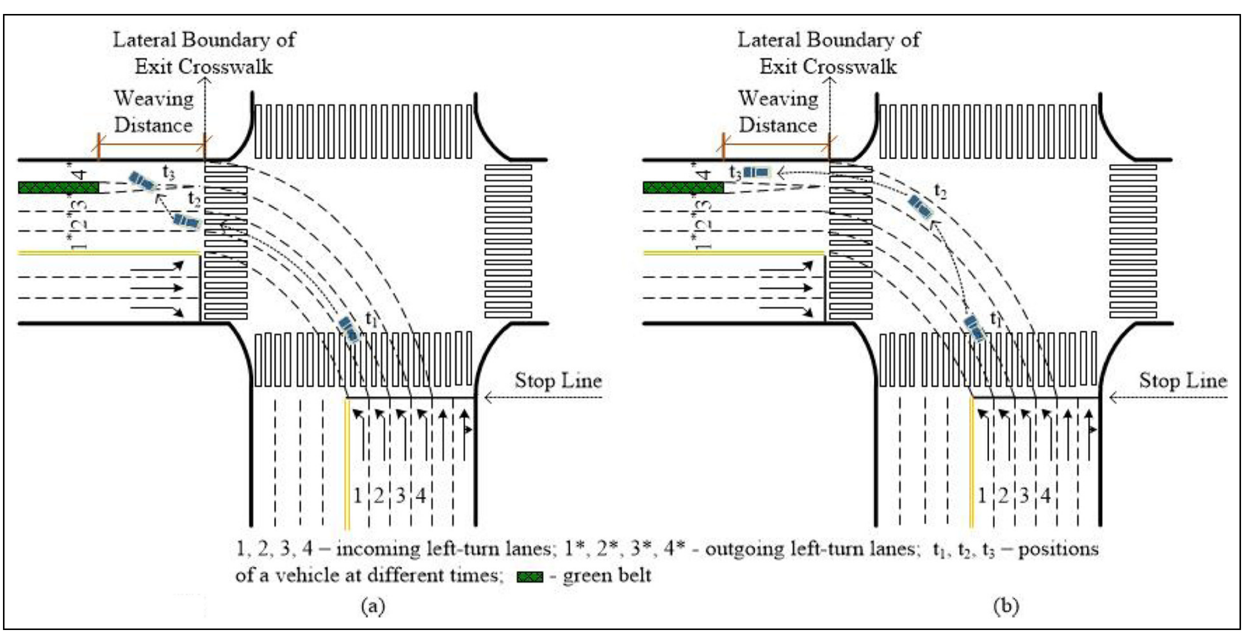

Figure 1. Lane-changing behaviors of left-turning vehicles at QLL intersections: (a) lane change after left turn and (b) lane change during left turn.

lane-changing vehicles.[1,16,17] These models usually were classified as mandatory lane-changing or discretionary lane-changing types by the maneuvers.[18–20] Gap acceptance behaviors were considered in some mandatory lane-changing models, and the distribution of accepted gaps was probed in these models.[21,22] Gap acceptance is the term used to indicate a safety opportunity selected by a driver to change lanes. The lead and lag vehicles are also considered to be significant variables to build microscopic lane-changing models.[23–26] The primary limitations are that they fail to consider the destination attractions and traffic conditions of the target lane. Moreover, the initial location of lane-changing vehicles is ignored in most microscopic lane-changing models. Fuzzy logic theory often was adopted to build lane-changing models for both mandatory and discretionary lane changes.[27–30] Some microscopic lane-changing models use classifiers or neural networks to predict lane-changing events.[31–34] Although these models perform well for resolving complex problems, the specific effects of individual contributing factors are difficult to address in detail.

Research objectives

Generally speaking, previous studies focused on lane-changing behaviors on roadway segments. Rarely were studies found to explore lane-changing behaviors in turning, especially at QLL intersections. The research objective of this study was to address the contributing factors that cause LCDL at QLL intersections. In particular, this study sought to

- Develop a lane-changing rate model to predict the LCDL rate at QLL intersections considering both I2O and O2I lane changes;
- Develop a logit model to identify the factors contributing to the probability of LCDL (e.g. I2O) for individual vehicles at QLL intersections.

Data collection

Four approaches with QLLs at two major signalized intersections in Changchun were selected for data collection. As shown in Figure 2, the selected intersections have the following characteristics:

- Both intersections connect an elevated expressway with a major urban arterial, with four left-turn lanes on major approaches, as shown in Figure 2.
- The intersections have similar geometries (except for weaving distance), traffic controls, and traffic conditions; there are no special road permission settings or temporary controls.
- The intersections represent two typical weaving distance designs in Changchun: long weaving distance (53–60 m), which accounts for 42% of major intersections, and short weaving distance (22–29 m), which accounts for 37% of major intersections.

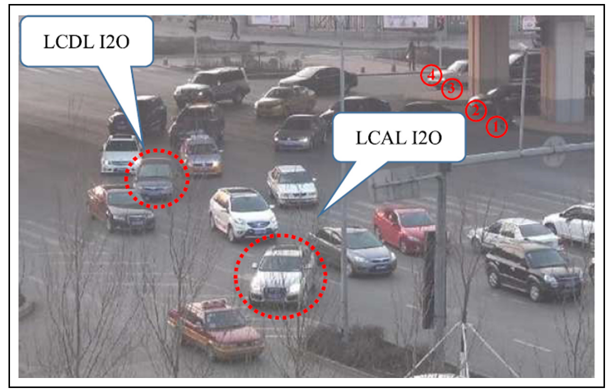

Figure 2. Example of lane changes during left turn at QLL intersection.

The operations of vehicles at QLLs of signalized intersections were recorded by video cameras. Lane-changing data were extracted from the videos using three criteria: (1) the data collection period lasted 1.5 months and covered morning and evening rush hours, (2) the data were collected during each left-turn green interval, and (3) 192 green intervals were observed for the macroscopic model, and information on 550 individual lane-change behaviors was collected as an appropriate sample size for the microscopic model. The descriptive statistics of the collected data are shown in Table 1.

The LCDL rate is defined in equation (1) as follows

$$LCDL\ rate = \frac{LCDL\ vehicles\ in\ traffic\ flow}{Traffic\ flow} \quad (1)$$

where *LCDL rate* is the rate of LCDL, *LCDL vehicles in traffic flow* is the volume of left-turning vehicles that make LCDL (both I2O and O2I) in a green interval, and *traffic flow* is the volume of left-turning vehicles that are released in a green interval. The mean LCDL rate is 0.46, indicating that almost one LCDL occurs for every two left-turning vehicles at a QLL intersection. This statistic indicates that the left-turning traffic at QLL intersections is extremely disordered in China. Possible reasons include improper geometric designs in upstream and downstream, ineffective traffic controls, aggressive driver behaviors, and lack of enforcement and education.

Table 1. Descriptive statistics of collected data.

Macroscopic model					
Continuous variable	Min.	Max.	Mean	Std deviation	
LCDL rate	0.2632	0.5909	0.4604	0.0662	
Traffic flow rate (vehicle(s)/min)	35	76	58.48	9.686	
Categorical variable	Code			Freq.	%
Large vehicle(s) percentage (P_{LV})	1: $P_{LV} = 0$			117	60.9
	2: $0 < P_{LV} \leq 5$			35	18.2
	3: $P_{LV} > 5$			40	20.8
Weaving distance	1: Short (22–29 m); 0: long (53–60 m)			112	58.3
Microscopic model					
Categorical variable	Code			Freq.	%
Lane-change behaviors (I2O only)	1: LCDL; 0: LCAL			334	60.7
Initial lane	1: Lane-changing vehicle starts from Lane 1			155	28.2
	2: Lane-changing vehicle starts from Lane 2			149	27.1
	3: Lane-changing vehicle starts from Lane 3			246	44.7
Weaving distance	1: Short (22–29 m); 0: long (53–60 m)			317	57.6
Traffic flow rate on left-side adjacent lane	1: Traffic flow rate ≤14 vehicles/min 0: Traffic flow rate >14 vehicles/min			456	82.9
Traffic flow rate on right-side adjacent lane	1: Traffic flow rate ≤11 vehicles/min 0: Traffic flow rate >11 vehicles/min			97	17.6

LCDL: lane changes during left turn; LCAL: lane changes after left turn.

Methodology

Two statistical models were developed in this study: a linear regression model was used to explore the factors contributing to the rate of LCDL (both I2O and O2I) at QLL intersections, and a logit regression model was used to quantify the probability of individual LCDL at QLL intersections.

Linear regression

The form of the linear regression model can be expressed in equation (2) as follows

$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i, \quad i = 1, \ldots, n \tag{2}$$

where y_i is the rate of LCDL, $x_{i1}, \ldots, x_{ip}$ are the independent variables, β_0 is a constant, $\beta_1, \ldots, \beta_p$ are the slope coefficients of the independent variables, i represents the ith observation, and ε_i is an error item that indicates unobserved noise.

Logit regression

If the initial lane of a left-turning vehicle is different from its target lane, the driver will exhibit a lane-changing behavior, either LCDL or LCAL. This choice is a typical binary variable; a logistic regression method is widely applied to describe the relationship between a binary dependent variable and explanatory (independent) variables. The form of the logistic regression model is given as equation (3)

$$\begin{aligned} Logit(P_i) &= LN\left(\frac{P_i}{1 - P_i}\right) \\ &= \lambda_0 + \lambda_1 X_{1,i} + \lambda_2 X_{2,i} + \cdots + \lambda_K X_{K,i} \end{aligned} \tag{3}$$

where P_i is the probability of LCDL occurring in ith observation, $\lambda_0, \lambda_1, \lambda_2, \ldots, \lambda_K$ represents the constant and slope coefficients that can be estimated by maximum likelihood estimation, and $X_{1,i}, X_{2,i}, \ldots, X_{K,i}$ are the independent variables. To transform equation (3), the probability of the ith left-turning vehicle taking LCDL can be expressed as equation (4)

$$P_i = \frac{EXP[\lambda_0 + \lambda_1 X_{1,i} + \lambda_2 X_{2,i} + \cdots + \lambda_K X_{K,i}]}{1 + EXP[\lambda_0 + \lambda_1 X_{1,i} + \lambda_2 X_{2,i} + \cdots + \lambda_K X_{K,i}]} \tag{4}$$

Model interpretation

To interpret the models, marginal effect (ME) and adjusted prediction (AP) were employed to explain the impacts of independent variables. ME is the change in probability due to an individual independent variable change (1 unit for continuous variables and 0–1 for categorical variables); all other variables were held

Table 2. Estimation results for macroscopic model.

Model parameters (dependent variable = LCDL rate)						
	Coeff.	Std error	*t*	*p*>|*t*|	95% Conf. interval	
Traffic flow rate (10 veh. per green minute)	0.1729	0.0049	6.54	0.000	0.1208	0.2250
(Traffic flow rate)^2	−0.0168	0.0024	−7.00	0.000	−0.0215	−0.0121
Large vehicle(s) percentage (P_{LV})						
1	(Baseline)					
2	−0.0319	0.0067	−4.76	0.000	−0.0451	−0.0187
3	−0.0618	0.0057	−10.92	0.000	−0.0730	−0.0507
Short weaving distance (22–29 m)	0.0762	0.0049	15.67	0.000	0.0666	0.0858
Constant	0.0136	0.0708	0.19	0.848	−0.1261	0.1533
Model statistics						
R^2	0.8418					
Adjusted R^2	0.8358					

LCDL: lane changes during left turn.

constant. In a linear regression model, the ME of an independent variable is its slope coefficient. Because the relationship between an independent variable and a dependent variable is assumed to be linear, the ME of a continuous variable can explain the impact of the variable through its whole range. In a non-linear model (such as a logistic model), ME represents an "average" change in the probability of the dependent variable rather than a constant change rate.

AP is defined as the predicted probability given independent variables. In this study, average MEs (AMEs), average AP (AAP), MEs at representative values (MERs), and AP at representative (APR) were used to explain the independent variables. A more detailed explanation of ME and AP can be found in a previous article.[35]

Estimation results and discussion

Macroscopic model

The macroscopic model was estimated by the STATA 12 package. The model has three independent variables: traffic flow rate (multiple of 10 vehicles per green minute), percentage of large vehicles in left-turn volume, and downstream weaving distance. The estimated results and goodness-of-fit are given in Table 2. The R^2 (0.8418) is close to 1, indicating that the regression line has a good fitting degree to the observation values.

According to the estimated model (Table 2), the downstream weaving distance significantly influences the LCDL rate ($p > 0.001$). Compared to a long weaving distance (53–60 m), a short weaving distance tends to increase the LCDL rate by 7.62%. This finding is intuitive to understand in that a long weaving distance provides more opportunities for a left-turning vehicle to make a lane change after completion of a left turn.

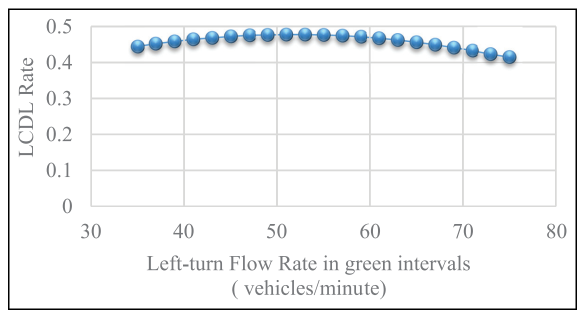

Figure 3. Average adjusted prediction of traffic flow rate in green interval.

The presence of large vehicles is another factor that significantly contributes to the LCDL rate. Compared to no presence of large vehicles in a green interval, the presence of 5% or less large vehicles is more likely to decrease the LCDL rate by 3.19%. If the percentage of large vehicles is more than 5%, the LCDL rate will be reduced by 6.18%. It is clear that the presence of large vehicles in left-turning traffic reduces available gaps (opportunities) for vehicles intending to make an LCDL. These vehicles have to seek lane-change opportunities after completion of the left turn.

The traffic flow rate of left-turning vehicles in a green interval is a significant factor influencing the LCDL rate. A high left-turning flow rate means high traffic density and less probability of available gaps for LCDL. On the other hand, a driver's intention to make an LCDL is low if the left-turning flow rate is small because, in this situation, he or she has enough opportunities to make an LCAL. In this situation, LCDL is an unnecessary risk for drivers. As shown in Table 2 and Figure 3, the relationship between the LCDL rate and the total left-turning volume in one green interval is quadratic rather than linear.

Table 3. Estimation and AME for microscopic models.

Model parameters	Coeff.	Std error	z	$p>\|z\|$	95% Conf. interval	
Traffic flow rate on left-side adjacent lane ≤14 vehicles/min	−1.0039	0.2936	−3.42	0.001	−1.5793	−0.4285
Traffic flow rate on right-side adjacent lane ≤11 vehicles/min	0.9262	0.3595	2.58	0.010	0.2216	1.6308
Short weaving distance (22–29 m)	0.8943	0.2018	4.43	0.000	0.4988	1.290
Initial lane						
1	(Baseline)					
2	−1.0770	0.3379	−3.19	0.001	−1.7392	−0.4148
3	−1.5635	0.2841	−5.50	0.000	−2.1203	−1.0067
Constant	1.694	0.3781	4.48	0.000	0.9532	2.4353
Model statistics						
Link function: logistic						
Log likelihood = −320.3695, pseudo R^2 = 0.1306						
AME for microscopic model						
	dy/dx	Std error	t	$p>\|t\|$	95% Conf. interval	
Traffic flow rate on left-side adjacent lane ≤14 vehicles/min	−0.1900	0.0498	−3.82	0.000	−0.2875	−0.0924
Traffic flow rate on right-side adjacent lane ≤11 vehicles/min	0.1773	0.0626	2.83	0.005	0.0547	0.3000
Short weaving distance (22–29 m)	0.1821	0.0397	4.59	0.000	0.1043	0.2600
Lane-changing vehicle starts from Lane 2	−0.2017	0.0608	−3.32	0.001	−0.3209	−0.0825
Lane-changing vehicle starts from Lane 3	−0.3112	0.0497	−6.26	0.000	−0.4086	−0.2138

AME: average marginal effect.
dy/dx for factor levels is discrete and change from 0 to 1.

Figure 3 shows the AAP of the LCDL rate over the left-turn traffic flow rate, holding other factors constant. The LCDL rate tends to increase when the left-turn traffic flow rate is low. With an increase in the left-turn flow rate, the lane-changing opportunities in downstream weaving areas decrease and the driver's intention to make an LCDL increases. If the left-turn flow rate is extremely high, the opportunity for an LCDL decreases gradually. In this stage, a driver must take lane changes in the downstream. As shown in Figure 3, the maximum LCDL rate (0.48) occurs in the vicinity of 52 vehicles/min.

It is interesting that the minimum LCDL rate in Figure 3 is still close to 0.4. At this time, the left-turn volume is close to congestion status (75 vehicles/min on four lanes = 1125 vehicles/h/lane (vphpl)). This shows that drivers have strong intentions to change lanes during left turns, even if the gap is very small (close to congestion status).

Microscopic model

The coefficients of the logit model for individual lane-changing vehicles and the AME for explanatory variables were estimated using the STATA 12.0, as shown in Table 3. Note that the microscopic model included LCDL-I2O only, as this is the major portion of LCDL at QLL intersections.

As shown in Table 3, a short weaving distance (22–29 m) is more likely to increase the probability of individual LCDL by 18.21%, compared to a long weaving distance (53–60 m). This finding is constant with the macroscopic model.

The traffic flow rate in the adjacent lane on the left side has a significant influence on the probability of individual LCDL-I2O. If the left-turn traffic flow rate in the adjacent lane on left side is 14 vehicles/min or less, the probability that individual LCDL will be 19.0% lower than the left-turn traffic flow rate is more than 14 vehicles/min. A high left-turn traffic flow rate on the left-side adjacent lane indicates an increased probability of lane change from the left lane to the current lane that the target vehicle is occupying. Thus, the target vehicle may receive the pressure from the lane-change vehicles on the left lane and is forced to change to the right lane. This chain reaction may result in a high probability of LCDL. On the contrary, a higher flow rate in the right-side lane indicates smaller gaps and lower opportunities of LCDL for its inside lane.

A vehicle targeting the right-most lane and starting from Lane 2 will have a reduction of 20.2% in the LCDL probability compared to that starting from Lane 1 (most inside). If the vehicle is starting from Lane 3, the reduction will be 31.1%. Usually, a vehicle whose target lane is the right-most lane (Lane 4) is

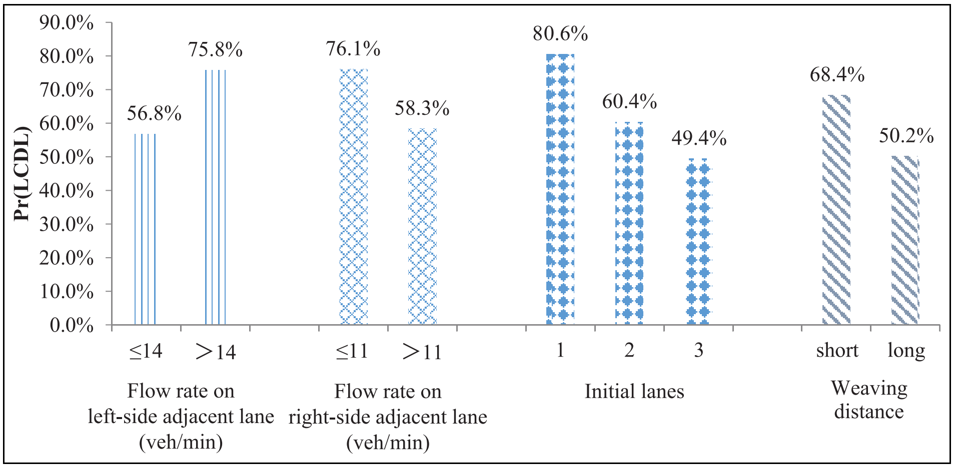

Figure 4. AAP of LCDL-I2O over traffic flow rates on left/right-side adjacent lanes, initial lanes, and weaving distance.

willing to stay on Lanes 4 as early as possible before a left turn; however, not all lane-changing vehicles have the opportunity. Many vehicles may enter Lanes 2 and 3, and a small portion may stay in Lane 1. LCAL from Lane 1 is more difficult than from Lane 2 or 3, especially in peak hours. Thus, Lane 1 has the highest likelihood of LCDL. Compared to starting a left turn on Lane 1, starting the left turn from Lane 2 has a less pressure to take an LCDL. Starting from Lane 3 has the lowest likelihood to take an LCDL.

The probabilities of LCDL by traffic flow rates on adjacent lanes, downstream weaving distances, and initial lanes are compared in Figure 4. It can be seen that the probability of LCDL for each scenario keeps a high level ($\geq$ 49.4%), confirming the disorder of the traffic stream at QLL intersections in China.

Conclusion and recommendations

In this study, the factors contributing to LCDL at QLL intersections in Jilin were identified from both the macroscopic and microscopic aspects. The following conclusions were drawn:

- The organization of left-turning traffic at QLL intersections in Jilin is very disordered. Based on the macroscopic and microscopic models, it can be estimated that more than 40% of left-turning vehicles make LCDLs.
- Extension of weaving distance in the downstream is an effective countermeasure to reduce LCDL behaviors. From a macroscopic aspect, replacing a short weaving distance (22–29 m) in the downstream with a long weaving distance (53–60 m) will reduce the LCDL rate by 7.6%. The microscopic model shows that this replacement will reduce the probability of LCDL (I2O) by 18.2%.
- The relationship between the LCDL rate and the left-turn traffic flow rate in a green interval is just like a quadratic curve. The left-turn traffic flow rate of approximately 52 vehicles/min experiences the maximum LCDL rate (0.48). Thus, countermeasures should be optimized for this flow rate range.
- From the microscopic aspect, a low traffic flow rate in the left adjacent lane ($\leq$ 14 vehicles per green light minute) results in the probability of LCDL (I2O) being 19% lower than a high volume (>14 vehicles/min). A low traffic flow rate in the right adjacent lane ($\leq$ 11 vehicles per green light minute) tends to increase the probability of LCDL (I2O) by 17.7% when compared to a high volume (>11 vehicles/min).
- The initial lane from which a left-turn vehicle starts is a significant factor that contributes to the probability of LCDL (I2O). Lane 1 (the most inside lane) experiences the highest probability (80.6%), followed by Lane 2 (60.4%) and Lane 3 (49.4%). Traffic warning signs and optimum geometric designs should be installed in the upstream to encourage drivers who target the outside lanes to stay on the right-most lane as early as possible before entering the intersection.

Based on the findings, some recommendations on countermeasures, aiming to reduce LCDL behaviors and improve traffic efficiency at QLL intersections, are proposed:

- Effective engineering countermeasures: (1) extend weaving distance to provide enough space to make LCAL; (2) add extension lines to indicate lane splits within intersections; (3) apply access management technology, moving access points from major roads to downstream side street so as to reduce the needs of instant lane change to right-most lane after left turn; and (4) advanced warning signs to guide drivers to make an early lane change before entering the intersection.

- Effective enforcement countermeasures: (1) ban vehicle LCDL behaviors and (2) enforce right-of-way limits for large vehicles at QLL intersections.
- Effective education countermeasures: (1) organize volunteers to identify dangerous behaviors and (2) distribute handbills, T-shirts, and other promotional materials to advocate following traffic rules.

In future, the influencing factors of QLL traffic operation should be explored in depth, because other influencing variables may exist that affect traffic operation efficiency, safety, and distribution, such as land use around intersections and lane channel types.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research was funded by the National Natural Science Foundation of China (grant no. 51278220) and the Doctoral Startup Foundation of Jilin Jianzhu University, and it was supported by the China Scholarship Council, 2017 Jilin Province Science and Social Science in Colleges and Universities of "Thirteen-Five" research plan project.

References

1. Gipps PG. A model for the structure of lane-changing decisions. *Transport Res B* 1986; 20: 403–414.
2. Winsum W, Waard D and Brookhuis KA. Lane change manoeuvres and safety margins. *Transport Res F* 1999; 2: 139–149.
3. Laval JA and Daganzo CF. Lane-changing in traffic stream. *Transport Res B* 2006; 40: 251–264.
4. Zheng Z, Ahn S and Monsere CM. Impact of traffic oscillations on freeway crash occurrences. *Accident Anal Prev* 2010; 42: 626–636.
5. Wei F, Guo W, Liu X, et al. Left-turning vehicle trajectory model and guide line setting at intersections. *Discrete Dyn Nat Soc* 2014; 2014: 950219.
6. Zheng Z. Recent developments and research needs in modeling lane changing. *Transport Res B* 2014; 60: 16–32.
7. Daganzo CF. A behavioral theory of multi-lane traffic flow. Part II: merges and the onset of congestion. *Transport Res B* 2002; 36: 159–169.
8. Kerer BS and Klenov SL. Microscopic theory of spatial-temporal congested traffic patterns at highway bottlenecks. *Phys Rev E* 2003; 68: 036130.
9. Duret A, Ahn S and Buisson C. Lane flow distribution on a three-lane freeway: general features and the effects of traffic controls. *Transport Res C* 2012; 24: 157–167.
10. Tian J, Treiber M, Ma S, et al. Microscopic driving theory with oscillatory congested states: model and empirical verification. *Transport Res B* 2015; 71: 138–157.
11. Chang GL and Kao YM. An empirical investigation of macroscopic lane-changing characteristics on uncongested multilane freeways. *Transport Res A* 1991; 25: 375–389.
12. Tang TQ, Wong SC, Huang HJ, et al. Macroscopic modeling of lane-changing for two-lane traffic flow. *J Adv Transport* 2009; 43: 245–273.
13. Lighthill MJ and Whitham GB. On kinematic waves. II. A theory of traffic flow on long crowded roads. *P Roy Soc* 1955; 229: 281–345.
14. Richards PI. Shockwaves on the highway. *Oper Res* 1956; 4: 42–51.
15. Jin W. A kinematic wave theory of lane-changing traffic flow. *Transport Res B* 2010; 44: 1001–1021.
16. Hidas P. Modelling lane changing and merging in microscopic traffic simulation. *Transport Res C* 2002; 10: 351–371.
17. Reimer B, Donmez B, Lavalliere M, et al. Impact of age and cognitive demand on lane choice and changing under actual highway conditions. *Accident Anal Prev* 2012; 52: 125–132.
18. Ahmed KI. *Modeling drivers' acceleration and lane changing behavior*. PhD Thesis, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, MA, 1999.
19. Toledo T, Choudhury CF and Ben-Akiva ME. Lane-changing model with explicit target lane choice. *Transport Res Rec* 2005; 1934: 157–165.
20. Qi HS, Wang DH, Chen P, et al. Location-dependent lane-changing behavior for arterial road traffic. *Netw Spat Econ* 2014; 14: 67–89.
21. Vivek G. Gap acceptance behavior in mandatory lane changes under congested and uncongested traffic on a multilane freeway. *Paper presented at the 86th annual meeting of Transportation Research Board*, Washington, DC, 21–25 January 2007. Washington, DC: Transportation Research Board of the National Academies.
22. Liu P, Wang X, Lu J, et al. Headway acceptance characteristics of U-turning vehicles at unsignalized intersections. *Transport Res Rec* 2007; 2027: 52–57.
23. Toledo T, Koutsopoulos HN and Ben-Akiva ME. Modeling integrated lane-changing behavior. *Transport Res Rec* 2003; 1857: 30–38.
24. Hidas P. Modelling vehicle interactions in microscopic simulation of merging and weaving. *Transport Res C* 2005; 13: 37–62.
25. Choudhury CF, Ben-Akiva ME, Toledo T, et al. Modeling cooperative lane-changing and forced merging behavior. *Paper presented at the 86th annual meeting of Transportation Research Board*, Washington, DC, 21–25

January 2007. Washington, DC: Transportation Research Board of the National Academies.
26. Rahman M, Chowdhury M, Xie Y, et al. Review of microscopic lane-changing models and future research opportunities. *IEEE T Intell Transp* 2013; 14: 1942–1956.
27. McDonald M, Wu J and Brackstone M. Development of a fuzzy logic based microscopic motorway simulation model. *IEEE Proc Intell Transp Syst* 1997; 82–87.
28. Das S and Bowles BA. Simulation of highway chaos using fuzzy logic. *Fuzzy Inf Process Soc* 1999; 130–133.
29. Peeta S, Zhang P and Zhou W. Behavior-based analysis of freeway car-truck interaction and related mitigation strategies. *Transport Res B* 2005; 39: 417–451.
30. Hou Y, Edara P and Sun C. A genetic fuzzy system for modeling mandatory lane changing. *IEEE Proc Intell Transp Syst* 2012; 1044–1048.
31. Hunt JG and Lyons GD. Modeling dual carriageway lane-changing using neural networks. *Transport Res C* 1994; 2: 231–245.
32. Tomar RS, Verma S and Tomar GS. Prediction of lane change trajectories through neural network. *IEEE Proc Comput Intell Commun Netw* 2010; 249–253.
33. Hou Y, Edara P and Sun C. Modeling mandatory lane changing using Bayes classifier and decision trees. *IEEE T Intell Transp* 2014; 15: 647–655.
34. Zheng J, Suzuki K and Fujita M. Predicting driver's lane-changing decisions using a neural network model. *Simul Model Pract Th* 2014; 42: 73–83.
35. Williams R. Using the margins command to estimate and interpret adjusted predictions and marginal effects. *Stata J* 2012; 12: 308–331.