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RESEARCH ARTICLE

Cut-Out Scenario Generation With Reasonability Foreseeable Parameter Range From Real Highway Dataset for Autonomous Vehicle Assessment

H. MUSLIM[1,2], S. ENDO[1,2], H. IMANAGA[1,2], S. KITAJIMA[1,2], N. UCHIDA[1,2], E. KITAHARA[2,3,4], K. OZAWA[2,3,5], H. SATO[2,3,6], AND H. NAKAMURA[1,2]

[1]Japan Automobile Research Institute, Tsukuba 305-0832, Japan
[2]Safety Assurance KUdos for Reliable Autonomous Vehicles (SAKURA) Project
[3]Japan Automobile Manufacturers Association (JAMA), Tokyo 105-0012, Japan
[4]Nissan Motor Company, Yokohama 220-8686, Japan
[5]Honda Motor Company Ltd., Tochigi 321-3393, Japan
[6]Toyota Motor Company, Nagoya 450-0002, Japan

Corresponding author: H. Muslim (ahusam@jari.or.jp)

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ABSTRACT This study aims to generate test cases for scenario-based assessment of automated driving systems (ADS) when encounter a cut-out maneuver where the lead vehicle having changed lanes, revealing a new lead vehicle that, in some cases, is slower than the original lead (the cutting-out) vehicle. We extracted the cut-out scenarios from an established real-world traffic dataset recorded by instrumented vehicles on Japanese highways and then defined them using vehicle kinematic parameters (velocities and distances). The extracted scenarios were analyzed based on the direct correlation between every two consecutive vehicles: a rear part that describes the correlation between the following vehicle and the cutting-out vehicle; and a frontal part that describes the correlation between the cutting-out vehicle and the preceding vehicle. Parameter ranges were quantified with a regression model and determined based on the risk acceptance threshold applied in the field of Japanese high-speed trains and annual exposure by professional highway drivers to produce a scenario space with a reasonably foreseeable range in which ADS may not produce crashes lest it performs worse than human drivers. A multi-dimensional distribution analytical approach was used to derive a correlation between the following and preceding vehicles considering the initial longitudinal velocities. Results suggest that when the time headway between the following vehicle and the cutting-out vehicle is equal to or more than 2 s, there should not have collision risks between the following vehicle and the preceding vehicle. These findings can help to understand normative driver behavior during cut-out scenarios and to generate accident-free scenario space for which ADS must perform flawlessly.

INDEX TERMS Connected and automated vehicles, car-following, lane change, logical scenarios, safety-test assessment, scenario-based approach.

I. INTRODUCTION

Autonomous vehicles (AVs) are expected to improve transportation comfort, performance, and safety compared to traditional (human-controlled) vehicles. Thus, car

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manufacturers worldwide aim to design automated driving systems (ADS) that outperform human drivers [1]. To achieve such expectations and goals, an ADS must exhibit the safest natural driving behaviors and render them with acceptable and flexible safety ranges for all road users and road boundaries [2]. However, the identification of safety ranges in natural driving is a challenge for those involved in ADS safety assessment. Thus, how to ensure and validate the safe operation of AVs before being introduced in real traffic remain a significant concern.

AVs' safety assessment approaches, such as scenario-based testing [3], [4], function-based testing [5], formal verification [6], shadow mode [7], multi-agent traffic simulation [8], and the staged introduction of AVs [9], are still under development. The scenario-based approach has been identified among the most promising methods that have been investigated by previous research projects (e.g., aFAS [10], ENABLE-S3 [11], and PEGASUS [12]) and are currently being pursued in ongoing research projects (e.g., SET Level [13], VVM [14], and Safety Assurance KUdos for Reliable Autonomous Vehicles (SAKURA) [15]). The required type of scenarios for scenario-based testing can be derived using a data-driven approach, a knowledge-driven approach, or both [16] and [17]. However, how to derive relevant test cases from the generated scenarios is still an open research question that is attempted to be addressed by ongoing research efforts.

For the abovementioned research and standardization bodies, such as ISO/DIS 34502 [18], IEEE Std 2846 [19], and SAE J3061_201601 [20], human driver performance and behavior have been established as a reference for ADS capabilities to avoid ''reasonably foreseeable events'' under their operational domain. The idea of reasonably foreseeable events suggests that it is possible to create, through careful examination by experts, a delimitation of events (different types and intensities) that must be included in ADS safety assessment to guarantee the comprehensiveness of the safety analysis. As it may sound, the term ''reasonably'' brings the issue of arbitrary delimitation of what is foreseeable and is defined as *forecastable by experts' examination of real-world data and evidence, or by attentive human drivers in situ* [21].

ADS capabilities to perform its intended function competently are often compared to competent and careful drivers [22], [23]. Such drivers drive their vehicles while safely implementing perception, decision-making, and other tasks with a high level of performance [24]. Further, they assume a defensive driving style, minimizing risky situations that might result in car crashes. Human driver behavior safe ranges must be understood and determined to impart such capabilities in ADS. Since the real driving behavior varies among human individuals and scenario types dependently, it is expected to be distributed over a wide range of variables for each scenario type. The conversion of these distributions (logical scenarios with parameter ranges) to a specific scenario space (concrete scenarios) from which test cases can be selected for to test the controllers of AVs is a part of the scenario-based approach [25]. In this study, we attempt to generate a scenario-specific safety range for ADS assessment by quantifying human driver behaviors during multiple cars following and cutting-out maneuvers, extracted from real driving data through the consideration of the concepts of reasonably foreseeable events that may occur in real traffic [26], annual exposure of the event, and risk acceptance threshold were adopted from other domains [27], [28].

A. RELATED WORKS

Many efforts have been made to quantify and model driver behavior through the use of naturalistic data acquired from real-world traffic to be used for ADS safety validation and verification [29], [30], [31]. However, naturalistic driving behaviors are typically developed for specific scenarios. For example, given that a subject vehicle does not change lanes and speed when driving on a multi-lane highway, three common scenarios are expected to interrupt its operation: a cut-in, cut-out, and deceleration by the surrounding vehicles [32]. Several methods are proposed to parametrize and quantify cut-in and deceleration scenarios from real driving data [33], [34], [35], [36], [37], [38]. Some methods convert real-world scenarios to scenarios in a virtual simulation environment [39], while other methods modify the parameterized scenarios toward the safety-critical ranges to exhibit the critical behavior of the system under test [40], [41]. Other studies further applied importance sampling techniques to automatically generate scenarios that stimulate particular behaviors of the system under test [42], [43]. While the generated scenarios for ADS assessment should represent real-world scenarios, very few methods have compared the generated scenarios with real-world driving, which resulted in significant differences. Those who compared the generated scenarios and the ground truth either did not consider the correlation between parameters [44] or did not verify their method applicability for more complex scenarios that contain more than two actors, such as cut-outs [36].

Currently, to our knowledge, there is no specific, unified method can comprehensively process real-world data, parameterize them, and quantify the result in a specific safety range applicable for every scenario type. SAKURA research proposes an analytical approach to extract and parameterize scenarios and quantify the parameter results with reasonably foreseeable parameter ranges based on risk exposure and acceptance to generate representative test cases [45]. The applicability of the proposed method has been elaborated by processing and comparing two different datasets from Japan and Germany with the use of cut-in and deceleration scenarios [35]. In this study, we adopted the SAKURA method to parametrize cut-out scenarios from naturalistic highway driving data in Japan. Although the cut-out maneuver has been identified as one of the essential scenarios to exhibit ADS behavior, it has been undermined as it is less safety-critical compared to cut-in and deceleration scenarios. Both the cut-in and the cut-out are lane change maneuvers; however, cutting-

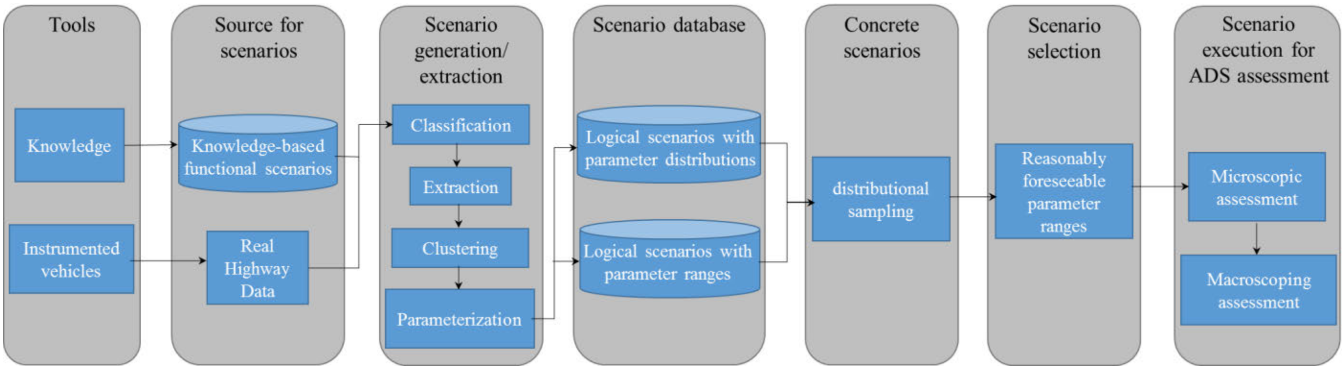

FIGURE 1. **Methodology framework and the workflow of the scenario-based approach based on the taxonomy developed by Riedmaier et al. [25].**

out is a more complex driving behavior as it may involve more than two cars in a row.

In the context of manual driving, careful drivers monitor the behavior of the immediate leading vehicle and the entire traffic stream. For example, when a driver follows a vehicle, s/he considers several vehicles ahead, such that when the leading vehicle changes lanes (i.e., cuts out), the following driver synchronizes (e.g., adjusts the speed and distance) with the revealing new leading vehicle. Investigating this phenomenon is essential for confirming the traffic safety of low-speed traveling vehicles and stationary vehicles (e.g., breakdown, end of congestion, and more) that suddenly reveal in front of the following drivers due to the cutting out of the leading vehicle.

In the context of autonomous driving, the behavior of the preceding vehicles is important for ADS performance and safety during multiple-car following. ADS detection of the cut-out maneuver is safety critical because, without the identification and awareness of traffic condition irregularities, no information processing, including decision-making on how to react to the situation perceived, is carried out. Particularly if the vehicle preceding the cutting-out vehicle is slower than the AV, a riskier cut-out may involve a leading vehicle changing lanes to avoid a stationary vehicle, traffic jam, or lane block. For example, cases where the adaptive cruise control ignores stationary or slower vehicles when the target vehicle changes lanes and instead accelerates to the stored speed have been reported [46], [47]. AVs' failure to detect and respond appropriately to such situations may result in a crash [48].

B. RESEARCH AIM

The ultimate goal of this study is to generate accident-free scenario space for which ADS must perform flawlessly or better than manual driving. Our research focuses on the cut-out scenario type, in which three vehicles follow each other in the same lane when the middle vehicle changes its lane, and the following driver needs to scan the road for a new target vehicle in range and synchronize the speed and distance according to the revealing vehicle. We defined and extracted the cut-out scenarios from real-world traffic data collected by instrumented vehicles from Japanese highways. The second aim is to apply the proposed analytical approach to parameterize scenarios based on the direct relationship between vehicles. Parameter distributions were illustrated and processed to quantify the probability occurrence of the cut-out maneuver and examine the cutting-out driver behavior. We also analyzed the correlation between parameter ranges to indicate the combined effects of different relative velocities and inter-vehicle distances.

Lastly, this study sought to determine the reasonably foreseeable parameter range, considering the estimated annual exposure of such scenarios and the risk acceptance threshold set by other domains, e.g., nuclear plants and railways. It is expected that ADS must not cause any accident within the resulting range from which test cases are generated. The importance and originality of this study are that it explores the effects of lane change behavior of the leading vehicle during car-following on automated driving safety. The findings should contribute to the scenario-based assessment of automated driving by generating test cases for experiments with a driving simulator or real autonomous vehicle on the track. They also shrink the gap between driving simulation and real-world testing. However, the reader should bear in mind that the study is based on real driving data collected from Japanese highways during a specific period and time of the day; thus, the resulting parameter range may differ from other regions. It is beyond the scope of this study to examine the preventability of risky or accident situations.

II. METHODOLOGY

A scenario-based approach is an efficient tool to assess various autonomous systems. The generation of scenario-specific test suites is critical for this approach. Several techniques have been developed to extract, parameterize, and generate test scenarios for scenario-based assessment; most of them are based on the extraction of specific scenarios from a real-driving dataset. In our previous research [45], we proposed a methodology to build a Gaussian mixture model from which representative test cases (that account for multi-dimensional dependencies) can be generated (see Appendix-A). The previous research focused on cut-in and deceleration scenarios extracted from real-world traffic data recorded by instrumented vehicles and infrastructure cameras under the SAKURA initiative (https://www.sakura-prj.go.jp/). This paper complements our previous research on the definition of reasonably foreseeable parameter ranges (i.e., the likelihood of encountering an event within this range in real life is above a certain threshold) to identify the most representative scenarios for scenario-based assessment of ADS. However, this paper demonstrates the application of the SAKURA methodology with a more complicated traffic maneuver that involves three consecutive vehicles, known as a cut-out scenario, which includes lane change and deceleration or acceleration. These scenarios were extracted from previously unpublished real driving data on Japanese highways.

Several sequential steps were performed to begin this process, as shown in Figure 1. The first step was to process the real driving dataset from which cut-out scenarios were extracted under certain conditions and modeled with kinematic parameters. Parameters that represented the behavior of the subject and surrounding vehicles in the cut-out scenario were defined, and the time series data were processed to extract and accumulate values for each parameter. The parameter ranges were assumed to follow a statistical distribution based on the extracted scenario data and were extrapolated using the confidence interval of the statistical distribution. Parameter distributions contain the probability of occurrence (exposure) of the specified scenario and therefore allow a weighting of the results to be weighed for an accurate statistical assessment. We performed an extrapolation to cover critical cases that may not have been observed during the data collection period and to reduce the biases caused by the timing, environmental, and regional factors. Then, the parameter range was considered with the correlation between parameters (i.e., calculate correlations between every two parameters). Once the correlation between the different parameters was analyzed and the statistical distribution was defined, we converted the probability distributions to annual encounters (assumption of the most frequent driver's travel distance) and accumulated numerically from the highest occurrence. Finally, a reasonably foreseeable range was defined with a risk acceptance threshold established in different fields and domains, such as the railway domain, in this research. Test cases for scenario execution were to be selected from the generated logical scenarios with reasonably foreseeable parameter ranges for ADS assessment. However, the last stage is out of the scope of the current study.

The advantages of such a methodology are its simplicity and applicability to any dataset in disregard to the data collection method. However, this method does not consider the highly critical cases (i.e., corner or edge cases). Moreover, the parameter range results are region-specific, in consideration of the traffic environment, rules, and driving behavior. It should be noted that this methodology is limited to a reasonably foreseeable ranges and does not cover the preventable ranges, which requires further research efforts that account for events avoidable by a competent and careful human driver and state-of-the-art technology.

A. DATA COLLECTION

For extraction of cut-out parameter ranges, the SAKURA dataset was adopted. The dataset was collected with three instrumented vehicles on limited-access highways in Japan [45]. The recordings took place between Nov. 2018 and March 2020 in different weather and traffic conditions. A driver and an operator in the front passenger seat whose responsibility is to guide the driver, monitor driving style, and supervise the equipment controlled by the instrumented vehicle. Each vehicle was equipped with four Lidar units (10 Hz), 10 Cameras (30 frames per second), and a Mobileye unit (10.64-10.87 frames per second) to record the surrounding traffic and road segment. The instrumented vehicle position, velocity, heading, and orientation in space were estimated with an inertial navigation system (GNSS/IMU sensors 10 Hz). In general, the sensors range was 70 m in front and behind and 50 m on either side of the subject vehicle. The tools can record the behavior of eight surrounding vehicles without occlusion. However, sometimes occlusion occurs in curved roadway sections and under bad weather conditions.

The targeted areas comprised interstate highways known as the national expressways connecting prefectures all over the country and intra-city highways known as the metropolitan expressways running above local roads and residential areas in some of the country's largest cities (Type 1 and Type 2 in Appendix-B). Although both highway types are controlled with toll gates and designed to accommodate high-speed traffic, they significantly differ in their designed capacity and speed limits [49], [50]. The variation in traffic conditions from fast free-flowing to slow stop-and-go (i.e., traffic jams) during the data collection time frame resulted in the cut-out maneuvers being recorded over a wide range of traffic speeds. No collisions were recorded within the dataset.

B. INSTRUCTIONS TO DRIVERS

For each vehicle, the recording operations were done in one of three working shifts during the day: an early shift (06:30-14:30), a regular shift (09:00-17:30), or a late shift (14:00-22:00) with a 15 minutes break once every hour of driving. Thus, each recording had an average duration of one hour, which amounts to a total recording time of 5-6 hours for a vehicle on duty per day. The drivers and operators were recommended to avoid overworked driving, take sufficient rest (at least 8 hours of rest), and be careful about situation awareness so as not to impair their attention. They were instructed to drive safely with strict compliance to legal speeds and adhere to traffic rules. Further, the drivers must keep a sufficient distance between vehicles such that they do not have to brake or start suddenly (i.e., defensive driving). However, both steering and braking maneuvers must be performed to avoid crashes.

C. LOGICAL SCENARIO DEVELOPMENT PROCESS

First, a model that represents the behavior of each vehicle in the cut-out functional scenario is defined using kinematic parameters, such as speed and distance between vehicles. Next, cases corresponding to the cut-out scenario are detected and extracted from the dataset. Third, values of each parameter are extracted from each case (e.g., relative position, speed, acceleration) to generate parameter distributions. Each parameter distribution is defined by the mean and the variance of the sample.

1) CUT-OUT SCENARIO DEFINITION

A scenario (i.e., a traffic situation) is a scene of interacting elements (e.g., vehicles, cyclists, pedestrians, and road structure) and events and actions (e.g., lane change, deceleration, braking, turning) that occurred in a specific duration [51]. The investigated cut-out scenario involves three vehicles following each other on the same lane of a multi-lane roadway, whereas a vehicle leaves from the middle (changes lanes) toward an adjacent lane while the following and preceding vehicles keep the lane, as shown in Figure 2. An action (deceleration or acceleration) has to be carried by the following vehicle depending on the relative speed and distance to the preceding vehicle.

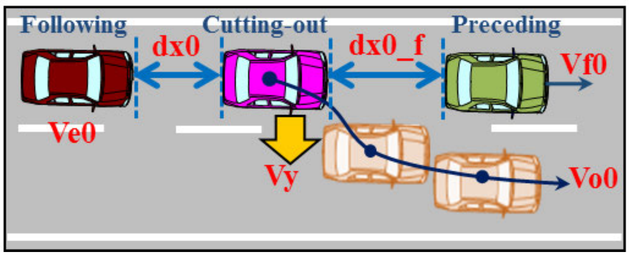

FIGURE 2. **Cut-out scenario involving three consecutive vehicles traveling in the same direction. When the vehicle in the middle changes lanes, the other vehicle continues driving in the same lane.**

2) DEFINITION OF LOGICAL SCENARIO PARAMETER RANGES

Functional scenarios are traffic disturbance models that can accurately reproduce dynamic events in real-world driving. Such models allow to process of large amounts of parameter combinations within a realistic range simply and efficiently. Logical scenarios provide a parameterized and quantified description of vehicles' behavior abstractly represented by the functional scenario. Their development requires the definition of parameter ranges for the scenario model. In other words, a wide range of vehicle behavior can be represented by different parameters combination.

Scenario parametrization is dependent on the relationship between the interacting objects within the scenario space and time frame. For this purpose, we divided the cut-out scenario into two parts based on the direct relationship between the interacting vehicles, as shown in Figure 3. Part-R of the scenario illustrates the relationship between the subject vehicle and the cutting-out vehicle that runs in front of the subject vehicle without obstacles between them. This part is described with three main variables: the initial longitudinal velocity of the subject vehicle (V_{e0}), the initial longitudinal velocity of the cutting-out vehicle (V_{o0}), and the initial longitudinal distance (d_{x0}) between the front end of the subject vehicle and the rear end of the cutting-out vehicle in the subject's lane. Part-F of the scenario illustrates the relationship between the cutting-out vehicle and the forward vehicle that travels in front of the cutting-out vehicle. In both parts, the cutting-out vehicle leaves the subject's lane toward an adjacent lane. This part is described with four variables: the initial longitudinal velocity of the cutting-out vehicle (V_{o0}), maximum lateral velocity of the cutting-out vehicle (V_y), the initial longitudinal velocity of the preceding vehicle (V_{f0}) in front of the cutting-out vehicle, and initial longitudinal distance (d_{x0_f}) between the front end of the cutting-out vehicle and the rear end of the preceding vehicle. All variables assigned initial values measured at the start of the cut-out maneuver except for the Vy, in which the maximum value was considered.

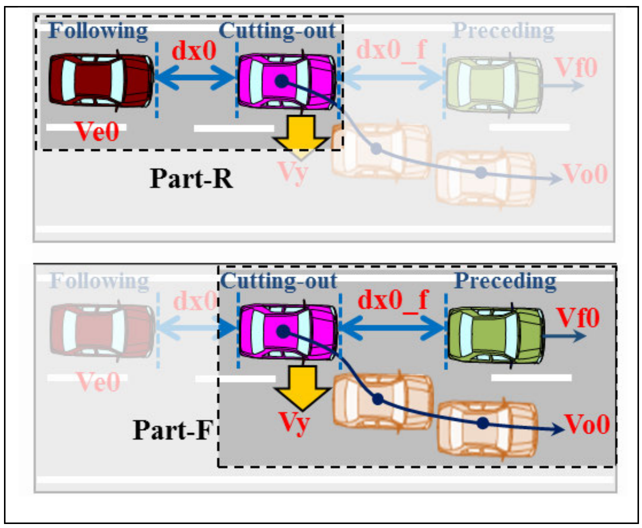

FIGURE 3. **Cut-out Part-R (top) describes the interaction between the following and cutting-out vehicles, and cut-out Part-F (bottom) describes the interaction between the cutting-out and preceding vehicles.**

3) CUT-OUT SCENARIO EXTRACTION

This section describes the process to extract cases from real traffic data used to define parameter distributions for the logical scenario. Part-R and part-F of the cut-out scenario were extracted separately from the data recorded by the instrumented vehicle. In this context, the instrumented vehicle did not involve directly in either part of the cutting-out maneuver. Specifically, the following, cutting-out, and preceding vehicles were vehicles surrounding the instrumented vehicle and were controlled by random drivers. The cut-out maneuver was considered when the cutting-out vehicle conducted a lane change while the following subject vehicle and the preceding vehicle traveled straight forward without changing lanes or speed. However, the longitudinal speed of the cutting-out vehicle may change (decrease or increase) during the lane-changing maneuver.

For both parts, the following, cutting-out, and preceding vehicles must be following each other, while the lateral velocity of a cutting-out vehicle remains constant in the same direction until it enters an adjacent lane. The longitudinal distance between vehicles involved is between 0 and 100 m, based on the sensors' range and driving environment conditions [52]. The maneuver starts when the lateral speed of the cutting-out vehicle increases from zero and ends when the lateral speed returns to zero, with the cutting-out vehicle driving straight forward in front of the following vehicle. The considered lateral speed of the cutting-out vehicle was set to positive values equal to or lower than 3 m/s for both lane-change directions [53].

III. RESULTS AND DISCUSSIONS

This chapter presents and discusses the processed data and the generated parameter ranges in accordance with the research aims mentioned in the introduction. The following is a brief description of the data distributions and sample size.

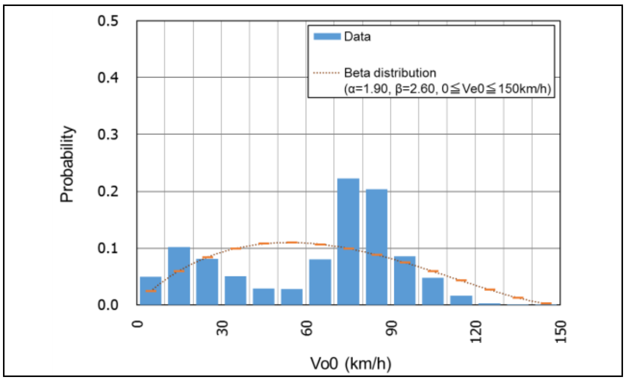

FIGURE 4. Probability distributions of the cutting-out vehicle longitudinal velocity during lane change initiation.

Figure 4 shows the probability distribution of the initial longitudinal velocity for the cutting-out vehicle when it started changing lanes. The V_{o0} distributions indicate a peak value over the low-speed range of around 15 km/h, while the high-speed range shows its maximum probability of occurrence at a velocity of around 75 km/h. Such parameter distributions were affected by external factors, such as highway type (interstate and intrastate highways), traffic flow during rush hours, and weather conditions. However, it may also be affected by cultural factors, such as the driving style in the country from which data were collected [35], [54]. To investigate the impact of traveling speed on each vehicle's behavior, we categorized the sample size based on the traffic speed into a low-speed range from 0-60 km/h and a high-speed range larger than 40 km/h.

Table 1 provides an overview of the sample size of part-R and part-F of the cut-out scenario categorized by speed ranges. On the one hand, the low-speed and high-speed ranges are overlapped to allow smooth extrapolation of parameter distributions and compensate for possible and rare cases that have not been observed during the data collection period. On the other hand, sensors limitation (maximum range is 60 m), obstruction by the surrounding vehicles, and road shape factors provided difficulties to capture the three consecutive vehicles (following, cutting-out, and preceding vehicles) simultaneously during the maneuver. Therefore, part-R and part-F were extracted independently. It should also be noted that the instrumented vehicle may not be directly involved in the cut-out scenario (i.e., the following vehicle can be the instrumented vehicle or any surrounding vehicle). As the instrumented cars traveled on the main lane of the highway, they were likely to encounter and record part-R more than part-F due to sensor and camera limitations caused by surrounding obstructions. Thus, the sample size is considerably different between the two parts.

TABLE 1. Cut-out scenario sample size categorized by speed range.

Speed range	Sample size (N)	
	Part-R	Part-F
Low (V_{e0} = 0~60 km/h)	17,358	729
High ($V_{e0} \geq$ 40 km/h)	36,507	4,236
Total	53,865	4,965

The analytical procedures (see Appendix C) and the results obtained from both parts are described in the next sections. In the first section, we present the probability distributions of each parameter range categorized by speed ranges. The second section, used regression analyses to investigate the correlation between parameter ranges for each part of the cut-out categorized by speed ranges. These two sections also aim to quantify parameter ranges to build logical scenario space. The third section attempts to connect the following vehicle from part-R and the preceding vehicle from part-F by proposing a hypothetical correlation between parameter ranges. The aim is to evaluate the safety and necessary actions after the cut-out maneuver based on the relative velocity and distance between the remaining two vehicles in the same lane. Having discussed how to define, parameterize, and quantify the cut-out scenario, the final section of this chapter presents how to derive reasonably foreseeable parameter ranges based on the annual exposure and risk acceptance measures. Test cases can then be generated from the resulting range to assess and compare AVs' performance.

A. PROBABILITY OF PARAMETER DISTRIBUTIONS

The first set of analyses examines the behavior of vehicles involved in the cut-out scenario by determining the probability distribution of parameter ranges. Starting with the cut-out part-R, analysis of the relative longitudinal velocity and distance between the following vehicle and the cutting-out vehicle are shown in Figure 5. The number of low-speed range data based on the following vehicle longitudinal velocity is N = 17,358, and the high-speed range data is N = 36,507. The probability occurrence of the relative speed

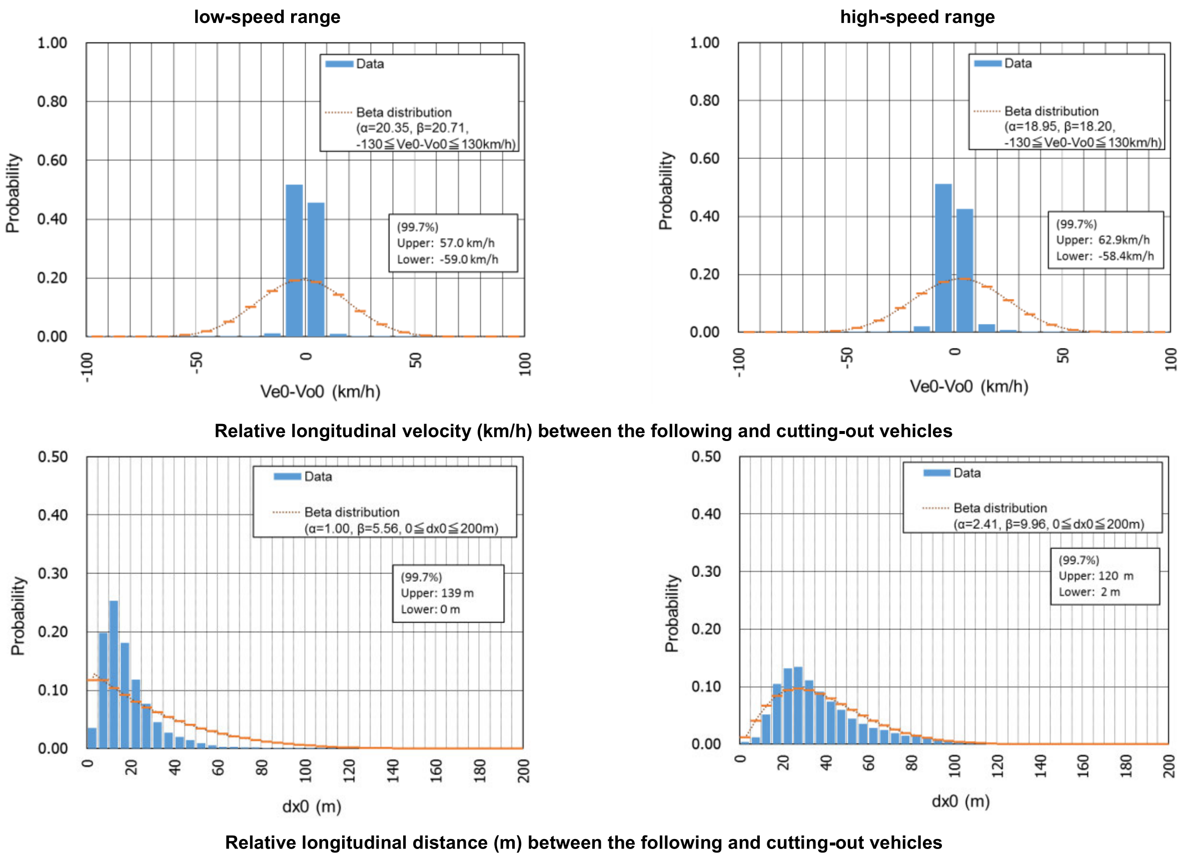

FIGURE 5. Estimation of parameter distributions corresponding to vehicles involved in Part-R of the cut-out scenario categorized by low and high-speed ranges.

shows similar trends (two main peaks around −5 and 5 km/h) under the low and high-speed ranges. This datashows that the cut-out occurs more frequently when the leading vehicle is faster than the following vehicle. However, the maximum probability occurrence of the relative longitudinal distance ranges around 7-17 m under the low-speed range and around 25-30 m under the high-speed range. While the relative longitudinal velocity did not affect by the speed range, the probability distributions indicate a shorter distance under the low-speed range. It is apparent from these results that the following drivers intend to maintain larger headway to ensure safety at higher speed ranges. In the context of automated driving, AVs shall maintain a proper inter-vehicle gap based on the speed of the leading vehicle. Therefore, part-R of the cut-out scenario might not be critical for automated driving until the ADS needs to respond to the new leading vehicle (i.e., after the cutting-out maneuver).

Next, the distribution of each parameter of part-F is shown in Figure 6. In this part, there is a limit to the sensor measurement range. Therefore, data with a relative speed of 15 km/h or more and an initial inter-vehicle distance of 55-58 m and data with an inter-vehicle distance near 0 m were excluded. The number of low-speed range data based on the cutting-out vehicle longitudinal velocity is N = 729, and the high-speed range data is N = 4,236. In Figure 6, although the maximum probability of the relative longitudinal velocity ranges around 0-10 km/h for the low and high-speed ranges, the high-speed data show a wider distribution range of speed differences than low-speed data. Unlike part-R, both low and high-speed data show a clear shift toward the positive direction, indicating that the cutting-out vehicle was faster than the preceding vehicle. Similar to part-R, the cutting-out drivers tend to enlarge the inter-vehicle gap as the traveling speed increases. However, the relative longitudinal distance maintained by the cutting-out drivers is shorter than that maintained by the following drivers (Figure 5), indicating that the cutting-out drivers may tend to reduce their headway before the lane change initiation. Previous research has highlighted such driving behavior during car overtaking [55].

These results indicated that the minimum TTC varies with travel speed, such that the distribution range became wider as the speed increased. For example, although the lateral velocity of the cutting-out vehicle appeared to be affected to a lesser extent by the speed range variation compared with other parameters, the distribution indicates a wider range of V_y under the high-speed range than the low-speed range. This result accords with our earlier observations of the lateral velocity in the cut-in scenario [45], which established that a lane-change maneuver that is performed with a lateral velocity less than or equal to 2 m/s is not aggressive

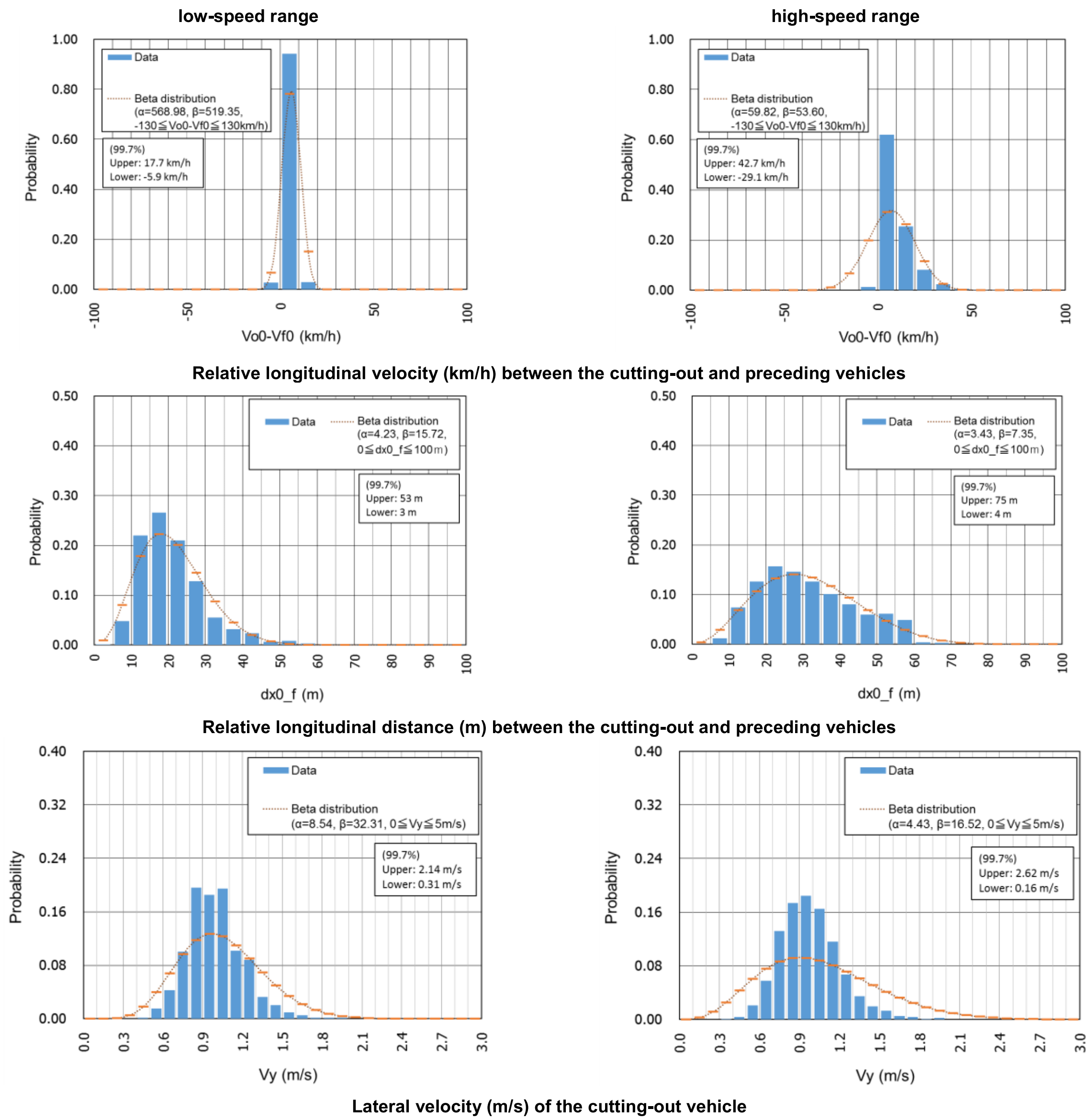

FIGURE 6. **Estimation of parameter distributions corresponding to vehicles involved in Part-F of the cut-out scenario categorized by low and high-speed ranges.**

(i.e., not time-critical maneuvers). However, these maneuvers can be safety-critical considering the distance to the surrounding vehicle and the relative velocity between vehicles, particularly when the involved vehicles are closing on one another.

B. PARAMETERS CORRELATION

Although the combination of parameters used to define the cut-out logical scenario was presented independently, they correlate to each other, and if this correlation is not taken into account, the obtained parameter ranges may generate unrealistic scenarios. For example, during a decrease in relative velocity between two vehicles in the same lane, the higher the relative speed between the vehicles is, the longer the inter-vehicle distance is. Therefore, it is necessary to confirm whether there is a correlation between the parameters in order to estimate the parameter interval in consideration of this relationship. Regression analyses were used to predict the correlation between relative speed and inter-vehicle distance in part-R and part-F, as follows:

Step 1: Distribute parameter range analysis for parameter Y-axis considering the value of parameter X-axis

Step 2: Partition parameter X-axis into equidistant classes. The size of these classes may be defined as a compromise between the size of the data set and the number of data points included in each sub-set. Outliers may be measurement failures, but they can also represent infrequent incidents of high safety relevance.

Step 3: Calculate the average (μ) and standard deviation (σ) for the parameter Y-axis for each class of parameter X-axis.

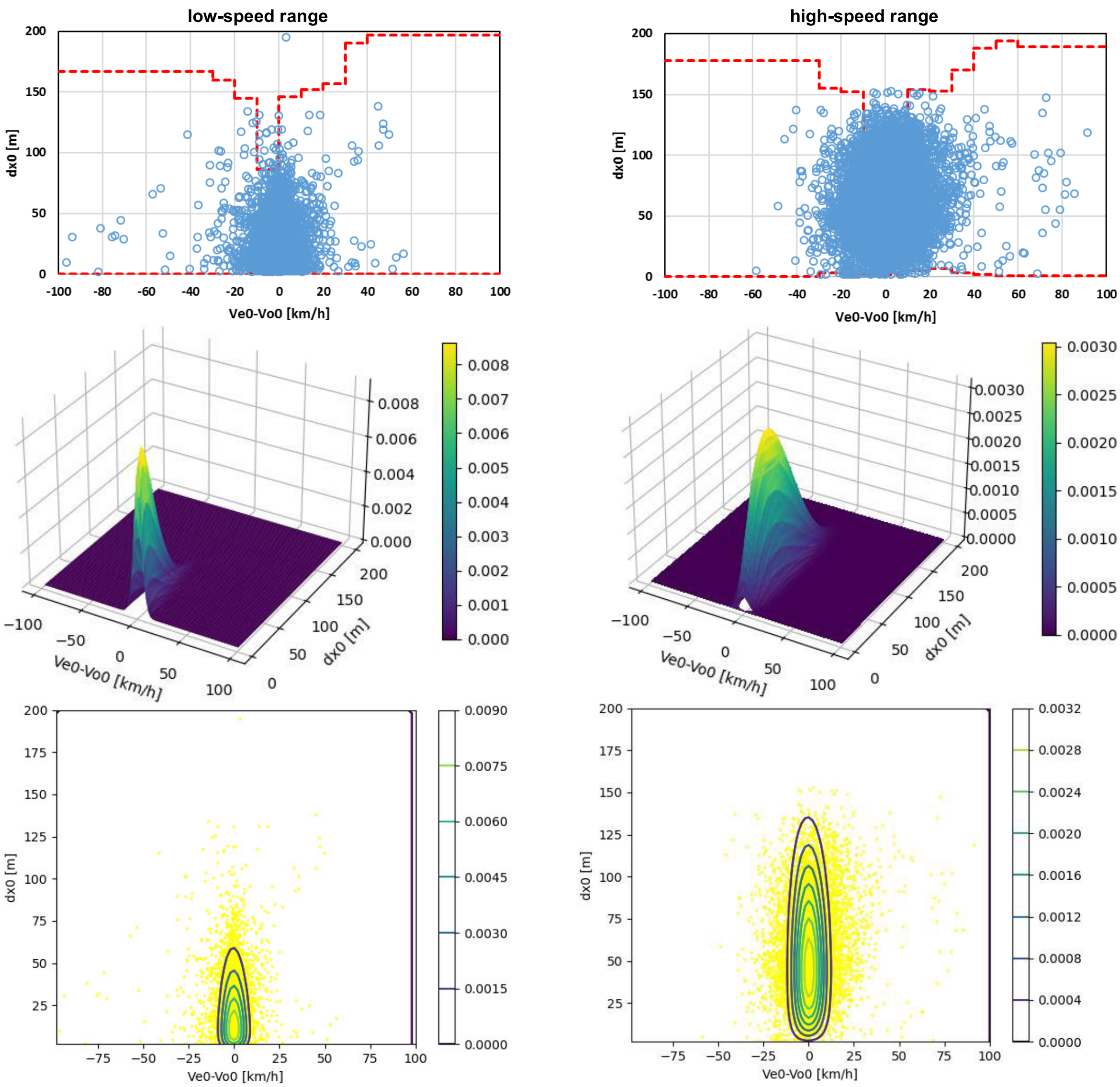

FIGURE 7. A scatter diagram and multi-dimensional distribution for the relative longitudinal velocity considering the relative longitudinal distance between the following vehicle and the cutting-out vehicle in part-R of the cut-out scenario.

Step 4: Develop a regression model that explains μ and σ for parameter Y-axis for each class of parameter X-axis. In this analysis, the linear regression model uses the relative initial longitudinal velocity speed as an explanatory variable and the average value and standard deviation of the initial inter-vehicle distance as objective variables. Although it did not occur in this estimation, when calculating the average value and standard deviation for each class, regression was performed by excluding classes with less than 10 data items in consideration of the effect on the stability of the analysis.

Step 5: Establish whether a correlation exists based on the regression analysis results performed in step 4. This analysis evaluates whether the relative velocity correlates with the initial inter-vehicle distance by the superiority of the slope parameter (when t 1.96). If this parameter is superior, the average value or standard deviation of the initial inter-vehicle distance will change with the change of (the class value of) the relative initial velocity.

Step 6: Set the parameter range equation for the parameter Y-axis relative to the parameter X-axis. The approach to setting a stable parameter range assuming a statistical distribution is taken. Here, it is assumed that each parameter follows the normal distribution (even when divided by class, it follows the normal distribution within each class), and the parameter range is set as $\mu \pm 3\ \sigma$ (99.73% of the whole is included)

Figures 7 and 8 present plots of the initial relative longitudinal velocity in consideration of the relative longitudinal distance in part-R and part-F, respectively. In each figure, the top is a scatter plot, the middle is a three-dimensional

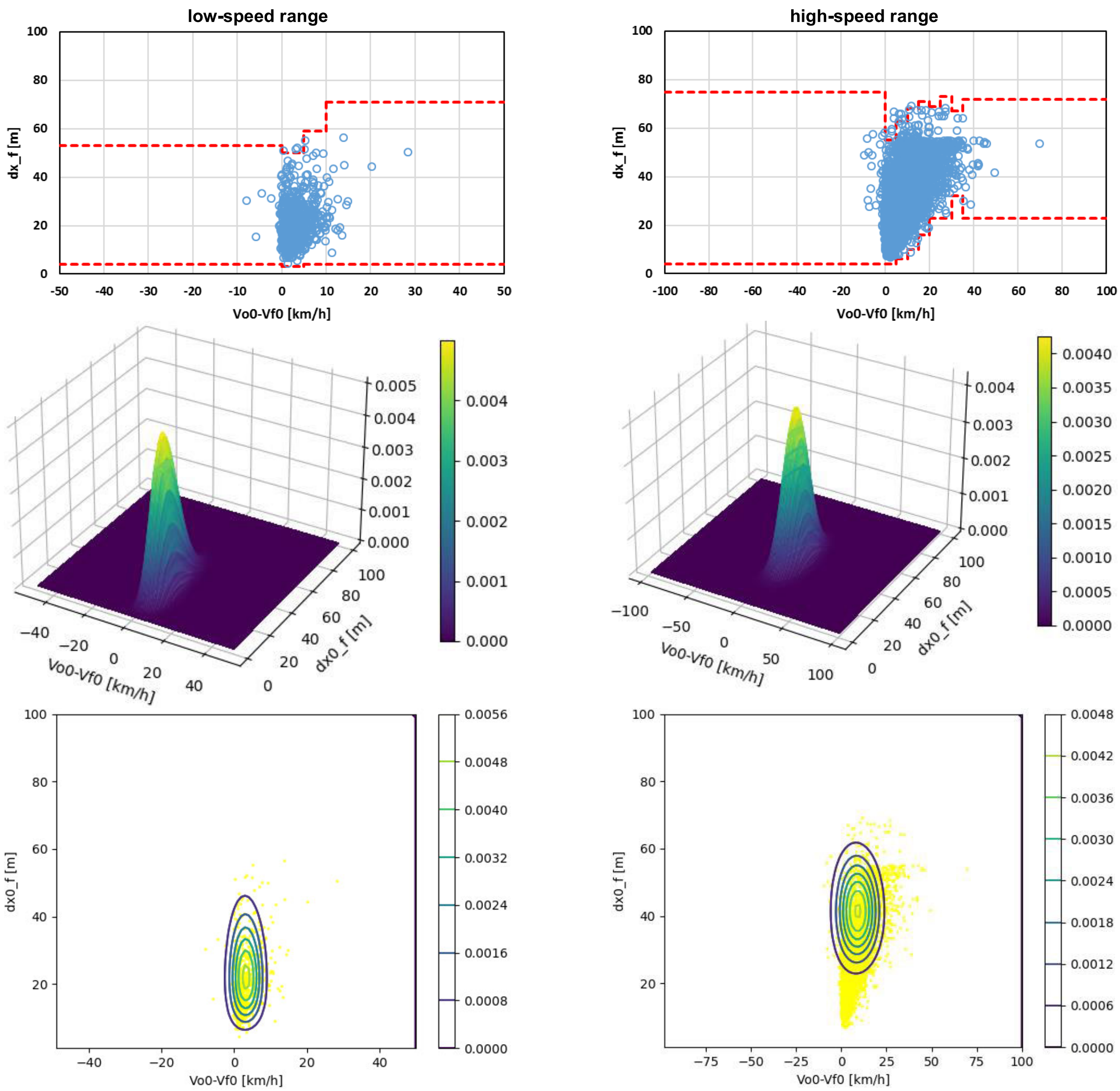

FIGURE 8. A scatter diagram and multi-dimensional distribution for the relative longitudinal velocity considering the relative longitudinal distance between the cutting-out vehicle and the preceding vehicle in part-F of the cut-out scenario.

display, and the bottom is a contour diagram expressing the three-dimensional diagram in a plane. Contour diagrams are often used to represent a two-variable function visually;; therefore, the contour diagram is overlaid with a scatter diagram. The significance of the correlation between the relative velocity and distance of both parts was assessed using T-tests, and the significance value was set to equal to or larger than 1.96. For part-R, there is a correlation between parameters such that the inter-vehicle distance decreases as the relative speed approaches 0 km/h (low-speed range $T = 0.62$; high-speed range $T = 25.59$). However, the correlation is not significant under the low-speed ranges. Again, this result can be attributed to external factors that may affect the following driver behavior during low-speed driving, such as traffic jams, accidents, roadway modification, and weather conditions.

Regarding the parameter range correlation of part-F, it can be seen that the initial relative longitudinal velocity tends to increase when the initial relative longitudinal distance increases greatly (low-speed range $T = 7.34$; high-speed range $T = 56.53$). The correlation under the high-speed range is stronger than that under the low-speed range. This difference is similar to that indicated in part-R. In Figure 7, the cut-out part-R scenarios seem distributed comparatively in the negative and positive ranges, with the inter-vehicle distance being increased proportionally with the travel speed. On the one hand, the number of events where the following vehicle and the cutting-out vehicle are closing on one another is comparable to that where the vehicles are pulling away from one another. On the other hand, the majority of cutting-out part-F (Figure 8) occurred where the cutting-out vehicle is closing on the preceding vehicle. A risky situation may

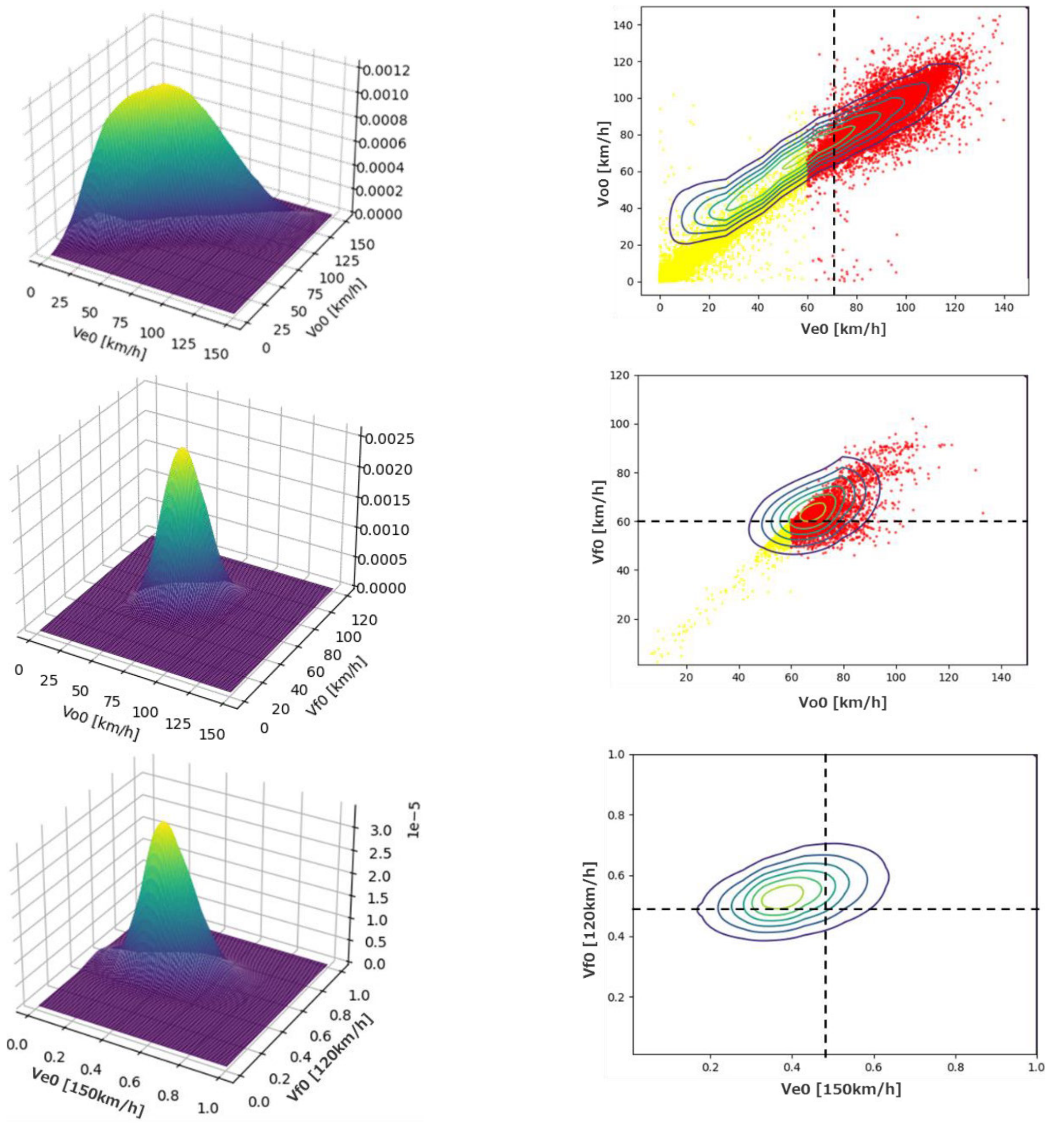

FIGURE 9. Multi-dimensional distribution and contour diagram for the overall cut-out maneuver considering the correlation between the initial longitudinal velocities of the three vehicles.

arise when the following vehicle is closing to the cutting-out vehicle, and the last is closing on a preceding vehicle before lane change initiation.

C. DETERMINING SYNTHESIS CORRELATION BETWEEN PART-R AND PART-F

Thus far, this paper has presented the cut-out scenario as two independent parts (part-R and part-F), focusing on analyzing the direct correlation between the two following vehicles prior to the cutting-out maneuver initiation. However, the correlation between the following vehicle in part-R and the preceding vehicle in part-F will also become direct after the cutting-out maneuver. We used an analytical approach using a multi-dimensional distribution method to derive a correlation between the following vehicle and the preceding vehicle considering the initial longitudinal velocities (see Appendix-D). The calculation results of the combined distributions in part-R and part-F are shown in Figure 9. For part-R, the figure reveals that the initial longitudinal velocities of the following vehicle and the cutting-out vehicle are proportional. The peak probability for the cutting-out occurrence is when the initial longitudinal velocity of the following and cutting-out vehicles is around 60 (km/h). For part-F, the graph also shows that there has been a relationship such that the initial longitudinal velocities of the cutting-out vehicle and the preceding vehicle are proportional. The cut-out peak density occurred when the longitudinal velocities of thecutting-out vehicle and preceding vehicle are around 70 (km/h).

Taken together (bottom part of Figure 9), the results reveal that the peak density of the cutting out occurs when the following vehicle velocity is 60 (km/h) and the preceding vehicle velocity is around 70 (km/h). However, there is a probability that the following vehicle would encounter a significantly slower preceding vehicle after the cutting-out maneuver. The following vehicle should have maintained a time headway to the cutting-out vehicle enough to enable a safe reaction time to avoid such critical situations. Although an ADS can be set to maintain safe inter-vehicle distance in car-following, it is essential to test the system's abilities to respond to a significantly slower or stopped preceding vehicle that suddenly appears after a cutting-out maneuver by the leading vehicle.

D. REASONABLY FORESEEABLE RANGE OF THE CUT-OUT SCENARIO

In the previous sections, we transferred levels of the scenario from functional, i.e., pictogram and linguistic descriptions, to the logical scenario, i.e., a state-space description with value ranges. We also described the selected parameters and their relationships. The aim is to generate executable test cases for ADS safety assessment. Thus far, logical scenario parameter ranges can be the origin of an infinite number of concrete scenarios, resulting in an unrealistically huge number of test cases. Therefore, we used the concepts of reasonably foreseeable and risk acceptance to generate concrete scenarios that are finite, representative, and critical to ADS performance. Finally, the derived concrete scenarios with reasonably foreseeable parameter ranges are used to generate test cases and test specifications.

Both cut-in and cut-out scenarios are lane change maneuvers, in which a front vehicle's lateral movement exceeds the boundary condition for a typical vehicle wandering by more than 0.375 m based on the actual traffic observation data, resulting in a lane change. Therefore, the following part of this paper moves on to derive the reasonably foreseeable parameter ranges of the cutting-out vehicle. For detailed information on how to calculate the reasonably foreseeable parameter ranges, we refer to Appendix-D and our previous research [45].

Similar to the cut-in and acceleration scenarios, the risk acceptance threshold of the cut-out parameter ranges is derived based on a risk assessment of the Japanese high-speed trains (Shinkansen) conducted at the design stage with accident probability occurrences not exceeding 10^{-6} times/year [27]. With the assumption that professional drivers perform an average of 8 hours a day of highway driving for 240 days a year, they would encounter approximately 3,867 lane changes by the car ahead per year. By converting the distributions provided in the previous sections to annual exposure probability, reasonably foreseeable parameter ranges of the cut-out can be expressed in Figure 10. For example, the result indicates that the driver on a Japanese highway encounters a cut-out with a relative speed of 20 km/h from 30 m or closer less than 10^{-6} times per year. The overall results suggest that there should be no risk of a collision between the following vehicle (e.i., AVs) and the preceding vehicle when the time headway between the AVs and the cutting-out vehicle is equal to or more than 2 s. However, this value can differ based on environmental factors (e.g., weather and light conditions), social factors (e.g., the driving style and risk acceptance threshold), and regional factors (roadway design, speed limits, and traffic regulations).

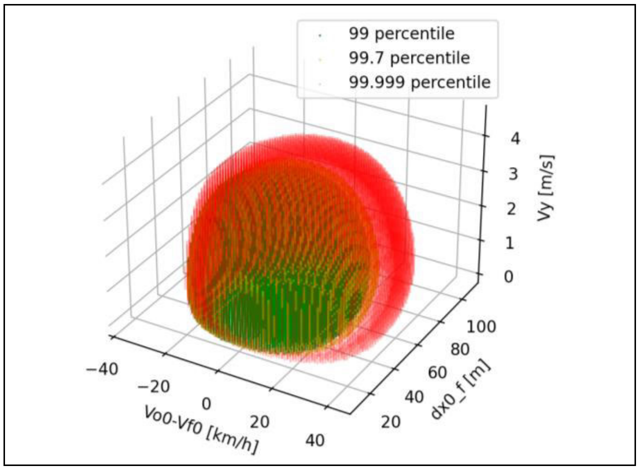

FIGURE 10. Derivation of reasonably foreseeable parameter ranges for the cut-out scenarios based on risk exposure that a driver may encounter on Japanese highways.

IV. CONCLUSION

This study establishes a scenario space with sufficient information about traffic events so that the ADS safety assessment can be conducted with a high confidence level. The scenario space is characterized by types of events and a range of values for the chosen modeling variables (speeds and distances). Given the event types, the main task is to find the ranges so that the vast majority of possible events of that type are considered in the scenario space.

We used real-world extracted cut-out scenarios to determine a reasonably foreseeable parameter range for scenario-based assessment of ADSs based on relevant exposure and risk acceptance as a reference for safe driving behavior during car following. The extracted scenarios are parameterized based on vehicle kinematics and correlations among the interacting vehicles and described in Poisson distributions. The results provide a parameter range within which the automated driving functions must operate safely and at least be as safe as non-automated driving, respecting the specified scenarios. It is demonstrated that the behavior of ADS shall not bring inconvenience, cause danger, or involve a crash within the reasonably foreseeable parameter range during car-following and cut-out scenarios. Such parameter range is essential for conducting the ADS assessment.

However, the generalizability of the proposed parameter space is subject to the driving behavior in the region from which the data were collected. The authors suggest repeating the study considering real data collected worldwide to develop a more comprehensive and region-neutral dimensional situation space where ADS can operate safely. We plan to extend the findings utilizing additional simulations and field experiments to validate and correct the proposed range.

APPENDIX

APPENDIX A
SAKURA METHODOLOGY GENERAL FRAMEWORK

APPENDIX B
TYPE OF HIGHWAYS IN JAPAN

APPENDIX C
DETAILS OF THE PARAMETER RANGE CORRELATION PROCESS AND DATA SOURCE AND ANALYSIS

APPENDIX D
COMBINING CUT-OUT PART-R AND PART-F FOR THE DERIVATION OF REASONABLY FORESEEABLE PARAMETER RANGES

Files are uploaded to Figshare:
https://figshare.com/s/6a51a354d4fb33310464

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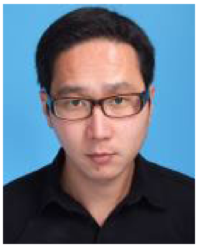
H. MUSLIM received the M.Sc. and Ph.D. degrees (cum laude) in engineering from the University of Tsukuba, Japan, in 2017 and 2020, respectively. He is currently with the Autonomous Driving Research Division, Japan Automobile Research Institute. He is also with the Faculty of Engineering, Information, and Systems, University of Tsukuba. His research interests include vehicle safety design, human factors in automotive automation, active safety systems, and human centered design.

S. ENDO received the B.S. and M.Sc. degrees in informatics and engineering from The University of Electro-Communications, Tokyo, Japan, in 2019 and 2021, respectively. He is currently an Assistant Researcher with the Japan Automobile Research Institute. His research interests include multidimensional time series data analysis and cognitive science.



H. IMANAGA received the M.Sc. and Ph.D. degrees in engineering from Chuo University, Japan, in 2001 and 2004, respectively. He is currently a Senior Researcher with the Japan Automobile Research Institute. His research interests include accident and near-crash analysis based on drive video recorder data, automated driving safety assessment methodology, and evaluation of safety features.

S. KITAJIMA received the M.Sc. degree in engineering from the Musashi Institute of Technology, Japan, and the Ph.D. degree in engineering from the University of Tsukuba, Japan. He is currently a Senior Researcher with the Japan Automobile Research Institute. His research interests include human error analysis based on drive video recorder data, automated driving safety assessment methodology, and multi-agent traffic simulation development.

N. UCHIDA was born in Japan, in 1968. He received the M.Sc. degree in experimental psychology from Hiroshima University, Japan, in 1994, and the Ph.D. degree in risk engineering from the University of Tsukuba, Japan, in 2014. Since 1994, he has been a Researcher with the Japan Automobile Research Institute. His research interests include the understanding of accident causation mechanisms and the simulation of common accident scenarios for developing better preventive measures.

E. KITAHARA received the bachelor's degree in control system engineering and the Ph.M. degree in mechanical engineering and science from Saitama University. Since 1997, he has been with Nissan Motor Company Ltd., where he is in charge of the development team for the chassis control system and AD/ADAS. Currently, he is the Manager of the CAE/Test Engineering Division. He joined JAMA AD Safety Assurance WG, in 2018.

K. OZAWA received the bachelor's degree in electronics from Tokyo Denki University, Japan, in 1990. Since 1990, he has been with Honda Motor Corporation, where he has been in charge of the development team for electric/hybrid vehicles. Since 2016, he has been developing simulation environments and processes of automated drive. He is currently the Vice-Chair of JAMA AD Safety Assurance WG. He is one of the experts related the international standards and regulations.

H. SATO graduated from Nihon University, in 1994. He is currently in charge of developing the safety assurance process and the method of automated driving with Toyota Motor Corporation. In 2018, he joined the Automated Driving Safety Evaluation Working Group, JAMA, where he promoted the construction of safety evaluation processes and methods using a scenario-based approach. Since 2022, he has been the Chair of the Automated Driving Safety Assurance Committee, JAMA.

H. NAKAMURA received the M.Sc. and Ph.D. degrees in engineering from the University of Tokyo, Japan, in 2010 and 2013, respectively. He is currently a Researcher with the Japan Automobile Research Institute. He is also a Machinery Condition Analyst (Vibration) Category 2 in accordance with ISO18436-2. His research interests include vehicle dynamics, noise and vibration, human factors in automotive automation, and human centered design.