

Scenario-based Parameter Boundary Reduction Approach for Highly Automated Driving Vehicles

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Abstract—Scenario-based testing is essential for Highly Automated Driving (HAD) vehicles to determine the safety-related input parameters and their boundaries. The increasing complexity, vehicle functions, and operational design pose new challenges for scenario-based testing, as the number of scenarios is enormous. Therefore, an efficient and systematic process is required in the various stages of scenario-based testing. The contribution of this study is to provide sensitivity information of safety-related parameters and support logical scenario reduction. This paper presents an approach that supports to optimize the safety-related parameters boundary towards logical scenario reduction. Additionally, sensitivity analysis is applied by computing Variance-Based Sensitivity Analysis (VBSA) indices and prioritize the input parameters. Two datasets are investigated by VBSA based on the input parameters. One dataset is based on the samples from real-world scenarios and other dataset is derived from the samples considering statistic distributions with a specific parameter range. Moreover, the proposed approach is applied to an exemplary use case and the outcomes are demonstrated.

Index Terms—lane change, sensitivity analysis, scenario reduction, simulation, highly automated driving

I. INTRODUCTION

Highly Automated Driving (HAD) vehicles are equipped with advanced functions to increase human comfort and reduce traffic accidents [1]. The HAD vehicles (SAE level 3 and/or higher automation levels) requires safety assurance by scenario-based testing to identify the safety-critical scenarios [2], [3]. According to Society of Automotive Engineers (SAE) J3061 the term, automated driving system is intended to describe the driving automation systems of level 3 (*Conditional Driving Automation*) to level 5 (*Full Driving Automation*) automation [4]. In this paper, the HAD vehicles is

used to define that, not entire Dynamic Driving Task (DDT) by means of operational and tactical function but a specific sub-task from the DDT has been considered. The sub-task that has been focused on this study is a vehicle maneuver during a lane change. Additionally, the study has been performed on a limited Operational Design Domain (ODD) for a lane change function of HAD vehicles.

Traditional validation procedures are not practical for HAD vehicles due to the complexity of the system, the decision-making process, and the human machine interface while driving on the road. Millions of test kilometers are not enough to ensure the safety of the HAD vehicle on the road [5]. Additionally, the trustworthiness of HAD vehicles has not yet been achieved in terms of safety, cybersecurity, assurance and others [6]. To ensure the safety of HAD vehicle, new test technologies and test strategies are in demand to revealing the unknown unsafe scenarios and developing the safety measures. Therefore, scenario-based testing is commonly used in automated vehicles for safety assessment [7]. Moreover, the resulting exploration of scenarios is still a challenge for ensuring the safety of HAD vehicles. Hereby, a sensitivity analysis has been carried out in a specific use case to optimize and reduce the input parameter boundaries for the logical scenarios.

The main contribution of the paper are as follows:

- Providing the sequence of input parameters by applying several variance-based sensitivity analysis methods. In other words, prioritize the input parameters for scenario simulation.
- Investigating the samples extracted from real-world scenarios and samples from statistic distribution with a specific parameter range to identify the sensitivity indices of each parameter.

- Optimization of the safety-related parameter boundary to support logical scenario reduction through scenario-based testing.

The outline of this paper is as follows: First, section II explains the key terminologies and the related background of sensitivity analysis. Next, section III describes the datasets used for scenario reduction, including the scope of ODD and an exemplary use case. After that, the results of the sensitivity analysis are presented with identified safe boundary of input parameters in section IV. Finally, section V summarizes and discusses the results of this study, including further work.

II. BACKGROUND

A. Scenarios and Operational Design Domain

A scenario describes the actions or events with additional information in a sequence of scenes and a snapshot of environment, scenery and other entities are defined as scene [8]. According to ISO 21448, Scenario is the *description of the temporal relationship between several scenes in a sequence of scenes, with goals and values within a specified situation, influenced by actions and events* [8]. The term scenario has been applied not only in the context of safety analysis but also in verification and validation of HAD vehicles [9].

Menzel has classified the scenarios into three categories: functional scenario, logical scenario and concrete scenario [10]. The functional scenario can be generated based on the knowledge, experience and publicly open scenario databases including the defined ODD. Logical scenarios required the parameter space parametrized ODD that can be used to model and simulate scenarios. Concrete scenario considered a particular scenario with concrete values of each parameter. Menzel defines, *functional scenarios are described in a linguistic way so that experts can talk about scenarios in the beginning of the development process. Logical scenarios specify parameters for the scenarios and define parameter ranges. Concrete scenarios specify a concrete value for each parameter and are thus, the basis for reproducible test cases* [10].

HAD vehicles are designed to operate in the defined operation can be expressed as ODD. An ODD is the fundamental for scenario-based testing to build safety concept and to support the verification and validation of HAD vehicle development. The major keywords to define an ODD are scenery, environmental conditions and other road users [11]. According to SAE J3061, ODD is defined as *operational conditions under which, a particular automated driving system or a function thereof is intended to operate, including, but not limited to, environmental, geographic, and time-of-day constraints and/or the required presence or absence of certain traffic or roadway features* [4].

Scenario-based testing is important to identify the unknown unsafe areas for HAD vehicles. However, road testing of HAD vehicles is not efficient in terms of time, cost, resources, technologies, and safety risks. In addition, not all scenarios in which HAD systems need to make driving decisions can

be tested on the road. Hence, simulation-based testing is an efficient approach and applied in HAD vehicle development [12], [13]. To confirm this statement, scenario-based testing including sensitivity analysis is performed to optimize the order of safety-related parameters and reduce the logical scenario for HAD vehicle safety assessment.

B. Variance-Based Sensitivity Analysis

Sensitivity analysis methods are applied in scenario analysis in various domains including automated driving systems [14]–[16]. Sensitivity analysis has allowed to evaluate the relative importance of inputs factors (e.g. parameters, initial assumptions). Three widely used approaches for sensitivity analysis are factor screening, local, and global [17]. Global sensitivity analysis methods have proven particularly useful in practice to understand the importance of individual parameters in a model and to compare different parameters [18]. In this investigation, Variance-Based Sensitivity Analysis (VBSA) as a global approach has been considered to determine the influence of the variation of the input parameters over the entire definition range.

VBSA measures investigate how input parameters contribute to the variance of the model output. The method can be applied to models with high uncertainty, with unknown linearity and non-additive models.

The “main effect index” or “first-order index” S_i represents the contribution of each input parameter to the variance of the output as the main effect [18]:

$$S_i = \frac{V(E(Y|P_i))}{V(Y)} \quad (1)$$

Here, $E(Y|P_i)$ represents the expected value of output Y with condition of P_i . Y is a model output that can be illustrated as $Y = F(P_1, P_2, P_3, \dots, P_k)$ with uncertain input parameters along decomposition of the variance V of Y by means of parameters interactions. The decomposition of variance is $V(Y)$ and the decomposition of variance for a i^{th} parameter (P_i) can be written as, $V(E(Y|P_i))$.

The “total-order index” or “total effect index” S_{T_i} has been expressed as [18]:

$$S_{T_i} = 1 - \frac{V(E(Y|P_{\sim i}))}{V(Y)} = \frac{E(V(Y|P_{\sim i}))}{V(Y)} \quad (2)$$

The total effect index S_{T_i} accounts for the total contribution to the output variation due to parameter P_i , is the main effect sensitivity index and higher-order effects due to interactions of other parameters. $P_{\sim i}$ denotes the matrix of all parameters except P_i .

The set of S_i and S_{T_i} provides the description of model behavior, if unknown beforehand. Based on these indices, it is possible to determine which parameters are important and which have no influence on the output. The indices are represented as a number between 0 to 1 [19]. For the variance-based sensitivity analysis various estimators exist [20], [21]. The estimator for S_i is as following:

$$V(E(Y|P_i)) \quad (3)$$

While for the S_{T_i} , the estimator is defined as:

$$E(V(Y|P_{\sim i})) \quad (4)$$

The scenario reduction technique has been supported by sensitivity analysis. Scenario reduction has been performed by varying the input parameters in sequence. The order in which the parameters have been applied in the scenario testing affects the results of the simulated scenarios.

III. SCENARIO REDUCTION APPROACH

A. Scenario Simulation Setup

In order to investigate the safety-related input parameters and determine the sensitivity of the input parameters, the scenarios are simulated to measure the Time-To-Collision (TTC). For the reduction of the logical scenarios, the parameter variation based reduction approach has been considered, in which the collision detection is viewed as the result of the simulation results.

a) Input Parameters: The input parameters set that are considered for sensitivity analysis and scenario reduction approach are:

- Ego vehicle speed (P1)
- Lane change gap (P2)
- Lane change duration (P3)
- Lagging Vehicle (V1) speed (P4)

b) use case: The use case defines an abstract description of the scenarios including the actions performed by the ego vehicle during the lane change as presented in Fig. 1. The highway scenario has been modeled with a width of 3.5 meters. The use case are modeled in CarMaker and simulated for TTC determination and collision detection. The lane change scenario is described as, ego vehicle turning from right lane to left lane.

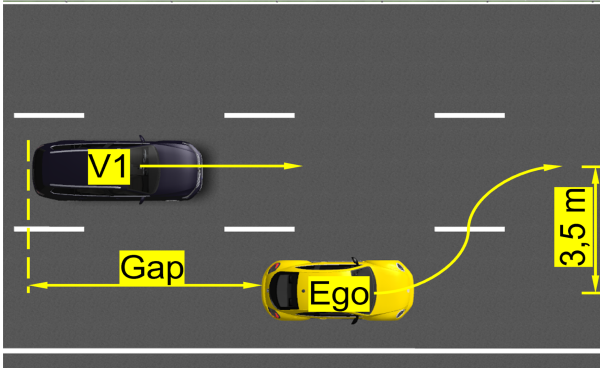


Fig. 1. Exemplary logical scenario-use case.

In other words, the change of the ego vehicle from the right to the left lane is the only use case with a limited ODD (good weather, straight road). While the ego vehicle is performing the lane change, a following/lagging vehicle (V1) is present

and driving straight ahead in the left lane. The initial inputs parameters and variation boundary of input parameters are listed in Tab. I.

TABLE I.
INPUT PARAMETERS BOUNDARY FOR SCENARIO SIMULATION

Input Parameters	Initial Value	Simulation Variation Boundary
Ego vehicle speed (P1)	130 km/h ^a	100 km/h to 160 km/h
Lagging vehicle speed (P4)	140 km/h	120 km/h to 160 km/h
Lane change gap (P2)	65 m ^b	0 m to 80 m
Lane change duration (P3)	3 s ^c	1 s to 3 s

^akilometer per hour (km/h) and ^bmeter (m) and ^csecond (s).

B. Datasets

a) Real-World Samples: To examine the behavior of the sensitivity analysis, real-world scenario catalog has been considered for real world samples generation. The real world samples have been extracted from the scenario database provided by Automatum [22]. The real-world scenario database has been created based on the raw data collected by the drone from a German highway [22]. The real-world samples (dataset 1) have been extracted from the scenario database using a list of input parameters that are similar to the defined use case.

b) Statistic Distributed Samples: The identification of corner case scenarios is a challenge in scenario-based assessment and aims to achieve uniform coverage of test cases with a parameter space [11]. The samples have been randomly generated using the Latin-Hypercube Sampling. This sampling method provides samples from equal divided parts of input space, where the random sampling might leave some areas uncovered. A random sample dataset based on Latin-Hypercube Sampling method has been generated by a uniform distribution. The bounds of the input parameters are shown in Tab. I. The range of input parameters has been taken into account during the generation of the logical scenario in CarMaker.

C. Reduction Approach

Simulation-based testing is required to investigate and identify the safety range of input parameters for HAD vehicles. The simulation-based techniques help to reveal the impact of the input parameters on the collision [23]. However, dealing with the number of scenarios at different stages of simulation is a major challenge and has yet to be solved. Therefore, this paper presents an approach to scenario reduction that focuses on the logical scenario stage. Scenario-based analysis can be used in various areas, such as risk analysis, safety assessment, and verification and validation processes. Sensitivity analysis has the potential to reduce the number of observed scenarios and is thus supporting scenario-based analysis.

The proposed approach has accounted for the order of input parameters based on the VBSA results, and a further reduction approach has been included on the basis of the parameter variation-based reduction approach as mentioned in [23]. The functional scenarios are reduced by addressing a limited ODD.

The reduction approach is presented in Fig. 2 that includes the datasets, tools and methods that are applied to reduce the logical scenarios.

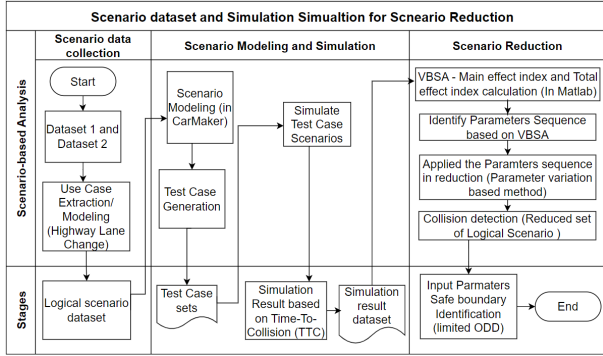


Fig. 2. Scenario reduction approach with sensitivity analysis

a) *The scenario reduction steps are:*

- Step 1: data extraction and datasets preparation based on input parameters.
- Step 2: scenario modeling and scenario simulation based on the input parameters to collect the outcomes of the scenarios in terms of TTC.
- Step 3: identification of input parameters sensitivity by VBSA. Different estimators are applied to estimate the input parameters impact.
- Step 4: applying the sequence of input parameters that has been identified by the VBSA to the parameter variation based method for logical scenario reduction. Additionally, the safe boundary of the input parameters has been realized.

b) *The detailed description of the scenario reduction steps are as follows:* **Step 1:** The scenario data are obtained from real-world samples and derived from statistic distributed samples, referred as dataset 1 and dataset 2 in Fig. 2. Dataset 1 is extracted from publicly open scenario database and extracted as a list of input parameters (Ego vehicle speed, lagging vehicle speed and lane change gap) that are related to the defined use case. Consecutively, only the upper and lower bounds of each the input parameters (Ego vehicle speed, lagging vehicle (V1) speed, lane change gap and lane change duration) are regarded in dataset 2 and samples are generated, which has been used to prepare test cases. The results for the simulated scenarios are based on TTC. Based on the datasets, the test cases have been generated and simulated to record the TTC for each combination of the input parameters. A limited scenarios are extracted from real-world by taking into account the defined used case and a set of test cases has been prepared.

The open Automatum processing program for the Python environment has allowed the extraction of parameters data for a defined scenario, with the exception of the duration of the lane change. The constraint of the real data is that the input parameter “Lane change duration” (P3) can not be extracted. For this reason, only three input parameters have been considered for VBSA. The extracted values have been converted to a text

file, which has been used in MATLAB to generate the script for test cases. The randomly-generated samples have been created with the help of the SAFE-Toolbox for MATLAB. SAFE-Toolbox is a collection of tools for performing the VBSA. Since the data have been randomly generated, four input parameters are used in statistical distribution samples.

Step 2: The use case scenario (see in Fig. 1) has been modeled and simulated in CarMaker with respect to TTC as outcomes based on the input parameters. Each of TTC values from CarMaker simulation have been stored into a vector. The vector has been used to calculate the sensitivity indices to identify the relative importance of input parameters.

Step 3: The calculation of sensitivity indices has required the allocation and recombination of samples for test case generation and simulation. Each of the input datasets has been divided into three matrices (XA , XB , and XC) to estimate the main effect and the total effect of each parameter. However, the input parameters are independent and have been used to create matrix XA and matrix XB . Matrix XC has been formed by replacing the column in XA with the column of XB . Therefore, the matrix XC has a size of XA or XB multiplied by the number of input parameters. The matrices XA and XB are represented in the estimators as matrix A and B , respectively (See Tab. II). $A_B^{(i)}$ or $B_A^{(i)}$ is a part from matrix XC where, column P_i of matrix A is replaced by column P_i of matrix B or vice-versa. Different estimators have been applied and outcomes of the VBSA in terms of “main effect index” and “total effect index” are estimated. A list of estimators that are applied in this study are listed in Tab. II.

TABLE II.
LIST OF ESTIMATORS APPLIED FOR SENSITIVITY INDICES ESTIMATION

First-order index (S_i)	Total-order index (S_{Ti})
Sobol/Saltelli Estimator [20]	
$\frac{1}{N} \sum_{r=1}^N f(\mathbf{A})_r f(\mathbf{B}_A^{(i)})_r - f_0^2$	$1 - \frac{\frac{1}{N} \sum_{r=1}^N f(\mathbf{B})_r f(\mathbf{B}_A^{(i)})_r - f_0^2}{V(Y)}$
Saltelli Estimator [21]	
$\frac{1}{N} \sum_{r=1}^N f(\mathbf{B})_r f(\mathbf{A}_B^{(i)})_r + f_0^2$	$1 - \frac{\frac{1}{N} \sum_{r=1}^N f(\mathbf{A})_r f(\mathbf{A}_B^{(i)})_r + f_0^2}{V(Y)}$
Janon Estimator [24]	
$\frac{\frac{1}{N} \sum_{r=1}^N f(\mathbf{B})_r f(\mathbf{A}_B^{(i)})_r - f_0^2}{V(Y)}$	$1 - \frac{\frac{1}{N} \sum_{r=1}^N f(\mathbf{A})_r f(\mathbf{A}_B^{(i)})_r - f_0^2}{V(Y)}$
Jansen Estimator [25]	
$V(Y) - \frac{\frac{1}{2N} \sum_{r=1}^N (f(\mathbf{A})_r - f(\mathbf{A}_B^{(i)})_r)^2}{V(Y)}$	$\frac{\frac{1}{2N} \sum_{r=1}^N (f(\mathbf{A})_r - f(\mathbf{A}_B^{(i)})_r)^2}{V(Y)}$

The outcomes of VBSA have been realized in terms of prioritization of the input parameters.

Step 4: The sequence of input parameters based on priority has been applied in the parameter variation based scenario reduction approach. Based on the VBSA results the input parameter sequence are considered for logical scenario reduction. Parameter variation based reduction approach has been applied for logical scenario reduction [23]. Additionally, input parameters boundary has been optimized based on the outcomes from parameter variation based reduction approach.

TABLE III.
VBSA BASED ON REAL-WORLD (DATASET 1)

Parameters	1000 Samples (N)		4000 Samples (N)		10000 Samples (N)	
	S_i	S_{T_i}	S_i	S_{T_i}	S_i	S_{T_i}
Sobol/Saltelli Estimator						
P2	0.0220	-0.1948	-0.0146	0.1041	-0.0093	0.0359
P1	-0.1116	1.0383	-0.1035	1.0552	-0.1001	1.0447
P4	-0.0557	1.0874	-0.0464	1.1074	-0.0344	1.1026
Saltelli Estimator						
P2	0.0134	-0.1862	-0.0054	0.0950	-0.0060	0.0326
P1	-0.0384	0.9651	-0.0141	0.9659	-0.0064	0.9510
P4	0.0452	0.9865	0.0491	1.0120	0.0592	1.0090
Janon Estimator						
P2	0.0123	0.0018	-0.0057	0.0021	-0.0060	0.0023
P1	-0.0501	0.9775	-0.0260	0.9556	-0.0173	0.9439
P4	0.0455	1.0043	0.0509	1.0169	0.0633	1.0164
Jansen Estimator						
P2	-0.0769	0.0021	0.0366	0.0019	0.0070	0.0023
P1	0.0955	0.9298	0.1602	0.7405	0.1716	0.7557
P4	0.2416	0.8886	0.2361	0.7739	0.2382	0.8126

IV. RESULTS

A. Comparing the VBSA Methods

The test case scenarios have been simulated based on the datasets. Around 168000 samples are collected from the real-world dataset (dataset 1) that are corresponding to the defined use case considering three input parameters. Whereas about 90000 samples are generated by uniform distribution (dataset 2) by taking into account the parameters boundary with four input parameters. Each of the datasets are shuffled for test case preparation to reveal the TTC as simulation results.

The number of samples is defined as N and samples are used to generate the matrix XA and XB (the number of samples to calculate the sensitivity of a single input parameter). The number of test cases that are simulated is calculated as, $2N + kN$, where k is the number of input parameters as described in section 3. In this investigation, $N=1000, 4000$ and 10000 samples have been considered for generating the matrix XA and XB . Therefore, the total test cases for three sets of samples are 75000 ($5000 + 20000 + 50000$) where, $k=3$ for simulating the dataset 1 and 90000 ($6000 + 24000 + 60000$) where, $k=4$ for simulating the dataset 2. The simulation results are applied in VBSA.

The simulation results of the test cases have been used as input for different VBSA methods. For the estimation of the sensitivity indices, four estimators have been investigated namely Sobol/Saltelli Estimator, Saltelli Estimator, Janon Estimator and Jansen Estimator [20], [21], [24], [25]. The summary of the VBSA results has been displayed in Tab. III that reflects the real-world scenarios (dataset 1), it has been observed that the samples of 1000 and 4000 are not plausible to estimate the impact or sensitivity of the parameters. Nevertheless, the Jansen estimator is more appropriate than other estimators.

For the samples for the statistical distribution (dataset 2), the samples of 1000 and 4000 are unlikely because of the negative values of the indices. Nevertheless, samples of 10000 yielded

TABLE IV.
VBSA BASED ON STATISTIC DISTRIBUTION (DATASET 2)

Parameters	1000 Samples (N)		4000 Samples (N)		10000 Samples (N)	
	S_i	S_{T_i}	S_i	S_{T_i}	S_i	S_{T_i}
Sobol/Saltelli Estimator						
P1	0.1126	0.9185	0.0726	1.0029	0.1061	0.9530
P2	0.0863	-0.5485	-0.274	0.0456	-0.0163	0.1059
P3	0.0866	-0.5485	-0.0272	0.0456	-0.0163	0.1058
P4	0.0215	0.9002	0.003	0.9092	0.0648	0.9167
Saltelli Estimator						
P1	0.0918	0.9394	0.0886	0.9869	0.1114	0.9477
P2	0.0521	-0.5143	-0.0241	0.0423	-0.0119	0.1015
P3	0.0523	-0.5141	-0.0239	0.0424	-0.0120	0.1015
P4	0.0350	0.8867	0.0069	0.9026	0.0700	0.9116
Janon Estimator						
P1	0.0811	0.9849	0.1006	0.9817	0.1158	0.9381
P2	0.0402	0.0001	-0.0246	0.0001	-0.0125	0.0001
P3	0.0403	0.0001	-0.0244	0.0001	-0.0126	0.0001
P4	0.0411	0.9276	0.0069	0.8952	0.0722	0.8992
Jansen Estimator						
P1	-0.0305	1.3359	0.2117	0.8410	0.1501	0.8561
P2	-0.1880	0.0001	-0.0047	0.0001	0.0366	0.0001
P3	-0.1877	0.0001	-0.0044	0.0001	0.0366	0.0001
P4	0.1922	1.0038	0.0284	0.8583	0.1024	0.8263

an acceptable results for the Jansen estimator as shown in Tab. IV).

According to the VBSA outcomes of dataset 1, input parameter P4 (Lagging vehicle, V1 speed) has the highest sensitivity compare to other input parameters P1 (Ego vehicle speed) and P2 (Lane change gap). Moreover, the input parameter P1 (Ego vehicle speed) has the highest sensitivity based on the VBSA output of dataset 2, compared to other input parameters. Since P2 (lane change distance) and P3 (lane change duration) have the same sensitivity indices, another iteration of VBSA has been conducted between P2 and P3 to determine the higher sensitivity among them. For the scenario reduction approach, the results of dataset 2 have been taken into account as four parameters are involved for VBSA, and similar amount of parameters have also been utilized in the scenario reduction approach [23].

B. Input Parameters Boundary

Several studies and road vehicle standards have addressed the topic of safety-critical scenario identification [3], [6], [8].

TABLE V.
INPUT PARAMETERS SAFE BOUNDARY OPTIMIZATION

Input Parameters	Simulation Variation Boundary	Safe Boundary
Ego vehicle speed (P1)	100 km/h to 160 km/h ^a	100 km/h to 160 km/h
Lagging vehicle speed (P4)	120 km/h to 160 km/h	120 km/h to 145 km/h
Lane change gap (P2)	0 m to 80 m ^b	64 m to 80 m
Lane change duration (P3)	1 s to 3 s ^c	1 s to 3 s

^akilometer per hour (km/h) and ^bmeter (m) and ^csecond (s).

For the HAD vehicle to identify such scenarios, the logical scenarios have to be examined by a scenario simulation process. To define the safe ODD, optimization of the input parameter limits is essential. Based on the VBSA results, including the scenario reduction approach, the safe boundary of the considered input parameters for the defined use case has been listed in Tab.V.

V. CONCLUSION

This paper has outlined the various steps and considerations in conducting a sensitivity analysis. The structure of the logical scenario reduction approach, with the tools and estimators has been presented. Moreover, regarding the estimators, Janon and Jansen are indeed fitted better than the Sobol/Saltelli and Saltelli estimators. Janon is superior for a smaller number of samples and Jansen for a larger number of samples and for a more straightforward interpretation, as it is less prone to generate negative sensitivity indices. The time required to compute additional indices with other estimators is negligible compared to the simulation time. The sequence of the input parameters is “Ego vehicle speed (P1)”, “Lagging vehicle (V1) speed (P4)”, “Lane change gap (P2)” and “lane change duration (P3)”, based on the scenario simulation outcome with dataset 2 and parameter variation based scenario reduction approach.

Furthermore, the variation of input parameters is required to explore the parameter space and unknown unsafe scenarios identification. Therefore, the safe boundary of the input parameters are optimized and presented in this paper as a research outcome by focusing the VBSA and Logical scenario reduction.

As future work, a verification process will be developed to ensure the accuracy of the defined safe limits of the input parameters. Moreover, the generated datasets and test cases can be used as input for any artificial network.

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