

Research Article

Determining E-Bike Drivers' Decision-Making Mechanisms during Signal Change Interval Using the Hidden Markov Driving Model

Sheng Dong ¹, Jibiao Zhou ,^{1,2} and Shuichao Zhang ¹

¹School of Civil and Transportation Engineering, Ningbo University of Technology, Fenghua Rd. #201, Ningbo 315211, China

²Department of Transportation Engineering, Key Laboratory of Road and Traffic Engineering, Ministry of Education, Tongji University, No. 4800, Cao'an Road, Shanghai 201804, China

Correspondence should be addressed to Jibiao Zhou; zhoujb2014@nbut.edu.cn

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Rapidly increasing e-bike use in China has resulted in new traffic problems including rising accident rates at intersections related to e-bike drivers' decision-making during multiple signal phases. Traditional one-step decision models (such as GHM) lack randomness and cannot adequately model e-bike drivers' complex behavior. Therefore, this study used a Hidden Markov Driving Model (HMDM) to analyze e-bike drivers' decision-making process based on high-resolution trajectory data. Video data were collected at three intersections in Shanghai and processed for use in the HMDM model. Five decision types (pass, stop, stop-pass, pass-stop, and multiple) composed of speed and acceleration/deceleration information were defined and used to analyze the impact of flashing green signals on e-bike drivers' behavior and decision-making processes. Approximately 40% of drivers made multiple decisions during the flashing green and yellow signal phases, in contrast to the traditional GHM model assumption that drivers only make one decision. Distance from stop-line had the most obvious influence on the number of decisions. The use of flashing green signals nearly eliminated the dilemma zone for e-bike drivers but enlarged the option zone, inducing more stop/pass decisions. HMDM can be applied to improve the accuracy of traffic simulation, the fine design of traffic signals, the stability analysis of traffic control schemes, and so on.

1. Introduction

Drivers approaching a signalized intersection during a signal change from green to yellow must quickly decide whether to enter the intersection or stop until the next green. This situation can make drivers anxious and result in incorrect decision-making. Several methods can be used to reduce the probability of incorrect decisions during signal-change intervals, including the application of flashing green signals. For example, most Chinese cities use a 3 s flashing green followed by a 3 s yellow.

In recent years, the use of e-bikes (bicycles equipped with electric motors) has drastically increased in China. As a result, smooth traffic flow in many cities is being increasingly disrupted, while the operational efficiency and safety of intersections are deteriorating. For example, data from Shanghai's Songjiang District indicate that 70% of accidents

at intersections occur during signal phase transitions, mostly relating to collisions between motor vehicles and e-bikes [1]. This is similar to patterns observed in other Chinese cities, where many such accidents involve undisciplined driver behavior such as red-light violations related to either intentional violations or incorrect stop/pass decisions. In China, motorized and nonmotorized traffic is controlled using the same signals at signalized intersections, so e-bike drivers' indecision or improper reactions during flashing green or yellow (along with insufficient clearance time) have become the major causes of collisions between vehicles and e-bikes. Thus, a better understanding of decision-making behavior and mechanisms during the flashing green phase is crucial for improving the safety performance of signalized intersections.

Drivers' stop/pass decision-making behavior at the end of a green phase was initially modeled by Gazis et al. in 1960,

which is usually referred to as the Gazis-Herman-Maradudin (GHM) model [2]. According to the GHM model, at a closer distance than the minimum stopping distance, a vehicle cannot safely stop before the stop-line. At a larger distance than the maximum crossing distance, a vehicle cannot safely pass the intersection during the yellow interval. Traditional GHM model is based on the maximum crossing distance and the minimum stopping distance, assuming that the driver makes only one decision (at the onset of the yellow light). However, many past studies have argued that observed driver behavior was considerably different from the theoretical assumptions of the GHM model. Some studies [3, 4] have shown that decision-making behavior during flashing green and yellow is more complex and drivers may adjust their stop/pass decisions several times. In addition, compared with motorized vehicles, e-bikes are more variable in size, power, control, performance capability, and driving characteristics, so previous research based on motorized vehicles may not apply to such nonmotorized vehicles.

Most relevant studies primarily consist of empirical analysis and lack analytical modeling of driver decision-making mechanisms in response to a combination of flashing green and yellow, while ignoring drivers' decision chain during the entire transition interval. As a result, the mechanisms of driver decision-making in these contexts have been improperly interpreted. In addition, insufficient research has focused on e-bike decision-making behavior, so further analysis is necessary in understanding the impacts of flashing green on e-bikes' stop/pass decision-making. Thus, this study investigated the mechanisms of Chinese e-bike users' stop/pass decision-making processes during flashing green and yellow intervals at intersections. The results may help decrease incorrect stop/pass decisions during flashing green and yellow situations and contribute to greater e-bike safety at intersections.

This paper is organized as follows. First, past studies on stop/pass decision-making behavior and the impacts of flashing green signals are reviewed. Second, the study sites are defined and the collection and processing methods for the trajectory data and important decision-making parameters are presented. Third, the basic theory of the Hidden Markov Model (HMM) is described, details of model development are given, an analytical model based on the HMM is developed, and the model estimation and validation results are presented. Fourth, e-bike users' stopping behavior with and without flashing green before yellow and their decision-making mechanism during flashing green are discussed. Finally, conclusions are presented and future research is summarized.

2. Literature Review

The GHM model initially proposed by Gazis et al. [2] is the most widely used for stop/pass decision modeling and has been further developed by other researchers [5–14]. In this model, drivers are assumed to make their stop/pass decision when approaching an intersection based on the maximum crossing distance or the minimum stopping distance at the onset of yellow, as determined by perception-and-reaction

time, approach speed, and acceleration capability. The GHM model has two limitations: (a) as a kinematic and deterministic model, it is not capable of assessing the randomness inherent in driving behavior, and (b) it assumes a one-step decision process that only accounts for behavior parameters at the onset of a yellow signal. For these reasons, several stochastic models such as the probit model, the logit model, and the fuzzy logic model have been developed to explain the randomness and uncertainty of stop/pass decision behavior [5–7, 15–23].

Many studies have considered flashing green signals in the past several decades. For example, Mahalel and Zaidel [24] defined the dilemma zone, option zone, and indecision zone based on behavioral considerations, finding that flashing green increased the size of the indecision zone and consequently increased the probability of rear-end collisions. Newton et al. [25] concluded that flashing yellow could reduce red-light violations and increase the size of the indecision zone, causing more rear-end collisions. Köll et al. [3] also found that flashing green reduced the dilemma zone and increased the option zone while increasing the possibility of rear-end collisions. These studies are consistent in showing that flashing green reduces red-light violations that may result in right-angle collisions but increases conflicts during approach that may result in rear-end collisions that call for immediate action rather than preparatory warnings. In addition, Tang et al. [26] and Dong et al. [27, 28] studied the impact of flashing green on e-bike driving behavior and found that potential time is the dominant independent factor explaining the stop/pass decision of e-bike drivers. In these cases, flashing green seemed to enlarge the option zone, bringing the indecision zone earlier and resulting in more aggressive driving behavior with regard to passing through intersections. Overall, driver behavior at intersections with a flashing green is more complicated and uncertain than at intersections lacking this feature. Thus, the GHM model's simplification of the stop/pass decision to a one-step process may be suitable for intersections with only yellow but cannot fully reflect decision-making at a flashing green intersection.

3. Data Preparation

3.1. Field Study Site Description. Studying e-bike decision-making behavior during the signal phase transition requires accurate individual driving behavior data, which can be obtained by field survey. Thus, three intersections in Shanghai were selected for data collection on traffic operation and e-bike behavior; each was a typical four-leg intersection with the following characteristics (details summarized in Table 1):

- (A) A dual-lagging, left-turn, four-phase plan (bicycles and pedestrians are released with the motorized traffic flow of the same direction);
- (B) An exclusive bicycle lane at each of the approaches and exits;
- (C) A 3 s red-and-yellow signal and a 3 s flashing green signal displayed before the green onset and the red-and-yellow onset, respectively;

TABLE 1: Characteristics of the studied intersections in Shanghai.

	Wuning Rd. & Daduhe Rd. (Westbound)	Guoding Rd. & Huangxing Rd. (Eastbound)	Dalian Rd. & Siping Rd. (Westbound)
Traffic volume	1380 veh/h	1917 veh/h	1607 veh/h
Speed limit	50 km/h	50 km/h	50 km/h
Width	40 m	45 m	45 m
Cycle length	220 s	161 s	178 s
Number of phases	3	4	4
Green time	53 s	40 s	38 s
Flashing green	3 s	3 s	3 s
Yellow time	3 s	3 s	3 s
All-red time	1 s	1 s	1 s
Transition signals	Flashing green and yellow	Flashing green and yellow	Flashing green and yellow

(D) An available on-site tall building allowing for easy mounting of detection equipment for monitoring bicycle volumes during the survey period.

3.2. Data Collection. The field survey was conducted during off-peak hours from 12:00 to 16:00 on 10 normal weekdays in 2014 under sunny weather conditions. Two high-resolution cameras were used at each intersection (Figure 1). One was placed on a building at a height of 20 m, approximately 60 m upstream of the intersection, perpendicular to the approach lanes. This camera was intended to obtain trajectories for e-bike stop/pass decision-making processes while approaching the intersection. The other camera was positioned at the roadside of the approach lane, angled across the intersection, in order to record the trajectories of e-bikes within the intersection. Signal timing and phase transitions were collected at the same time.

3.3. Data Reduction. Over 60 h of video data (approximately 1,800 cycles) were recorded and analyzed. Only the last-to-stop e-bikes after the onset of flashing green were selected for the analysis to avoid the influence of existing leading vehicles.

The image processing software George 2.1, developed by Nagoya University [1, 26] with a resolution of 1/30 s, was used for data reduction. This allowed every e-bike's position to be tracked after it entered the camera's scope along with signal states for each time. The raw trajectory data were used to automatically reproduce a complete e-bike trajectory with a very high accuracy. A total of 344 travel trajectories, including 230 passes and 114 stops, were obtained during signal phase transitions (Figure 2).

4. Model Development

4.1. Hidden Markov Model. A Markov chain is a sequence of stochastic states that are determined only by the immediately previous state. A Hidden Markov Model (HMM) indicates that the sequence of states producing the observable data is not available (hidden) even though outputs are dependent on them. Observed states are associated with hidden states by probability distributions. The output results present real information about the sequence of states with the help of an

HMM. Therefore, the HMM can be considered as a double stochastic process or a partially observed stochastic process [29].

The Markov process has been proved to be capable of modeling highly stochastic systems in the field of transportation, such as path choice and traffic control strategy [30, 31]. The use of Markov models in microcosmic driving behavior research has gradually increased in recent years, but the prediction of decision-making behavior based on Markov models is still in its infancy [1, 32, 33].

4.2. Model Construction. As the stop/pass decision-making process is comprised of multiple discrete action states that are partially observable, these states can represent driver maneuvers since observed e-bike movements are the consequences of drivers' actions. Thus, this study developed a driving model based on HMM using behavioral recognition including continuous trajectories or discrete sequences of measurable properties such as position, speed, and acceleration/deceleration. The resulting Hidden Markov Driving Model (HMDM) can present a series of dynamic states revealing e-bike drivers' decision-making processes during signal phase transitions.

An HMDM can be formulated using (1), in which Q , O , A , B , and π are defined by (2)–(6), respectively,

$$\lambda = (Q, O, A, B, \pi) \quad (1)$$

$$Q = \{q_1, q_2\} \quad (2)$$

$$O = \{o_{11}, \dots, o_{1j}, \dots, o_{i1}, \dots, o_{ij}\}$$

$$= \left\{ \begin{array}{c} (v_1, a_1), \dots, (v_1, a_j) \\ \dots \\ (v_i, a_1), \dots, (v_i, a_j) \end{array} \right\} \quad (3)$$

$$A = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \quad (4)$$

$$B = \begin{bmatrix} p_{11} & \dots & p_{1m} \\ p_{21} & \dots & p_{2m} \end{bmatrix} \quad (5)$$

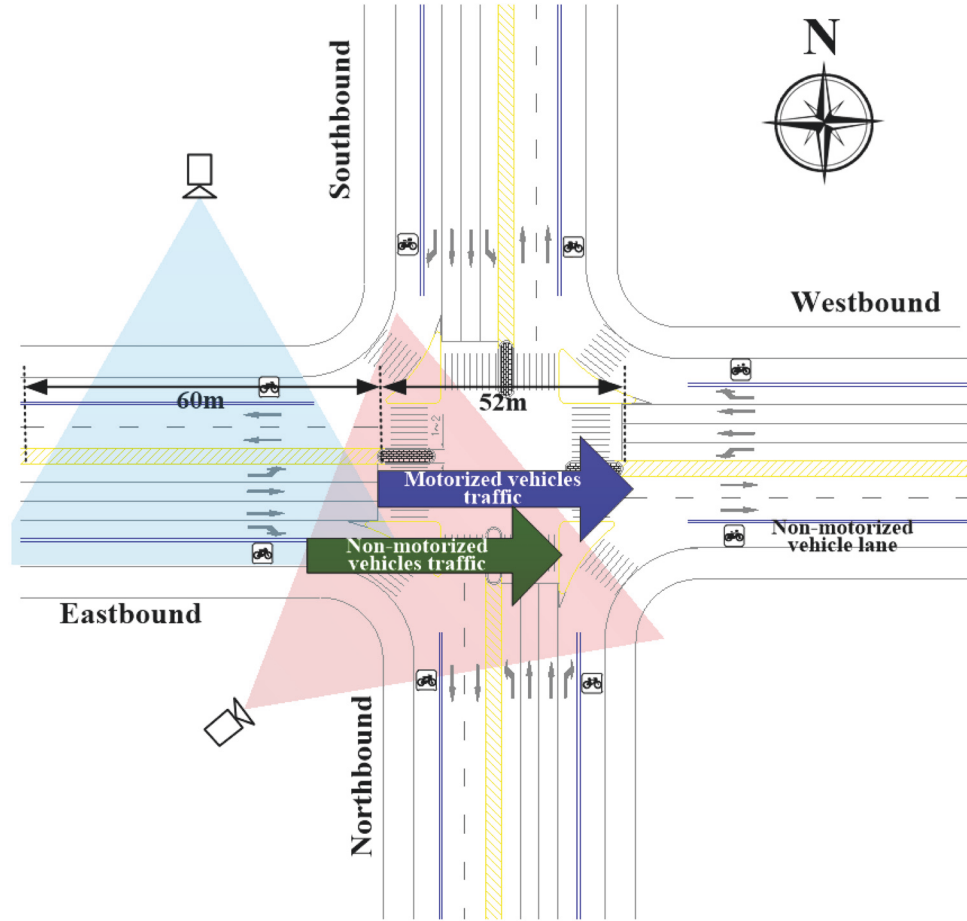


FIGURE 1: Diagram of trajectory collection at intersections. Blue camera was mounted 20 m above the road and red camera at road height.

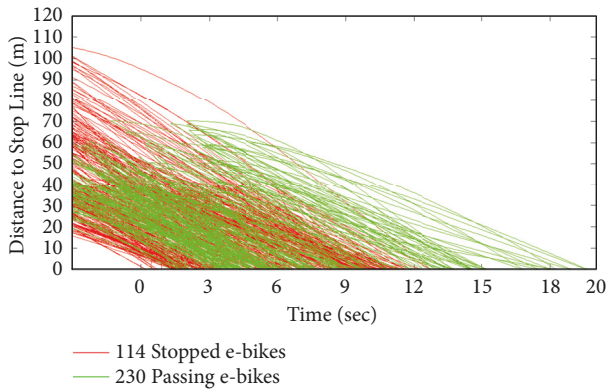


FIGURE 2: Observed e-bike trajectories at study intersections.

$$\pi = \{\pi_1, \pi_2\} \quad (6)$$

where Q is the finite set of the hidden states and is regarded as a driver's time-dependent decision on whether to stop or pass; O is the finite set of the observed states O_{ij} defined by the states of speed $v = \{v_1, v_2, \dots, v_i\}$ and acceleration $a = \{a_1, a_2, \dots, a_j\}$; A is the transition matrix, in which $a_{ij} = P\{Q_t = q_j \mid Q_{t-1} = q_i\}$ is the transition probability from

state i to state j , representing a time sequence of probability that drivers change their decision from pass to stop (or vice versa) at each time step; $B = \{b_{ij}\}$ is the emission matrix, where $b_{ij} = P\{Q_t = o_j \mid Q_t = q_i\}$ is the probability of the observation state j when the hidden state is i , referring to a time sequence of probability that a driver decides to stop or pass at each time step under a given observed state; π is the initial probability of stop or pass at the onset of flashing green under a given observed state, which can be estimated from empirical data; m is the total number of observable states defined by O_{ij} ; $\pi = \{\pi_i\}$ is the initial probability distribution; and $\pi_i = P\{Q_t = q_j\}$ is the initial probability of hidden state, where $\pi_1 = P_0\{Q_0 = q_1\}$, $\pi_2 = P_0\{Q_0 = q_2\}$ = the probability of the initial state.

4.3. Solution Procedure and Algorithms. As both of the observed and the hidden states are time-dependent and each state must be defined on a basis of a time step, this is appropriate for capturing the mechanism of drivers' decision-making behavior. A time step of 0.1 s was used in the proposed model, such that 60 observation and hidden states are included during the entire phase transition period, composed of a 3 s flashing green and a 3 s yellow.

According to the basic concepts behind HMMs, there are three fundamental problems that need to be solved: the estimating problem, the decoding problem, and the training problem. These can be solved by the Forward-Backward algorithm, the Viterbi algorithm, and the Baum-Welch algorithm, respectively, using methods presented in full by Tang et al. [1].

5. HMDM Model Building

5.1. Determination of Initial Conditions

5.1.1. Observation & Hidden States. Measured e-bike behavior is usually predefined as a set of discrete events or states in HMDMs. In the case of e-bike decision-making processes, these behaviors could be sequences of acceleration, deceleration, or cruising, and drivers' attitudes can be characterized by driving parameters such as speed and acceleration. Therefore, this study's HMDM started with e-bike speed and acceleration as the observed states and driver attitudes (stop or pass) as the hidden states.

Statistical analysis of all e-bike samples found that most drivers chose to stop at speeds below 10 km/h and to pass at speeds above 30 km/h. Therefore, the total set of speeds was divided into four groups: $v = \{v_1 (0\text{--}10 \text{ km/h}), v_2 (10\text{--}20 \text{ km/h}), v_3 (20\text{--}30 \text{ km/h}), \text{ and } v_4 (> 30 \text{ km/h})\}$. As the 85th percentile acceleration/deceleration was $\pm 0.15 \text{ m/s}^2$, this was set as the threshold for identifying e-bike acceleration/deceleration, defining the three basic states of e-bike dynamics as $a = \{a_1 (< -0.15 \text{ m/s}^2), a_2 (-0.15 \text{ to } 0.15 \text{ m/s}^2), \text{ and } a_3 (> 0.15 \text{ m/s}^2)\}$. Finally, 12 combinations of speed and

acceleration/deceleration were defined as observation states for the HMDM. In addition, the hidden states were defined as 1 (pass) and 2 (stop).

5.1.2. Initial State Vectors. The initial state vectors were determined by analysis of the observed data during flashing green and yellow lights; for stop (π_1) and pass (π_2), these were 0.67 and 0.33, respectively.

5.1.3. Initial Transition Matrix. In order to reduce errors from the initial state vector set, this study adopted the A Priori method to determine the initial transfer matrix. Taking half of all samples for model training ($n = 172$) produced 115 passes samples and 57 stops. Comparative analysis of the initial and final states for these training samples found that the initial 115 passes contained 91 passes and 24 stops, while the initial 57 stops contained 50 stops and 7 passes. Hence, the initial transition matrix can be calculated as

$$A = \begin{bmatrix} \frac{91}{115} & \frac{24}{115} \\ \frac{7}{57} & \frac{50}{57} \end{bmatrix} = \begin{bmatrix} 0.79 & 0.21 \\ 0.13 & 0.87 \end{bmatrix} \quad (7)$$

5.1.4. Initial Confusion Matrix. Setting 12 observation states and 2 hidden states in the HMDM formed a 2×12 confusion matrix: $\{0 < v < 10, 10 \leq v < 20, 20 \leq v < 30, v \geq 30\} \times \{a < -0.15, -0.15 \leq a \leq 0.15, a > 0.15\}$. The initial and final state of each training sample was used to calculate initial confusion matrix:

$$B = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 0.00 & 0.08 & 0.00 & 0.04 & 0.68 & 0.04 & 0.02 & 0.13 & 0.01 \\ 0.00 & 0.00 & 0.04 & 0.00 & 0.28 & 0.15 & 0.01 & 0.35 & 0.14 & 0.00 & 0.02 & 0.01 \end{bmatrix} \quad (8)$$

5.2. Analysis of Learning Results. The HMM toolbox in MATLAB software was used to solve the HMDM; learning results are shown in Figure 3. Observation states 6 and 8 contributed most to the hidden state "stop", while observation states 8 and 11 contributed most to the hidden state "pass." The transition probability from "pass" to "stop" was 0.21, and that from "stop" to "pass" was 0.13.

Setting aside the model's prediction accuracy, hidden states at successive time steps tended to remain as the previous state. However, there were still many conversions between the two states, especially from "pass" to "stop." A more detailed analysis of these hidden state changes using mechanism analysis of e-bike decision-making process is presented in a subsequent section.

6. Comparative Analysis between GHM Model and HMDM Model

6.1. GHM Model Specification

6.1.1. Model Building. Considering the influence of speed at decision point and distance from decision point to stop-line

during the decision-making process, GHM model is constructed, which is a binary logistic regression model. In order to make the model more accurate and forward: LR is used to screen the independent variables. Forward stepwise regression method based on maximum likelihood estimation is used to select the independent variables based on Core test statistics. The rejected variables are based on the likelihood ratio test results of maximum partial likelihood estimation. The results are shown in Table 2.

The fitted logistic regression model is as follows:

$$\log it(p) = 0.541 + 0.123V - 0.084S. \quad (9)$$

Namely,

$$P(\text{pass}) = 1 - \frac{1}{1 + 1/(0.541 + 0.123V - 0.084S)} \quad (10)$$

In (9) and (10), V is the instantaneous speed at decision point and S is the distance from decision point to stop-line. In the model, the regression coefficient of speed is positive and the regression coefficient of distance is negative, which

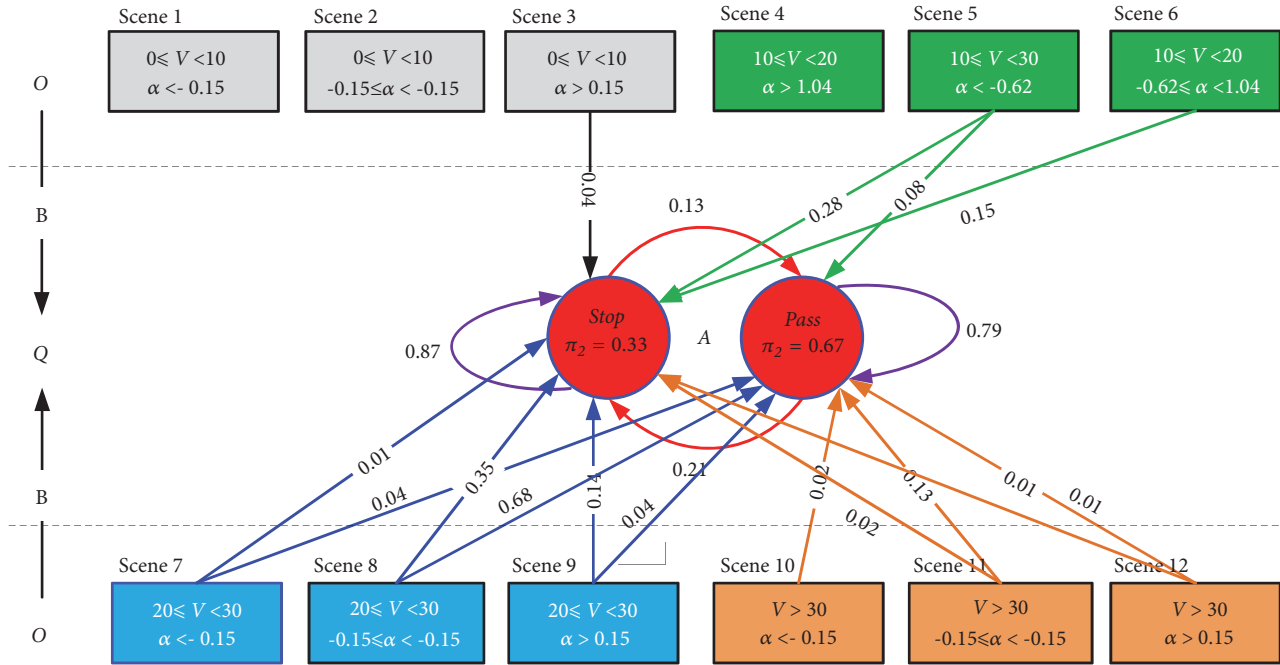


FIGURE 3: Training results for e-bike behavior.

TABLE 2: Variables in the equation.

	B	S.E.	Wald	df	Sig.	Exp (B)	95% C.I. for EXP(B)	
							Lower	Upper
Step 1 ^a Speed at the decision p+oint	.123	.032	14.895	1	.000	1.131	1.062	1.204
Distance between decision point and stop-line	-.084	.019	19.001	1	.000	.920	.886	.955
Constant	.541	.702	.594	1	.441	1.717		

a. Variable(s) entered on step 1: speed at the decision point, distance between decision point and stop-line.

indicates that the larger the vehicle speed and the smaller the distance from the stop-line, the higher the probability of choosing the decision-making, which is consistent with the actual situation.

6.1.2. Model Estimation. The GHM model test is divided into significance test and goodness-of-fit test. The test results are shown in Table 3.

6.2. Comparison between GHM Model and HMDM. The prediction accuracy of HMDM was obtained by comparison between the hidden state of the final time step predicted by the model and the actual states from observed data, and the GHM model was developed to test the accuracy of HMDM (results presented in Figure 4).

The hit ratio reached 97.1% for stopped and 84.6% for passing e-bikes, with an overall hit ratio of 88.74%. The relatively low prediction accuracy for passing e-bikes could be explained by a commonly observed pattern in which some e-bikes, especially those with a high speed, decelerated rapidly when approaching the intersection but still crossed the stop-line. Such trajectories with a large deceleration rate were wrongly classified as being stopped in the model.

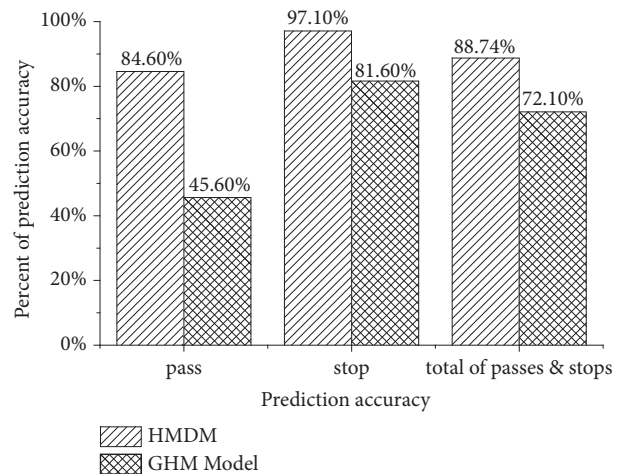


FIGURE 4: Comparison of prediction accuracy between HMDM and GHM model.

The total hit ratio of the HMDM was significantly higher than that of the GHM model, particularly for the pass hit ratio, suggesting that the HMDM was very capable of interpreting e-bike drivers' decision-making processes and

TABLE 3: Variables in the equation.

	Chi-square	df	Sig.
Omnibus Tests of Model Coefficients	30.51	2	0
	30.51	2	0
	30.51	2	0
Hosmer and Lemeshow test	Chi-square	df	Sig.
	14.787	8	0.063
Model summary	-2 Log likelihood	Cox & Snell R ²	Nagelkerke R ²
	182.204 ^a	0.169	0.233
	<i>a.</i> Because the change range of parameter estimation is less than 0.001, the estimation terminates at 4 iterations.		

Sig. of Omnibus Tests of Model Coefficients less than 0.05, indicating that it is significant; Sig. of Hosmer and Lemeshow test greater than 0.05, indicating that goodness-of-fit test of the model is significant; -2 Log likelihood, Cox & Snell R², and Nagelkerke R² showing that the fitting degree of the model is reasonable.

more effective at identifying their decision states compared with the GHM model.

7. HMDM Model Application

The predicted hidden state sequence of 1 (pass) and 2 (stop) can represent the vehicle driver's decision-making process and is closely related to the observation states of speed and acceleration/deceleration. To identify how many times an individual e-bike driver modified his decisions during flashing green and yellow lights, five decision types were defined according to analysis of trajectory data, similar to methods used in Tang et al. [1]:

- (i) Type 1: one-step decision (pass)
- (ii) Type 2: one-step decision (stop)
- (iii) Type 3: two-step decision (stop-pass)
- (iv) Type 4: two-step decision (pass-stop)
- (v) Type 5: multiple-step decision

Based on these five types, the estimated frequencies of each group among all e-bike samples were analyzed; the results with typical speed and acceleration/deceleration profiles are presented in Figures 5 and 6.

Approximately 60% of e-bike drivers did not change their initial decision (Types 1 and 2), ~34% modified their initial decision once (Types 3 and 4), and 6% modified their decisions more than once (Type 5). Further analysis showed that Type 4 mainly included two kinds of e-bike trajectories. One consisted of drivers who decided to pass at the onset of flashing green but later changed to stop. This transformation was mainly due to changes in the surrounding traffic environment such as remaining flashing green or yellow light timing, distance from stop-line, driving conditions (such as current speed), and driving habits (e.g., conservative or aggressive). The other consisted of those who had initially decided to stop, but whose hidden states were identified as "pass" at the beginning because they did not slow down obviously until their distance to the stop-line was very short. Overall, a large percent of e-bike drivers clearly made multiple decisions during the signal phase transition instead of only one initial decision as commonly assumed by GHM models.

8. Conclusion, Implications, and Future Works

Based on the high-resolution trajectory data of e-bikes, this study developed a model for e-bike driver decision-making under flashing green and yellow signal conditions based on the HMM (i.e., a HMDM); five decision types related to the speed and acceleration/deceleration of the e-bikes were analyzed to determine the number and type of e-bike driver decisions and the impact of flashing green on their decision-making behavior. It was found that HMDM was able to accurately identify e-bike drivers' stop/pass decisions and clearly revealed their decision-making mechanisms during flashing green and yellow lights. Several conclusions are as follows.

Because HMDM can reflect dynamic decision-making process of e-bike drivers during signal change interval, therefore, compared with GHM model, the developed HMDM has higher prediction accuracy of stop/pass decisions.

HMDM reveals that approximately 40% of e-bike drivers made multiple decisions when they encounter a flashing green or yellow light.

For e-bikes, flashing green mostly eliminated the dilemma zone while significantly enlarging the option zone; this caused earlier initial stop/pass decisions but also increased subsequent changes in decision-making.

The distance to the stop-line at the decision point was the most influential factor for the number of stop/pass decisions. The power performance of e-bike is very prominent. The acceleration and deceleration of e-bike are large and its operation is flexible. However, unlike motor vehicles, e-bikes are easily disturbed by other bicycles or pedestrians and then adjust their speed. Therefore, the instantaneous speed of e-bikes fluctuates greatly during decision-making process. When encountering flash green or yellow light, e-bike drivers first judge the approximate distance to the intersection. If the distance is relatively small, they will immediately determine whether to pass or stop. But if the distance is relatively far from the intersection, they will not immediately determine whether to pass or stop. Most of them try to pass first and then adjust their decision of pass or stop in time according to the distance to the intersection. Although the most essential factor affecting pass/stop decision-making is the time to the

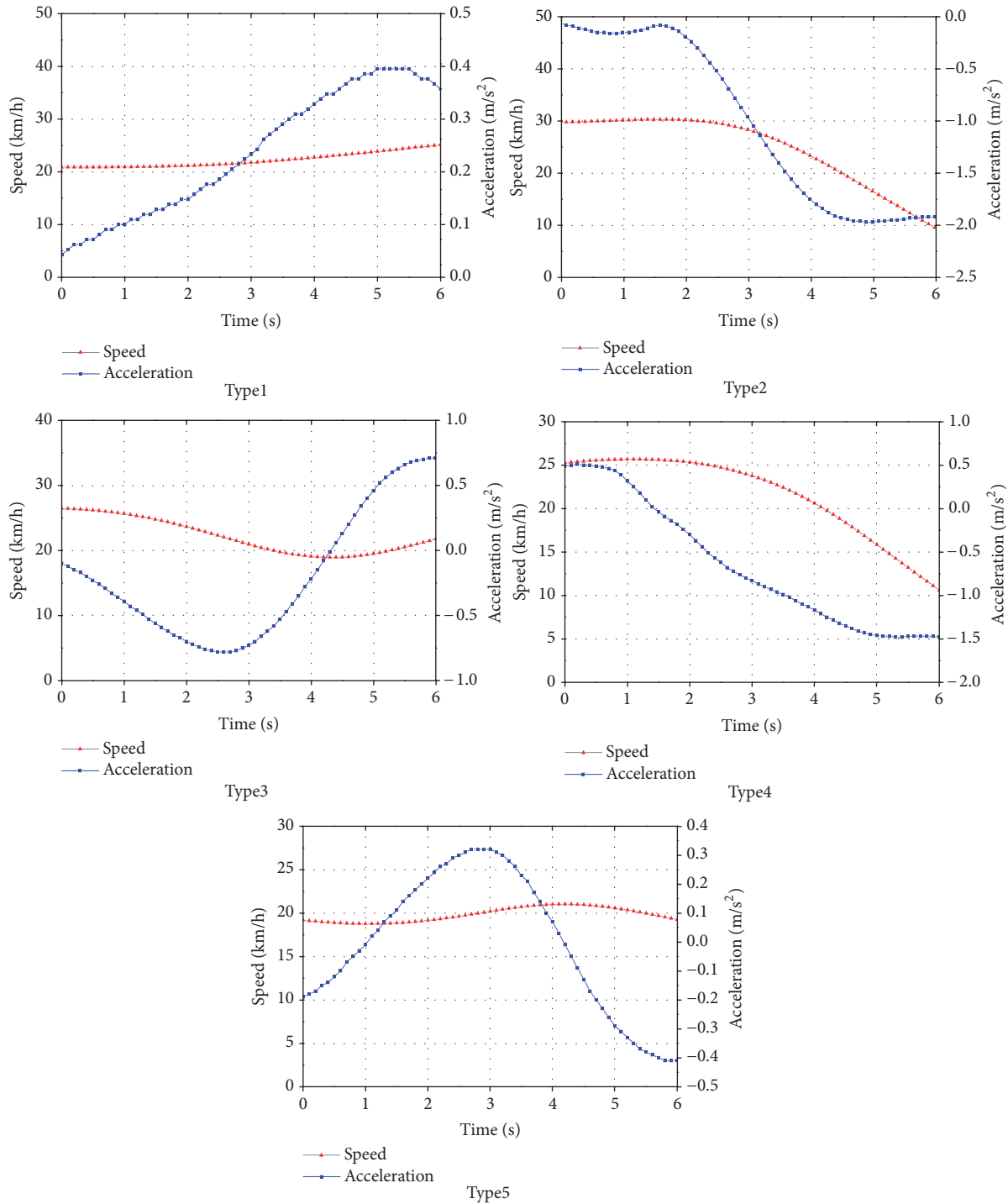


FIGURE 5: Typical speed and acceleration profiles of each decision type: 1 (pass), 2 (stop), 3 (stop-pass), 4 (pass-stop), and 5 (multiple).

stop-line, the most direct and sensitive factor is the distance to the intersection.

HMDM is a decision-making prediction model based on fine-grained e-bike driving characteristic parameters and it can be used to analyze the mechanism of the influence of transition signals on decision-making behavior. The model has several significant applications for intersections with flashing green signals. Firstly, compared with the GHM

model, HMDM achieves a more accurate prediction of stop/pass decisions by establishing the identified probabilistic relationship between the driver's time-dependent decisions of stop or pass and its instantaneous acceleration rates and speeds. Therefore, HMDM is helpful for traffic engineers to proactively recognize potential wrong decisions and dangerous driving behavior when encountering transitional signals, to realize the reasonable processing of yellow light

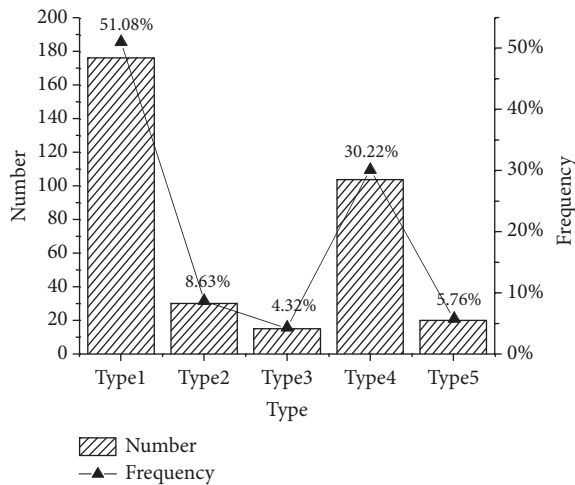


FIGURE 6: Profiles of each decision type: 1 (pass), 2 (stop), 3 (stop-pass), 4 (pass-stop), and 5 (multiple).

dilemma zone and the fine design of transitional signals such as yellow light, all-red light, and flashing green signal and to improve traffic safety at intersections. Secondly, the typical microscopic traffic simulation models such as VISSIM are based on GHM model, and both motor vehicles and nonmotorized vehicles adopt a unified model, which cannot truly reflect nonmotorized drivers' perception-and-reaction process. HMDM can identify the dynamic change of nonmotorized vehicle driver's decision-making behavior and make a reliable prediction of decision chain and then effectively improve the accuracy of traffic simulation.

For the improvement and application of the model, several tasks need to be carried out in the future. Firstly, in view of the adaptability of the model, it is necessary to extend it to other cities besides Shanghai. Secondly, the analysis can be extended to other road users such as cars and trucks. Thirdly, in order to further improve the prediction accuracy of the model, we can try to adjust the indicators reflecting decision-making driving behavior. Fourthly, the application of HMDM in the fine design of intersection signal control and microscopic traffic simulation is also important for the extension of the presented study.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Supplementary Materials

Supplementary materials include three excel tables. Supplementary Material 1 lists the e-bike trajectories data of stop samples. Supplementary Material 2 lists the e-bike trajectories data of pass samples. According to the data in Supplementary Material 1 and Supplementary Material 2, the trajectory diagram of all samples in the decision-making process can be obtained (Figure 2 in Manuscript V3.0). Supplementary Material 3 provides speed and acceleration data for some typical e-bike samples. Based on these data, we can judge the decision-making process of e-bike riders. Thus, five typical decision-making types can be concluded and are shown in Figure 5 of Manuscript V3.0. (*Supplementary Materials*)

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