SCIENCE CHINA
Technological Sciences

• Article •

https://doi.org/10.1007/s11431-019-1565-9

A framework for rapid on-board deterministic estimation of occupant injury risk in motor vehicle crashes with quantitative uncertainty evaluation

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Received November 17, 2019; accepted March 18, 2020; published online July 23, 2020

Accurate on-board occupant injury risk prediction of motor vehicle crashes (MVCs) can decrease fatality rates by providing critical information timely and improving injury severity triage rates. The present implemented prediction algorithms in vehicle safety systems are probabilistic and rely on multi-variate logistic regression of real-world vehicle collision databases. As a result, they do not utilize important vehicle and occupant features and tend to overgeneralize the solution space. This study presents a framework to address these problems with deterministic and computationally efficient lumped parameter model simulations driven by a database of vehicle crash tests. A 648-case mixed database was generated with finite element and multi-body models and validated under the principal directions of impact with experimental results for a single vehicle body type. Using the finite element database, we developed lumped parameter models for four principal modes of impact (i.e., frontal, rear, near side and far side) with parameters identified via genetic algorithm optimization. To obtain confidence bounds for the injury risk prediction, the parameter uncertainty and model adequacy were evaluated with arbitrary and bootstrapped polynomial chaos expansion. The developed algorithm was able to achieve over triage rates of 17.1% ± 8.5%, whilst keeping the under triage rates below 8% on a finite element-multi body model database of a single vehicle body type. This study demonstrated the feasibility and importance of using low-complexity deterministic models with uncertainty quantification in enhanced occupant injury risk prediction. Further research is required to evaluate the effectiveness of this framework under a wide range of vehicle types. With the flexibility of parameter adjustment and high computational efficiency, the present framework is generic in nature so as to maximize future applicability in improved on-board triage decision making in active safety systems.

occupant safety, injury prediction, lumped parameter model, motor vehicle crash, uncertainty quantification

Citation: Bance I, Yang S C, Zhou Q, et al. A framework for rapid on-board deterministic estimation of occupant injury risk in motor vehicle crashes with quantitative uncertainty evaluation. Sci China Tech Sci, 2020, 63, https://doi.org/10.1007/s11431-019-1565-9

1 Introduction

According to the World Health Organization, there were 256180 road traffic deaths in China in 2018 [1]. This number could be significantly reduced by improving the accuracy of on-board injury risk prediction, and as a result triage rates of motor vehicle crashes (MVC) [2]. A typical active vehicle safety system that heavily relies on accurate occupant injury risk prediction is the advanced automatic crash notification (AACN) system. By providing occupant injury risk information to the emergency medical services (EMS) post-collision, response times can be reduced and triage rates improved. These systems are already in active use, with a 2011 study estimating that more than 12 million vehicles on US roads are equipped with (A)ACN systems [3]. According to recent estimates, their complete implementation and adoption by EMS could have led to an estimated 361–721 lives saved in 2017 in the US alone [2].

Existing on-board occupant injury risk prediction algo-

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rithms mostly rely on multi-variate logistic regression of real-world accident data sets, covering a wide range of vehicle types (Table 1) [4–12]. This method of supervised machine learning regresses categorical data to predict the probability of sustaining an injury above a certain severity level. The most common decision factors include: belt use, collision delta-v, occurrence of multiple impacts and principal impact mode, i.e., frontal, rear, near side and far side. The two main injury severity criteria used are the maximum abbreviated injury score (MAIS) and the injury severity score (ISS) (Appendix A), where MAIS3+ or ISS15+ indicate that the occupant should be sent to a high level trauma center. Most algorithms have trained and validated their models with US publicly available accident data sets, e.g., the National Automotive Sampling System Crashworthiness Data System (NASS CDS) database. Some studies have explored vehicle collision databases from other countries, i.e., the German in-depth accident study (GIDAS) [4] and the institute for traffic accident research and data analysis (ITARDA) for Japan [5, 6]. The current state-of-the-art on-board injury risk prediction algorithm on the EDR triggered subset of the NASS CDS database is the OTDA algorithm [7]. The OTDA algorithm has achieved over-triage (OT) and under-triage (UT) rates of 50% and 7% (frontal); 49% and 9% (near side); 49% and 6% (far side); 25% and 8% (rear), respectively. The American College of Surgeons recommends to keep OT rates at least below 50% and UT rates below 5% [13]. Optimal triage rates have, thus, not yet been achieved with probabilistic algorithms utilizing logistic regression.

For advanced vehicle safety systems that predict occupant injury risk to make life-threatening decisions a quantification of prediction uncertainty is necessary to develop a comprehensive solution. To our knowledge, the combined prediction uncertainty of both model adequacy and parameter uncertainty of injury risk prediction algorithms has remained unquantified to date. The use of limited size real-world MVC databases for probabilistic model training impede the application of classic forward uncertainty propagation methods, such as Monte Carlo sampling. Rapid developments in non-sampling based polynomial chaos expansion (PCE) methods have shown promise to reduce the necessary number of function evaluations to estimate statistical moments [14]. This can also be combined with bootstrapping to generate bootstrap replications, termed as bPCE, to return an error estimate of the uncertainty quantification itself [15, 16].

Due to the inherent complexity and uncertainty of real-word accident databases, numerical data sets of these complex collision environments have been created with biofidelic occupant injury model simulations. This approach has become increasingly attractive with the rise of "parallel" driving system theory, where a limited amount of real data is augmented with validated numerical data [17]. Two existing studies have explored such an approach to tackle the limitations of logistic regression on a real-world vehicle collision

Table 1 Overview of recent injury risk prediction models for MVC occupant injury risk

Category		URGENCY (2001) [10]	OnStar (2011) [11]	Bose (2011) [9]	Katagiri (2013) [8]	Lubbe (2014) [4]	Weaver (2015) [12]	Honda-Nihon (2016) [5]	Toyota-Nihon (2017) [6]	OTDA (2016) [7]
Vehicle	Seat belt use		X	X	X	X	X	X	X	X
	Airbag use			X	X					X
	Vehicle interior			X						
	Omni-vehicle coverage	X	X	X	X	X	X	X	X	X
Impact type	Crash pulse use			X						
	Impact angle				X					
	Impact modes		X		X	X		X	X	X
	Multiple impacts	X	X			X		X	X	X
	Oblique impacts	X	X		X	X		X	X	X
	Roll-over									X
Occupant	Posture			X						
	Gender	X	X	X						
	Age	X	X			X		X	X	
	Morphology			X	X					
	Multiple occupants		X							
	Body region injuries			X	X		X			
Methodology	Low-complexity	X	X		X	X	X	X	X	X
	Type	LR	LR	Multi-body model	LR	LR	LR	LR	LR	LR
	Decision metric	MAIS3+	ISS15+	N/A	N/A	ISS15+	N/A	ISS15+/MAIS3+	Serious injury	ISS15+
	Database	NASS CDS	NASS CDS	NCAP	MB-FE	GIDAS	NASS CDS	ITARDA	ITARDA	NASS CDS

database. Katagiri et al. [8] generated an artificial collision database with a multi-body (MB) modeling solver to obtain a more detailed database that contains information on occupant stature and impact angle. Improved accuracy was obtained, but the approach was still probabilistic and, therefore, limited by the difficulty of generalizing the dozens of logistic predictors over the entire solution space. The second approach consists of simulating the collision with a MB solver after it has taken place [9, 18]. As a result, important injury predictors can be considered, such as vehicle crash pulse [19], vehicle interior layout, occupant posture and occupant morphology [20–22]. These higher complexity simulations are computationally expensive and require significant computational resources, which largely limit the feasibility of being used onboard a vehicle system for rapid injury risk estimation.

As computationally efficient tools, lumped parameter models (LPM), which are simplified lumped representations of mechanical systems, have been used extensively for preliminary rapid evaluation of restraint systems and injury risk at a whole-body level [23–28]. Such models have been developed for frontal, near side and rear collision scenarios, to estimate chest, head and neck primary collision injuries based on kinetic responses. The extensive research and application in industry of these simplified models have demonstrated their prediction robustness and accuracy for low computational costs [25, 29].

This study proposes a framework for rapid and abbreviated injury scale (AIS)-level accuracy injury risk estimation of common collision scenarios demonstrated with a single vehicle type. With a balance of computational efficiency and modeling capability, LPMs in the primary direction of impact were used over other more complex modeling approaches. A methodology for LPM parameter uncertainty and model adequacy quantification is proposed with arbitrary and bootstrapped PCE. Such a framework can form the basis for a new tool of on-board, accurate and rapid post-collision injury risk assessment of vehicle occupants to reduce current MVC triage and fatality rates.

2 Methods

This study's technical framework consisted of two main phases: the mixed database creation phase and the LPM development-evaluation phase (Figure 1). For the creation of a finite element (FE) model vehicle collision database and a FE-MB model occupant injury database, simulation platforms LS-DYNA R8.0 (Livermore Software Technology Corporation, US) and MADYMO R7.5 (TNO MADYMO BV., Netherlands) were used, respectively. A publicly available Toyota Yaris vehicle model was selected as a representation of a typical passenger car. The most representative cases of the generated database were validated with respect to existing experimental crash test results of the National Highway Traffic and Safety Administration (NHTSA) and the Insurance Institute for Highway Safety (IIHS). In the second phase, LPMs for four common collision scenarios were developed. The re-

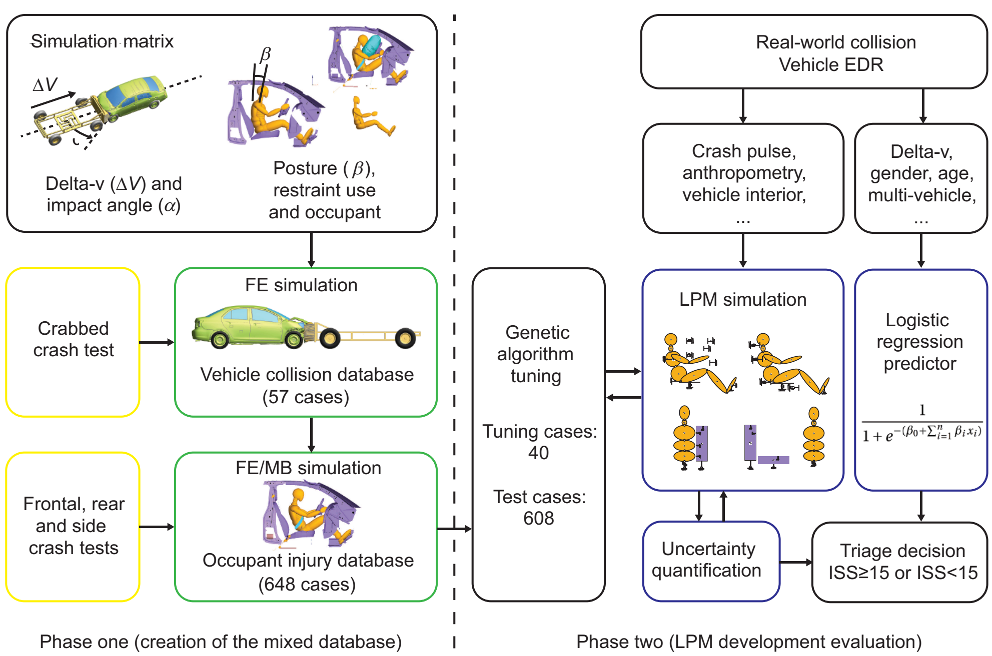

Figure 1 (Color online) Technical framework for rapid occupant injury risk prediction with low-complexity deterministic models and uncertainty quantification.

maining part of the database was used for validation, given the crash pulse from the event data recorder (EDR), occupant information (i.e., gender, posture and morphology), and restraint configuration (i.e., belt use, airbag use, belt load limiting force, pre-tensioner force and airbag firing time). To mitigate the risk and uncertainty associated with occupant injury risk estimation, prediction accuracy confidence bounds were determined with arbitrary and bootstrapped PCEs for each occupant injury model.

2.1 FE vehicle collision database

This database was generated with George Washington University National Crash Analysis Center's (NCAC) FE model of a production 2010 Toyota Yaris vehicle [30] and LS-DYNA's FMVSS 214 MDB shell elements FE model [31]. Both models have individually been validated with NHTSA experimental crash test results. To obtain a wide range of collision scenarios, the Toyota Yaris vehicle was set to be the target vehicle and the MDB the bullet vehicle. This is in accordance with the usage methodology of the NHTSA's FMVSS 214 side-impact crash tests. Fifty-seven different collision scenarios were considered at different collision Δv (40, 50 and 60 km/h) and impact angles (0° to 180° at a 10° interval), as illustrated in Figure 2(a). For this exploratory study, symmetry around the longitudinal axis was assumed to reduce the computational burden. To gain a better understanding of the obtained vehicle collision database, the vehicle acceleration time histories were parametrized to a haversine function with peak acceleration and duration parameters (1). This function is commonly used in occupant restraint collision tests for its simplicity and accuracy in representing vehicle crash pulses [32].

$$a_{\mathrm{veh}} = A \sin^2\left(\frac{\pi\theta}{2}\right), \tag{1}$$

where a_{veh} is the vehicle C.G. acceleration, A represents the crash pulse amplitude and θ is the duration.

2.2 FE-MB occupant injury database

The occupant-vehicle interior simulations were performed in a FE-MB solver with a modified NCAC model of the production 2010 Toyota Yaris interior [33] (Figure 2(b)). Some modifications were made to the model to accommodate all the considered crash modes. The center console, door window and door frame were modeled with multi-body elements according to the dimensions of NCACs Toyota Yaris FE model used for the vehicle collision database. Vehicle doors made of up of trim, foam and metal frame multi-body ellipsoids were added. Door crush significantly influences occupant injury for side-impact collisions [24]. Hence, door and seat motion were also simulated by utilizing the door crush and seat displacement time-histories obtained from the vehicle collision simulations.

A wide range of occupant, restraint and collision combinations were simulated with a FE-MB solver, amounting to 648 cases. Only the driver was simulated to minimize the size of the simulation matrix, as well as reduce the computational burden for this exploratory study. The simulation matrix included variations in collision Δv (40, 50 and 60 km/h), impact angle (0° to 360° in 10° intervals), restraint configuration (belted w/o frontal airbag, unbelted w/o frontal airbag,

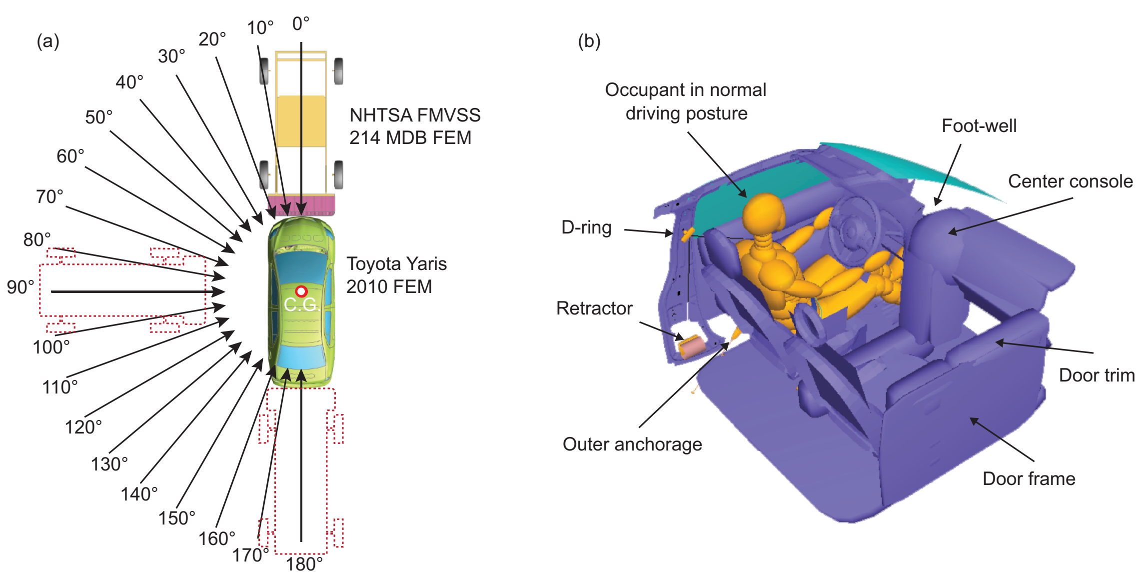

Figure 2 (Color online) Vehicle collision database and occupant injury database FE and MB models. (a) FE MDB-vehicle model; (b) FE-MB vehicle interior-occupant model.

belted w/ frontal airbag and unbelted w/ frontal airbag), occupant (50th percentile male and 5th percentile female ellipsoid MB models) and occupant posture (normal: lumbar flexion of 5.8° and forward leaning: lumbar flexion of 25°; as illustrated in Figure S1). The forward leaning posture was selected based on a recent study that determined this posture angle to be especially prone to increased injury severity [20].

The recorded injury measures included the highest severity injuries recorded in experimental crash tests for the Toyota Yaris vehicle: HIC, N_{ij}, CTI (for side impact), C_{comp} (for frontal impact) and VC_{abdomen} (for side impact) (Appendix A). Three comparable experimental crash tests were used to validate this database in three principal directions of impact: frontal (56 km/h rigid wall crash test for 50th percentile male [34]; NCAP-MGA-2006-011), near side (50 km/h MDB crash test for 5th percentile female without side airbags [35]; CES0639) and rear (32 km/h sled test for 50th percentile male [36]; SER06044).

2.3 LPM structure

Four two-dimensional LPMs were developed to simulate the most common collision scenarios (Figure 3). The contact mechanics were joint-, C.G.- and body perimeter-based, depending on the given constraint. To capture the injury mechanism and occupant response with minimal computational resources, linear springs and dampers were utilized. The frontal LPM was developed to account for a wider range of restraint and occupant configurations, compared to existing LPM designs [23, 25, 26]. Knee bolster, steering and dash were included, in addition to lap belt, shoulder belt and airbag. A seat friction coefficient of 0.5 was used, based on the validated NCAC Toyota Yaris interior MADYMO model. Belt pre-tensioning and load limiting was accounted for in the belt spring forces, with the thresholds set to the NCAC models settings. The airbag consisted of a damper and constant force spring that activates when the airbag reaches full deployment. The airbag firing time was identical to the NCAC model's settings. Based on the frontal crash test performed by the NHTSA, it was determined that for the Toyota Yaris, head, neck and chest injuries are the primary modes of injury for the driver in frontal collisions [34]. To determine the severity of these injuries the HIC, N_{ij} and C_{comp} were selected (Appendix A). The C_{comp} was evaluated by including a chest stiff-

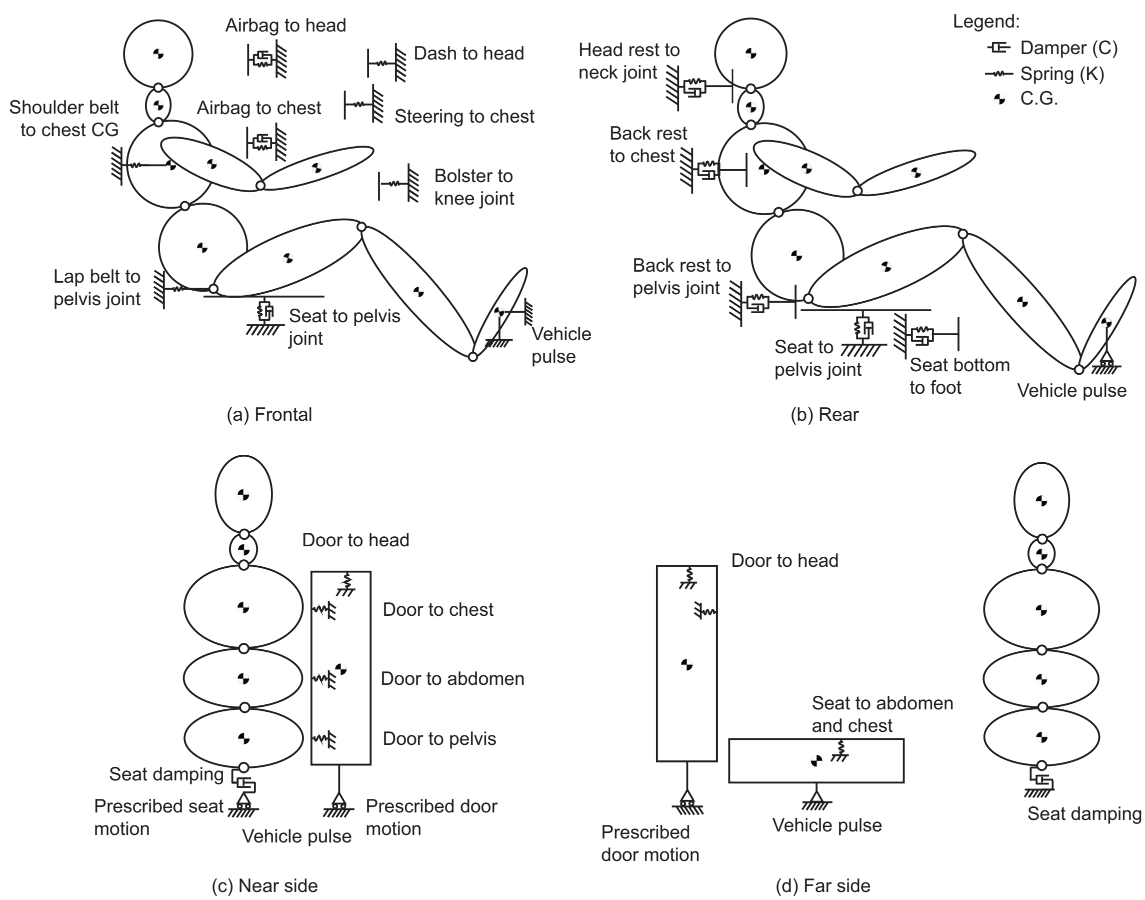

Figure 3 (Color online) Frontal (a), rear (b), near side (c) and far side (d) LPM designs.

ness spring, from which the chest deflection could be derived. The N_{ij} was evaluated at the upper neck joint with recorded normal and moment loads.

The developed rear LPM differed significantly from the very limited existing ref. [32]. Since occupant sliding is significant with high speed rear impacts, the occupant feet had an additional longitudinal DOF, but were limited in motion when contacting the seat bottom. Back and head rest spring dampers were also included. The IIHS rear sled test results indicated that head and neck injuries are the primary modes of injury for the Toyota Yaris vehicle [19]. Hence, HIC and N_{ij} were the evaluated injury measures for the rear LPM. The developed near side LPM, similarly to existing side LPMs [24, 27, 37], included door crush, but differed in that it models the entire upper body of the occupant. This was done so as to account for all the primary modes of injury in near side impact for the Toyota Yaris, as indicated by the NHTSA side impact crash tests [38]. This includes head, neck, chest and abdomen injury, for which the HIC, N_{ij}, VC and CTI measures were selected.

The mass of the upper extremities was included in the chest body element and the mass of the lower body was included in the mass of the pelvis element. The door and seat motion time-histories were obtained from the vehicle collision database. To simulate the restriction in body motion for belted occupants, the seat slip constraint damping was increased by a fixed tunable factor. To our knowledge, no literature exists on far side LPMs. Our proposed design used the same body segmentation as the near side LPM with an added far side door and seat. The seat stiffness and damping properties were identical to the three aforementioned LPMs. Since driver seat displacement in far side collisions is minimal, it was decided to not include it in the far side LPM. All LPMs were developed on MATLAB Simulinks Simscape Multi-body platform R2017b (The Mathworks Inc., US).

2.4 LPM tuning and validation methodology

Parameters in the developed LPMs were identified via genetic algorithm (GA) meta-heuristic optimization. A four-step process was employed. During the first global optimization, a 6- to 8-case set, including varying belt use, airbag use and gender, was used for concurrent optimization of all the parameters. A population size of 50 was used to introduce sufficient diversity into the initial GA generation. Next, the results were used to perform individual base case optimizations, where the optimization parameters were limited to case relevant ones, e.g., belt and airbag parameters for the "belt and airbag in use" cases. With fewer optimization parameters, the population size was reduced to 20. After this, the occupant optimization was executed to obtain the occupant joint related coefficients for occupant types that had not been previously optimized for. Finally, the obtained coefficients were evaluated and validated with the remaining unseen cases of the FE-MB database. The optimization cost function used was equal to the sum of injury level prediction errors and ISS prediction error, with a constraint of a 10 s simulation time on an Intel i7-8550U 1.8 GHz system (2). The ground truth was assumed to be the FE-MB database predicted injury levels, i.e., AIS for each injury type and ISS for whole-body injury.

$$\min \quad \sum_{i=1}^{n} (e_{\mathrm{AIS}_i}) + e_{\mathrm{ISS}}, \tag{2}$$

$$\text{s.t.} \quad T_{\mathrm{sim}} \leqslant T_{\mathrm{lim}}, \tag{3}$$

where e_{AIS_i} represents the error in injury level predicted (AIS level) for n considered injuries, e_{ISS} represents the error in whole-body injury level predicted (ISS level), T_{sim} is the simulation time in seconds and T_{lim} is the simulation time constraint. The simulation time was constrained to accelerate convergence to the optimal solution and avoid excessively large damping factors, which are computationally expensive. To minimize the off-set from the ground truth (i.e., the FE-MB database), coefficients were selected according to the aforementioned tuning framework and verified to be coherent within a single LPM coefficient basis and between different LPM models.

2.5 Quantitative prediction uncertainty evaluation

Forward uncertainty propagation with PCEs was applied for parameter uncertainty and model adequacy quantification. This was achieved by making a surrogate model $\mathcal{M}^{PC}(\boldsymbol{X})$ of the computational model $\mathcal{M}(\boldsymbol{X})$ (4).

$$\mathcal{M}(\boldsymbol{X}) \approx \mathcal{M}^{PC}(\boldsymbol{X}) = \sum_{\alpha\in\mathcal{A}} y_\alpha \psi_\alpha(\boldsymbol{X}), \tag{4}$$

where $\boldsymbol{X}$ represents the random component vector, $y_\alpha \in \mathbb{R}$ the multivariate polynomial coefficients and ψ_α the multivariate polynomials that are orthonormal to the joint probability density function of $\boldsymbol{X}$. The arbitrary polynomial form (aPCE) was used, because it does not assume a probability density function form.

Such an approach was implemented for our model in a MATLAB extension, called Uncertainty Quantification lab (UQlab, ETH Zurich, Switzerland). Two sensor input variables of the LPM were selected: occupant posture (defined as lumbar flexion from the neutral 5.8° angle) and seating position (defined as seat track location from neutral position). These were selected because they do not require tuning of new body types or vehicle interior coefficients. Sensor measurement errors of the occupant posture and seating position were assumed to not exceed 5° and 5 cm, respectively, 95% of the time, following a Gaussian error distribution. A PCE metamodel was used with a least angle regressions (LAR) optimization approach to determine the arbitrary PCEs. The polynomials were truncated to a maximum degree of 15. A set of 50 sample simulations were run with a latin hypercube sampling approach. Next to the two sensor measurements, the varied parameters included: collision Δv (40–60 km/h), impact angle (0°–360°), restraint configuration (belted with/without frontal airbag, unbelted with/without frontal airbag, belted with frontal airbag and unbelted with frontal airbag) and occupant (50th percentile male and 5th percentile female ellipsoid MB models). One hundred and fifty bootstrap replications were used for the bootstrapped PCE, as recommended in ref. [15].

2.6 Triage performance evaluation

The triage performance for the LPM based injury risk estimation was evaluated with the FE-MB occupant injury database within the impact angle coverage of all LPMs (excluding the training cases). The FE-MB database was used for evaluation, since available real-world data sets, e.g., NASS-CDS, do not include a sufficient number of cases involving a Yaris vehicle model. The triage decision metric used was ISS15+. A recent LR injury risk estimation algorithm was also compared on the same database with its logistic regression based injury risk predictors [7]. This algorithms was selected because it utilizes the ISS15+ metric for triage decision, covers all four principal directions of impact and has been shown to obtain the best triage rates on the NASS CDS data set. The performance of the OTDA algorithm was evaluated for its recommended RT [7]. To serve as a comparison, the performance of the OTDA algorithm was evaluated using the present FE-MB database and compared to its reported performance on the EDR triggered subset of the NASS CDS database.

3 Results

First, the created vehicle collision and occupant injury databases are presented. Next, the tuned LPM coefficients and impact angle coverage are given, followed by their prediction performance and uncertainty evaluation. Finally, the model injury risk triage performance is presented and compared to existing algorithms.

3.1 FE vehicle collision database validation

The vehicle collision database setup was validated by simulating an experimental crabbed side impact collision performed by the NHTSA [38]. Similarity of the simulated and experimental vehicle acceleration time-histories for both longitudinal and lateral directions was assessed via CORrelation and Analysis (CORA) [39]. An average CORA score of 0.724 and 0.863 was obtained, indicating a fair to good fit between the simulation and experiment. However, short acceleration peaks around 10 ms were observed for the simulation results in both directions that were not observed in the experimental results (Figure S2).

The post-collision side impact patterns exhibited a mid-door maximum exterior static crush of 221 and 230 mm for the experimental and simulation results, respectively [38]. For visualization and comparison, the vehicle collision database was parametrized to a haversine function with a mean parametrization r-squared value of 65.0%±9.8% (Figure 4). Side impact collisions resulted in significantly higher peak accelerations and smaller crush zones. Collision duration was not highly correlated with delta-v, but systematically longer for oblique impact angles.

3.2 FE-MB occupant injury database validation

The occupant injury database was validated in the three principal directions of impact by simulating experimental crash tests performed by the NHTSA and IIHS [34–36, 40]. These experimental collisions were compared with simulation results of relevant injury metrics for the developed LPMs, including: HIC, N_{ij}, maximum neck shear force, maximum neck tension force, maximum thorax acceleration, etc. Most injury measures agreed well with an average error of 16.6% ± 22.4% (Table S1). A notable exception was the maximum neck shear force recorded during the rear collision sled test, for which a discrepancy of 178 N from 31 N was observed.

The FE-MB resulting database possessed a satisfactory distribution in injury levels with 52.8% of cases being ISS<15 and 47.17% of cases being ISS⩾15. The obtained injury levels were used to generate "delta-v-impact angle" injury maps for different occupants, restraints and postures. To illustrate, the obtained injury map for the normal posture 50th percentile male with restraint is given (Figure 5). For a restrained 50th percentile male occupant, only the side impact MVCs were serious, i.e., ISS⩾15, due to the absence of side impact airbags.

3.3 Fine-tuned LPM angle coverage and prediction accuracy

The LPMs exhibited low injury prediction errors for all injury types and impact directions (with median whole-body injury prediction errors ranging between 5% and 12%), except for N_{ij} in far side collisions. The parameters obtained from the GA tuning procedure for the four LPMs can be found in Ap-

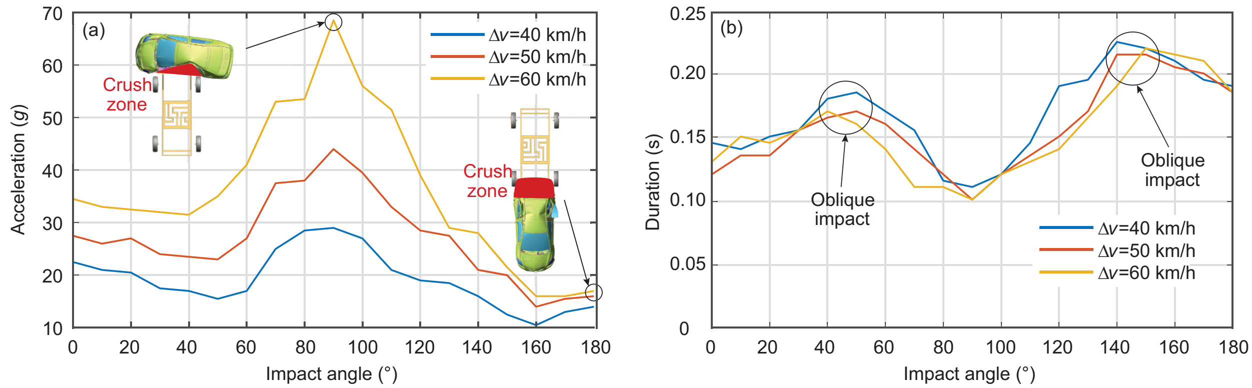

Figure 4 (Color online) Vehicle collision database (a) amplitude and (b) duration parameters from haversine parametrization.

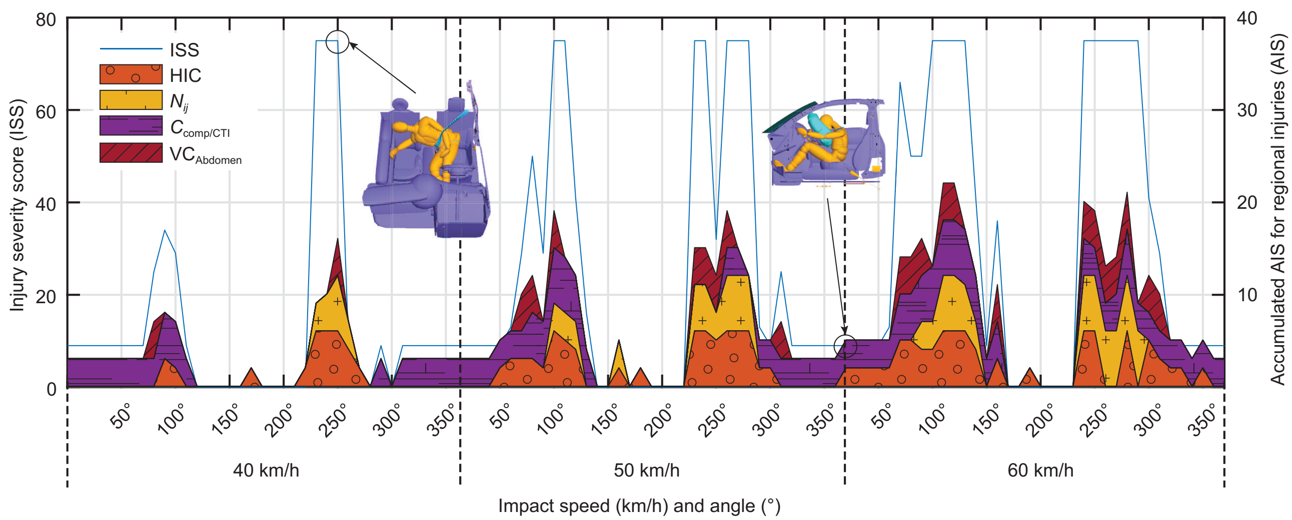

Figure 5 (Color online) Occupant injury database accumulated injury levels for regional injuries (AIS) and overall body injury (ISS) (shown: normal posture 50th percentile male with airbag and belt in use).

pendix E, Tables S2–S5. These parameters are valid over a range of low oblique impact angles: frontal (340°–30°), near side (80°–110°), rear (140°–210°) and far side (250°–280°) (Figure 6).

These ranges were determined by allowing a maximum deterioration in injury level prediction accuracy of 5% compared to the base scenarios, i.e., 0°, 90°, 180° and 270°. Outside of these ranges, the occupant body undergoes highly three-dimensional motions, that cannot be represented by two-dimensional LPMs. The injury level prediction accuracy of the four LPMs is shown in Figure 7.

From the error box-plot, it can be deduced that the lowest prediction error was obtained for chest and abdomen injuries, where the errors did not range beyond zero. The longitudinal impact LPMs outperformed the lateral impact LPMs for most injury types. These also tended to underestimate injury severity, whilst the lateral LPMs mainly overestimated injury severity. The mean computational time for all the LPMs did not exceed 10 s on an Intel i7-8550U 1.8 GHz platform (7.23±0.92, 8.66±1.82, 3.68±0.73 and 3.05±0.83 s for the frontal, rear, near side and far side LPM, respectively).

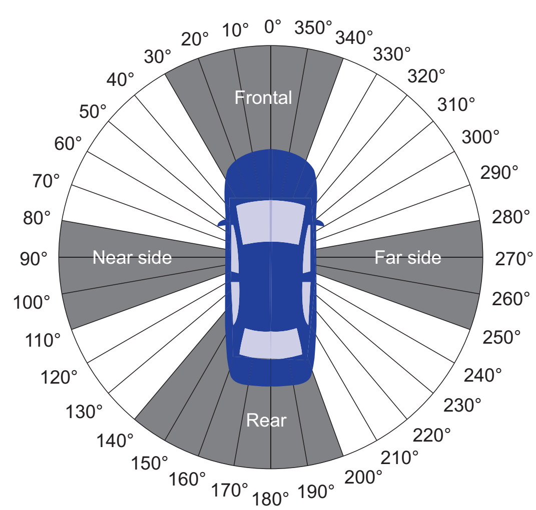

Figure 6 (Color online) LPM simulation impact angle coverage (grey).

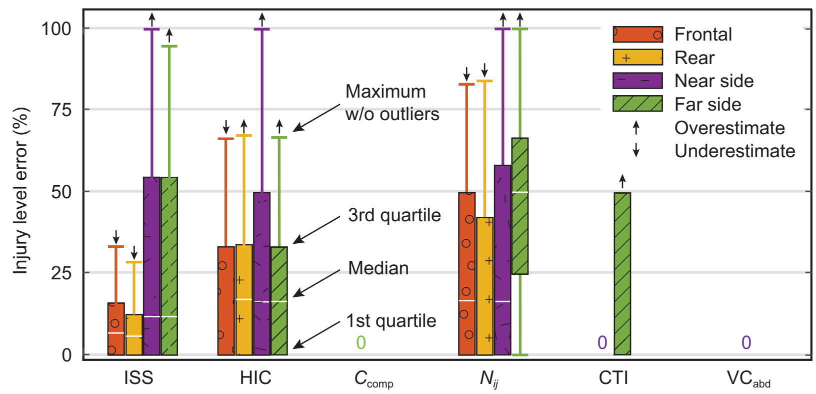

Figure 7 (Color online) LPM absolute injury level prediction error box-plot.

3.4 Model adequacy and parameter uncertainty quantification

The second order statistical moment estimation from the aPCE analysis for incorrect inputs of occupant posture and seating position due to possible sensor measurement inaccuracy on the OT and UT rates is shown in Table 2. LPM parameter and model uncertainty (σ) was on average 5.5%±2.7% for OT rates and 3.1%±3.0% for UT rates.

The maximum PCE degrees, which define the PCE multivariate polynomial degree and are a sign of uncertainty metamodel complexity, were larger for the higher complexity LPMs. The leave-one-out (LOO) error, which captures lack of generalization capability of the PCE, was observed to be higher for the near side LPM, i.e., LOO of 0.37 and 0.74. The results for the frontal, rear and side LPMs indicated satisfactory PCE fitting was achieved with bootstrap confidence bounds being narrow and close to the validation basis, as shown for the frontal LPM (Figure 8).

With the possible inaccurate sensor measurements of occupant posture (defined as lumbar flexion from neutral 5.8° angle) and seating position (defined as seat track location from neutral position) incorporated into the LPM, the obtained OT and UT rates were generally larger. A positive posture off-set indicates a sensor overestimating occupant posture, i.e., a sensor returning a higher value of occupant posture than the actual value input to the LPM simulation. In this way, the effect of limited sensor measurement accuracy (termed as "parameter uncertainty"), as well as the effects of model accuracy (termed as "model adequacy"), on the accuracy of the predictions can be evaluated. In some instances, lower OT and UT rates were achieved with incorrect sensor inputs, however, the values at which this occurred varied widely and were observed to be contradictory. This can, for example, be observed for the seating off-set of the frontal LPM (Figure 8).

Table 2 aPCE uncertainty quantification for all principal modes of impact for the developed LPM

Parameter	OT rate			
	Frontal	Rear	Near side	Far side
Max. degree	10	5	3	3
LOO	0.14	0.08	0.37	0.15
SD (σ)	5.1	9.4	1.8	5.5
Parameter	UT rate			
	Frontal	Rear	Near side	Far side
Max. degree	7	4	2	3
LOO	0.08	0.08	0.74	0.06
SD (σ)	2.1	1.1	1.0	8.2

3.5 Triage performance evaluation

The developed deterministic approach consistently achieved lower OT rates compared to the OTDA algorithm, whilst keeping the UT rates below 8% levels. The triage performance for the deterministic LPM based injury risk estimation was evaluated with the FE-MB validation subset within the impact angle coverage of all LPMs, by comparing it with a state-of-the-art LR based algorithm [7]. The LR based algorithm performance on the data set was obtained by using the reported LR functions to predict ISS⩾ 15 and comparing it with the FE-MB database results for OT and UT. The previously reported performance on the NASS CDS data set was also included for further comparison (Figure 9).

The FE-MB database and NASS CDS OT performance for the LR based algorithm was largely similar, except for the rear impact model OT rate, where a large discrepancy of more than 40% was present. The obtained UT rates for the LR based algorithms were significantly lower when evaluated on the FE-MB database.

4 Discussion

Rapid, accurate and reliable occupant injury risk prediction remains a necessary and challenging problem for active vehi-

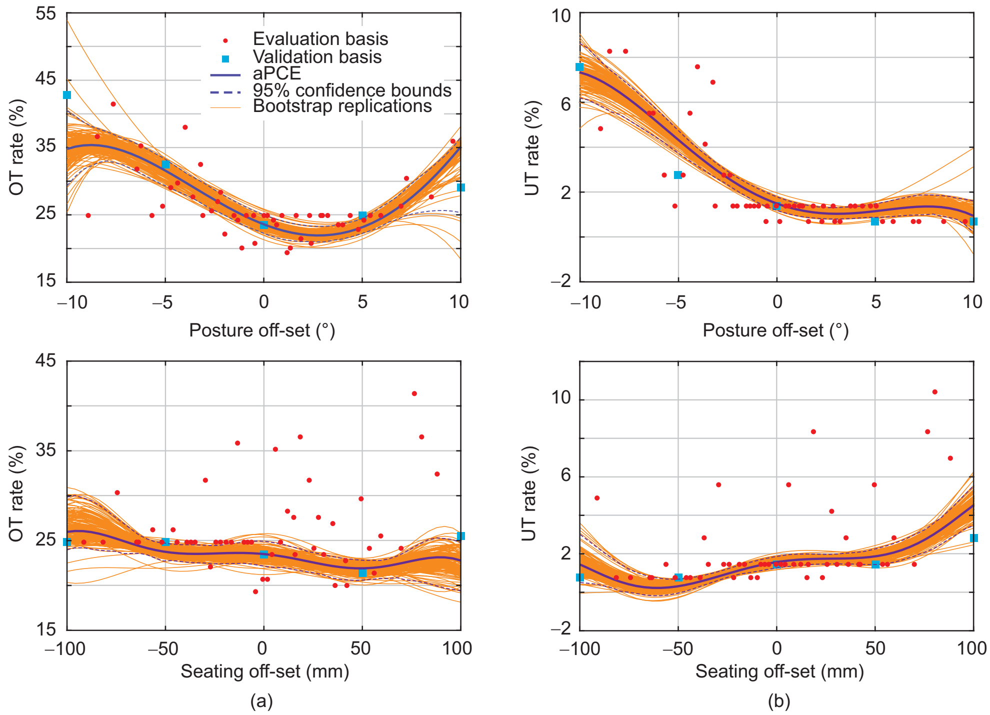

Figure 8 (Color online) Arbitrary PCE and bootstrapped PCE uncertainty quantification with corresponding confidence bounds for the frontal LPM posture and seating position measurement error (a) OT rate and (b) UT rate.

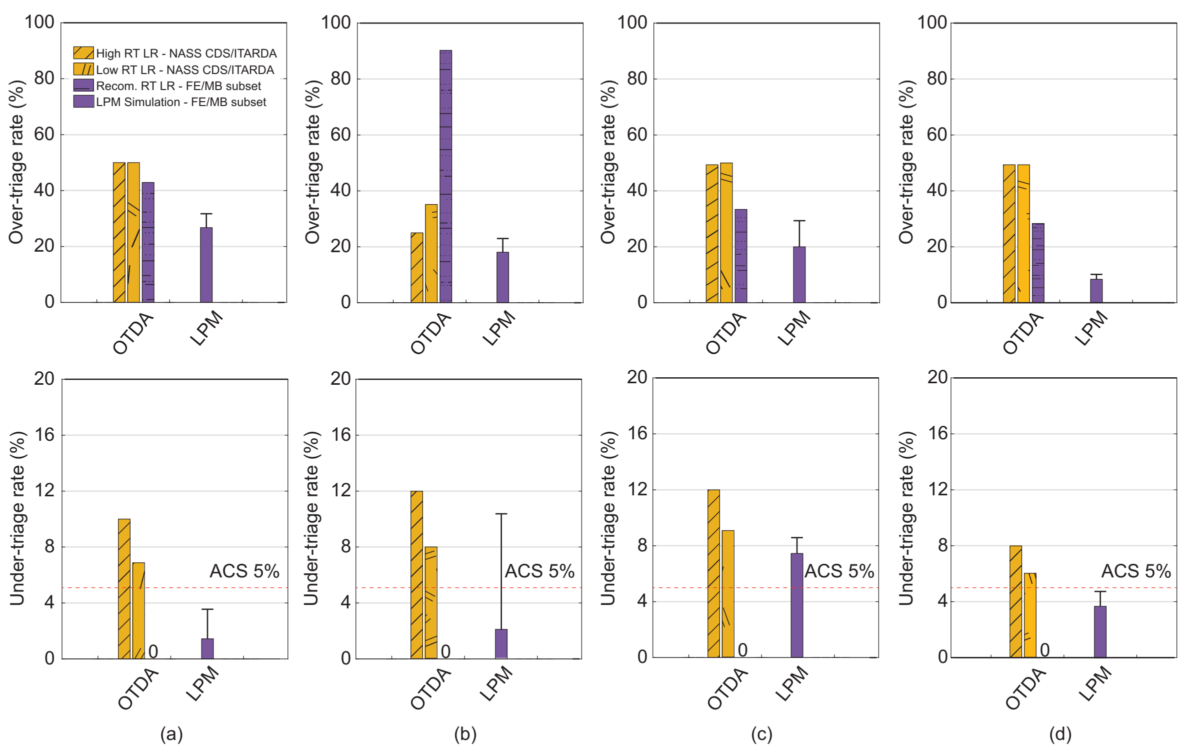

Figure 9 (Color online) Over-triage and under-triage comparison for a state-of-the-art injury prediction model [7], as well as the LPM model, on the FE-MB validation subset and NASS CDS data set with different risk thresholds (RT). From left to right: (a) frontal, (b) rear, (c) near side and (d) far side.

cle safety systems. Current injury risk estimation algorithms mostly rely on probabilistic tools using a portion of the available occupant and vehicle information, and lack robust uncertainty quantification. The aim of this study was to develop a framework that uses simplified deterministic models with uncertainty quantification to predict occupant injury risk levels based on occupant morphology, posture, vehicle interior and collision deceleration time-history information. This was demonstrated with new LPM designs that were tuned with GA optimization and evaluated for prediction uncertainty with arbitrary and bootstrapped PCEs.

4.1 Vehicle collision and occupant injury database validation

The FE vehicle collision and FE-MB occupant injury databases were validated with experimental crash test results from the IIHS and NHTSA to demonstrate their credibility for training occupant LPMs. The two databases were developed on different platforms to reduce the computational burden. The validation case for the vehicle collision database setup showed moderate to good similarity between the experimental and simulation results in vehicle response and structural deformation. The observed peaks in acceleration around 10 ms in the simulation results are likely the result of having increased the stiffness of the FE model seat foam materials, to prevent the occurrence of negative volumes, which would result in simulation failure. For the FE-MB occupant injury database, all of the injury measures were predicted within acceptable bounds for injury level prediction for the frontal and side impact crash tests. A 178 N neck shear force discrepancy for the rear crash test was most likely caused by the simplified representation of the driver seat head rest. For the occupant injury database, the side impact collisions resulted in the highest severity injury levels, which was due to the absence of side airbags. The crash test vehicle has been shown to perform poorly without side airbags in side collisions, as evidenced by a crash test performed by the IIHS, where the simulated occupant HIC value exceeded 2000 [35]. Lower extremity injuries were also recorded and found to be minimal for the 50th percentile male occupant, which agrees well with existing experimental results [34].

4.2 LPM performance evaluation

The four LPMs exhibited moderate to good prediction accuracy on their respective validation sets except for the neck injury prediction of the far side impact. C_{comp} and VC_{abd} were not discretized into six severity levels, since such AIS probability functions have not been found or fully validated yet. This reduced discretization meant that the LPMs were able to achieve injury severity level prediction errors that did not range beyond zero. The LPM that obtained the lowest ISS prediction errors was the rear impact model (μ_e=5%), followed by the frontal (μ_e=6%), near side (μ_e=11%) and far side (μ_e=11%) models. Occupant injury response is highly dependent on how the human body interacts with its environment. Hence, a small off-set in impact location or timing, heavily influences occupant injury risk. As a result, larger occupant motions result in larger errors in injury risk prediction for LPMs. This can be seen with the poor prediction accuracy of neck injury of the far side impact LPM. Note that this did not translate to poor triage rates for far side collisions, since the error is mainly between AIS severity levels 3 and 5, both commonly observed for $ISS \geqslant 15$. Previous studies on initial occupant posture have also shown that a slight change in posture can lead to significant changes in injury outcome [20]. The obtained occupant stiffness and damping coefficients were coherent between different impact modes for identical vehicle interior elements and occupant joints, but differed in cases where occupant body joints exhibit motion-dependent stiffness and damping. To illustrate, the neck stiffness and damping were higher (by 7 $\frac{N}{m}$ and 4.5 $\frac{Ns}{m}$, respectively) in dorsi-flexion than in flexion, which agrees with existing research [41]. The LPMs were found to be capable of simulating occupant injury under low oblique impact angles, where occupant motion could still be simplified to a two dimensional problem. Seventy-one percent of vehicle-to-vehicle collisions are within a 30° range of the principal directions of impact [42]. Thus, a large portion of vehicle collisions could be simulated with these simplified deterministic models. Finally, the required computational time for a 200 ms LPM collision simulation on an Intel i7-8550U 1.8 GHz 26.43 Giga FLoating point Operations Per Second (GFLOPS) platform required less than 10 s. Current state-of-the-art vehicle computational systems, like the 2019 Nvidia Drive Xavier series, can deliver 5 FP16 TFLOPS of performance [43].

4.3 Prediction uncertainty evaluation

Due to the limited sample size, which is common in automotive crash safety research, typical uncertainty quantification techniques, such as Monte Carlo simulation, are not feasible. At the same time, simply computing the statistical moments of a small sample increases the probability of poor out-of-sample performance. This is why, for this study, prediction uncertainty for individual LPMs under inaccurate occupant posture and seating position inputs was evaluated with arbitrary PCEs. The second order statistical moment were minimal: 5.5%±2.7% and 3.1%±3.0% for OT rate and UT rate, respectively (Figure 8). The near side LPM was not heavily affected by the inaccurate measurement inputs of occupant posture and seating position, as indicated by the low standard deviations. Consequently, the achieved degree of generalization of the PCE was also lower (LOO_{OT}=0.37; LOO_{UT}=0.74). The bootstrapped PCEs showed good agreement with the arbitrary PCEs, as shown for the frontal case in Figure 8. The aPCE predictions were within the 95% bPCE confidence bounds for most of the validation basis. The results demonstrated that a combined aPCE and bPCE uncertainty quantification approach is capable of providing model injury risk prediction reliability estimates. This method could be extended to existing probabilistic approaches, such as LR, to provide injury severity prediction confidence bounds to EMS for improved triage decision.

4.4 Triage performance evaluation and comparison

To evaluate the designed LPMs as computationally efficient tool for improved injury level prediction, they were tested on the validated FE-MB occupant injury database within the impact angle coverage of all LPMs and compared with a state-of-the-art LR based algorithm. A real-world accident database was not used for further comparison given the limited number of recorded MVCs involving the studied vehicle model, i.e., Toyota Yaris. It should also be noted that the far side collision database was not validated experimentally, due to the lack of existing far side crash tests for the Toyota Yaris vehicle, meaning that the far side triage results should be taken with caution. Thus, the comparison can be used on a relative basis, but error rates should not be taken in absolute terms. The obtained improvements in OT rates are partly due to the use of a deterministic model, where occupant, restraint and vehicle related predictors can be taken into account in more detail. Moreover, the predictions include a whole body level injury risk estimate and body part specific injury risk estimates. The UT rate was non zero, but remained below 8% for all impact modes. Since OT and UT rates depend highly on the database on which they are evaluated, reported performance on the NASS CDS database was also compared. The OT rate was generally similar for the existing LR algorithms on the FE-MB database and the NASS CDS database, except for rear-end collisions. This is probably due to the absence of higher severity rear-end collisions in the NASS CDS database, resulting in an over-estimation of injury severity. The UT rate differed significantly between the two data sets. LPMs are incapable of accounting for internal and tissue level injuries. This is because injury measures to estimate the probability of a certain AIS severity levels currently do not exist [44]. As a result, they cannot be taken into account, meaning that the LPM will tend to underestimate injury severity, if these types of injuries are present.

4.5 Limitations and future research

Several limitations of this study should be noted. First and foremost, the use of LPMs offers high computational efficiency, especially for demonstrating the proposed framework of injury prediction on-board, yet remains simplified with regard to the structural characteristics and the interaction of the vehicle and human models. For example, the detailed interactions between the occupant with the interior largely affect the resultant injury risks and are beyond the modeling capability of LPMs. More biofidelic FE human body models, which allow injury evaluation and assessment up to the tissue level, could be adopted for more accurate estimation of the loads in crash when more on-board computational resources will be available. Secondly, the GA tuning procedure of the LPMs is time consuming with no assurance of obtaining global minima. The developed LPMs for this study have been validated for Toyota Yaris under low oblique impact angles. Although such boundary conditions were assumed to be representative of the majority of accident scenarios of a typical passenger car, the results do not fully reflect the real-world variance on vehicle models and human factors in collisions. Also note that since no experimental far side collision of the Yaris vehicle was available, the far side LPM could not be validated. Next, because of the exploratory nature of this study, only a single vehicle model was used. Further validation under different vehicle models, which are representative of real world MVCs, is necessary for a direct comparison between existing probabilistic algorithms and the developed deterministic ones. Furthermore, the proposed framework was validated on the large-scale FE-MB database instead of a real-world database, such as NASS CDS. This decision was made given the fact that the real-world NASS CDS data set does not contain any high severity injury Toyota Yaris collisions; and cannot cover the complete simulation scope of the developed LPMs. Hence, further validation of this methodology with a different vehicle that is well represented within the NASS CDS data set is also recommended. As a result, such a deterministic approach remains vehicle-model specific, since optimization and validation would have to be performed for each vehicle type in order to provide a verified and validated alternative to LR based prediction.

Despite these current limitations, the enhancing capabilities that rapid deterministic models offer, in parallel to a LR based injury risk estimation algorithm, are significant (Table 1). It would enable body level injury prediction that is vehicle- and occupant-specific at limited computational costs. To this end, proposed further development of this framework include: validating the approach on a real-world or high-fidelity FEM database, adding side collision occupant airbags, modeling multiple occupants and including age specific risk injury criteria to account for occupant age. Finally, more severe lower extremity injuries are common in the NASS CDS data set, hence, it is recommended to include this type of injury in future studies when considering other vehicle models.

5 Conclusions

The present study developed a computational framework that uses rapid and AIS-level accurate deterministic models with PCE uncertainty quantification to enhance existing injury risk estimation algorithms. The advantage of such an approach compared to state-of-the-art logistic regression based algorithms was evidenced by the improved OT rates and under 8% UT rates achieved on the numerical collision database. The present results suggest that deterministic LPMs may lead to comparable triage rates of current post-collision injury risk estimation algorithms at low computational cost by providing occupant, restraint system, vehicle interior and crash pulse specific occupant injury risk estimates. Further validation with other data sets and vehicle models is necessary when real-world data sets will be available.

This study provides an alternative and computationally feasible method of injury risk prediction that is non-probabilistic for advanced vehicle safety systems. With high computational efficiency and flexibility of parameter adjustment, and with further development and validation, it may offer an alternative to injury risk prediction algorithms and decision making for implementation into vehicle safety systems.

This work was supported in part by the National Natural Science Foundation of China (Grant Nos. 51705276 and 51675295), Tsinghua University Initiative Scientific Research Program (Grant No. 2019Z08QCX13), and the National Key R&D Program of China (Grant Nos. 2017YFE0118400 and 2018YFE0192900).

Supporting Information

The supporting information is available online at tech.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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