Stop-and-Go Decision-making Mechanism Analysis of E-bikes During Signal Change Interval

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Abstract

The widespread use of e-bikes in China has resulted in a large number of traffic problems, the most significant of which is the sharp increase of accidents related to e-bike riders during the signal change interval. Therefore, it is necessary to analyze the decision-making behavior and decision-making mechanism of e-bike riders. In this paper, high-precision trajectory data is used to analyze the decision-making behavior and decision-making process of e-bike drivers. The driving behavior data were collected at two similar intersections in Shanghai. 262 passing samples and 106 parking samples were obtained. E-bikes arriving during the signal change interval from the end of green light to the beginning of red light are divided into four types to be analyzed, and five decision types are identified. The influence of these decision types on driving decision-making behavior is analyzed. The results show that about 50% riders made multiple decisions with green countdown, however, most riders made only one decision with flashing green. Green countdown could bring an early decision opportunity for riders and thus drivers may modify their decisions before or after encountering with the yellow light. The results of this paper can be applied to improve the fine design of traffic signals.

Keywords: Electric bicycle, Stop-and-go decision, Driver behavior, Signal change interval

1 Introduction

Drivers approaching an intersection at the end of the green light must choose between continuing to move forward into the intersection or stopping in front of the stop line. For some drivers, it is difficult to make the stop-and-go decision correctly every time when the decision-making position falls into the optional decision zone. In addition, some drivers are far away from the intersection but choose to pass aggressively, which may lead to red light running, thus reducing traffic safety; some drivers are close to the intersection but choose to stop conservatively, thus reducing traffic efficiency. Drivers often experience anxiety when faced with these above mentioned situations, which will lead to two kinds of accidents, one is the rear-end collision between the leading and following vehicles, the other is the right-angle collision between the vehicle running red light in the current direction and the vehicle in the cross direction [1]. At present, there are some measures to reduce the occurrence of the occurrence of the incorrect stop-and-go decisions. As a reminder signal, the flashing green or green countdown light is one of the effective methods.

In China, flash green and green countdown are the two of the most common forms of green-red transition signal which can provide drivers with the pre-signal termination of green phase information. In most cases, the sequence of the two indicators is green-flashing green or green countdown-yellow-red-green. The main difference among them is the amount of their showing information. The flashing green only announces that the green will end, but the green countdown also provides the remaining green time in addition to warning about the end of the green. However, both of them are part of the green, i.e. drivers can and should proceed as normal. Although transition signals such as flashing green and green countdown are widely used, the operation effect of them has not been fully verified. Previous study of driving behavior in transitional signal setting mainly focused on motor vehicles, but few of them involved e-bikes. In recent years, with the increasing number of e-bikes, accidents involving e-bikes increase rapidly. This leads to the further deterioration of the operational efficiency and safety at intersections. During the five years from 2013 to 2017, there were 56,200 road traffic accidents in China, resulting in 8,431 deaths [2].

When approaching the intersection, the flexible and fast characteristics of e-bikes decide that the decision-making of cyclist will not be carried out only once, but

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adjust the decision-making results according to the comprehensive judgment of the distance to the intersection and the effective travel time before the start of red light. Thus, it is necessary to research on the influence of transition signal setting to the behavior of e-bikes. The research result can provide communications department with the scientific guidance, so as to reduce the occurrences of traffic violations and improve the intersections' safety and efficiency. Hence, it is contributes practical significance. This paper studies e-bikes' operation characteristics under flashing green or green countdown, especially focus on the stop-and-go decision-making process of the individual e-bike rider.

2 Past Research

In the past few decades, the research on stop and go decision model and decision mechanism is in the ascendant. Gazis et al. [3] proposed the classic GHM model, i.e. the traditional stop-and-go model, which assumes that the driver makes the decision based on the maximum driving distance or the minimum stopping distance when the yellow light is on, i.e. the driver only makes a decision once. Liu et al. [1] extended the GHM model and added the two parameters of acceleration and instantaneous speed. Based on the assumption that vehicles make decisions when the yellow light is on, Crawford et al. [4], Chang et al. [5] used vehicle dynamics and deterministic model to analyze the decision-making mechanism. Olson et al. [6] observed that some vehicles often regard the yellow light as the extension of the green light. Through analysis, May et al. [7] found that some vehicles avoid the dilemma zone by accelerating or decelerating (yellow light trap). Liu et al. [8], Wei et al. [9] found that the driving behavior in the actual decision-making process is different from the theoretical hypothesis through observation Other researchers such as Rakha et al. [10] and Hurwitz et al. [11] further developed the GHM model by using fuzzy logic theory.

In general, although the above studies take into account the uncertainty of decision-making, they all assume that the driver executes a decision in the decision-making process. The stop-and-go model based on single decision will cause a lot of information in the process of decision-making to be ignored. Therefore, the model can not reasonably reveal the mechanism of decision-making. In view of this, Prashker et al. [12], Tang et al. [13], Li, et al. [14] try to reveal the decision-making behavior of drivers through random methods. Dong et al. [15] used hidden Markov method to simulate the decision-making process of e-bikes, and used Monte Carlo simulation to verify the model. The results show that the decision-making model of e-bike based on Hidden Markov chain has high accuracy.

There are some studies on the driving behavior of bicyclists during the signal change interval. Dong et al. [16-17] and B. Howey et al. [18] compared start-up behaviors and decision-making types of bicycles at the onset of the green flashing and green countdown. Taylor et al. [19] observed the acceleration of the bicycle at cruising speed and the deceleration at the yellow light. Tang et al. [20] analyzed the expected speed, start-up acceleration, perception–reaction time and other characteristic parameters of e-bikes, and built the empirical models. In addition, some scholars, such as Figliozzi et al. [21] and Rubins and Handy [22], have demonstrated the relationship between the behavior of bicycles crossing the street and the factors such as age and gender.

These studies mainly reflect the characteristics of bicycles and play a positive role in improving the safety of bicycle driving, but there are few studies on the decision-making process and behavior of bicycles. The traditional Gazis-Herman-Maradudin (GHM) model only aims at the first decision-making results of motor vehicle drivers, and does not consider the repeated decision-making process in the driver's decision-making process. Therefore, it cannot truly reflect the complexity of stop and go decision-making behavior of electric bicycle drivers.

Therefore, it is necessary to study the decision-making mechanism of e-bikes, analyze their driving behavior characteristics in the decision-making process, and then provide reference for the development of decision-making model applicable to s-bikes, and provide theoretical guidance for the engineering practice of e-bikes.

3 Data Investigation and Analysis

3.1 Site Description

The two large intersections which are Guoding Road and Huangxing Road and Guoding Road and Siping Road in Shanghai were selected to observe e-bike riders' behavior. The location of the two intersections is shown in Figure 1.

The selected intersection has the following characteristics.

- The selected intersections are conventional four-leg intersections and there is an exclusive bicycle lane on the entrance road in the direction of Guoding Road.
- The signal timing scheme is fixed-time and four-phase plan. Bicycles and motor vehicles share the same traffic signal.
- E-bikes crossing the intersection at the eastbound approach were selected as the study subjects. At the same time, it ensures that there is available high observation point around the intersection and high non-motor vehicle traffic volume during the survey period.

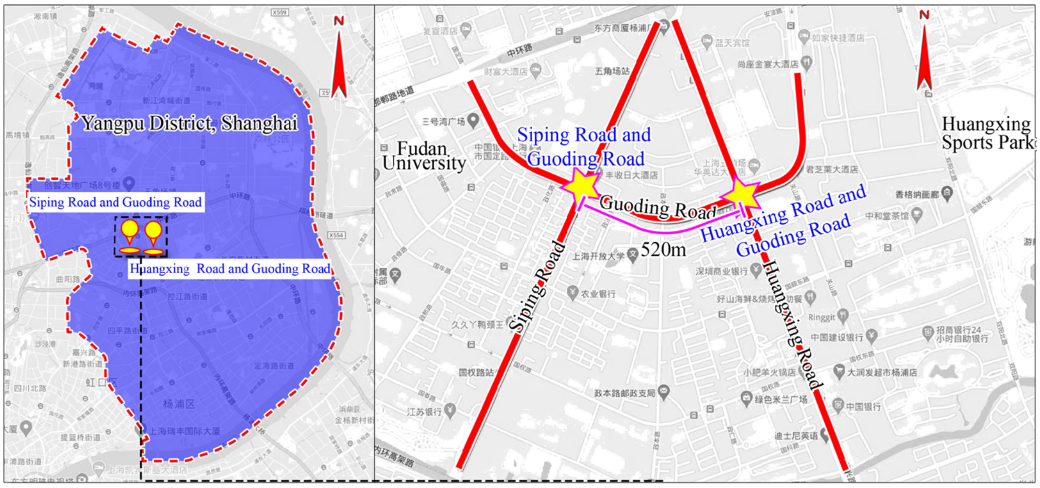

Figure 1. Location of the surveyed intersection

Detailed features of the two intersections are as follows, see Table 1.

Table 1. Characteristics of the observed intersections

Category	Factor		Intersection name: Guoding and Huangxing Rd.	Intersection name: Guoding and Siping Rd.
Traffic Characteristics	Approach traffic volume		1917 veh/h	1830 veh/h
	Speed limit		40km/h	40km/h
	Mean approach speed		21.07km/h	21.97km/h
Signal operation	Signal cycle length		161s	145s
	Yellow duration		3s	3s
	All-red time		1s	1s
	Phase number		4	4
	Transition signal	Green-red	Flashing green 3s	Green countdown 12s + Flashing green 3s
		Red-green	Yellow & red 3s	Red Countdown 12s
Geometry	Approach grade		Flat	Flat
	Intersection type		Crossing	Crossing
	Width		45m	43m
Driver information	Signal visibility		Good	Good
	Signal conspicuity		LED indication; 12”lense	LED indication; 12”lense
	Advance warning (Y/N)		N	N
Traffic operation	Signal coordination (Y/N)		N	N

3.2 Data Collection and Processing

In order to avoid the lateral driving interference among e-bikes and the influence of bad weather, the data survey is arranged during the off peak period of the working day from 12:00 to 16:00. The purpose of acquisition is to obtain the driving behavior data of during the signal change interval. Therefore, two high-definition cameras are required to record synchronously. One of the cameras is installed on the high building near the intersection, which can cover the 60m-long area upstream of the bicycle lane stop-line, so as to record the movement trajectory of the whole decision-making process of e-bike completely Another camera is set at the intersection to record traffic signals synchronously. Taking Huangxing Road and Guoding Road intersection as an example, the process of data acquisition is introduced, as shown in Figure 2.

The acquisition of e-bikes’ travel trajectories relies on image processing software. It is located by the international coordinates of five related points in the shooting lens. Through residual analysis and t-test, it is ensured that the accuracy error is not more than 0.15 m and 0.1 s. The time interval of the software is controlled at 0.1s. Therefore, using the software, high-precision travel trajectories data such as the speed, acceleration and deceleration of the e-bike and the position of each step can be obtained. Matching the trajectories data with the signal change timing, driving behavior parameters such as the start-up time, the perception- response time can be further obtained. Finally, 368 valid samples were obtained. Observed e-bike trajectories at study intersections as shown in Figure 3.

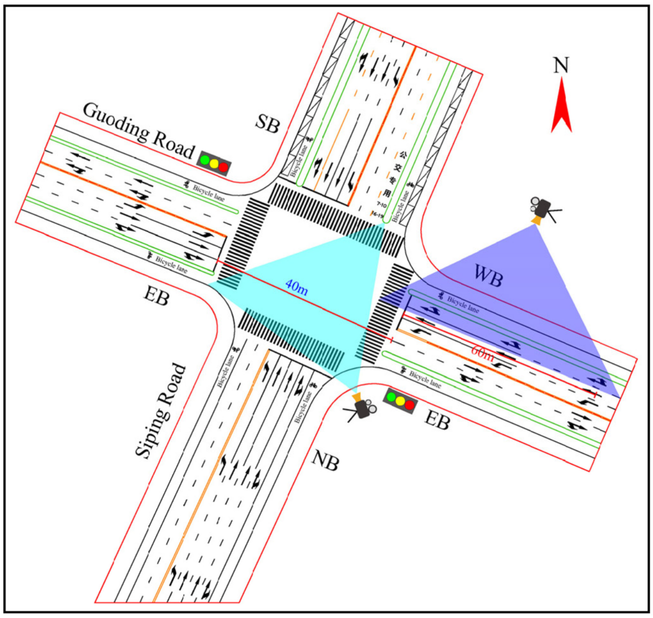

Figure 2. Data acquisition and camera settings

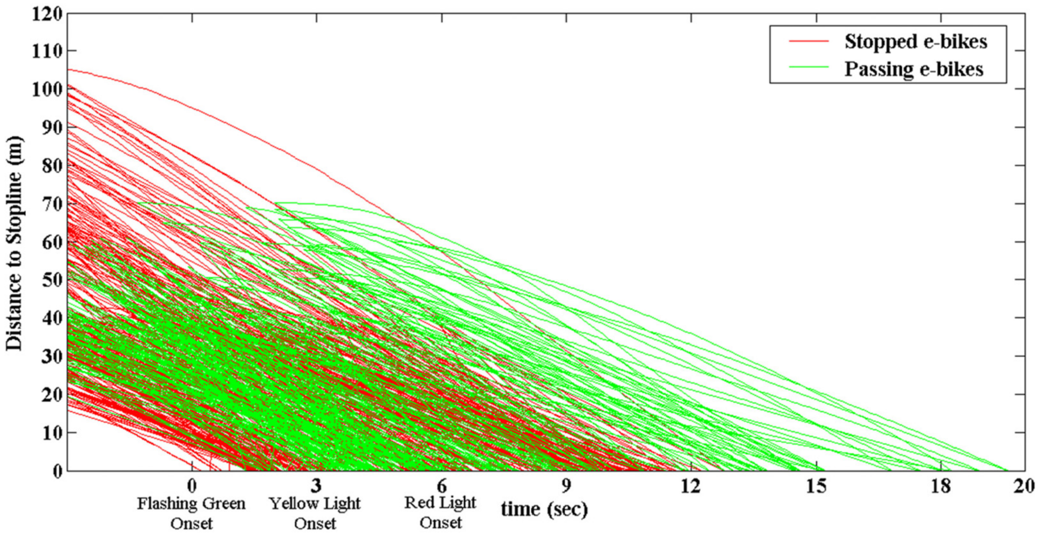

Figure 3. Observed e-bike trajectories at study intersections

4 Comparative Analysis of E-Bike Riders' Instantaneous Speed Through Stop-Line Under the Two Transition Signals

The instantaneous speed of a e-bike passing through the stop-line may be affected by many factors, such as e-bike performance, intersection environment, traffic signal, human character and so on. Among the above factors, previous studies have shown that the display mode at the end of the green time has an important impact on the rider's speed. Figure 4 and Figure 5 show the passing speed of e-bikes with flashing green and green countdown, respectively.

Comparing with the green light countdown, the speed of e-bike entering the intersection under flashing green is obviously higher. The main reason is that the countdown lasts longer. Riders know that the green light signal is coming to an end earlier, and they will be slowed down speed appropriately for safety. The display time of flashing green is relatively short, and the time for riders to adjust the speed is limited, resulting in little difference between the speed entering intersection and speed on the road section.

5 Stop-and-go Decision Process Analysis and Decision Point Discrimination

5.1 Classification of Decision-Making Types

The approaching e-bike riders during the signal change interval can be classified into several types according to the degree of non-compliance with signals, which are "late arrivals", "racers", "runners", "stops". Figure 6 shows the four types.

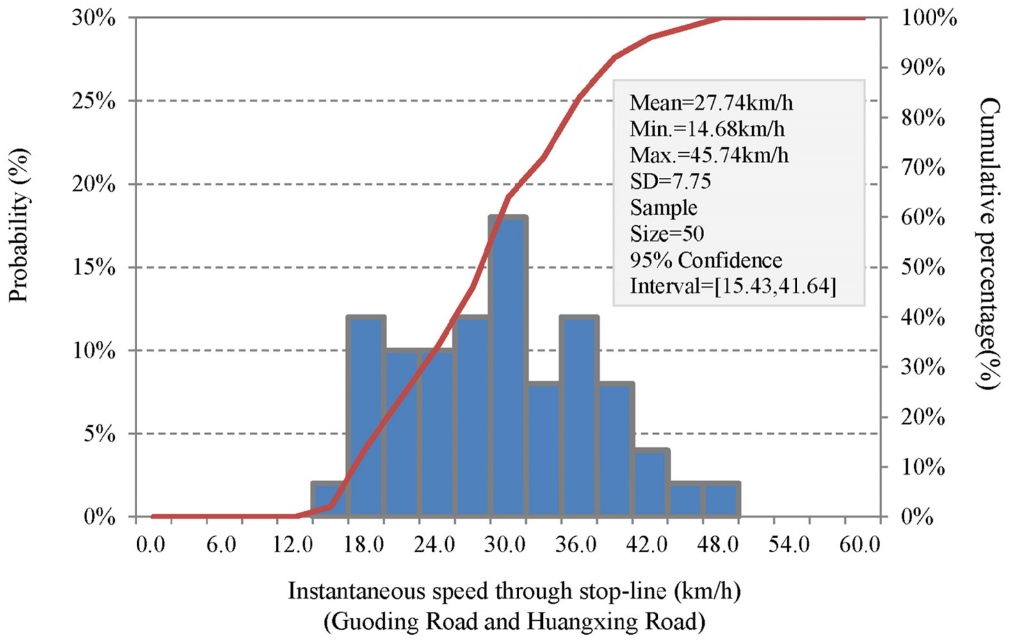

Figure 4. Histograms of instantaneous speed through stop-line (Guoding Road and Huangxing Road)

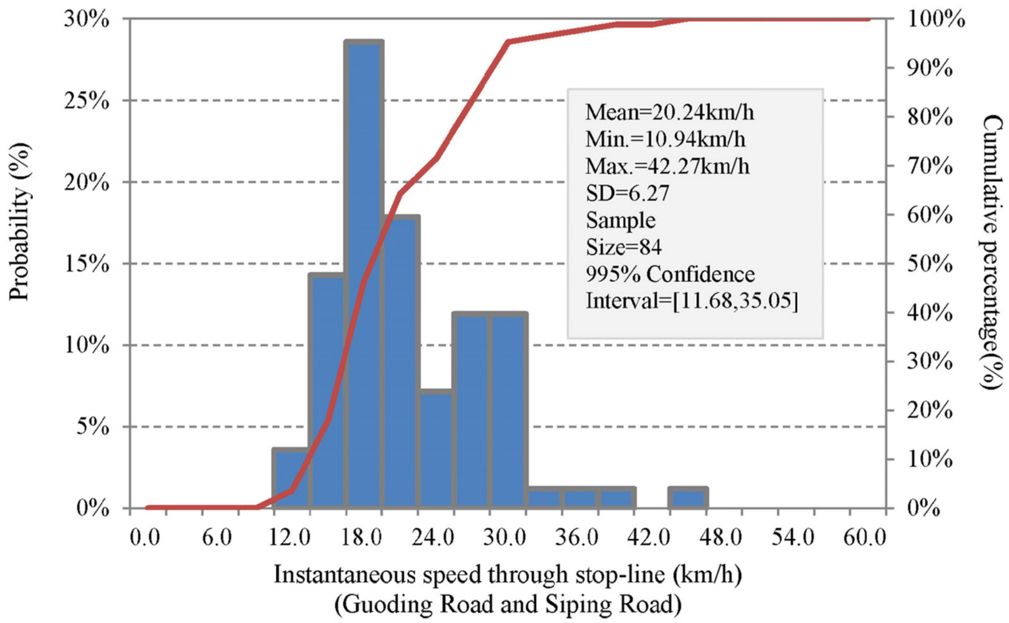

Figure 5. Histograms of instantaneous speed through stop-line (Guoding Road and Siping Road)

Previous studies have shown that the median entry time of a red-light violator is less than 0.5 s and about 90 percent of drivers pass the stop line within 2 s after the onset of red light (i.e., end of yellow) [23], so the considering time interval of this research is 7.0s which is from 3s before the end of green phase to 4.0s after the start of red signal. Each type represents the driving behavior of e-bike riders arriving at intersections at different time stages. “Late arrivals” refers to riders arriving at and crossing intersections during flashing green or green countdown; “Racers” refers to riders arriving and accelerating into intersections during the yellow light period; “Runners” refers to red-light violators who arrive at and continue to enter intersections during the red light period; “Stops” refers to the parkers who arrive at intersections during the research period.

In terms of Guoding Road and Huangxing Road with flashing green, the numbers of “late arrivals”, “racers”, “runners”, “stops” respectively were 57, 48, 25, 59. In terms of Guoding Road and Siping Road with green countdown, the numbers of “late arrivals”, “racers”, “runners”, “stops” respectively were 48, 44, 40, 47. The total data statistics show that 262 samples make pass decision and 106 samples make stop decision.

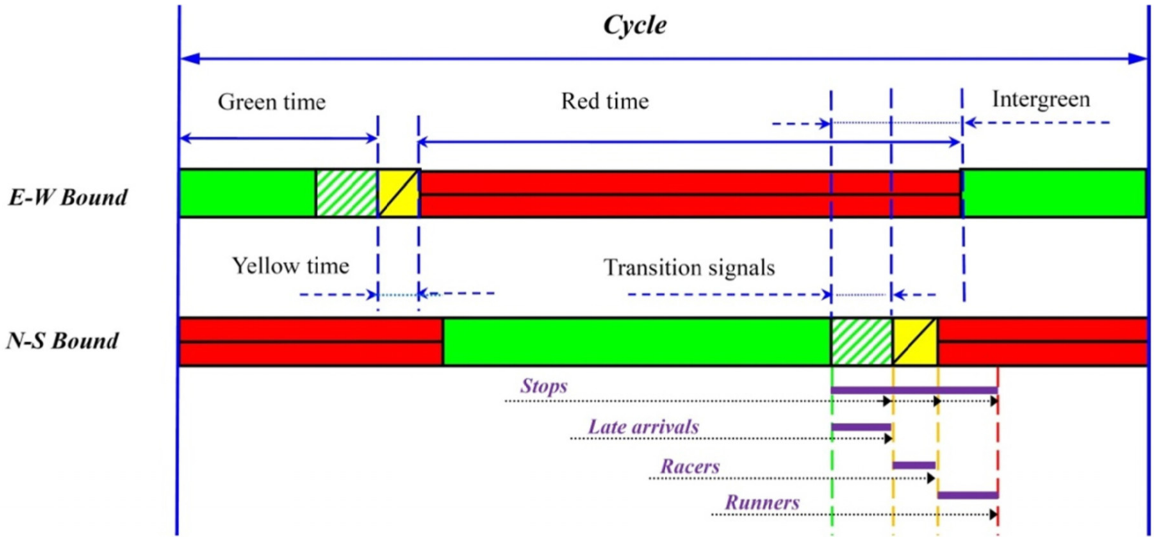

Figure 6. Types of stops/late-arrivals/racers/runners

5.2 Discrimination of Stop-and-Go Decision Points

After the transition signal such as yellow light or green flashing light is on, the e-bike rider will use the brake if he makes a parking decision. With the continuous action of brakes, the deceleration will increase rapidly until the rider is convinced that the speed is small enough to stop safely in front of the parking line. Similar situations are reflected in the decision-making process. Once there is no interference from pedestrians crossing the street and non-motorized vehicles waiting to turn left, e-bike riders will accelerate and the acceleration will continue to increase until it is sure that the speed is large enough to enter and pass the intersection smoothly. Thus, acceleration and deceleration are the most direct performance of riders in the decision-making process. The trend of acceleration or deceleration of e-bikes during the signal change interval is used as the main index to identify the decision point.

Influenced by such factors as green countdown, flashing green and the yellow light, non-motorized drivers will have a significant change in acceleration and deceleration after the start of the transition signal, which will show a certain change trend, and the starting point of this change trend is determined as the decision-making point. In this study, the acceleration and deceleration during signal change interval are used to identify the decision points of e-bikes at intersections. Of course, although acceleration is the most important criterion in the process of decision-making point, it is not the only one. Only by combining acceleration with speed, considering the actual operating environment of samples, and eliminating the disturbed samples, the obtained samples can be used as effective samples. The case of using acceleration and deceleration speed and corresponding speed to distinguish decision points is shown in Figure 7. The left figure represents the operation characteristics of the typical sample making the pass decision, and the right figure represents the sample making the stop decision.

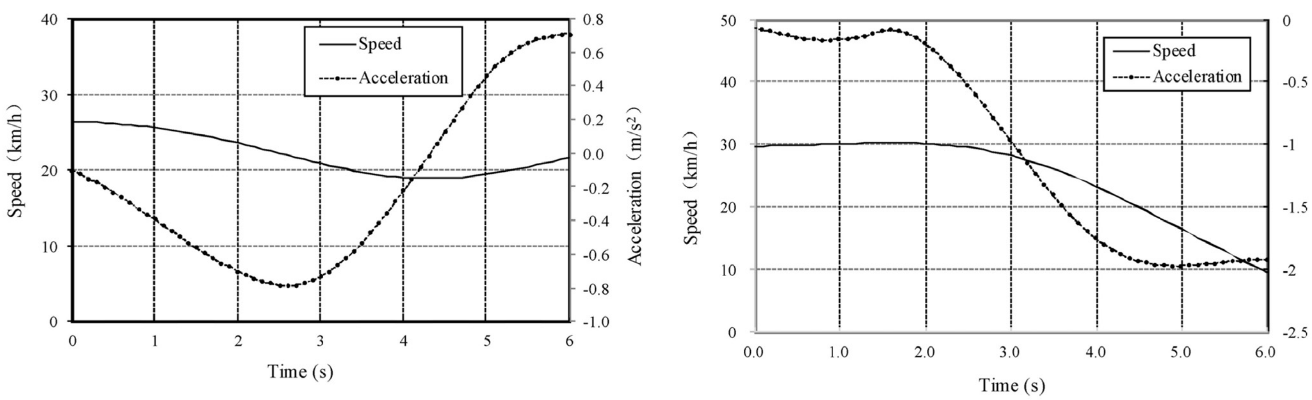

Figure 7. Typical cases of decision point discrimination based on acceleration and speed

5.2.1 Pass-Decision Process and Behavior

The acceleration presented here represents the behavior of e-bikes as they approach at a signalized intersection during the signal change interval. Figure 5 and Figure 6 show the acceleration changes of the pass-decision-making process of the e-bike riders at the intersection with flashing green or green countdown, respectively. The dotted boxes in Figure 8 and Figure 9 represent the critical decision time domain, i.e. the decision zone, as well as the dotted boxes in Figure 8. "0" in the abscissa indicates the start of the yellow light.

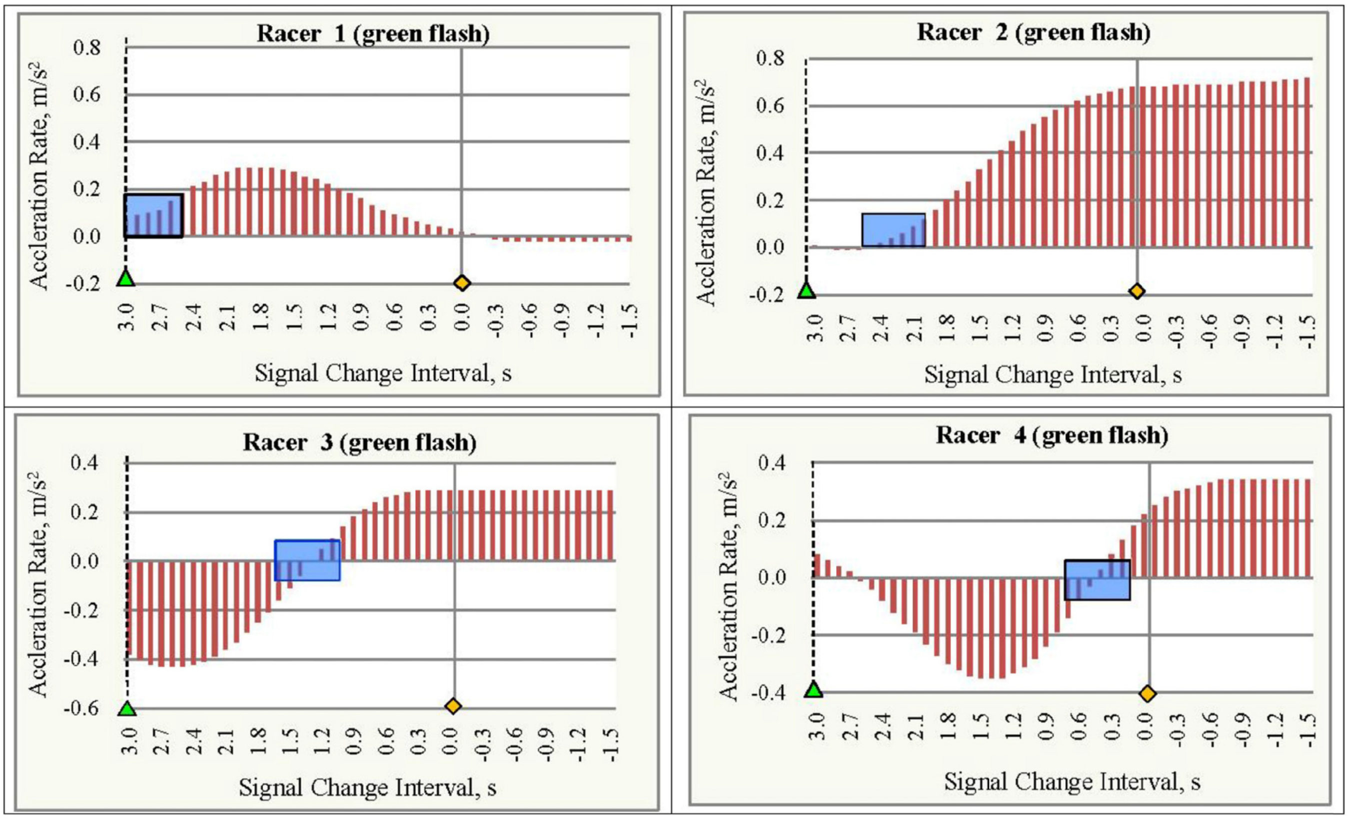

Figure 8. E-bike riders' pass decision process with flashing green

As shown in Figure 8 it represents the four typical types of e-bike riders before making pass decision with flashing green. "Racer 1" represents the rider was at accelerate before the start of flashing green and then pressed the accelerator with greater power when he received the flashing signal. "Racer 2" indicates the rider was at a constant speed and decided to accelerate at the moment of flash beginning. In spite of "Racer 3" was at decelerate taking into account his approaching intersection, he immediately changed driving status when the green began to flash. Different from the three types of behavior above, "Racer 4" reflected the decision hesitation or the lag of reaction to transition signal. The decision points of the four were 2.7s, .2.0s, 2.3s and 1.4s before the onset of yellow light, respectively.

"Racer 5", "Late arrival 1", and "Late arrival 2" represents three different types of e-bike riders crossing intersection during green countdown in Figure 9 Similar with "Racer 4", "Racer 5" indicates riders' decision hesitation. "Late arrival 1" displays the riders' immediate decision-making after receiving the signal change. Different from the former two, "Late arrival 2" didn't make decision at once. The decision points of the three were 8.8s, 11.2s and 5.4s before the onset of amber, respectively.

5.2.2 Stop-Decision Process and Behavior

Figure 10 shows e-bike riders' stop decision process with flashing green or green countdown. The dashed box in Figure 8 means the stop-decision zone of the whole decision process. The time corresponding green symbol and red symbol respectively means 3.0s before the end of green (or start of flashing green) and the start of red light. "0" is defined as the onset of the yellow light.

As shown in Figure 10, "Stops 1" and "Stops 2" display two typical types of e-bike riders' behavior before making stop-decision with flashing green, and the decision points were 2.3s, 1.5s respectively. "Stops 3" and "Stops 4" display two typical types of that with green countdown and their decision points were 2.5s, -1.0s respectively. Before making the stop decision, "Stops 1" and "Stops 3" were at acceleration, "Stops 2" and "Stops 4" maintained a constant speed. At the

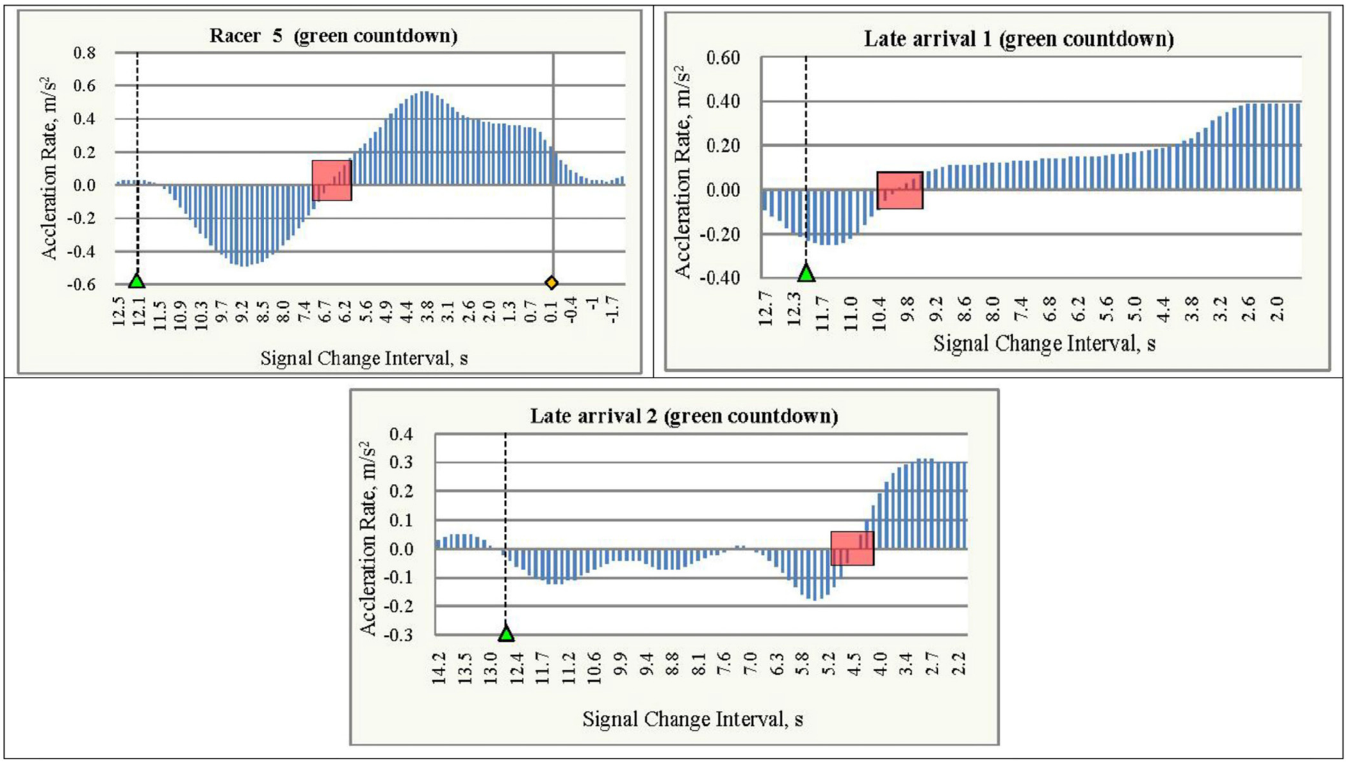

Figure 9. E-bike riders' pass decision process with green countdown

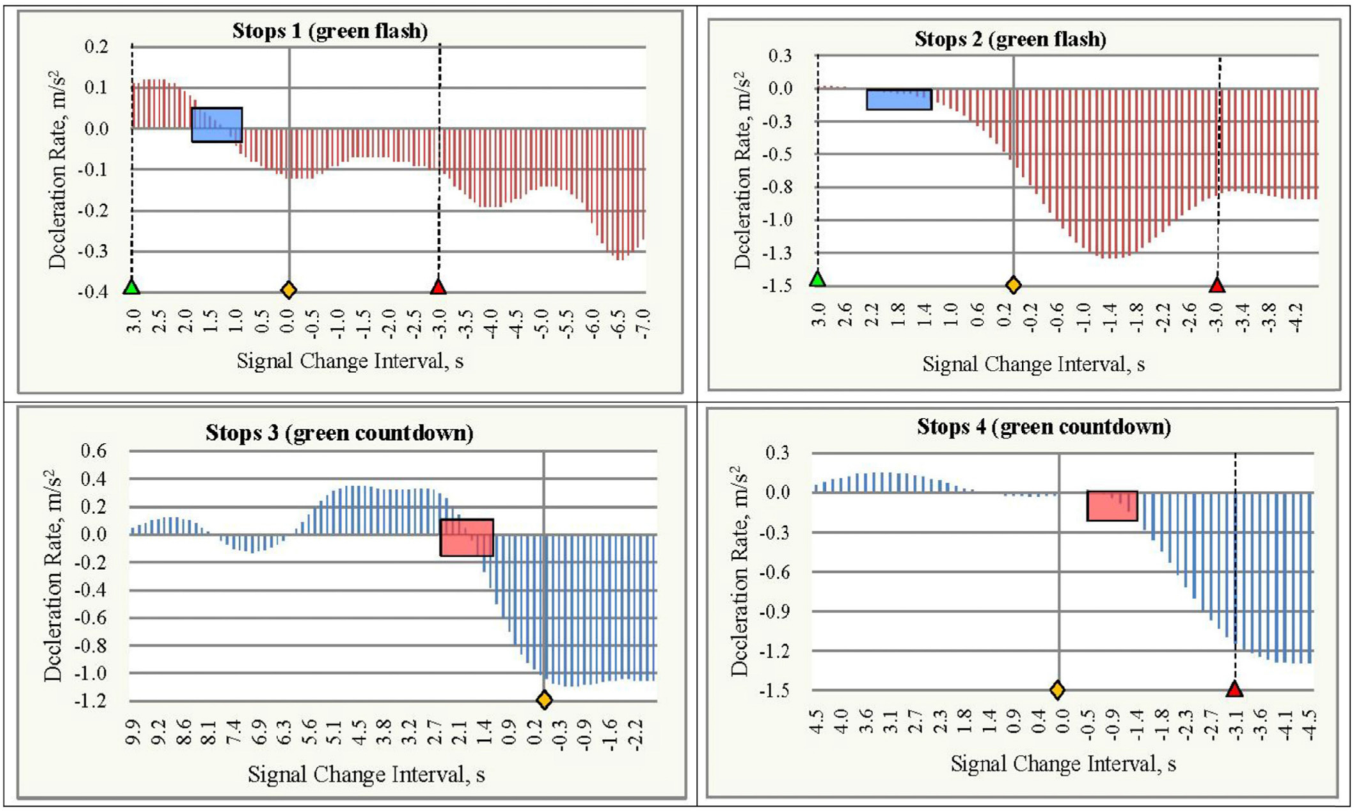

Figure 10. E-bike riders' stop-decision process with flashing green and green countdown

green flashing-intersection, the mean value of riders' pass-decision points is 1.1 s before the start of the yellow light, while the value is 2.4 s before the start of the yellow light at the green countdown intersection.

5.3 Prediction Accuracy Analysis

Logit models are widely used in transportation research because of their closed-form formula and explicit interpretation. Assuming Y is a binary response variable in a binary logit model, Y = 1 if the decision is pass, otherwise Y = 0. The probability of making pass decision (Y = 1) can be estimated by the Table 2.

Table 2. The estimated binary logit model

Parameters	B	S.E	df	Sig.
V Speed at the decision point	0.123	0.032	1	0.000
D Distance to the stop-line	-0.084	0.019	1	0.000
Constant	0.541	0.702	1	0.441
Binary logit model	$\ln\frac{p}{1-p}=0.123V-0.084D+0.541$			

As seen in Table 3, the comparison results show that the prediction accuracy of the proposed method is 88.3%, and the binary logit model is 72.0%. For pass decisions, the accuracy of the proposed method is much higher than that of the logit model, which are 84.7% and 68.3% respectively. For stop decisions, the accuracy of the two methods is higher, 97.2% and 81.1% respectively.

Table 3. Comparisons of Model Prediction performance

Estimated Model	The developed method		Binary logit model	
Decisions (pass/stop)	Pass	Stop	Pass	Stop
Observed samples	222	103	179	86
Detection rate, %	84.7%	97.2%	68.3%	81.1%
Overall rate, %	88.3%		72.0%	

5.4 Analysis Results

The statistical results of decision point data are as follows:

(*a*) The onset of yellow light is defined as 0s, the overall 15th, 50th, 85th percentile decision points for e-bike riders at the flashing-green-intersection respectively are 0.1s, 2.2s, 5.3s, and that for e-bike riders at the green-countdown-intersection are 0.3s, 3.3s, 6.6s, respectively. The results show that compared with the green flashing lights, riders can make decisions earlier when facing the green light countdown, which is caused by the longer duration of the green light countdown.

(*b*) The mean of decision points of “late arrivals”, “racers”, “runners”, “stops” with flashing green are respectively 4.9s, 1.9s, -0.7s, 1.1s, and that with green countdown are 5.8s, 3.2s, -0.1s, 3.9s. Compared with 1.1s, “3.9s” implies that green countdown has the greater impact on conservative e-bike riders than flashing green. “4.9s” means most of “late arrivals” with flashing green made pass decision before the start of flashing green, so flashing green signal has little influence on them.

(*c*) At the beginning of the green light countdown, if the location of the e-bike is far from the stop-line, most e-bike riders will not make decisions immediately considering the remaining green light time is long. It was observed that only about 30% of riders made immediate decisions.

6 Mechanism of Stop-and-go Decision-Making Process

In order to further identify the decision-making behavior of e-bike riders during the signal change interval, five decision types are defined based on the analysis of the travel trajectory data, namely, one-step-pass decision, one-step-stop decision, two-step-stop decision, two-step-pass decision and multi-steps decision [24-27].

The trajectory curves of five types of decisions are obtained by analyzing the data of all decision points, as shown in Figure 11. A considerable percentage of stopping e-bikes were found in the pass zone, while much more passing e-bikes were found in the stop zone. It indicates that some riders accelerate and try to pass the intersection though they could not be able to make it considering the remaining flashing green and yellow time. Also, many more riders choose to stop though they are good to pass. In addition, the speed-distance distribution of the stopping and passing riders is not consistent with which defined by the GHM model. The finding implies that the conventional DZ theory with a fundamental assumption of one-time decision process would not be able to capture the nature of driver’s multiple decision-making behaviors.

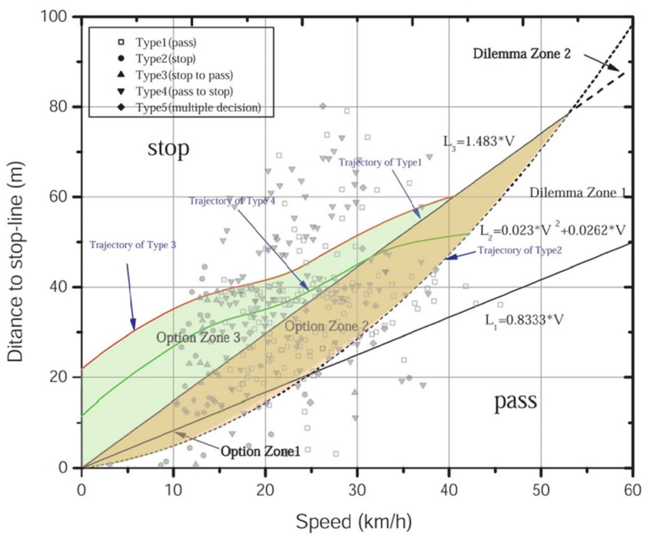

Figure 11. Distribution of e-bikes' stop-and-go decisions

Two types of "dilemma zone" situations may arise for drivers when they faced with a yellow indication on the approach to a signalized intersection. The Type I dilemma zone was first referenced in the literature by Gazis et al (3). The Type I dilemma zone describes the situation of a driver who, when presented a yellow indication while approaching a signalized intersection will, because of the physical parameters of the situation, be unable to safely pass through the intersection or stop prior to the stop bar. The Type II dilemma zone describes the area in which the driver experiences difficulty making the correct stop/go behavior. The Type II and more common dilemma zone situation occur as a result of differences in driver behavior and decision making. The Type II "indecision zone" is typically defined as the area upstream from the stop line between which 10 percent and 90 percent of the drivers will stop in response to the yellow indication (11). In this paper, type I dilemma zone is expressed as dilemma zone, and type II "indecision zone" is expressed as option zone.

By comparison of decision zone (option zones and dilemma zones), it can be found that how the flashing green and the green countdown affect e-bikes' decision-making behavior. As is shown in Figure 11, type 1 represents passing e-bikes with constant speed during flashing green, its running track is a straight line; type 2 represents stopping e-bikes without acceleration during flashing green, its running track is a standard deceleration and stopping curve; type 3 represents passing e-bikes with acceleration during flashing green or the green countdown; and type 4 represents stopping e-bikes with acceleration during the flashing green or the green countdown; respectively. The curve of type 3 finally intersects with the running track line of type 1, completing the process from the beginning of making stop decision to the final adjustment of pass decision, and the curve of type 3 finally intersects with the curve of type 2, completing the process from the beginning of making pass decision to the final adjustment to stop decision.

The dilemma zone 1 and option zone 1, dilemma zone 2 and option zone 2 are based on yellow light, flashing green, respectively. Option zone 3 is calculated by green countdown. Compared with decision zone of flashing green, green countdown results in a larger option zone, this means that the rider can decide to stop or pass more freely. The dilemma zone, on the other hand, is significantly reduced. Distribution of sample decision-making points shows that only when speed at decision-making point reaches 40 km/h, e-bikes have a high probability to be trapped in a dilemma zone. According to observation data, the proportion of e-bikes which speeds exceed 40 km/h is less than 1%, therefore, the dilemma zone caused by flashing green or green countdown for e-bikes is almost nonexistent in the real-world practice.

By analyzing the change between option zone 1 and option zone 3, it can be found that the impact of green countdown on e-bikes' decision-making behavior mainly reflects on the enlargement of option zone size. Larger option zone means the more freedom on decision-making. For the e-bikes that are far away from intersection, e.g., more than 50 m to the intersection, e-bike riders would usually accelerate because they tend to make pass decision after the onset of green countdown due to difficulty in determining whether to stop or to pass. Until they are close to intersections, most riders don't make the stop-and-go decision considering their current speeds and distances from the stop-line. From the sample size, the number of type 3 is small, but the number of type 4 is large enough to confirm this conclusion.

7 Conclusion and Future Work

In this paper, the e-bike riders arriving during signal transformation are classified into four types: late arrivals, racers, runners and stops. Acceleration/deceleration are extracted to recognize e-bikes' stop-and-go decision points. Five decision types (pass, stop, stop-pass, pass-stop, and multiple) are proposed to analyze the decision-making mechanism of riders under the two transitional signals: flashing green and green countdown. The conclusion is as follows:

The occurrence time of stop-and-go decision-making varies greatly. Because the duration of flashing green at intersection is only 3 seconds and the time is short, it will force the rider to make a quick decision. Therefore, the decision-making and stop decision-making will be made soon after start of flashing green, and it is basically a one-time decision. Different from the decision-making characteristics with flashing green, the pass decision will be made quickly after start of green countdown, but stop decision is often made around the onset of yellow light. The reason is that the countdown often starts more than 10 seconds before the yellow light and lasts longer. So the green countdown makes it easier for riders to fall into the option zone.

Riders tend to make optimistic estimates and tend to make decisions at the beginning of the yellow light. Some riders will make a new decision according to instantaneous speed and distance to the intersection. At this time, they usually make a stop decision. Therefore, at countdown intersection, e-bike riders often make a stop decision twice or even many times. This is because riders adjust their behavior after they recognize their initial failure in decision-making. Again, their adjustments may not be one-time decisions. Instead, the adjustments are a series of actions until the final decision is made. It means that riders are most likely to change their decisions around the onset of yellow light. It also supports that the green countdown could bring an early decision opportunity for riders and thus riders may modify their decisions before or after encountering with the yellow light.

Future work is needed to address behavioral differences under various conditions, such as alterations in signal control and intersection size. More widespread observations are also necessary to increase the sample size and reinforce the conclusions drawn in this study. The development of a new design method for the signal change, safety countermeasures as well as a microscopic simulation model are also important for the extensions of the presented study.

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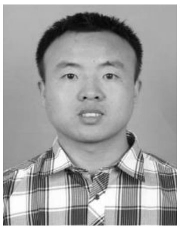

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