BETA SIMULATION SOLUTIONS

physics on screen

White paper

Simulation enabling technologies

Prediction of occupant safety utilizing Machine Learning and CARLA autonomous drive simulation software

Incorporating CARLA data and Machine Learning can enhance vehicle safety by using "real-case" data to predict occupant injuries, optimize safety parameters, and improve design methods beyond regulated scenarios.

Introduction

Currently, simulations of crash tests, such as physical crash tests, are conducted within a controlled "lab" environment, utilizing prescribed scenarios and regulations. Load cases and boundary conditions are meticulously and precisely defined to ensure the safety of occupants and pedestrians within acceptable limits, as well as to certify the vehicle for road use. Although these design methods and safety protocols have continually improved vehicle safety, "real-case" crash scenarios are not much tested.

In this work, "real-case" data from an autonomous driving software was employed for crashworthiness simulations, extending beyond regulated scenarios, through the utilization of Machine Learning. The CARLA software, a simulator for autonomous driving, is capable of reconstructing and simulating real-world traffic accident scenarios, involving various vehicle types, and providing pre-crash data such as speed, position, and angle.

The data from the reconstructed accident scenarios are utilized as input in Finite Element Crash analysis to yield results pertaining to occupant injuries. Datasets featuring various Finite Element models and diverse crash scenarios, assessing occupant safety, are created for the training of Machine Learning models capable of predicting occupant injuries. These Machine Learning models are employed to optimize the control of occupant safety parameters, such as airbag deployment time and seatbelt triggering.

More precisely, in this study, CARLA provided data related to a specific vehicle involved in a rear crash scenario, one of the most common types of accidents. The input parameters included speed, velocity, and the relative position of the two vehicles. Finite Element analyses were conducted for several variations of the crash to measure occupant injuries, thereby establishing an appropriate dataset for training a Machine Learning model. The trained Machine Learning model was subsequently utilized to predict the occupant injury criteria based on various inputs from CARLA and optimize safety system parameters to enhance the safety of vehicle designs.

Scenario selection

According to vehicle safety institutions (i.e. IIHS, NHTSA and the NSC [1], [2],[3],[6]), the most common crash scenarios that inflict more injuries and deaths are the vehicle-to-vehicle collisions. The highest percentage of such crash scenarios refers to Rear-End or Angle collisions (see Figure 1). Additionally, crash statistics on the conditions of the crashes in terms of speed, type of crash, weather conditions, time of day, etc., show that the vast majority of such accidents happen during daylight in clear weather conditions.

For this study, a rear-end collision between two sedan vehicles was chosen as it is the most common traffic accident. The CARLA software was employed to collect various rear-end crash data. CARLA is an open source software used for testing and validating autonomous driving systems. In this case, a sedan model was simulated in CARLA using the Unreal Engine. To simulate the physics of such crash scenarios, we utilized CARLA's Scenario Runner framework, where during each time step of the scenario execution, extracted collision related data such as speed, position, and rotation information for each simulated vehicle.

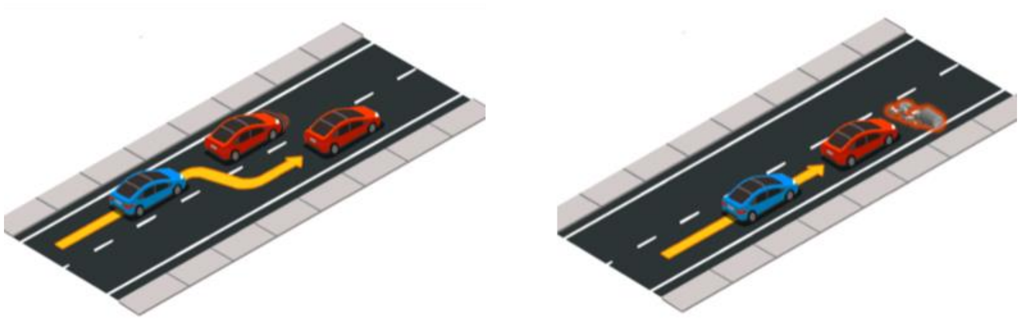

Figure 1: Selected NHTSA inspired pre-crash scenarios

Finite Element modelling – DOE

To simulate the crash between the two vehicles, Finite Element models of a sedan car were used. The leading vehicle remained stationary without applying any braking, while the rear vehicle was in motion. The rear Finite Element model was equipped with a passenger airbag and a seatbelt restraint system. The passenger Anthropomorphic Testing Device (ATD) used was the LSTC 50% rigid FE dummy.

In order to be able to simulate the crash for various rear-end collisions, three design variables were controlled to position the speeding vehicle prior to the crash (refer to Figure 2). These variables included initial velocity, overlap, and angle. Two additional design variables controlled the timing of airbag and seatbelt ignition.

The responses for each Finite Element analysis were the Head Injury Criteria (HIC), that indicate the severity of the collision (see Figure 3). HIC15 (max value in 15ms) was selected as the most commonly used head injury criterion among regulations.

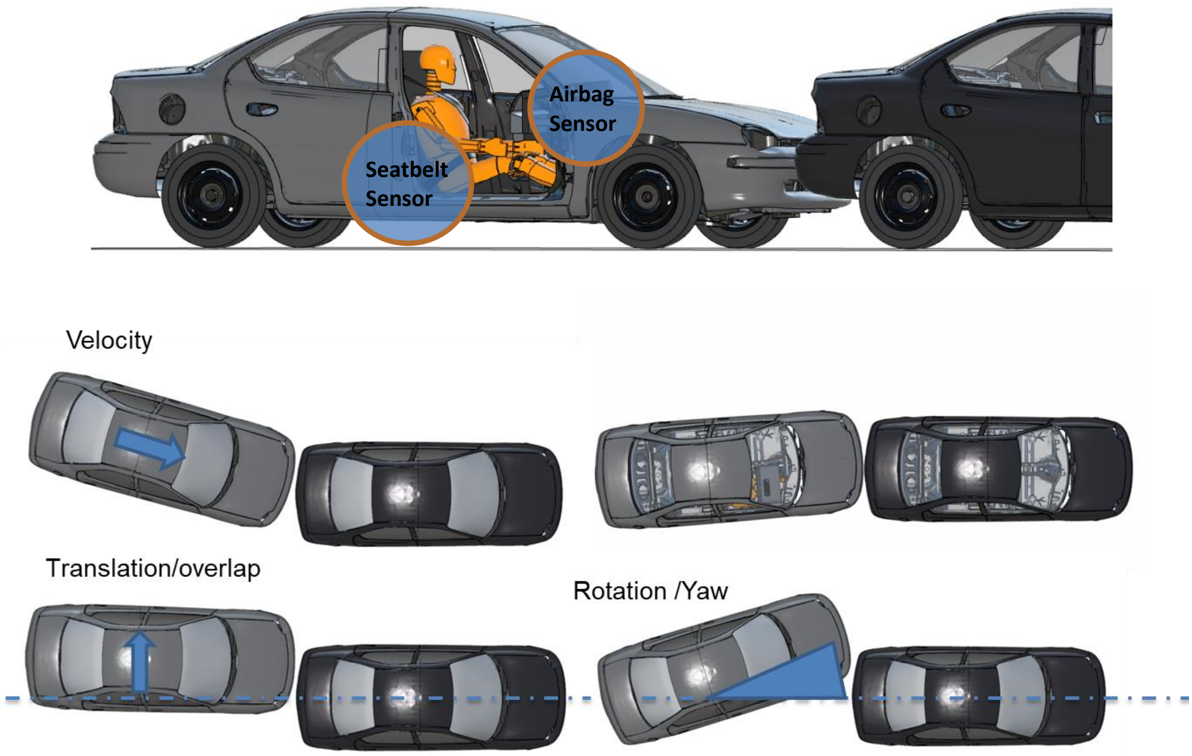

Figure 2: Crash scenario Position variables

A Design of Experiments (DOE) process created 35 designs using the Optimal Latin Hypercube algorithm and ran the FE analysis for each one. The post-processing was performed accumulatively for all experiments in an automated manner, to extract curves, pictures, videos, and the important key values needed for the Machine Learning training.

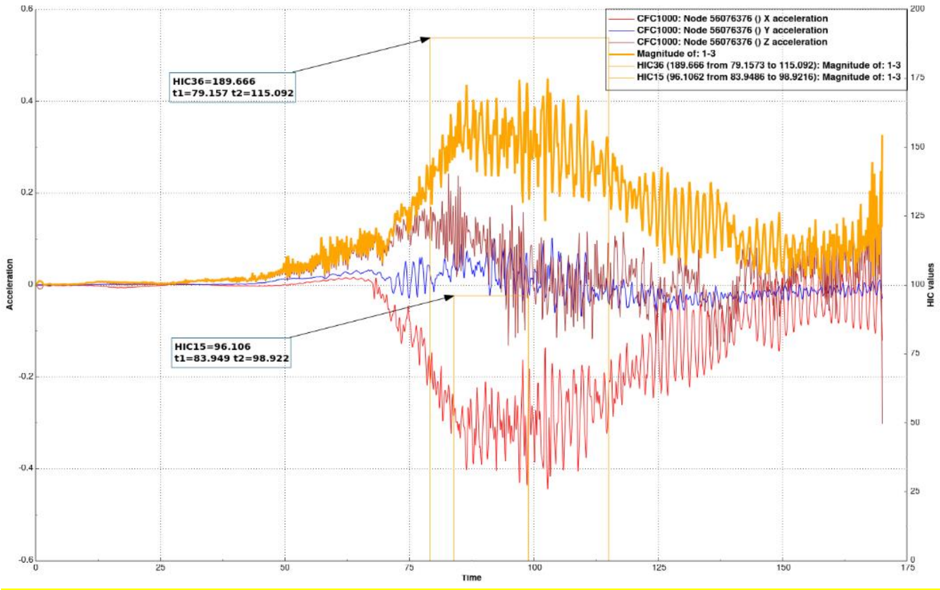

Figure 3: Head acceleration curves and HIC values

Machine Learning – Optimization

The DOE served as the initial dataset for training predictive models also referred as Predictors, designed to predict responses within seconds.

Utilizing a data-driven Machine Learning approach, a Predictor was developed to forecast the HIC15 responses (refer to Figure 4). Through the utilization of Key Performance Indicators (KPIs) and an additional validation process, this Predictor was thoroughly validated, and its accuracy was deemed suitable for the purposes of this study. The KPIs also aided in identifying the most influential design variables and in evaluating the overall performance, as evidenced by the target versus prediction overlay and learning curve (refer to right side of Figure 4).

The trained Predictor was capable of providing responses like the HIC15 and other related metrics, instantly, making it an invaluable tool for expeditious optimization studies. The objective was to pinpoint optimal parameter values that would minimize head injury-related responses, applicable across various crash scenarios with varying velocities and crash angles.

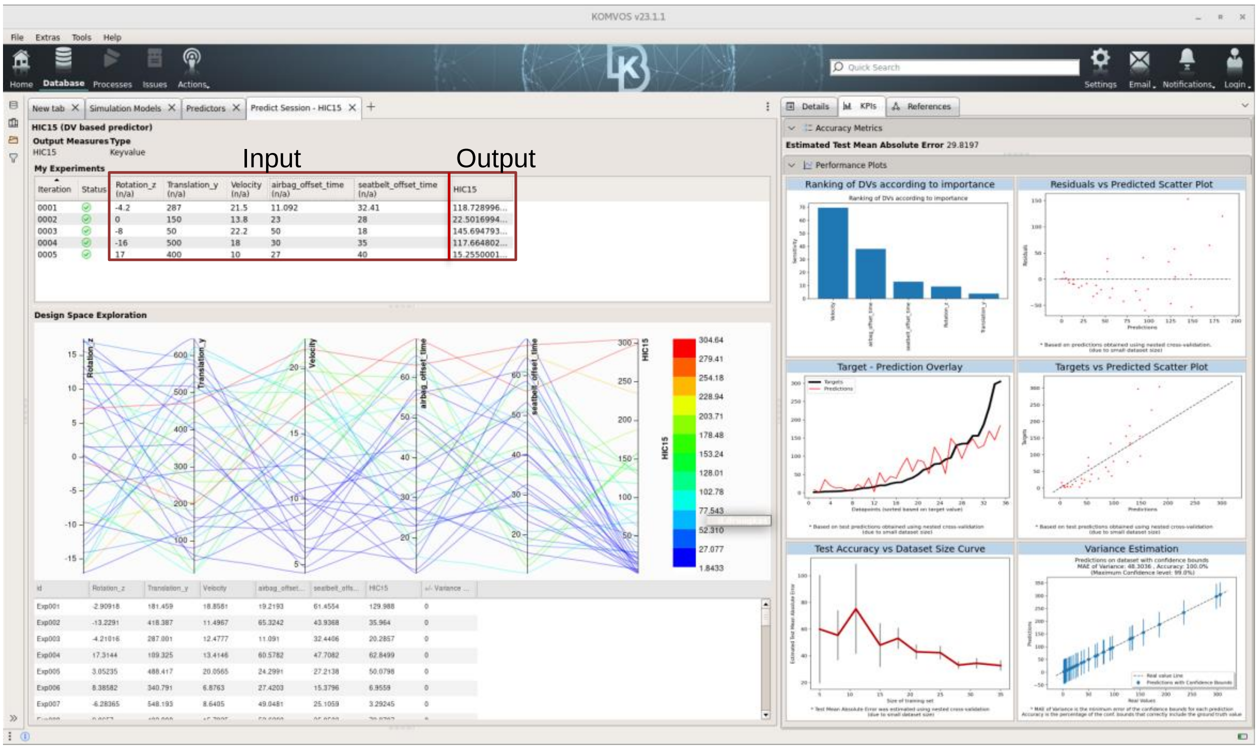

Figure 4: HIC15 Prediction for theoretical scenarios

Random crash scenarios generated with CARLA

To achieve our objective it was necessary to have a Predictor that would be able to predict the optimum parameter values for the seatbelt and airbag trigger offset time for every possible crash scenario. In order to create such a predictor, it was required to collect crash data from multiple real rear-end crash cases. Since we were not able to collect crash data from actual accidents, we employed CARLA, a software that supports development, training and validation of autonomous driving systems. In our study, we simulated 65 scenarios involving collisions (see Figure 6). The vehicle utilized within CARLA was carefully customized to match the same dimensions, center of gravity coordinates, and mass as our Finite Element (FE) model in order to have consistency between the FE analysis input and the collisions simulated in CARLA. For each of these scenarios, we systematically recorded data related to Velocity, Rotation, and Translation (abbreviated as V, R, T), as generated by CARLA software (refer to Figure 5).

```
Frame: 2443
        First Actor\Car:
        Coordinates: (0.0, 0.0, 0.0) (m)
        Rotation(Roll, Pitch, Yaw): (-6.103515625e-05, 9.56226431299001e-05, 0.025603188201785088) (deg)

        Ego Car:
        Coordinates: (-4.489141400073389, 0.0907816611885199, 0.0005099102854728699) (m)
        Rotation(Roll, Pitch, Yaw): (0.013231619261205196, -0.05990075692534447, -0.02273559384047985) (deg)
        Velocity: 69.94589683661746(km/h)
------------------------------------------------------------
        COLLISION:
Frame: 2444
        Intensity: 32273.26057267041 N*sec(kg*m/sec)
```

Figure 5: Crash scenario characteristics (Coordinates, Rotation and Velocity of both vehicles)

Figure 6: CARLA: Autonomus driving simulation software interface. Collision simulation

A distinct optimization study was defined for each specific crash scenario simulated in CARLA. In each of these optimization studies, the design variables related to velocity and position, which were derived from CARLA, remained constant, while the variables associated with airbag and seatbelt trigger offset times were allowed to vary (see Figure 7). The objective of these optimization studies was the minimization of the head injury. The optimum experiments would provide the optimal values for trigger offset times, while achieving the lowest possible HIC15 value.

Running 65 optimization studies, one for each collision scenario with the DIRECT method, meaning going through the stages of pre- processing, FE solution and post- processing, would require huge amounts of resources in terms of time and computational power. For this reason, all optimization studies were defined to run with the Response Surface Model (RSM) method. This means that instead of going through the aforementioned steps, the previously created Predictor was used throughout the optimization to predict the required HIC15 response value. With this method, the 65 different optimization studies ran within minutes, saving a considerable amount of time and CPU usage.

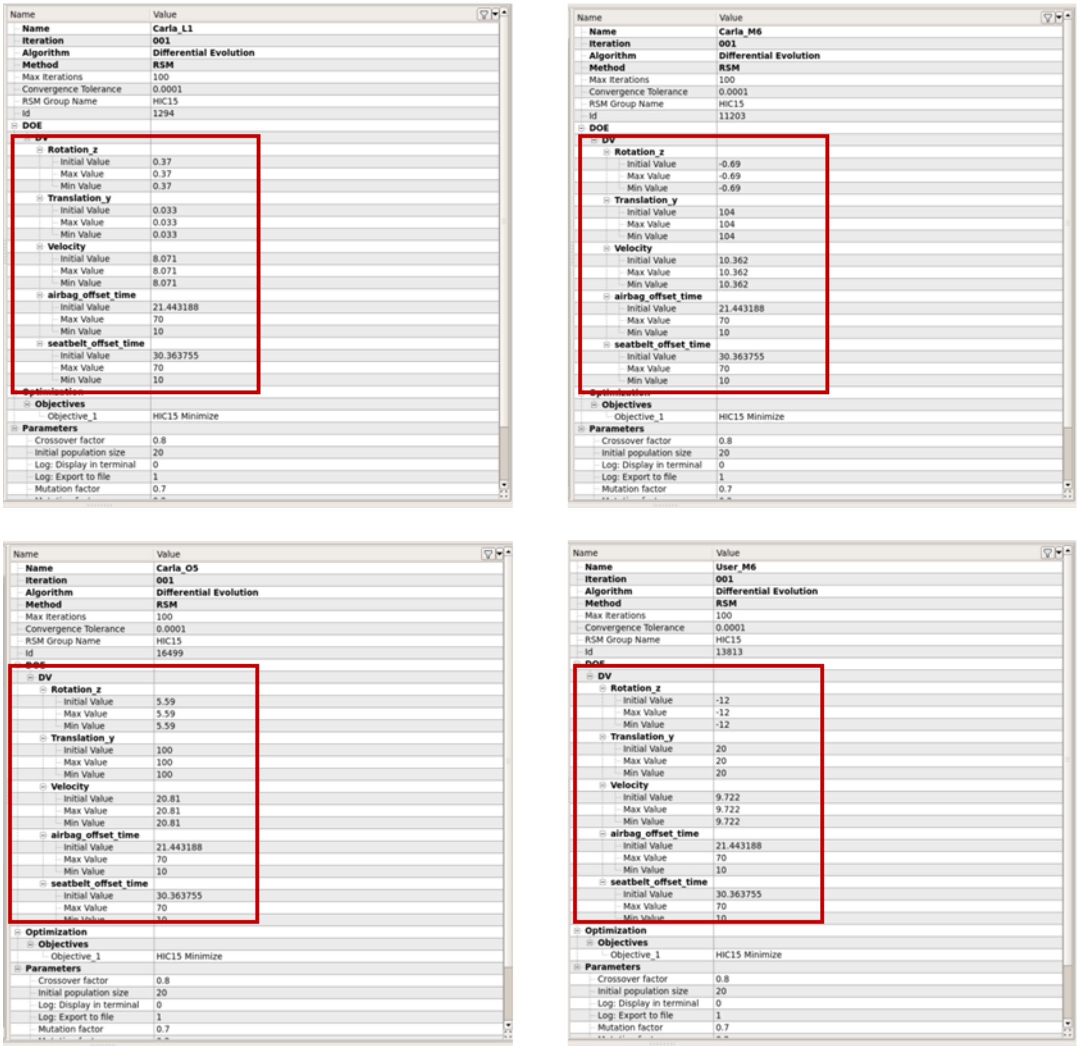

Figure 7: Optimization Studies for different crash scenarios

Each optimization study ran for an average of 200 experiments (Figure 8). From each of these optimization studies, only the best experiments (two or three optimum experiments per study) with minimized HIC15 and optimum trigger values were collected, thus creating a new dataset of 150 experiments. This new dataset contained experiments of all the possible collision scenarios simulated with CARLA, with the optimum trigger offset times for airbag and seatbelt sensors. Essentially, this dataset had answers to the question, “what should be the trigger offset time for the airbag and seatbelt, if the crash occurred in a specified way (velocity, overlap, angle) in order to get the minimum head injury”.

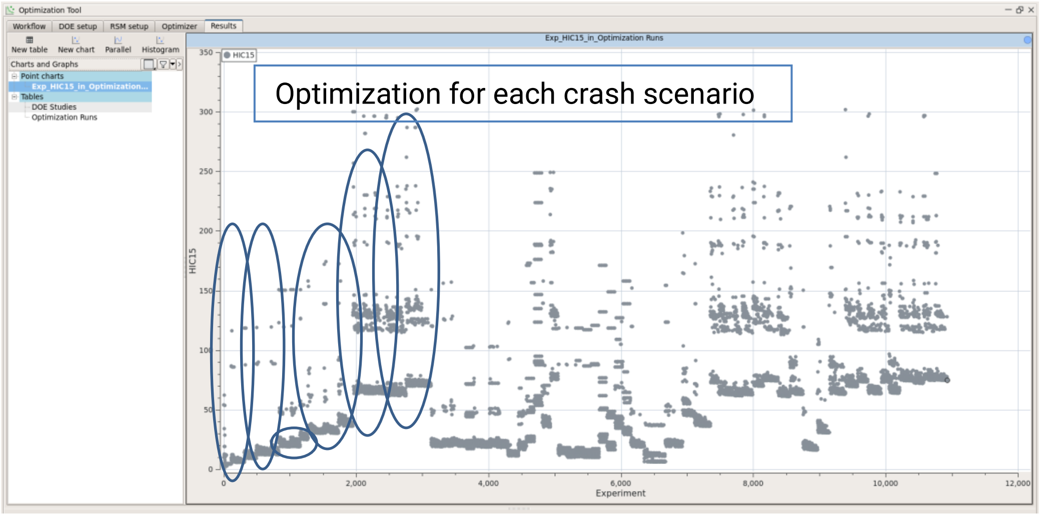

Figure 8: Optimization results for all optimization studies

Prediction of optimum ignition time

The previously created dataset of 150 selected optimum experiments was used to train a new predictor.

Figure 9: Predictor trained with the optimized dataset to predict optimum airbag and seatbelt trigger offset times for minimum head injury

The resulting Predictor was able to instantly predict the optimum values for the trigger offset times with a given input of velocity, overlap and angle (see Figure 9). Meaning that for any possible crash (within the parameters range given during the training) the vehicle's safety systems would operate in the best possible way (optimum trigger offset values) to reduce the occupants' injury, which was the aim of this study.

Validation

To verify the accuracy and potential of this process, validation experiments were defined, checking whether the HIC15 prediction values were similar to those the FE Analysis would calculate.

Six random experiments with random Velocity, Rotation and Translation values were selected as input values. Using the latest created predictor, the responses of airbag, seatbelt trigger offset values, and HIC15 values were predicted. These input parameter values (Velocity, Rotation and Translation) were then applied to the initial parametric model and the FE Analysis ran for each of the six experiments to compare the HIC results (predicted vs FE-calculated).

Scenario	Input			Output Prediction			FE Result	Absolute error
	Rotation Z (Deg)	Translation Y (mm)	Velocity (mm/ms)	Airbag offset (ms)	Seatbelt offset (ms)	HIC15	FE HIC15	
1	0	150	13.8	**23.2431**	**28.1003**	23.974	29.838	5.864
2	-8	50	22.2	**20.2567**	**27.7276**	75.198	85.339	10.140
3	0	0	9	**24.1967**	**27.6094**	9.172	5.554	3.618
4	-5	80	12	**22.9283**	**28.033**	18.887	14.681	4.206
5	-5.06	259.9	11.4	**22.2304**	**27.7675**	17.366	15.542	1.824
6	-16	500	18	**25.86.22**	**27.7982**	75.798	90.86	15.062

As we can see in the Table above, the difference between predicted and calculated HIC15 values is relatively small, suggesting that this process can be considered as successful.

Summary

In this study we have defined a DOE with a parametric two car crash case considering a dummy, a seatbelt, and a passenger airbag. A Machine Learning Predictor was trained using the DOE, to “replace” the solver and predict the simulation results for theoretical future experiments.

Random rear-end crash scenarios were generated in CARLA, based on the most common crash cases according to NHTSA, to obtain Velocity, Rotation and overlap data. The previously created predictor was used in optimization studies as response surface models to quickly identify optimum airbag and seatbelt offset times, minimizing the head injury criterion for each of the generated crash scenarios.

Finally a second predictor was trained based on the previous optimization results, to provide optimum airbag and seatbelt trigger offset time values when given a new crash scenario (Velocity, Rotation, overlap). The validation of the predictor was made with a six random experiments and demonstrated small difference between predicted HIC and calculated HIC, for the optimum trigger offset times.

Conclusion

Today’s vehicles could take advantage of such a functionality that can provide optimum systems settings (such as passive or active safety features) customized to the accident while it takes place, aiming to achieve the lowest possible injury. Additionally such predictors could be constantly updated as vehicles in the field can provide data similar that what was provided from CARLA in this study.

In more detail, predictors could be exported in an FMU (Functional Mockup Unit) format that is universal, to be used by systems modeling software. If the predictor is embedded in a vehicle’s control module, it could continuously collect data from several sensors (speed, distance, angle, overlap, etc.) currently implemented in today’s vehicles. Such information can be accessed by predictors right before an accident as input. As output, it could instantly assign the optimum ignition time for the seatbelt and airbags (or other safety features) right before the accident, based on the specific input during that accident, to achieve the minimum head injury (HIC15) for the occupants.

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