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Deep Learning-Based Rapid Prediction for Occupant Injury in Vehicle Restraint System Design

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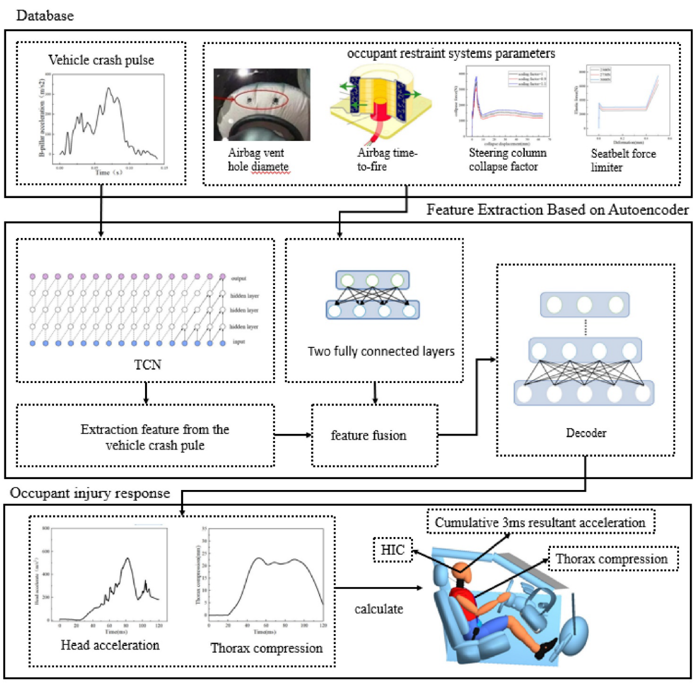
Abstract

Accurate prediction of occupant injury responses is essential for the effective design and optimization of vehicle occupant restraint systems (ORS). To address the complexity and time-consuming nature of injury prediction in existing occupant restraint system (ORS) design workflows, this study proposes a deep learning-based method tailored for frontal collision scenarios. The proposed method enables rapid injury prediction by simultaneously processing crash waveform signals and ORS parameters as inputs. It enables accurate prediction of time-dependent biomechanical response curves across multiple occupant body regions, effectively capturing the complex, nonlinear interactions between dynamic impact conditions and restraint system characteristics. The proposed method requires only 2.7 seconds to predict the occupant's head acceleration–time curve and thorax compression–time curve, as well as to compute the corresponding injury assessment indicators (C-NCAP 2024). The predicted curves achieve a similarity score of over 0.86, and the accuracy of the selected injury assessment indicators exceeds 0.80. Compared with multi-rigid body simulations, the computational efficiency is improved by 533 times. These results demonstrate the model's potential for intelligent, data-driven, and time-efficient ORS design.

Keywords

vehicle collision, time-dependent biomechanical response curves, injury assessment indicators, injury prediction, occupant restraint system (ORS), deep learning

Graphical Abstract



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1. INTRODUCTION

In the field of vehicle safety, regulatory agencies worldwide have established stringent requirements for vehicle occupant protection performance during collisions. Upon completion of vehicle design, full-scale crash tests under specified impact conditions (e.g. frontal and side collisions) must be conducted to verify compliance with safety regulations. During the design phase, engineers aim to meet the highest safety standards by optimizing both vehicle crash structures and occupant restraint systems (ORS). However, vehicle crash tests are highly destructive and require significant financial and material resources. To reduce the number of costly physical tests, shorten development cycles, and lower overall costs, computational simulations are commonly employed during the design phase. These simulations are used to predict injury metrics or time-dependent biomechanical response curves of various body regions (e.g., head, thorax, lower limbs), thereby providing guidance for vehicle and ORS design optimization.

Nevertheless, predicting occupant injuries remains a highly challenging task. The complexity arises from several sources: the plastic deformation of vehicle structures during crashes, the strong nonlinear behavior of restraint systems (such as seatbelts and airbags), and the intricate biomechanical properties of the human body. These factors often limit the accuracy of simulation models. Additionally, inter-individual variability—such as differences in body size, posture, and age—further increases prediction uncertainty.

Currently, two primary methods are widely used in the industry: multi-rigid body dynamic simulations (e.g., MADYMO) and finite element (FE) simulations (e.g., LS-DYNA). Multi-rigid body simulations offer high computational efficiency and are well-suited for parameter optimization and design screening, but they lack the capability to capture localized tissue deformation. In contrast, FE simulations can model detailed mechanical responses of human tissues with high accuracy, but they are computationally intensive and require complex model setup, making them less suitable for rapid design iteration. Therefore, achieving fast and accurate prediction of occupant injury metrics and biomechanical response curves is a critical challenge in the current design and optimization of automotive restraint systems.

In recent years, deep learning (DL) has shown significant promise in the field of vehicle safety due to its ability to model nonlinear relationships and automatically extract features from complex datasets. DL-based methods have been successfully applied to tasks such as injury severity estimation, collision type recognition, and occupant motion prediction, leveraging input data formats including image, time-series signals, and 3D data.

Numerous studies have explored rapid occupant injury prediction using data-driven models. Bance et al. developed a computational framework that combines fast, AIS-level-accurate deterministic models with Polynomial Chaos Expansion (PCE)-based uncertainty quantification to enhance existing injury risk estimation algorithms. Wang et al. proposed a two-stage kinematic feature-based algorithm for near real-time injury severity prediction. In the first stage, Long Short-Term Memory (LSTM) and Temporal Convolutional Network (TCN) models were employed to predict the Abbreviated Injury Scale (AIS) levels of vehicle occupants, with TCN demonstrating superior performance. In the second stage, a Support Vector Machine (SVM) was used to refine the predictions, achieving near real-time performance without compromising accuracy. To further reduce computational complexity, the authors developed a lightweight pre-crash prediction model by distilling knowledge from a post-crash model, resulting in improved efficiency. Liu introduced a high-precision, near real-time occupant injury prediction model for autonomous vehicles, which incorporates collision conditions, vehicle characteristics, and occupant features. Yang et al. addressed the variability in occupant seating posture caused by swivel seats in self-driving cars by developing a posture-aware injury prediction model. This model achieved validation accuracies of 82.8% on simulated data and 62.9% on real-world datasets, with an average computation time of only 4.86 ± 0.33 ms. In a separate line of research aimed at incorporating restraint system parameters, Heo et al. constructed a machine learning framework to predict Euro NCAP injury assessment indicators for dummies with various ORS configurations, thereby contributing to early-stage design evaluation. Mathieu et al. employed reinforcement learning with a penalty function targeting injury minimization, showing adaptability across different vehicle types. Zhang applied a hybrid LSTM-Feedforward Neural Network (FFNN) model to rapidly predict whiplash injury responses based on simulation data under various design conditions, demonstrating effectiveness in accelerating seat design evaluation.

However, most existing methods are developed for real-time safety decision-making or categorical injury classification, with relatively few focusing on the prediction of detailed occupant time-dependent biomechanical response curves, which are essential for vehicle crashworthiness and occupant restraint system design. Moreover, many current models overlook the mechanical characteristics of occupant restraint systems (ORS). In most cases, only the specific ORS components (e.g. airbag usage) are used as input during model training, rather than the actual design parameters themselves—despite the fact that these parameters play a critical role in influencing occupant kinematics during a collision.

To address these gaps, this study proposes a deep learning-based method for the rapid prediction of occupant injury response in frontal collisions. The model utilizes Temporal Convolutional Networks (TCN) to capture both the temporal dynamics of crash pulse and the influence of key ORS parameters. This framework enables simultaneous prediction of time-dependent biomechanical response curves across multiple occupant body regions (e.g., head and thorax), providing a fast and accurate alternative to traditional simulation methods.

The proposed approach is validated using a multi-rigid body simulation dataset based on MADYMO, with results demonstrating strong generalization, high accuracy, and significantly reduced computation time. This study provides a feasible solution for efficiently evaluating occupant injury responses, especially in the early stages of vehicle safety analysis and system prototyping.

2. METHODOLOGY

The occupant restraint system (ORS) is a critical component of a vehicle's crash safety system, and its design quality directly affects occupant protection during collisions. The ORS mitigates impact forces and reduces injuries through coordinated subsystems such as seat belts, airbags, seats, instrument panels, and steering mechanisms. These subsystems exhibit complex, nonlinear, and coupled dynamic behaviors, making parameter design highly challenging (Fig. 1). In addition, ORS inputs (e.g. vehicle acceleration) are inherently variable, while outputs include occupant responses and injury metrics across multiple body regions and spatial axes. Due to the nonlinear and noise-sensitive nature of these parameters, the ORS input–output relationship cannot be expressed as a deterministic function, further increasing design complexity.

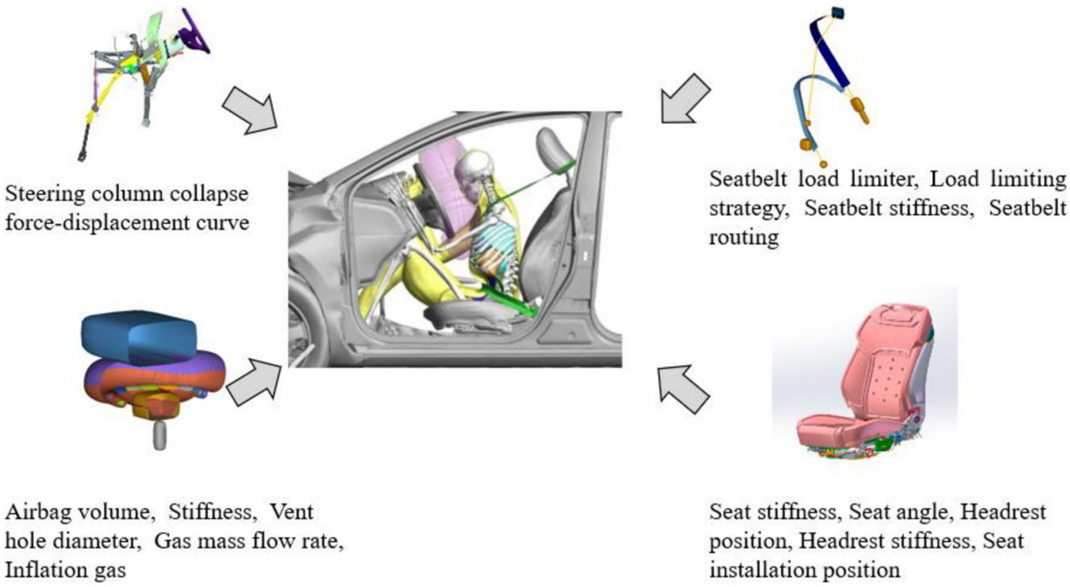


Fig. 1 Partial design parameters of the occupant restraint system.

In the design stage, numerical simulations are typically employed to predict occupant time-dependent biomechanical response curves and injury assessment indicators, which serve as a basis for guiding restraint system design. However, building and executing simulation models is a complex and time-consuming process, making it unsuitable for rapid iteration during the design phase. In order to improve the efficiency of vehicle restraint system design, this paper established a deep learning model based on TCN for fast prediction of occupant injury response based on Frontal Full Width Rigid Barrier Impact Test (FRB). The model can predict the response of multiple parts of the occupant (e.g., head acceleration and chest compression over time) and calculate the occupant injury assessment indicators. Fig. 2 shows the research framework of the proposed method, which is divided into the following three steps (i.e., dataset, OIPM, and result). The general steps of the proposed method are described below.

Step 1: Key injury response metrics and influencing parameters were identified, and the corresponding parameter space was defined. Latin Hypercube Sampling (LHS) was applied to generate diverse parameter combinations. Multi-rigid body simulations were then conducted to obtain occupant injury responses under various conditions. The resulting raw data were preprocessed by removing outliers and performing normalization to enhance training stability.

Step 2: A TCN-based neural network architecture was designed and implemented to construct the occupant injury prediction model (OIPM). Hyperparameters were optimized via grid search and model performance was evaluated using K-fold cross-validation to ensure robustness and prevent overfitting.

Step 3: The generalization ability and stability of the OIPM were evaluated through 5-fold cross-validation results. And the efficiency and accuracy of the OIPM were analyzed through an application example.

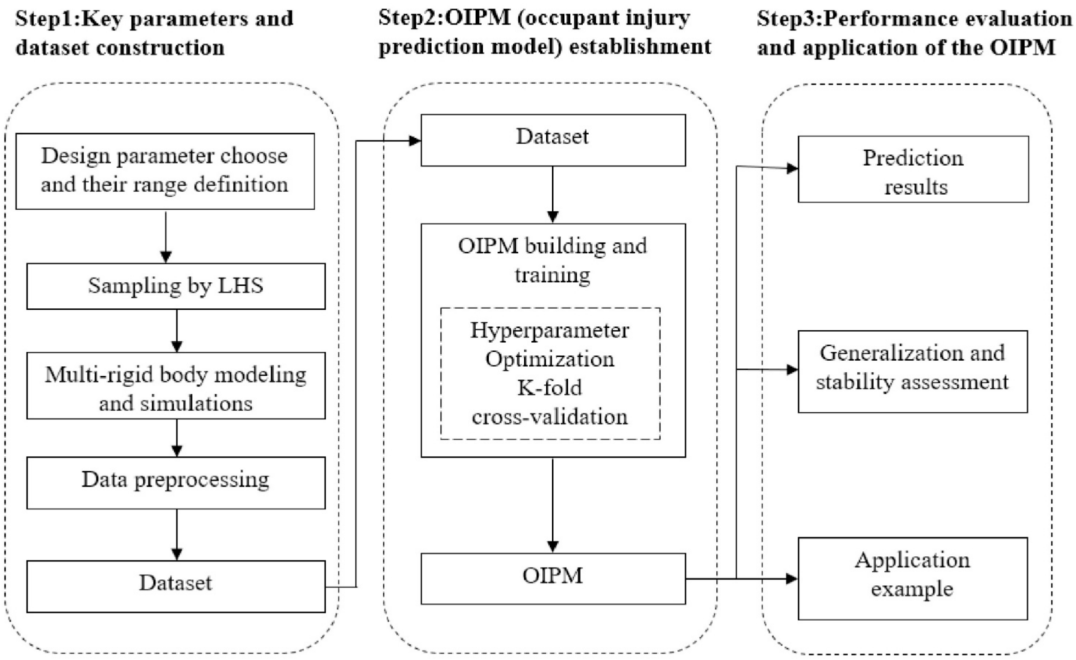


Fig. 2 Research framework.

3. KEY PARAMETERS AND DATASET CONSTRUCTION

The dataset is the foundation of deep learning model building, and its quality, scale and diversity determine the training efficiency and accuracy of the model. In order to build the OIPM and ensure its accuracy, this paper established a frontal collision occupant crash response system dataset that contains occupant response, ORS parameters, and other key influencing factors.

3.1 Key Parameters

3.1.1 Occupant Injury metrics on C-NCAP (2024)

In traffic accidents, the head and chest of occupants rank the top two fatalities, and are included in the evaluation standards set by different countries and regions. China's new car assessment standard (C-NCAP) 2024 uses HIC15 (Head Injury Criterion) as shown in Eq.(1) and cumulative 3ms synthetic acceleration value to evaluate the impact strength and injury risk of the occupant's head in the collision process. Similarly, the score for the dummy's thorax is determined by measuring relevant dummy indicators, including the compression deformation and the viscosity criterion (VC). Among these, the compression deformation is more commonly used and emphasized in practical engineering applications; therefore, this study adopts chest compression as the primary evaluation metric for thoracic injury.

$$HIC_{15} = max\left\{(t_2 - t_1)\left[\frac{1}{t_2-t_1}\int_{t_1}^{t_2}\frac{a}{g}dt\right]^{2.5}\right\} \tag{1}$$

where a represents the head acceleration response value during the collision process; g is the gravitational acceleration; t1 and t2 are two moments during the collision process, with a maximum time interval of no more than 15ms, the significance of which is that the maximum value is obtained by the above HIC15 formula in a certain time interval under the condition that the time interval of t1 and t2 is no more than 15ms.

In addition to the above injury assessment indicators, as shown in Fig. 3 and Fig. 4, the head acceleration and thorax compression versus time curves can visualize occupant motion and injury, facilitate observation of dynamic response characteristics in a collision, and help identify potential injury risk factors, and are also used as data set parameters.

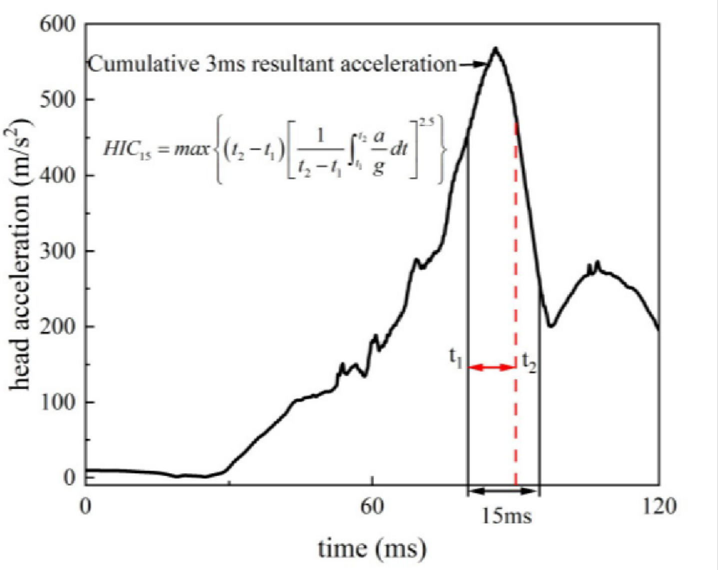


Fig. 3 Head acceleration-time curve.

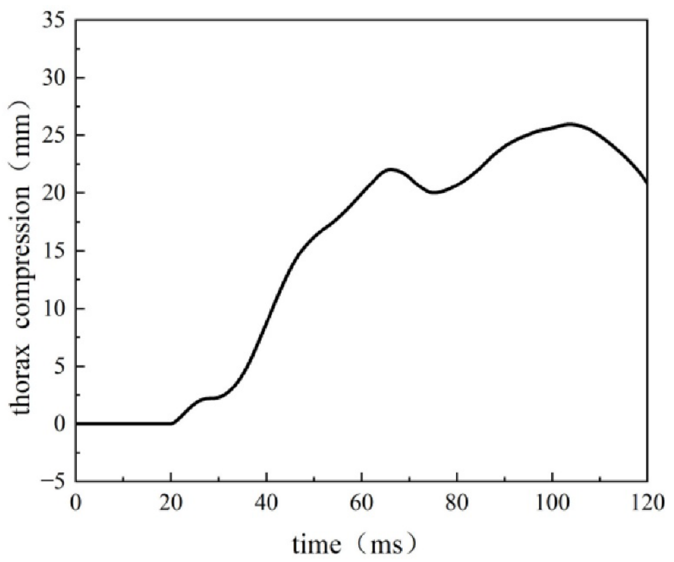


Fig. 4 Thorax compression-time curve.

3.1.2 Factors Affecting Occupant Injury Severity

The degree of occupant injury is influenced by various parameters in the entire system of the vehicle and occupant,including the crashworthiness of the vehicle, the parameters of the restraint system and the parameters of the human-machine layout of the vehicle's interior.

(1) Front crash pulse

During a frontal collision, the vehicle's front-end structure deforms to absorb impact energy and mitigate occupant injury, as shown in Fig. 5. The acceleration measured at the B-pillar is commonly used as a representative signal of crash severity and is typically referred to as the front crash pulse of a vehicle, which characterizes the dynamic loading conditions during frontal impacts. The front crash pulse, which reflects vehicle mass, energy absorption capacity, and structural stiffness, is strongly correlated with injury outcomes and varies across vehicle platforms. As shown in Fig. 5, the front crash pulse serves as comprehensive indicator of impact dynamics and are used as primary loading input in this study.

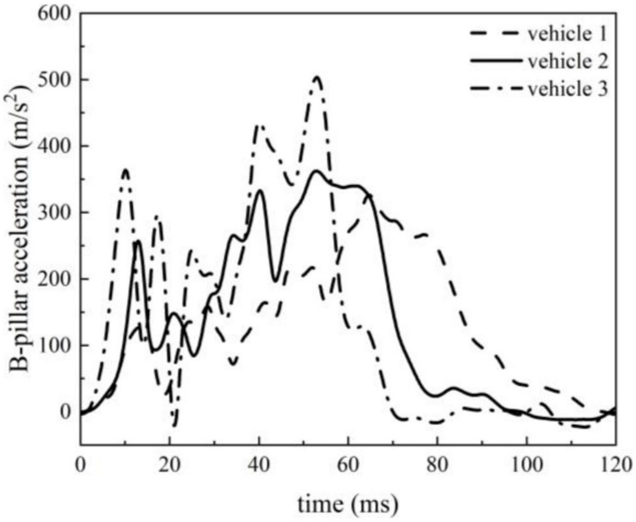


Fig. 5 Front crash pulse.

(2) ORS parameters

The ORS consists of multiple subsystems, including the seat belt, airbag, steering system, seat, and instrument panel, each involving parameters with different data modalities—numerical values, time-series curves, and images. To avoid redundant information and model overfitting, this study selects only those parameters that have high design sensitivity and a wide feasible range. The selected parameters and their formats are summarized in Table 1.

Table 1 The selected ORS parameters

parameters	expressions
Airbag time-to-fire (TTF) [ms]	value
Airbag vent hole diameter [mm]	value
Seatbelt force [N]	curve
Steering column collapse force-displacement curve	curve

3.2 Parameter Space and Dataset

To ensure both data scalability and modeling efficiency, this study utilized multi-rigid body simulations for data generation and dataset construction. The multi-rigid body model of the Toyota Camry is shown in Fig. 6. Fig. 6 has been rigorously validated in previous studies conducted by our research group. Its predictive reliability in occupant injury assessment has been demonstrated across various frontal crash conditions, and the results are shown in Fig. 7.

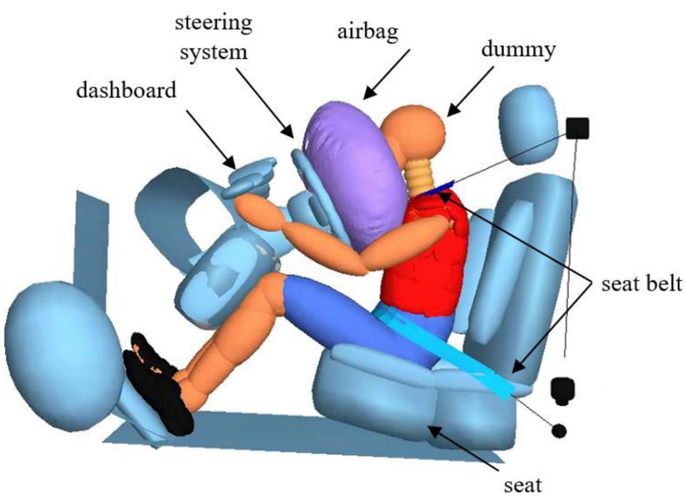
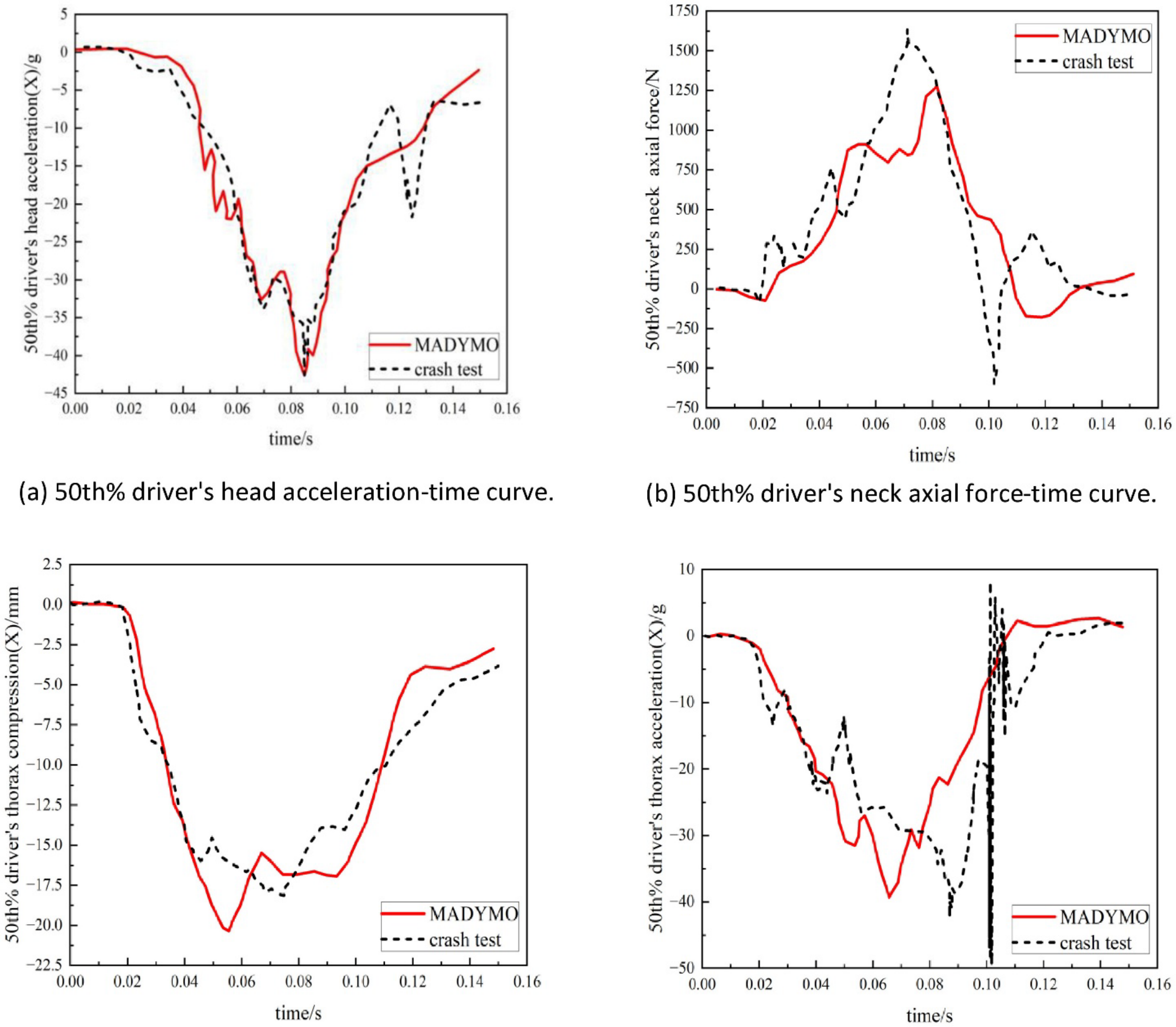


Fig. 6 The multi-rigid body model of the Toyota Camry



(a) 50th% driver's head acceleration-time curve. (b) 50th% driver's neck axial force-time curve.

(c)50th% driver's thorax acceleration-time curve. (d)50th% driver's thorax compression-time curve.

Fig. 7 driver's time-dependent biomechanical response curves between MADYMO and crash test.

Based on the established multi-rigid body model, a large number of samples were generated by systematically varying the input conditions. The input parameters were primarily categorized into two aspects: crash pulse characteristics and occupant restraint system (ORS) parameters. To ensure broad and uniform coverage of the multidimensional parameter space while maintaining statistical representativeness, Latin Hypercube Sampling (LHS) was applied. This approach yielded 750 unique input combinations, which were subsequently used to conduct multibody simulations, each producing a corresponding occupant response output. The considered parameters consist of the following two parts:

(1)Crash pulse:Due to variations in vehicle structure, mass distribution, and front-end stiffness, crash pulses differ significantly across vehicle platforms and directly influence the dynamics of energy transfer and structural deformation during a collision. In this study, crash pulses from 55 different vehicles obtained from Frontal Full Width Rigid Barrier Impact Test (FRB) were selected as input waveforms, as illustrated in Fig. 8.

(2)ORS parameters:Four key design-sensitive ORS parameters were selected based on their substantial influence on occupant injury outcomes. The parameters and their value ranges, summarized in Table 2, were determined through a combination of literature review and engineering practice. To enhance data diversity and ensure sufficient sample representation, interpolation techniques were applied within the defined ranges. It should be noted that while these ranges are tailored to the chosen vehicle platform and simulation settings, they may not be universally applicable to all vehicle configurations. Nevertheless, the constructed dataset provides a robust foundation for evaluating and validating the proposed ORS parameter design methodology.

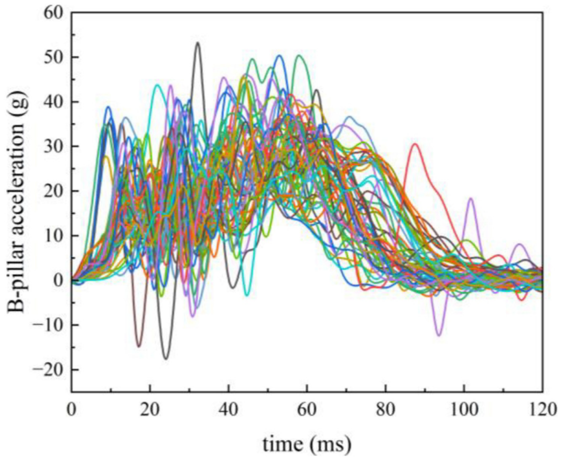


Fig. 8 Frontal crash pulses from 55 different vehicles.

Table 2 ORS parameter range.

parameters	Lower limit	Upper limit
Airbag time-to-fire (TTF) [ms]	13	30
Airbag vent hole diameter [mm]	30	70
Seatbelt force limiter [N]	2500	5000
Steering column collapse factor (normalized)	0.1	1.5

3.3 Data Preprocessing

To ensure that OIPM effectively interprets the input data, appropriate data representation and preprocessing steps were performed. In the dataset, the chosen ORS parameters were represented in the numerical form, while the crash pulses and occupant response curves were formatted as time-series data to capture the dynamic characteristics of the impact event. To improve the training and learning performance of the machine learning algorithm and eliminate the different order of magnitude differences between the model input and output parameters due to different sizes and units, data preprocessing operations were carried out on the original input and output parameters in the dataset. Specifically, the input and output parameters were normalized and scaled using minmax normalization technique. Moreover, due to unreasonable configurations of certain ORS parameter combinations, a small number of samples exhibited abnormal occupant responses, such as sudden data spikes or missing values as illustrated in Fig. 9. To address this, we conducted a detailed analysis of the head acceleration–time curve, focusing on peak values and overall trends, and subsequently removed these anomalous data points from the dataset to ensure the robustness and reliability of the training data.

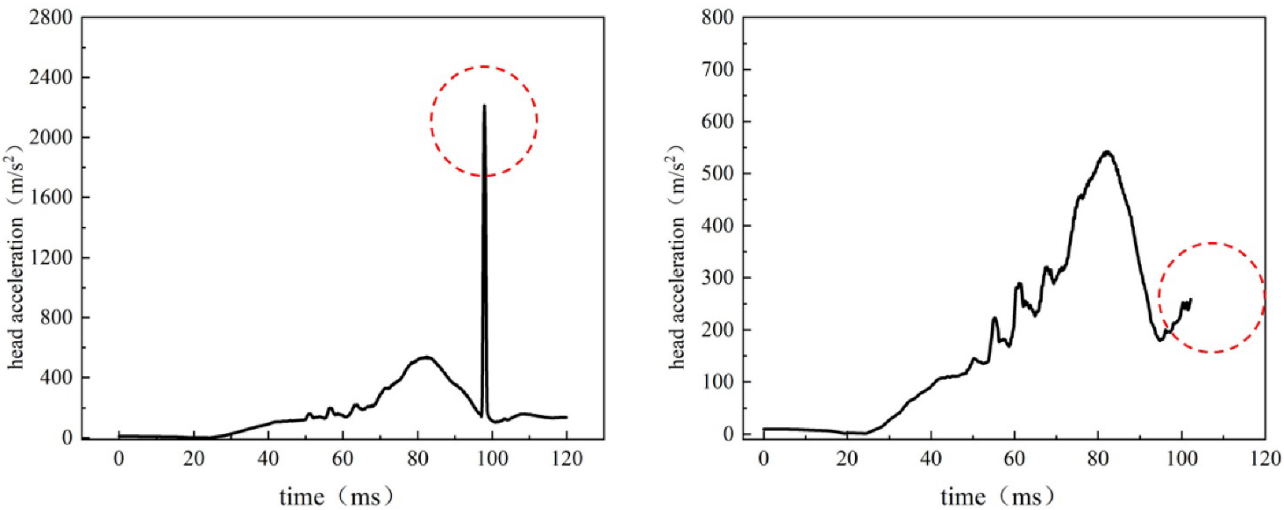


Fig. 9 Abnormal occupant response.

4. OCCUPANT INJURY PREDICTION MODEL (OIPM)

Occupant injury prediction is a crucial component in the design and optimization of occupant restraint systems (ORS). To enable rapid and accurate prediction of occupant injuries across multiple body regions during the vehicle design phase, this study integrates the mechanical characteristics of restraint system parameters and develops an occupant injury prediction model (OIPM) based on deep learning techniques.

4.1 Model Framework

The model is designed to predict multiple occupant responses and injury outcomes based on vehicle crash waveforms and occupant restraint system parameters, with both inputs and outputs containing time-series data. Recurrent neural networks (RNNs) possess short-term memory capabilities and have been widely used for time-series prediction tasks. However, standard RNNs often suffer from gradient vanishing or exploding problems as the sequence length increases. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks address these issues effectively by incorporating gating mechanisms. More recently, the Temporal Convolutional Network (TCN) has emerged as a powerful alternative, combining the strengths of both RNNs and Convolutional Neural Networks (CNNs). These four architectures (RNN, LSTM, GRU, and TCN) are extensively employed in time-series prediction across various engineering fields. For example, Wang etc. developed and compared three advanced deep learning models (TCN, LSTM, and Transformer) for near real-time prediction of injury severity in vehicle collisions, concluding that TCN outperformed the other models. Based on these findings, TCN was chosen as the modeling framework for this study.

To address the challenge that conventional TCN face in simultaneously processing time-series data and scalar numerical inputs, this study proposes a conditionally constrained encoder–decoder architecture named the Occupant Injury Prediction Model (OIPM), as illustrated in Fig. 10. In this architecture, the TCN serves as the encoder, effectively extracting temporal features from the crash waveform data. Meanwhile, key occupant restraint system (ORS) parameters are incorporated into the model as conditional variables to represent the mechanical characteristics of the restraint system. In the decoding phase, a dual-branch architecture is adopted, wherein each branch is responsible for predicting dynamic occupant responses of distinct body regions (i.e. head acceleration-time curve and thorax compression-time curves). By combining the time-series modeling capability of the TCN with conditional embeddings of scalar ORS parameters, the proposed architecture enables more comprehensive and simultaneous prediction of multiple injury indicators, which is critical for the efficient design and evaluation of occupant restraint systems.

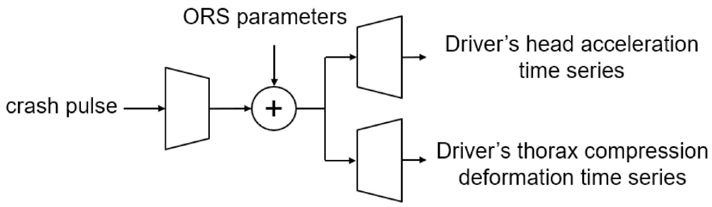


Fig. 10 OIPM framework.

4.2 Performance Metrics

This study evaluates the model performance by assessing both occupant dynamic responses (expressed as time-series data) and injury assessment indicators (expressed as scalar numerical values). Given the multi-modal nature of the data, different evaluation strategies were employed for time-series and scalar outputs:

1) For time-series data (e.g., head acceleration–time curves), evaluation was performed in accordance with the ISO/TS 18571 standard. This method decomposes the total crash pulse error into four components: corridor error, phase error, magnitude error, and morphology error. A weighted composite score E is then computed to quantify the overall similarity between the predicted and target curves. The evaluation framework of ISO/TS 18571 is illustrated in Fig. 11.

2) For scalar injury metrics (e.g., HIC15, 3 ms acceleration), model performance was quantified using Root Mean Squared Error (RMSE) and prediction accuracy. These metrics are defined as follows:

$$RMSE = \sqrt{MSE} = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{n}} \tag{2}$$

$$accuracy = 1 - \frac{100\%}{n} * MAE = 1 - \frac{100\%}{n} * \frac{\sum|y_i - \hat{y}_i|}{y_i} \tag{3}$$

where, y_i denotes the real value , $\hat{y}_i$ denotes the predicted value obtained by the ORS-PDM, and n denotes the number of samples in the dataset.

This dual evaluation strategy ensures that both the temporal accuracy and numerical precision of the model are thoroughly assessed, which is essential for validating its effectiveness in occupant injury prediction applications.

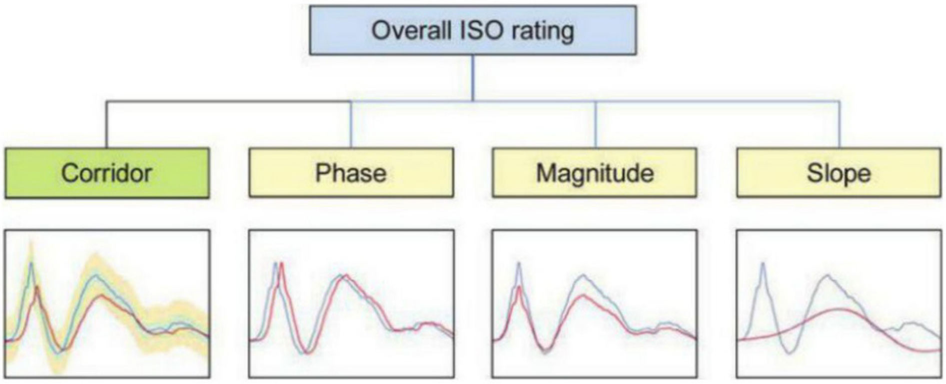


Fig. 11 ISO/TS 18571.

4.3 Tuning of Hyperparameters

The performance and accuracy of the OIPM are highly dependent on the appropriate configuration of hyperparameters. In this study, the core architecture of the OIPM consists of a Temporal Convolutional Network (TCN) for temporal feature extraction and a Multi-Layer Perceptron (MLP) for regression output. The TCN is constructed using a stack of dilated causal convolution layers, which enables the network to capture long-range temporal dependencies across different time scales by adjusting the dilation rates.

To ensure optimal model performance, several key hyperparameters were systematically tuned and evaluated, including the number of convolutional filters (kernels), the depth of the network (i.e., the number of hidden layers), and the number of neural units per layer. A grid search strategy was employed to explore the influence of these parameters on model accuracy and generalization capability. In the final configuration, the TCN module is constructed with 4 hidden layers, each comprising 100 units. A convolution kernel size of 5 is used, with a dropout rate of 0.25. The learning rate is initialized at 0.0001, and a gradient decay rate of 0.001 is applied.

4.4 K-fold cross-validation

The trained performance of the model depends largely on the data distribution of the training and validation sets. To avoid the incomplete evaluation of the model prediction accuracy due to the randomness and chance of the dataset division, and to make full use of all the data in the sample dataset, the five-fold cross-validation method was used for ORS-PDM training in this study, as shown in Fig. 12. In each iteration, the dataset was divided into training and testing sets in an 80%-20% proportion.

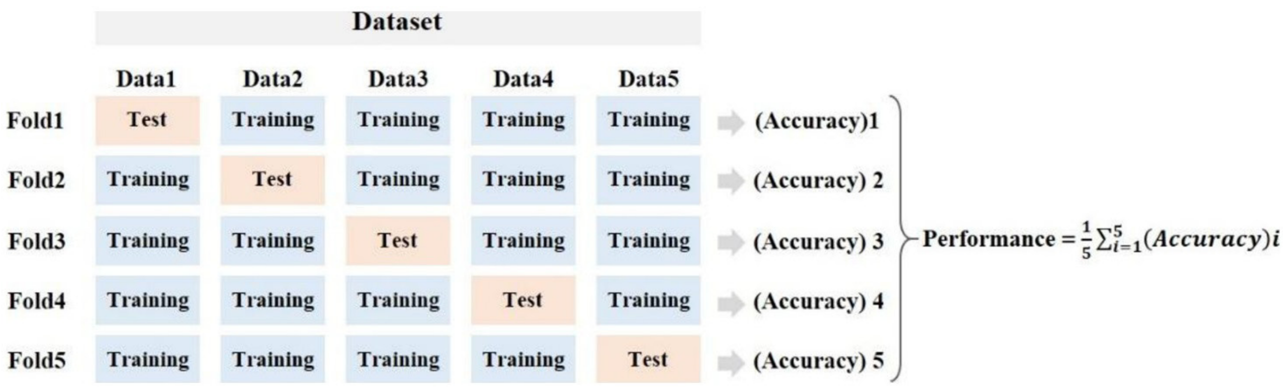


Fig. 12 Five-fold cross-validation.

5. PERFORMANCE EVALUATION AND APPLICATION OF THE OIPM

5.1 Prediction Results of the OIPM

The deep learning model OIPM was constructed based on the TCN architecture and trained using the prepared training dataset. The final model is capable of simultaneously predicting occupant injuries to both the head and thorax regions. To evaluate the prediction performance of the model, the validation dataset was used. The predicted head acceleration–time curves for four representative samples are shown in Fig. 13, while the corresponding thorax compression–time curves are presented in Fig. 14. As observed, the OIPM model is able to capture the overall dynamic trends of the time-series responses, with the predicted curves closely matching the ground truth in both curve shape and timing of the peak values. These results demonstrate the model's ability to learn the essential patterns of occupant responses. Quantitative comparisons between the true and predicted values for several key injury metrics in C-NCAP (2024) are summarized in Table 3. The results indicate that the OIPM model achieves high prediction accuracy across all selected samples.

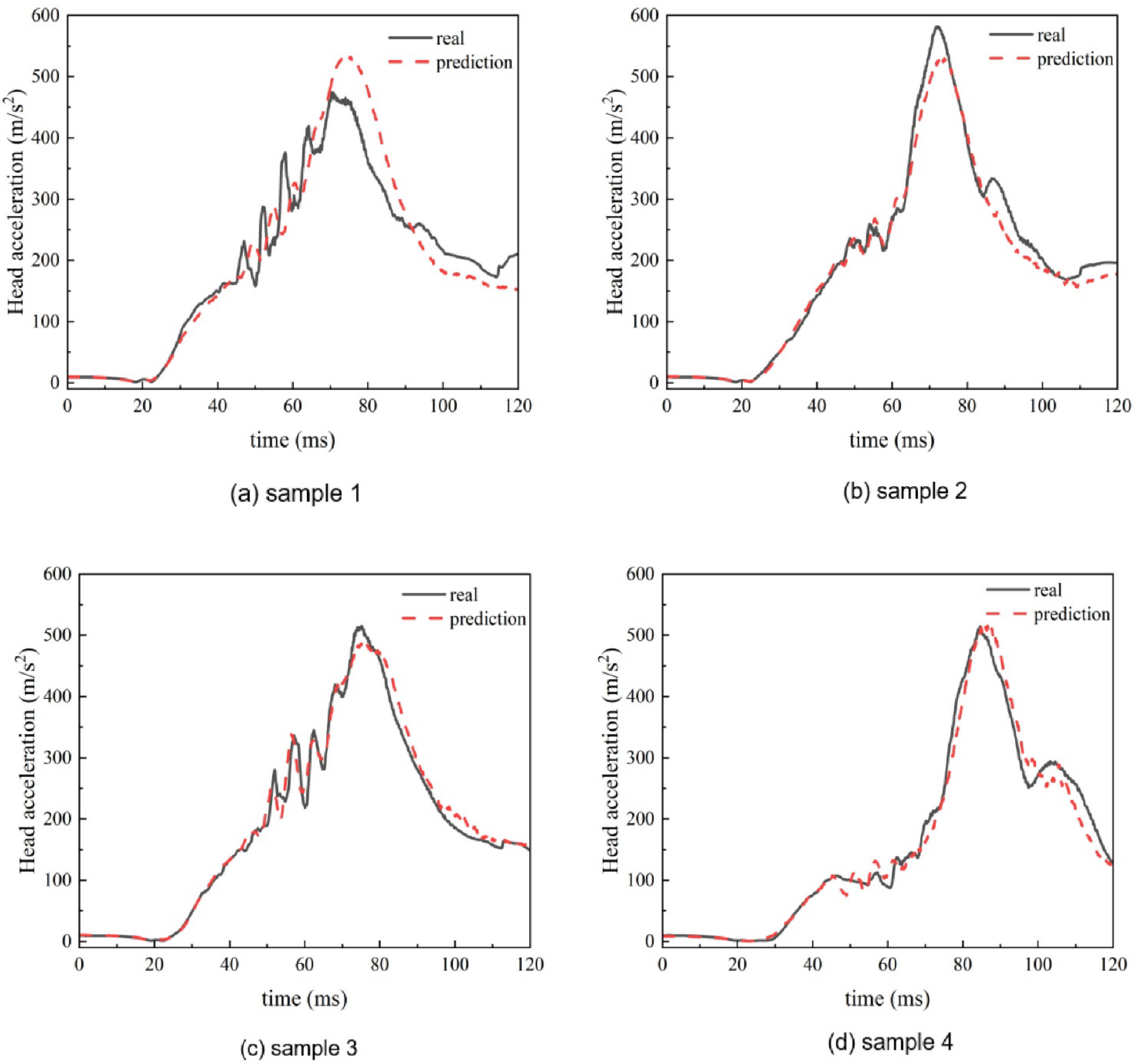


Fig. 13 Head acceleration–time curves for four representative samples.

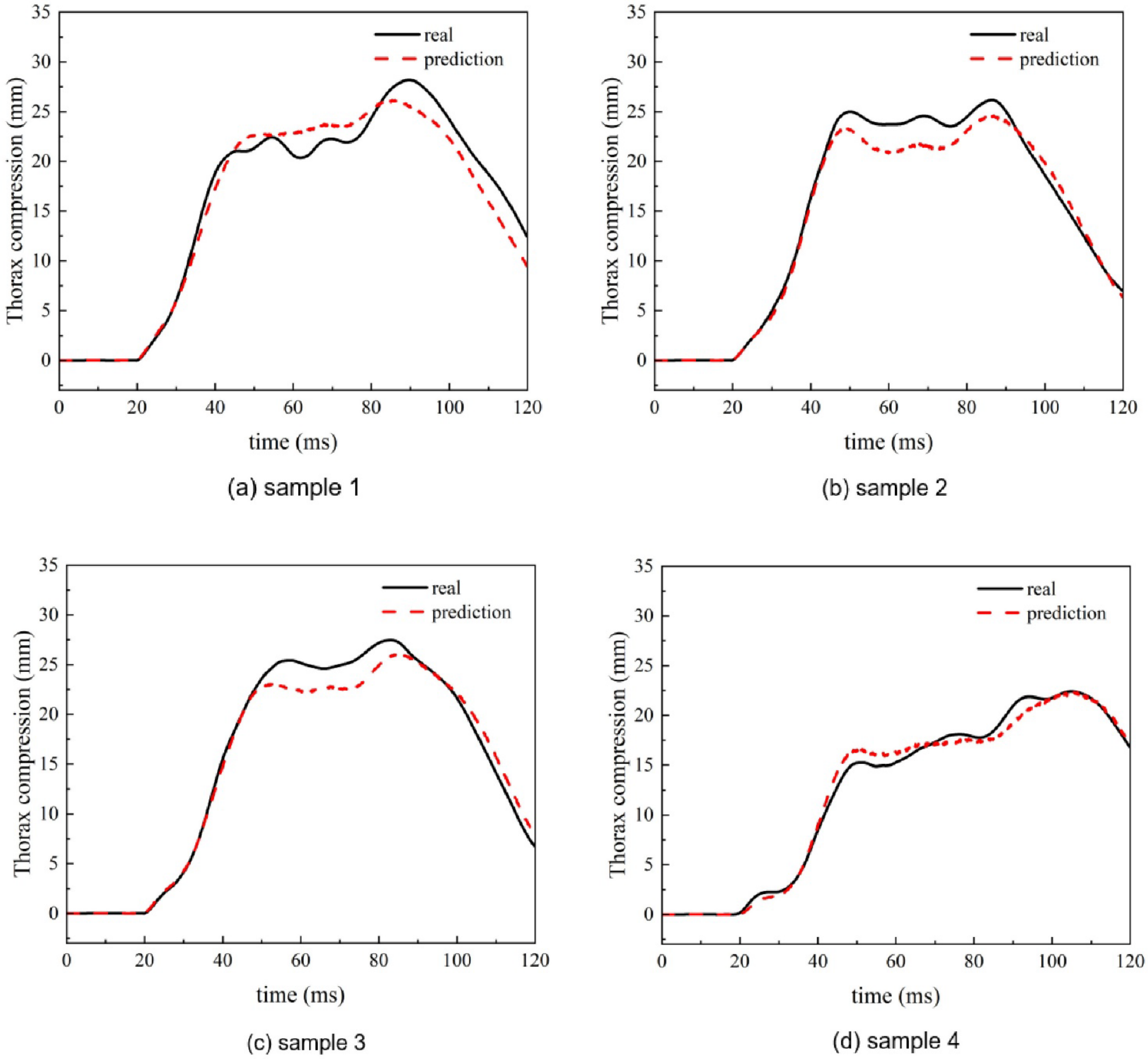


Fig. 14 Thorax compression–time curves for four representative samples.

Table 3 Indicators for four representative samples.

sample	HIC15		Cumulative 3ms resultant acceleration		E-head	thorax compression		E-thorax
	true	prediction	true	prediction		true	prediction	
1	189.4	274.99	474.2	533.07	0.8571	28.17	26.34	0.9367
2	279.37	267.05	582.03	550.92	0.9134	26.16	25.05	0.9121
3	223.1	212.78	515.36	472.29	0.923	27.46	25.59	0.9166
4	213.75	214.45	514.59	520.00	0.8988	22.41	22.92	0.8735

5.2 Generalization and Stability Assessment of OIPM

In order to judge the generalization ability and stability of the occupant injury prediction model, this study adopts the method of 5-fold cross-validation for model training. In this process, the dataset was randomly divided into five equal parts. For each iteration, one part was used as the validation set and the remaining four parts were used for training. This approach allows the model's predictive performance to be assessed across diverse data partitions and avoids bias from a single train-test split.

The prediction results of each validation set are shown in Table 4, the design effect of cross-validation at each fold is different, indicating that the dataset has an impact on the model. However, the variations in the results across different folds for each indicator are minimal, indicating that the model exhibits high stability across different datasets.

Table 4 5-fold cross-validation results of OIPM.

k-fold	HIC15		Cumulative 3ms resultant acceleration		E-head	compression		E-thorax
	accuracy	RMSE	accuracy	RMSE		accuracy	RMSE	
K1	0.8039	85.34	0.8957	85.81	0.8787	0.9539	1.58	0.9189
K2	0.8159	80.89	0.8910	96.24	0.8761	0.9553	1.51	0.9263
K3	0.8095	75.02	0.9017	78.51	0.8739	0.9493	1.64	0.9195
K4	0.8109	83.76	0.8966	80.11	0.8663	0.9552	1.48	0.9139
K5	0.7823	82.73	0.8651	102.92	0.8431	0.9440	1.78	0.9245
average	0.8045	81.15	0.8900	88.72	0.8676	0.9515	1.60	0.9206

5.3 Application Example

The OIPM model is capable of predicting occupant injuries across different body regions for various vehicle types in Frontal Full Width Rigid Barrier Impact Test (FRB) rapidly. To illustrate its practical applicability, this section presents an application example using Vehicle A, which is a vehicle under development in an actual design project. The design and optimization of Vehicle A were previously validated through finite element (FE) simulations. Before the occupant restraint system parameter design, the crash pulse of the vehicle had already been obtained through finite element (FE) simulations, as shown in Fig. 15. The associated occupant restraint system parameters for this case were as follows:

Airbag vent hole diameter: 54 mm; Airbag time-to-fire (TTF): 19 ms; Seatbelt force limiter: 4500 N; Steering column collapse factor: 1.2

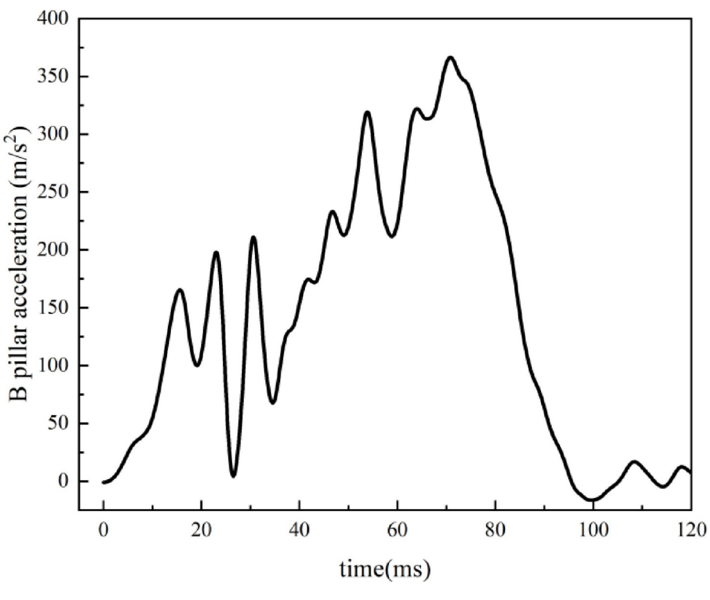


Fig. 15 Crash pulse of vehicle A.

Using the above inputs, occupant injury prediction was performed with both multi-rigid body software MADYMO and the proposed OIPM model. The computational time required for MADYMO was 24 minutes, whereas the OIPM model generated results within 2.7 seconds, highlighting its superior efficiency. The injury assessment indicators obtained from both methods are summarized in Table 5, and the corresponding head acceleration – time curves and thorax compression - time curves are illustrated in Fig. 16 and Fig. 17. The comparison shows that the OIPM model achieves highly consistent predictions with MADYMO across all evaluated indicators.

The results demonstrate that the OIPM model can provide accurate and efficient injury predictions, with errors in key indicators such as HIC15 and thorax compression maintained within acceptable margins. Furthermore, the prediction curves closely match those generated by the validated MADYMO model, confirming the reliability of OIPM in practical engineering applications. This case study highlights the potential of OIPM as a real-time decision-support tool during the occupant restraint system design phase.

Table 5 Indicators of Vehicle A obtained from MADYMO and OIPM.

indicators	MADYMO	OIPM	accuracy
HIC15	259.82	256.27	0.9863
Cumulative 3ms resultant acceleration	555.21	533.88	0.9616
E-head	——	——	0.8908
Thorax compression	27.22	25.53	0.9379
E-thorax	——	——	0.9288
Time consumption	24 min	2.7s	

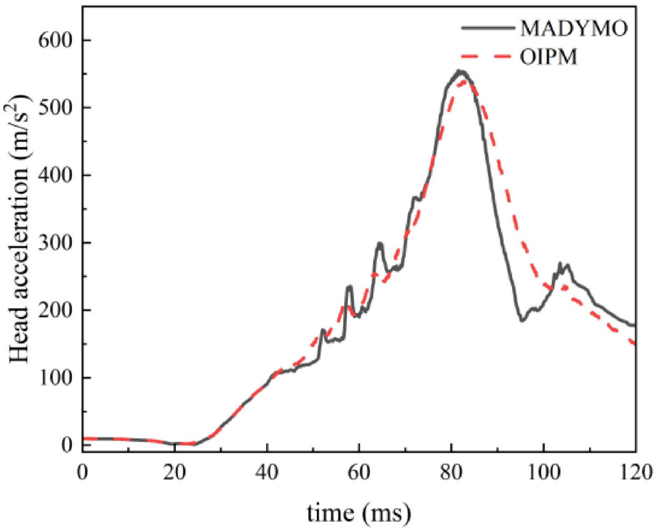


Fig. 16 Head acceleration – time curve of Vehicle A obtained from MADYMO and OIPM.

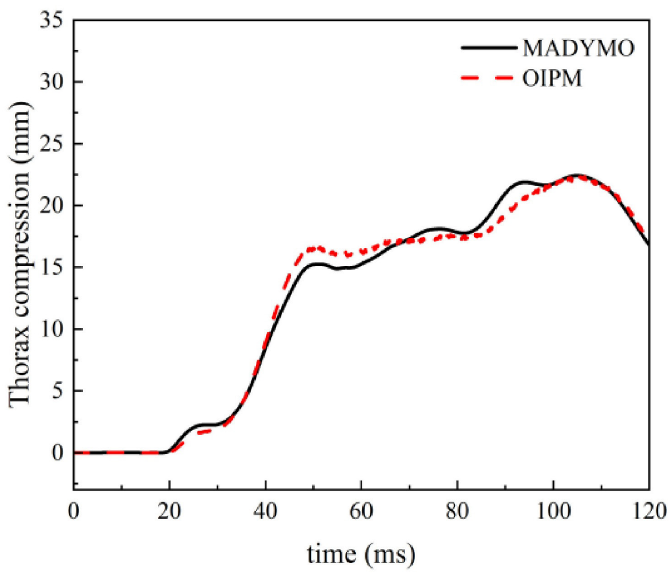


Fig. 17 Thorax compression– time curve of Vehicle A obtained from MADYMO and OIPM.

6. CONCLUSIONS

To enhance the efficiency of occupant restraint system (ORS) design, this study proposed a deep learning-based occupant injury prediction method that effectively captures the coupled effects of crash pulse waveforms and ORS parameters on occupant injury outcomes. The proposed occupant injury prediction model (OIPM) demonstrates promising performance in terms of both predictive accuracy and computational speed. The key contributions of this study are summarized as follows:

(1) The proposed method is oriented toward ORS design and explicitly incorporates the mechanical characteristics of restraint components. A hybrid prediction framework was established, enabling rapid occupant injury prediction. The OIPM can generate predictions within 2.7s, and the prediction accuracy of each indicator exceeds 0.8.

(2) The model allows for the simultaneous prediction of multiple site-specific occupant responses (e.g., head acceleration time series, chest deflection time series) and corresponding injury assessment indices (e.g., HIC15), enabling comprehensive injury evaluation within a unified framework.

While the proposed method demonstrates strong prediction accuracy, some potential limitations should be considered. The ORS parameters selected for this study focus on key parameters that are highly sensitive and easy to adjust, so they are limited in number and form and need to be continued to be refined. In addition, the stability of the trained model may be affected by the different vehicle types, and the model's generalization to novel designs or new test conditions, such as different dummy, MPDB, remains unvalidated. Therefore, the model needs to be further refined and evaluated when new types of data are required.

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