Logical Scenarios Parameterization for Automated Vehicle Safety Assessment: Comparison of Deceleration and Cut-In Scenarios From Japanese and German Highways

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ABSTRACT This study compares real-traffic deceleration and cut-in scenarios, which were established as critical to automated vehicles (AVs) safety, between Japanese and German highway trajectory datasets. Both scenarios were extracted from two different traffic data previously collected in Japan with both instrumented vehicles and fixed cameras over highways (SAKURA dataset) and in Germany with drones (highD dataset). Five vehicle kinematic variables (lateral and longitudinal distances, velocities, and accelerations) were used to parameterize both scenarios and compared them between datasets using correlation and intersection objective measures and safety metrics: Time-to-Collision and Time Headway. Despite the differences in the rule of the road (e.g. speed limits left- and right-hand traffic), road design, and data sources between the two countries, data comparison results revealed significant correlations and intersections of parameters distribution for both scenarios. The Time-to-Collision significantly overlapped between countries for both scenarios. However, differences in the Time Headway indicate that the safety distance varied across both countries, suggesting that safety assessment methodologies need to be tailored to different environments and regions to ensure safety. These results highlight the potential to develop safety indicators applicable at the international level and warrant further data collection and comparative studies that support the development of harmonized, widely applicable, and region-neutral AVs safety assessment methodologies.

INDEX TERMS Scenario-based approach, cut-in, deceleration, international traffic datasets, parameterization, safety metric, automated driving systems, highway.

I. INTRODUCTION
Automated driving systems (ADSs) safety has been a prevalent field of research and development within the automotive industry over the last decade and the related technologies are starting to penetrate the market. Verification and validation of ADSs are crucial to ensure that automated vehicles (AVs) are safe to operate on public roads worldwide. For this reason, AVs safety assessment methodologies are being developed. Such development is illustrated by several international standardizations (ISO/TC22/SC33/WG9) and regulatory (ECE/TRANS/WP.29/2020/81) initiatives that are currently consolidating methodologies and processes to evaluate ADSs safety [1], [2]. The majority of these initiatives are adopting a scenario-based safety assessment approach [3], [4]. The adopted scenario-based approach depends heavily on real traffic and naturalistic driving data to extract and generate test scenarios for scenario-based approval of AVs. This research examines the emerging role of the data source in finding the set of representative scenarios by comparing scenarios extracted from two datasets collected from Japanese and German highways using different tools.
A. SCENARIO-BASED SAFETY ASSESSMENT

Scenario-based testing is a well-established approach commonly applied to evaluate the safety of complex systems in domains like aviation and nuclear power plants [5], [6]. Recently, several large scale research projects in the road transportation sector for the specific ADS safety assessment have adopted and developed this approach, such as PEGASUS and its successor VVMethoden in Germany, [4], [7], MOOVE in France [8], StreetWise in the Netherlands [9] and SAKURA in Japan [3]. In addition, the UN R157 Automated Lane-Keeping System (ALKS) Regulation [2], which is the first-ever international Regulation for Level 3 ADSs has partially adopted the scenario-based approach.

In the scenario-based safety assessment process, relevant traffic situations are assigned to scenarios [10]. These scenarios may have different scopes depending on the objective of the test. In order to cover certain sensor phenomena, scenario catalogs can be generated with various environmental factors. Other catalogs may focus on the behavior of surrounding objects in relation to the vehicle under observation (subject vehicle) [11]. Nevertheless, scenario-based testing aims to generate limited test cases based on specific scenario parameterization and appropriate pass/fail criteria. The test case generation must create representative and safety-critical test cases of a scenario to evaluate the behavior of the subject vehicle in the limit range [12].

Due to the broad use of scenario-based testing, it is crucial to have a common understanding of the term “scenario”. The term “scenario” generally refers to the abstraction and general description of a temporal and spatial traffic constellation [13]. ISO/DIS 34501 defined test scenarios for ADSs as a sequence of the scenes integrated with the ADSs and their interactions with the surroundings in the process of performing a specific dynamic driving task [14]. Several different abstraction levels for scenario description are distinguished. [1] proposed to separate between functional, logical and concrete scenarios. Functional scenarios are a representation of scenarios using either non-formal natural language or a predefined machine-readable scheme. A logical scenario consists of a state-space description for deriving technical requirements with valid and non-valid value ranges. It is a model of the time sequence of scenes whose parameters are defined as ranges [13].

To account for an uncertain behavior of the subject vehicle, the logical scenario may not further specify the vehicle behavior from a defined point in time. Concrete scenarios represent a combination of values for a logical scenario that can be utilized in a simulation or on a test track to generate test cases. In consistence with the logical scenarios, the specific behavior of the vehicle under test is not further specified in concrete scenarios. Replay scenarios are not regarded unless the behavior of all road users is predetermined based on real-world data [13]. Accordingly, these scenarios are not represented by a parameterized combination of logical scenarios. Replay scenarios use the unchanged data from the real world and are a particular reduced form of a concrete scenario, as there is no abstraction to a model.

B. SCENARIO IDENTIFICATION

Two complementary approaches are predominantly used to identify scenarios: knowledge-based and data-driven approaches. Knowledge-based approaches implement a knowledge representation in an ontology and generate a scenario catalog based on the ontology [15]. The completeness of the scenario catalog can thus be considered using ontology. However, this method does not consider the practical implementations of scenarios and might create physically impossible scenarios.

Data-driven approaches leverage the iterative improvement of the catalog by collecting new data [4] and are used to create extensive and plausible scenario catalogs. While most data-driven approaches attempt to identify predefined logical scenarios, some approaches utilize machine-learning methods. For this purpose, unsupervised machine learning is used to identify scenario parameters without previously defined knowledge [16], [17]. However, when applying machine learning, the completeness of the scenario catalog depends on the quality and completeness of the dataset. Furthermore, an additional effort is required to assign a meaning to the individual scenarios, for example, to assess the relevance of the scenarios for the safety assessment.

The derived scenario database is a key enabler for understanding scenarios in traffic and the derivation of test cases [18]. With the help of this, concrete scenarios can either be recognized and parameterized from field data or generated artificially. The recognition of scenarios in field data has the advantage that the extracted scenarios are always valid with the limitation of the measurement and scenario abstraction accuracy. Thus, several approaches have been established to gather real-world traffic data, which is relevant for verifying the approaches and the parameterization of the scenario spaces.

C. TRAFFIC DATA ANALYSIS

The most common data sources for ADS safety assessment include driving tests, naturalistic driving studies (NDS) [19], FOTs [20], and pilot studies [21], which are used to record the vehicles’ environment and onboard data. More recent researches observe traffic through infrastructure sensors installed at dedicated roadside masts [22] or street lights, permanently measuring a particular road segment. However, those measurement methods come with various drawbacks. Due to the mounting position, static or dynamic objects like a passing truck may occlude objects. Furthermore, road users are often distracted by those sensors and may not behave naturally, resulting in extra attention or feeling disturbed in privacy. Chen et al. propose a method, which uses an aerial perspective by utilizing camera-equipped unmanned aerial vehicles (UAV) to measure data for safety assessment at intersections [23]. The “bird’s eye view” allows keeping track of exact longitudinal and lateral positions of objects.
Moreover, occlusions between road users are resolved to a large extend, and all road users have an uninfluenced behavior because they do not notice the UAV being in high altitudes [24]. Nevertheless, the method currently lacks in providing data in high winds or during rainy conditions.

D. RESEARCH JUSTIFICATION AND AIMS

One of the scenario-based safety assessments’ primary goals is to test case generation based on the scenarios’ parameterization and defined pass-fail criteria of the key performance indicators. The derived test cases are generated from real-world driving data or validated artificial data. Real-world driving data is recorded in different operating domains and countries to generate logical and then concrete scenarios with a suitable parameterization based on such driving data.

Representative scenario parameterization is still an unsolved problem and is becoming more and more essential. A large amount of data is required to generate valid test cases that reflect real-world situations; hence, the possibility of combining international datasets would be challenging but helpful. International efforts to collect data across countries, such as L3Pilot [21], and international databases, such as Safety Pool [25], aim to store scenarios from different countries. Although various analyses of traffic data have been conducted in the literature, there is still a lack of comparison of real-world driving data within the same driving domain but in different regions or countries. In [26], pre-crash scenarios are extracted from the initiative for the global harmonization of accident data (IGLAD) and clustered to specific domains to compare different regions. Though the data is not focusing on highways [27] presents a small comparison for the parameters of a cut-in scenario for data from Germany and Japan. Nevertheless, the number of recognized scenarios is low, and only two parameters are used in the comparison. A detailed comparison of car-following behavior in terms of the safety indicators is presented in [28] using the metrics time headway (THW), gap distance, and time-to-collision (TTC) to compare data from Sweden and China.

From one perspective, the THW is observed to be constant over specific speed ranges and is, therefore, less sensitive to speed variations during car following [29]. Conversely, the TTC value indicates the actual occurrence of a collision, and therefore, the braking initiation of the driver and control are affected by the TTC value [30]. While the THW can inform the design of Adaptive Cruise Control (ACC) systems, the TTC can be used to inform the design of Automatic Braking Systems (ABS). Both ACC and ABS are critical for ADS safety.

Another open question that arises with the new international regulations on ALKS [2], which only specifies boundary conditions for the scenarios’ parameters, is whether the same parameterization can be used for different regions and countries. It is not proven whether different datasets collected from different environments and traffic systems can be combined or whether each dataset needs to be analyzed independently. This paper aims to compare two highway datasets from Japan and Germany to parameterize two logical scenarios, deceleration and cut-in, to demonstrate the potential development of harmonized, widely applicable, and region-neutral AVs safety assessment methodologies. Therefore, similarities and differences in the explored data are highlighted and explained. The influence on the safety metrics TTC and THW is investigated. The outcomes of this study can be used to validate the applicability of the SAKURA approach for real-traffic data processing [3] to different data sources.

II. METHODOLOGY

This paper analyzes two pre-existing traffic datasets recorded in Japan and Germany to extract and compare deceleration and cut-in scenario parameters. A consistent methodology was applied for the processing of these datasets, shown in Figure 1. First, data reduction was applied. Within this step, the same limitations were implemented to ensure comparable data. The same scenario extraction and parameterization approach developed by SAKURA methodology [3] was applied to detect the two scenarios in this step. After detecting the logical scenario, the parameter set of each scenario is extracted and stored as a concrete scenario. The final step included comparing the parameters and safety metrics of each scenario across the datasets to find similarities and...
correlations as well as differences that can affect the safety assessment methodology in different countries.

A. DATA SOURCES
To compare the results of the scenario extraction between the two data sets, the introduction of each dataset is made by providing a rough overview of their general information such as duration of recording, number of captured vehicles, and the location the data has been recorded.

1) SAKURA DATA
Three sources of data collection between 2017 and 2020 were combined to set up the SAKURA data: In Source-1 professional drivers performed more than 1,047 hours of recorded driving on highways with instrumented vehicles. Source-2 recorded real-world traffic data with fixed cameras over highways. Finally, Source-3 incorporates regular drivers, who performed 350 hours of recorded driving on expressways using instrumented vehicles. Detailed descriptions concerning these datasets are described in [31]

2) highD DATA
The highD dataset includes post-processed trajectories of 110,000 vehicles, including cars and trucks extracted from unmanned aerial vehicle (UAV) video recordings at German highways around Cologne during 2017 and 2018. At six different locations, 60 recordings were made with an average length of 17 minutes (16.5 h in total) covering a road segment of about 420 m in length. Each vehicle is visible for a median duration of 13.4 s. From these recordings, vehicles were extracted automatically using computer vision algorithms and manually annotated road markings. More details can be found in [24]

B. DATA COMPARISON
In order to substantiate the later described similarities and differences, the datasets are compared by utilizing the SixLayer Model (6LM) to structure parameters used to define logical scenarios [32] To provide insight to the comparison of the two datasets, we presented general, technical, and digital information in Table 1.

| Parameter Information | Scenario Specific Parameterization |
|-----------------------|-----------------------------------|
| **Parameter**          | **Abbr.** | **Deceleration** | **Cut-In** |
| Subject Initial velocity | $v_{in}$ | Start value | Start value |
| Initial relative velocity | $v_{rel} = v_{in} - v_{de}$ | Start value | Start value |
| Lateral velocity | $v_{l}$ | Maximum value | - |
| Deceleration | $a$ | Maximum value | - |
| Jerk | $j$ | Average value* | - |
| Initial distance | Long. | $d_{in}$ | Start value | Start value |
| Initial distance | Lateral | $d_{l}$ | - | Start value |

* The value is calculated from the beginning of the scenario until the deceleration reaches its maximum value.

above and under the local roads in some of the largest urban areas of Japan. For interstate highways, the legal speed limit is usually 100 km/h; however most passenger cars tend to drive at speeds between 100 and 120 km/h [34]. For intra-city highways, the speed limit is usually 80 km/h [35]. Traffic on these highways is usually denser than on interstate highways. Thus, the traffic may move significantly slower than the set speed limit. In highD, all locations are recorded for the same type of highway with an advisory speed limit of 130 km/h.

While highD includes a total of 2.5 km of diverse highway sections the SAKURA data comprises a remarkably greater distance on highways due to the use of measurement vehicles. Thus, there are more diverse highway sections included in the data.

In the highD and SAKURA datasets two and three lanes per direction are apparent in the data. Lanes in highD each span a width of 3.5 to 3.7 m [36] compared to 3.2 to 3.5 m in Japan [31]

2) LAYER 2 (L2) - ROADSIDE STRUCTURES
In both datasets, the direction of the highway is constructively separated. Additional information on L2 is excluded since it does not play a significant role.

3) LAYER 3 (L3) - TEMPORARY MODIFICATIONS OF L1 AND L2
Neither locations with temporary modifications of L1 and L2 were recorded nor processed to detect the two scenarios in highD. Thus, no scenarios with roadwork signs or temporary markings are included in the datasets. However, the SAKURA data comprise construction zones for both scenarios.

4) LAYER 4 (L4) - DYNAMIC OBJECTS
Different types of objects such as cars or trucks are detected in highD. In contrast to highD, the driving data from Japan contains both scenarios driven by professional and regular drivers.
vehicle. During a cut-in scenario the subject vehicle remains on the same lane while the challenging vehicle starts to decelerate in front of the subject vehicle. The subject vehicle remains on the same lane while the challenging vehicle changes its lane from an adjacent lane to the lane of the ego vehicle. These two scenarios account for more than 43% of all crashes where the light-duty vehicle makes the critical action [37]. In addition, these two scenarios are included in the newly released ALKS Regulation [8].

With regards to the SAKURA approach, logical scenarios are described with a specific parameter set. The deceleration scenario starts when the acceleration of the decelerator vehicle starts to take a negative value from 0 m/s² and ends when the acceleration of the decelerator vehicle returns to 0 m/s². While the deceleration scenario focuses on the longitudinal description, the cut-in scenario focuses on the lateral description between the ego and the challenging vehicle. The cut-in scenario starts when the lateral velocity value of the cut-in vehicle increases from 0 m/s (Positive value to the right of the subject vehicle) and ends when the lateral velocity of the cut-in vehicle returns to 0 m/s.

Table 2 presents a detailed list of all parameters used to describe logical scenarios. In total, five parameters were selected for each logical scenario to be extracted from the time-series data. Apart from the lateral velocity and the jerk, all other parameters consider the start value during the observed scenario. The lateral velocity uses the maximum value from the start to the end of the cut-in scenario as a representative value. The reasoning behind using the maximum value is to include high-speed cut-ins that are considered more dangerous in the scenario ranges. The jerk value is a mean value considering the time between the start of the scenario and the maximum deceleration during the deceleration scenario.

E. EXTRATION OF SCENARIOS FROM REAL-WORLD DATA
To identify the two proposed scenarios in real-world data, we applied specific extraction conditions as criteria for detecting each scenario. While the duration of the cut-in scenarios was between 2 and 16 s, the duration of deceleration scenarios was larger than 0 s and lower than 120 s. During the duration of each scenario, the subject vehicle was traveling straight forward without changing lanes or accelerating when encountering a cut-in or a decelerating vehicle. The considered lateral speed of the cut-in vehicle was set to positive values equal or lower than 5 m/s, considering road-to-tire grip limits in lateral motion.

A deceleration scenario was considered when a reduction of the headway distance between vehicles was caused by the deceleration of a preceding vehicle and not by the acceleration of the subject vehicle. The initial longitudinal velocity of the decelerating vehicle could either be lower, greater than or equal to the initial longitudinal speed of the subject vehicle. The relative longitudinal distance may decrease, increase or remain unchanged during the scenario. Furthermore, no other vehicle must be present between the subject and the challenging vehicles. During the scenario, the acceleration of the other vehicle must be continuously negative (e.g. a constant breaking action) while remaining on the same lane.
### TABLE 2. Parameters used for the scenario parameterization.

| Attributes | Japan (SAKURA) | Germany (highD) |
|------------|----------------|-----------------|
| **Source-1** | Instrumented Vehicle | Unmanned Aerial Vehicle (UAV) |
| Main purpose of data acquisition | To collect driving behaviors of vehicles travelling on the expressway (within the instrumented vehicle’s vicinity) | To understand regular driver behavior on the expressway (driving operations, visual actions, safety precautions when anticipating danger, etc.) |
| Data gathering period | Nov. 2018 to Mar. 2020 | Jan. 2017 to Mar. 2018 |
| Data coverage areas | Metropolitan express way (Tomel/SHIN-TOMELI Expressway and Shimizu JCT-Tokyo IC) | Six locations in Germany around Cologne at Autobahn (A4, A46 and A61) |
| Number of lanes per direction | 1-4 | 1-4 |
| Road side construction | No | No |
| Traffic condition | Varying from free flowing to traffic jam | Varying from free flowing to traffic jam |
| Weather condition | Sunny/cloudy/rainy/windy, no precipitation | Sunny/cloudy, no precipitation |
| Data volume (hours) | 2,968 | 31 |
| Lidar | 360° (from 9 units) unavailable | 360° (Front: 80° x 3, Side: 120° x 2, Rear: 120°) 84° 4K camera |
| Camera | 360° (from 6-10 units) unavailable | 2-4 units, Bird’s-eye view, 360° (from building rooftops or overpasses) |
| Mobileye | Available | Available |
| Information processing | Vehicles and trajectory data are captured and extracted based on the Lidar cloud point data. | Vehicles and trajectory data are captured and extracted based on camera data. |
| Precisions | Target trajectory accuracy (Lateral: 10 cm; Longitudinal: 50 cm) Depends on data state | Unknown (Depends on commercialization level, and other development accuracy) |
| Recording frequency (frames per second (fps) or Hz) | Total: 10 fps Image: 30 fps LIDAR: 10 Hz IMU: 10 Hz MOBEYE: 10.64-10.87 fps | Total: 10 fps Image: 30 fps IMU: 10 Hz MOBEYE: 12.5-16.67 fps |
| Subject Vehicle Position | GNSS/IMU | Camera (4K) |
| Distance between vehicles | From Lidar data (point cloud data) | Camera (4K) |
| Surrounding Vehicle Acceleration | From Lidar data (point cloud data) | Mobileye |
| Measurement data | Road information | Surrounded Vehicles Position | Mobileye |
| measurement range | -70 m in front and behind of subject vehicle -50 m on either side of subject vehicle The range depends on the weather condition | -70 m in front and behind of subject vehicle Sensor range unknown on either side of subject vehicle | -400-420 m of road section |
its lane in front of the subject vehicle. Thereby, the scenario starts as soon as the acceleration of the front vehicle decreases below zero and ends once the vehicle reaches a positive acceleration. However, certain thresholds below and above zero are applied to account for the data volatility and noise.

The cut-in scenario was extracted under conditions that the longitudinal speed of the subject vehicle is lower, equal or greater than the longitudinal speed of the challenging vehicle. To extract a cut-in scenario the lateral velocity of the challenging vehicle must remain positive/ negative. Hence, scenarios with swerving of other objects are excluded. Notwithstanding, the challenging vehicle must enter the lane of the subject vehicle from an adjacent lane in a way that no other vehicle is between both vehicles. With these extraction conditions the cut-in starts as soon as the lateral velocity value of the challenging vehicle changes from zero. A positive lateral velocity represents a cut-in from the right, while negative values describe cut-ins from the left. As an additional limitation, it is ensured that the challenging vehicle did not cross the lane markings before the starting point. The closest distance between the subject and challenging vehicles is chosen to calculate the lateral distance.

III. RESULTS

After applying the above-defined extraction conditions, the number of scenarios shown in Table 3 was identified. When evaluating and comparing the data, the parameters defined for both logical scenarios are first compared in a histogram including a kernel density estimation. The histogram generally shows the skewness and range of the data. Following this step, two parameters are used to quantify the similarity of the histograms. A Pearson correlation is used to identify how strongly a parameter from one dataset correlates with the same parameter from the other dataset. For each correlation value, the corresponding p-value is given in relation to three thresholds (see Figure 3 and Figure 4).

The intersection of the histograms is used to quantify the overlap. Both the calculation of the Pearson correlation and the intersection consider only those scenarios from Germany that are within the sensor range of the SAKURA data. Thus, highD scenarios are considered only when they occur within a distance smaller than 70 m to prevent distortion of the values and enable the comparison of the datasets. Furthermore, the range between the 2.5% and 97.5% quantile is considered to give less weight to extreme outliers.

### TABLE 3. Number of scenarios in total after the application of the extraction conditions.

| Scenario  | SAKURA | highD |
|-----------|--------|-------|
| Deceleration | 8822   | 26846 |
| Cut-in     | 1561   | 1017  |
A. DECELERATION SCENARIO

In this chapter we compare the datasets’ characteristics with the five parameters of the deceleration scenario (see Figure 3), starting with the initial speed of the subject vehicle (see Figure 3a). A noticeable shift of 40 km/h for the initial velocity of the subject vehicle is seen between both datasets based on the datasets’ peak values and the low intersection (64%). While the SAKURA data ranges between 0 and 104 km/h with its peak value around 75 km/h, highD shows its maximum relative frequency at a velocity around 115 km/h. The maximum velocity in highD is 186 km/h. However, few scenarios with such high velocity are present in highD. Both data contain lowspeed scenarios, but, compared to the flattened curve in highD, the relative frequency in the Japanese data increases for velocities smaller than 40 km/h. Hence, there is a slightly pronounced correlation between the datasets (44%).

Despite the remarkable initial speed shift of the subject vehicle, the relative initial speeds between the subject vehicle and challenging vehicle have a strong overlap with 84% intersection (see Figure 3b). A correlation of 97% further supports the substantial overlap. The German data is nearly symmetrically shaped around 0 with a spread between −11 and 12 km/h accounting for 90% of the data. The symmetry is less pronounced in Japan since the 90% data spread is between −20 and 8 km/h. Thus, this dataset tends to include more scenarios in which the relative velocity is negative. In those scenarios, the velocity of the challenging vehicle is greater than the velocity of the subject vehicle resulting in an increasing distance if the front vehicle would not break. In line with the data from Japan, a significant number of deceleration scenarios occurred in highD in a range of up to 70 m, the maximum sensor range of the measurement vehicle (see Figure 3c). With around 25 km/h, the peak value in highD is half as high as the maximum peak value in Japan. However, highD contains a noticeable number of scenarios above 70 m with few initial longitudinal distances greater than 200 m. Although the longitudinal distance in highD dataset was limited to the maximum sensor range in SAKURA, the results indicated an intersection of 79% and a correlation of −5%.

Apart from the peak value for prolonged decelerations, the relative frequency of the maximum decelerations is less congruent, which is also reflected in the intersection value of 66% (see Figure 3d). highD comprises weaker maximum decelerations since 95% of the scenarios are characterized by a deceleration weaker than −0.8 m/s² compared to −1.6 m/s² in the SAKURA data. Nevertheless, both datasets comprise scenarios with decelerations stronger than −5 m/s².

The mean jerk remarkably accumulates for small values in both datasets (see Figure 3e). The peak values are close to zero. Nonetheless, the 2.5% quantile in Japan is smaller (−3.3 m/s³) than in highD (−0.33 m/s³). This
difference is reflected in the less pronounced correlation (68%) and intersection (53%). Despite the significant amount of collected data, the spread of the mean jerk is remarkably high. Thus, the figure is trimmed to the relevant part.

**B. CUT-IN SCENARIO**

Figure 4 compares the cut-in scenario parameters between the two datasets. Similar to the deceleration scenario, there is a clear speed shift for the initial velocity speed of the subject vehicle (see Figure 4a). While the peak value in Japan is around 95 km/h, highD has its peak value at 115 km/h, which is similar to the deceleration scenario. In contrast to the deceleration scenario, only a few low-speed cut-in scenarios are comprised in both datasets. The subject vehicle velocity ranges in Japan from 21 to 138 km/h, above the maximum speed limit in Japan, respectively 15 to 182 km/h in highD. Thus, the correlation is less distinct (9%). However, in contrast to the deceleration scenarios the subject vehicle velocity overlaps more substantially (69%).

Except for the remarkable peak value in the SAKURA data at around −8 km/h, the relative frequency of the initial relative speed is similar for both datasets (see Figure 4b). Such similarity is supported by the significant intersection (82%). Similar to the deceleration scenario, there are more positive relative initial speeds in highD. In addition, the spread of the relative frequency of the highD is greater since 90% of the data is located between −25 and 30 km/h compared to −19 and 24 km/h in Japan. However, the correlation is less distinct due to the SAKURA data peak values (52%).

While the relative frequency of the initial longitudinal distance in highD is constantly decreasing between 0 and 210 m, the SAKURA data incorporates two peak values at distances nearly 17 m and 65 m with a sudden decrease at 70 m (see Figure 4c). In addition, the initial distance for the cut-in scenario in Japan is at least 8.3 m. These findings result in a small correlation (16%) but a greater intersection (70%) due to the reduction of the German data.

Because the data is captured on highways measuring cut-in vehicles performing cut-in maneuvers from left to right was required. Thus, the initial lateral distance includes positive and negative values in both datasets (see Figure 4d). The lateral distance of the cut-in in Japan is nearly equally distributed for positive and negative values in terms of the relative frequency of the peak value. However, there is a slight trend towards positive values where the location is less symmetrical since the peak value for cut-ins from the left is 1.5 m compared to −2 m for cut-ins from the right. This effect is counteractive in Germany because the peak value is 2 m for cut-ins from the left and −1.8 m from the right. However, the frequency is less equally distributed since more cut-ins occurred from the right side. The disparity in the lateral distances mainly caused by the difference in cut-in direction between the two traffic systems weakened the correlation between both datasets (61%).

The symmetrical form of the lateral velocity was similar to the lateral distance (see Figure 4e). The peak values in Japan occur with almost the same relative frequency but with a shift of its location (−3.5 km/h vs. 3.2 km/h). In highD, the peak values’ frequencies are less equally distributed because the data contains more cut-ins from the right. Though, the absolute values of the lateral velocities from left and right are closer together in highD (−3.5 km/h vs. 3.6 km/h). Despite the shift for the lateral distances, the data for the lateral velocity is even more correlated (92%) and intersected (86%).

**IV. DISCUSSION**

An initial objective of this study was to identify the relationship between two real-traffic highway datasets obtained via different measurement methods from two countries with different traffic systems. The aim of presenting similarities and differences between the two datasets was to develop safety metrics applicable at the international level and warrant further data collection and comparative studies that support the development of harmonized, widely applicable, and region-neutral AD safety assurance methodologies. It is interesting to note that in both examined scenarios of this study, four of the five deceleration scenario parameters (\(v_{0}, v_{d}, v_{d0}, a_{x}, \) and \(a_{y0}\)) and three of the five cut-in scenario parameters (\(v_{0}, v_{d}, d_{0}, \) and \(v_{y}\)) are significantly correlated between countries. Differences between Japanese and German datasets may have been influenced by the traffic system (e.g., speed limit), driver behavior (e.g., relative distance), and driving habits (e.g., maneuvering speed).

Although the relative longitudinal velocity indicates a significant correlation and overlap between the two datasets for the deceleration scenarios, the relative longitudinal
distance revealed no significant correlation. A possible explanation for this might be related to driving behavior and driver perception of risk. For the cut-in scenarios, although the lateral distance and velocity indicate significant correlations between the datasets, the lateral distance revealed differences when comparing the direction of the maneuvers. For example, the peak value for cut-in from the left is 1.5 m in the Japanese dataset compared to 2 m in the German dataset, while the peak value for cut-in from the right is −2 m in the Japanese dataset compared to −1.8 m in the German dataset. These differences might be partially caused by the different traffic systems (i.e., left-hand traffic in Japan and right-hand traffic in Germany).

To explain the influence of the similarities and differences of the parameter on safety metrics for safety assurance, we discussed the highlighted findings in terms of the basic safety metrics TTC and THW

A. DECELERATION SCENARIO

The calculations of the TTC and THW for SAKURA and truncated highD datasets are shown in Figure 5, accounting for the measurement methods’ different maximum line of sight. The measured TTC values are approximately congruent with an intersection of 93% and a correlation of 91%, as shown in Figure 5a. Such high percentages are valid not only for TTC values close to zero but also for greater values, where the absolute relative velocity between the object and subject vehicle is relatively low. The values broadly overlap, despite the clear shift for the initial speed of the subject caused by the different legislation in the countries. This overlap is mainly due to the similarity of the scenarios with respect to the relative initial speed. While the considered parts of highD only include sections with an advisory speed limit of 130 km/h, the SAKURA dataset contains measurements with different speed limits depending on the driven highway. Thus, peak values around these speed limits are observed. The second peak value for low subject vehicle initial speeds in the SAKURA data is induced by the data collection method since denser traffic was recorded on intracity highways. In highD, hardly any congestion situations are available, whereas different traffic flows are observed. Therefore, highD shows another peak value for the subject vehicle’s initial speed around 90 km/h.

The THW shows a shift towards higher values for the SAKURA data, but the shape of THW is congruent in a direct comparison of both datasets (see Figure 5b). Although the relative speed in Japan and Germany is similar, the comparison of THW shows that drivers in Germany tend to maintain a closer distance to the vehicle in front and thus have less time to react. This is in line with the higher frequency of lower initial velocities of the subject vehicle and the higher frequency of distances between 30 and 60 m in Japan.

The increased relative frequency of the initial distances between 0 to 60 m in the SAKURA dataset is caused by two factors. First, the limited range of the vehicle’s sensors induces the data cut-off after 60 m. If the highD data is truncated at 60 m, the relative frequency in the lower range increases and the histograms overlap even more (see Figure 5). Second, the SAKURA data has pronounced relative frequency of low distances results from the increased number of comprised traffic congestion scenarios. In those scenarios the longitudinal distance is lower than in high-speed scenarios.

Since some scenarios in Japan are recorded during traffic congestions, a peak value for decelerations close to 0 is indicated due to the stop-and-go traffic that often prevails in denser traffic. This observation is supported by the substantial accumulation of low mean jerk values (see Figure 6). However, the calculated values for the mean jerk should be evaluated with caution, as the spread is large and most of the values are located in the same small range. In addition, low decelerations do not only occur in low-speed ranges since highD recorded a noticeable number of low decelerations as well.

B. CUT-IN SCENARIO

In line with the findings for the deceleration scenario, there is substantial overlap for positive TTC values across both datasets despite the shift in subject vehicle initial speed (see Figure 6a). The intersection (82%) and the correlation (88%) are highly rated. However, there is a slight trend in highD to comprise a more significant number of lower TTC values between 0 and 10 s. This trend is similar to the decreased distance behavior of the drivers in Germany.

Like the TTC, the shape of the THW is similar to some extent in both datasets. There is an offset of around 0.5 s within the Japanese data toward larger THWs (see Figure 6b). Thus, the safety distance in Germany is typically lower than...
in Japan. However, the following mechanism needs to be recognized. The parameterization of the cut-in starts as soon as the lateral movement of the challenger vehicle begins. The highD data show that the cut-in often starts early at high speeds and low (negative) relative velocities, resulting in a small longitudinal distance between the subject vehicle and challenger vehicle. Thus, the cut-in usually begins sooner in scenarios in which the challenging vehicle travels much faster than the subject vehicle. However, due to the sensor setup used for the Japanese measurement vehicles, there are certain sensor visibility limitations for objects close to the vehicle, so they are not always fully detected. These scenarios were previously removed from the dataset, as only complete scenarios are considered. This effect is also visible for the initial longitudinal distance because only distances from 8 m upwards are covered in the Japanese data. In addition, this impact is further strengthened by the speed shift between Japan and Germany.

The different lane widths in Japan and Germany are to some extend apparent in the analysis of the initial lateral distance. Due to the right-hand driving rule in Germany, the highD data accumulate with negative values. Thus, more scenarios with lane changes to the right lane are observed in Germany. This trend is also observed for the SAKURA data due to the left-handed traffic. Although such driver characteristic is less distinct than those in Germany, this effect is visible for the lateral velocities. While the drivers in Germany tend to conduct more aggressive lane changes towards the faster lane (left) and re-enter the slower lane at lower lateral speeds, the drivers in Japan show a tendency to more aggressive lane changes towards the right lane.

C. IMPLICATIONS AND LIMITATIONS
This study can have implications in developing widely applicable and region-neutral ADS safety assessment methodologies as well as related international standards and regulations. In particular, as the UN R157 ALKS regulation [2] consolidates and expands to other systems to operate at higher speeds, including lane change maneuvers, evidence on the applicability of the technical contents of the regulations worldwide level become necessary. As a first step, the current results show that, despite the difference in driving speeds associated with the different local speed limit rules on German and Japanese highways, the measurements of the relative speeds between vehicles highly overlap. This correlation suggests that drivers in Germany and Japan show similar behavior in judging and adapting their behavior based on comparatively simple relative velocity mechanisms. Therefore, this opens the possibility of evaluating AD systems safety based on relatively simple safety metrics and thresholds in a way that, after approval, can be safely deployed in different countries or regions with diverse local regulations.

However, these implications are subject to some limitations and need to be interpreted with caution. For instance, the scope of this study was limited in terms of differences in data collection tools, time frame, weather conditions, road design, and traffic conditions and regulations. These different factors were mainly due to the different objectives behind collecting each dataset, even for the same country For example, SAKURA dataset were collected using different tools under different traffic conditions. Whilst this study did not confirm the effects of such differences in data collection methods, it did partially substantiate the need for more research on how to attenuate the effect of different measuring factors and increase the validity of future comparisons, considering the approximation in the environmental and traffic conditions, road design, and time frame.

It could also be argued that the positive results were due to the limited number of scenarios and parameters considered in this study. Therefore, examining more types of driving maneuvers under more complex conditions would be significant as a real-world driving environment is highly dynamic and complex. However, since this study extracted and compared single scenarios, traffic conditions are not substantial. In different traffic conditions (if there are more or fewer vehicles on the road), the frequency of the extracted scenario may change, but not the parameters to identify the scenario.

In spite of its limitations, the study certainly is a milestone in the way of global verification and validation of automated driving systems. Before SAKURA methodology is introduced globally, we intend to conduct similar studies to compare datasets from more than two countries.

V. CONCLUSION
This study is the first to compare scenario parameter ranges extracted from two large highway datasets recorded in Japan and Germany. The comparison identifies similarities and differences in two national datasets (SAKURA and highD) by parameterizing deceleration and cut-in scenarios relevant to driving on highways. Additionally, the paper explores the parameters’ influence on the safety metrics time-to-collision and time headway. Despite the differences in the rule of the road, roadway design, and data collection tools between the two countries, there was a significant overlapped in the deceleration and cut-in scenarios. These outcomes can be used to validate the adoption of real-traffic data processing and parameterization methodologies to analyze scenarios extracted from different data sources and regions.

The data analysis findings provide potential in the ongoing development of harmonized safety metrics for safety assurance of automated driving. Datasets from different international sources may have similarities and overlaps, considering the region-specific traffic laws and the driver’s behavior. Therefore, widely applicable and internationally harmonized metrics can be tested and agreed upon using such kinds of traffic data processing method. In order to consolidate and generalize the results, further comparative work including more datasets, more scenarios and other environments outside highways is required. It would also be interesting to investigate the effects of measurement in Japan and Germany.
principles tools, environmental and traffic conditions on driver behavior and the extracted scenarios and thus the comparison outcomes.

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