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Development of ML Models to Predict Pedestrian aPLI Injury Responses

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Traditionally, vehicle safety designs and evaluations for pedestrian safety rely on physical tests and/or Finite Element (FE) modelling with leg or head impactors. Building vehicle prototypes for large amount of physical tests and developing the detailed FE models for virtual tests require significant cost and time.

A method is proposed to use the critical front-end vehicle parameters for pedestrian safety to develop Machine Learning (ML) models to predict the impact responses of the advanced pedestrian legform impactor (aPLI).

Method

A method is illustrated on how to use vehicle parameters that are critical for pedestrian safety to develop the ML models to predict the aPLI impact responses as shown in the four steps below:

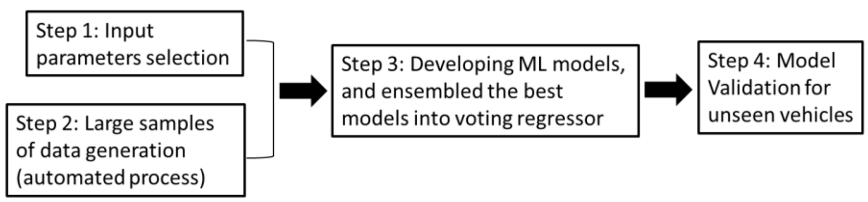
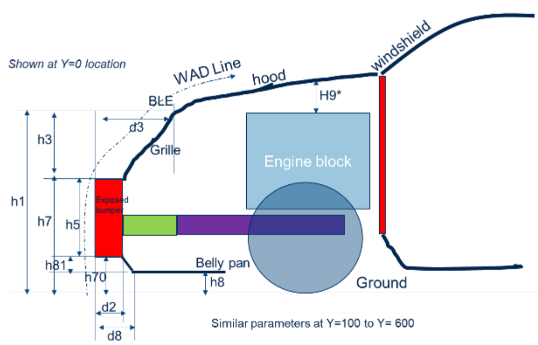


Figure 1. Schematic of the approach

Step 1: Input parameters - Critical vehicle front-end geometrical and stiffness parameters were measured as input parameters, for light truck vehicles (LTV) with exposed bumpers and passenger vehicles (PV) with hidden bumper.



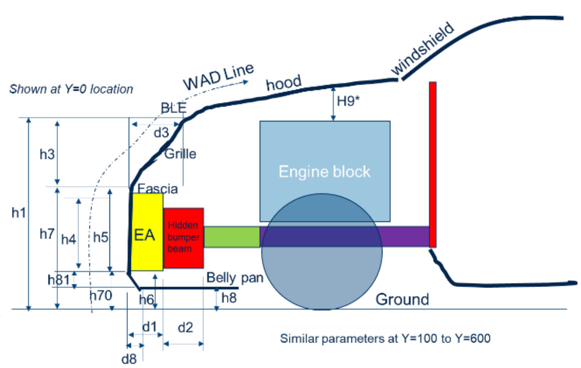


Figure 2. The parameters for LTVs   Figure 3. The parameters for PVs

Step 2: Data generation - Vehicle FE models covering different types, including LTVs with bumper exposed and PVs with bumper hidden, were used to set up impact configuration with aPLI and generate aPLI impact responses as output data. Vehicle models were geometrically scaled in X and Z directions to generate large samples of data. A framework to automate the FE simulations and postprocessing of the impact responses were set up in the modeFRONTIER. The aPLI impact responses included femur and tibia bending moments and knee elongations.

Step 3: Developing ML models - ML models were developed and tested in Python, including both parametric and non-parametric models, separately for LTVs and PVs. The mean absolute error (MAE) was used to evaluate the prediction accuracy for each specific response. The voting regressor models are the ensembled estimator fits of those selected best models, like the Random Forest, Extra Tree, Gradient Boosting, XGBoost, and CATBoost.

Step 4: Model Validation for unseen vehicles - The validations for unseen vehicles were performed for data generated from each vehicle using leaving one vehicle out method. The overall MAE of the validation for unseen vehicles is the mean value of the MAEs for each vehicle left out.

Conclusion

Using this method, overall, more than 85% prediction accuracy was observed. In conclusion, ML models for LTVs and PVs were developed using the critical front-end vehicle parameters for pedestrian safety to predict the aPLI impact responses. The ML models are fast, low cost and have acceptable accuracy. The ML models will provide efficiency in the safety design at early stage of vehicle development for pedestrian protection.

Disclosed anonymously